Three Essays in Pricing Asset Characteristics

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Abstract

This dissertation contains three essays on the non-pecuniary preferences pertaining to financial asset characteristics and their implications for asset pricing. The first essay considers the pricing implications of screens adopted by socially responsible investors. A model including such investors reconciles the empirically observed risk-adjusted sin-stock abnormal return with a systematic "boycott risk premium" which has a substantial financial impact that is, however, not limited to the targeted firms. The boycott effect cannot be displaced by litigation risk, a neglect effect, and liquidity considerations, or by industry momentum and concentration. The boycott risk factor is valuable in explaining cross-sectional differences in mean returns across industries and its premium varies directly with the relative wealth of socially responsible investors and with the business cycle.

The second essay generalizes Fama (1996)'s concept of Multi-Factor Efficiency without being limited by additional random state variables that must affect future investment opportunities. Incorporating non-pecuniary preferences into a representative investor's utility function generates multi-factor pricing implications. A representative investor chooses among expected returns, variances, and levels of characteristics according to their taste, which gives rise to an N-fund separation theorem with static characteristics. If a portfolio is built to maximize the exposure to the asset characteristics, the covariance between asset returns and this portfolio returns will be identical to the underlying characteristics. Such identity makes obsolete any attempts to distinguish between characteristics and

risk exposures as the driving forces behind the cross-sectional variation in stock returns.

The third essay develops a procedure for deriving systematic factors from characteristics, based on maximizing each factor's exposure to a characteristic subject to a given level of factor variance. The resulting characteristic-mimicking portfolios (CMP) price mean asset returns identically as the original characteristics, irrespective of the underlying model. Accordingly, differences in the performance of mimicking factors and characteristics in explaining mean returns should be interpreted as an artifact of arbitrary procedural choices for generating mimicking factors. Factors and characteristics may be distinguished usefully only by determining if CMPs have significant explanatory power for the time series of returns.

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Contents

Chapter One: Introduction

This dissertation clarifies the role of characteristics in comparison to risk factor loadings in explaining the cross-sectional differences in asset returns.

The first essay is empirically motivated by the recent social divestment movement regarding "sin" stocks - the stocks issued by firms engaged in socially or morally objectionable activities – have sizable abnormal positive returns (documented by Fabozzi, Ma and Oliphant (2008), Hong and Kacperczyk (2009), and others). Existing explanations view sin stocks as characterized by litigation risk, illiquidity, and neglect, aspects that raise average returns. In contrast, we view the act of voluntarily abstaining from investing in certain undervalued stocks for non-financial reasons as practically boycotting these stocks. Translating this investment phenomenon into a formal model, this essay builds on earlier work concerning segmentation in the investor base of Errunza and Losq (1985) and Merton (1987).

In a partial equilibrium framework, we model two groups of representative investors: the arbitrageurs and self-restricted investors who voluntarily refrain from investing in certain stocks with characteristics that are distasteful to them, implying reduced investment opportunities. This violation of the standard identical investment opportunities assumption in the standard Capital Asset Pricing Model gives rise to an additional systematic risk factor – an investment boycott risk factor, supplementing the traditional market factor. Given that publicly traded sin stocks exist, the market clearing condition forces arbitrageurs to overweight sin stocks compared to a typical market portfolio while restricted investors have to hold more non-sin stocks relative to the market, however, with heavier weights on non-sin stocks that have the highest correlation to the stocks which they boycott. These overweighed stocks in restricted investors' portfolio are exactly underweighted by arbitrageurs. This is a win-win situation for both types of investors when restricted investors insist on boycotting the sin stocks regardless of the pecuniary losses. To acquire sin stocks, unrestricted investors have to sell some stocks and use the proceeds to buy sin stocks. For arbitrageurs, selling these stocks that resemble sin stocks in terms of return variation minimizes the impact of carrying these extra sin stocks relative to the theoretical market portfolio. In the meantime, these stocks are the closest and eligible substitutes for the restricted investors, causing these stocks to be overrepresented in restricted investors' optimal portfolios. The swap between sin stocks and their non-sin stock substitutes in two representative investors' portfolios results in two separate optimal portfolios for each type of investor, which jointly determine the conventional market portfolio. As long as there is a fraction of wealth represented by self-restricted investors, the market portfolio will always deviate from the arbitrageurs' optimal portfolio, which would give the highest Shape ratio and theoretically would price all the assets if self-restricted investors did not exit. Therefore, the non-pecuniary preference caused by boycotting sin stocks makes the market portfolio fail to price assets.

Our model decomposes the unobservable unrestricted investors' optimal portfolio into two alternative observable portfolios, the market and the boycotted portfolio. Consistent with the theory, the boycott portfolio is a zero-investment portfolio of sin stocks hedged to remove the common variation with the remainder of the market. The selection of boycotted sin stocks are based on common social screens imposed by norm-constrained investors (Hong and Kacperzyk 2009, Liston and Soydemir 2010, etc.). We present the results with two sets of boycott factors proxies: the narrow boycott factor consisting of tobacco, alcohol and coal industry firms and the broad boycott factor containing also additional fossil fuel industries.

The boycott factor prices assets well in the cross section. First, the estimated boycott risk premium of 1.33% per month is close to the average of realized boycott factor returns and other documented sin-stock premium (Fabozzi, Ma and Oliphant (2008)). Second, this boycott premium is always positive as suggested by the model to lure unrestricted investors to deviate from their optimal portfolios that would otherwise be the market portfolio when there was no investment boycott. Third, the loadings on boycott factor contribute almost an additional 50% of explained variation in addition to the market betas in explaining the cross sectional variation of industry portfolio returns. Fourth, the cross-sectional intercept, which would have otherwise been considered as sin-stock abnormal returns, is reduced by 0.70% per month to almost zero and become statistically insignificant. These results are generally in dependent of the choice of test assets, imposed social screens, and robust for the time period when socially responsible investments were less formal and less prevalent.

Furthermore, the essay challenges the existing characteristic-based explanations on sin-stock abnormal returns by the systematic boycott risk explanations. We show that despite the good pricing ability of the neglect effect proxied by analyst coverage, illiquidity risk originated from the lack of investor base, litigation risk measured by the number of legal settlements, industry momentum, and competition intensity, the boycott factor loadings still dominate alternative existing characteristic-based measures[1]. We show that stocks with clearly no sin characteristics, nevertheless, earn a boycott risk premium if their returns correlated with sin stocks. A zero-investment portfolio formed on non-sin stocks' sensitivities to the boycott factor loadings can generate 5% annualized abnormal returns. These sensitivities are caused by payoff covariance with the payoffs of boycotted industries regardless of whether these companies are affiliated with the sin industries.

Lastly, we confirm the model prediction that the boycott risk premium is driven by the relative wealth represented by the self-restricted investors relative to arbitrageurs. Given that the average returns of sin stocks are higher, refraining from sin stocks is more costly when the marginal utility of wealth is higher, which is typically accompanied by economic downtowns. Empirically, we show that

[1] The boycott factor is a portfolio of sin stocks financed by shorting the portfolio of non-sin stocks that has the highest possible return correlation with the sin stock portfolio. This zero-investment portfolio is derived in the segmented investor base model in Chapter 2. It should not be confused with the characteristic-mimicking portfolio that is designed to capture maximum exposure to the underlying degree of sinfulness derived in Chapter 3.

more capital is committed to boycotting sin stocks during economic booms even when the boycott risk premium is higher.

Overall, this essay shows that non-pecuniary preferences pertaining to the moral content of the underlying activities financed by investment in their securities have pervasive pricing effects that are not limited to the boycotted stocks.

Intrigued by the finding of the pricing pervasiveness of non-pecuniary preferences on assets, in the second essay we add preference for characteristics directly into an investor's utility. This additional dimension in a utility function leads to a similar interpretation of adding a source of risk, however, without requiring original characteristics to be stochastic. As long as a representative investor cares about certain characteristics of the assets, there will be a risk premium compensating these characteristics. This means that the conventional market betas no longer suffice to explain the expected returns even when the investor's portfolio is still mean-variance efficient. A representative investor will not take on more variance unless she is rewarded by either higher return or some particular characteristics of her preference. The former is the mean-variance framework while the later was the generalization of Fama (1996). However, instead of requiring an additional state variable that affects the marginal utility of wealth as in Merton (1973), characteristics can directly be interpreted as an additional systematic risk factor if the associated characteristics-mimicking portfolios explain more time-series variation than an equal number of random portfolios. Therefore, an identical boycott factor as in the first essay will also arise in an exact fashion without involving separately modeling two types of investors. The boycott factor and market factor will not only form a mean-variance frontier, they will also form the multifactor efficient frontier which gives a representative investor the optimal tradeoff among average return, variance, and the level of acceptable sin content in her optimal portfolio. Unlike the sign of the premium for a state-variable risk which is ambiguous in Merton (1973), the sign of the risk premium associated with a particular characteristic is determined by whether a representative investor derives positive or negative marginal utility from increasing exposure to this characteristic in the optimal portfolio.

We formalize this concept in the framework of Fama (1996). Rather than imposing a given level of exposure to a certain state variable, we replace this exposure by a predetermined level of exposure to a characteristic for a representative investor. This yields to an optimal portfolio being a linear combination of two frontier portfolios -- the standard tangency portfolio and a characteristic-mimicking portfolio (CMP). Therefore, once allowing investors to care about certain characteristics associated with assets, the simple two-fund separation has to be replaced by an N-fund separation theorem without, however, imposing additional randomness on future investment opportunities. While this finding generalizes Fama's concept of Multi-factor Efficiency, it renders any attempt to distinguish the covariance with risk factors and their underlying characteristics for explaining the variation in asset returns, which leads us to the third essay on how we can circumvent this issue.

The third essay in Chapter 4 shows that when a portfolio is formed to maximize the exposure to a certain characteristic of an agent's interest – that is, a characteristic mimicking portfolio – both the characteristic and the covariance with this CMP will price the assets equally in the cross section. The identical pricing ability of characteristics and covariance with the CMP makes obsolete any attempts to argue which better explains the average asset returns. Evidence of characteristics driving out their factor loading counterparts or vice versa (Jagannathan and Wang, 1996) is merely a statistical fluke in the cross section even when factor loadings or characteristics are theoretically motivated. CMPs offer a potential solution to circumvent the indistinguishable nature of characteristics and their counterpart, covariance risk.

Instead of focusing exclusively on traditional second-pass statistical measures prescribed in Lewellen, Nagel and Shanken (2010) and the joint statistical significance of first-pass alphas (Gibbson, Ross, and Shanken, 1989), we explore the often ignored criteria in the literature by measuring the reduction in idiosyncratic risk. In a characteristic model, since there is no randomness in characteristics, return shocks are total shocks. Whereas, in a characteristic-mimicking factor model, return shocks can be partially absorbed by the randomness offered by realized asset returns. We evaluate if a CMP, like any other time-series factor, can significantly reduce the error variance in realized returns, whereas a model with characteristic alone cannot offer any reduction in time-series variance because of its constant impact on returns, which naturally serves as our null hypothesis.

The reduction in error variance of asset returns can be identically measured by three methods when the factors are CMPs: First, from the variance-weighted average time-series R-squared of regressing asset returns on CMPs. Second, from the total variance of the CMPs based on the portfolio shares of the CMPs as a fraction of the total asset return variations. Third, from the total variance of the CMPs based on the original characteristics of the CMPs as a fraction of the total asset return variations.

As an informal guide, we use the eigenvalues to identify the potential number of factors that should have significant explanatory power for different test assets. Cautioned by LNS and as evidenced by the steep descending of eigenvalues, assets with strong factor structure, such as the famous Fama-French 25 size and value sorted portfolios, with little room for potential factors other than the market, size and value factors are only used as secondary evidence. Our tests focus more extensively on Fama-French industry portfolios, which are not presorted based on any chosen characteristics.

While recognizing that any tradable factors may explain fractions of return variance purely by chance, we pose the question – can a CMP explain a larger fraction of variance than what is expected by chance? To answer this question, we compare the actual R2 generated by [2] or [3] to a critical value constructed by randomly permuting either the characteristics or the CMP shares cross-sectionally across the assets. This “bootstrapping” approach allows the simulations to be independent of the distributions of the characteristics or the weights associated with CMPs, thus avoiding matching distribution parameters of different candidate characteristics or factor shares. If the actual R2 is smaller than the simulated critical values, we cannot reject the null hypothesis that this factor does not reduce the error variance, the underlying characteristic is better viewed as a characteristic even if this factor explains the asset mean variations well. Therefore, following Pukthuanthong and Roll (2014), for a factor to be considered as a pervasive risk factor, it not only needs to explain the cross-sectional variation well but also reduce total return variation in time-series more than random factors do.

Prior to implementing the test, we verify the potential bias of our simulation methods between [2] and [3]. For a given asset return covariance matrix, characteristics and their corresponding CMP shares are functions of each other, which leads to four ways of simulations with two ways of permuting either characteristics or CMP shares. However, the size test suggests that it is only appropriate to permute CMP when characteristics are exogenously given and permute factor shares when factor shares are exogenously given. Only in these two scenarios, the empirical rejection probability is close to nominal rejection probability. The remaining scenarios will always lead to either falsely reject or never reject null hypotheses. To level the comparative footing between CMPs and exogenous factors, we augment all exogenous factors into the test assets.

Armed with the unbiased testing device, we subject the Fama-French three factors and the size- and value-characteristic mimicking portfolios to the question -- can these factors individually or/and jointly reduce error variance more than random factors do? In the single-factor tests, the market factor stands out to be the only systematic factor that explains more time-series variations than 95% of randomly simulated challenging factors whereas the results for other remaining factors are mixed. After removing the variation explained by the market, we compare the marginal contribution of the remaining factors. Yet, the remaining factors do not provide convincing evidence that they should be viewed as systematic risk factors. Overall, our test suggests that the market factor can be unequivocally viewed as a systematic risk factor while the statistical evidence on the remaining factors is inconclusive.

The factors investigated in the third essay are for an illustrative purpose. The essay in its current form serves as a springboard to investigate otherwise indistinguishable differences between covariance risks and characteristics in explaining the cross-sectional variation of asset returns. Given the fairness of the test demonstrated in the empirical and normal size comparison and provided that there are already 113 proclaimed systematic factors and 212 characteristics (Harvey, Liu, and Zhu, 2015), the approach has a large scope for future research.

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Chapter Two: *Social Screens and Systematic Investor Boycott Risk*

1. Introduction

This paper evaluates the extent to which average expected stock return differences across industries may be attributed to a "boycott" risk premium. We derive a testable two-factor asset pricing model based on the assumption that morally guided investors are self-restricted from investing in controversial stocks. Formally the model supplements the segmented investor base frameworks of Errunza and Losq (1985) and Merton (1987), and empirically we are motivated by the frequently observed abnormal sin-stock returns (e.g., Fabozzi, Ma and Oliphant, 2008; Hong and Kacperczyk, 2009; Statman and Glushkov, 2009; Salaber, 2009).

The boycott factor is derived as a systematic risk factor supplementing the conventional market factor. The additional risk dimension arises from the non-pecuniary preferences of a group of investors regarding a set of boycotted assets. "Arbitrage" by traditional investors exclusively interested in the pecuniary aspects calls for these investors to overweight boycotted assets in their portfolios, requiring a larger compensation for risk. The model explains the commonly observed sin stock return premium as resulting from the systematic boycott risk premium. The degree of "mispricing" is captured by a stock's sensitivity to the boycott risk factor. The pricing errors of any stocks, not only sin stocks, may be reduced by the systematic boycott risk factor: the boycott of particular stocks extends to other stocks whose returns happen to be positively correlated with boycotted stocks (for instance stocks of firms that employ similar inputs or produce substitute products).

The model shows that the boycott risk premium is always positive, with the magnitude of the premium determined by the proportional amount of financial capital represented in the group of morally constrained investors. Empirically, we compare the boycott risk premium through time, across periods during which norm-constrained institutions enhance the impact of moral constraints, and periods in which boycotting is mostly a private statement.

Following the prescriptions of Lewellen, Nagel, and Shanken (2010) in using the two-stage cross-sectional regression method, our boycott-augmented CAPM model dominates alternative models such as the CAPM, the Fama-French three-factor model (Fama and French, 1993), and the Carhart four-factor model (Carhart, 1997). We find robust pricing of a boycott risk premium across different industry-based test assets. The boycott risk premium is mostly quite similar across test assets.

Our paper supplements the existing literature on the financial impact of boycotts in two directions. First, we study the financial impact of extensive industry-wide boycotts as opposed to the individual-event-driven boycotts examined by Teoh, Welch, and Wazzan (1999). Second, besides explaining the superior performance of the so-called sin stocks relative to regular stocks, our model allows us to clarify the financial impact of boycotts on all stocks, including non-sin stocks.

2. Some Stylized Facts Concerning Boycotted Industries

Most boycotted industries fall into the category of “sin” industries. Depending on the definition of sin and the cultural or legal context of these sin industries, research reveals the following common features of sin firms.

Risk-Adjusted Returns of Boycotted Stocks

The majority of studies on the topic of sin stocks focus on sin-stock or Vice-Fund performance relative to other traditional benchmarks. Utilizing sin-firm data from 1970 to 2007, Fabozzi, Ma and Oliphant (2008) (FMO hereafter) show that on average a portfolio of sin stocks produces an annual return of 19.02 percent, while the average market return is only 7.87 percent annualized.[2] Hong and Kacperczyk (2009) (HK hereafter), using time series regressions for the sample period 1965-2006, hold a portfolio of sin stocks and sell short a portfolio of non-sin stocks. This strategy produces abnormal returns of 26 basis points per month. In a cross-sectional regression, after accounting for market size, past return and market-to-book ratio, they find that sin stocks outperform comparable stocks by 29 basis points per month. Statman and Glushkov (2009) construct a reverse sin portfolio, "accepted minus shunned", revised annually over the period 1991-2007. They find that this portfolio has a negative 2.6 percent annualized excess return by the Fama-French three-factor benchmarks; and a negative 3.3 percent annualized excess return by the CAPM benchmark. Other anecdotal evidence regarding positive abnormal returns for sin stocks includes Lemieux (2003), Ahrens (2004), and Waxler (2004).

The consensus on the superior sin-stock performance has inspired a stream of studies about the determinants of the sin premium. Salaber (2007) explores the sin premium of European stocks from a legal and a religious perspective. She shows that Protestants require higher risk-adjusted returns on sin stocks than do Catholics. She further finds that sin stocks have higher risk-adjusted returns if these sin stocks are in an environment subject to higher litigation risks and excise taxation. Salaber (2009) studies sin-stock returns over the business cycle. She finds an indication of higher risk in that an abnormal number of these stocks exit during recessions. Durand, Koh, and Tan (2013) link sin stock performance world-wide to cultural variables. They find that when cultures become more individualistic, sin stocks tend to outperform other stocks. FMO propose possible arguments for the sin stocks' abnormal returns. They speculate that sin

[2] Their annual sin stock return is numerically very close to the boycott premium implied from our model, even though our set of boycotted stocks differs substantially from the set FMO uses.

industries are typically less competitive and are more subject to litigation and headline risks. These risks lead to a permanent discount in valuation. They further attribute the positive risk-adjusted returns to initial IPO undervaluation resulting from the nature of the business of these firms.

Norm-Constrained Institutions Hold Fewer Boycotted Stocks

HK (2009) represent another stream of empirical research that ties the undervaluation of sin stocks to the lack of investor base. Their work is motivated by Merton's (1987) theory for the excess returns of neglected stocks. HK show that due to the increasingly popular social screens, sin stocks have lower levels of institutional ownership. The reduced popularity of sin stocks dampens analyst coverage of these sin stocks further. Less coverage of sin stocks decreases awareness of these stocks which increases the sin-stock risk premium based on Merton's neglect effect. Sin firms seem to be aware of at least the asymmetric information component of this negative neglect effect on their market value. Kim and Venkatachalam (2011) show that financial reporting quality of sin firms is superior relative to their control groups. Leventis, Hasan, and Dedoulis (2013) find moreover that sin firms are willing to pay higher fees to have their financial statements audited.

Selection Process of Boycotted Firms

Boycotted industries are typically controversial industries and are difficult to categorize objectively. Therefore, we base our selection procedure on previous studies as well as on surveys from real practices in the investment industry (in particular, the US Social Investment Forum, SIF, 1995-2012 biannual surveys).

Socially Responsible Investing (SRI) as an investment category was implemented on a significant scale starting in the mid-1990s. See Table 1. According to the Social Investment Forum (SIF) 2012, more than one of every nine dollars under professional management in the US is now invested according to SRI guidelines. Over 90% of the funds following SRI guidelines use three or more screens to constrain their investments in controversial businesses. The top five screens based on the SIF biannual surveys between 1995 and 2005 were tobacco, alcohol, gaming, weapons, and environment. While the first three are lumped together as "sin" industries (see, for example, Salabar 2007; FOM 2008; HK 2009), the screen on environment is fueled by concerns of global warming and fossil fuel divestment.[3]

To identify a representative portfolio of boycotted stocks we follow a two-pronged approach by selecting first a minimal list of habitually boycotted stocks, and second a more extensive list of less universally boycotted stocks. The first has the advantage of excluding from classification as "boycotted" those that are not uniformly boycotted by most SRI funds over the period considered, while the second provides a broader, more diversified portfolio. The top five industries that are screened most frequently by SRI funds are alcohol, fossil fuel, gaming, weapons, and tobacco. Each is screened by around 80 percent or a higher fraction of the SRI funds (see Table 3). We take a value-weighted portfolio of all CRSP firms in these industries as our more extensive boycott factor portfolio.

Several components of the extensive set of boycotted firms are questionable as reliable indicators of a boycott, making a case for concentrating on the narrower group of boycotted

[3] The primary goal of fossil fuel divestment is to pressure government and fossil fuel industries (oil, gas, coal) to undergo "transformative change" with the objective of causing a drastic reduction in carbon emissions. This divestment campaign has gained prominence on university campuses and mission driven institutions – a phenomenon that is quite similar to the history of divestment from South Africa in protest against South Africa's system of Apartheid.

firms. First, including the gaming industry is problematic. Since the late 1990s, an increasing number of states in the US has deregulated casino style gambling. According to a survey of casino entertainment by the National Gaming Association, by 2013, 23 states had legalized casino-style gambling. The wave of legalization of casino-style gaming suggests that gaming has become more socially acceptable in recent years. This observation is enforced by the significant drop in the percentage of gaming screens used by the SRI portfolios, from its peak of 86% in 1999 to less than 20% in the beginning of 2003. If sensitivity to a boycott factor depressed prices of gaming firms, a systematic reduction of this sensitivity would lead to a positive impact on returns spuriously attributed to the boycott factor.[4]

Second, including all fossil fuel firms is difficult. According to the "Stranded Assets Program," a report by Oxford University, commissioned by HSBC's Climate Change Centre of Excellence, oil and gas together account for about 10%, 11%, and 20% of the total market cap of the Russell 1000, the S&P 500, and the FTSE 100, respectively. In contrast, coal is a much smaller and more fragmented industry. The coal industry's size and its salient pollution make it a more likely scapegoat among the three fossil industries. For instance, the world's largest

[4] Additionally, including gaming firms is problematic for the earlier part of our sample due to a survivorship bias. As noted by Chari, Jagannathan, and Ofer (1986), stocks move in and out of the COMPUSTAT list depending on their performance. All gaming firms identified in previous studies are based on the COMPUSTAT Segment Current File. The Current File only covers stocks starting from 1985. HK (2009) back-fill firms in 1985 to 1926. This practice, while legitimate for their study creates survivorship bias for our full sample period regressions. Additionally, HK (2009)'s gaming firms are identified by the North American Industry Classification System (NAICS) which was not implemented until 1997. Therefore, gaming firms that did not survive through 1997 were not on the list. Moreover, firms that report data in the Segment File are typically large firms operating in multiple sectors. Including these firms will cause our value-weighted boycott factor to be strongly influenced by firms that only partially operate in boycotted industries. Consequently, the degree of "sinfulness" in our boycott factor is watered down. For example, Coco Cola would be on the list of boycotted firms based on the Segment File (as part of its operations involves alcohol), whereas it is also part of the FTSE KLD 400 social index.

sovereign wealth fund, the Government Pension Fund of Norway, has divested itself from 13 coal extractors without similar actions toward oil and gas companies.

Third, we follow the literature in dropping weapons as a morally questionable industry, following Salabar (2007) and HK (2009). The resulting narrower list of boycotted firms consists of alcohol, coal, and tobacco firms. Table 2 provides systematic year-by-year summary statistics regarding the boycotted stocks beginning in 1963 and ending in 2012. Over the entire sample period, there are per year on average 33 boycotted stocks in our narrow boycott measure and 199 boycotted stocks in our broader boycott measure.

The selection of a limited number of clearly boycotted stocks is meant to deliver the best proxy for a more abstract larger portfolio of assets boycotted to different degrees, with each asset's weight in the portfolio depending positively on its market weight as well as the degree to which it is boycotted. Thus, while the combined market value of the average of 33 boycotted stocks is negligible, it is used as a proxy for a portfolio with a total market value more similar to or larger than the total value of capital invested in institutions with social screens. Our narrow measure is conservative in the sense that only stocks are included that are pervasively and persistently shunned by socially responsible investors. We further consider a broader classification of boycotted stocks that includes around 200 firms on average.

3. Derivation of Boycott Implications

The position of boycotted stocks in the overall financial market is interesting. Boycotted firms still have access to the financial market but face reduced demand from a group of morally influenced investors. To attract a sufficient amount of investment, boycotted firms must offer higher returns. Hong and Kacperczyk (2009) offer this explanation for the sin stock premium, based formally on Merton's (1987) "neglect" framework in which investors refuse to buy stocks that they are not sufficiently familiar with.

In Merton idiosyncratic risk is priced because investors insist on holding exclusively stocks they are familiar with, and thus have only limited diversification opportunities. Neglected stocks face higher idiosyncratic risk as their risk is split over a smaller group of investors. HK point out that, in application to sin stocks, a risk premium then arises from two sources: limited participation which causes the idiosyncratic risk to be divided over fewer investors (reduction in q_k in Merton's equation 16), and increased idiosyncratic risk inherent to sin firms who must deal with litigation risks (increase in σ_k^2 in Merton's equation 16).

The Merton (1987) model has several limitations as an explanation for the sin premium. First, the Merton model is a one-factor model in which idiosyncratic risk is priced. It relies on dramatically reduced diversification opportunities to the extent that, in spite of assets having a strict factor structure, no investors are able to diversify sufficiently to arbitrage the pricing effect of idiosyncratic risk. In a world where no investors hold more than just a few assets this makes more sense than in a setting where only some assets face reduced participation.

Second, Merton's framework cannot examine the systematic impact of commonalities in the neglect of assets. It assumes a diagonal covariance matrix for return errors and provides no formal explanation for what neglected assets may have in common. Simple CAPM alphas will be positive and increasing in the degree of an asset's neglect, but his assumption of white noise errors together with lack of structure regarding which investors neglect particular assets makes it problematic to identify an additional risk factor. Ignoring commonalities is reasonable under the incomplete information interpretation since acquiring information is costly for basically any asset. If neglect is due to moral distaste, however, it is straightforward to identify the assets avoided by a group of investors and it is possible to look closely at the implied systematic pricing effects for all assets.

A potentially more suitable framework for examining the systematic pricing effect of the boycott of sin stocks is that sketched by Fama and French (2007). They argue that investors may have non-pecuniary preferences for holding assets: "[investors] get direct utility from their holdings of some assets, above and beyond the utility from general consumption that the payoffs on the assets provide." (Fama and French, 2007, p.675). In the boycott case this is disutility from holding sin stocks. Fama and French cite SRI as an example with specific reference to tobacco companies and gun manufacturers (p.675).

As does Merton (1987), Fama and French (2007) point out that the simple CAPM fails to hold in this setting. Empirically, the implication is merely that there is no longer a reason for market CAPM alphas to be zero. However, whereas in contrast to Merton (1987) there are no covariance restrictions in their model, Fama and French do not pay attention to the commonalities in the investor tastes that cause the CAPM to fail in a specific way that can be captured by an additional systematic risk factor. As the direct distaste for assets follows a pattern and applies to a specific (non-negligible) market segment (group of assets and investors), it is feasible to identify a systematic factor that not only describes but is sufficient for describing the way in which the CAPM fails to hold theoretically.

We follow the suggested perspective in Fama and French (2007) to its logical conclusion when we identify distaste by particular investors for a specific group of assets. The resulting model is also formally similar to Merton (1987) with two crucial differences. First, market participation is sufficient to allow idiosyncratic risk to be diversified to the point where it has no or negligible pricing impact. Second, instead of the diagonal covariance structure assumed by

Merton, here stock returns have a general covariance structure which formally allows us to examine the importance of boycotting as a systematic risk variable. The resulting model setup resembles the segmented markets model of Errunza and Losq (1985) in that effectively access to some markets (assets) is denied to a group of investors.[5]

The Theoretical Framework

The effect of social screens is incorporated in the model by assuming that a fraction of investors is morally influenced. These investors refuse to invest in assets whose underlying activities they find morally objectionable. An immediate implication is that two types of investors no longer have identical investment opportunities. Two types of investors with different investment opportunity sets generally choose different optimal portfolios. This implies that the standard CAPM is no longer valid and that, in addition to the market factor, a second systematic risk factor emerges which we shall refer to as the "boycott" factor.

The formal model is presented in the Appendix. The introduction of a group of restricted/responsible investors (*R*-Investors) next to the standard unrestricted/unconstrained investors (*U*-Investors) in an otherwise standard Sharpe-Lintner CAPM generates a two-factor model that provides a specific boycott factor as well as implications concerning the determinants of the boycott risk premium and its effect on both sin and non-sin assets.

Figure 1 provides a synopsis of our model and how it relates to Fama and French (2007). The portfolio frontier for the restricted investors (*R*-Frontier) lies entirely inside that of the unrestricted investors (*U*-Frontier). As a result the tangency portfolio of the unrestricted

[5] Errunza and Losq (1985) consider international market segmentation in which investors in one country are restricted from investing in the other country, but not the other way around. Key modeling differences with our model, however, are that they assume in effect constant absolute risk aversion, which is not necessary in our context. They further superimpose a factor structure on asset returns which also is not necessary in our case.

investors (T_U) has a larger Sharpe Ratio than the tangency portfolio of the restricted investors (T_R). Because all investors hold risky assets only in portfolios T_U and T_R, the market portfolio (M) must be a convex combination of the two as shown. Thus the Sharpe Ratio of the market is below the maximum Sharpe Ratio (SR_U). As we know from Roll (1976) then the CAPM fails so that assets have non-zero alphas when their returns are adjusted for market risk. This is essentially the reasoning in Fama and French (2007) (see their Figure 1). However, they stop short of explaining the levels of the alphas.

Also from Roll (1976), if we knew the tangency portfolio of the restricted investors the return on this portfolio would be a sufficient factor to explain the cross-section of the mean returns of all non-sin stocks; whereas the tangency portfolio of the unrestricted investors would explain the mean returns of both sin stocks and non-sin stocks. However, neither portfolio is directly observable. Unrestricted investors will not just hold the market portfolio but, to diminish the risk from sin stocks being over-represented in their portfolios (unrestricted investors as a group hold all sin stocks), will hold fewer of those non-sin stocks that are positively correlated with sin stocks. Similarly, in equilibrium, the restricted investors will not just hold the portfolio of non-sin stocks, but will hold more of those non-sin stocks that are positively correlated with the sin stocks they cannot hold.

Two alternative portfolios, the market portfolio M and the boycott portfolio B, that are observable in principle are sufficient to attain the maximum Sharpe Ratio SR_U at T_U (as shown in Figure 1) and therefore should price all assets.[6] These portfolios are held in positive quantities by the unrestricted investors to reach their tangency portfolio (so that T_U lies in between M and B);

[6] Huberman and Kandel (1987), Grinblatt and Titman (1987), and Jobson and Korkie (1985) showed that equality of the maximum Sharpe Ratio for the factor portfolio and for the asset portfolio is necessary and sufficient for the factors to price all assets.

whereas the restricted investors need only hold M and short B to reach their tangency portfolio (so that T_R lies to the right of M and the net holdings of the sin stocks are zero at T_R. Note that, while T_R can be decomposed into M and B, both of these portfolios contain sin stocks, and the restricted investors of course would not hold these portfolios individually but just the combination that has zero net holdings of sin stocks). The case drawn in Figure 1 is typical in that the mean portfolio returns of the restricted are lower than those of the unrestricted. Here the mean return of the boycott portfolio must exceed the average market return, even though the market and boycott Sharpe Ratios may be similar.

Implications and Intuition

Cross-sectional variation in mean returns

The formal model provided in the Appendix implies that:

$$\mu_i = \beta_{im}\mu_m + \beta_{ib}\mu_b . \tag{1}$$

The mean excess return of any asset i is determined by the asset's sensitivity to the market risk factor β_{im} as well as by its sensitivity to a "boycott" factor β_{ib} . The boycott factor, as defined is equation (A11), is the zero investment return on the portfolio of all sin stocks hedged to remove the correlation of sin stock returns with the remainder of the market.[7] Borrowing the interpretation in Errunza and Losq (1985) translated to our alternative context, the boycott

[7] While the model generates a second systematic factor, it is doubtful that this factor would make a major difference in pricing all test assets. Any diversified portfolio that is not particularly selected along dimensions of social acceptability of the real activities of the underlying assets (selection based on statistical criteria or typical firm characteristics) will likely end up with zero or close to zero boycott betas. Harvey, Liu, and Zhu (2014) expand on the issue of data snooping and publication biases to argue that the hurdle for accepting new risk factors should be high. While this is reasonable in general, the implication that finance research has uncovered too many risk factors, is not warranted, at least not in the present context: simple non-homogeneities across groups of investors are quite common (e.g., location, age, tastes, market access, tax circumstances, employment risk, family situation). Theoretically, these give rise to new risk factors along the lines of the model presented here. However, they are not likely to be pervasive so that careful construction of test assets is required to identify differences in exposure. If the issue is whether a particular finding of an anomaly, just as clearly subject to data snooping or publication biases, can be explained as a reward for risk or not, it does not make sense to increase the hurdle for identifying a risk factor.

portfolio consists of two components: long the value-weighted portfolio of sin stocks and short a hedge portfolio of non-sin stocks designed to offset as much as possible of the risk of the sin portfolio. Thus the boycott factor represents the risk characteristics of the part of the sin portfolio that is a distinct addition to the market, constituting a sufficient statistic of the risk diversification opportunities lacking for the restricted investors.

The intuition for the two risk factors is that they capture the preferences and portfolio choices of two distinct groups of investors (morally restricted – R – and morally unrestricted – U). Theoretically, the (different) tangency portfolios for the representative investors of these two groups suffice as the risk factors. However, these portfolios are not observable. The unrestricted investors, for instance, do not simply hold the market portfolio but in equilibrium as a group hold all the sin stocks while reducing those holdings of non-sin stocks that have returns positively correlated with the sin stocks now over-weighted in their portfolios relative to the market portfolio. The market portfolio and the boycott portfolio together represent the (unobservable) tangency portfolios of both investor types: the restricted investors hold the market portfolio and short the boycott portfolio (so that their net holdings of sin stocks are zero) while the tangency portfolio of the unrestricted investors consists of a mix of the market and the boycott portfolio.

In market equilibrium, a holder of the market portfolio or the boycott portfolio removes risk from the market and receives a systematic risk premium in return. Any asset is priced by how much risk it contributes to each of the two portfolios (β_{im}, β_{ib}) and by how much the market values the risk of each (μ_m, μ_b). One may take risks unrelated to these two portfolios, but as it does not remove risk from the market this risk is not priced and does not affect mean returns.

Payoff Covariance

The price P_i of any security i equals the certainty-equivalent payoff discounted by the risk free rate r_f:

$$P_i = \frac{\bar{x}_i - \gamma \Sigma_{im} - \delta \Sigma_{ib}}{1 + r_f}. \tag{2}$$

Here $\gamma = [(q_R \overline{w}_R / \rho_R) + (q_U \overline{w}_R / \rho_U)]^{-1}$ and $\delta = \gamma \left(\frac{q_R \overline{w}_R / \rho_R}{q_U \overline{w}_R / \rho_U} \right)$ are positive constants with q_R, q_U the number of investors in each investor group, and ρ_R, ρ_U measures of the degree of relative risk aversion and $\overline{w}_R, \overline{w}_U$ the wealth of the representative investor in each group. Further, $\bar{x}_i$ is the expected payoff and Σ_{im}, Σ_{ib} are the payoff covariances of asset i with market portfolio payoffs and boycott portfolio payoffs, respectively. Since $\delta > 0$ (as long as responsible investors exist so that $q_R > 0$), equation (2) shows that the price of boycott factor risk is positive and that the price of an asset is reduced based on its payoff covariance with the boycott factor. An asset's payoff covariance with the boycott portfolio return is typically, but not always, related to its sin content.

The lower the asset's price the higher its mean excess return, $\mu_i = (\bar{x}_i / P_i) - (1 + r_f)$. Thus, the existence of type-*R* investors raises the mean returns of assets that are correlated with the boycott factor. Boycotts will increase the mean returns of assets positively correlated with the boycott factor whether they are sin stocks or not. It is not whether the asset is boycotted by the moral investors which determines the premium, but how much the asset's payoff covaries with the boycott factor. For instance, a sin firm and a non-sin firm may use the same inputs. If the boycott factor is also influenced by these input prices, the boycott will have the effect of discouraging investment in the activities of both the sin stock and the non-sin stock.

If the goal of SRI is to increase the cost of capital of socially questionable businesses and consequently discourage their influence, equations (1) and (2) suggest that this goal is achievable. To the extent that the correlated assets are sin assets, the boycott accomplishes the desirable objective of the moral investors to lower values of objectionable businesses, reducing the incentive to expand these businesses. Alternatively put, the lower prices for given payoff distribution raise the expected returns and thus the cost of equity of these assets, reducing investment in related activities. For this reason, boycotting sin stocks is an effective but somewhat blunt instrument for discouraging morally or socially objectionable activity.

The Boycott Factor Risk Premium

Appendix equation (A19) provides the boycott factor risk premium if the relative risk aversion levels of both investor groups are assumed to be equal:

$$\mu_b = (1+r_f)\, f\left(\frac{\theta_m \Sigma_b}{\bar{x}_b (1-RWR)}\right), \quad \text{with} \quad f(\cdot) > 0 \quad \text{and} \quad f'(\cdot) > 0. \tag{3}$$

Here $RWR \equiv q_R \overline{w}_R / q_M \overline{w}_M$ and θ_m is a measure of the market's average level of absolute risk aversion. It is easy to infer that μ_b: (a) is always positive, and (b) increases in *RWR*. The risk premium depends directly on the payoff variance of the boycott risk factor relative to the average payoff and the degree of absolute risk aversion in the economy. *RWR* is the ratio of total wealth invested by responsible investors and total market wealth. Intuitively, the pervasiveness of a boycott should affect the risk premium. If a larger fraction of investors participates in SRI, the risk of the sin portfolio is spread over fewer unrestricted investors who then require a larger boycott risk premium for holding these assets and other assets positively correlated with them.

Discussion

Unconstrained investors do not arbitrage away the sin premium because, as a group, they hold all sin stocks so that they are over-weighted in these stocks relative to the market portfolio, to the point that changes in the holdings of these sin stocks affect portfolio risk, even given market risk and full diversification. In addition to the fact that (as of 1999) more than 10% of investment under management formally applies moral investment constraints, an unknown fraction of funds without formal moral constraints or screens as well as private investors is guided at least in part by such tastes. Thus, we argue that the group of restricted investors is large enough that "arbitrage" by unrestricted investors does not eliminate the return premium.

In other words, the reduced demand from the morally guided investors lowers the price of the boycotted stock which makes it more attractive for "arbitrage" by unrestricted investors. As the unrestricted investors accumulate boycotted stocks in addition to their market holdings, the supplementary risk, to the extent that it is unrelated to the market, starts to carry an additional risk premium in equilibrium necessary to entice the unrestricted investors to hold the surplus of boycotted stocks. In total, underpricing resulting from reduced participation is only partly reversed by the arbitrage efforts of the unrestricted investors. The remaining underpricing covers the unrestricted investors for the extra risk not captured by the market factor.

The extra risk may be interpreted as a true "boycott" risk: returns on the group of sin stocks will vary with investor tendencies to boycott socially undesirable activities. The number of responsible investors and the extent of their participation in avoiding sin stocks changes with fluctuations in social norms as well as economic conditions. So, one way of viewing the boycott risk premium is as compensation for additional price risk resulting from sentiment swings regarding socially or morally objectionable ventures.

The boycott risk premium is mediated by the "arbitrage" of the unrestricted and this fact causes the risk premiums of individual assets to depend on the payoff distribution rather than just the sin content (zero-one in this simple model) – it is the asset's covariance with the risk factor that matters rather than the sin characteristic of the asset. The risk premium on the boycott beta increases when the number and market impact of socially responsible investors increases because a smaller group of arbitrageurs must absorb more boycotted shares, implying a further tilt in their portfolios towards boycotted stocks consistent with a larger risk premium beyond the regular market risk premium.

The Risk Premia and Underlying Macro Risk

The underlying real macroeconomic risks that are represented by our two risk factors are not identified in the model. This is most easily understood by superimposing for the moment a factor structure on the thus-far general mean-variance structure of the returns and assuming that a large number of assets exists with finite idiosyncratic risk. If we had a one factor model with, say, unanticipated aggregate production growth as the sole factor shock then the risk content of both the market factor and the boycott factor would be reducible to this aggregate production risk only, and could be summarized by the loadings on the one risk factor. On the other hand, if there were a K-factor model consisting of $K > 2$ underlying real shocks, the market factor and boycott factor would become distinct linear combinations of the K shocks. Although the K real factor values then cannot be fully identified from the market and boycott portfolio returns, the two portfolios are nevertheless sufficient to capture the risk that is priced in the market. The upshot is that, in our model, it is possible that the two factors represent recognizable macroeconomic risks, but in a world with a variety of macroeconomic state variables the relation between risk factors and underlying macro risk may be complex.

4. From Theory to Measurement

We can now test this two-factor CAPM by finding the appropriate factor proxies and by specifying the test assets. The boycott factor return $r_b = (\mathbf{x} - \mathbf{p})' \overline{\mathbf{n}}_B / P_b$, with portfolio holdings $\overline{\mathbf{n}}_B$ given in equation (A11), is the zero-investment return created by holding the sin stock portfolio and shorting a portfolio that accounts for the part of sin stock payoffs already contained in the market. The resulting portfolio payoffs are the unique payoffs that the group of sin stocks contributes to the market. This portfolio can be well approximated by considering a zero-investment portfolio of sin stocks constructed to have no correlation with the rest of the market. To represent the theoretical concept of the value-weighted portfolio return of all stocks eschewed by morally guided investors we choose a value-weighted portfolio of stocks that are the most unequivocally boycotted, in the sense of being screened by many Socially Responsible Investing funds, To work with test assets that display variation in the boycott betas, we rely on industry portfolios.

The mean returns of industry portfolios have been notoriously hard to explain with standard asset pricing models. Fama and French (1997) first document the problems of their three-factor model in accounting for differences in the cost of equity across industries. More recent research (see for instance Lewellen, Nagel, and Shanken 2009, hereafter LNS, and Chou, Ho, and Ko 2012) confirms that standard asset pricing models fail to explain cross-sectional differences in mean industry returns. The industry portfolios, moreover, are suitable test assets for our purposes as they are likely to display significant variation in the nature of their real activities and, accordingly, should differ along the dimension of moral and social desirability.

LNS emphasize that a good fit in multifactor models is superficial if the test assets have a strong factor structure. As long as the factors correlate with the common sources of variation in the returns, loadings on proposed factors will explain the cross-sectional returns well, even if the empirical factors are mostly unrelated to the true factors. They propose to augment the popular 25 Fama-French portfolios sorted by size and book-to-market values with additional test portfolios that have weaker factor structures, sorted, for example by beta, firm characteristics, or by industry affiliation. But Lo and MacKinlay (1990) suggests that sorting on beta and other interesting characteristics known to be correlated with returns generates a data-snooping bias. This bias is exacerbated as more researchers sort on multiple characteristics, and consequently form a larger number of portfolios (Conrad, Cooper, and Kaul 2003). In contrast, sorting by industry affiliation is based on the nature of the firms' business and does not fall into the data-snooping trap.

Additionally, it is important to understand that our model does not stipulate a new factor that prices all portfolios. The boycott factor is relevant only for pricing portfolios that differ systematically in their loadings on this factor. Typical well-diversified portfolios, be they sorted by beta, size, value, or momentum, for instance, are unlikely to display clear differences in their boycott factor loadings. However, most of the social screens are industry-based – for example tobacco, gaming, alcohol – and accordingly industry portfolios ought to display significant differences in their exposure to the boycott factor. Industry portfolios, furthermore, do not have a strong factor structure and tend to generate considerable dispersion in average returns, and hence present a challenge to any asset testing model. In fact, the test results of most existing asset pricing models do not hold up well when industry portfolios are involved (LNS, Table 1).

The cross-sectional evaluation criteria primarily follow LNS (2009). Our model predictions are the following. *First*, the sign of the coefficient estimates on the boycott beta should be positive as predicted in our model. *Second*, the risk premium magnitudes for the market and boycotting factor portfolio should be close to their average excess returns. *Third*, the difference between realized and predicted portfolio returns should be zero on average. This is equivalent to verifying that the estimated second-pass intercept is zero, and may be interpreted as an indication that the risk-free asset is priced correctly. *Fourth*, by adding boycott factor betas in the second pass, the adjusted R^2 in our two factor model should show a significant improvement over competing models. *Fifth*, a proper model should in principle yield the same risk premium for any set of test assets. Thus, in employing various test portfolios we will compare the magnitudes of the implied factor risk premiums.

Other implications of the model relate to the time series properties of the boycott risk premium and the importance of return covariance rather than sin content per se. *Sixth*, the boycott risk premium should be positive but also vary over time depending on the economic importance of the group of responsible investors $q_R \overline{w}_R$ (the number of investors avoiding sin stocks times their average wealth), directly affecting the boycott risk premium in equation (3). While informal individual restraint in holding controversial stocks may have existed for a long time, formally announced explicit social screens were not prominent until the late 1990s. Therefore, the boycott risk premium is expected to be higher when a recent sample is used. More specifically, we hypothesize that the boycott risk premium should be increasing in the fraction of wealth invested by socially responsible investors.

Seventh, maintaining SRI principles has a cost (Adler and Kritzman, 2008) and may be viewed as a luxury good which fewer individuals are likely to adopt, and to a lesser extent, if the economy is weak. Thus, if the economy is in a recession, we hypothesize that the boycott risk premium is lower: the boycott risk premium is pro-cyclical. Note, in contrast, that a weak economy might imply a higher market risk premium because investors are more risk averse in a recession (Chen, 1991). Nevertheless, the risk premium on sin stocks increases by less or decreases compared to non-sin stocks, causing the boycott risk premium to decrease. *Eighth*, as implied by equation (2), higher payoff covariance between any asset and the boycott factor lowers the price of the asset and raises its expected return. While the sin characteristic of the asset should correspond to a potentially large extent to the covariance with the boycott factor, the covariance and not the sin content is the ultimate driver of the boycott risk premium.

5. Data

We employ mostly two versions of the boycott factor: the narrow version based on all alcohol, coal, and tobacco firms; the broad version based on all alcohol, fossil fuel, gaming, weapons, and tobacco firms. We identify the appropriate firms from historical SIC codes which guarantees that firms are classified in the appropriate industry at each particular time. We construct the value-weighted *boycott* return as,

$$r_{bt} = \frac{\sum_{i=1}^{N} p_{it-1} I_{it-1} r_{it}}{\sum_{i=1}^{N} p_{it-1} I_{it-1}} \tag{4}$$

I_{it-1} and p_{it-1}, respectively, are the zero-one variable indicating whether asset i is in the boycott portfolio (i.e., screened according to either the narrow or the broad criterion), and the market value of stock i in the previous month; r_{it} is the monthly excess stock return of asset i. The monthly boycott factor begins in January 1963 and ends in December 2012. Summary statistics are presented in Table 4.

The popularity of SRI funds increased sharply since the mid-1990s, as based on the screen usage reported in Social Investment Forum (2012). After 1999, funds employing screens crossed the $1-trillion threshold, which is about 10% of the total wealth under professional management based on the Thomson Reuters Nelson tracked assets, as presented in Table 1.

The stock return data for the boycotted firms are from the CRSP Monthly Stock File using the SIC codes associated with the relevant screens. We admit all stocks listed on NYSE, AMEX, and NASDAQ between 1963.01 and 2012.12, but exclude ADRs, REITs, closed-end funds, and primes and scores (share type code of 10 or 11). The primary test assets are the 30 (FF30) and 48 (FF48) value-weighted industry portfolios provided by Kenneth French. The market excess return and size, value, and momentum risk factors are also from Kenneth French's website.

6. Empirical Results

Table 5 presents the empirical comparison between our boycott-augmented model, the CAPM, the Fama-French three-factor model (FF3), and the Carhart four-factor model (FF4). The Boycott-CAPM is given in equation (1). To further illustrate the impact of the boycott behavior on cross-sectional returns, we augment the Fama-French and the Carhart specifications with the boycott factor. Estimation employs the standard two-pass approach of Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). Our approach reflects the Black-Jensen-Scholes approach, commonly used since Fama and French (1992), in which factor loadings are estimated in the first pass utilizing the full time series for each test asset, and their significance levels are from cross-sectional estimates for each time period using the constant factor loading estimates.[8]

The Boycott Risk Premium

We first consider the period since January 1999 for which the boycott impact is likely to be clearest.[9] The boycott factor is constructed, consistent with the theory, as a zero-investment portfolio that is long on sin stocks and short on non-sin stocks and removing all correlation with the market. As discussed the boycott premium should be positive. The estimated boycott risk premium coefficient in Panel A of Table 5 confirms this prediction for the FF30 portfolios. The estimated monthly boycott risk premium is 1.33%, implying an annualized factor risk premium of around 16%, which is twice as large as the market risk premium. This implies that stock returns are actually rewarded more for their associations with boycott risk than for market risk. This number is quite high but of similar magnitude as the excess sin returns found by FMO.[10]

The magnitude of the boycott risk premium is similar to the average excess boycott factor returns presented in Table 4. The difference between the Boycott-CAPM implied risk premium and the average excess boycott factor is 0.56% per month, sizeable but not of the order-of-magnitude difference that should raise a red flag, following LNS. The boycott factor is not only economically important, but also is statistically significant at the 5% level.

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[8] The advantage of this method over the rolling factor loading estimates of the Fama-MacBeth approach is that factor loadings are estimated more efficiently if they are stationary. See Chan and Chen (1988) on this issue.

[9] The period January 1999 – December 2012 includes 168 months. While SRI funds existed before 1999 (see Table 1) it is important to avoid including a transition period in our sample during which the boycott premium increased substantially as this would imply falling prices, generating spuriously low average returns.

[10] The economic significance of the boycott risk premium depends on the dispersion of the boycott sensitivities across assets. For the quintile of industries with the highest boycott betas, the average boycott beta is around 0.55 and for the quintile with the lowest, the average boycott betas is around -0.12. Thus, the annualized expected return difference between these quintiles based on their boycott sensitivities is around 11% (16% times 0.67).

The empirically observed risk-adjusted sin stock abnormal returns can be reconciled with the positive boycott risk premium. We infer from equation (1) that

$$\frac{\partial(\mu_i - \beta_{im}\mu_m)}{\partial \beta_{ib}} = \mu_b > 0, \qquad \forall i \,. \tag{5}$$

The numerator is interpreted as the risk-adjusted abnormal return (alpha) if the basic CAPM applies. In the investment world, this abnormal return is what a “vice fund” typically would brag about. Equation (5) states that the risk-adjusted abnormal return is an increasing function of the stock’s sensitivity to the boycott factor. Trivially, if a vice fund only picks sin stocks its fund index will be highly correlated with the boycott factor, implying a high β_{ib}. Consequently, a vice fund is expected to beat the market index which has a relatively low β_{mb}. Table 6, Panel A confirms this observation by showing that the tobacco, alcohol and coal industries are indeed quite sensitive to the boycott factor, with boycott betas of 1.20, 0.33, and 0.64, respectively. If the stocks’ excess returns were boycott-risk adjusted, the abnormal return should disappear. The relatively small and insignificant intercept of -0.29% for the boycott-augmented CAPM in Table 5 supports this claim.

Model Comparisons

Table 5, Panel A presents six models, three of which are boycott-factor-augmented. The Carhart model (FF4) has the highest R^2 among the three competing base models. Nevertheless, when the FF4 factors are augmented with the boycott factor, the adjusted R^2 improves by more than 10%. The most noticeable R^2 improvement is when the boycott factor is added to the CAPM model. The boycott factor addition raises the R^2 by almost 50 percentage points. This is a substantial improvement compared to a negative adjusted R^2 for the CAPM model. A similar improvement is observed when the boycott factor is added to the FF3 model. The boycott factor is significantly positive at the 5% level, and all other factors are insignificant, reflecting the poor performance of traditional factor models in explaining mean returns across industry portfolios.[11]

The improved explanatory power for expected return differences is further accompanied by decreases in the intercepts. Whenever the boycott factor is included in a model, the second-pass intercept in absolute value is generally about 0.15% per month closer to zero. The actual decrease in the intercept is around 0.70% per month. This is approximately the amount that is elsewhere claimed as the sin stocks' abnormal returns (Salaber 2009 and FOM 2008).

To visually compare the performance of our boycott-augmented specifications against the other models, we plot the fitted expected returns, computed by using the estimated parameter values from the models, against the realized average monthly test portfolio returns (shown for the CAPM and FF4 models and their boycott-factor-augmented versions). When $\hat{\beta}_{im}$ alone is used, the predicted expected returns show virtually no dispersion, whereas the actual average returns vary substantially across the 30 industry portfolios (Figure 2, top panels). The performance improves when $\hat{\beta}_{ib}$ is added (Figure 2, bottom panels).

Alternative Test Assets

As long as the portfolios have sufficient variation in their sensitivities to the risk factor, a good asset pricing model should yield the same risk premium regardless of the choice of test portfolios. Table 5, Panel B provides the implied risk premium when the FF48 industry returns are used as alternative test assets. The magnitudes of the market and boycott risk premiums are

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[11] We also consider a conditional CAPM perspective intermediate between the CAPM and the boycott-augmented CAPM that could provide an interesting alternative explanation for the sin premium if the market betas of sin stocks are positively correlated over time with the market return. However, using the rolling beta approach in Petkova and Zhang (2005), we find that the time-varying betas for sin industries are either negatively correlated or uncorrelated with the market risk premium and accordingly the conditional CAPM cannot explain the sin premium (results available from the authors).

consistent across the different sets of test assets for all boycott-risk-enhanced model specifications. For the FF48 industry case, the boycott risk premium is a bit smaller, 1.23% per month versus 1.33% per month for the FF30 industries. The boycott risk premia are again significant at the 5% level. The intercepts are even closer to zero. These observations are again confirmed by the improvements in the fit when the boycott factor is added.

We also consider the combination of the traditional FF25 size- and value-sorted assets with the FF30 portfolios, suggested by LNS, as well as the FF25 assets by themselves in Panels C and D of Table 5. We may expect these test portfolios to perform relatively worse for our model because the FF25 assets are unlikely to have much dispersion in their boycott factor sensitivities. For the F55 case, the boycott risk premium continues to be significant (though only marginally for the augmented CAPM), with high R-square and similar magnitude. In the FF25 case, the Fama-French factors already explain a significant fraction of cross-sectional variation in mean returns; the boycott-augmented model, with correction for the Fama-French and Carhart factors, has a boycott risk premium that has similar magnitude as for the other test assets but is not significant. A possible reason that even the FF25 test assets perform reasonably here may be that selecting on value causes boycotted stocks, having relatively low prices, to be put in high book-to-market portfolios. Thus the value effect would arise here because value stocks tend to load more highly on the boycott factor. Panel B of Table 6 illustrates that, indeed, the boycott betas of high book-to-market portfolios are considerably larger for every size class compared to the boycott betas of low book-to-market portfolios.

Extended Time Series

While SRI screens became economically significant only in the late-1990s, it is probable that private boycotts, i.e., a decreased appetite for morally or socially undesirable stocks in particular industries, had a market impact well before that time. To investigate this possibility, we extend our sample back to 1963. Table 5, Panels E, F, G and H show that the results are quite similar for the FF30, FF48, FF55 and FF25 sets of portfolios, with sizable improvements in the R-squares when the boycott factor is added, significant boycott factor risk premia (except for the FF25 assets), and small intercepts. The key difference is that the boycott factor risk premia, although again similar across specifications, are substantially smaller, about 40 percent of the size for the post-1999 period. The smaller boycott risk premium is consistent with our model given that, in the period before SRI became popular, a smaller fraction of investors (lower *RWR*) restricted itself from investing in sin stocks. Figure 3 illustrates for the 1963-2012 sample the cross-sectional explanatory power of the CAPM and FF4 models (top panels) versus augmented CAPM and FF4 models (bottom panels) for the FF30 industry portfolios.[12]

The Broad Boycott Factor and other Sin Screens

To examine the robustness of our results with respect to the choice of boycotted industries, we consider the broader version of the boycott factor based on screening all alcohol, fossil fuel, gaming, weapons, and tobacco firms. As presented in Table 2, this amounts to an annual average number of around 200 boycotted firms. Table 3 shows that the broader boycott factor BCTb has a correlation with the narrower boycott factor BCTn of 62% for the January

[12] As the sample here extends to more than 50 years, the betas are less likely to be stationary over the full period. The change in social norms and passage of certain legislation over time, in addition to basic changes in operations, may change investors' perception on particular industries. See, for instance, Liu, Lu, and Veenstra (2011). Thus, we also consider the Fama-MacBeth approach of rolling estimation of betas with 60 previous monthly observations. The first cross-sectional betas are generated by using the sample period January 1958 – December 1962, and the average risk premiums are for the period January 1963 – December 2012 (for all test assets except the FF48 for which the first betas are obtained from July 1969 – June 1974 and the first cross-sectional regression starts July 1975). The results are available from the authors. They are very similar for each group of test assets to those in Panels E, F, G, and H, in terms of magnitude and significance of the boycott risk premium, and in terms of explanatory power (R-square). The intercept, however, is larger in all cases but not statistically significant.

1999 – December 2012 period. Its mean return is a larger 1.21% a month compared to 0.77% for BCTn.

Table 7 confirms that replacing the narrow boycott factor BCTn by the broader boycott factor BCTb has only a modest impact on the results for the January 1999 – December 2012 period. The magnitude and significance of the boycott risk premium is similar, and so are the R-square and the intercept, for each of the four groups of test assets, compared to the results in Table 5.[13]

Controlling for Industry-Wide Characteristics

Do the boycott risk premiums substitute for other known determinants of industry portfolios returns? Chou et al. (2012) find that, in addition to the value and size attributes, a major part of the variation in industry returns is explained by (1) the industry momentum of Moskowitz and Grinblatt (1999) and (2) the degree of industry concentration of Hou and Robinson (2006). Industry momentum is an important control especially because Table 5 already shows that even unspecified momentum is a powerful determinant of industry returns. As Moskowitz and Grinblatt find, observed momentum effects for an individual asset are largely due to momentum throughout the asset's industry. Thus, a once-lagged industry return (with lag anywhere from 1 month to 1 year) positively forecasts the current return in the same industry. So, for instance, industries will have systematic exposure to momentum risk (in the sense of Carhart, 1997) which may be larger for sin industries. We add industry momentum by including lagged industry returns in the cross-sectional regressions following Moskowitz and Grinblatt (1999).

[13] Results for all cases with the narrow and broad sin screens, as well as for intermediate choices of sin screens, are available from the authors and are quite similar for both the 1999-2012 and the 1963-2012 periods. The only exception is the broad sin screen for the 1963-2012 period for which the boycott risk premium is smaller and not statistically significant for both the FF30 and FF48 test assets. However, the broad sin screen is problematic for the extended period because the gambling industry classification was not available through much of the period before 1999 and because of the changing nature of fossil fuel's image over the full period .

Industry concentration is the other industry control. It is particularly important to take into account in the sin context since FMO argue that a common characteristic of sin industries is that they are less competitive. We follow Hou and Robinson (2006) in measuring industry concentration by means of the Herfindahl Index.

Table 5 (Panels A and B) showed that controlling for the Carhart version of momentum risk decreases the boycott risk premium as is consistent with Moskowitz and Grinblatt, but it does so by less than a quarter of its value while retaining significance. As the Carhart factor reflects systematic momentum risk only for a 1-year lag and may not capture idiosyncratic momentum, we adopt the approach of Moskowitz and Grinblatt (1999) using their various momentum lengths and industry-specific momentum metric (one, three, six, nine, and 12-month lagged industry excess returns). Panel A of Table 8 documents for the 1999-2012 period that the boycott risk premium stays robustly significant and of similar size after controlling for industry momentum for each lag, for both the FF30 and FF48 test assets. Panel B provides the results for the full period (1963-2012 for the FF30 and 1969-2012 for the FF48 test assets). Again the boycott risk premium significance and size are little changed for the FF30 test assets and for all momentum lags. The exception is the one-month momentum lag for the FF30 assets for which the boycott risk premium is reduced and now only marginally significant. For the FF48 assets the size of the boycott risk premium is reduced in the full sample and becomes insignificant in three out of five cases (the one-, three-, and six-month momentum lags).[14]

[14] Reduced significance might be attributed to the fact that, for industry portfolios (as opposed to individual firms), the industry momentum factor (lagged industry returns drawn from the same distribution as current industry returns) is spuriously correlated with current industry returns. Separately, the insignificance of the industry momentum effect in the post-1999 data in Panel A of Table 8 may be related to the post-publication (i.e., post Moskowitz and Grinblatt, 1999) disappearance of the result conform the pattern stressed by McLean and Pontiff (2015).

To account for the level of market concentration as an industry characteristic following Hou and Robinson (2006) we obtain the Herfindahl Index for firm level sales (SALE from the Compustat North American Annual File) by industry and include it in our cross-sectional regressions as an industry characteristic. Panel C of Table 8 shows that including the Herfindahl index has no noteworthy impact on the boycott risk premium. We note, however, that our industry classification differs from that in Hou and Robinson. Likely owing to the alternate industry grouping, when the Herfindahl index is included by itself, our results are opposite to the results in Hou and Robinson: a higher Herfindahl Index (more concentration), instead of lowering, raises industry returns, and this effect is marginally significant. Once we add the boycott risk sensitivities the Herfindahl Index effect becomes insignificant and sometimes reverses. This occurs probably because boycott risk sensitivities (related to sin content) and concentration are positively correlated, since sin firms face less competition as FMO suggest.[15]

The results remain similar when we also control for industry momentum (using the most significant six months lag). The presence of the Herfindahl Index somewhat strengthens the boycott premium (possibly because controlling for it removes the confounding impact of the higher concentration of typical sin industries, following Hou and Robinson, leading to lower average returns). Panel D, finally, illustrates that the boycott risk premium remains significant in all specifications for the 1963-2012 sample period: for both groups of test assets, when we control for concentration and industry momentum individually and jointly.

[15] Hou and Robinson (2006) argue that less competition implies lower required returns (firms have more cushion to weather aggregate shocks) whereas FMO (2008) argue that less competition implies higher required returns (firms may lose their competitive edge as aggregate circumstances vary). To see which argument prevails, it is important to adjust for boycott risk because sin stocks appear to be in less competitive industries, as FMO suggest and as evidenced by higher Herfindahl indexes. For instance, for the firms in the narrow boycott factor the average Herfindahl index of their industries is HHI (sin)=0.243, while for other firms the average index is HHI(non-sin)=0.141. Our results show that controlling for boycott risk sensitivities, the net effect of concentration on required returns via the channels advocated by Hou-Robinson and FMO is insignificant.

7. Alternative Explanations

The literature has provided several alternative theoretical explanations for the empirically identified sin premium and we compare these explanations explicitly to the systematic boycott risk explanation proposed here. The alternative explanations are that sin firms or boycotted firms: (1) face more litigation risk (FMO 2008), (2) are less liquid (HK 2009), or (3) are neglected (Fang and Peress 2009 and HK 2009).

Litigation Risk or Systematic Boycott Risk

Consistent with Merton (1987), when investors have limited attention idiosyncratic risk matters for pricing. This idiosyncratic risk is highlighted by the nature of the business. Businesses that have a negative environmental impact or do not conform to the social norms are more subject to litigation risks. The abnormal returns observed for sin firms in previous research may merely be a compensation for the idiosyncratic risk of operating in a legally hostile environment that matters in a Merton (1987) world. If this hypothesis is true, average industry test portfolios returns are mainly driven by the litigation risks associated with the business nature of these industries. This implies that the cross-sectional returns may potentially be influenced by a litigation "characteristic" instead of the systematic boycott risk factor predicted by our model.

To rule out the possibility that cross-sectional returns are driven by the idiosyncratic risk of litigation issues associated with each industry we construct a variable *LTG*, as a proxy for the litigation risk. [16]

[16] For each FF30 or FF48 industry, we count the total non-missing number of after-tax settlement entries (Annual Item SETA in Compustat North American), both Litigation and Insurance, and scale them by the total number of firm-year observations for this industry. This ratio is called LTG and is used as a proxy for the litigation characteristic in an industry. Two issues may potentially make this a noisy measure for the litigation risk. First, we are not able to identify the nature of each lawsuit. We are interested in lawsuits originating from the nature of a firm's business. Lawsuits such as malpractice, financial class action, etc. have to be assumed to occur evenly across all industries. Second, some lawsuits may last longer than others and some settlement probabilities may be re-

To test for the influence of the litigation "characteristic", we adopt the methodology employed by Jagannathan and Wang (1996, 1998). We include the constructed litigation variable *LTG* as a proxy for a characteristic – the degree of sinfulness of an industry as revealed through litigation. If our boycott factor is indeed a systematic risk factor, this additional proxy for sinfulness or boycott risk should not explain any residual variation in average returns across the industry portfolios. On the other hand, if $\hat{\beta}_{ib}$ (the boycott beta) cannot stand up to a test against this cross-sectional variable, *LTG*, the systematic boycott factor should not be in the model.

Before we proceed to test if the boycott factor is a proper risk factor, we need to validate our proxy. Table 9 shows that the litigation variable is both economically and statistically significant: when the FF30 and FF48 portfolios are used as test assets, on average, if an industry's proportional number of law suits increases by 100%, average monthly cross-sectional portfolio returns will increase by 5.5% and 4.3%, respectively. Including the proxy also bring up the cross-sectional R^2 by about 10% in both cases and significantly reduces the pricing errors. Thus, our litigation-based proxy *LTG* appears to be a good indicator for the industry characteristics associated with the sin premium. The second model in Table 9 shows that when $\hat{\beta}_{ib}$ is added, the t-values for the *LTG* coefficients drop significantly from 2.05 to 0.32 when the FF30 portfolios are used and from 2.03 to 1.02 when the FF48 portfolios are used. The magnitudes of the characteristics coefficients also decrease substantially in both cases. In contrast, the boycott factor risk premiums remain both economically and statistically significant. The magnitudes and t-values for $\hat{\beta}_{ib}$ are similar compared to those before *LTG* was added.

evaluated multiple times. So, lingering suits may overstate the count. There are two major advantages of using this proxy, however. First, it is conservative. The conditions for a SETA to be non-missing are quite strict. SETA is a special item in the income statement. Firms are not allowed to include a SETA entry in their accounts unless (1) lawsuits are filed and (2) loss is probable based on lawyer assessments. Second, the claims have to be larger than 10 percent of the company's current assets. This implies that any non-missing observations on SETA almost guarantee a substantial lawsuit initiated against the firm.

Therefore, we rule out the possibility that average industry portfolio returns are explained by litigation-risk-type characteristics as opposed to our systematic boycott risk factor.

Liquidity or Systematic Boycott Risk

Idiosyncratic liquidity risk

The boycott risk premium we find may instead be a liquidity-related phenomenon. Boycotted stocks have a smaller investor base: some investors, particularly morally constrained investors, do not hold these stocks in their investment portfolios. We argue that this fact causes arbitrageurs to hold these stocks in excess and that it is their concomitant increase in portfolio risk that generates the boycott risk premium. However, an alternative explanation is that the reduced investor base implies that in a liquidity-driven sell situation boycotted stocks will not be moved, unless there is a ready investor who happens to be "morally unconstrained".

There are other reasons for why boycotted stocks may be less liquid. One is that advertising to attract additional investors may be difficult for boycotted firms. Headline risk, as proposed by FMO (2008), refers to the risk that news stories about a controversial business, true or not, will always be interpreted as bad. In this sense norm-violating firms are better off operating quietly under the social radar. Second, the empirical work of HK (2009) suggests that sin firms tend to have fewer institutional investors compared to regular firms. Additionally, sin firms have less financial analyst coverage (sin firms are neglected). These findings suggest potentially less liquidity for boycotted stocks.

To investigate the liquidity perspective that competes with our risk perspective, we follow Amihud (2002) in constructing a measure of illiquidity based on the asset's return impact per dollar of trading volume.[17] If the lack of a broad investment base represents an arbitrage opportunity, it may only persist if large impediments prevent morally unconstrained investors from trading on it.[18] "Illiquidity" might be one type of friction that prevents morally indifferent investors from arbitraging away the difference. The regular- and boycotted-stock return differential may be a compensation for "illiquidity" instead of the boycott premium claimed in Section 6.

To rule out the "illiquidity premium" explanation, we use Amihud (2002)'s illiquidity measure as a portfolio characteristic. As shown in Table 9, when we incorporate this illiquidity measure *ILQ* as an industry cross-sectional characteristic in the second pass, the implied "illiquidity premium" is statistically insignificant and negative rather than positive as expected. This suggests that the industry-specific "illiquidity" is not compensated and thus certainly cannot explain the boycott premium. Most pertinently, Table 9 shows that including the illiquidity characteristic *ILQ* does not affect the level and significance of the boycott risk premium.

Systematic liquidity risk

An alternative mechanism by which liquidity may affect returns is via the Pastor-Stambaugh traded liquidity factor serving as an aggregate liquidity risk factor. Boycotted firms being presumably less liquid may have higher sensitivity to an aggregate market liquidity factor. If an industry portfolio only delivers higher returns when market liquidity is high, the marginal utility of wealth will be lower. Stocks whose highest returns occur when market liquidity is high will require higher rates of return. If boycotted stocks (or any stocks that have positively correlated returns with boycotted stocks) have larger exposures to market liquidity, higher risk

[17] Using data from the CRSP Daily Stock File we follow Amihud (2002) in calculating the illiquidity measure. Details are available from the authors.

[18] This idea of friction is borrowed from the "Impediments to Trade" hypothesis proposed in Fang and Peress (2009).

premiums would be driven by these stocks' sensitivities to aggregate liquidity instead of their sensitivities to the boycott factor. If this hypothesis is true, we expect to see that expected stock returns shall be attributed to the liquidity factor loadings as opposed to the boycott factor loadings.

The second-pass results in Table 9 show that the systematic liquidity factor *SLQ* has significant explanatory power for explaining bot the FF30 and FF48 test assets. However, the boycott factor continues to have significant marginal explanatory power for these test assets. Neither the sensitivity to liquidity nor the boycott factor sensitivity muffles the importance of the other. When one factor is added to the model, the economic importance of the other factor decreases somewhat. The addition of the boycott factor dramatically lowers the intercept which is not the case when the liquidity factor is added. Including both the liquidity and the boycott factor with the CAPM generates an R-square of 76% for the FF30 test assets, and 64% for the FF48 test assets. Thus, while market liquidity risk appears to be separately relevant in pricing the industry portfolios, it does not diminish the importance of boycott risk.

Neglect Effect or Systematic Boycott Risk

Merton (1987) attributes a divided investor base to the investors' concern about asymmetric information among investors. When a firm releases public information to both current and potential shareholders, the effective information received by current shareholders will not be the same as that received by potential investors. Current investors are supposedly more informationally engaged with the stocks they own because of the sunk cost that they have incurred. For a potential investor, the fear of being taking advantage of in conjunction with the fixed cost necessary to obtain information will cause typical investors to follow only a subset of traded stocks. Merton divides the information costs into two parts: (1) the cost of transmitting information from one party to another and (2) the cost of gathering and processing information. Increases in either type of information costs cause a firm to be followed by fewer investors which leads to it requiring a higher return in Merton's view.

The impact of costs of transmitting information has been studied by Fang and Peress (2009). They find that stocks not covered by media earn significantly higher future returns than stocks that are heavily covered. Barber and Odean (2008) show that individual investors are net buyers of attention-grabbing stocks. Investors often face difficulties in choosing which stocks to buy from a large pool of stocks. Thus, attention-grabbing stocks are more likely to enter their choice sets. As suggested in FMO (2008), sin stocks tend to suffer "headline risk". Sin industries are constantly under public scrutiny, so that news is almost always interpreted as bad. Therefore, sin stocks are better off staying away from the public media. Consequently, attention-avoiding sin stocks are expected to have higher "media" premiums.

Information gathering and processing is generally conducted by financial analysts. If a firm is followed by relatively more analysts, the quality of information for a more heavily covered firm is expected to be higher than for a less covered firm. As sin stocks are followed by fewer financial analysts (see HK 2009), observed higher sin stock returns might merely be a compensation for the poor information available for this firm, and it would be the neglect effect that gives rise to the higher sin-stock abnormal returns. Arbel, Carvell, and Strebel (1983) find that the neglected firm effect persists after the usual adjustment for risk, and this effect is robust across firm size classes. Although the reason for sin stocks being neglected here is different from that in Arbel et al. the outcome of particular stocks being screened from the investment universe of certain investors is the same. The research concentration of analysts is dictated by institutions' predilections. Therefore, as long as social screens exist, the neglect premium should persist.

Under the light of less institutional ownership of sin stocks, persistent higher sin stock returns are consistent with the finding in Hong, Lim, and Stein (2000) that stocks lightly covered tend to have higher average returns than heavily covered stocks. To rule out the possibility that cross-sectional returns are driven by this neglect effect instead of the systematic boycott factor, we construct *analyst coverage* as a proxy for the neglect effect. [19] [20]

For each industry, we take the log of the total number of analysts in the industry scaled by this industry's market capitalization. We use this ratio as a proxy for the analyst coverage. The top three least covered industries among the FF30 industries are tobacco, coal and alcohol (not shown). The overall ranking by analyst coverage is consistent with the results reported by HK (2009) that sin industries are less covered by financial analysts.

Table 9 shows that our constructed analyst coverage ratio is a good proxy for the neglect effect. The significant negative estimated coefficient in Table 9 on the coverage ratio is consistent with the HK results: the asymmetric information issue is alleviated by analyst coverage. The expected payoff will not be discounted as much as when there is no coverage at all. The estimated coefficient, -0.177, means that when the number of analysts (adjusted by market cap) increases by 1%, the expected return in this industry, on average, will decrease by 0.177 percent per month. This negative risk premium is also statistically significant which suggests that the neglect effect as an industry characteristic affects equity pricing.

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[19] Even though it might be expected that sin industries are more closely monitored by the government or the public media, Fang and Peress (2009), p. 2030 find that the extent of media coverage is virtually identical across industries.

[20] We follow Hong, Lim, and Stein (2000) in constructing the analyst coverage proxy using the IBES History Summary File (STATSUM_EPSUS) and the CRSP Monthly Stock File (MSF). Details are available from the authors.

However, when we add the boycott factor loadings into the CAPM along with the coverage ratio, the boycott factor dominates. The neglect effect is statistically subsumed by the boycott factor. The "transparency" supposedly increased by analyst coverage no longer decreases the required rate of return. The significance and magnitudes of the boycott risk premium continue to be quite consistent across all specifications. This suggests that our boycott factor is indeed a systematic risk factor, overshadowing the characteristic-based risk source suggested by HK (2009, p.17).

Table 9 also presents the result of including each of the characteristics (LTG, NGL, and ILQ) as well as systematic liquidity (SLQ) together with the boycott risk factor and the other standard systematic risk factors. The characteristics are insignificant in all cases. For the FF30 test assets the boycott risk premium again keeps its magnitude and significance, both for the narrow and for the broad boycott factor measure. For the FF48 assets the magnitude of the boycott risk premium is significant for the broad boycott factor but somewhat reduced and marginally significant for the narrow boycott factor. Overall it appears that the characteristics used in previous explanations for the sin premium are simply proxies for boycott risk sensitivities.

8. Validating the Boycott Premium as a Systematic Risk Premium

To further validate the model we examine implications beyond explanatory power for cross-sectional mean returns. First, return premiums must be related more directly to payoff covariances than to sin characteristics. Second, fluctuations in the boycott premium should be consistent with the theory.

Portfolios Sorted by Boycott Factor Loadings

The theory implies that boycotts can increase targeted firms' investment hurdle rates (required returns), but also affect the hurdle rates of firms whose returns happen to be statistically positively correlated with targeted firms. Therefore, any stocks without the sin characteristic that nonetheless have similar exposure to the boycott factor (maybe because of shared inputs or other un-priced common factors), ought to have similar returns. To explicitly illustrate this implication, we construct a portfolio of stocks that are clearly non-sin. We employ all sin criteria used by either practitioners or researchers and consider the union of all these criteria. The advantage of including all these criteria is that we avoid a gray area, so that remaining stocks that are statistically positively correlated with the boycott factor are clearly not sin stocks.

We remove all stocks that, either by SIC or NAICS code, are classified in any one of the eight screens listed in Table 3. Additionally, we identify the industry classifications of the stocks that were at any point in time included in the Vice Fund.[21] For example, Playboy is part of the Vice Fund stock holdings and the SIC code of Playboy, 2721, is the industry classification. We consider the entire set of firms so classified as "sin" firms for this purpose.

Our "sin net" captures 2766 sin firms out of the 9912 firms that are admitted into our data set. Approximately 28% of the firms are filtered out by this extensive sin screen. We obtain boycott factor loadings for the remaining stocks (with superscript *N* indicating non-sin stocks).

$$r_{it}^{N} = \alpha_i + \beta_{1i}Mkt_t + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}UMD_t + \beta_{5i}r_{bt} + \varepsilon_{it} \qquad (6)$$

Non-sin stocks are ranked based on the sin factor loadings generated from equation (6). These stocks are assigned to five portfolios based on their individual rankings. The equal-weighted

[21] Vice Fund data is from Thomson Reuters Mutual Fund Holdings (S12 file – fund identifier 7386). The Vice Fund data starts from 2002 and provides updated holdings on a quarterly basis.

monthly mean excess returns are reported in Table 10, Panel A, for each of the five portfolios of non-sin stocks and also for five portfolios of sin stocks from the narrow boycott factor, similarly sorted by their boycott betas. In general, stocks that are more susceptible to the boycott factor have relatively higher monthly excess returns for both sin stocks and non-sin stocks. Predictably this pattern is not as strong as when sin stocks are included since we removed most of the stocks with high boycott factor loadings. This is clear by comparing in Panel A the boycott betas for the sin stocks (average boycott beta of 0.60) and the non-sin stocks (average boycott beta -0.05).

We then construct a zero-investment portfolio p by taking a long position in the quintile of non-sin stocks that are most positively correlated with the sin factor and a short position in the least positively correlated quintile of non-sin stocks (those with the lowest correlation with the boycott factor). The zero-investment portfolio is regressed on the FF3 or FF4 (Carhart) risk factors as in equation (7):

$$r_{pt}^{N} = \alpha_p + \beta_{1p}Mkt_t + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}UMD_t + \epsilon_{pt} \tag{7}$$

The results are in Table 10, Panel B and suggest that stocks that have clearly no sin characteristics nevertheless may earn a boycott risk premium if their returns happen to be correlated with sin stocks so that they have positive sensitivity to the boycott risk factor. The alpha is fairly sizable at around 5% annualized, but only marginally significant.

Payoff Covariance or Sin Characteristic

A further indication that it is not the sin character but rather covariance with the boycott factor that drives average returns is obtained by looking directly at payoff covariances. We first identify the systematic component of an asset's variation in earnings:

$$X_{it} = a_i + b_{iM}X_{Mt} + b_{iB}X_{Bt} + \varepsilon_{it}, \tag{8}$$

where X_{it} represents the payoffs (we use earnings before extraordinary items, item IB from the Compustat North American Merged Fundamental Annual File data) of firm *i* at time *t* and X_{Mt} and X_{Bt} refer to market and boycott factor payoffs, respectively. The coefficient b_{iB} then reflects asset *i*'s systematic risk stemming from covariance with aggregate boycott factor payoffs. If estimated boycott betas $\hat{\beta}_{iB}$ are measures of an asset's underlying systematic risk, they should be directly related to the estimated boycott payoff covariances $\hat{b}_{iB}$:

$$\hat{\beta}_{iB} = \gamma_0 + \gamma_1 \hat{b}_{iB} + \gamma_2 C_i + \eta_i , \qquad (9)$$

with $\gamma_1 > 0$ and any characteristics variables C_i having little explanatory power not already incorporated in $\hat{b}_{iB}$ (i.e., $\gamma_2 = 0$).

It can be inferred from the earlier Table 6 that the boycott betas and boycott payoff covariances (the latter obtained as the $\hat{b}_{iB}$ from equation 8) are significantly positively correlated as expected. For the FF30 assets the correlation is 0.750 for the recent sample period (starting from 1999) and 0.903 for the full sample period (starting from 1963); for the FF48 assets the correlation is 0.661 for the recent sample period (starting from 1999) and 0.837 for the full sample period (starting from 1969 for the 48 industries).

Table 11 provides the regression results for equation (9). In all cases (the 1999-2012 and 1963-2012 sample periods for both the FF30 and FF48 test assets) the γ_1 estimates are positive and strongly significant. In addition, once payoff covariances are taken into account, the characteristics variables (neglect, idiosyncratic liquidity, and litigation) and industry controls (only concentration here since the average momentum by industry is almost perfectly correlated with each industry's average return) have little explanatory power for the boycott betas.[22]

The Boycott Risk Premium

The boycott risk premium should vary over time with the economic clout of investors that exercise moral restraint in investment practices. We consider the following implications of this connection. First, as boycotting sin stocks becomes more popular, the boycott premium should increase. However, the willingness of investors to forgo investment returns may vary endogenously over the business cycle. Thus, second, since responsible investing is costly (see also Adler and Kritzmann, 2008), if moral restraint is a luxury good, the extent of moral investing should decrease in a recession, causing a decrease in the boycott risk premium.

We estimate the following process for the boycott premium:

$$BCT_t = c_0 + c_1 YMP_{t-1} + c_2 RWR_{t-1} + e_t . \qquad (10)$$

The state of the economy is captured by YMP_{t-1}, aggregated output relative to potential, for which a low value is associated with a recession. If indeed moral investing is a luxury good then we expect $c_1 > 0$. The aggregate preference for moral investing is captured by RWR_{t-1}. More interest in moral investing should imply a higher boycott premium: $c_2 > 0$.

The time series regression employs the monthly realized boycott risk premium BCT_t as estimated for each month from the second-pass cross-sectional regressions. YMP_{t-1} is the

[22] Replacing the boycott beta by the boycott payoff covariance in the various risk models in Table 5 should work to the extent that it is truly the fundamental boycott risk that is priced. However, asset prices respond not just to current earnings but also to information about future earnings. The latter fundamental is better captured by the boycott beta than by the payoff covariance measure. Results available from the authors show that indeed the boycott payoff covariance is priced significantly (for the FF30 and FF48 test assets over both the post-1990 and post-1963 test periods), but does not perform as well as the boycott beta, in that its contribution to the explanation of average industry returns (measured by the cross-sectional R-square) is substantially lower.

previous quarter's log aggregate output minus log potential output, both available from the St. Louis Fed (Seasonally adjusted real GDP, GDPC1, and potential output, GDPPOT). The quarterly availability implies that the boycott risk premium aggregated over three months is paired with the output gap lagged by three months).

The aggregate preference toward socially responsible investing is captured by the ratio of investment in mutual funds that hold *no sin stocks* in the previous period to total investment in mutual funds, RWR_{t-1}. We use the Thomson-Reuters S12 data to identify mutual fund holdings of sin stocks starting in 1980, thus restricting our sample period here to go from 1980.q1 to 2012.q4. For any mutual fund with a reporting date during a particular quarter we identify whether it holds any of the sin stocks in our narrow boycott factor. If it holds any sin stocks it is classified as unrestricted; if it holds no sin stocks it is classified as restricted (for the particular quarter)[23]. The RWR_t is found as the ratio of the value of all holdings in quarter t of mutual funds classified as restricted to the value of the holdings of all mutual funds. This measure is lagged by one reporting period which is two quarters.[24]

Figure 4 provides an overview of the pattern of co-movement of BCT_t and RWR_t over the business cycle. BCT_t has a quarterly mean return of 1.63 percent, varying from a high of 74.6 percent to a low of -19.7 percent and standard deviation of 10.7 percent. RWR_t has a mean

[23] In addition to the reason of abiding to the social screens, there are certainly other motivations for not holding sin stocks in mutual fund portfolios. An alternative proxy for identifying social responsible mutual funds is to label the funds that have never included stocks that were ever held by known vice funds. Nevertheless, given the social norm evolve over time, some industries that once considered as sin industries may no longer deemed as sinful as it used to be (e.g., gambling). Using quarterly holdings is meant to capture the dynamic of social swings. The essay will benefit from a cleaner measure of RWR.

[24] There are several reasons for describing the current state based on a two-quarter lag. First, throughout much of the sample period, funds are required to report their holdings only twice annually. Second, holdings commonly are valued after they are reported, using then prevailing asset prices. Third, our procedure implies that existing mutual funds newly classified as restricted must have been selling sin stocks in the preceding quarter, thus in effect participating in the boycott at that time. Note that the two-quarter lag in the restricted wealth ratio means that investors in real time are able to forecast the boycott premium which is consistent with the notion of a time-varying risk premium.

level of 44.7 percent varying between 13.6 and 84.6 percent over the sample period with standard deviation of 12.3 percent. Since BCT_t in particular is a highly volatile series, and we are focusing on required returns, we show a (one-year) moving average of both variables. It is difficult to provide a precise timing of events because mutual funds report bi-annually, making it difficult to pinpoint the timing of changes in socially responsible investment wealth.

Comparing the one-year moving average of the boycott risk premium with the one-year moving average of the restricted wealth ratio lagged by one reporting period (two quarters), the two series move together fairly closely with a correlation coefficient of 0.36 that is statistically highly significant. Figure 4 captures clearly the steep ascent in the boycott risk premium when socially responsible investing takes off in the late 1990s. After 2002, the boycott risk premium diverges, falling below the level consistent with the relative wealth of socially responsible investors. A possible explanation is that the Vice Fund started operating in 2002, making arbitrage (esp. international arbitrage) by unconstrained investors easier and cheaper. Figure 4 also illustrates clearly that the boycott premium decreases during recessions (the shaded areas), as we expect if moral responsibility is a luxury good.

More formally, we estimate equation (10). Table 12 shows that, individually, both YMP_{t-1} and RWR_{t-1} have the predicted positive sign on BCT_t at the 5% level of significance. However, when we use both variables jointly to explain BCT_t the business cycle variable loses its significance. A plausible reason is that both relative socially responsible wealth (RWR_t) and the business cycle measure (YMP_t) are alternative proxies for the theoretical variable q_R (the number of socially responsible investors) with some overlapping information. The conclusion is unaltered when we add the FF4 (Carhart) risk factors in explaining the boycott risk premium.

These standard risk factors have only limited explanatory power for BCT_t with the exception of the value premium HML_t which has a strongly significant positive impact on BCT_t. The latter is consistent with our observation that sin stocks are underpriced and thus behave like value stocks.

The *realized* boycott risk premium BCT_t is the sum of both the required boycott risk premium and the boycott factor return shock. The latter adds noise to the required boycott risk premium which we may absorb by including contemporaneous surprise shocks on the right-hand side of the regression. Thus to improve estimation efficiency we include ΔRWR_t and ΔYMP_t in the regression to capture surprise shocks during the return period. A positive shock to either the relative wealth ratio or the business cycle measure means that the future required boycott risk premium increases. For this to occur, the current price of the boycott factor must fall, implying a negative current boycott return shock. Thus, ΔRWR_t (the change in the relative wealth ratio during the period) and ΔYMP_t (measured as realized GDP growth over the next four quarters, assuming that signals about GDP improvement over the upcoming year are reflected in current stock prices, as Fama, 1991, argues) are expected to affect BCT_t with a negative sign.

Table 12 shows that this is indeed the case although only ΔYMP_t is significantly negative.[25] In principle, inclusion of these shock variables should improve estimation of the coefficients on the original state variables. However, the significance of the YMP_{t-1} variable decreases a bit. Thus, while the lagged restricted wealth ratio consistently positively and

[25] The significant link between the boycott risk premium and future aggregate output is also consistent with the result in Liew and Vassalou (2000) that (the size and value factor) risk premiums forecast aggregate output. In the Merton (1973) view all risk factors other than the market factor are state variables reflecting future investment opportunities. A risk factor realization must then represent a change in future investment opportunities that should be accompanied by a change in future aggregate output. Our model neither requires nor rules out such a link (see also our discussion at the end of Section 3).

significantly explains the boycott risk premium, the business cycle measure positively affects the boycott risk premium, as expected if moral investing is a luxury good, but is only marginally significant.

9. Conclusion

The classical result of two-fund separation is based on several critical assumptions, including that investors have identical investment opportunities. However, if social screens are prevalent in economically relevant measure, this assumption is violated. Boycotted stocks are not available to a group of morally constrained investors, who face a reduced investment opportunities set. The violation of the identical investment opportunities assumption gives rise to an additional source of risk – a boycott risk factor: absorption of boycotted stocks by unconstrained investors requires compensation for the extra risk of holding these stocks in excess of the otherwise efficient market weights.

We derive a boycott-augmented CAPM by explicitly segregating the investor base into two groups based on their moral constraints. The model implies that the risk premiums of any stocks are linear combinations of the market and boycott risk factors and sheds light on the commonly observed abnormal return on sin stocks. By incorporating the boycott risk factor, this abnormal return disappears. The perceived superior performance of sin stocks identified in previous studies is because of their close association with the boycott factor.

In a two-stage cross-sectional regression framework, we evaluate the CAPM, FF3 and FF4 models relative to their boycott-augmented versions by considering the incremental contribution of the proposed boycott factor to each model's overall explanatory power. We find that the boycott risk premium is both theoretically and empirically positive. The magnitude of the boycott risk premium is generally close to the average return of the portfolio of boycotted stocks regardless of the choice of the test assets. Furthermore, while the boycotted firms face beyond-normal litigation risk, neglect, and illiquidity, the boycott risk premium cannot be driven out by the litigation risks suggested by HK (2009), the neglect effect of Merton (1987), and measures of idiosyncratic liquidity (Amihud, 2002) or systematic liquidity exposure (Pastor and Stambaugh, 2003). Similarly, accounting for standard industry characteristics such as industry momentum and concentration does not diminish the importance of the boycott risk premium.

The boycott factor results provide a strong indication that non-pecuniary preferences regarding the underlying activities funded by securities may have pervasive pricing effects, as previously argued by Fama and French (2007). Distaste for particular activities systematically reduces the demand for financing these activities, exerting downward price pressure on the securities. Risk arbitrage by unencumbered investors is limited by the specific risk of these securities, causing the prices of any securities with comparable risk characteristics, but potentially unrelated underlying activities, to be affected as well. The boycott event here represents a measurable instance of reduced demand for non-pecuniary reasons.

Appendix

Unrestricted investors

Investor type U (unrestricted/unconstrained) represents the representative morally unrestricted investor. In the traditional single-period CAPM setting, the terminal wealth of the unconstrained investor is fully consumed: $c_U = w_U$, with w_U the end of period wealth of the unrestricted investor. The investment problem of an unrestricted investor under the aforementioned assumptions is as follows:

$$\underset{\mathbf{n}_U}{Max}\ E[U(w_U)],\quad s.t.\quad w_U = (\overline{w}_U / P_f) + \mathbf{n}'_U\ (\mathbf{x} - \mathbf{p})\ . \tag{A1}$$

The wealth constraint follows from $w_U = \mathbf{n}'_U\ \mathbf{x} + n_U^f$, where $\mathbf{n}_U$ is a vector representing the number of shares Investor U purchases in each of the N existing risky assets, and $\mathbf{x}$ is the vector of payoffs per share in each of the N risky assets; n_U^f is the number of risk free discount bonds with unit payoff purchased by Investor U, and $\overline{w}_U = \mathbf{n}'_U \mathbf{P} + n_U^f P_f$, where $\overline{w}_U$ is the initial wealth of Investor U, $\mathbf{P}$ the vector of prices of the risky assets, and P_f the price of the discount bond. The constraint in (A1) is obtained by eliminating n_U^f from the initial and final wealth equations and defining $\mathbf{p} = \mathbf{P} / P_f$. The first-order conditions for the investment choices of the unrestricted investors from (1) are

$$E[U'(w_U)(\mathbf{x} - \mathbf{p})] = 0\,. \tag{A2}$$

Under the assumption that payoffs $\mathbf{x}$ are multivariate normally distributed we may apply Stein's Lemma after using the definition of covariance in equations (A2) to obtain:

$$\overline{\mathbf{x}} - \mathbf{p} = \theta_U\, \mathbf{\Sigma}\, \mathbf{n}_U \tag{A3}$$

where $\theta_U = -E[U''(w_U)] / E[U'(w_U)]$ is akin to the degree of absolute risk aversion of the unconstrained investor, which will depend on initial wealth of Investor U and other model parameters (unless we assume CARA utility). The covariance matrix of the payoffs for the risky assets is given by $\mathbf{\Sigma}$ and the expected payoffs of the risky assets are represented by $\overline{\mathbf{x}}$.

Morally guided investors (restricted or responsible investors)

The investment decision problem for the representative morally guided investor, investor type *R* (restricted/responsible), is similar except that this investor chooses to boycott what are considered to be "sin" stocks – stocks issued by firms whose activities this investor finds morally or socially unacceptable. Final perceived consumption/wealth for Investor *R* is given now by $w_R = \mathbf{n}'_R\, \mathbf{x} + n_R^f$. Given $\overline{w}_R = \mathbf{n}'_R\, \mathbf{P} + n_R^f P_f$, Investor *R*'s decision problem is

$$\underset{\mathbf{n}_R}{Max}\ E[U(w_R)], \quad s.t. \quad w_R = (\overline{w}_R / P_f) + \mathbf{n}'_R\, (\mathbf{x} - \mathbf{p})\ , \tag{A4}$$

where $\mathbf{n}_R$ is a vector representing the number of shares Investor *R* purchases in only the N_N risky assets that are not morally objectionable. The first-order conditions for Investor *R* are

$$E[U'(w_R)(\mathbf{x} - \mathbf{p})] = 0, \tag{A5}$$

leading to

$$\overline{\mathbf{x}}_{\mathbf{N}} - \mathbf{p}_{\mathbf{N}} = \theta_R\, \mathbf{\Sigma}_{\mathbf{N}}\, \mathbf{n}_R\,, \tag{A6}$$

where the matrix of asset payoff covariances is partitioned into those related to "sin stocks" from morally objectionable firms (S) and non-sin (N) firms: $\mathbf{\Sigma} = \begin{pmatrix} \mathbf{\Sigma_N} & \mathbf{\Sigma_{NS}} \\ \mathbf{\Sigma_{SN}} & \mathbf{\Sigma_S} \end{pmatrix}$ so that $\mathbf{\Sigma_N}$ represents the payoff covariance matrix of all stocks that are not boycotted and $\overline{\mathbf{x}}_{\mathbf{N}}, \mathbf{p}_{\mathbf{N}}$ are the vectors of mean payoffs and prices, respectively, of the non-boycotted assets.

Market equilibrium

Assuming that there are q_U investors of type *U* and q_R investors of type *R*, the demand for assets may be obtained and set equal to the exogenous supply of shares, $\overline{\mathbf{n}} = \begin{pmatrix} \overline{\mathbf{n}}_{\mathbf{N}} \\ \overline{\mathbf{n}}_{\mathbf{S}} \end{pmatrix}$, and zero for the risk free asset, yielding the conditions for market equilibrium:

$$\overline{\mathbf{n}} = q_U\, \mathbf{n}_U + q_R\, \mathbf{n}_R\,, \quad 0 = q_U n_U^f + q_R n_R^f\ . \tag{A7}$$

Solving for the risky asset demands of both groups from equations (3) and (6) gives

$$\mathbf{n}_U = (\theta_U\, \mathbf{\Sigma})^{-1}\, (\overline{\mathbf{x}} - \mathbf{p})\,,\ \mathbf{n}_R = (\theta_R\, \mathbf{\Sigma_N})^{-1}\, (\overline{\mathbf{x}}_{\mathbf{N}} - \mathbf{p}_{\mathbf{N}}), \tag{A8}$$

and substituting into equation (A7) yields:

$$\overline{\mathbf{n}} = \left[(\mathbf{\Sigma}\,\theta_U / q_U)^{-1} + \begin{pmatrix} \mathbf{I} \\ \mathbf{0} \end{pmatrix} (\mathbf{\Sigma_N}\,\theta_R / q_R)^{-1} (\mathbf{I} \quad \mathbf{0}) \right] (\overline{\mathbf{x}} - \mathbf{p})\,. \tag{A9}$$

A standard inversion identity states that given matrices $\mathbf{X_1}, \mathbf{X_2}, \mathbf{X_3},$ and $\mathbf{X_4}$, with $\mathbf{X_1}$ and $\mathbf{X_4}$ invertible, we have (see, for instance, Söderström 1994, pp. 156-157):

$$(\mathbf{X}_1^{-1} + \mathbf{X_2}\mathbf{X}_4^{-1}\mathbf{X_3})^{-1} = \mathbf{X_1} - \mathbf{X_1}\mathbf{X_2}(\mathbf{X_4} + \mathbf{X_3}\mathbf{X_1}\mathbf{X_2})^{-1}\mathbf{X_3}\mathbf{X_1}\,.$$

Use this identity to manipulate the inverse of the term in brackets in equation (A9):

$$\left[(\mathbf{\Sigma}\,\theta_U / q_U)^{-1} + \begin{pmatrix} \mathbf{I} \\ \mathbf{0} \end{pmatrix} (\mathbf{\Sigma_N}\,\theta_R / q_R)^{-1} (\mathbf{I} \quad \mathbf{0}) \right]^{-1} =$$

$$(\theta_U / q_U) \left[\mathbf{\Sigma} - \left(\frac{(\theta_U / q_U)}{(\theta_U / q_U) + (\theta_R / q_R)} \right) \mathbf{\Sigma} \begin{pmatrix} \mathbf{\Sigma}_\mathbf{N}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \mathbf{\Sigma} \right] \tag{A10}$$

Then we obtain

$$\overline{\mathbf{x}} - \mathbf{p} = \gamma\,\mathbf{\Sigma}\,\overline{\mathbf{n}} + \delta\,\mathbf{\Sigma}\,\overline{\mathbf{n}}_\mathbf{B}\,,$$

$$\overline{\mathbf{n}}_\mathbf{B} = \begin{pmatrix} -\mathbf{\Sigma}_\mathbf{N}^{-1}\mathbf{\Sigma}_\mathbf{NS}\overline{\mathbf{n}}_\mathbf{S} \\ \overline{\mathbf{n}}_\mathbf{S} \end{pmatrix}, \quad \gamma = \frac{1}{(q_R \overline{w}_R / \rho_R) + (q_U \overline{w}_R / \rho_U)}\,, \quad \delta = \gamma \left(\frac{q_R \overline{w}_R / \rho_R}{q_U \overline{w}_R / \rho_U} \right). \tag{A11}$$

where $\overline{\mathbf{n}}_\mathbf{B}$ represents the “boycott” portfolio of shareholdings. Further $\overline{w}_R$ and $\overline{w}_U$ are the average wealth levels and ρ_R, ρ_U are measures of the degree of relative risk aversion of the investor types, where $\rho_R \equiv \theta_R \overline{w}_R$ and $\rho_U \equiv \theta_U \overline{w}_U$.

Convert equation (A11) into an expression for mean returns rather than expected net payoffs, using that gross stock returns equal $1 + r_i^s = x_i / P_i$. Therefore, $x_i - p_i \equiv x_i - (P_i / P_f)$ equals $P_i(r_i^s - r_f)$ because $P_f \equiv 1/(1 + r_f)$. Define the excess return as $r_i \equiv r_i^s - r_f$ and the mean excess return as $\mu_i \equiv \mu_i^s - r_f$. Since $1 + r_i^s = x_i / P_i$ the covariance matrix of risky asset *returns* $\boldsymbol{\sigma}$

is related to the covariance matrix of risky asset *payoffs* $\mathbf{\Sigma}$ such that for a specific element σ_{ij} of this matrix we have that $\sigma_{ij} = \Sigma_{ij} / P_i P_j$. Then we can write for a particular element of the vector in equation (A11):

$$\mu_i = \gamma \, P_m \sigma_{im} + \delta \, P_b \, \sigma_{ib} , \tag{A12}$$

where m represents the market, $P_m = q_m \overline{w}_m = q_U \overline{w}_U + q_R \overline{w}_R$ is the cost of the market portfolio, and P_b the cost of the boycott portfolio. Apply equation (A12) to the market portfolio and the boycott portfolio to obtain equations for μ_m and μ_b:

$$\mu_m = \gamma \, P_m \sigma_m^2 + \delta \, P_b \, \sigma_{mb} , \qquad \mu_b = \gamma \, P_m \sigma_{bm} + \delta \, P_b \, \sigma_b^2 . \tag{A13}$$

Then solve equations (A13) for γP_m and δP_b , and substitute the resulting expressions into equation (A12) to generate the two-factor result

$$\mu_i = \beta_{im} \mu_m + \beta_{ib} \mu_b , \tag{A14}$$

where β_{im}, β_{ib} are the population values of the slope estimates for a linear regression of the return of asset i on the market portfolio return and the boycott portfolio return:

$$\beta_{ib} = \frac{\sigma_{ib} \, \sigma_m^2 - \sigma_{im} \, \sigma_{mb}}{\sigma_b^2 \, \sigma_m^2 - \sigma_{bm}^2}, \quad \beta_{im} = \frac{\sigma_{im} \, \sigma_b^2 - \sigma_{ib} \, \sigma_{mb}}{\sigma_b^2 \, \sigma_m^2 - \sigma_{bm}^2} \quad . \tag{A15}$$

Covariance with Cashflows of Boycotted Firms

From equation (A11), the solution for the relative price vector of the risky assets is solved in terms of underlying variables as:

$$\mathbf{p} = \overline{\mathbf{x}} - (\gamma \, \mathbf{\Sigma} \, \overline{\mathbf{n}} + \delta \, \mathbf{\Sigma} \, \overline{\mathbf{n}}_{\mathbf{B}}) , \tag{A16}$$

pre-multiplying by a vector of holdings of portfolio i yields for a specific asset or portfolio i that

$$p_i = \overline{\mathbf{n}}_{\mathbf{i}}' \, \mathbf{p} = \overline{x}_i - \gamma \, \Sigma_{im} - \delta \, \Sigma_{ib} , \tag{A17}$$

which becomes equation (2) in the text given that $p_i = P_i / P_f = P_i (1 + r_f)$.

The Boycott Risk Premium

The existence of morally guided investors of type *R* means that $q_R > 0$. It follows that $\delta > 0$ (defined in equation A11), meaning that the *price of boycott risk is positive*: the larger an asset or portfolio *i*'s payoff covariance, $\Sigma_{ib} \equiv \bar{\mathbf{n}}_{\mathbf{i}}' \, \boldsymbol{\Sigma} \, \bar{\mathbf{n}}_{\mathbf{B}}$, with the boycott factor payoff, the lower its price relative to the risk free asset, $p_i = P_i / P_f = P_i(1+r_f)$, and the higher its expected excess return, $\mu_i = (\bar{\mathbf{n}}_{\mathbf{i}}' \bar{\mathbf{x}} / P_i) - (1/P_f)$.

The boycott risk premium, μ_b, can be derived from equation (A11) and the construction of the boycott factor as $x_b - p_b \equiv \bar{\mathbf{n}}_{\mathbf{B}}'(\mathbf{x} - \mathbf{p})$. Taking expected value we have $\bar{x}_b - p_b = (\gamma + \delta)\Sigma_b$, with $\Sigma_b = \bar{\mathbf{n}}_{\mathbf{S}}' \, (\boldsymbol{\Sigma}_{\mathbf{S}} - \boldsymbol{\Sigma}_{\mathbf{SN}} \boldsymbol{\Sigma}_{\mathbf{N}}^{-1} \boldsymbol{\Sigma}_{\mathbf{NS}}) \, \bar{\mathbf{n}}_{\mathbf{S}}$ which is strictly positive because $\boldsymbol{\Sigma}$ is positive definite. Since we can write the mean return as $\mu_b = [(\bar{x}_b - p_b)/p_b]/P_f$ we have

$$\mu_b = \frac{(\gamma + \delta) \; \Sigma_b (1 + r_f)}{\bar{x}_b - (\gamma + \delta) \; \Sigma_b}, \tag{A18}$$

The denominator reflects the price of the boycott factor portfolio: $P_b = [\bar{x}_b - (\gamma + \delta) \; \Sigma_b]/(1 + r_f)$. The price of this boycott portfolio must be positive in general equilibrium. This is true because the boycott portfolio represents the value of the payoffs from sin stocks after hedging the payoffs that are already available in the market. Since the sin stocks could not otherwise exist in positive supply (at least not in our one-period context) the value of the residual payoffs is positive.

If we assume that the relative risk aversion levels of both investor groups are equal, $\rho_R = \rho_U$, then from (A11) and (A18) we obtain equation (3) in the text:

$$\mu_b = (1 + r_f) f\left(\frac{\theta_m \Sigma_b}{\bar{x}_b (1 - RWR)} \right), \quad \text{with} \;\; f(\cdot) > 0 \,, \;\; f'(\cdot) > 0 \,, \;\; \text{and} \;\; RWR \equiv \frac{q_R \bar{w}_R}{q_M \bar{w}_M} \qquad .$$

It follows that μ_b: (a) is always positive; and (b) increases in *RWR*.

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Table 1 Socially Responsible Investing Trends in the United States

This table shows for the U.S. the year-by-year amounts of assets (in units of $1 trillion) under professional management, invested in Socially Responsible Investing funds, and subject to screens.

Total Assets: all Assets tracked by Thomson Reuters Nelson. E.g. $16.30 in 1999 means that according to the *1999 Thomson Reuters Nelson' Directory of Investment Managers*, there were $16.30 trillion in investment assets under professional management in the U.S.

SRI Assets: Socially Responsible Investing Assets. E.g. $2.16 in 1999 means that among the $16.30 trillion assets under professional management (including pension funds, mutual fund families, foundations, religious organizations and community development financial institutions), $2.16 trillion assets were considered as following Socially Responsible Investing policy.

Screened Assets: E.g. $1.50 in 1999 means that of the $2.16 trillion SRI assets, $1.5 trillion assets employed at least one negative screen restricting investment in certain industries.

	1995	1997	1999	2001	2003	2005	2007	2010	2012
Screened Assets	$0.16	$0.53	$1.50	$2.01	$2.14	$1.69	$2.10	$2.51	$3.31
SRI Assets	$0.64	$1.19	$2.16	$2.34	$2.18	$2.29	$2.71	$3.07	$3.74
Total Assets	$7.00	$13.70	$16.30	$19.90	$19.20	$24.40	$25.10	$25.20	$33.30

Table 2 Profile of Boycotted Stocks

This table reports the number of firms by year and average market capitalization (in units of $1 million) of the boycotted stocks subject to the most prevalent screens used by SRI portfolios. The definitions of Tobacco, Alcohol, Coal, Fossil (Coal, Oil, and Gas), and Weapons are based on the Fama-French SIC based classification scheme. Stocks with SIC codes of 2100-2199 belong to the tobacco industry, those with SIC codes of 2080-2085 are in the alcohol industry, and those with SIC codes of 1200-1299 are in the coal industry. Stocks with SIC codes of 1300-1389 are in the oil and gas industry, and those with SIC codes of 3769-3769, 3795, and 3480-3489 are in the weapons industry. Gaming stocks are identified following HK (2009)'s NAICS codes: 7132, 71312, 713210, 71329, 713290, 72112, and 721120.

	Number of Firms						Average Market Capitalization ($ Million)					
Year	Tobacco	Alcohol	Coal	Fossil	Weapons	Gaming	Tobacco	Alcohol	Coal	Fossil	Weapons	Gaming
1963	10	9	3	22	4	n/a	316	148	69	157	220	n/a
1964	12	9	4	26	4	n/a	335	158	158	172	177	n/a
1965	12	10	4	30	4	n/a	342	184	160	180	194	n/a
1966	13	10	5	51	4	n/a	279	151	127	122	186	n/a
1967	10	12	4	52	4	n/a	348	192	119	162	202	n/a
1968	10	12	4	54	4	n/a	379	229	160	223	209	n/a
1969	10	14	4	59	4	n/a	388	223	152	219	197	n/a
1970	10	14	4	62	4	n/a	415	210	202	173	133	n/a
1971	11	13	5	64	4	n/a	583	234	224	231	186	n/a
1972	11	13	5	69	4	n/a	705	335	170	239	176	n/a
1973	11	22	8	100	7	n/a	632	241	94	173	84	n/a
1974	11	21	10	106	8	n/a	545	171	105	141	69	n/a
1975	10	20	10	112	8	n/a	708	179	194	152	72	n/a
1976	10	20	11	123	7	n/a	829	219	238	163	113	n/a
1977	10	19	11	122	8	n/a	873	167	207	184	118	n/a
1978	10	19	9	127	8	n/a	925	170	209	186	298	n/a
1979	10	19	8	158	10	n/a	1022	212	263	230	368	n/a
1980	9	19	8	212	9	n/a	1355	251	357	365	464	n/a
1981	9	17	8	302	9	n/a	1651	310	322	260	507	n/a
1982	8	17	8	334	8	n/a	2008	378	217	133	438	n/a
1983	9	18	8	331	8	n/a	2330	448	239	166	630	n/a
1984	8	18	10	319	9	n/a	2866	371	177	158	576	n/a
1985	6	18	11	301	8	8	4374	465	179	186	671	113
1986	7	17	13	284	9	7	4732	730	150	191	703	199
1987	6	16	13	252	8	7	5797	951	153	282	769	249
1988	7	17	13	235	8	8	4962	895	191	280	863	226
1989	7	17	13	228	8	8	7360	894	277	382	870	302
1990	7	17	9	237	8	12	7380	892	229	445	799	296
1991	7	16	9	233	10	10	12066	1233	214	404	860	389
1992	6	16	10	230	11	11	15760	1291	195	406	854	520
1993	6	18	10	248	11	25	11328	1075	230	461	963	665
1994	6	18	11	243	10	34	11237	1035	264	460	656	441
1995	6	22	11	239	11	35	13999	1122	262	521	1734	455
1996	7	23	11	237	12	37	16064	1128	646	742	2386	494
1997	9	26	9	226	12	37	16418	1302	397	993	2666	426
1998	8	26	5	197	12	31	15933	1554	507	735	3007	391
1999	6	26	5	162	10	26	16047	2046	351	864	1925	672
2000	4	24	6	155	6	20	3432	2108	289	1156	2555	851
2001	6	19	7	163	8	22	23805	2518	857	1260	3197	822
2002	5	17	5	133	9	22	22347	3233	1051	1344	3645	1255
2003	5	17	5	125	9	22	18913	3080	1106	1629	2790	1357
2004	5	14	5	124	10	19	24576	4030	2045	1907	3213	1889
2005	5	13	10	136	10	20	32670	3969	2682	2726	3724	3188
2006	5	12	12	157	10	18	20152	4078	3211	2930	4936	4013
2007	7	13	11	162	10	17	20238	4141	3240	3131	5763	6444
2008	7	11	11	157	10	16	26950	1277	4258	3705	5234	3113
2009	7	11	11	153	10	14	22441	1076	2464	2731	4013	1628
2010	7	12	10	139	9	14	26614	995	3831	3468	4596	3127
2011	7	13	8	145	8	14	34665	1098	4976	4269	5763	4475
2012	6	13	9	140	6	15	42626	1879	2710	3658	3591	4223
Average	8	17	8	166	8	13	10054	1106	823	909	1567	984

Table 3 Investment Screens in Previous Literature

This table provides a survey of the previous academic literature regarding the investment screens applied to identify sin firms. NAICS stands for the North American Industry Classification System, SIC stands for the Standard Industry Classification Code, Permno is a stock identifier. HK is Hong and Kacperczyk (2009). Other papers following the HK criteria are Liston and Soydemir (2010), Salaber (2007, 2009), Chong, Her and Phillips (2006), Liu, Lu, and Veenstra (2014), and Visaltanachoti, Zheng, and Zou (2011). KV is Kim and Venkatachalam (2011). RHZ is Renneboog, Horst, and Zhang (2008, 2011). RHZ's ethical negative screens include animal testing, abortion, genetic engineering, non-marital insurance. RHZ's social negative screens cover workplace diversity, human rights, and labor standards. RHZ's environmental negative screens include firms that: have low environmental standards, contribute to global warming, and/or operate nuclear power plants. FMO is Fabozzi, Ma, and Oliphant (2008). LW is Lobe and Walkshäusl (2011). SRI % refers to the percentage of SRI funds employing the particular screen as reported in the Social Investment Forum for 1999.

Screen	SRI %	HK	KV	RHZ	FMO	LW
Tobacco	96	SIC	SIC	Y	Y	Y
Alcohol	83	SIC	SIC	Y	Y	Y
Gaming	86	NAICS	NAICS	Y	Y	Y
Weapons	81	(SIC)*		Y	Y	Y
Pornography			PERMNO	Y	Y	Y
Ethical	23**			Y	Y	
Social				Y		
Environmental	79			Y		Y
Region	World	US	US	World	World	World

* Only used in robustness tests

** Abortion, Abortifacients, Contraceptives, and Family Planning in the SIF 1999 report

Table 4 Factor Summary Statistics

This table provides summary statistics for the risk factors used in the model comparisons. We consider both the recent period, 1999-2012, and the full sample period, 1963-2012. The meanings of the factor abbreviations are described in the label column. Italics indicate *p-values*.

Panel A. Period 1999-2012

Factor	N	Mean	Std.	Min	Max	Label
MKT	168	0.220	4.730	-17.230	11.340	Market Excess Return (percent)
SMB	168	0.471	3.731	-16.390	22.020	Size Factor Return (percent)
HML	168	0.321	3.611	-12.680	13.870	Value Factor Return (percent)
UMD	168	0.306	6.133	-34.720	18.390	Momentum Factor Return (percent)
BCTn	168	0.766	5.010	-11.772	19.433	Market-Orthogonalized Boycott Factor Return (percent) [Narrow Screen]
BCTb	168	1.210	4.821	-11.781	16.220	Market-Orthogonalized Boycott Factor Return (percent) [Broad Screen]

Corr.	MKT	SMB	HML	UMD	BCTn	BCTb
MKT	1.000	0.290	-0.166	-0.337	0.003	0.013
		0.000	*0.031*	*0.000*	*0.970*	*0.863*
SMB		1.000	-0.363	0.123	-0.225	-0.141
			0.000	*0.111*	*0.003*	*0.068*
HML			1.000	-0.156	0.407	0.399
				0.044	*0.000*	*0.000*
UMD				1.000	-0.064	0.005
					0.411	*0.952*
BCTn					1.000	0.619
						0.000
BCTb						1.000

Panel B. Period 1963-2012

Factor	N	Mean	Std.	Min	Max	Label
MKT	600	0.469	4.498	-23.240	16.100	Market Excess Return (percent)
SMB	600	0.250	3.120	-16.390	22.020	Size Factor Return (percent)
HML	600	0.394	2.891	-12.680	13.870	Value Factor Return (percent)
UMD	600	0.702	4.279	-34.720	18.390	Momentum Factor Return (percent)
BCTn	600	0.323	3.942	-15.506	17.926	Market-Orthogonalized Boycott Factor Return (percent) [Narrow Screen]
BCTb	600	0.382	3.423	-11.696	16.088	Market-Orthogonalized Boycott Factor Return (percent) [Broad Screen]

Corr.	MKT	SMB	HML	UMD	BCTn	BCTb
MKT	1.000	0.309	-0.301	-0.128	0.005	0.005
			0.000	*0.002*	*0.913*	*0.899*
SMB			-0.227	-0.009	-0.146	-0.032
			0.000	*0.833*	*0.000*	*0.428*
HML			1.000	-0.153	0.152	0.168
				0.000	*0.000*	*0.000*
UMD				1.000	-0.017	0.056
					0.681	*0.169*
BCTn					1.000	0.503
						0.000
BCTb						1.000

Table 5 Model Comparison for the Narrow Boycott Factor

The table reports the risk premiums estimated from the cross-sectional regressions of the CAPM, Boycott-CAPM, FF3, Boycott-FF3, FF4, and Boycott-FF4 models. The test assets are the FF30 and FF48 industry test portfolios, the FF25 value and size sorted portfolios and the FF55 portfolios (the FF30 and FF25 portfolios jointly). The narrow boycott factor (BCTn) is the value-weighted return of the tobacco, alcohol, and coal industries firms. The first-pass factor loadings are estimated based on sample period 1999.01-2012.12 for Panels A through D, 1963.01-2012.12 for Panels E, G and H, and 1969.07-2012.12 for Panel F (due to the unavailability of the health industry portfolio within the FF48 portfolios before 1969.07). The BJS (Black-Jensen-Scholes) *t*-statistics are for the cross-sectional regression slopes with betas estimated over the full sample period, and the GMM *t*-statistics are based on 12 monthly lags. R^2 is the adjusted R-squared for the cross-sectional fit between predicted and realized mean returns.

Panel A. 1999.01-2012.12

FF30	Const	MKT	SMB	HML	UMD	BCTn	R^2
RP	0.415	0.111					-0.026
BJS-t	*1.315*	*0.236*					
GMM-t	*1.157*	*0.220*					
RP	-0.286	0.594				1.332	0.481
BJS-t	*-0.765*	*1.156*				*2.287*	
GMM-t	*-0.615*	*0.940*				*2.063*	
RP	0.584	-0.173	0.711	0.234			0.063
BJS-t	*1.657*	*-0.345*	*1.366*	*0.714*			
GMM-t	*1.778*	*-0.337*	*1.769*	*0.660*			
RP	-0.211	0.552	0.027	0.198		1.327	0.455
BJS-t	*-0.574*	*1.066*	*0.059*	*0.600*		*2.197*	
GMM-t	*-0.480*	*0.883*	*0.072*	*0.516*		*2.207*	
RP	0.301	0.159	0.583	0.356	1.761		0.420
BJS-t	*0.845*	*0.306*	*1.196*	*1.056*	*1.574*		
GMM-t	*0.731*	*0.260*	*1.419*	*0.950*	*1.895*		
RP	-0.148	0.542	0.155	0.287	0.855	1.045	0.557
BJS-t	*-0.438*	*1.054*	*0.332*	*0.841*	*0.829*	*2.088*	
GMM-t	*-0.385*	*0.876*	*0.369*	*0.745*	*0.848*	*2.294*	

Panel B. 1999.01-2012.12

FF48	Const	MKT	SMB	HML	UMD	BCTn	R^2
RP	0.479	0.068					-0.017
BJS-t	*1.523*	*0.150*					
GMM-t	*1.305*	*0.136*					
RP	-0.127	0.498				1.231	0.400
BJS-t	*-0.425*	*1.063*				*2.199*	
GMM-t	*-0.342*	*0.870*				*1.903*	
RP	0.372	0.061	0.221	0.213			0.035
BJS-t	*1.382*	*0.137*	*0.592*	*0.648*			
GMM-t	*1.466*	*0.124*	*0.841*	*0.571*			
RP	-0.039	0.426	0.126	0.173		1.270	0.415
BJS-t	*-0.140*	*0.933*	*0.343*	*0.524*		*2.294*	
GMM-t	*-0.112*	*0.746*	*0.459*	*0.452*		*2.267*	
RP	0.166	0.314	0.290	0.300	1.451		0.349
BJS-t	*0.598*	*0.678*	*0.757*	*0.905*	*1.479*		
GMM-t	*0.519*	*0.559*	*0.913*	*0.759*	*1.720*		
RP	-0.064	0.493	0.195	0.239	0.822	1.045	0.512
BJS-t	*-0.223*	*1.047*	*0.516*	*0.718*	*0.904*	*2.179*	
GMM-t	*-0.178*	*0.813*	*0.622*	*0.612*	*0.964*	*2.290*	

Panel C. 1999.01-2012.12

FF55							
RP	0.437	0.135					-0.007
BJS-t	*1.226*	*0.273*					
GMM-t	*1.071*	*0.259*					
RP	-0.142	0.590				0.998	0.254
BJS-t	*-0.414*	*1.158*				*1.716*	
GMM-t	*-0.352*	*0.972*				*1.512*	
RP	0.425	-0.062	0.379	0.322			0.228
BJS-t	*1.455*	*-0.132*	*1.280*	*1.071*			
GMM-t	*1.487*	*-0.125*	*1.580*	*0.937*			
RP	0.037	0.283	0.389	0.257		1.136	0.488
BJS-t	*0.109*	*0.566*	*1.312*	*0.857*		*1.968*	
GMM-t	*0.094*	*0.468*	*1.606*	*0.752*		*1.957*	
RP	0.178	0.245	0.360	0.376	1.671		0.502
BJS-t	*0.524*	*0.470*	*1.216*	*1.233*	*1.728*		
GMM-t	*0.430*	*0.381*	*1.499*	*1.117*	*2.062*		
RP	-0.015	0.391	0.373	0.316	1.135	0.909	0.597
BJS-t	*-0.041*	*0.732*	*1.256*	*1.043*	*1.322*	*1.827*	
GMM-t	*-0.033*	*0.568*	*1.551*	*0.952*	*1.344*	*1.909*	

Panel D. 1999.01-2012.12

FF25							
RP	0.507	0.121					-0.039
BJS-t	*0.565*	*0.128*					
GMM-t	*0.573*	*0.137*					
RP	0.089	0.494				0.298	-0.060
BJS-t	*0.198*	*0.776*				*0.351*	
GMM-t	*0.209*	*0.749*				*0.332*	
RP	1.046	-0.738	0.401	0.353			*0.570*
BJS-t	*2.552*	*-1.314*	*1.355*	*1.226*			
GMM-t	*2.794*	*-1.325*	*1.677*	*1.055*			
RP	1.016	-0.761	0.448	0.302		1.841	0.600
BJS-t	*2.479*	*-1.357*	*1.534*	*1.060*		*1.481*	
GMM-t	*2.420*	*-1.183*	*1.901*	*0.894*		*1.509*	
RP	0.221	0.162	0.421	0.367	2.803		0.645
BJS-t	*0.414*	*0.236*	*1.429*	*1.273*	*2.816*		
GMM-t	*0.327*	*0.181*	*1.722*	*1.164*	*2.414*		
RP	0.328	0.013	0.446	0.335	2.533	1.179	0.643
BJS-t	*0.636*	*0.019*	*1.527*	*1.174*	*2.813*	*0.984*	
GMM-t	*0.545*	*0.016*	*1.904*	*1.024*	*2.773*	*0.871*	

Panel E. 1963.01-2012.12							
FF30	Const	MKT	SMB	HML	UMD	BCTn	R^2
RP	0.618	-0.025					-0.035
BJS-t	*2.657*	*-0.084*					
GMM-t	*2.637*	*-0.080*					
RP	0.164	0.360				0.535	0.480
BJS-t	*0.695*	*1.183*				*2.628*	
GMM-t	*0.636*	*1.095*				*2.402*	
RP	0.707	-0.104	0.051	-0.064			-0.089
BJS-t	*2.521*	*-0.314*	*0.277*	*-0.406*			
GMM-t	*2.570*	*-0.319*	*0.261*	*-0.353*			
RP	0.210	0.335	0.036	-0.123		0.523	0.494
BJS-t	*0.757*	*1.011*	*0.192*	*-0.784*		*2.511*	
GMM-t	*0.750*	*1.044*	*0.181*	*-0.698*		*2.341*	
RP	0.584	0.027	0.083	-0.024	0.516		-0.022
BJS-t	*1.918*	*0.076*	*0.434*	*-0.144*	*0.880*		
GMM-t	*1.756*	*0.072*	*0.406*	*-0.128*	*0.876*		
RP	0.178	0.374	0.051	-0.103	0.201	0.507	0.494
BJS-t	*0.592*	*1.046*	*0.262*	*-0.607*	*0.342*	*2.509*	
GMM-t	*0.539*	*0.995*	*0.248*	*-0.550*	*0.328*	*2.376*	

Panel F. 1969.07-2012.12							
FF48	Const	MKT	SMB	HML	UMD	BCTn	R^2
RP	0.767	-0.214					0.035
BJS-t	*3.077*	*-0.677*					
GMM-t	*3.176*	*-0.641*					
RP	0.399	0.098				0.475	0.214
BJS-t	*1.539*	*0.298*				*1.986*	
GMM-t	*1.486*	*0.277*				*1.746*	
RP	0.580	0.014	-0.258	-0.014			0.096
BJS-t	*1.938*	*0.038*	*-1.339*	*-0.083*			
GMM-t	*2.076*	*0.039*	*-1.280*	*-0.071*			
RP	0.246	0.298	-0.234	-0.077		0.524	0.288
BJS-t	*0.790*	*0.809*	*-1.222*	*-0.448*		*2.166*	
GMM-t	*0.834*	*0.830*	*-1.153*	*-0.396*		*1.934*	
RP	0.469	0.135	-0.255	-0.000	0.343		0.106
BJS-t	*1.557*	*0.371*	*-1.314*	*-0.002*	*0.586*		
GMM-t	*1.473*	*0.356*	*-1.262*	*-0.002*	*0.566*		
RP	0.206	0.345	-0.233	-0.068	0.142	0.514	0.278
BJS-t	*0.655*	*0.921*	*-1.215*	*-0.384*	*0.238*	*2.111*	
GMM-t	*0.612*	*0.874*	*-1.151*	*-0.342*	*0.224*	*1.907*	

FF55	**Panel G. 1963.01-2012.12**						
RP	0.760	-0.111					-0.008
BJS-t	*3.105*	*-0.359*					
GMM-t	*2.959*	*-0.332*					
RP	0.456	0.159				0.382	0.069
BJS-t	*1.928*	*0.521*				*1.903*	
GMM-t	*1.768*	*0.482*				*1.759*	
RP	0.935	-0.395	0.171	0.258			0.313
BJS-t	*3.974*	*-1.328*	*1.307*	*2.066*			
GMM-t	*4.149*	*-1.341*	*1.253*	*1.801*			
RP	0.632	-0.136	0.205	0.244		0.426	0.432
BJS-t	*2.706*	*-0.455*	*1.574*	*1.955*		*2.120*	
GMM-t	*2.617*	*-0.447*	*1.513*	*1.715*		*1.961*	
RP	0.691	-0.135	0.172	0.278	0.707		0.380
BJS-t	*2.392*	*-0.386*	*1.316*	*2.210*	*1.355*		
GMM-t	*2.117*	*-0.350*	*1.263*	*1.973*	*1.314*		
RP	0.463	0.050	0.203	0.261	0.544	0.412	0.473
BJS-t	*1.577*	*0.142*	*1.555*	*2.085*	*1.061*	*2.078*	
GMM-t	*1.358*	*0.126*	*1.494*	*1.867*	*1.005*	*1.979*	

FF25	**Panel H. 1963.01-2012.12**						
RP	1.169	-0.430					0.044
BJS-t	*3.044*	*-1.018*					
GMM-t	*2.875*	*-0.957*					
RP	0.877	-0.158				0.466	0.009
BJS-t	*2.846*	*-0.456*				*0.669*	
GMM-t	*2.956*	*-0.496*				*0.654*	
RP	1.145	-0.650	0.188	0.432			0.704
BJS-t	*4.057*	*-1.915*	*1.444*	*3.562*			
GMM-t	*3.884*	*-2.025*	*1.369*	*3.063*			
RP	0.918	-0.502	0.248	0.354		2.530	0.800
BJS-t	*3.096*	*-1.447*	*1.925*	*2.933*		*3.228*	
GMM-t	*2.324*	*-1.199*	*1.793*	*2.462*		*2.641*	
RP	0.451	0.078	0.211	0.439	2.540		0.730
BJS-t	*1.255*	*0.190*	*1.620*	*3.625*	*3.338*		
GMM-t	*0.980*	*0.168*	*1.490*	*3.244*	*2.247*		
RP	0.173	0.277	0.274	0.360	2.752	2.700	0.836
BJS-t	*0.450*	*0.650*	*2.122*	*2.987*	*3.542*	*3.385*	
GMM-t	*0.274*	*0.450*	*1.976*	*2.470*	*1.938*	*1.888*	

Table 6 Market and Boycott Factor Loadings

Panel A. This table reports the market β_{iM} and boycott factor β_{iB} loadings for industries *i* obtained from the time-series regressions of the Boycott-CAPM (with the narrow boycott factor), using the monthly data over the periods stated in the first row of the table. It also shows the sensitivities b_{iB} of each industry's earnings (before extraordinary items – Compustat Annual file item IB) to the aggregate earnings of the boycotted industries (narrow measure) generated by following regressions: $X_{it} = a_i + b_{iM} X_{Mt} + b_{iB} X_{Bt} + \varepsilon_{it}$, where X_{it} is individual Fama-French industry's annual earnings, X_{Mt} is earnings of all industries combined, and X_{Bt} is the earnings of the three boycotted industries combined.

1999-2012				**1963-2012**			
FF30	β_{iM}	β_{iB}	b_{iB}	**FF30**	β_{iM}	β_{iB}	b_{iB}
Smoke	0.446	1.204	3.661	Smoke	0.674	1.187	2.942
Coal	1.310	0.635	-0.011	Coal	1.161	0.402	0.966
Util	0.406	0.393	0.095	Beer	0.761	0.400	0.362
Mines	1.000	0.381	0.451	Food	0.713	0.354	0.261
Beer	0.322	0.333	0.503	Util	0.530	0.223	0.212
Oil	0.754	0.305	0.671	Hlth	0.832	0.212	0.100
Food	0.403	0.299	0.203	Hshld	0.820	0.181	0.237
Carry	0.962	0.254	0.398	Meals	1.074	0.150	0.046
Whlsl	0.818	0.225	0.034	Whlsl	1.074	0.119	0.016
Cnstr	1.128	0.216	-0.176	Cnstr	1.186	0.099	-0.028
Txtls	1.340	0.205	-0.072	Paper	0.950	0.086	0.024
Hshld	0.477	0.185	0.089	Mines	0.953	0.082	0.180
Chems	1.080	0.177	0.071	Fin	1.068	0.081	-0.076
Hlth	0.524	0.171	0.221	Carry	1.118	0.074	0.303
Paper	0.862	0.157	-0.083	Chems	1.040	0.066	0.086
Fin	1.030	0.156	-0.292	Other	1.084	0.064	0.104
Meals	0.670	0.155	0.086	Oil	0.790	0.059	0.302
Trans	0.885	0.112	-0.054	Clths	1.130	0.055	0.043
Other	0.847	0.089	0.208	Txtls	1.135	0.033	-0.030
Books	1.038	0.086	-0.248	Rtail	0.998	0.021	0.122
Clths	1.017	0.051	0.068	Books	1.072	0.015	-0.076
Games	1.396	0.036	-0.128	Trans	1.081	0.004	0.003
ElcEq	1.303	0.032	0.012	ElcEq	1.214	-0.004	0.041
Autos	1.418	0.029	-0.563	Games	1.330	-0.004	-0.077
FabPr	1.405	0.022	0.193	Telcm	0.767	-0.044	-0.603
Steel	1.810	-0.012	-0.309	FabPr	1.226	-0.063	0.070
Telcm	1.001	-0.046	-0.207	Autos	1.138	-0.080	-0.150
Rtail	0.813	-0.082	0.179	Steel	1.295	-0.113	-0.139
Servs	1.327	-0.285	0.045	Servs	1.325	-0.153	-0.020
BusEq	1.606	-0.335	-0.124	BusEq	1.286	-0.269	-0.129
Mean	*0.980*	*0.172*	*0.164*		*1.027*	*0.108*	*0.170*
Std.	*0.381*	*0.274*	*0.709*		*0.208*	*0.252*	*0.579*

1999-2012				**1969-2012**			
FF48	β_{iM}	β_{iB}	b_{iB}	**FF48**	β_{iM}	β_{iB}	b_{iB}
Smoke	0.446	1.204	3.661	Smoke	0.673	1.177	2.941
Coal	1.310	0.635	-0.009	Coal	1.182	0.413	0.967
Util	0.406	0.393	0.094	Beer	0.755	0.402	0.361
Gold	0.332	0.374	0.175	Food	0.677	0.372	0.198
Ships	1.070	0.374	0.123	Soda	0.846	0.285	0.817
Mines	1.344	0.340	0.729	Drugs	0.784	0.239	0.138
Beer	0.322	0.333	0.502	Util	0.525	0.236	0.211
Hlth	0.611	0.323	0.123	Hlth	1.142	0.228	0.069
Oil	0.754	0.305	0.669	Hshld	0.804	0.202	0.236
Food	0.352	0.303	0.123	Ships	1.088	0.184	0.126
Insur	0.878	0.283	-0.473	MedEq	0.897	0.182	0.034
Soda	0.573	0.254	0.509	Insur	0.964	0.161	-0.158
Guns	0.346	0.250	0.220	Meals	1.056	0.154	0.046
Aero	0.972	0.249	0.523	Guns	0.818	0.126	0.181
RlEst	1.203	0.226	-0.002	Whlsl	1.043	0.121	0.016
Whlsl	0.818	0.225	0.034	Agric	0.863	0.120	-0.006
BldMt	1.129	0.209	-0.114	Banks	1.073	0.110	-0.147
Txtls	1.340	0.205	-0.072	PerSv	1.103	0.100	0.022
Hshld	0.477	0.185	0.088	BldMt	1.165	0.100	0.019
Chems	1.080	0.177	0.070	Gold	0.641	0.098	0.056
Cnstr	1.181	0.174	-0.241	Paper	0.967	0.091	0.018
Banks	0.981	0.170	-0.373	Mines	1.103	0.082	0.362
Drugs	0.497	0.170	0.284	Aero	1.134	0.077	0.396
Paper	0.850	0.156	-0.075	Oil	0.792	0.065	0.299
Meals	0.670	0.155	0.085	Rubbr	1.063	0.064	-0.024
FabPr	1.158	0.146	-0.049	Chems	1.037	0.063	0.085
PerSv	0.769	0.144	0.073	Clths	1.129	0.055	0.043
MedEq	0.663	0.121	0.109	Boxes	0.956	0.049	0.040
Trans	0.889	0.113	-0.063	Toys	1.167	0.046	-0.054
Boxes	1.032	0.100	-0.101	Other	1.150	0.044	0.103
Agric	0.701	0.090	0.084	Txtls	1.127	0.041	-0.030
Other	0.887	0.083	0.207	RlEst	1.196	0.032	0.001
Rubbr	0.981	0.076	-0.065	Rtail	1.005	0.023	0.122
Toys	0.949	0.075	-0.289	Cnstr	1.301	0.020	-0.076
Clths	1.017	0.051	0.068	Books	1.060	0.018	-0.090
Books	1.000	0.049	-0.289	Fun	1.361	0.013	-0.082
Fun	1.507	0.045	-0.030	Trans	1.067	0.005	-0.001
ElcEq	1.303	0.032	0.013	FabPr	1.091	0.001	-0.007
Autos	1.418	0.029	-0.560	ElcEq	1.207	-0.010	0.041
Mach	1.410	0.020	0.216	Telcm	0.781	-0.039	-0.606
Steel	1.810	-0.012	-0.313	Mach	1.227	-0.074	0.075
Telcm	1.001	-0.046	-0.211	Autos	1.133	-0.096	-0.148
Rtail	0.813	-0.082	0.178	Steel	1.295	-0.138	-0.142
Fin	1.505	-0.163	-0.162	Fin	1.241	-0.149	-0.006
LabEq	1.416	-0.260	0.057	LabEq	1.333	-0.167	-0.006
BusSv	1.341	-0.290	0.043	BusSv	1.307	-0.186	-0.023
Comps	1.604	-0.339	0.134	Comps	1.235	-0.261	-0.101
Chips	1.629	-0.346	-0.306	Chips	1.413	-0.305	-0.193
Mean	*0.974*	*0.152*	*0.112*		*1.041*	*0.091*	*0.128*
Std.	*0.383*	*0.248*	*0.587*		*0.206*	*0.220*	*0.479*

Panel B. Test Asset Boycott Factor Loadings for the FF25 Assets

The boycott factor betas (BCT Beta = β_{iB}) for each of the 25 size and value sorted assets obtained in the context of the two-factor boycott-augmented CAPM are presented for the 1999.01-2012.12 and 1963.01-2012.12 periods.

1999-2012 (Size across columns, Value down rows)

BCT Beta	Smallest	2	3	4	Largest
Lowest	-0.366	-0.255	-0.220	-0.196	-0.035
2	-0.194	-0.020	0.064	0.163	0.130
3	-0.116	0.070	0.182	0.217	0.161
4	-0.050	0.101	0.232	0.231	0.283
Highest	0.025	0.128	0.206	0.277	0.228

1963-2012 (Size across columns, Value down rows)

BCT Beta	Smallest	2	3	4	Largest
Lowest	-0.257	-0.165	-0.140	-0.107	0.047
2	-0.149	-0.048	-0.001	0.048	0.082
3	-0.089	0.006	0.046	0.081	0.049
4	-0.056	0.022	0.083	0.109	0.121
Highest	-0.034	0.019	0.068	0.113	0.085

Table 7 Model Comparison for the Broad Boycott Factor

The table reports the risk premiums estimated from the cross-sectional regressions of the CAPM, Boycott-CAPM, FF3, Boycott-FF3, FF4, and Boycott-FF4 models. The test assets are the FF30 and FF48 industry test portfolios, the FF25 value and size sorted portfolios and the FF55 portfolios (the FF30 and FF25 portfolios jointly). The broad boycott factor (BCTb) is the value-weighted return of the tobacco, alcohol, coal, oil, gas, weapons, and gaming industries firms. The first-pass factor loadings are estimated for the period 1999.01-2012.12. The BJS (Black-Jensen-Scholes) *t*-statistics are for the cross-sectional regression slopes with betas estimated over the full sample period, and the GMM *t*-statistics are based on 12 monthly lags. R^2 is the adjusted R-squared for the cross-sectional fit between predicted and realized mean returns.

Panel A. 1999-2012							
FF30	Const	MKT	SMB	HML	UMD	BCTb	R^2
RP	0.119	0.161				1.080	0.682
BJS-t	*0.364*	*0.341*				*2.162*	
GMM-t	*0.284*	*0.295*				*1.993*	
RP	0.283	0.050	0.085	0.110		1.056	0.694
BJS-t	*0.833*	*0.101*	*0.187*	*0.330*		*2.080*	
GMM-t	*0.754*	*0.090*	*0.259*	*0.303*		*1.955*	
RP	0.313	-0.012	-0.008	0.042	-0.413	1.174	0.695
BJS-t	*0.878*	*-0.024*	*-0.018*	*0.123*	*-0.455*	*2.515*	
GMM-t	*0.746*	*-0.019*	*-0.022*	*0.126*	*-0.435*	*2.204*	

Panel B. 1999-2012							
FF48	Const	MKT	SMB	HML	UMD	BCTb	R^2
RP	0.102	0.213				1.066	0.644
BJS-t	*0.336*	*0.470*				*2.211*	
GMM-t	*0.254*	*0.395*				*1.996*	
RP	0.209	0.155	-0.045	0.116		1.113	0.675
BJS-t	*0.782*	*0.348*	*-0.123*	*0.349*		*2.236*	
GMM-t	*0.647*	*0.287*	*-0.169*	*0.305*		*2.049*	
RP	0.236	0.108	-0.096	0.084	-0.309	1.190	0.675
BJS-t	*0.856*	*0.237*	*-0.260*	*0.248*	*-0.374*	*2.492*	
GMM-t	*0.664*	*0.189*	*-0.340*	*0.226*	*-0.407*	*2.210*	

FF55	Panel C. 1999-2012						
RP	0.126	0.296				0.864	0.396
BJS-t	*0.377*	*0.600*				*1.808*	
GMM-t	*0.302*	*0.523*				*1.692*	
RP	0.437	-0.134	0.416	0.198		1.013	0.672
BJS-t	*1.500*	*-0.285*	*1.400*	*0.657*		*2.075*	
GMM-t	*1.393*	*-0.255*	*1.747*	*0.590*		*1.998*	
RP	0.414	-0.101	0.412	0.210	0.427	0.986	0.666
BJS-t	*1.287*	*-0.204*	*1.391*	*0.709*	*0.560*	*2.136*	
GMM-t	*1.054*	*-0.167*	*1.787*	*0.674*	*0.540*	*1.992*	

FF25	Panel D. 1999-2012						
RP	-0.147	0.673				0.649	0.001
BJS-t	*-0.294*	*0.991*				*0.994*	
GMM-t	*-0.332*	*1.045*				*0.914*	
RP	1.067	-0.836	0.476	0.302		1.116	0.659
BJS-t	*2.595*	*-1.481*	*1.637*	*1.059*		*1.712*	
GMM-t	*2.828*	*-1.401*	*2.060*	*0.901*		*2.056*	
RP	0.529	-0.228	0.468	0.325	2.137	1.070	0.674
BJS-t	*0.995*	*-0.339*	*1.610*	*1.141*	*2.454*	*1.640*	
GMM-t	*0.976*	*-0.303*	*2.030*	*0.989*	*2.657*	*1.766*	

Table 8 Industry Controls

Panel A presents the estimated coefficients from the Black-Jensen-Scholes cross-sectional regressions of the CAPM, narrow Boycott-CAPM, FF4 (Carhart, 1997), and Boycott-FF4 models together with industry momentum controls using monthly data during 1999.01-2012.12. The test assets are the Fama French 30-industry (left) and 48-industry (right) portfolios. The right-hand side factor loadings are generated from full sample observations between 1999.01 and 2012.12. IM_k is the industry momentum variable equal to each industry's past excess return over a k-month period. The *t*-statistics are in italics.

	FF30 1999-2012							FF48 1999-2012						
k	Const.	MKT	SMB	HML	UMD	BCTn	IM_k	Const.	MKT	SMB	HML	UMD	BCTn	IM_k
1	0.058	0.384					0.033	0.259	0.224					0.018
	0.191	*0.858*					*1.133*	*0.881*	*0.525*					*0.768*
1	-0.411	0.629				1.097	0.021	-0.230	0.529				1.162	0.009
	-1.200	*1.285*				*2.033*	*0.784*	*-0.825*	*1.167*				*2.166*	*0.397*
1	0.096	0.252	0.380	0.407	1.470		-0.014	0.085	0.264	0.280	0.370	1.529		-0.010
	0.263	*0.464*	*0.729*	*1.143*	*1.356*		*-0.643*	*0.312*	*0.564*	*0.738*	*1.095*	*1.575*		*-0.532*
1	-0.231	0.537	0.018	0.325	0.785	1.014	0.000	-0.116	0.436	0.164	0.317	0.954	1.096	-0.007
	-0.670	*1.000*	*0.037*	*0.909*	*0.779*	*1.972*	*0.004*	*-0.413*	*0.923*	*0.437*	*0.924*	*1.033*	*2.249*	*-0.353*
3	0.359	0.183					0.016	0.483	0.116					0.015
	1.112	*0.403*					*0.539*	*1.640*	*0.277*					*0.627*
3	-0.447	0.771				1.582	0.006	-0.108	0.540				1.286	0.009
	-1.260	*1.614*				*2.824*	*0.212*	*-0.368*	*1.238*				*2.399*	*0.380*
3	0.228	0.169	0.497	0.513	2.246		0.013	0.231	0.155	0.324	0.433	1.553		0.008
	0.649	*0.323*	*1.027*	*1.479*	*2.049*		*0.554*	*0.849*	*0.339*	*0.792*	*1.301*	*1.617*		*0.401*
3	-0.256	0.568	0.006	0.374	1.052	1.261	0.006	-0.010	0.338	0.230	0.343	0.836	1.111	0.001
	-0.757	*1.101*	*0.012*	*1.090*	*1.062*	*2.465*	*0.255*	*-0.035*	*0.734*	*0.568*	*1.027*	*0.928*	*2.238*	*0.031*
6	0.479	0.025					0.046	0.508	-0.025					0.032
	1.481	*0.055*					*1.561*	*1.650*	*-0.057*					*1.354*
6	-0.131	0.415				1.287	0.045	-0.052	0.351				1.251	0.032
	-0.368	*0.849*				*2.197*	*1.732*	*-0.177*	*0.768*				*2.208*	*1.444*
6	0.340	0.097	0.477	0.440	1.563		0.031	0.213	0.186	0.279	0.318	1.353		0.023
	0.975	*0.189*	*0.969*	*1.215*	*1.407*		*1.375*	*0.774*	*0.401*	*0.729*	*0.948*	*1.396*		*1.283*
6	-0.054	0.387	0.188	0.388	0.915	1.050	0.027	-0.030	0.343	0.219	0.267	0.792	1.084	0.022
	-0.162	*0.758*	*0.384*	*1.078*	*0.885*	*2.023*	*1.264*	*-0.103*	*0.727*	*0.577*	*0.795*	*0.876*	*2.170*	*1.235*
9	0.466	-0.102					-0.004	0.648	-0.193					-0.005
	1.389	*-0.214*					*-0.131*	*2.092*	*-0.435*					*-0.255*
9	-0.289	0.415				1.525	-0.004	0.002	0.265				1.387	-0.001
	-0.765	*0.798*				*2.603*	*-0.145*	*0.007*	*0.560*				*2.432*	*-0.054*
9	0.567	-0.237	0.583	0.356	1.091		0.008	0.418	-0.004	0.229	0.362	1.043		0.002
	1.587	*-0.459*	*1.172*	*1.041*	*0.982*		*0.415*	*1.524*	*-0.008*	*0.581*	*1.054*	*1.037*		*0.115*
9	-0.038	0.309	0.083	0.235	0.043	1.257	0.002	0.154	0.204	0.146	0.281	0.427	1.175	-0.007
	-0.108	*0.591*	*0.173*	*0.686*	*0.042*	*2.353*	*0.086*	*0.538*	*0.434*	*0.376*	*0.819*	*0.457*	*2.347*	*-0.419*
12	0.523	-0.168					0.013	0.642	-0.172					0.002
	1.591	*-0.346*					*0.435*	*2.153*	*-0.381*					*0.102*
12	-0.203	0.342				1.398	0.003	0.028	0.275				1.341	-0.005
	-0.532	*0.652*				*2.390*	*0.120*	*0.091*	*0.567*				*2.367*	*-0.253*
12	0.397	-0.069	0.546	0.488	1.475		0.000	0.305	0.100	0.375	0.427	1.533		-0.013
	1.121	*-0.129*	*1.109*	*1.418*	*1.285*		*0.000*	*1.094*	*0.207*	*0.943*	*1.263*	*1.496*		*-0.717*
12	-0.215	0.487	0.059	0.384	0.348	1.361	-0.014	0.042	0.329	0.339	0.336	0.908	1.204	-0.021
	-0.616	*0.902*	*0.122*	*1.110*	*0.339*	*2.500*	*-0.568*	*0.145*	*0.668*	*0.856*	*0.987*	*0.958*	*2.347*	*-1.150*

Panel B presents the estimated coefficients from the Black-Jensen-Scholes cross-sectional regressions of the CAPM, narrow Boycott-CAPM, Carhart, and Boycott-Carhart models together with industry momentum controls using monthly data from 1963.01-2012.12 for the FF30 test assets and from 1969.07-2012.12 for the FF48 test assets. The right-hand side factor loadings are generated from full sample observations. IM_k is the industry momentum variable equal to each industry's past excess return over a k-month period. The *t*-statistics are in italics.

	FF30 1963-2012							FF48 1969-2012						
k	Const.	MKT	SMB	HML	UMD	BCTn	IM_k	Const.	MKT	SMB	HML	UMD	BCTn	IM_k
1	0.416	0.161					0.075	0.563	0.046					0.049
	1.871	*0.575*					*5.304*	*2.319*	*0.150*					*3.752*
1	0.177	0.364				0.341	0.079	0.389	0.197				0.274	0.049
	0.764	*1.247*				*1.688*	*5.456*	*1.506*	*0.599*				*1.152*	*3.758*
1	0.301	0.326	0.021	-0.047	0.615		0.056	0.367	0.300	-0.145	-0.030	0.572		0.028
	1.031	*0.939*	*0.113*	*-0.289*	*1.126*		*4.270*	*1.243*	*0.822*	*-0.773*	*-0.174*	*1.002*		*2.394*
1	0.071	0.530	-0.024	-0.088	0.430	0.390	0.059	0.252	0.397	-0.138	-0.050	0.473	0.325	0.026
	0.245	*1.519*	*-0.128*	*-0.542*	*0.784*	*1.908*	*4.489*	*0.822*	*1.060*	*-0.748*	*-0.286*	*0.811*	*1.350*	*2.283*
3	0.581	-0.066					0.013	0.668	-0.062					0.012
	2.512	*-0.228*					*0.985*	*2.725*	*-0.203*					*0.952*
3	0.116	0.320				0.539	0.014	0.387	0.177				0.359	0.011
	0.497	*1.083*				*2.605*	*1.008*	*1.513*	*0.552*				*1.500*	*0.894*
3	0.475	0.069	0.118	0.059	1.163		0.014	0.478	0.192	-0.176	-0.012	0.569		0.008
	1.591	*0.193*	*0.631*	*0.363*	*2.096*		*1.085*	*1.609*	*0.531*	*-0.935*	*-0.069*	*0.999*		*0.751*
3	0.106	0.379	0.059	-0.054	0.758	0.502	0.015	0.244	0.379	-0.168	-0.088	0.352	0.453	0.007
	0.366	*1.081*	*0.317*	*-0.334*	*1.370*	*2.454*	*1.162*	*0.792*	*1.020*	*-0.897*	*-0.511*	*0.609*	*1.859*	*0.621*
6	0.671	-0.036					0.025	0.786	-0.131					0.025
	2.885	*-0.125*					*1.800*	*3.141*	*-0.428*					*1.985*
6	0.235	0.322				0.576	0.028	0.476	0.118				0.452	0.027
	1.006	*1.100*				*2.776*	*1.944*	*1.807*	*0.365*				*1.824*	*2.125*
6	0.615	0.065	0.052	0.068	0.402		0.019	0.595	0.119	-0.139	0.004	0.372		0.013
	2.062	*0.185*	*0.272*	*0.398*	*0.722*		*1.444*	*1.987*	*0.331*	*-0.734*	*0.021*	*0.645*		*1.145*
6	0.268	0.340	0.031	0.020	0.134	0.541	0.024	0.376	0.273	-0.118	-0.051	0.173	0.491	0.016
	0.910	*0.966*	*0.158*	*0.120*	*0.241*	*2.622*	*1.855*	*1.208*	*0.738*	*-0.631*	*-0.292*	*0.294*	*1.985*	*1.384*
9	0.534	0.101					0.033	0.697	-0.012					0.024
	2.298	*0.347*					*2.355*	*2.806*	*-0.038*					*1.978*
9	-0.010	0.562				0.654	0.029	0.389	0.239				0.427	0.024
	-0.041	*1.856*				*3.120*	*1.994*	*1.474*	*0.733*				*1.760*	*1.931*
9	0.517	0.150	0.120	-0.054	0.461		0.034	0.526	0.212	-0.106	-0.080	0.338		0.022
	1.762	*0.433*	*0.641*	*-0.327*	*0.832*		*2.606*	*1.777*	*0.597*	*-0.562*	*-0.462*	*0.582*		*1.952*
9	0.072	0.531	0.132	-0.140	0.254	0.559	0.028	0.306	0.376	-0.080	-0.145	0.205	0.427	0.021
	0.242	*1.509*	*0.706*	*-0.850*	*0.461*	*2.699*	*2.153*	*0.989*	*1.026*	*-0.425*	*-0.830*	*0.348*	*1.762*	*1.871*
12	0.643	-0.084					0.045	0.691	-0.052					0.044
	2.733	*-0.289*					*3.213*	*2.783*	*-0.169*					*3.629*
12	0.206	0.292				0.531	0.044	0.414	0.180				0.381	0.047
	0.863	*1.002*				*2.585*	*3.058*	*1.596*	*0.563*				*1.593*	*3.813*
12	0.451	0.210	-0.039	-0.087	0.500		0.038	0.412	0.319	-0.157	-0.083	0.530		0.035
	1.509	*0.603*	*-0.205*	*-0.526*	*0.905*		*3.005*	*1.382*	*0.895*	*-0.806*	*-0.484*	*0.922*		*3.091*
12	0.057	0.546	-0.062	-0.164	0.132	0.560	0.038	0.226	0.455	-0.119	-0.140	0.312	0.434	0.036
	0.193	*1.590*	*-0.324*	*-0.989*	*0.240*	*2.722*	*2.935*	*0.740*	*1.257*	*-0.622*	*-0.804*	*0.536*	*1.805*	*3.306*

Panel C reports the narrow boycott risk premium after controlling for industry concentration (the industry's Herfindahl Index, HHI) and lagged 6-month industry momentum (IM_6). The risk premiums are estimated by Black-Jensen-Scholes cross-sectional regressions with boycott factor loadings estimated from the sample period 1999.01-2012.12. The left (right) panel reports the risk premiums based on the FF30 (FF48) industry portfolios as test assets. Constants are omitted because they do not have the usual interpretation when the right-hand-side variables are not all tradable assets. The *t*-statistics are in italics.

		FF30	**1999-2012**							**FF48**	**1999-2012**		
MKT	SMB	HML	UMD	BCTn	HHI	IM_6	MKT	SMB	HML	UMD	BCTn	HHI	IM_6
0.121					1.421		0.129					0.740	
0.257					*1.728*		*0.286*					*1.519*	
0.653				1.513	-0.861		0.510				1.176	0.377	
1.208				*2.104*	*-0.808*		*1.088*				*2.097*	*0.802*	
0.220	0.480	0.284	1.808		1.297		0.406	0.219	0.244	1.488		0.744	
0.429	*1.011*	*0.838*	*1.603*		*1.683*		*0.870*	*0.573*	*0.738*	*1.510*		*1.696*	
0.534	0.161	0.283	0.889	1.015	0.107		0.551	0.147	0.201	0.897	0.980	0.576	
1.031	*0.343*	*0.834*	*0.844*	*1.819*	*0.146*		*1.165*	*0.390*	*0.604*	*0.978*	*2.032*	*1.304*	
0.026					1.416	0.044	0.031					0.642	0.034
0.057					*1.774*	*1.503*	*0.071*					*1.354*	*1.438*
0.483				1.424	-0.631	0.043	0.358				1.193	0.317	0.034
0.941				*2.000*	*-0.630*	*1.733*	*0.782*				*2.083*	*0.680*	*1.516*
0.136	0.410	0.390	1.719		1.146	0.025	0.269	0.227	0.268	1.424		0.575	0.021
0.266	*0.845*	*1.067*	*1.530*		*1.499*	*1.107*	*0.577*	*0.595*	*0.797*	*1.463*		*1.294*	*1.179*
0.396	0.225	0.384	1.090	0.978	0.215	0.027	0.398	0.187	0.233	0.868	1.051	0.401	0.021
0.772	*0.457*	*1.061*	*1.031*	*1.700*	*0.286*	*1.237*	*0.840*	*0.492*	*0.693*	*0.952*	*2.104*	*0.909*	*1.169*

Panel D. reports the narrow boycott risk premium after controlling for industry concentration (the industry's Herfindahl Index, HHI) and lagged 6-month industry momentum (IM_6). The risk premiums are estimated by Black-Jensen-Scholes cross-sectional regressions with boycott factor loadings estimated from the sample period during 1963.01-2012.12 for FF30 (left panel) and 1969.07-2012.12 for FF48 (right panel). Constants are omitted because they do not have the usual interpretation when the right-hand-side variables are not all tradable assets. The *t*-statistics are in italics.

		FF30	**1963-2012**							**FF48**	**1969-2012**		
MKT	SMB	HML	UMD	BCTn	HHI	IM_6	MKT	SMB	HML	UMD	BCTn	HHI	IM_6
-0.028					0.808		-0.108					0.230	
-0.095					*2.374*		*-0.337*					*0.962*	
0.348				0.518	0.060		0.095				0.458	0.089	
1.114				*2.105*	*0.155*		*0.290*				*1.861*	*0.369*	
0.036	0.056	-0.078	0.482		0.853		0.188	-0.276	-0.039	0.337		0.321	
0.100	*0.293*	*-0.459*	*0.821*		*2.500*		*0.516*	*-1.420*	*-0.220*	*0.575*		*1.415*	
0.343	0.048	-0.106	0.223	0.458	0.176		0.363	-0.249	-0.088	0.154	0.480	0.212	
0.943	*0.249*	*-0.627*	*0.384*	*1.957*	*0.489*		*0.971*	*-1.300*	*-0.497*	*0.258*	*1.925*	*0.909*	
-0.069					0.698	0.023	-0.206					0.178	0.026
-0.237					*2.052*	*1.600*	*-0.670*					*0.770*	*2.036*
0.336				0.618	-0.147	0.026	0.041				0.458	0.066	0.028
1.113				*2.462*	*-0.383*	*1.783*	*0.129*				*1.808*	*0.276*	*2.194*
0.030	0.033	0.034	0.401		0.685	0.015	0.126	-0.223	0.017	0.337		0.263	0.015
0.085	*0.169*	*0.196*	*0.712*		*2.017*	*1.145*	*0.348*	*-1.170*	*0.099*	*0.587*		*1.157*	*1.357*
0.326	0.035	0.019	0.130	0.558	-0.065	0.022	0.261	-0.198	-0.020	0.155	0.487	0.156	0.018
0.907	*0.179*	*0.111*	*0.234*	*2.311*	*-0.178*	*1.664*	*0.705*	*-1.050*	*-0.111*	*0.267*	*1.925*	*0.665*	*1.600*

Table 9 Alternative Explanations

The risk premiums are provided for the narrow (upper panel) and broad (bottom panel) boycott factors, in model variants with the FF4 (Carhart) factors and the Pastor-Stambaugh systematic liquidity factor (SLQ) together with the premiums attributed to industry characteristics: litigation (LTG), neglect (NGL), and idiosyncratic liquidity (ILQ). The estimates are generated from Black-Jensen-Scholes cross-sectional regressions with factor loadings estimated from time-series regressions for the 1999.01 - 2012.12 period. R^2 is the adjusted R-squared for the cross-sectional fit between predicted and realized mean returns. Constants are omitted because the variables are not all tradable assets. The *t*-statistics are in italics.

				FF30		**1999-2012**										**FF48**		**1999-2012**		
	MKT	SMB	HML	UMD	BCTn	LTG	NGL	ILQ	SLQ	R^2	MKT	SMB	HML	UMD	BCTn	LTG	NGL	ILQ	SLQ	R^2
RP	0.065					5.483				0.083	0.087					4.297				0.096
t-stat	*0.139*					*2.053*					*0.192*					*2.030*				
RP	0.573				1.291	0.704				0.463	0.470				1.358	1.967				0.412
t-stat	*1.095*				*2.135*	*0.321*					*1.004*				*2.272*	*1.016*				
RP	0.142						-0.177			0.153	0.107						-0.128			0.091
t-stat	*0.302*						*-1.992*				*0.236*						*-1.880*			
RP	0.607				1.375		0.014			0.462	0.549				1.347		-0.016			0.441
t-stat	*1.180*				*2.184*		*0.195*				*1.022*				*2.191*		*-0.288*			
RP	0.102							-0.306		0.024	0.098							-0.216		0.033
t-stat	*0.218*							*-1.180*			*0.217*							*-1.258*		
RP	0.575				1.288			-0.084		0.467	0.559				1.358			-0.025		0.439
t-stat	*1.140*				*2.291*			*-0.360*			*1.080*				*2.483*			*-0.103*		
RP	-0.156								1.453	0.560	-0.119								1.314	0.444
t-stat	*-0.333*								*1.933*		*-0.261*								*1.902*	
RP	0.239				0.957				1.146	0.759	0.237				0.942				1.064	0.638
t-stat	*0.510*				*1.959*				*1.612*		*0.532*				*1.856*				*1.598*	
RP	-0.142					2.693	-0.066	0.025	1.332	0.604	-0.036					2.453	-0.082	-0.047	1.132	0.551
t-stat	*-0.301*					*1.168*	*-0.850*	*0.114*	*1.805*		*-0.078*					*1.059*	*-1.070*	*-0.283*	*1.674*	
RP	0.238				1.041	1.519	0.044	0.119	1.221	0.747	0.203				0.765	1.823	-0.032	-0.012	1.033	0.650
t-stat	*0.505*				*1.970*	*0.651*	*0.649*	*0.561*	*1.693*		*0.459*				*1.488*	*0.809*	*-0.427*	*-0.070*	*1.568*	
RP	-0.216	0.418	0.139	0.746		3.382	-0.024	0.058	1.067	0.604	0.145	0.021	0.151	0.564		2.201	-0.074	-0.052	0.840	0.570
t-stat	*-0.425*	*0.860*	*0.423*	*0.796*		*1.378*	*-0.378*	*0.310*	*1.666*		*0.330*	*0.056*	*0.456*	*0.669*		*0.990*	*-1.080*	*-0.367*	*1.384*	
RP	0.139	0.141	0.028	-0.065	1.052	1.587	0.047	0.194	1.319	0.733	0.241	0.077	0.078	0.330	0.781	2.057	-0.031	0.026	0.903	0.643
t-stat	*0.280*	*0.297*	*0.083*	*-0.074*	*2.026*	*0.664*	*0.745*	*1.098*	*2.054*		*0.552*	*0.200*	*0.235*	*0.399*	*1.591*	*0.927*	*-0.427*	*0.179*	*1.478*	
	MKT	SMB	HML	UMD	BCTb	LTG	NGL	ILQ	SLQ	R^2	MKT	SMB	HML	UMD	BCTb	LTG	NGL	ILQ	SLQ	R^2
RP	0.001				0.835	2.172	-0.001	0.070	0.803	*0.707*	0.114				0.817	1.657	-0.025	-0.031	0.651	0.679
t-stat	*0.002*				*1.893*	*0.938*	*-0.012*	*0.325*	*1.156*		*0.257*				*1.746*	*0.724*	*-0.363*	*-0.184*	*1.008*	
RP	-0.230	0.144	-0.083	-0.328	1.006	2.033	0.009	0.186	0.830	*0.723*	0.082	-0.095	0.027	-0.180	0.979	1.705	-0.029	0.027	0.533	0.683
t-stat	*-0.453*	*0.296*	*-0.244*	*-0.358*	*2.298*	*0.852*	*0.153*	*1.056*	*1.257*		*0.186*	*-0.247*	*0.079*	*-0.218*	*2.168*	*0.758*	*-0.449*	*0.199*	*0.883*	

Table 10 Excess Returns of Portfolios Sorted by Boycott Factor Loadings

Panel A. Starting with all NYSE/AMEX/NASDQ stocks we remove all stocks that have any sin characteristics: all stocks that, either by SIC or NAICS code, are classified in any one of the eight screens listed in Table 3, as well as the industry classifications of the stocks that were at any point in time included in the Vice Fund. The remaining stocks are sorted based on their boycott factor loadings. The boycott loadings are obtained by regressing the individual non-sin stock returns on the FF3 factors plus the narrowly defined boycott factor or on the FF4 factors plus the narrowly defined boycott factor for the period 1999.01-2012.12. All non-sin stocks are assigned to five portfolio in order of these boycott factor loadings. Similarly, all sin stocks from the (narrow) boycott factor are assigned to five portfolios by their boycott factor loadings. The numbers provided are boycott betas based on either the augmented FF3 or augmented FF4 model (BCT β) and the equal-weighted average monthly excess returns of each portfolio (FF3 or FF4).

BCT Loading	Sin Stocks				Non-Sin Stocks			
Ranked	BCT β	FF3	BCT β	FF4	BCT β	FF3	BCT β	FF4
Average	0.569	1.074	0.602	1.108	-0.058	0.840	-0.054	0.833
1 (Least)	-0.676	0.904	-0.585	1.132	-1.042	0.515	-1.041	0.405
2	0.031	0.761	0.082	0.877	-0.233	0.822	-0.231	0.815
3	0.300	0.998	0.302	0.827	-0.007	0.949	-0.006	0.994
4	0.848	1.291	0.851	1.291	0.191	0.972	0.188	0.963
5 (Most)	2.341	1.415	2.361	1.415	0.800	0.943	0.819	0.986
5-1	3.017	0.511	2.946	0.283	1.842	0.428	1.860	0.581

Panel B. The risk-adjusted return of a zero-investment strategy utilizing only non-sin stocks (using the criteria described in Panel A) is obtained based on equation (7). The time-series regression result is reported. The dependent variable is the return on an equal-weighted portfolio that longs the most boycott-sensitive and shorts the least boycott-sensitive non-sin stocks.

	Estimate	*t-stat*	Estimate	*t-stat*
Alpha	0.445	1.626	0.420	1.596
MKT	-0.169	-2.825	-0.056	-0.900
SMB	-0.272	-3.390	-0.271	-3.463
HML	0.009	0.114	0.090	1.155
UMD			0.130	2.768

Table 11 Boycott Loadings and Payoffs

This table shows the relationship between industry portfolios' estimated boycott factor loadings $\hat{\beta}_{iB}$ and their estimated earning sensitivities $\hat{b}_{iB}$ to the aggregate earnings of boycotted industries: $\hat{\beta}_{iB} = \gamma_0 + \gamma_1 \hat{b}_{iB} + \gamma_2 C_i + \eta_i$, where C_i controls for any industry-specific characteristics. The $\hat{\beta}_{iB}$ and $\hat{b}_{iB}$ are listed in Table 6. The control variables are litigation (LTG), neglect (NGL), idiosyncratic liquidity (ILQ), the Pastor-Stambaugh systematic liquidity factor (SLQ), and the Herfindahl index based on sales (HHI).

	FF30 1999-2012							**FF48 1999-2012**						
$\hat{\beta}_{iB}$	LTG	NGL	ILQ	SLQ	HHI	$\hat{b}_{iB}$	R^2	LTG	NGL	ILQ	SLQ	HHI	$\hat{b}_{iB}$	R^2
estim	3.179						0.090	2.266						0.072
t-stat	*1.963*							*2.162*						
estim		-0.146					0.334		-0.104					0.217
t-stat		*-3.940*							*-3.740*					
estim			-0.163				0.027			-0.106				0.023
t-stat			*-1.350*							*-1.440*				
estim				0.217			0.002				0.169			-0.001
t-stat				*1.025*							*0.978*			
estim					1.555		0.223					0.494		0.065
t-stat					*3.053*							*2.062*		
estim						0.294	0.564						0.283	0.437
t-stat						*6.210*							*6.127*	
estim	0.301	-0.116	-0.141	-0.008	0.395		0.286	0.717	-0.117	-0.117	-0.054	-0.178		0.217
t-stat	*0.181*	*-1.650*	*-1.230*	*-0.037*	*0.469*			*0.617*	*-2.950*	*-1.600*	*-0.316*	*-0.560*		
estim	-0.356	-0.092	0.079	0.306	-0.596	0.312	0.687	0.497	-0.072	-0.009	0.130	-0.168	0.249	0.503
t-stat	*-0.320*	*-1.970*	*0.919*	*1.979*	*-1.020*	*5.625*		*0.535*	*-2.190*	*-0.147*	*0.927*	*-0.663*	*5.014*	

	FF30 1963-2012							**FF48 1969-2012**						
$\hat{\beta}_{iB}$	LTG	NGL	ILQ	SLQ	HHI	$\hat{b}_{iB}$	R^2	LTG	NGL	ILQ	SLQ	HHI	$\hat{b}_{iB}$	R^2
estim	3.074						0.102	2.072						0.078
t-stat	*2.073*							*2.233*						
estim		-0.119					0.253		-0.075					0.135
t-stat		*-3.290*							*-2.890*					
estim			-0.124				0.007			-0.079				0.009
t-stat			*-1.100*							*-1.190*				
estim				-0.024			-0.035				-0.041			-0.020
t-stat				*-0.119*							*-0.267*			
estim					1.432		0.222					0.392		0.047
t-stat					*3.048*							*1.826*		
estim						0.395	0.815						0.386	0.700
t-stat						*11.340*							*10.520*	
estim	0.927	-0.098	-0.142	-0.244	0.327		0.250	1.055	-0.094	-0.098	-0.231	-0.215		0.161
t-stat	*0.588*	*-1.480*	*-1.310*	*-1.190*	*0.411*			*0.986*	*-2.570*	*-1.460*	*-1.480*	*-0.738*		
estim	-0.282	-0.069	0.067	-0.137	-0.847	0.426	0.835	0.396	-0.038	0.015	-0.168	-0.211	0.374	0.707
t-stat	*-0.376*	*-2.220*	*1.207*	*-1.420*	*-2.150*	*9.289*		*0.622*	*-1.710*	*0.353*	*-1.810*	*-1.220*	*8.909*	

Table 12 Determinants of the Boycott Risk Premium

The dependent variable is the boycott risk premium obtained from monthly BJS (constant beta) cross-sectional regressions of the FF30 industry portfolio excess returns on the narrow boycott factor loadings. This monthly boycott risk premium is compounded to quarterly holding period returns. MKT, SMB, HML, and UMD are the four monthly Carhart (1997) factors compounded into quarterly frequency. YMP is the log difference between current seasonally adjusted real GDP and current real Potential GDP, both obtained from the St. Louis Federal Reserve Economic Database, lagged by one quarter. ΔYMP is the future real GDP growth rate, defined as the log difference between four-quarter ahead real GDP and current real GDP. RWR is the restricted wealth ratio lagged by two quarters (one required reporting period). ΔRWR is the difference in the restricted wealth ratio between current and two quarters ago. The last column reports the adjusted R-squares. The *t*-statistics are in italics.

BCTn	MKT	SMB	HML	UMD	RWR	YMP	ΔRWR	ΔYMP	R^2
estim					0.212				0.052
t-stat					*2.836*				
estim						0.719			0.021
t-stat						*1.945*			
estim					0.193	0.600			0.064
t-stat					*2.566*	*1.630*			
estim					0.178	0.474	-0.087	-0.902	0.093
t-stat					*2.354*	*1.283*	*-0.991*	*-1.940*	
estim	0.053	-0.186	0.585	-0.037					0.099
t-stat	*0.441*	*-0.890*	*3.709*	*-0.312*					
estim	0.059	-0.207	0.586	-0.001	0.207				0.151
t-stat	*0.499*	*-1.010*	*3.805*	*-0.011*	*2.895*				
estim	0.052	-0.132	0.574	-0.073		0.694			0.118
t-stat	*0.435*	*-0.634*	*3.672*	*-0.615*		*1.915*			
estim	0.055	-0.165	0.576	-0.033	0.187	0.544			0.160
t-stat	*0.468*	*-0.807*	*3.752*	*-0.284*	*2.589*	*1.506*			
estim	0.161	-0.270	0.608	-0.056	0.174	0.449	-0.052	-1.040	0.195
t-stat	*1.295*	*-1.290*	*3.912*	*-0.482*	*2.414*	*1.243*	*-0.615*	*-2.250*	

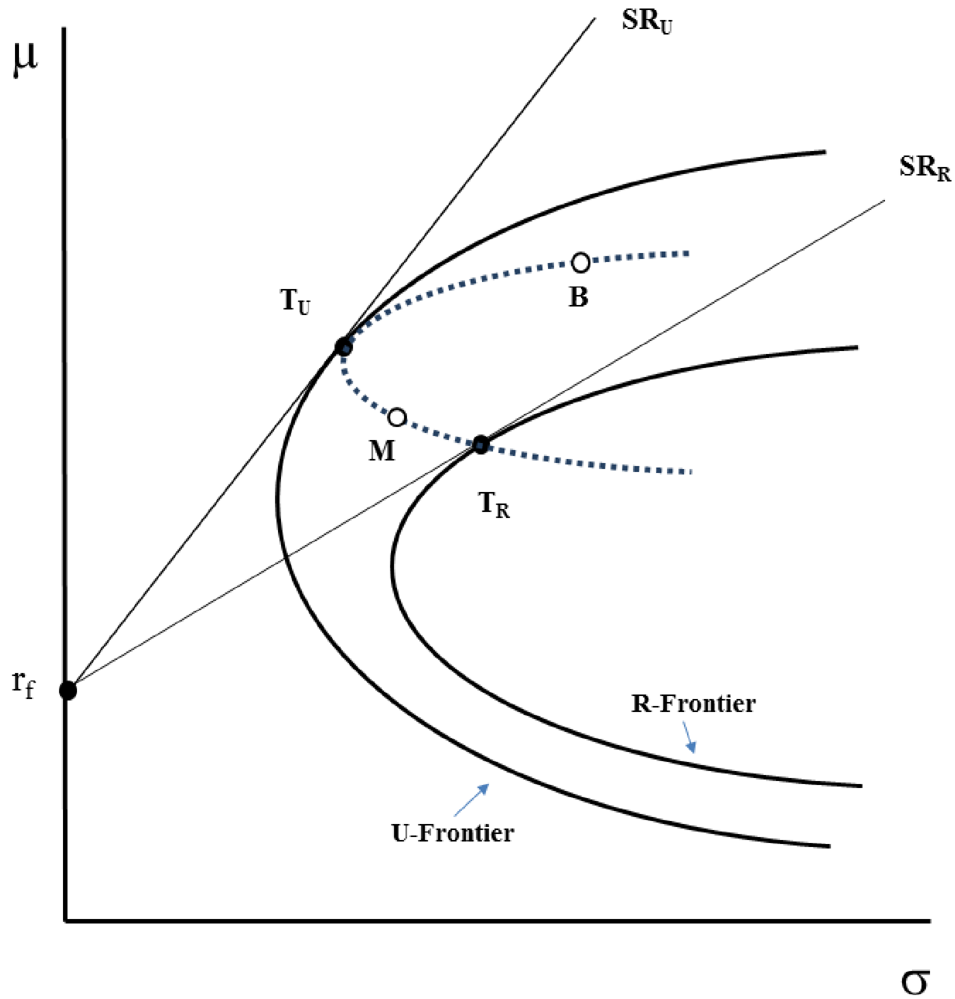

Figure 1
The Boycott and Market Factors

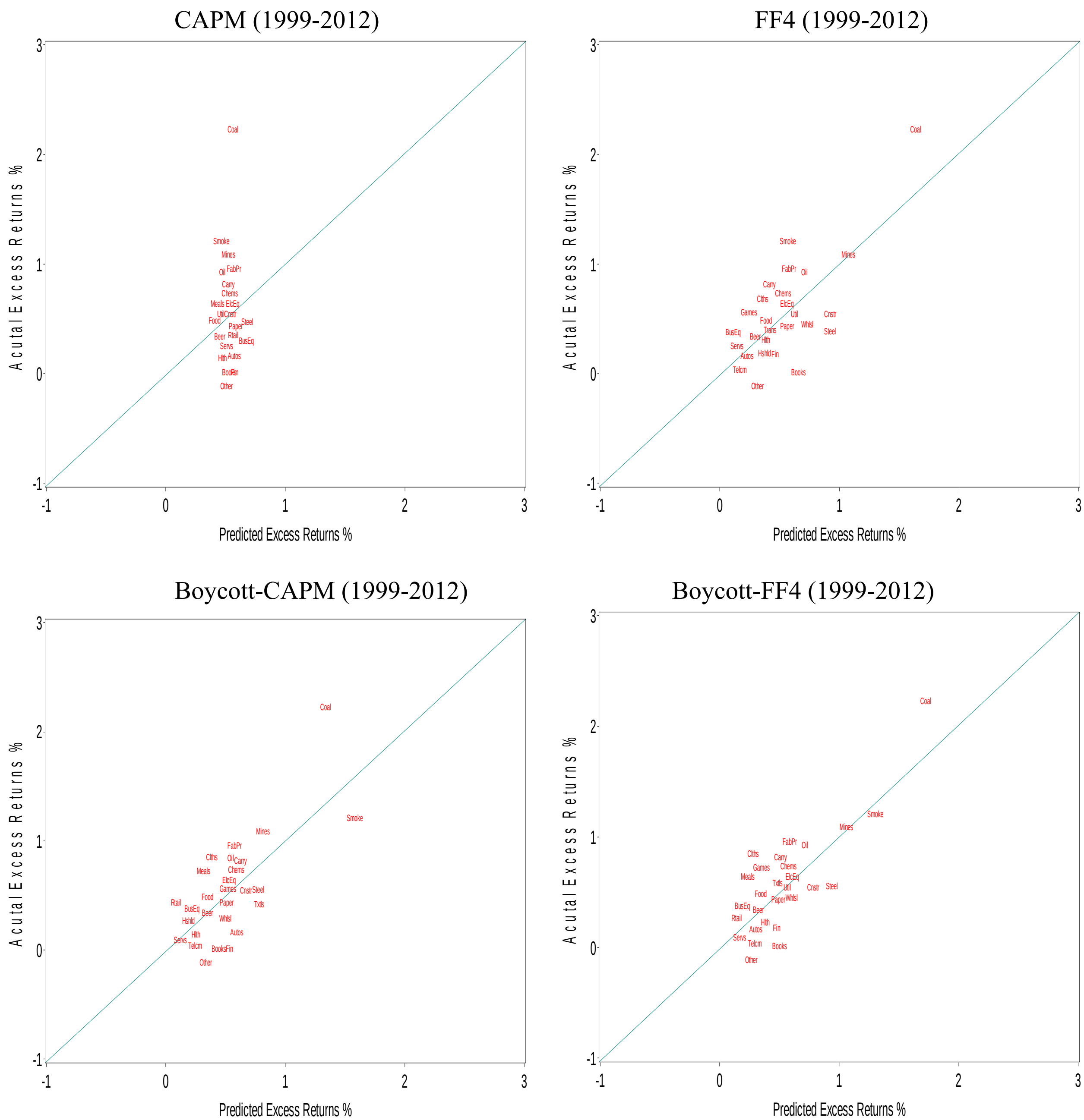
CAPM (1999-2012)
FF4 (1999-2012)
Boycott-CAPM (1999-2012)
Boycott-FF4 (1999-2012)
Acutal Excess Returns %
Predicted Excess Returns %

Figure 2

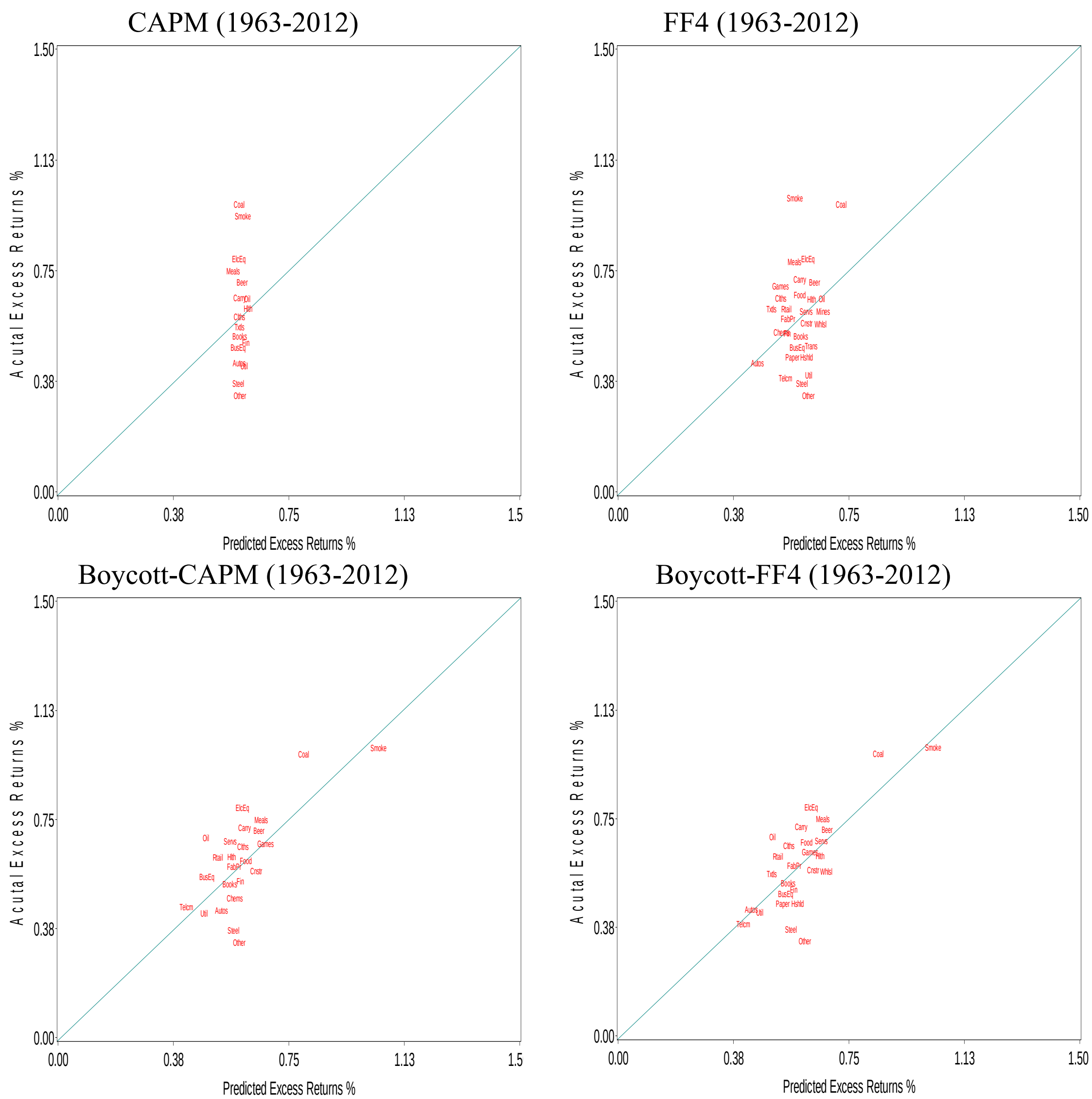
CAPM (1963-2012)
FF4 (1963-2012)
Boycott-CAPM (1963-2012)
Boycott-FF4 (1963-2012)
Acutal Excess Returns %
Predicted Excess Returns %
0.00
0.38
0.75
1.13
1.50
1.5
Coal
Smoke

Figure 3

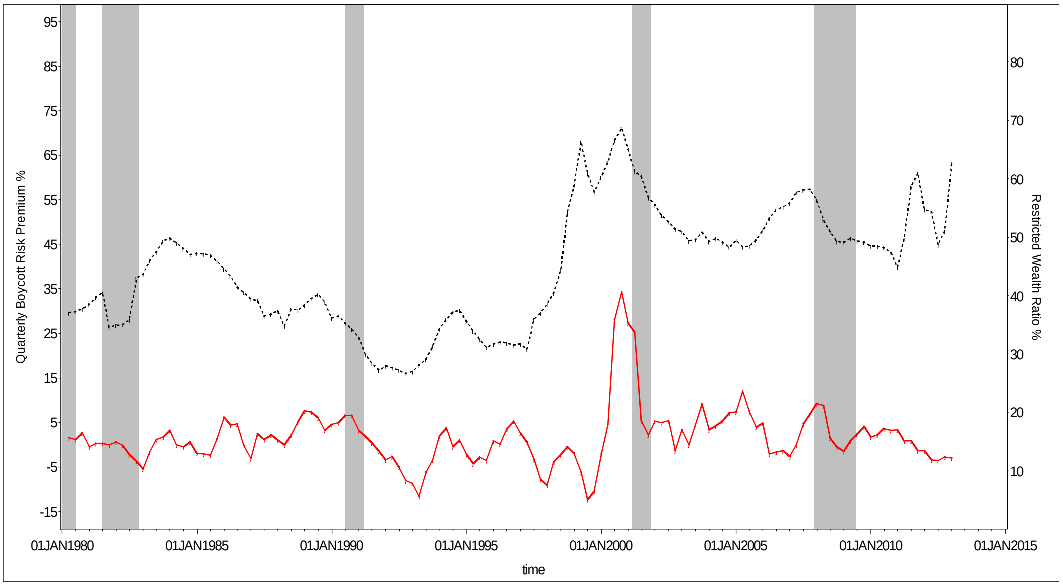

Figure 4 Boycott risk premium and boycott intensity

This figure shows the one-year moving average of the restricted wealth ratio, *RWR* (dotted black) lagged by two quarters and the one-year moving average of the quarterly boycott risk premium, *BCT* (in solid red) obtained from monthly BJS cross-sectional regressions of the FF30 industry portfolio excess returns on the boycott factor loadings. Shaded areas are NBER-defined recession periods. The left vertical axis is the boycott risk premium scale in percentage terms and the right vertical axis is the restricted wealth ratio scale in percentage terms. *RWR* has a mean value of 44.69% and a standard deviation of 12.25%. BCT has a mean value (annual) of 9.19% and a standard deviation of 17.36%. The correlation coefficient between these two series is 0.363 with $p < 0.0001$.

Chapter Three: *Asset Characteristics and Multi-Factor Efficiency*

1. Introduction

A large body of literature, starting with the work of Daniel and Titman (1997), Jagannathan and Wang (1996), and Daniel, Hirshleifer, and Subhramanyam (2001), has differentiated between covariance-risk and characteristics-based explanations for asset returns, with however contradictory findings.[26] A recent paper by Kozan, Nagel, and Santosh (2015) has a similar objective to our paper by cautioning against distinguish covariance-risk and characteristics in the cross section. It argues that it is difficult to separate rational and behavioral explanations of returns by distinguishing factors and characteristics (unless an explicit model is specified that accounts for preferences); in contrast our argument goes further in that distinguishing factors and characteristics, in a meaningful way, is pointless to begin with.

We find that a characteristic-mimicking portfolio (CMP) constitutes a factor that has identical pricing implications as the original characteristic. Vice versa, a factor-mimicking characteristic (FMC) has identical pricing implications as the original factor. This is empirically true no matter how assets are priced, fully rationally, fully behaviorally, or by partially rational and behavioral investors. The choice of CMP is dictated objectively by a procedure that maximizes

[26] Recent papers include Hou et al. (2011), Daniel and Titman (2012), Luo and Balvers (2017), and Pukthuanthong and Roll (2014).

exposure of the factor portfolio to the underlying characteristic subject to a particular level for the return variance of the mimicking factor.

The result is in part related to the Roll identity (Roll, 1977) which implies that a set of test assets is priced correctly by a set of factors if and only if the maximum Sharpe ratio of the factors equals the maximum Sharpe ratio of the test assets (Grinblatt and Titman, 1987). Thus, it is possible to find factors to explain (in ex post data) any pricing outcome generated by characteristics. Our result, however, is more general in that it also applies when a model does not price the test assets correctly and it further applies when characteristics are not stochastic.

In the context of a particular theory, specifying preferences (as Kozan et al., 2015, advocate), our perspective may be viewed as a generalization of Fama (1996). We model rational as well as irrational choice by allowing for "non-pecuniary" preferences that lead to investors caring about particular attributes or characteristics of financial assets which become reflected in asset returns.[27] Investors then logically choose only minimum variance portfolios subject to both a particular mean return as well as subject to a particular level of exposure of the portfolio to the characteristic. In Fama (1996) the exposure constraint pertains only to covariance with a state variable; in our case, the state variable may be deterministic and the characteristic can be – but generally is not – a covariance.

[27] The distinction between rational and irrational is a matter of semantics here. If one views "acting consistent with objectives" as rational, then any non-pecuniary component of the objective function – even if completely unrelated to aspects of the objective return distribution – must be viewed as involving rational decision making. If any particular behavior cannot be explained as consistent with some (likely non-standard) objective it simply cannot be explained in a systematic way.

Thus, the results of Fama (1996) – that investors hold only multi-factor efficient portfolios – apply with the CMP multi-factor efficient and characteristics priced whether or not investors are "rational".

In the following, we first discuss further the literature in Section 2 and then present a model with priced characteristics in Section 3. We show in Section 4 that a mimicking factor has equivalent pricing implications and Section 5 extends the analysis of Fama (1996). Section 6 concludes.

2. Context

Fama and French (1992) established empirically that the size (average log of market value) characteristic and value (average log of book-to-market ratio) characteristic of stock portfolios explained differences in mean returns across portfolios much better than market factor loadings. Fama and French (1993) then constructed risk factors based on the size and value characteristics and concluded that these mimicking portfolios functioning as risk factors explained average asset returns in accordance with equilibrium pricing models. Their construction of the mimicking portfolios lacked a formal motivation but consisted roughly of taking the return of the smallest 50% of firms minus the return of the biggest 50% of firms in each period as the size-mimicking factor return; and taking the return of the 30% highest book-to-market value firms minus the return of the 30% lowest book-to-market firms as the value-mimicking factor return.

As both size and value characteristics and size and value risk factors separately performed well in explaining average return differences, the natural question became which one performed better. Daniel and Titman (1997) and Jagannathan and Wang (1996) introduced simple approaches for comparing the importance of characteristics and the mimicking risk factors derived from the characteristics. Daniel and Titman sorted portfolios separately by factor loadings and by characteristics and compared the return differences of the sorted portfolios. Jagannathan and Wang added both the factor loadings and the characteristics themselves to a regression explaining cross-sectional differences in mean returns. The regression results determined whether factor loadings drive out the characteristics or vice versa.

Extensive and continuing application of both approaches has led to diverging results, with sometimes characteristics beating factor loadings (e.g., Brennan et al. 1998 and Chordia et al. 2015), at other times factor loadings beating characteristics (e.g., Davis et al. 2000 and Gao 2012), or the results varying by characteristic (Hou et al. 2011). Daniel and Titman (2012) argue that a sharper empirical distinction is needed in creating separate portfolios based on characteristics and factor loadings to accurately identify which works better.

Recent literature has attempted to further clarify the distinction between characteristics and factors. Lin and Zhang (2012) appeal to the production-based asset pricing context in which firm characteristics are related to investment returns and thus naturally represent loadings on investment risk which must relate to return risk. Presupposing an arbitrage pricing context Kozak, Nagel, and Santosh (2015), hereafter KNS, and Pukthuanthong and Roll (2014) argue that, insofar as characteristics do not match the loadings on systematic risk factors, priced characteristics represent near-arbitrage opportunities (very large Sharpe ratios). Thus, the identifying criterion of (priced) characteristics vis-à-vis factor loadings is that they represent potential for high Sharpe ratios. KNS further provide a theoretical model that illustrates that it is not possible to distinguish irrational from rational explanations for market outcomes. They argue that investors irrationally focusing on asset characteristics may cause price deviations, presenting opportunities for rational investors. If the deviations correlate with a systematic risk factor the "arbitrage" will not eliminate much; if the deviations are uncorrelated with systematic risk the arbitrage should eliminate most of the price deviations.

Gao (2011) provides an approach for employing characteristics to model asset covariances based on the similarity of assets in terms of their characteristics. The covariances now perform better than factor loadings in explaining return differences across assets and drive out the characteristics. This supports the view that it is risk factors, although not approximated through factor loadings, which are more relevant than behavioral factors proxied by characteristics. Moskowitz (2003), Connor (2007) and Suh et al. (2014) also provide methods for relating factor loadings (or, similarly, covariances) to characteristics that differ from the approach of Fama and French (1993). Taylor and Verrecchia (2015) show that given delegation of investment both risk factors and individual characteristics will be priced. Chordia, Goyal, and Shanken (2015) contribute to the debate on loadings versus characteristics by focusing on individual stocks rather than portfolios and adjusting for the substantial measurement error bias that results from estimating loadings for individual stocks. They find that characteristics perform relatively better than factor loadings in explaining average return differences.

The intent in the recent literature is to sharpen the distinction between characteristics and factor loadings, whereas our objective in part is the opposite: to emphasize that the distinction between characteristics and factor loadings is immaterial for explanations of mean returns. Characteristics are identical to factor loadings but on a factor that is generally only trivially different (in construction, not by impact as Kogan and Tian, 2015, argue). Because the factor mimicking portfolio is chosen haphazardly, the difference with the characteristic mimicking portfolio is not fundamental, and basing tests on the difference between the two seems beside the point.

Consider the iconic example of the size characteristic. The idea of Fama and French (1993), hereafter FF, was to explain the empirical importance of the size characteristic for average returns from a risk-taking perspective: for whatever reason, smaller-size firms are more exposed to risk. Accordingly, they construct a risk factor as the return of a factor-mimicking portfolio formed, roughly, by holding the 50% smallest firms and shorting the 50% largest firms. Empirically, the resulting “size factor” helps to explains differences in mean returns well. However, why construct the risk factor in this manner? A theoretical motivation for the construction would protect against data mining. If the idea is that smaller firms are more sensitive to risk, why not construct a risk factor such that the sensitivity to this factor is indeed directly related to firm size? The latter is in fact the CMP generated by our approach. The CMP also provides the theoretical justification that it is the minimum variance portfolio with the largest exposure to the size characteristic.

It is not our intent to provide a factor that is simply a variant to the size factor generated by FF. Our key point is that comparing factor loadings and characteristics is mostly meaningless. Trivially the tests initially proposed by Daniel and Titman and Jagannathan and Wang cannot be performed when CMPs are the mimicking portfolios. While other mimicking portfolios, typically generated from ad hoc assumptions, may produce differences between factor loadings and characteristics, these differences are nonessential from a theoretical perspective, even though Kogan and Tian (2015) argue they may nevertheless be essential empirically.

We further want to point out that CMPs can readily be applied for practical purposes. By constructing a mimicking portfolio for a specific characteristic it becomes possible to estimate a future value of a firm’s characteristic (before it is observed) from observation of the firm’s factor loading on the CMP, which is typically observed at a higher frequency than the characteristic itself.

Mimicking portfolios were first advocated to represent macro risk factors by Breeden (1979), Grinblatt and Titman (1987), and Huberman et al. (1987) and applied to represent consumption risk by Breeden et al. (1989). These mimicking portfolios convert systematic risk tied to realizations of macro-economic variables into tradable asset portfolios with returns that explain average asset returns just as well as the original macro factors. Lamont (2001) devised an alternative construction of mimicking portfolios, "tracking portfolios", to represent expectations of macro variables. As a key application, Kapadia (2011) used this approach to capture distress risk. Ferson et al. (2006) consider the optimal use of mimicking portfolios representing macro risk factors in the context of predictable time variation. Much earlier, Fama (1976, pp. 326-329) pointed out (see also Ferson et al. 1999) that estimates of risk premia based on Fama-MacBeth (1973) regressions, potentially using characteristics, may be interpreted as portfolios of the assets, with the portfolio weights depending on the characteristics. The approach of Fama and French (1993) provides an alternative without formal validation that generates mimicking portfolios representing aggregate risks. Back et al. (2013) empirically consider the performance of both approaches, terming aptly the Fama (1976) mimicking portfolios as "characteristic pure plays."

Not only does our approach mimic an aggregate risk associated with a desired characteristic, it also provides a vehicle for estimating firm-level characteristics based on measuring factor loadings on the mimicking portfolio. As such it is akin to Lamont (2001) in the limited sense that it can be used to provide estimates of unobservable variables. But rather than generating estimates of expectations of macro variables, we use the CMP to provide estimates of *firm-level* characteristics that cannot be observed in real time. In the context of time variation of the characteristics we anticipate combining our approach with the approach of Ferson et al. (2006) to incorporate conditioning information. Jiang, Kan, and Zhan (2015) provide guidance concerning how to deal with the measurement error issues inherent in the use of mimicking portfolios.

3. A Model with Priced Asset Characteristics

To construct a simple model in which asset characteristics may be priced we start from the traditional single-period Sharpe-Lintner CAPM setting, in which the terminal wealth of each investor k is fully consumed ($c_k = w_k$ with w_k the end of period wealth of the investor), the n risky returns have a multivariate normal distribution and a riskfree asset exists, markets are perfect, and investment opportunities and expectations are homogeneous. We introduce one critical additional assumption: investors may care about features of each risky asset unrelated to the ultimate financial payoff generated.

The utility function thus incorporates what we refer to as "non-pecuniary" preferences. We offer two distinct interpretations for such preferences. First, they may be viewed as purely rational preferences for an economically relevant attribute of an asset such as liquidity, or more broadly as a liking or dislike for the underlying activities financed by the asset. Second, the preferences for particular attributes (such as momentum or glamour, or industry) of assets may reflect an irrational perspective, that deviates from objective expectations, regarding the payoff distribution of the asset. The maximization of the investor objective then simply implies that the investor consistently acts according to the irrational perspective. Kogan, Ross, Wang, and Westerfield (2006) show formally how irrational investor choice may be captured by an attribute added to the utility function and Fama and French (2007) also consider the important of investor tastes.

The investment problem of an investor under the aforementioned assumptions is as follows:

$$\underset{\mathbf{s}_k}{Max} \quad E[u^k(w_k, x_k)], \tag{1}$$

Subject to,
$$w_k = \overline{w}_k(1 + r_f + \mathbf{s}_k' \ \mathbf{r}) \tag{2}$$

$$x_k = \mathbf{s}_k' \ \mathbf{x} \tag{3}$$

In equation (1) the utility function is investor specific as reflected by the superscript *k*. Utility depends on w_k, the end of period wealth of the investor, as well as on a non-wealth attribute of the investor's portfolio summarized by x_k, which we will take to be one-dimensional for simplicity. The wealth constraint in equation (2) states that final wealth equals initial wealth $\overline{w}_k$ times the portfolio return which equals the gross riskfree rate $1 + r_f$ plus the excess return equal to the vector of portfolio shares in the risky assets $\mathbf{s}_k$ times the vector of excess returns $\mathbf{r} = \mathbf{R} - r_f \mathbf{1}$ (where $\mathbf{R}$ is the vector of asset returns and $\mathbf{1}$ is an *n*-vector of ones; the prime indicates the vector transpose). Equation (3) provides the portfolio attribute/characteristic x_k as the value-weighted average of the characteristics of the individual assets in the portfolio, the vector of portfolio shares in the risky assets $\mathbf{s}_k$ times the vector of (deterministic) individual asset characteristics $\mathbf{x}$. For simplicity we have set the characteristic of the riskfree asset equal to zero. Note that the sum of the portfolio shares in the risky assets need not be equal to one because the investor may hold the riskless asset.

Substituting equations (2) and (3) into (1), the first-order conditions for the investment choices of investor k are

$$E[u_w^k(w_k, x_k)\,\overline{w}_k\,\mathbf{r}] + E[u_x^k(w_k, x_k)\,\mathbf{x}] = 0\,, \tag{4}$$

where subscripts indicate partial derivatives.

Rewrite the first term in equation (4) by applying the definition of covariance and, given the assumption that returns are multivariate normally distributed[28], applying Stein's Lemma to obtain:

[28] When the multivariate normal assumption on returns is violated, additional moments will show up in the pricing equation. This essay focuses on the pricing implication of non-pecuniary preference instead of seeking for the maximum cross-sectional fit in the data. While taking higher moments into consideration may potentially improve the empirical results in the cross-section, it does not facilitate the discussion on the impact of characteristics on mean returns.

$$\boldsymbol{\mu} = Cov(\mathbf{r}, w_k)\frac{-E[u_{ww}^k(w_k, x_k)]}{E[u_w^k(w_k, x_k)]} + \mathbf{x}\frac{-E[u_x^k(w_k, x_k)]}{\overline{w}_k\ E[u_w^k(w_k, x_k)]}, \tag{5}$$

where we define the vector of expected excess asset returns as $\boldsymbol{\mu} = E(\mathbf{r})$. Further define: $\theta_w^k \equiv -E[u_{ww}^k(w_k, x_k)] / E[u_w^k(w_k, x_k)]$ and

$\theta_x^k \equiv -E[u_x^k(w_k, x_k)] / \overline{w}_k\ E[u_w^k(w_k, x_k)]$, then:

$$\boldsymbol{\mu} = Cov(\mathbf{r}, w_k)\theta_w^k + \mathbf{x}\,\theta_x^k. \tag{5'}$$

Sum equation (5') over all investors k (which we are able to do because all investors face the same investment opportunities) to obtain

$$\boldsymbol{\mu} = Cov(\mathbf{r}, r_m)\overline{w}_m\theta_w + \mathbf{x}\theta_x. \tag{6}$$

Equation (6) holds given $\theta_w \equiv \sum_{k=1}^{K}\theta_w^k$ and $\theta_x \equiv \sum_{k=1}^{K}\theta_x^k$ and given that the gross market returns equals $1 + r_m \equiv w_m / \overline{w}_m$ with $w_m \equiv \sum_{k=1}^{K} w_k$ and $\overline{w}_m \equiv \sum_{k=1}^{K}\overline{w}_k$. Thus, the price of market covariance risk is $\overline{w}_m\theta_w$ and the characteristics premium is θ_x. Given the standard definition of simple betas: $\boldsymbol{\beta} = Cov(\mathbf{r}, r_m) / \sigma_m^2$ we can alternatively state

$$\boldsymbol{\mu} = \boldsymbol{\beta}\sigma_m^2\overline{w}_m\theta_w + \mathbf{x}\theta_x, \tag{7}$$

where now $\sigma_m^2\overline{w}_m\theta_w$ is the market risk premium. Clearly, in this model the Sharpe-Lintner CAPM does not generally hold. The CAPM alphas are given by

$\boldsymbol{\alpha} = \mathbf{x}\theta_x$ and it then follows from Roll's analysis that the market portfolio is not efficient (unless $\theta_x = 0$ or $\mathbf{x} = 0$). Since $\theta_w > 0$ if utility functions are concave in wealth and since $\mathbf{x}$ is unrestricted, we examine $\theta_x \equiv \sum_{k=1}^{K} \theta_x^k$ with $\theta_x^k \equiv -E[u_x^k(w_k, x_k)\,]/\,\overline{w}_k E[u_w^k(w_k, x_k)\,]$. The CAPM would continue to hold only if $\theta_x = 0$. This is certainly possible if for some investors $E[u_x^k(w_k, x_k)\,] > 0$, they like the characteristic, whereas for others $E[u_x^k(w_k, x_k)\,] < 0$, they dislike the characteristic. However, generally, if the characteristic matters in the same direction to a sufficient number of investors, it will be priced and the CAPM will fail to hold. Note that "arbitrage" by a subset of investors who are indifferent to the characteristic, $E[u_x^k(w_k, x_k)\,] = 0$, or have preferences against the grain of the representative investor, will not generally be sufficient to force the characteristics premium to zero, $\theta_x = 0$. The reason is that there is no riskless way of taking a particular position in the characteristic. Nevertheless, such investors will generally hold different portfolios from the representative investor and will benefit from the characteristics premium.

In summary, adding non-pecuniary preferences to the CAPM provides a formal specification for asset characteristics to be priced separately from standard risk characteristics. Whether the non-pecuniary preferences are viewed as rational or as presenting an irrational preference for particular assets, the result is the same that a positive (negative) aggregate preference for a characteristic, $\theta_x < 0$

($\theta_x > 0$), implies a negative (positive) characteristics premium, and mean returns will decrease (increase) in the size of the characteristic. In the following we will start from equation (7) and consider its implications, irrespective of the model employed to generate it.

4. Characteristic-Mimicking Factors

It is always possible to create a "characteristic-mimicking portfolio" (CMP) to function as an additional factor that prices all assets in the same way as the original characteristics, and converts the premium associated with a deterministic set of asset characteristics to a premium for systematic risk associated with a stochastic risk factor.

Define a characteristic-mimicking factor as a portfolio of the risky assets that: (1) maximizes the exposure to the characteristic, subject to (2) a particular portfolio variance. The covariance matrix of the returns of the N risky assets is given by a positive definite $\mathbf{\Sigma}$. Notation otherwise is identical to that of the model in section 2.

$$\underset{\mathbf{s}_x}{Max}\ (\mathbf{s}_x'\mathbf{x}), \qquad \text{s. t.} \qquad \tfrac{1}{2}\,(\mathbf{s}_x'\mathbf{\Sigma}\,\mathbf{s}_x) = \bar{\sigma}^2, \qquad (8)$$

where $\mathbf{s}_x$ is the vector of portfolio shares of the characteristic-mimicking portfolio. Given the Lagrangian formulation with multiplier λ, the first-order conditions based on equation (8) become

$$\mathbf{s}_x = (1/\lambda)\ \mathbf{\Sigma}^{-1}\ \mathbf{x}\ , \tag{9}$$

which provides the portfolio shares of the zero-investment characteristic-mimicking factor with return $r_x = (1/\lambda)\ \mathbf{r}'\ \mathbf{\Sigma}^{-1}\ \mathbf{x}$. Note that the scale as affected by λ is unimportant for the factor choice since we have a zero-investment portfolio.

> **PROPOSITION:** The characteristics formulation, producing equation (7), prices all assets identically as the factor formulation in which the set of characteristics $\mathbf{x}$ is replaced by a single characteristic-mimicking factor (CMP) with factor return given by $r_x = (1/\lambda)\ \mathbf{r}'\ \mathbf{\Sigma}^{-1}\ \mathbf{x}$.

PROOF. Standard derivation of a two-factor model including the market factor generates

$$\boldsymbol{\mu} = g\ Cov(\mathbf{r}, r_m) + h\ Cov(\mathbf{r}, r_x)\ \ . \tag{10}$$

However, $Cov(\mathbf{r}, r_x) = \mathbf{\Sigma}\ \mathbf{s}_x$. Hence, from equation (9), equation (10) becomes

$$\boldsymbol{\mu} = g\ Cov(\mathbf{r}, r_m) + (h/\lambda)\ \mathbf{x}\ \ . \tag{11}$$

Comparison to equation (6) shows that $g = \overline{w}_m \theta_w$ and $h = \lambda\ \theta_x$ implies equal pricing. □

It is straightforward to generalize the analysis to include many characteristics and factors, which we omit. The general implication, however, is that for pricing purposes one may replace a particular risk factor by a set of deterministic characteristics, or vice versa a set of deterministic characteristics by an equivalent systematic risk factor. Our perspective here, relating factors to deterministic characteristics, represents an extension of the concept of multi-factor efficiency explored by Fama (1996) as we explore next.

5. Multi-Factor Efficiency with Characteristics

Fama (1996) introduces the concept of multi-factor efficiency in the context of an equilibrium pricing theory such as the Merton model in which investors care about wealth as well as about state variables affecting what can be done with the wealth, investment opportunities. In this context, "efficient" portfolio choice may be defined as maximizing expected return subject to a given level of portfolio variance and a given portfolio covariance with the state variables. In our case, investors care instead about a given exposure to characteristics. The characteristics may include covariance with the state variables as a special case but may include a broader set of attributes. In particular, the state variables captured by the characteristics need not be stochastic in which case covariance with the state variable would not be defined. Thus, we can generalize the concept of the multi-factor minimum variance frontier as follows:

$$\underset{\mathbf{s}}{Min} \quad \tfrac{1}{2}\,(\mathbf{s}'\,\boldsymbol{\Sigma}\,\mathbf{s}), \text{ s.t. } \mathbf{s}'\boldsymbol{\mu} = \bar{\mu} \quad \text{and} \quad \mathbf{s}'\,\mathbf{x} = \bar{x}, \tag{12}$$

where $\mathbf{x}$ represents the vector of asset covariances with the state variable in Fama (1996), but may be interpreted more broadly in our case. The multi-factor frontier portfolios then become for any investor k:

$$\mathbf{s}_k = \phi_k \, \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} + \delta_k \, \boldsymbol{\Sigma}^{-1}\mathbf{x} \ . \tag{13}$$

Here ϕ_k , δ_k are the Lagrange multipliers for the constraints in (12). Thus, these frontier portfolios are a linear combination of investment in standard tangency portfolios, $\mathbf{s}_T = \phi \, \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$, and the characteristic-mimicking portfolio, $\mathbf{s}_x = \delta \, \boldsymbol{\Sigma}^{-1}\mathbf{x}$. Efficient investors will hold only these portfolios (in different proportions); they do not accept variance other than that related to mean return or exposure to the characteristic. It follows that, in equilibrium, the market portfolio, $\mathbf{s}_m$, is a linear combination of such frontier portfolios and is accordingly also a multi-factor frontier portfolio. Hence, any investor, in different proportions, ends up holding the market portfolio and the characteristic-mimicking portfolio. It also follows that pricing in the original formulation, in which the characteristic is added to the CAPM, is equivalent to pricing in the two factor model with market return and the characteristic-mimicking portfolio return as the factors.

In equation (13), an investor who does not care about the characteristic will have $\delta_k = 0$ and holds only the tangency portfolio. However, since the market portfolio here generally differs from the tangency portfolio, this investors holds in effect a combination of the market portfolio and the characteristic-mimicking portfolio.

The investment in the CMP for this investor is actually an "arbitrage" portfolio that takes (limited) advantage of the characteristics premium in returns; limited because the CMP, as opposed to the characteristic itself, carries risk.

It is interesting to note that the covariance of an asset return *i* with the CMP is given by $\sigma_{ix} = \mathbf{s}_i' \mathbf{\Sigma}\, \mathbf{s}_x$ and, because $\mathbf{s}_x = \delta\, \mathbf{\Sigma}^{-1}\mathbf{x}$ for the CMP, this implies that $\sigma_{ix} = \delta\, x_i$. Thus, the covariance of the return on any asset *i* with the CMP is proportional to the characteristic of this asset. Likewise it follows that, in comparison to Fama (1996), we replace "covariance with the state variable" by "covariance with the CMP."

6. Conclusion

An overwhelming number of factors and characteristics has been considered for pricing financial assets. Harvey, Liu, and Zhu (2015) distinguish 113 common (systematic) factors and 212 characteristics. We argue here that current common method in distinguishing factors and characteristics makes a distinction that is a statistical artifact. Essentially, each of the 212 characteristics may be just as well modeled as a systematic risk factor; and each of the 113 systematic factors may be converted to a characteristic. Neither would impact the explanatory power for pricing assets. The difference has no empirical implications of any kind as long as the characteristic-mimicking factor (CMP) is chosen to maximize the factor's exposure to the characteristic for any specific level of factor variance. In this case, the loading/exposure/sensitivity/factor beta of the CMP return for any asset return is exactly equal to the characteristic of the asset.

There are other ways, of course, to produce mimicking factors from a given set of characteristics. Fama and French (1993) prominently generated value and size factors from value and size characteristics of individual firms. Their method was to rank firms from high to low in terms of their characteristics and then utilize the return differences of firms with the high characteristic level compared to firms with the low characteristics level as the mimicking factors for each characteristic (value and size). Apart from such practical considerations as to whether to compare the high and low 30%, or high and low 50% characteristics, there is no theoretical criterion suggesting Fama and French's particular approach and one may think of a host of alternative approaches for creating the mimicking portfolios. This fact, we think, is crucial because there is a reasonable process, with solid underlying foundation, for creating the CMP which leads to the resulting factors as being empirically indistinguishable from the characteristics.

It is our view that, while mimicking factors obtained by alternative methods will be distinguishable from the underlying characteristics, the distinction is an artifact of the assumed mimicking procedure which has little theoretical backing. Any difference found between the pricing impact of the factor as different from the characteristic's pricing impact is therefore an artifact of the arbitrary mimicking process and not a robust feature of asset pricing.

There are some potentially interesting further implications resulting from the CMP approach. For instance, when applied to the impact of liquidity on asset returns, we have theories such as Amihud and Mendelson (1986) which imply an idiosyncratic liquidity premium for assets related to the proportional bid-ask spreads of the assets. This is an instance of assets being priced by a characteristic, with no theoretical role for systematic liquidity risk. However, the CMP approach generates an idiosyncratic-liquidity-mimicking factor that is indistinguishable from a systematic liquidity factor. On the other hand, Pastor and Stambaugh (2003) provide a theory for a specific systematic liquidity factor. Our analysis implies that the two theories may be separated by the specifics of the construction of the systematic liquidity factors. However, it is incorrect to argue that just any findings of a systematic liquidity factor support Pastor and Stambaugh (2003) over Amihud and Mendelson (1986) or vice versa.

We also plan to apply the procedure for obtaining CMP's in reverse: for a given set of factor portfolio weights we can obtain the characteristics that price assets equivalently. Thus, we may find factor-mimicking characteristics (FMC). These may be useful in a variety of applications. For instance, in the liquidity case we may infer liquidity characteristics for any firm based on the Pastor-Stambaugh liquidity factor. This will make it possible to find correlations with other firm-specific liquidity measures. More generally, obtaining characteristics would facilitate applying the approach of Clarke (2015) more broadly. Clarke regresses firm returns on a set of characteristics, and infers expected return based on the results. He then sorts the firms by their expected returns before isolating factors that explain these returns. Being able to generate characteristics from factors will increase the set of variables that can be used for these purposes.

Our ultimate objective is to apply CMPs to learn about underlying firm characteristic from high-frequency market information. For the applications we intend to create CMPs according to eq. (17). Then calculate **B** as in eq. (18) from high-frequency returns and use it to infer the characteristics **X** that are not yet available. To do so accurately we intend to be more specific about stochastic time variation in the characteristics and the loadings and how to efficiently utilize lagged values of the characteristics in conjunction with factor loadings estimated from recent and past observations. We will follow the approach of Ferson et al. (2006) to properly incorporate conditioning information.

We are in the process of applying the approach to continuous *tracking of bank risk* and risk absorption capacity. The characteristics of interest are 46 publicly traded banks' key balance sheet items that measure capital and liquidity as well as risk. The variables involved in measuring characteristics **X** are available from the FDIC's quarterly Call Reports at the bank portfolio level and proprietary information on these banks' securities holdings collected through Federal Reserve Board of Governors FR Y-14 forms (shared with the Office of the Comptroller of the Currency). This information allows us to calculate the CMP weights for any specific characteristic we are interested in as an indicator of risk or liquidity. A simple example is the capital-asset ratio. The loadings, **B**, on the CMP will be estimated from daily CRSP stock returns of these banks traded on NYSE.

We further intend to apply our analysis to *unobservable actions of mutual funds* taken between snapshots of their required holding report dates. Kacperczyk, Sialm, and Zheng (2008) show there is a difference between reported mutual fund returns and returns constructed from mutual fund holdings. The identity between risk loadings and characteristics allows us to attribute this discrepancy to particular trading strategies measured from inferred changes in holdings of particular asset groups (fraction of cash, value stocks, etc.) viewed as characteristics. The holdings information at the portfolio level is available to us from Thomson Reuters' 13f and s12 files in which money managers are required by the SEC to report their stock holdings (when their portfolio's value exceeds $100 million) within 45 days after the last day of each quarter. The returns on these mutual funds are in the CRSP Mutual Funds Quarterly file and constructed from the holdings information in the s12 files. The holding information on stocks, bonds, and cash values will be mapped to TAQ and CRSP daily return files to construct the various characteristics. The liquidity characteristic of mutual fund portfolios can be measured based on Corwin and Schultz (2011), Amihud and Mendelson (1986), and Amihud (2002).

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Chapter Four: ***Distinguishing Factors and Characteristics with Characteristic-Mimicking Portfolios***

1. Introduction

A large literature has attempted to disentangle whether cross-sectional differences in asset returns are best explained by exposure to systematic factor risk or by asset-specific characteristics. Our paper argues that, for the explanation of mean returns, the distinction between risk factors and characteristics has no empirical meaning, and that advantages of using one approach over the other are mostly of a technical nature. However, for the explanation of variations in returns, it is possible to make a meaningful distinction between factors and characteristics. Given a natural choice of a characteristic-mimicking portfolio (CMP) as a factor, the covariance of each asset with the factor is identical to the asset's characteristic. It follows that using either the CMP or the characteristic to explain mean returns provides identical results. But the CMP varies substantially across time and, potentially, can explain a significant degree of time series variation in returns. If so, the CMP has value for hedging purposes and the factor formulation may then dominate the characteristics formulation.

Ever since the influential work of Fama and French (1993, 1996) it has become commonplace to explain anomalies in asset pricing with covariance-risk factors constructed as portfolios that are long on securities of firms with high values of a particular characteristic and short on securities of firms with low values of the characteristic. In this formulation, former anomalies are reduced by the risk premia associated with these covariance risks and may be reinterpreted as rewards for risk associated with the constructed risk factor.

Starting with Daniel and Titman (1997), Jagannathan and Wang (1996), and Daniel, Hirshleifer, and Subhramanyam (2001), a substantial literature has attempted to differentiate between covariance-risk and characteristics-based explanations for asset returns, with varying results.[29] Ferson, Sarkissian, and Simin (1999) question whether it is possible to effectively distinguish between risk factors and characteristics. They employ a variant of the Fama and French approach, first suggested by Fama (1976, pp. 326-329) who pointed out that estimates of risk premia based on so-called Fama-MacBeth (1973) regressions, potentially using characteristics, may be interpreted as portfolios of the realized asset returns, with the portfolio weights depending on the characteristics. The risk-premia here in effect may be viewed as factors that mimic characteristics. Using this approach, Ferson et al. (1999) find that a nonsense factor such as the alphabet factor they create based on company names becomes a significant risk factor. In addition to showing that it is easy to generate a risk factor, they show at the same time that it is difficult to distinguish the effect of the characteristics from the effect of a risk factor mimicking this characteristic.

Balduzzi and Robotti (2008) take the argument a step further. Providing an econometric analysis of the difference between using a two-pass approach versus using factor-mimicking portfolios to evaluate the performance of non-tradable factors, they

[29] Recent papers include Hou et al. (2011), Daniel and Titman (2012), Chordia, Goyal, and Shanken (2015), Luo and Balvers (2017), and Pukthuanthong and Roll (2014).

additionally point out an observational equivalence between characteristics-based and risk-based models, showing that it is always possible to create a factor that implies factor loadings which for each asset are equal to the asset characteristic. While they do not further pursue the implications, they define the CMPs that we will be using here (with minor differences). The CMPs are also quite similar to the mimicking portfolios discussed by Fama (1976) and Ferson et al. (1999) except that the portfolios they consider do not imply that factor loadings and characteristics are aligned unless the covariance matrix of asset returns is diagonal.

A recent paper by Kozan, Nagel, and Santosh (2015) provides a quite different argument for why it is difficult to distinguish risk factors and characteristics explanations. If some investors are rational in the conventional sense and some invest with behavioral motives then the behavioral investors focusing on particular asset characteristics may cause price deviations, presenting opportunities for rational investors. If the deviations correlate with a systematic risk factor the "arbitrage" will not eliminate much; if the deviations are uncorrelated with systematic risk the arbitrage should eliminate most of the price deviations. In either case, however, the pricing in equilibrium is consistent with the first-order conditions of both types of investors. Focusing on the behavioral investor first-order conditions one would find a characteristics explanation; focusing on the rational investor first-order conditions a risk-based explanation works better. Yet both views explain the same price observations.

Our argument goes further in that distinguishing risk-factor and characteristics explanations is pointless to begin with for asset pricing purposes, i.e., explaining the mean returns of assets. To evaluate if a characteristic or a related risk factor works better, it is not reasonable to compare their performances in explaining cross-sectional differences in mean returns: either the performances are exactly identical or the characteristic-mimicking factor was obtained ad hoc so that any performance difference is arbitrary. Characteristics and factors, nevertheless, may still be differentiated by their explanatory power for return shocks: while the risk premia for characteristics are viewed as constant over time, the risk premia for the CMP loadings are the OLS estimates and realized asset returns which must vary stochastically over time. If the CMPs explain a significant part of return variation they are valuable for hedging risk and portfolio management, and dominate the corresponding characteristics formulation. The same procedure for comparing factor and characteristic specifications works just as well if the original formulation is in the risk factor form, in which case we would simply use the loadings on this risk factor to serve as the characteristics.

We follow Pukthuanthong and Roll (2014) in considering whether a factor is truly a risk factor by evaluating both if the factor has significant pricing power for the assets *and* whether it explains a significant part of return variability. However, presupposing an arbitrage pricing context Pukthuanthong and Roll (2014) as do Kozak, Nagel, and Santosh (2015) argue that, insofar as characteristics do not match the loadings on systematic risk factors, priced characteristics represent near-arbitrage opportunities (very large Sharpe ratios). Thus, for them the identifying criterion of (priced) characteristics vis-à-vis factor loadings is that they represent potential for high Sharpe ratios. The drawback of using Sharpe ratios in this manner is that we know that the maximum Sharpe ratio is that of the (ex post) tangency portfolio and a higher Sharpe ratio means mechanically higher correlation with this tangency portfolio. Thus, translating their criterion to our terms, the CMP is a "good" factor if it has a high Sharpe ratio. But this does not rule out a characteristics interpretation; it merely suggests that a group of investors cares a lot about the characteristic for this interpretation to hold. So, it is not clear, definitely not from a practical perspective, what Sharpe ratio should be considered too high to rule out a characteristics explanation. On the other hand, in our approach we simply admit that both interpretations are equally likely as far as explaining mean returns is concerned. Subsequently, we check if the CMP explains a significant extra quantity of return variability. If so, interpreting the variable as a risk factor is fruitful because it allows for better risk management.

In the following, we first discuss the properties of CMPs in Section 2. We present in Section 3 a direct comparison of characteristics and risk factor formulations and discuss in Section 4 how they may be distinguished theoretically. In Section 5 we show the empirical results of distinguishing the characteristics and factor formulations for a standard set of factors and characteristics and standard test assets. Section 6 concludes.

2. Characteristic-Mimicking Factors

It is always possible to create a "characteristic-mimicking portfolio" (CMP) to function as an additional factor that prices all assets in the same way as the original characteristics, and converts the premium associated with a deterministic set of asset characteristics to a premium for systematic risk associated with a risk factor that changes stochastically over time.

Following Balvers and Luo (2017), Define a characteristic-mimicking factor as a portfolio of the risky assets that: (1) maximizes the exposure to the characteristic, subject to (2) a particular portfolio variance. The covariance matrix of the returns of *N* risky assets is given by a positive definite **Σ.** A particular characteristic for all assets is represented by the vector **z**; $\mathbf{s_z}$ is the vector of portfolio shares of the characteristic-mimicking portfolio; and $\overline{\sigma}^2$ is the pre-determined portfolio variance.

$$\max_{\mathbf{s_z}} \; (\mathbf{s_z'z}), \qquad \text{s. t.} \qquad \mathbf{s_z'\Sigma s_z} = \overline{\sigma}^2 \quad , \tag{1}$$

Given the Lagrangian formulation with multiplier ½ λ, the first-order conditions based on equation (1) become

$$\mathbf{s_z} = (1/\lambda)\, \mathbf{\Sigma}^{-1}\, \mathbf{z}\,, \tag{2}$$

which provides the portfolio shares of the zero-investment characteristic-mimicking factor with return $r_{\mathbf{z}} = (1/\lambda)\, \mathbf{r'}\, \mathbf{\Sigma}^{-1}\, \mathbf{z}$. Note that the scale as affected by λ is unimportant for the factor choice since we have a zero-investment portfolio and, even if we did not have a zero-investment portfolio, would have no impact on the explanatory power of the factor.

For empirical purposes we choose $\bar{\sigma}^2$ for each characteristic so that $\lambda = 1$ for each mimicking factor. In this case it follows that $r_{\mathbf{z}} = \mathbf{r}' \boldsymbol{\Sigma}^{-1} \mathbf{z}$ and $\mu_{\mathbf{z}} = \boldsymbol{\mu}' \boldsymbol{\Sigma}^{-1} \mathbf{z}$ so that:

$$Cov(\mathbf{r}, \mathbf{r}_{\mathbf{z}}) = E[(\mathbf{r} - \boldsymbol{\mu})(\mathbf{r}_{\mathbf{z}} - \boldsymbol{\mu}_{\mathbf{z}})] = E[(\mathbf{r} - \boldsymbol{\mu})(\mathbf{r} - \boldsymbol{\mu})']\boldsymbol{\Sigma}^{-1} \mathbf{z} = \mathbf{z} \tag{3}$$

Thus, for any set of characteristics it is possible to create a characteristic mimicking factor (CMP) for which the covariance with any of the assets generates the asset's characteristic. In the next section we will show that for pricing purposes one may replace a particular risk factor by a set of deterministic characteristics, or vice versa a set of deterministic characteristics by an equivalent systematic risk factor without changing the pricing results.

3. Empirical Specification

We present next a general empirical formulation. To distinguish characteristics and risk factor loadings explanations we present two simple models (similar to the models in Balduzzi and Robotti, 2008). In the first a set of characteristics (in addition to regular systematic risk factors) linearly affects returns for all assets and time periods. In the second the characteristics are replaced with risk factors which also (partially) explain returns for all assets but with stochastic risk premia in all periods, as is necessary for a risk factor. We then generate the CMPs. Once we obtain the CMPs we discuss how they can be used to suitably distinguish characteristics and risk factor specifications.

We focus here on the development and application of CMPs which we may define outside of the context of a particular model and for cases in which asset prices are explained only partially. Consider a given set of *N* firms issuing financial assets. The firms are characterized by *K* different characteristics captured by the *N x K* matrix $\mathbf{Z}$, which we assume to be constant over time. Under the *characteristics view*, for each time period we have:

$$\mathbf{r}_t = \mathbf{Zc} + \mathbf{e}_t \,, \tag{4}$$

where $\mathbf{r}_t$ is a *N x 1* vector of excess returns with *N x 1* vector of time series means $\boldsymbol{\mu}$ of the asset excess returns and $\boldsymbol{\Sigma}$ the covariance matrix of the asset excess returns, that may already have been adjusted for known factor risk. $\mathbf{c}$ is *K x 1*, and $\mathbf{e}_t$ is the *N x 1* vector of errors. Note that $\mathbf{Z}$ may include $\mathbf{1}_N$, a *N x 1* vector of ones, to capture a constant in the characteristics estimation (we would then define also $\mathbf{Z} = (\mathbf{1_N} \quad \mathbf{X})$ and $\mathbf{c} = (a \quad \mathbf{b})'$). Pool over all time periods to estimate $\mathbf{c}$. If we estimate $\mathbf{c}$ efficiently from eq. (4) by Generalized Least Squares (GLS) then we obtain

$$\mathbf{c} = (\mathbf{Z}'\boldsymbol{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu} \,, \tag{5}$$

Alternatively, we have the *risk factor specification* with tradable assets serving as risk factors

$$\mathbf{r_t} = \boldsymbol{\alpha} + \mathbf{Br_t^Z} + \mathbf{u_t} \,, \tag{6}$$

Where $\mathbf{r}_t$ is as above, $\boldsymbol{\alpha}$ is *N x 1*. $\mathbf{u_t}$ is i.i.d. *N x 1*. $\mathbf{r_t^Z} = \mathbf{S'r_t}$ which is *K x 1* and $\mathbf{S}$ is an *N x K* matrix of portfolio shares. Suppose the *K* risk factors are chosen according to equation (3), with $\lambda = 1$ and aggregating all characteristics, as the following portfolios of the N assets:

$$\mathbf{S} = \mathbf{\Sigma}^{-1}\mathbf{Z}, \tag{7}$$

where $\mathbf{\Sigma} = \mathbf{E[(r_t - \mu_t)(r_t - \mu_t)']}$ is the covariance matrix of the N asset returns. Thus, $Cov(\mathbf{r_t}, \mathbf{r_t^Z}) = E[(\mathbf{r_t} - \boldsymbol{\mu})(\mathbf{r_t} - \boldsymbol{\mu})']\mathbf{\Sigma}^{-1}\mathbf{Z} = \mathbf{Z}$.

Given eq. (6) we find the "betas" from the standard first-pass time series regressions:

$$\mathbf{B} = \mathbf{\Sigma S(S' \Sigma S)}^{-1}. \tag{8}$$

From eqs. (7) and (8) we may infer that $\mathbf{B} = \mathbf{Z(Z' \Sigma^{-1} Z)^{-1}}$. Taking expectations in both models (4) and (6) implies that $\boldsymbol{\alpha} = E(\mathbf{e}_t)$, where the expectation represents the time series average. Both models provide the same estimates for mean returns. It follows that we can generate a CMP for every set of assets and every characteristic.

If $\mathbf{Z}$ includes a unit vector to add a constant in the specification, so that $\mathbf{Z} = (\mathbf{1_N} \quad \mathbf{X})$, then the set of mimicking portfolios must be supplemented with a constant-mimicking portfolio which has investment weights $\mathbf{S_C} = \mathbf{\Sigma}^{-1}\mathbf{1_N}$ and with which every asset has identical unit covariance. This portfolio is up to scaling equal to the global minimum variance portfolio and has zero explanatory power for differences in mean return across the assets. The lack of cross-sectional explanatory power is intuitively clear because all assets load equally on this factor.

If $\mathbf{Z}$ consists of a vector $\boldsymbol{\mu}$ of the mean returns of the test assets then the mimicking portfolio is (again up to a scaling factor) equal to the tangency portfolio: $\mathbf{S}_{\mathbf{T}} = \boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}$. By design, therefore, the "mean return" characteristics as well as the associated CMP perfectly explain the mean returns of all test assets. Arbitrage Pricing Theory implies that a factor explaining all of the mean returns should also explain all of the undiversifiable risk. Accordingly, the CMP for mean returns (equal to the tangency portfolio) also should explain more of the time series variation than any other factor. Note that this implication need not hold for equilibrium asset pricing theories not based on arbitrage pricing.

4. Distinguishing Factors and Characteristics

With properly chosen CMP there is no difference between characteristics and covariance with the factor, in terms of pricing (i.e. explaining average returns). However, the characteristics have a constant impact on returns whereas the risk factor realizations are stochastic in each time period. As a result, the factors may explain *variation* in realized returns better. Comparing the unexpected returns for both models:

$$\mathbf{r}_{\mathbf{t}} - \boldsymbol{\mu} = \mathbf{e}_t - E(\mathbf{e}_t)\,. \tag{4'}$$

$$\mathbf{r}_{\mathbf{t}} - \boldsymbol{\mu} = \mathbf{B}(\mathbf{r}_{\mathbf{t}}^{\mathbf{Z}} - \boldsymbol{\mu}^{\mathbf{Z}}) + \mathbf{u}_{\mathbf{t}}\,, \tag{6'}$$

where $\boldsymbol{\mu}^{\mathbf{Z}} = \mathbf{S}'\boldsymbol{\mu}$. The right-hand sides are equal in both specifications, and both represent unpredictable components, but the error in eq. (6') includes the *factor risk component* which may be hedged to eliminate part of the risk. So, for the factor model to be better it must be that the variance of error $\mathbf{u_t}$ in eq. (6') is significantly less than the variance of error $\mathbf{e}_t - E(\mathbf{e}_t)$ in eq. (4'). In that case, a hedging strategy of holding asset i and shorting $\mathbf{Z}_i(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z}\ )^{-1}$ units of each factor should significantly reduce risk ($\mathbf{Z}_i$ is the row vector of asset i's K characteristics), which could be true only by coincidence under the characteristics interpretation

We use as the performance criterion the equal-weighted average of the error variance pooled over all time periods and assets. The reduction in error variance (equal-weighted) due to $\mathbf{Z}$ alone then equals $Tr\{E[\mathbf{B}(\mathbf{r_t^Z}-\boldsymbol{\mu}^\mathbf{Z})(\mathbf{r_t^Z}-\boldsymbol{\mu}^\mathbf{Z})'\mathbf{B}']\}$, where Tr represents the trace of the matrix. Given $\boldsymbol{\mu}^\mathbf{Z} = \mathbf{S}'\boldsymbol{\mu}$ and $\mathbf{S} = \mathbf{\Sigma}^{-1}\mathbf{Z}$, then, using eq. (8),

$$Tr(\mathbf{\Sigma}) - Tr(\mathbf{uu'}) = Tr[(\mathbf{e}_t - E(\mathbf{e}_t))(\mathbf{e}_t - E(\mathbf{e}_t))'] - Tr(\mathbf{uu'}) = Tr[\mathbf{Z}(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}'], \tag{9}$$

where $\mathbf{u}$ is a $T\ x\ N$ vector of all asset errors for all time periods.

It is straightforward to show (see Appendix) that given the interpretation of $Tr(\mathbf{uu'})$ as the equal-weighted average of the error variance pooled over all time periods and assets, that the R-squared of a pooling regression of equation (6) over all periods and assets is identical to the value-weighted average R-squared of the separate time-series regressions of all assets ($R^2_{AVG} = \sum_{i=1}^{N} w_i R_i^2$,with $w_i = \sigma_i^2 / \sum_{i=1}^{N} \sigma_i^2$, where R_i^2 is the time-series R-squared and σ_i^2 the return variance of asset i), which may be computed directly as:

$$R^2_{AVG} = Tr[\mathbf{Z}(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}'] / Tr(\mathbf{\Sigma}) \tag{10}$$

If we substitute $\mathbf{S} = \mathbf{\Sigma}^{-1}\mathbf{Z}$ from equation (7) then we obtain alternatively:

$$R^2_{AVG} = Tr[\mathbf{\Sigma}\,\mathbf{S}(\mathbf{S}'\,\mathbf{\Sigma}\,\mathbf{S})^{-1}\mathbf{S}'\,\mathbf{\Sigma}]\,/\,Tr(\mathbf{\Sigma})\,. \tag{11}$$

Either specification may be employed to evaluate the explanatory power for time-series variation of a set of factors or the CMPs associated with a set of characteristics.[30]

Empirical Testing Procedure

It may be that the CMP due to random variation explains more or less of return variance. To adjust for this we provide a formal statistical test. The right-hand side of eq. (9) is in the form of a generalized Rayleigh Quotient (see for instance Li, 2015) and must be positive and no larger than the sum of the K largest eigenvalues of $\mathbf{\Sigma}$ (as well as no smaller than the sum of the K smallest eigenvalues of $\mathbf{\Sigma}$). Thus, we propose a test to distinguish characteristic and loading formulations entirely based on the error variance: compare the trace in eq. (9) for actual data to a critical value. By this method we adjust for the fact that any tradable factor will naturally explain some of its variance, and also take into account the specifics of the cross-sectional distribution of each characteristic that may otherwise affect the outcome.

The methodology discussed above must be adjusted depending on the nature of the risk factor or characteristic considered. This is a subtle theoretical issue but one that is

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[30] The scaling of the characteristics (by a possibly different proportion for each characteristic), so that we obtain $\mathbf{ZD_Z}$, where $\mathbf{D_Z}$ is an invertible KxK diagonal scaling matrix, or scaling of the portfolio weights of the factors, so that we obtain $\mathbf{SD_S}$, where $\mathbf{D_S}$ is an invertible KxK diagonal scaling matrix, has no impact on the R-square measure in equations (10) or (11), as is easy to derive using these equations.

quantitatively important in our simulations as shown in Figure 1 below. We need to distinguish between treating (a) a risk factor that is derived as a CMP from a characteristic (the CMP approach) and (b) a risk factor that is directly available as a portfolio of the assets (henceforth FF approach).

Permuting Characteristics or Portfolio Shares?

From eq. (9) or (10) we focus on $Tr[\mathbf{Z(Z'\Sigma^{-1}Z)^{-1}Z'}]$ as our measure of additional variation explained by the risk factor as opposed to the characteristic. However, since $\mathbf{S}=\mathbf{\Sigma^{-1}Z}$ from eq. (7) we may focus alternatively on $Tr[\mathbf{\Sigma S(S'\Sigma S)^{-1}S'\Sigma}]$ in eq. (11). To provide a distribution under the null hypothesis that the CMP explains no additional variation in returns, we propose to use the original distribution of cross-sectional characteristics $\mathbf{Z}$ but permuted cross-sectionally for some of the characteristics: $\mathbf{Z_P}=[\mathbf{Z_1}\ \mathbf{PZ_2}]$, where we consider the significance of the CMPs from the set of characteristics $\mathbf{Z_2}$ (which could include anywhere between all of $\mathbf{Z}$ or as little as one column). Keeping the characteristics in $\mathbf{Z_1}$ constant, we randomly change the order of the characteristics as they are assigned to the different assets by multiplying $\mathbf{Z_2}$ by the (orthogonal) permutation matrix $\mathbf{P}$ which randomly permutes the order of the rows of $\mathbf{Z_2}$. The resulting CMPs are given as

$$\textit{Permuting}\,\mathbf{Z}:\mathbf{r_t^{Z_P}}=\mathbf{S_P'r_t}=(\mathbf{\Sigma^{-1}Z_P})'\mathbf{r_t}=[\mathbf{\Sigma^{-1}Z_1}\ \ \mathbf{\Sigma^{-1}PZ_2}]'\mathbf{r_t}=\begin{pmatrix}\mathbf{Z_1'\Sigma^{-1}r_t}\\ \mathbf{Z_2'P'\Sigma^{-1}r_t}\end{pmatrix}=\begin{pmatrix}\mathbf{r_t^{Z_1}}\\ \mathbf{r_t^{Z_{2P}}}\end{pmatrix} \quad (12)$$

Clearly, the permutation results in changing only the CMPs related to the second group of characteristics which are to be assessed. Apart from aspects of the original distribution of characteristics which remain unchanged, the CMPs based on the permuted characteristics should have no inherent explanatory power for return variations and accordingly are an appropriate benchmark for the null hypothesis that the original CMPs based on $\mathbf{Z_2}$ explain no additional variation in returns.

Alternatively, it is possible to test the null hypothesis that the CMPs based on $\mathbf{Z_2}$ explain no additional variation in returns by permuting the portfolio shares $\mathbf{S}$ of the CMPs directly. In that case we obtain

$$\textit{Permuting } \mathbf{S}: \qquad \mathbf{r}_\mathbf{t}^{\mathbf{Z_P}} = \mathbf{S_P}'\mathbf{r_t} = [\mathbf{S_1} \;\; \mathbf{PS_2}]'\mathbf{r_t} = \begin{pmatrix} \mathbf{Z_1}'\boldsymbol{\Sigma}^{-1}\mathbf{r_t} \\ \mathbf{Z_2}'\boldsymbol{\Sigma}^{-1}\mathbf{P}'\mathbf{r_t} \end{pmatrix} = \begin{pmatrix} \mathbf{r}_\mathbf{t}^{\mathbf{Z_1}} \\ \mathbf{r}_\mathbf{t}^{\mathbf{Z_{2P}}} \end{pmatrix}. \tag{13}$$

The CMPs associated with the $\mathbf{Z_1}$ characteristics are still unchanged but the CMPs based on $\mathbf{Z_2}$ are different under permutation of $\mathbf{Z}$ compared to under permutation of $\mathbf{S}$.

For the case of CMPs derived from characteristics, permuting $\mathbf{S}$ is inappropriate for finding a benchmark distribution for the null hypothesis. The reason is that the portfolio shares $\mathbf{S}$ are not exogenous and are calculated from $\mathbf{Z}$. Permuting $\mathbf{Z}$, however, is appropriate because the CMP shares undergo the same type of transformation both under the original and the permuted cases.

For the case of factor portfolio shares provided directly, permuting $\mathbf{Z}$ is inappropriate. The factor loadings are determined to optimize explained time series variation, for the original factor. For the permuted $\mathbf{Z}$ the portfolio shares are determined indirectly via eq. (7). The inferred portfolio shares, of course, explain the time series of returns also via an optimization regression determining the regression sloped $\mathbf{B}$ which are tied to the permuted $\mathbf{Z}$. However, the whole process has the effect of mechanically taking the product $\mathbf{B}\mathbf{S'}$ further away from the maximum associated with the first eigenvector. Thus, permuting $\mathbf{Z}$ leads to a benchmark distribution in this case (in which factor portfolio shares are provided directly) that would bias toward accepting the null hypothesis.

Permuting $\mathbf{S}$, however, is appropriate when factor portfolio shares are provided directly: the associated factor loadings undergo the same type of transformation both under the original and the permuted cases.

Accordingly: (a) when treating risk factors derived as CMPs from characteristics we permute the appropriate part of the $\mathbf{Z}$ matrix to establish a benchmark to evaluate the null hypothesis that a particular set of factors explain no additional time-series variation. We can then straightforwardly calculate the distribution of the average time-series R-squared based on the permuted cases by computing $Tr[\mathbf{Z}(\mathbf{Z'}\boldsymbol{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z'}]/Tr(\boldsymbol{\Sigma})$ for each permutation; and (b) when treating risk factors that are directly available as portfolios of the assets we permute the appropriate part of the $\mathbf{S}$ matrix to establish a benchmark to evaluate the null hypothesis. We then calculate the distribution of the average time-series R-squared by computing $Tr[\boldsymbol{\Sigma}\mathbf{S}(\mathbf{S'}\boldsymbol{\Sigma}\mathbf{S})^{-1}\mathbf{S'}\boldsymbol{\Sigma}]/Tr(\boldsymbol{\Sigma})$ for each permutation.

We discussed four different scenarios for providing appropriate “bootstrapped” distributions to evaluate the explanatory power of factors for the time series of test asset returns. The four scenarios are the 2x2 intersection of (a) evaluating actual (candidate) factors determined by the FF approach or the CMP approach, and (b) constructing alternative (useless) factors via the FF approach or the CMP approach. Figure 1 (Panels A through D) demonstrates that the only reasonable approaches are to (1) construct alternative factors via the FF approach for factors provided by the FF approach, and to (2) construct alternative factors via the CMP approach for factors provided by the CMP approach. These simulations allow several inferences. First, it is not reasonable to use the same method for evaluating time series performance of factors derived from characteristics and factors derived as exogenous portfolios of the assets. Second, the bootstrapping methods comparing actual candidate factors to similarly generated useless factors appear to be quite accurate in terms of having empirical size very similar to the nominal size of the tests.

The bootstrapping simulations are constructed as follows. We utilize the actual excess returns of our main test assets, the Fama-French 30 monthly industry portfolios for the period 1963.07 to 2015.12. The average time-series R-squares for the "actual" CMP factors (derived from exogenous random characteristics) are created by randomly drawing J=1000 30x1 vectors from standard normal distributions to serve as the characteristic and then using equation (10), to calculate $R^2_{AVG,j} = Tr[\mathbf{Z}_j(\mathbf{Z}_j'\mathbf{\Sigma}^{-1}\mathbf{Z}_j)^{-1}\mathbf{Z}_j'] / Tr(\mathbf{\Sigma})$ for each draw j, for all 1000 draws. The average time-series R-squares for the "actual" FF factors (derived from exogenous random factor portfolios) are created by randomly permuting approximately market-neutral factor portfolios, with 1 and -1 assigned to two of the 30 assets and zeros assigned to the remaining assets, J=1000 times. Then we use equation (11) to calculate $R^2_{AVG,j}$ = $Tr[\mathbf{\Sigma S}_j(\mathbf{S}_j'\mathbf{\Sigma S}_j)^{-1}\mathbf{S}_j'\mathbf{\Sigma}]/Tr(\mathbf{\Sigma})$ for each draw j . In all cases, these factor are intended to represent "useless" factors that should have no inherent explanatory power for the time series of the test assets. The question is how formal tests based on bootstrapped distributions would perform, and specifically how often the null hypothesis that the factor is "useless" ends up being rejected incorrectly. That is, we examine the empirical size of each of four testing strategies.

For each draw of a factor (either a FF factor or a CMP factors) we construct a bootstrapped distribution by randomly permuting across the 30 assets 5000 times either the characteristics (the assignment of the characteristics to each asset are scrambled) or the factor shares (the weights on each asset in the factor portfolios are scrambled) and then calculate the R-square in each case. This yields the four different scenarios. For each of the 1000 factor draws we decide if the R-square is larger than 95% (or 90% or 99%) of the R-squares of the 5000 permutations. If so, we reject the null hypothesis of no-explanatory-power for the time-series. The fraction of these rejections provides the empirical size of the test because the rejections are incorrect since the generated factors are random and have no inherent explanatory power.

Figure 1, Panel A shows that using randomly permuted CMP factors to test the explanatory power of CMP factors generates an empirical size of 5.3% very close to the nominal size of 5%. In addition, the average R-square is quite similar for the original factors compared to the permuted factors. On the other hand, in Panel B also testing

CMP factors, if we use randomly permuted factor portfolio shares to construct the background distribution, the empirical size is 0% for a nominal size of 5% or even 10%. The null hypothesis is never rejected and, in fact, R-squares for the CMP factors are everywhere below the R-squares for the permutations of the factor portfolio shares.

When the factors are FF factors, Panel D shows the results for when the background distribution for the R-squares is generated by permuting the factor portfolio shares. In this case, the empirical size is 5.0%, equal to the nominal size of 5%. The average R-square across the factors is very similar to the R-square average for the permuted factors. In Panel C, the background distribution is obtained by permuting the characteristic (that is, permuting the covariance of asset returns with the factor across assets). Here the empirical size is very large at 96.2% for the nominal size of 5%. The R-squares for the actual factor almost always exceed the 95% band for the R-squares of the factors inferred from permuted characteristics.

Only the approaches in Panels A and D are applicable. We cannot use one test for both CMP and FF factors. However, a different test for each of the CMP and FF factors appears to be quite reliable at least in terms of size and we will employ these in the empirical analysis below.

5. Empirically Differentiating Risk Factor and Characteristics Explanations

We apply our methodology to standard cases in which conflicting characteristics and risk factor explanations have been proposed. As our test assets we will be concerned with the 30 industry portfolios, the 25 value- and size-sorted portfolios, and the combined

55 portfolios, as constructed by Fama and French. Each of these test asset groups are concatenated with the three risk factors we consider (guaranteeing that any of the factors we consider are tradable within the set of test assets). The industry portfolios are interesting because they are diversified but have not first been sorted based on specific characteristics with controversial pricing impact (ignoring the industry selection as a natural criterion). For illustrative purposes and for their ubiquitous usage we focus on characteristics and factors associated with the market, value, and size.

A. Explanatory Power for Mean Return Differences

We start by evaluating the performance of factors vs. characteristics for 30 industry portfolios. We consider the Fama-French (1993) market, size and value factors, and the CMPs of each. Factors representing the systematic risk related to a characteristic in practice have been formed quite differently from the way we construct the CMP. For instance, Fama and French (1993) find the *value risk factor* by first collapsing the value characteristic, BE (the log of book to market equity), into +1 for the 30% highest BE firms and -1 for the 30% lowest BE firms, and call the returns of this factor at each time the *HML* factor (the value factor from the FF approach). There is no clear objective basis for this particular choice. We contend that the distinction created between factor and characteristic in this fashion is not a robust and fundamental one but rather a hollow one arising from differences in the technical details of the mimicking factor construction.

In contrast, as the alternative value factor, the *value-CMP* factor (the value factor from the CMP approach) for which the loading of each asset equals the asset's covariance with the factor, we use our approach to calculate $r_{\mathbf{t}}^{\text{value-CMP}} = \mathbf{r_t}'\mathbf{\Sigma}^{-1}\mathbf{BE}$ (where **BE** represents the vector of value-measures for each test asset). While there is little theoretical reason to expect either the HML factor or the value-CMP factor to outperform the other, it is useful to consider both specifications since Kogan and Tian (2015) argue that the empirical performance of factor and characteristics formulations in explaining mean returns is quite different.

We stress, however, that whether the CMP approach or the FF approach performs better is irrelevant for the determination of whether to adopt a characteristics or a risk-factor explanation (it will just favor *one particular proxy* for measuring the value impact or the size impact over another). We do expect, though, that typically both versions will perform similarly in explaining time series variation so that either both or neither would support a risk-factor explanation over a characteristics explanation. Moreover, while under the FF approach of constructing factors the characteristics and the covariance between the characteristic-based factor and returns are not the same, showing that both characteristics and the characteristic-based factor matter jointly is not evidence of a characteristics effect; it is just an indication that two reasonable proxies of the same attribute are sufficiently dissimilar and each contain different noisy information regarding the same underlying variable.

Table 1 shows the standard test for the explanatory power of characteristics in addition to the loadings of the factor. We employ the Fama-MacBeth (1973) cross-sectional two-pass approach with the proviso that, as in Black-Jensen-Scholes (1972) the factor loadings are estimated once for the full period. We also consider the first-pass results to examine the economic and statistical significance of the alphas. Results for the 30 industry portfolios for the period July 1963 – December 2015 are in Panel A. As is consistent with previous studies (e.g., Lewellen, Nagel, and Shanken (2010), the various standard models consisting of combinations of the market, value, and size factors have little explanatory power for the mean returns of these industry portfolios: the cross-sectional R-squares are low and the prices of risk are not significant. The BE characteristic appears to be the only significant variable, but it has the opposite sign of what is expected (higher value her lowers expected returns). Nevertheless, the GRS test (Gibbons, Ross, and Shanken, 1989) does not reject the null hypothesis that the alphas, mean pricing errors, are zero. And the absolute values of the alphas are quite small, typically less than 2% annualized.

The overall weak results here stem from the fact that the industry portfolios are not explicitly selected to enhance differences in portfolio means. As a result, there is not much cross-sectional variance in the mean returns to be explained. It is accordingly not so surprising that significance of the prices of risk is hard to come by and that the cross-sectional R-square is low due to a low signal-to-noise ratio. Alphas are small simply because mean return differences are small.

On the whole, therefore, regarding the 30 industry portfolios, we find little evidence either for or against the variables considered in terms of their explanatory power for mean returns. However, note our key point that this performance in terms of explaining *mean returns* is completely irrelevant as far as the decision is concerned of whether to interpret and use the variables as factors or as characteristics. (To that end we should only consider the "first-pass" time-series fits, as we discuss in the next subsection).

Results for the 25 value- and size-sorted portfolios for the period July 1963 – December 2015 are in Panel B. Consistent with the ample literature which has considered these test assets, the cross-sectional R-squares are considerably higher and many of the prices of risk are significant. However, the GRS test formally resoundingly rejects all specifications. The standard Fama-French 3-factor model provides the typical results: a cross-sectional R-squared of 69.5% with significantly positive prices of risk for MKT and HML while the price of risk for SML is positive but insignificant. The p-value for the GRS test is very close to one, but the absolute alpha is less than 10 bps per month. As Fama and French (1996) emphasize, the power of the GRS test is sufficiently high in this context that even economically small deviations from zero alphas will lead to statistical rejection. Accordingly, it is important to consider the economic significance of the deviations.

Explanatory power for the size and book-to-market characteristics (SZ and BE) is quite similar as for the size and value factors (SMB and HML). When both SZ and BE are added in addition to SMB and HML loadings, SZ drives out SMB but HML drives out BE. In the view of Jagannathan and Wang (1996) this suggests that the size characteristic drives out the size factor but the value factor drives out the value characteristic. However, our interpretation is that the CMP proxy for size and FF proxy for value work slightly better than the FF proxy for size and CMP proxy for value, generating no evidence in favor of either characteristics or factors at this point. The variables overall appear to have more explanatory power for the 25 value- and size-sorted portfolios. In view of Lewellen, Nagel, and Shanken (2010), this is not unexpected due to the strong factor structure of these test assets.

Results for the 55 portfolios (combining the 30 industry portfolios with the 25 value- and size-sorted portfolios) provide intermediate cross-sectional R-square levels, whereas the GRS statistics again reject all versions. None of the variables have significant prices of risk except for BE, this time with the anticipated sign. Arguably, all models could be rejected based on their explanatory power for mean returns of the 55 portfolios. However, as we pointed out earlier, whether or not we reject the model has no bearing on whether we may best view the variables as factors or as characteristics (or a combination of the two).

B. Explanatory Power of Shocks to the Risk Factors

The only reasonable way to distinguish factor and characteristic views is to examine if the CMPs (or the factors based on the Fama-French approach) explain a significant part of the return variation over time. If so, the variables are useful for portfolio management and risk management.

Table 2, Panel A provides some diagnostics regarding how much of return variability of the various test portfolios it is possible for a factor to explain for each of the three groups of test assets. Based on an eigenvalue decomposition generating the principal components, for the 30 industry portfolios plus three Fama-French factors, the most one factor can explain is a variance of 721.53 out of total variance (the sum of the variances of the 30 industry portfolios) of 1176.87 for an R-square of 61.3%. A second factor may explain at most a variance of 94.78 giving a marginal R-square of only 8.1%. For the 25 portfolios, with a stronger factor structure, the first principal component explains a variance amounting to an R-square of 82.5%, whereas the second principal component would generate an R-square of 7.1%.

C. Results for single factors

The actual explanatory power of the factor shocks for the 30 industry portfolios combined with the three Fama-French factor portfolios is provided in Table 3, Panel A where we look at the impact of various Fama-French style factors and CMPs on the explained variance of the portfolios (the FF30+3). We examine here the explanatory power of each factor or CMP in isolation. The results are as follows. Starting with the FF factors individually, MKT has an R-square of 57.0%, SMB 10.2%, and HML 4.4%.

To see if these levels of explanatory power are statistically significant, we provide a simulation under the null hypothesis that the factor has no explanatory power. Naturally, any random factor will register some explanatory power, in part because it will have a 100% R-square in explaining the time series of itself. Therefore we provide a background distribution under the null by drawing random factors from the test assets. For MKT we permute the investment share of 1 in MKT among the test assets but excluding the factors (since these are suspected of having actual explanatory power for the time series of the test assets). Based on 5000 random permutations generating the simulated factors we rank the associated measured R-squares (using equation 11), providing the levels at 10%, 50%, 90%, 95%, and 99% in Panel A. The critical value at the 95% level is 51.6%. Accordingly, we conclude that MKT, providing an average time series R-square of 57.0%, has significant explanatory power at the 5 percent level of significance (and even at the 1% level).

For SMB and HML, which are roughly market neutral factors, a more reasonable background distribution under the null hypothesis is found by permuting portfolio shares of 1 and -1 among the industry portfolios to create (roughly market neutral) simulated factors without explanatory power. For SMB at the 95% level the critical R-square is 42.4% which is larger than the observed R-square of 10.2%. Therefore, there is no evidence for the FF-approach based size factor explaining significant time series variation. Similarly, for HML, the actual R-square of 4.4% is less than the critical value of 42.5% at the 95% level, so the FF-approach based value factor has no significant power for explaining time series variation.

For the CMP factors, the R-square for size (SZ) is 3.0% and for value (BE) it is 3.2%. Conform our discussion in the previous section, the background distribution for the CMP-approach based factors should be obtained by randomly permuting the characteristics (5000 times across all 33 test assets) and subsequently using the CMP approach to generate the simulated factors. The associated measured R-squares (using equation 10 or 11) are again ranked and the levels at 10%, 50%, 90%, 95%, and 99% provided in Panel A. At the 95% level, the critical R-square is 3.9% for SZ and 3.3% for

BE which is larger than the R-squares for both the SZ-CMP (3.0%) and the BE-CMP (3.2%). The CMP-approach based size and value factors lack significant explanatory power for the time series of returns.

The results are qualitatively similar for the FF25+3 and FF55+3 test assets as displayed in Panel B. The only differences are that the explanatory power for MKT for the FF25+3 assets, even at an R-square of 72.5% and at the 10 percent level, is insignificant (as the 90% critical R-square is 76.9%); and that the BE-CMP is significant at the 10 percent level for both the FF25+3 and FF55+3, even at R-squares of only 0.44% and 0.27%, respectively (with critical R-squares at 90% of 0.34% and 0.20%, respectively.

Overall, the market factor behaves consistent with being a risk factor, representing a systematic risk. However, whether obtaining factors from the FF approach or the CMP approach, the size and value factors do not appear to explain a significant degree of time series variation. They accordingly do not represent systematic risk and should not be viewed as factors but instead should be viewed as characteristics (explaining mean returns equally well compared to factor form). Of course, for the CMP approach the size and value characteristics are captured by market value and book-to-market ratios for each test asset, whereas for the FF approach the size and value attributes are to be obtained as the covariance of an asset's return with the SMB and HML factors, respectively.

Part of the explanatory power of the different factors may be related to their correlation with the market factor. However, in many risk models the market factor is necessarily included as one of the factors. Accordingly, we consider the marginal impact of each factor once the market factor is already included. Table 4 contains the results of adding any of the factors to the model, given that we have already accounted for market risk. In effect we examine the fraction of additional time-series variation explained by each factor after removing market exposure.

D. Single-factor results for market-risk adjusted return variation

Table 4 presents the average time-series R-squares for models that include the market factor MKT as well as one of the additional factors. This allows us to examine the significance of the additional factor in explaining time-series variation once a large fraction of the variation has already been absorbed by MKT. The marginal significance may be assessed by considering random alternative factors (without explanatory power) while keeping MKT constant. For the FF-approach factors, 5,000 random factors are generated as weights of +1 and -1 on the non-factor test assets; for the CMP-approach, 5,000 random factors are generated by permuting the BE or SZ characteristics, while maintaining the MKT characteristics (MKT covariances with the test assets) and then generating the simulated CMP factors from the partially permuted characteristics.

The results presented in Table 4 are mostly consistent with those in Table 3. No factors are significant in Panel A for the FF30+3 assets although BE is significant at the 10 percent level as the R-square (based on MKT and the BE-CMP) equals 57.66% whereas the critical value at 90% equals 57.64%. In Panel B no factors are significant except for SMB which is significant at the 5 percent level for both the FF25+3 and the FF55+3 test assets. Hence, there is some evidence that the FF-based size factor is indeed a systematic risk factor as it explains a significant fraction of the remaining time-series variation not explained by MKT.

E. Multiple-factor results for risk adjusted return variation

In Table 5 we consider the joint significance of groups of factors added to a particular model. The total R-square may be compared to a simulated distribution of R-squares obtained by leaving the factors of the initial model unchanged while simulating the added factors by appropriate permutations of the factors (for the FF approach) or the characteristics (for the CMP approach). For more details see the notes to Table 5.

Panel A for the FF30+3 test assets shows again that MKT is significant, either when added to SMB plus HML or when added to SZ-CMP plus BE-CMP. In addition, the SZ-CMP is significant at the 10 percent level when added to MKT plus SMB, while the BE-CMP is significant at the 5 percent level when added to MKT plus HML. In addition, SZ-CMP together with BE-CMP is significant at the 5 percent level when added to MKT and also when added to the Fama-French model, MKT, SMB, and HML. On the other hand, adding SMB or HML is not significant in any combination.

For the FF30+3 test assets it appears that the size and value factors based on the CMP approach are better proxies for the underlying size and value attributes than those based on the FF approach. Based on the CMP proxies, value and size may be viewed as capturing systematic risk and may best be considered factors rather than characteristics. The conclusion is reversed based on the FF proxies for value and size: both are best viewed as characteristics.

The results in Panel B for the FF25+3 and FF55+3 test portfolios paint a very different picture. Both HML (for the FF25+3 assets) and SMB (for both the FF25+3 and the FF55+3 assets) are significant at the 5 percent level when added to MKT plus SMB and MKT plus HML, respectively. In addition, adding HML and SMB jointly to either MKT or MKT plus BE-CMP and SZ-CMP delivers significance at the 5 percent levels for both groups of test assets. On the other hand, adding BE-CMP and SZ-CMP to the three Fama-French factors provides insignificant added explanatory power.

F. Overall choice between factors and characteristics

Clearly, the market should be viewed as a factor rather than as a characteristic. However, it is difficult to provide an overall conclusion regarding the size and value attributes. Whether these may be viewed as factors or characteristics varies based on the test assets and based on whether we use a CMP approach or an FF approach, as well as based on which other factors are already included.

For the FF30+3 it appears that the value attribute, the BE-CMP, adds significant explanatory power to the MKT factor and may be usefully viewed as a risk factor. For the FF25+3 HML, and to a lesser degree SMB, add significant explanatory power to the MKT factor. The latter result may be unsurprising as the FF25 portfolios are deliberately sorted based on value and size characteristics to have a factor structure so that much of the variation may be explained by value and size attributes. On the other hand, the FF30 portfolios have more idiosyncratic risk so that it becomes more difficult to pick out a risk factor. Hence, it may make sense to put larger weight on the results for the FF30+3 portfolios. Either way, there is limited evidence for viewing either value or size (by some proxy) as a risk factor.

6. Conclusion

In empirical asset pricing the overwhelming focus has been on identifying which factors best explain the cross-section of mean asset returns. While asset pricing models have typically generated predictions regarding mean asset returns only, their explanatory power for time-series fluctuations is possibly equally as important. Nevertheless, in standard methodology the focus is on explaining alphas or on second-pass performance if not all factors are tradable. Rarely any attention is paid to first-pass R-squares; after all they just provide a measure of the fraction of risk that is idiosyncratic, concerning which the theory has little to say. We argue here, however, that, at least on the issue of using characteristics or factors in asset pricing, the (weighted average) first-pass R-squares are crucial, since models (correctly) explaining more risk as systematic are more useful, and provide the only way to distinguish factors and characteristics.

An overwhelming number of factors and characteristics has been considered for pricing financial assets. Harvey, Liu, and Zhu (2015) distinguish 113 common (systematic) factors and 212 characteristics. We argue here that we cannot meaningfully distinguish factors and characteristics when it comes to pricing implications for average returns. Essentially, each of the 212 characteristics may be just as well modeled as a systematic risk factor; and each of the 113 systematic factors may be converted to a characteristic. Neither would impact the explanatory power for determining “required” asset returns.

The difference has no pricing implications of any kind as long as the characteristic-mimicking factor (CMP) is chosen to maximize the factor's exposure to the characteristic for any specific level of factor variance. In this case, the covariance of the CMP return with any asset return is proportional to the characteristic of that asset.

There are other ways, of course, to produce mimicking factors from a given set of characteristics. Fama and French (1993, 1996) prominently generated value and size factors from value and size characteristics of individual firms. Their method was to rank firms from high to low in terms of their characteristics and then utilize the return differences of firms with the high characteristic level compared to firms with the low characteristics level as the mimicking factors for each characteristic (value and size). Apart from such practical considerations as to whether to compare the high and low 30%, or high and low 50% characteristics, there is no theoretical criterion suggesting Fama and French's particular approach and one may think of a host of alternative approaches for creating the mimicking portfolios. This fact, we think, is crucial because there is a reasonable process, with solid underlying foundation, for creating the CMP which leads to the resulting factors as being empirically indistinguishable from the characteristics for pricing purposes.

It is our view that, while mimicking factors obtained by alternative methods will be distinguishable from the underlying characteristics, the distinction is an artifact of the assumed mimicking procedure which has little theoretical backing. Any difference found between the pricing impact of the factor as different from the characteristic's pricing impact is therefore an artifact of the arbitrary mimicking process and not a robust feature of asset pricing.

However, asset pricing models are not only useful for pricing assets, i.e., finding required returns. They also are relevant for portfolio choice, risk management and hedging. For these purposes, better models explain more of the time series variation of asset returns. Using this criterion allows a useful distinction between characteristics and risk-factor based models that is aided by considering CMPs as a way to separate issues and focusing only on the time-series variation in which the two approaches differ.

We employ a bootstrapping-type approach of randomly permuting characteristics or factor shares to provide a benchmark distribution for testing the null-hypothesis that converting a characteristic to a risk factor (with identical pricing implications) has no improvement in cross-sectional explanatory power. The results are that, while the market excess return may clearly be viewed as a risk factor for all test assets, the evidence for size and value attributes as risk factors is limited. The proxies derived from the Fama-French factor approach provide slightly better evidence for both the size and value variables to be viewed as factors compared to the CMP approach.

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Appendix: Proof that $Tr[\mathbf{Z}(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}']/Tr(\mathbf{\Sigma})$ is the variance-weighted average time-series R-squared of all assets (R^2_{AVG}).

Since $\mathbf{\Sigma S} = \mathbf{Z}$ we have

$$R^2_{AVG} = Tr[\mathbf{Z}(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}']/Tr(\mathbf{\Sigma}) = Tr[\mathbf{\Sigma S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}]/Tr(\mathbf{\Sigma}). \tag{A1}$$

For the time series we have that

$$\mathbf{r}_{it} = \boldsymbol{\alpha}_i + \mathbf{B}_i \mathbf{r}_\mathbf{t}^\mathbf{Z} + \mathbf{u}_{it}, \text{ with } \mathbf{r}_\mathbf{t}^\mathbf{Z} = \mathbf{S}'\mathbf{r}_\mathbf{t} \text{ and } \mathbf{B}_i = \mathbf{\Sigma}_i'\mathbf{S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}, \tag{A2}$$

with $\mathbf{\Sigma}_i' = [\sigma_{i1}\ \sigma_{i2} \ldots \sigma_{iN}]$.

The R-squared of the time-series regression in (A2) is

$$R_i^2 = \mathbf{B}_i \mathbf{\Sigma}_\mathbf{Z} \mathbf{B}_i' / \sigma_i^2, \text{ where } \mathbf{\Sigma}_\mathbf{Z} = \mathbf{S}'\mathbf{\Sigma S}. \tag{A3}$$

Substitute in $\mathbf{B}_i = \mathbf{\Sigma}_i'\mathbf{S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}$ yields:

$$R_i^2 = \mathbf{\Sigma}_i'\mathbf{S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}_i / \sigma_i^2. \tag{A4}$$

It is easy to see by inspection that

$$Tr[\mathbf{\Sigma S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}] = \sum_{i=1}^{N} \mathbf{\Sigma}_i'\mathbf{S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}_i. \tag{A5}$$

Hence,

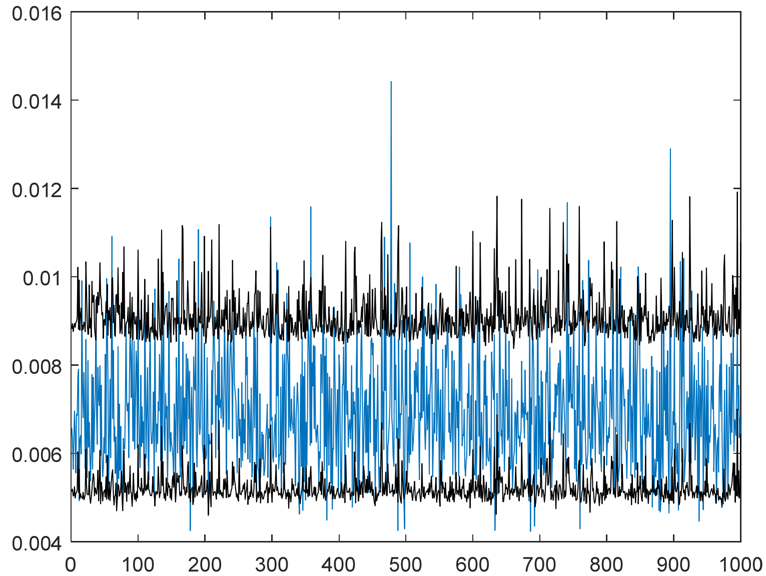
$$R^2_{AVG} = Tr[\mathbf{\Sigma S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}]/Tr(\mathbf{\Sigma}) = \sum_{i=1}^{N} w_i R_i^2, \tag{A6}$$

$$\text{with } w_i = \sigma_i^2 / Tr(\mathbf{\Sigma}) = \sigma_i^2 / \sum_{i=1}^{N} \sigma_i^2.$$

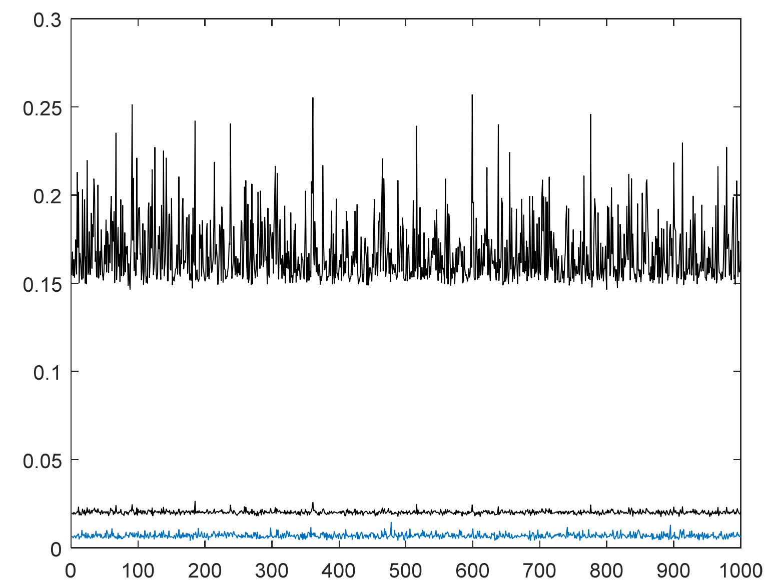
Thus, the following four criteria are equivalent: (1) the explained variance pooled over all time periods and assets divided by the sum of all these variances (the pooled R-square); (2) $Tr[\mathbf{Z}(\mathbf{Z}'\mathbf{\Sigma}^{-1}\mathbf{Z})^{-1}\mathbf{Z}']/Tr(\mathbf{\Sigma})$; (3) $Tr[\mathbf{\Sigma S}(\mathbf{S}'\mathbf{\Sigma S})^{-1}\mathbf{S}'\mathbf{\Sigma}]/Tr(\mathbf{\Sigma})$; and (4) the variance-weighted average time-series R-squared of all assets.

Figure 1

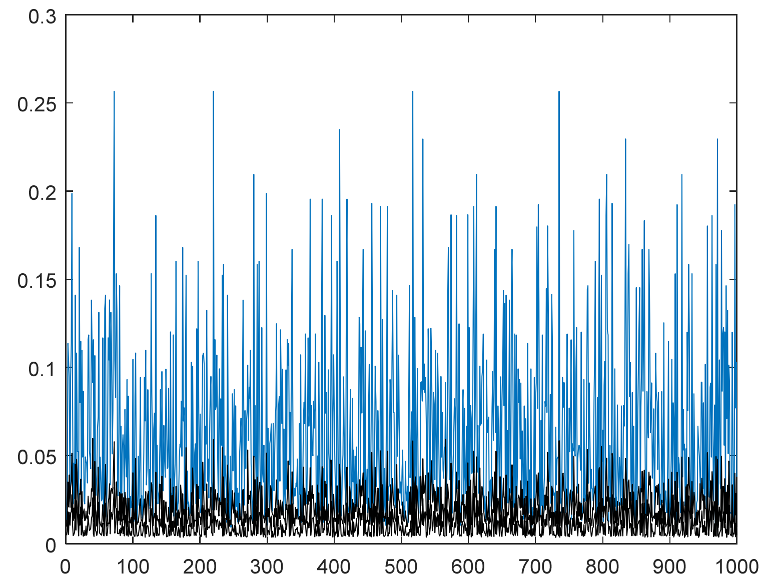
Panel A. Exogenous **Z,** Permute **Z**
Empirical Size (Nominal Size): 1.5% (1%); 5.3% (5%); 10.5% (10%)
Mean Actual R^2 = 0.7; Mean Simulated R^2 = 0.7



Panel B. Exogenous **Z**, Permute **S**
Empirical Size (Nominal Size): 0.0% (1%); 0.0% (5%); 0.0% (10%)
Mean Actual R^2 = 0.7; Mean Simulated R^2 = 5.7



Panel C. Exogenous **S**, Permute **Z**
Empirical Size (Nominal Size): 89.4% (1%); 95.9% (5%); 98.1% (10%)
Mean Actual R^2 = 6.6; Mean Simulated R^2 = 1.5



Panel D. Exogenous **S,** Permute **S**
Empirical Size (Nominal Size): 1.7% (1%); 5.6% (5%); 9.7% (10%)
Mean Actual R^2 = 6.6; Mean Simulated R^2 = 5.2

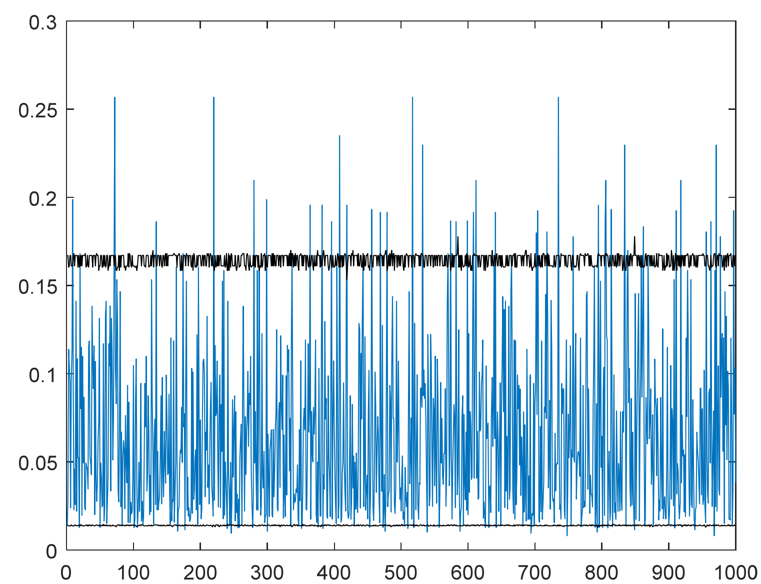


Table 1 Model Performance in Explaining Mean Returns

The test assets are the Fama-French 30 (FF30) value-weighted industry portfolios, the 25 value- and size-sorted portfolios (FF25), and the combined FF30 and F25 portfolios plus the three Fama-French factors. We consider monthly excess returns for the period 1963.07 - 2015.12. The left panel reports the prices of risk associated with the three Fama-French factors MKT, SMB, HML, and the characteristic-mimicking portfolio returns (CMPs) of averages of the log of market capitalization (SZ), and book-to-market ratios (BE). The estimated price of risk (first row) and their t-statistics (second row in italics) are based on the second pass of standard Fama-MacBeth (1973) regressions. The explanatory variables are either the exogenous characteristics or the covariances between asset excess returns and risk factors for the full sample period. The R^2 column reports the cross-sectional fit between the predicted and realized mean excess returns. The right panel reports the GRS *F*-statistics, the p-value with numerator degrees of freedom of T-N-K and denominator degrees of freedom of N-K, and the mean absolute alphas of each time-series regressions.

Panel A

FF30+3	Const.	MKT	SMB	HML	SZ	BE	R^2	GRS-F	p-value	|alpha|
Estimate	0.432	0.008					0.088	1.044	0.596	0.149
t-stats	*4.945*	*0.753*								
Estimate	0.411	0.014	-0.020				0.177	1.160	0.746	0.155
t-stats	*5.161*	*1.425*	*-1.221*							
Estimate	0.460	0.005		-0.008			0.100	1.421	0.933	0.180
t-stats	*5.048*	*0.451*		*-0.408*						
Estimate	0.454	0.011	-0.022	-0.013			0.205	1.593	0.975	0.200
t-stats	*5.129*	*1.000*	*-1.286*	*-0.628*						
Estimate	-0.046	0.010			0.066		0.161	1.114	0.691	0.178
t-stats	*-0.125*	*1.066*			*1.236*					
Estimate	0.693	0.006				-0.372	0.311	1.226	0.811	0.166
t-stats	*4.253*	*0.633*				*-1.938*				
Estimate	0.308	0.009			0.051	-0.349	0.353	0.810	0.245	0.131
t-stats	*0.855*	*0.885*			*0.986*	*-1.862*				
Estimate	0.200	0.013	-0.014		0.030		0.185	0.864	0.323	0.149
t-stats	*0.495*	*1.369*	*-0.796*		*0.553*					
Estimate	0.723	0.013		0.025		-0.541	0.377	1.380	0.912	0.175
t-stats	*4.323*	*1.170*		*1.138*		*-2.556*				
Estimate	0.217	0.016	0.006	0.029	0.069	-0.552	0.428	0.903	0.388	0.118
t-stats	*0.534*	*1.438*	*0.264*	*1.132*	*1.238*	*-2.535*				

Panel B

FF25+3	Const.	MKT	SMB	HML	SZ	BE	R^2	GRS-F	P-value	|alpha|
Estimate	0.453	0.011					0.095	4.042	1.000	0.250
t-stats	*4.571*	*1.094*								
Estimate	0.459	0.009	0.004				0.101	4.136	1.000	0.225
t-stats	*4.891*	*0.937*	*0.296*							
Estimate	0.077	0.037		0.057			0.588	3.521	1.000	0.148
t-stats	*2.920*	*3.801*		*3.611*						
Estimate	0.046	0.031	0.020	0.066			0.695	3.529	1.000	0.098
t-stats	*2.965*	*3.128*	*1.412*	*4.366*						
Estimate	0.796	0.008			-0.045		0.190	4.185	1.000	0.249
t-stats	*3.157*	*0.825*			*-1.400*					
Estimate	0.088	0.016				0.326	0.561	4.055	1.000	0.244
t-stats	*2.556*	*1.562*				*4.412*				
Estimate	0.094	0.011			-0.876	0.341	0.566	2.211	0.999	0.228
t-stats	*3.329*	*0.885*			*-0.436*	*4.801*				
Estimate	1.636	0.026	-0.053		-0.167		0.377	4.288	1.000	0.225
t-stats	*4.961*	*2.707*	*-2.821*		*-4.928*					
Estimate	0.045	0.029		0.035		0.156	0.624	3.614	1.000	0.149
t-stats	*2.145*	*2.835*		*1.534*		*1.682*				
Estimate	0.385	0.030	0.001	0.047	-0.044	0.077	0.711	3.779	1.000	0.098
t-stats	*2.831*	*2.946*	*0.058*	*2.598*	*-2.594*	*1.398*				

Panel C

FF55+3	Const.	MKT	SMB	HML	SZ	BE	R^2	GRS-F	P-value	|alpha|
Estimate	0.512	0.006					0.028	3.304	1.000	0.195
t-stats	*4.603*	*0.576*								
Estimate	0.508	0.005	-0.007				0.031	3.050	1.000	0.233
t-stats	*4.773*	*0.456*	*-0.282*							
Estimate	0.481	0.011		0.799			0.043	1.615	0.996	0.229
t-stats	*4.706*	*1.023*		*0.782*						
Estimate	0.470	0.011	-0.010	0.899			0.049	1.590	0.994	0.251
t-stats	*5.149*	*0.921*	*-0.416*	*0.877*						
Estimate	0.825	0.003			-0.039		0.081	3.331	1.000	0.194
t-stats	*3.234*	*0.279*			*-1.134*					
Estimate	0.313	0.008				0.215	0.207	3.165	1.000	0.190
t-stats	*2.941*	*0.769*				*2.622*				
Estimate	0.546	0.006			-0.027	0.201	0.233	3.204	1.000	0.190
t-stats	*2.275*	*0.577*			*-0.804*	*2.497*				
Estimate	0.822	0.002	-0.007		-0.039		0.085	3.086	1.000	0.232
t-stats	*3.230*	*0.166*	*-0.304*		*-1.140*					
Estimate	0.303	0.010		0.347		0.210	0.210	1.566	0.993	0.229
t-stats	*3.087*	*0.932*		*0.330*		*2.493*				
Estimate	0.515	0.011	0.017	0.333	-0.027	0.229	0.255	1.549	0.990	0.247
t-stats	*2.278*	*0.922*	*0.740*	*0.346*	*-0.836*	*3.213*				

Table 2 Descriptive Statistics of Time Series Features of the Test Assets

This table reports the 10 largest eigenvalues (EV) of the test asset excess returns between 1963.07 and 2015.12. Total variance (the sum of the variances of all test assets) is stated in the last row. The fraction of the total variance explained in time series regressions is listed below the column named R^2, The test assets are the 30 monthly value-weighted Fama-French industry returns (FF30), the 25 value and size sorted (FF25) portfolio returns, and the FF55 (the combined FF30 and FF25 asset groups) plus the three Fama-French factors for the period 1963.07 - 2015.12.

	FF30+3		FF25+3		FF55+3	
	EV	R^2	EV	R^2	EV	R^2
1	721.530	61.310	685.673	82.532	1355.513	68.804
2	94.784	8.054	58.797	7.077	98.079	4.978
3	49.955	4.245	34.926	4.204	93.239	4.733
4	38.221	3.248	9.129	1.099	58.840	2.987
5	36.481	3.100	5.733	0.690	43.386	2.202
6	25.422	2.160	4.521	0.544	34.510	1.752
7	21.113	1.794	3.412	0.411	27.504	1.396
8	16.857	1.432	2.763	0.333	21.813	1.107
9	16.046	1.363	2.649	0.319	17.584	0.893
10	13.755	1.169	2.616	0.315	15.717	0.798
$Tr\sum$	1176.865		830.793		1970.111	

Table 3 Actual and Simulated Average Time-Series R^2 for Individual Factors

This table reports the actual and simulated average time-series R^2s of characteristics-mimicking portfolios (the CMP approach) and Fama-French style factors (the FF approach). The test assets in Panel A are the monthly value-weighted Fama-French 30 industry portfolios augmented with three risk factors (FF30+3) between 1963.07 and 2015.12. The test assets in Panel B are the monthly value-weighted Fama-French 25 value- and size-sorted portfolios augmented with three risk factors (FF25+3) as well as the sum of the industry portfolios and size- and value-sorted portfolios together with the risk factors (FF55+3) between 1963.07 and 2015.12. Exogenous characteristics are the averages of the log portfolio market capitalization (SZ) and the book-to-market ratios (BE), The risk factors are the three Fama and French (1993, 1996) factors: market excess returns (MKT), size (SMB), and value (HML).

For each factor individually the actual average time-series R-square calculated from equation (11) is reported as R2. In addition R-squares for simulated factors are sorted based on their magnitudes. Panel A reports the critical values at the 10-, 50-, 90-, 95-, and 99-percentile cutoffs. Panel B reports the critical values at the 50-, 90-, and 95-percentile cutoffs. The simulated factors are created for MKT by randomly performing 5,000 draws among the FF30, FF25, and FF55 assets for each of the respective test asset groups. For SMB and HML the simulated factors are created as 5,000 permutations of weights 1 and -1 in the FF30, FF25, and FF55 assets for each of the test asset groups. For SZ and BE the simulated factors are created by 5,000 random permutations of each characteristic $\mathbf{Z}$ across each of the test assets, and subsequently obtaining the factor weights as $\mathbf{S} = \mathbf{\Sigma}^{-1}\mathbf{Z}$ from equation (7).

Panel A

FF30+3	R2	10-R2	50-R2	90-R2	95-R2	99-R2
MKT	57.000	24.836	42.455	48.853	51.564	51.786
SMB	10.245	1.785	6.693	30.156	42.455	47.653
HML	4.413	1.785	6.693	30.156	42.455	47.653
SZ	3.007	2.400	3.058	3.713	3.904	4.257
BE	3.199	1.062	1.922	2.953	3.313	4.012

Panel B

	FF25+3				FF55+3			
	R2	50-R2	90-R2	95-R2	R2	50-R2	90-R2	95-R2
MKT	72.479	71.570	76.917	77.471	63.530	51.290	61.229	62.321
SMB	32.385	13.670	64.207	71.570	19.174	5.536	19.900	44.544
HML	8.348	13.670	64.207	71.570	5.628	5.536	19.900	44.544
SZ	0.062	0.110	0.197	0.235	0.048	0.081	0.125	0.148
BE	0.440	0.119	0.340	0.466	0.273	0.089	0.204	0.261

Table 4 Marginal Actual and Simulated Average Time-Series R^2

This table reports the actual and simulated marginal average time-series R^2s of characteristics-mimicking portfolios (the CMP approach) and Fama-French style factors (the FF approach) for individual factors when added to the market factor. The test assets in Panel A are the monthly value-weighted Fama-French 30 industry portfolios augmented with three risk factors (FF30+3) between 1963.07 and 2015.12. The test assets in Panel B are the monthly value-weighted Fama-French 25 value- and size-sorted portfolios augmented with three risk factors (FF25+3) as well as the sum of the industry portfolios and size- and value-sorted portfolios together with the risk factors (FF55+3) between 1963.07 and 2015.12. Exogenous characteristics are the averages of the log portfolio market capitalization (SZ) and the book-to-market ratios (BE), The risk factors are the three Fama and French (1993, 1996) factors: market excess returns (MKT), size (SMB), and value (HML).

For each factor individually together with MKT the actual average time-series R-square calculated from equation (11) is reported as R2. In addition R-squares for simulated factors are sorted based on their magnitudes. Panel A reports the critical values at the 10-, 50-, 90-, 95-, and 99-percentile cutoffs. Panel B reports the critical values at the 50-, 90-, and 95-percentile cutoffs. The simulated factors are created for SMB and HML as 5,000 permutations of weights 1 and -1 in the FF30, FF25, and FF55 assets for each of the test asset groups, leaving the MKT factor constant. For SZ and BE the simulated factors are created by 5,000 random permutations of each characteristic across each of the test assets, leaving the market characteristics (covariance between MKT and each portfolio's return) constant and subsequently obtaining the factor weights as $\mathbf{S} = \mathbf{\Sigma}^{-1}\mathbf{Z}$ from equation (7), where $\mathbf{Z}$ includes the unpermuted market characteristics together the permuted characteristics of either BE or SZ.

Panel A

FF30+3	R2	10-R2	50-R2	90-R2	95-R2	99-R2
SMB	59.318	58.314	59.367	61.162	63.716	64.448
HML	59.768	58.294	59.323	61.101	63.641	64.577
SZ	57.431	57.334	57.378	57.438	57.459	57.502
BE	57.661	57.371	57.481	57.640	57.689	57.801

Panel B

	FF25+3				FF55+3			
	R2	50-R2	90-R2	95-R2	R2	50-R2	90-R2	95-R2
SMB	86.085	78.058	82.693	83.682	70.200	65.945	67.792	68.238
HML	78.315	77.975	82.819	83.761	67.257	65.923	67.780	68.222
SZ	72.491	72.501	72.523	72.532	63.536	63.540	63.551	63.556
BE	72.639	72.537	72.650	72.693	63.610	63.564	63.629	63.663

Table 5 Multi-Factor Marginal Actual and Simulated Average Time-Series R^2

This table reports the actual and simulated average time-series R^2s of characteristics-mimicking portfolios (the CMP approach) and Fama-French style factors (the FF approach). The test assets in Panel A are the monthly value-weighted Fama-French 30 industry portfolios augmented with three risk factors (FF30+3) between 1963.07 and 2015.12. The test assets in Panel B are the monthly value-weighted Fama-French 25 value- and size-sorted portfolios augmented with three risk factors (FF25+3) as well as the sum of the industry portfolios and size- and value-sorted portfolios together with the risk factors (FF55+3) between 1963.07 and 2015.12. Exogenous characteristics are the averages of the log portfolio market capitalization (SZ) and the book-to-market ratios (BE), The risk factors are the three Fama and French (1993, 1996) factors: market excess returns (MKT), size (SMB), and value (HML).

For each group of factors the actual average time-series R-square calculated from equation (11) is reported as R2. The question is how much a particular set of factors contributes to the R-square when added to a given set of initial factors. To this end we evaluate R-squares in comparison to the distribution of R-squares that arises from leaving the initial factors unchanged but replacing the added factors by simulated factors obtained by permuting either factor shares (for the FF-approach factors) or permuting characteristics (for the CMP-approach factors). R-squares for to each group of initial factors together with simulations for the added factors are sorted based on their magnitudes. Panel A reports the critical values at the 10-, 50-, 90-, 95-, and 99-percentile cutoffs. Panel B reports the critical values at the 50-, 90-, and 95-percentile cutoffs. The simulated factors are created for MKT by randomly performing 5,000 draws among the FF30, FF25, and FF55 assets for each of the respective test asset groups. For SMB and HML the simulated factors are created as 5,000 permutations of weights 1 and -1 in the FF30, FF25, and FF55 assets for each of the test asset groups. For SZ and BE the simulated factors are created by 5,000 random permutations for all characteristics for the added factors $\mathbf{Z_2}$ across each of the test assets, and subsequently obtaining the factor weights as $\mathbf{S} = \mathbf{\Sigma}^{-1}(\mathbf{Z}_1\ \mathbf{PZ}_2)$ based on equation (12), where $\mathbf{P}$ is a permutation matrix and $\mathbf{Z_1}$ denotes the unpermuted characteristics associated with the initial factors.

Panel A

LHS	RHS	R2	10-R2	50-R2	90-R2	95-R2	99-R2
MKT,SMB	HML	62.204	60.504	61.480	63.278	65.909	66.669
MKT,HML	SMB	62.204	60.935	61.877	63.887	66.305	67.156
SMB,HML	MKT	62.204	35.278	47.552	54.507	55.512	56.531
MKT	SMB, HML	62.204	60.217	61.748	65.443	66.447	67.511
MKT,SZ	SMB	60.185	58.695	59.808	61.669	64.156	65.007
MKT,BE	HML	60.651	58.904	60.083	61.882	64.282	65.111
MKT,SZ,BE	SMB	61.466	59.954	61.065	62.967	65.292	66.108
MKT,SZ,BE	HML	61.676	59.975	61.062	63.070	65.408	66.038
MKT,SZ,BE	SMB,HML	65.521	62.154	63.824	67.197	67.757	68.628
MKT,SMB	SZ	60.185	59.929	60.035	60.162	60.202	60.277
MKT,HML	BE	60.651	60.215	60.476	60.835	60.927	61.108
MKT	SZ,BE	58.733	57.836	57.996	58.217	58.294	58.489
MKT,SMB,HML	SZ	64.219	63.756	64.115	64.387	64.466	64.601
MKT,SMB,HML	BE	64.593	62.853	63.395	63.884	64.024	64.293
MKT,SMB,HML	SZ,BE	65.521	64.431	64.729	65.027	65.114	65.293

Panel B

		FF25+3				FF55+3			
LHS	RHS	R2	50-R2	90-R2	95-R2	R2	50-R2	90-R2	95-R2
MKT,SMB	HML	92.348	87.815	90.596	90.913	74.196	71.639	72.954	73.413
MKT,HML	SMB	92.348	83.460	89.050	89.752	74.196	69.176	71.422	71.918
SMB,HML	MKT	92.348	87.999	88.799	88.885	74.196	63.985	71.028	71.332
MKT	SMB, HML	92.348	82.246	86.328	87.432	74.196	68.135	70.210	70.802
MKT,SZ	SMB	86.131	77.836	82.289	83.456	70.222	65.905	67.746	68.134
MKT,BE	HML	78.381	78.049	82.437	83.632	67.302	65.943	67.803	68.183
MKT,SZ,BE	SMB	86.489	78.185	82.559	83.764	70.401	66.033	67.916	68.306
MKT,SZ,BE	HML	78.462	78.185	82.660	83.725	67.349	66.037	67.880	68.335
MKT,SZ,BE	SMB,HML	92.686	82.534	86.484	87.478	74.377	68.335	70.284	70.826
MKT,SMB	SZ	86.131	86.144	86.186	86.200	70.222	70.228	70.246	70.254
MKT,HML	BE	78.381	78.389	78.518	78.564	67.302	67.299	67.371	67.419
MKT	SZ,BE	72.760	72.717	72.898	72.960	72.760	72.717	72.898	72.960
MKT,SMB,HML	SZ	92.420	92.454	92.520	92.540	74.234	74.252	74.283	74.295
MKT,SMB,HML	BE	92.597	92.458	92.615	92.672	74.329	74.258	74.346	74.400
MKT,SMB,HML	SZ,BE	92.686	92.675	92.805	92.838	74.377	74.394	74.486	74.514

Chapter Five: *Conclusion*

The first essay extends the literature on the topic of financial divestment. First, if the goal of divestment is to discourage morally questionable business activities by increasing their financing costs, abstaining from investing in these stocks can indeed raise the required returns on these stocks, even in the presence of arbitrageurs. However, other stocks with no underlying similar business activities are also affected if these stock returns are statistically correlated to boycotted stocks. Second, this unintended spillover effect from boycotting sin stocks to non-sin stocks is rooted in the perverseness of the boycott risk factor. By separating the investor base along a moral dimension, the paper reconciles the empirically observed positive sin-stock abnormal returns with a systematic boycott risk premium. This boycott premium varies with boycott intensity captured by the relative wealth represented by socially responsible investors. While the current literature attributes positive sin-stock abnormal returns to the lack of investor base, higher litigation risk, and neglected coverage, we challenge this view in a two-stage cross-sectional regression framework and show that the boycott premium cannot be driven out by the existing characteristic-based explanations. This essay provides a strong indication that non-pecuniary preferences regarding the characteristics of the stocks can become pervasive pricing factors.

The second essay generalizes the concept of Multi-factor Efficiency by incorporating preference for asset characteristics directly into investors' utility. While identical two-factor testable implication arises as in the first essay, the characteristic-based factors can replace state variables that would otherwise be required to be stochastic to affect the marginal utility of wealth. This identical testable implication anchors on the observational equivalence between the characteristics and covariances between asset returns and the characteristic mimicking portfolios constructed to maximize the exposures to the same characteristics (CMP).

The third essay takes advantage of CMPs' time-series randomness to circumvent indistinguishable nature between characteristics and covariance risks in the cross section. A typical CMP is constructed by maximizing the factor's exposure to the underlying characteristics for a given level of variance. Based on a form of generalized Rayleigh Quotient, we devise a fair test to ask if factors, whether they be CMPs or other tradable factors, can reduce a larger fraction of error variance in the time-series R-squares relative to randomly simulated factors. Our simulation method is sufficiently flexible to accommodate either CMPs or other tradable factors without matching the distribution parameters of the original characteristics of other candidate CMPs' or factor shares. Our test suggests that the market factor is the only pervasive risk factor among the factors considered in this essay.