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The Sin Effect:

An Analysis of Sin Stock Returns in the US, UK and Japan

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Abstract

Our paper examines the existence of a "sin premium" for alcohol, tobacco and gaming stocks in the US, UK and Japan, and analyses historical stock returns of sin stocks while correcting for common return predictors and industry effects. Our paper differs from earlier works on the subject on several counts. In addition to conducting Fama-MacBeth regressions, our paper is the first to use a Kalman filter approach to examine sin stock returns. With emphasis on meticulous data collection, our analysis has been manually corrected for misclassifications in popular databases that may have affected previous studies. At 346 identified sin stocks for the three countries, the paper has one of the largest sin stock samples to be analyzed to date. Results from the Fama-MacBeth regressions indicate a return premium for sin stocks in the US and UK. The Kalman filter supports the conclusion for the US, but is inconclusive for the UK. Neither methods find significant evidence for a sin premium in Japan.

Acknowledgements:

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1. Introduction

In this paper we examine stocks in the alcohol, tobacco and gaming industry, three industries that are shunned by certain investors because of the perceived harm they impose on society. For reasons that we will soon discuss, we want to test whether these stocks are subject to a return premium, i.e. outperformance not easily explained by normal predictors of stock returns. Due to the somewhat controversial nature of the industries in question, they are sometimes categorized under the conspicuously named umbrella "sin stocks". For simplicity, we will use this term throughout the paper without any religious connotations or passing any moral judgment on the appropriateness of the term.

In this introductory chapter we will briefly discuss the subject of socially responsible investing and the theory for how it may impact the returns of stocks. After touching upon the previous literature written on the subject we will present our hypothesis which we will later test using two different regression methodologies - the Fama-MacBeth cross-sectional regressions and the Kalman filter. Detailed description of data gathering and methodology will follow in the later chapters.

1.1 Socially Responsible Investing - History and Concepts

It is difficult to define socially responsible investing (SRI), a topic that has been the subject of lengthy debates. What makes corporations socially responsible, and what constitutes a socially responsible investor? Nobel laureate Milton Friedman (1962), argued that providing profits for shareholders is in itself socially responsible, and that the interests of shareholders and the interests of the public are aligned in an efficient society. Others might claim that corporations need to conform to certain environmental, social and corporate governance (ESG) standards within their communities, in order to be considered socially responsible. The Social Investment Forum (SIF)[1] defines socially responsible investing (SRI) as "an investment

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[1] The Social Investment Forum is a non-profit organization based in the United States, working for the promotion and growth of socially responsible investing. It has over 400 members, including investment management and advisory firms, mutual fund companies, banks, non-profit organizations and other members of the investment community.

process that considers the social and environmental consequences of investments, both positive and negative, within the context of rigorous financial analysis." In simple terms, SRI is generally considered to be the act of consistently investing in companies that are believed to have a positive impact on society, and/or avoiding companies that affect society in negative way.

SRI is not a new phenomenon. Traditionally it has had strong ties to religion, an early example being the sermons of John Wesley (1703-1791)[2], the founder of Methodism. In a sermon titled "The Use of Money", Wesley proclaimed that good Christians should "gain all [they] can without hurting [their] neighbor" (Jackson 1872). This entailed abstaining from making money off the sale of alcohol, among other things. Fittingly, the founders of the first well diversified, publicly available mutual fund to screen their investments using social criteria, Luther Tyson and Jack Corbett, both had ties to the United Methodist Church (Pax World 2010). Since Tyson and Corbett founded the Pax World Fund in 1971, the popularity of SRI has expanded well beyond the borders of organized religion.

SRI, in the definition of the Social Investment Forum, has increased substantially over the past decades, and is now a significant movement within asset management. SIF divides SRI into three different categories; screening, shareholder advocacy, and community investing. In their biennial SRI Trend Report for 2007, they identify $ 2,711 billion in assets under management in the United States, utilizing one or more of these SRI strategies (SIF 2008), accounting for approximately 11 % of the total assets under management[3]. Social screening is by far the most common form of socially responsible investing, with over 77% of the total SRI assets employing either positive or negative screens (SIF 2008). Positive screening

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[2] There are of course far earlier examples of religiously imposed restrictions on investments than Wesley. One of the oldest in recorded history is probably the Judaic law against receiving interest on loans. Deuteronomy 23:19 reads "Thou shalt not lend upon usury to thy brother", and while usury has come to mean unreasonable or relatively high rates of interest in modern English, it is actually derived from the Latin word usura, that simply means interest. The fact that the original Hebrew term used for interest, neshekh, means "a bite indicating oppression" (Lister, R.J. 2006) makes it also possible to interpret the law both as simply prohibiting unreasonable interest rates and as prohibiting interest rates altogether.

[3] Total assets under management in the US tracked by Nelson Information's Directory of Investment Managers equaled $ 25.1 trillion dollars according to the 2007 SRI Trend Report.

involves actively seeking out and investing in companies with a desirable social profile, or socially "best-in-class" companies. When deciding upon an investment, other concerns in addition to projected cash flows become apparent. Depending on the investor's moral or social preferences, the investor might look favorably upon companies with good ESG profiles, well treated employees, safe products or similar characteristics. Negative screening, on the other hand, involves excluding companies that are incompatible with the social profiles that SRI investors aim to uphold. This may include the exclusion of companies within whole industries, such as tobacco, alcohol, gambling, pornography or armament, or the exclusion of companies with undesirable business practices such as employers of child labor, the manufacturers of personnel mines or cluster bombs, or significant polluters. Positive screening is often considered to be a more aggressive approach to socially responsible investing, as it is usually more restricting and puts the investment prospects under tougher ethical scrutiny. Funds utilizing positive screening processes are frequently marketed as dedicated SRI funds, thus attempting to profit from the SRI label. Nonetheless, negative screening remains the preferred methodology for the bulk of funds wanting to project an ethical profile.

1.2 Negative screening

In this paper, we will investigate whether investors require a premium for investing in sin stocks, which are stocks that are frequently subject to negative screening. We hope to contribute to a field of research where opinions are often more emotional than fact based. For mutual funds in the United States, the most popular industries to exclude from investment portfolios are the industries dealing with tobacco, alcohol and gambling (SIF 2008). Tobacco and Alcohol are quite dominant at the first and second place of the most popular screens, followed by the gambling and defense industries at a close third and fourth. Traces of the same pattern can be found when looking at other countries as well, among others the native country of the authors: Norway. The Norwegian petroleum endowment fund, or *Government Pension Fund – Global*, recently excluded all tobacco companies from their portfolio following new directives from the Ministry of Finance (Finansdepartementet

2009)[4]. The Norwegian fund follows in the footsteps of The California Public Employees' Retirement System (CalPERS), who in 2000 removed tobacco from their investment universe[5].

1.2.1 Why do investors employ negative screens?

There can be several reasons to why an investor would decide to exclude sin stocks from his portfolio. Being conscious of the motives is important, since any cost associated with excluding certain stocks should be compared to the benefits. Below, we present three of what we believe to be important reasons for why investors employ negative screens.

"SRI is profitable"

If an investor believes the financial performance of his portfolio will gain from negative screening, it is obvious why he would employ such a screen. There can be a variety of reasons why an investor would believe this, one being religion. Just like some religious people believe that bad actions will be punished, some worry that investing in industries condemned by the faith will lead to bad performance (Ruthie 2009). However, there is little theoretical foundation to substantiate why an SRI fund doing negative screens should outperform a less discriminatory counterpart in an efficient market. The explanation is simple. Imagine two different sets of investors; the ethical investors have restricted themselves to an ethical subset of the investment universe through for instance negative screening of morally objectionable industries. The indiscriminate investors on the other hand face no such restrictions on their investment activity, and can thus invest in the complete universe of stocks. While the indiscriminate investors can invest in all the stocks in the ethical subset, it is not the other way around. Should the ethical subset of stocks presumably be the most efficient stocks to hold, the indiscriminate investors could still choose to hold this portfolio, thus earning the same returns as the ethical investors. In the case where the most efficient portfolio lies outside of the ethical investment universe, the indiscriminate

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[4] The Norwegian petroleum endowment fund is among the world's largest sovereign wealth funds, and currently holds approximately 1% of the world's stocks (NBIM 2010). The tobacco exclusion is the first time they employ screens against an entire industry. Previously, companies had only been excluded on a discretionary basis, based on the decisions of a council of ethics.

[5] The exclusion of tobacco stocks by CalPERS in 2000 was advocated by then state treasurer Philip Angelides and was opposed by CalPERS staff (Barber 2007). The decision reportedly cost CalPERS roughly 650 million USD in forgone returns from 2000 to 2006 (Barber 2007).

investors would outperform their ethical colleagues. In the Markowitz (1952) world of portfolio theory with otherwise homogenous investors, both set of investors would in equilibrium hold the market portfolio on the efficient frontier within their investment universe, provided they have mean-variance preferences. From a portfolio perspective, restrictions can never be beneficial. Since the ethical investors are faced with restrictions on their investments, their efficient frontier can only be lower[6].

"Change the world for the better"

An alternative explanation for conducting negative screens could be that the investor has a desire to hurt and/or change certain industries for the better. If the utility he gains from changing or hurting what he perceives to be sin industries is greater than the utility he loses from any reduction in financial performance, this is a rational choice.

The concept of negative screening has been the source of some controversy in this regard. As a means of incentivizing companies to behave more ethically, de Colle and York (2009) argue that exclusion based on industry screening is flawed. The reason being that a company operating within a sin industry does not have an incentive to change other than changing their entire industry focus, which for most companies might necessitate shutting down all together. For well diversified companies, it might be feasible to spin off an unpopular subdivision, but for most companies shutting down would mean forsaking their comparative advantages, industry know-how and brand loyalty. For instance, an investor out to lessen the effects of smoking might have more impact if he states that he will not invest in companies that market themselves heavily in the third world.

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[6] For an interesting exercise that illustrates the cost of SRI with a Monte Carlo simulation, we refer to Adler and Kritzman (2008). They illustrate how the cost of removing a portion of stocks from the investment universe hurt portfolio performance, and that the cost increases with the fund manager's stock picking abilities, and decreases with the size of his investment universe. If the fund manager only picks stocks with a 50/50 chance of performing well, removing a portion of stocks from his available investments should have no effect on his performance. However, when the fund manager has a stock picking ability that is slightly better than random, stock exclusion might begin to hamper performance when potentially good opportunities are excluded.

Another issue is whether negative screening sufficiently impairs companies to make it beneficial for them to change their ways. Besides any negative hit to their reputation, the main harm that can befall a company from the negative screening of their stocks is an increase in the cost of capital, something that may become an expensive problem if the company decides to issue new stocks or bonds. Davidson, Worrell and El-Jelly (1995) argue that protesting by way of divestiture will not have any effect on a firm, because it does not directly affect the firm's cash flow. Based on an event study of divestiture announcements, they argue that as the value of a stock is decided by the value of its underlying future cash flow, other investors will still be willing to pay the correct price. We will return to the theory on the effects of negative screening in section 1.3.

Heinkel, Kraus and Zechner (2001) introduce an alternative model which concerns the cost of capital increase incurred by significant polluters that are faced with negative screening by environmentally conscious investors. In order for a polluter to reform, the cost of capital increase (that is attributed to reduced risk-sharing among investors) must be more than the (assumed) cost to reform. They calculate that the proportion of green investors must be around 25% to induce significant polluters to reform, but that a 10% share of green investors are enough to notably raise the cost of capital.

"What would the neighbors think?"
Another reason to why an investor would want to have negative screening conducted on his portfolio is the reputation issue, i.e. a fear of the consequences following a public disclosure of his shareholdings, if these shareholdings conflict with his or the community's shared beliefs. The rationale behind negative screening, even if one expects to lose money because of the screening, can thus be understood in the context of social norms. Akerlof (1980) provides a theory that can explain the continued existence of social norms that are of pecuniary benefit for the individual to break. Akerlof shows that these types of norms can persist provided that the individual who disobeys the norm is sanctioned by a corresponding loss of reputation. This seems to fit well with regard to sin stocks. Perceived hypocrisy can after all be devastating, possibly ruin a career, and at the very least garner much unwanted

attention. The cost of disobeying a norm is the highest for those who have put a lot of effort into building an image of high morals related to the specific norm; at the same time, those that are most likely to get caught while breaking the norm would probably have a higher propensity to conform to it[7]. Ultimately it would seem to come down to a trade-off between the costs of conforming and the punishment for not conforming, related to the likelihood of being caught.

1.3 The sin premium

The last two reasons in section 1.2 give a theoretical foundation for how a premium on sin stocks might be sustained. However, it does not explain why not arbitrage on the part of unconstrained/indiscriminate investors would take such a premium away.

The Merton model

Merton (1987) provides a theoretical basis for understanding how divestitures may increase the cost of capital beyond what the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) suggests. In the context of neglected stocks and market segmentation, Merton's model explores cases where some investors are unable to diversify away idiosyncratic risk. While the model was originally intended for illustrating the effects of information asymmetries, it is also applicable when investigating market segmentation effects resulting from negative screening of stocks. Merton's model concerns the case where investors are divided into two groups: One group willing to invest in a company, and one that is not. The model states that if a significant amount of investors refuse to invest in a certain stock, and the company still is to raise sufficient capital those that are left to invest will have to take a larger ownership share than what can be justified by an optimally diversified portfolio. A rational investor will require a return premium for not being able to diversify all the idiosyncratic risk inherent in the stock, and thus the stock price may become depressed relative to the CAPM. Merton's model hinges on the assumption that a sufficient number of investors screen against the stock, and that the stock comprises a significant

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[7] For example, a fund forced to disclose shareholdings (such as a government pension fund) may face tougher scrutiny than an anonymous investor, regardless of their previously communicated moral standards.

enough portion of the market portfolio, so that some non-constrained investors will actually have to bear diversifiable risk. Otherwise the sin premium would disappear through arbitrage. Using the framework of Merton (1987), James and Rivoli (1997) argue that only screening of momentous proportions would incur a serious cost upon the firm, at least in low growth industries. For an example of this see Appendix 1, where a formulation of the Merton model is presented.

Barriers to entry

One popular explanation to why sin stocks may outperform other stocks has been that heavy regulations create barriers of entry that protect incumbent firms from excessive competition. This is similar reasoning as staunch SRI advocates often use, namely that social responsibility is good for business and therefore provides excess stock returns. While regulations may create a desirable competitive climate for sin stocks, and ethical behavior might very well be good for business, these are all cash flow related arguments. Theoretically speaking, cash flow related issues such as these should be reflected in the pricing of the stocks, and thus we would not expect these arguments to validate any kind of systematic risk-adjusted outperformance. While unexpected cash flow events may have distorted certain historical samples, we cannot expect such anomalies to continue in the future.

1.4 Previous research

Previous empirical research on the performance of sin stocks has not been extensive. The bulk of available research on this subject, or the subject of socially responsible investing for that matter, has only surfaced during the last decade. Much of the writing on sin stock performance has been limited to anecdotal evidence, often the results of merely observing the returns of indices or selected sin stocks. Nevertheless, there have been some significant papers written over the last few years, notably Hong and Kacperczyk (2009), a paper from which we have drawn inspiration regarding methodology. Hong and Kacperczyk investigate the effects of social norms on the US market, and document outperformance among tobacco, alcohol and gambling stocks after controlling for a range of factors. They also find

that sin stocks have less analyst coverage and are less likely to be owned by institutional investors than comparable stocks that do not carry the same stigma. Hong and Kacperczyk explain sin stock outperformance in the context of Merton's (1987) model. In addition to the market segmentation effect mentioned above, stemming from some investors refusing to invest, Hong and Kacperczyk argue that the segmentation is exacerbated by high idiosyncratic litigation risk among sin stocks, as well as neglect from analysts. A relatively lower number of analysts following the stocks is assumed to equate to lower quality of information in accordance with Arbel, Carvell and Strebel (1983[8]), and related to incomplete information that was the original basis of Merton's model.

Other research includes Fabozzi, Ma and Oliphant (2008) whose results also indicate the presence of sin stock outperformance in international markets. Salaber (2007) looks at behavior of tobacco, alcohol and gaming stocks in Europe within a religious and litigious setting, and find that the sin stock premium is higher in protestant than catholic countries. She also finds that a higher density of lawyers in a country has an effect, possibly because more lawyers mean a more litigious society and thus higher litigation risk. Kim and Venkatachalam (2008) hypothesize that a potential US sin stock premium could be due to poor visibility in financial reporting contributing to a neglect effect, but find that the reporting of sin stock financials generally holds very high quality.

When detailing fund performance, however, research such as Bauer et al (2005) and Statman (2000) come to the conclusion that, within the time interval they study, there are no significant differences between SRI funds and regular funds. The existence of a sin stock premium would seemingly be at odds with this conclusion, although differences in managerial skill are hard to control for. Statman and Glushkov (2009) reconciled this somewhat paradoxical result. While their research echoed the results of Hong and Kacperczyk (2009), i.e. that there is a sin stock premium, they also found that companies scoring high on certain measures of social responsibility outperformed the market index in

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[8] Arbel, A., S. Carvell and P. Strebel. 1984. "Giraffes, Institutions and Neglected Firms". *Financial Analysts Journal.* Vol. 39. No. 3 (May/June). p. 57-63

the same time period. Statman and Glushkov argue that since SRI funds tend to tilt their portfolios towards the latter type of stocks, the negative effects of excluding sin stocks may have been offset so far, and conclude that the best strategy may be to exclude no firms, but to tilt the portfolio towards best-in-class socially responsible firms.

As mentioned above, we find little theoretical foundation for a sustainable premium for social responsible investment. However, we believe there is sufficient theoretical backing for the presence of a sin premium. In the following we specify our hypothesis, and then present our methodology for empirically investigating the hypothesis.

1.5 Hypothesis

Our hypothesis is that investors will be rewarded with a premium for investing in sin stocks. We thus expect to find evidence of sin stock outperformance. We hypothesize that there exists a premium that will be robust even after correcting for most commonly used risk factors. Based on the arguments above, a sin premium could be attributed to maket segmentation, neglect effects and/or compensation risk factors specific to sin industries, such as litigation risk.

2. Methodology

To test whether or not stocks that are perceived as sinful outperform the market, we first need to somehow isolate this "sin factor" from any other factors that might determine stock performance. A sensible point of departure is the capital asset pricing model. In the CAPM, beta is the systematic risk component of a given stock, and according to theory the only factor relevant for pricing, seeing as idiosyncratic risk is diversifiable. There is, however, much empirical evidence that suggests that the CAPM in reality does not capture all the relevant risk factors that determine return. Studies such as Fama and French (1992, 1993) have found other robust predictors of stock returns, such as small firms outperforming their bigger counterparts, and value stocks outperforming growth stocks. Another predictor of

stock return is the momentum anomaly of Jegadeesh and Titman (1993), the tendency of winner stocks outperforming losers in the short term, as included in Carhart's (1997) four factor model.

In addition to controlling for these risk factors, we have, in a similar manner as Hong and Kacperczyk (2009), included comparable companies in the statistical models. These are companies that operate within industries considered to be similar to those of the sin companies, although lacking the sin element. Similarities can include elements such as similar products, customer segments, input factors, demand drivers, business cycles and/or competitive environment. The rationale behind the use of the comparable companies is to control for any industry specific effects that might have affected the sin companies in the sample period. Ideally, the comparable companies should be completely identical to the sin companies apart from the sin factor, in which case there would be no need to control for other factors. Unfortunately, identifying perfect comparables is an almost impossible task. Hence we both control for possible predictors of stock returns, and select comparable companies from industries believed to exhibit similar behavior.

All these aspects could seemingly be included in an ordinary least squares regression. However, an OLS regression assumes that the regression coefficients are constant. Over the course of years, it is not unreasonable to expect that stocks may experience somewhat changing characteristics. Market capitalizations can move up or down, financial decisions and changes in leverage can affect a stock's market Beta, and market-to-book values can fluctuate as investors revise their assessment of the value of assets. For example, studies such as Fabozzi and Francis (1978), Sunder (1980), Bos and Newbold (1984), and Harvey (1989) find evidence that betas are much more dynamic than the common CAPM model assumes. The studies of Jagannathan and Wang (1996) and Lettau and Ludvigson (2001) later showed that this variation meant that the conditional CAPM model outperforms the unconditional CAPM. We thus employ a time conditional approach to our regressions, believing this yields more accurate results also when including other return factors.

We have chosen to employ two different regression methodologies to investigate time-varying coefficients: The cross-sectional regression methodology of Fama and MacBeth (1973), and the Kalman filter for dynamic linear models originated by Kalman (1960). By using two methodologies, we perform a form of robustness check by testing whether the results are sensitive to the choice of methodology. The Kalman filter method is detailed in chapter 4, with the Fama-Macbeth method in chapter 5. The two methodologies are utilized on data sets for three countries: The United States (US), the United Kingdom (UK), and Japan. The main reason for choosing the US, UK and Japan for closer analysis is that these three countries taken together have about 79 percent of the total market value of sin stocks, among 22 countries where Fama-French data is also readily available (see chapter 3.8). A second reason for choosing these countries is that there may be reasons for assuming that the sin stock premium, if any, might differ between them. The US and UK are Western countries, with a dominant Protestant-Christian culture; Japan is an Eastern country, traditionally associated with a Buddhist and/or Shinto culture. It may be that societal norms concerning what is regarded as "sinful" behavior varies somewhat between these countries. Furthermore, the US is regarded as a country more prone to use litigation as a means to influence behavior, including the behavior of firms, than both the UK and Japan. Besides, they differ in the extent SRI screens are employed. According to the Association for Sustainable and Responsible investment in Asia (ASrIA) 2003) SRI funds in Japan had a market share of less than 0.01 percent in 2003, compared to their estimate of 15 per cent in the US and 12 percent in the UK. We must emphasize, though, that we do not intend to test empirically the importance, if any, of different societal norms, litigation practice or SRI fund market dominance on sin stock premiums. That would demand a further set of variables and another type of analysis. But these differences were also reasons why we chose the US, UK and Japan (rather than other countries) to check the robustness of our findings across countries. We return briefly to these questions in the conclusion.

Another reason for choosing the US, UK and Japan to check the robustness of the empirical findings is that fairly long time series on sin stock performance versus other stock

performance can be constructed for these three countries. These data were not readily available given our choice of methodologies, however; and one of the contributions of this thesis is the construction of data bases that can shed new empirical light on our hypothesis. We describe the construction of these data bases in chapter 3. After the analytical section (chapters 4 and 5), we sum up and compare the results from using the different methods in chapter 6.

3. Sample selection

In the following we will detail how we went about collecting the necessary data to test our hypothesis. Note that Datastream allows for extracting share prices adjusted for dividend payouts, splits, or other capital changes, something we do with all return data in order to reflect the total return of the securities.

3.1 Identifying sin stocks

A significant hurdle when researching sin stock performance is the arduous task of selecting and classifying the sin stocks. The value and validity of the obtained results relies crucially on the quality of the underlying data, making data gathering perhaps the most important part of a paper such as this one, and possibly the most demanding part as well. Not surprisingly, earlier papers have taken somewhat different approaches to the data gathering issue. Hong and Kacperczyk (2009) based the selection of sin stocks on the industry classifications defined by Fama and French (1997)[9]. They extracted data from Compustat using SIC codes from the Fama-French industry groups; beer (4), smoke (5), and for comparable companies; food (2), soda (3), fun (7), and meals and hotels (43). In addition to this, they extracted gambling companies from Compustat using relevant NAICS[10] codes. Fabozzi, Ma and Oliphant (2008) on the other hand, based the screening process on the industry classifications in Datastream, and claims to have identified stocks based on their revenue

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[9] The complete range of SIC (Standard Industrial Classification) codes for the 48 industry groups is available for download from Kenneth R. French's website.

[10] North American Industry Classification System

share from sin industries. Other researchers, such as Statman and Glushkov (2009), have classified socially responsible and irresponsible stocks based on scoring systems developed by third party research agencies[11].

Using already defined industry classification codes such as SIC or NAICS and databases compatible with them, can significantly reduce the burden of stock screening for the purpose of research. However, there can be several pitfalls when employing such codes, or Datastream's industry classifications for that matter. First and foremost, there is always a certain risk that some companies are erroneously classified. For example, in order to identify alcohol companies, Hong and Kacperczyk used Fama-French's industry grouping "Beer & Liquor", which consists of SIC-codes 2080-2085. An issue with this approach is that the SIC code 2080, beverages, - includes such companies as A&W, whose only beer product is a root beer. Another difficulty is the classifications of those companies that, although they receive a significant part of their revenues from the sectors we wish to explore, they are classified under different SIC and NAICS codes reflecting other aspects of the business. A somewhat common classification for multi-faceted corporations is the SIC and NAICS (2007) category *Offices of Holding Companies* (SIC - 6719, NAICS – 551112). For instance, the NAICS code for alcoholic beverages does not include companies like Pernod Ricard or LVMH, some of the largest producers of wine and spirits in Europe. We find both these companies under the *Offices of Holding Companies* classification.

A manual screening of thousands of companies is demanding. For one, you cannot determine what kind of business a company is in based on name alone[12]. To classify companies we used a combination of the companies' own websites and company information sites, such as Businessweek's company profile directory. For some small companies that were delisted early in our time period, information was scarcer, and we had

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[11] Statman and Glushkov (2009) used SRI scores from KLD Research & Analytics, a company producing social investment research (acquired by RiskMetrics in 2009).

[12] In some cases, the name can even be deceiving, such as in the case with the US company Sin Holdings, which would seem like an obvious candidate to include in our sin portfolio, but who does in fact produce web portals directed at senior citizens.

to search through old press releases etc to get an idea of their business. A small number of firms were impossible to identify due to small market caps, early delisting and very generic company names. These were not included.

3.2 The selection of tobacco companies

Tobacco stocks are classified reasonably well in Datastream. However, some additions had to be made to the data set. For instance, issues with Datastream's industry classifications have surfaced in connection with ownership changes for the major tobacco labels. The reason for this is the fact that a company in Datastream can only belong to one industry group at the time, whereas we know that some buyouts of large tobacco companies have been by conglomerates that have a different core business than tobacco. An example is the merger between the tobacco producer RJ Reynolds, and the food conglomerate Nabisco, in which the merged company, RJR Nabisco[13], were classified as a food producer. Another example is the takeover of Imperial Tobacco Group by Hanson, which still did not place Hanson in the tobacco industry classification[14]. Because the tobacco market is relatively concentrated, losing one or two major players for a period of years could distort the data quite a bit. It is therefore still necessary, even when companies have been grouped by Datastream, to do extensive manual screening, where we for instance examine the history of all major brands.

3.3. The selection of gambling companies

The first screening of gambling companies was carried out through Datastream's own classification in the *Gambling* industry group. However, the Datastream classification of gambling companies only includes companies that are currently listed on the stock exchanges, which means that dead stocks are not included. Dead stocks are companies that

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[13] The closing stock price of RJR Nabisco of 84.5 dollars quoted by Datastream puzzled us, as the famous takeover by KKR ended with an offer of 109 dollars per share. We contacted Datastream support, and they confirmed that the given price was indeed correct. Apparently, seeing as the offer consisted of more than just cash, investors did not value the offer at its stated 109 dollar price.

[14] Hanson was included in the time period it owned Imperial Tobacco Group; from the takeover in April 1986, till it spun off the tobacco business in October 1996.

have either been de-listed, gone bankrupt, merged with another listed entity, or otherwise been removed from the exchanges and are no longer traded. The *Gambling* company classification of Datastream is a sub-group of the broader classification *Travel and Leisure* companies, a more comprehensive list that also includes dead stocks. To find dead gambling stocks, we thus had to manually go through the list of all dead *Travel and Leisure* companies and identify all stocks associated with gambling, such as casino owners and operators, internet gaming and betting enterprises, as well as other providers and facilitators of gambling activities. Similar to the screening of alcohol and tobacco companies, we had to make certain discretionary decisions about whether to include a company or not. For instance, it is difficult to determine the revenue share stemming from gambling activities for a medium sized company de-listed in 1983. Thus using a simple screening algorithm based on revenue or profit splits becomes unfeasible. Instead we consult various information sources to establish a view of the activities carried out by the company in question, in addition to cross checking with SIC and NAICS classification codes. Furthermore, a company's involvement in the gambling industry is not necessarily static, thus we had to take measures to insure that a company is only included in the sample during the time interval when it is actually involved in a relevant sin industry[15]. Another issue that must be addressed is where to make the distinction of what kinds of business activities comprise a gambling company. For instance, we have chosen to include companies owning and operating horse racing tracks and greyhound tracks, but we have not included horse breeders, even though it could be argued that breeders are involved in the gambling business when some of their horses are used for racing and betting purposes. Nonetheless, the distinction has to be made somewhere, and the decisions made on this matter could always be debatable.

3.4 The selection of alcohol companies

The basis for our selection of alcohol stocks are Datastream's *Breweries* and *Distillers and Vintners* industry groups. Similar to the *Gambling* classification, these groups only encompass active firms so in order to find dead companies we need to comb through all

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[15] For instance, the US hotel group Ramada is included from 1980 to 1989, during which time it owned several casinos, including the Tropicana casino resorts in Las Vegas and Atlantic City. The casino business was spun off into the listed Aztar Corporation following a restructuring of Ramada in 1989.

dead stocks within the broader *Beverages* group. Even the *Breweries* industry group is not sufficiently accurate, including such companies as spring water producers. Hence this list also needed manual cross-checking. To supplement our search we controlled our list by comparing it to the relevant SIC-codes used by Hong and Kacperczyk (2009), as we also did for tobacco and gambling stocks. We have already mentioned that the SIC codes for alcohol falsely classify some companies as alcohol producers. Another issue with the SIC-codes is that they encompass all forms of alcohol production. We chose not to include companies producing alcohol for other purposes than consumption by human beings. We do not have any data as to whether SRI-funds make this distinction. However, it seems like a fair assumption to make, given that the generally accepted disadvantages of alcohol are related to (excess) human consumption. There are many industrial applications of alcohol, it can be used as a solvent, a fuel, and as a raw material in the chemical industry, uses that are generally not considered unethical by the public. Accordingly, we remove producers of industrial alcohol from our sample to make sure the pure sin effect is not watered down[16].

We only include companies that have sin activities as a significant part of their operations. As previously mentioned, revenue-split algorithms to determine the sin focus of a given firm is difficult to employ due to the scarcity of information regarding companies that ceased to exist 20 so years ago. However, for companies where revenue or profit splits are available, it can be useful to determine a threshold of sin involvement. We placed the sin involvement threshold to include a company at 30% of either revenue or profit. This percentage might sound arbitrary, and it is. The threshold implies that a company like LVMH is included[17], while Coca Cola[18] and Starbucks[19] are not. It seems sensible to set the threshold so low that LVMH is included. SRI funds can hardly say with credibility that they exclude alcohol

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[16] For instance, we excluded American Fuel Technologies, a company that converted cow manure to ethanol for use as fuel.

[17] With the wines and spirit segment contributing just under 20 percent of total revenues for the last three years, but constituting around 30 percent of total profits in the period LVMH is just barely classified as an alcohol company. Note that LVMH, being a French listed company, does not figure in the sample for the main analysis, as this only includes stocks from the US, UK, and Japan.

[18] Coca Cola is sold and jointly marketed with some of Diageo's alcoholic beverages in the form of so-called "pre-mixes", i.e. Coca Cola and Smirnoff Vodka in a pre-mixed bottle.

[19] In 2009 Starbucks began experimenting with a few outlets selling beer and wine.

producers, while at the same time owning a company whose alcohol portfolio is one of the largest in the world. On the other hand, companies like Coca Cola and Starbucks have a relatively small part of their revenues coming from alcohol-related business, which will probably allow them to slip under the radar of many SRI funds. This is illustrated by the fact that both companies are included in the FTSE KLD 400 Social Index (formerly KLD's Domini 400 Social Index), an index of companies with a positive socially responsible profile.

3.5 The selection of comparable companies

It is important to choose comparable companies appropriately. If comparable companies are chosen without caution, and without clearly similar industry characteristics as the sin stocks we aim to investigate, any consistent under- or over-performance by these companies would only distort the analysis with unrelated industry effects.

Hong and Kacperczyk (2009) used comparable companies from the Fama and French (1997) industry groups food (2), soda (3), fun (7), and meals and hotels (43), on the basis that these groups were often bundled together with respectively tobacco, alcohol and gambling companies under other company classification schemes. Our choice of comparable companies has considerable similarities with the ones used by Hong and Kacperczyk. As primary comparable to tobacco stocks, we used the Datastream industry grouping *Food Producers*. Relative to tobacco products, we can find similarities in manufacturing and processing of many food products, and the produce can be purchased by consumers in normal convenience stores. With regards to the addictive qualities of tobacco, one can argue that food has definite habit forming characteristics. As a primary comparable to alcohol producers, we have used the companies in Datastream's industry grouping *Beverages*, with the exception of those companies identified as producers of alcoholic beverages. As we can recall, the *Breweries* and the *Distillers and Vintners* classifications in Datastream are both included in the broader *Beverages* group. As for gambling stocks, the primary comparables were extracted from the industry grouping *Travel and Leisure*, again with the natural exception of those companies previously identified as gambling stocks. Companies under the Travel and Leisure umbrella, which includes gambling companies, are generally considered

to be surplus phenomena, i.e. recreational activities that we commonly find high up in Maslow's (1943) hierarchy of needs. Hotels and leisure resorts are good comparables to casino resorts, while businesses such as race tracks, lotteries, and online gambling services have similarities with other companies profiting from pastime desires.

3.6 Other sin industries

Tobacco, alcohol and gambling stocks, although they are the most popular stocks to exclude, are not the only industries screened against by socially conscious mutual funds. The producers of weaponry and other defense equipment frequently figure on the black lists of SRI investors. For this reason, it could be interesting to include the defense industry in the analysis. However, as previous studies have found[20], making a clear classification of which companies produce "sinful" products within the defense industry is much harder than with tobacco, alcohol and gambling. The big question is what type of defense activities an investor would object against. Some companies get excluded from fund portfolios because of their involvement in the production of handguns, mines or cluster bombs, but these companies are often excluded on a case by case basis, whereas the exclusion of the entire industry is perhaps less common. There is also a strong link between defense and aviation. A majority of companies within the aviation industry are also involved in the military segment, though the extent can be very hard to identify, and may fluctuate from year to year. Furthermore, the products themselves vary greatly in how controversial they are. Producers of bullet proof vests and mine clearing equipment would seem less likely to be screened against than a maker of machine guns and bombs. Between the two we have a murky grey area, ranging from companies making flight simulators that include military mission training, and companies making air conditioning units for military helicopters. Because of these issues, as well as to avoid including too much of a subjective bias in our sample of sin stocks, we have chosen not to include defense stocks in our analysis of sin stock performance.

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[20] See Hong and Kacperczyk (2009), Fabozzi. Ma and Oliphant (2008)

3.7 Choice of database

For return data and time series of company characteristics in the United States, CRSP/Compustat provides a very comprehensive database with company characteristics such as size, market-to-book value etc. from back to 1963. Therefore, it is not surprising that Compustat has become a favorite among researchers analyzing the US market, among them Hong and Kacperczyk (2009). However, for time series of company characteristics for other markets, such as the European or Asian countries, we find that Datastream provides a better source of data, although the samples do not extend as far back in time. In this paper, we are interested in analyzing abnormal sin stock performance in several markets, with emphasis on the US, UK and Japanese markets. Accordingly, for comparative purposes, we have chosen Datastream as our primary source of data. Ince & Porter (2006) has compared individual equity return data from Thomson Datastream with the data from CRSP/Compustat, and document issues to keep in mind when screening and selecting data using Datastream. Our methodology of screening and validating the data is largely similar to Ince & Porter; it does however differ slightly on some areas. As an example we can look at the way Datastream and CRSP output the data from dead stocks. Whereas CRSP output no data after delisting, Datastream repeats the last known value indefinitely. Ince & Porter suggest deleting all observations from the end of the sample up until the last non-zero return. As they point out, this can lead to the exclusion of some valid zero-return data points at the end of the sample. We have instead employed screens based on the turnover of a given stock. If after a certain date a stock ceases to trade, we simply delete all data points after this date. This procedure involves downloading data for stock turnover as well, and will certainly be more demanding when it comes to handling large sets of data. In addition to this, we have also performed extensive manual cross-checking with the actual date of delisting on a number of stocks, including all of the sin stocks in our sample.

3.8 Choice of countries

Before we decided upon using the US, UK and Japan as the countries for testing the sin stock hypothesis, we collected data for all the 22 countries covered in Kenneth French's data library. As can be seen from table 3.8.1 we identified a total of 640 stocks belonging to the three sin industries, Alcohol and gaming have roughly the same amount of companies at around 300 each, while there are just over 50 tobacco companies. After downloading the data, we decided to limit our further research to three markets, based on which ones had the highest concentration of sin stocks, believing that this would lead to more robust results, as well as other concerns mentioned in section 2.

	Tobacco	Alcohol	Gaming	Total		Tobacco	Alcohol	Gambling	Total
Austria	1	9	4	14	Austria	0.08 %	0.70 %	0.20 %	0.40 %
Australia	2	30	20	52	Australia	0.45 %	3.57 %	4.04 %	2.39 %
Belgium	1	7	0	8	Belgium	0.10 %	2.19 %	0.00 %	1.00 %
Canada	2	26	16	44	Canada	2.73 %	4.19 %	0.33 %	3.25 %
Denmark	0	7	0	7	Denmark	0.00 %	1.85 %	0.00 %	0.84 %
Finland	0	2	0	2	Finland	0.00 %	0.12 %	0.00 %	0.05 %
France	2	29	6	37	France	0.28 %	11.99 %	0.81 %	5.66 %
Germany	1	41	7	49	Germany	0.00 %	2.84 %	0.06 %	1.36 %
Hong Kong	0	7	4	11	Hong Kong	0.00 %	0.28 %	0.38 %	0.19 %
Ireland	1	3	1	5	Ireland	0.14 %	0.23 %	0.16 %	0.19 %
Italy	0	2	2	4	Italy	0.00 %	0.16 %	0.95 %	0.21 %
Japan	1	11	14	26	Japan	3.99 %	13.94 %	9.06 %	9.35 %
Malaysia	2	2	7	11	Malaysia	0.88 %	0.32 %	4.39 %	1.04 %
Netherlands	3	4	0	7	Netherlands	0.00 %	6.74 %	0.00 %	3.08 %
New Zealand	0	6	1	7	New Zealand	0.00 %	0.12 %	0.38 %	0.11 %
Norway	0	0	1	1	Norway	0.00 %	0.00 %	0.01 %	0.00 %
Singapore	2	3	2	7	Singapore	0.41 %	0.85 %	0.01 %	0.56 %
Spain	0	8	1	9	Spain	0.00 %	0.31 %	0.04 %	0.15 %
Sweden	1	3	9	13	Sweden	0.45 %	0.01 %	0.19 %	0.22 %
Switzerland	0	5	1	6	Switzerland	0.00 %	0.13 %	0.01 %	0.06 %
UK	7	29	38	74	UK	27.50 %	23.86 %	13.81 %	24.08 %
USA	25	63	158	246	USA	62.97 %	25.60 %	65.18 %	45.82 %
SUM	**51**	**297**	**292**	**640**	**SUM**	**100.00 %**	**100.00 %**	**100.00 %**	**100.00 %**

Table 3.8.1: Identified sin stocks by country   **Fig 3.8.2:** Average MV weight of sin stocks/country

Seeing as the number of firms can be somewhat misleading as to the relative importance of the industry in a given country, we based our choice to a large extent on the average market cap weight of sin stocks pertaining to the different countries. This is shown in table 3.8.2. Not surprisingly we find that the largest presence is found in the US, followed by the UK and Japan. Together, these three account for about 79 percent of the total market value of sin

stocks, and are the countries where we will be investigating the statistical nature of a sin premium.

3.9 Calculating the market premium

As previously mentioned, we will be controlling for the beta factor of the CAPM. In order to do this we need to calculate the time-varying market premium; that is the difference between the return of the market portfolio and the risk free rate in a given month. We have chosen to use a value-weighted stock market index from each of the individual countries as a proxy for the market portfolio. Value-weighting is done to mimic the CAPM's assumption that the aggregation of all investors correctly prices risk and return forecasts. As Roll (1977) pointed out, an inherent weakness of the CAPM is the difficulty in indentifying the true market portfolio, and there are several pitfalls related to choosing a proxy. Nevertheless, this is the way it is commonly done by practitioners, and all the previous studies on our subject have used a similar proxy as us **(e.g. Hong and Kacperczyk 2009 and Fabozzi et. al. 2008)**. For the risk free rate we used treasury bills from the respective countries. While the recent crisis has shown that there are risks of default on sovereign debt also in the industrial world, it is as close a proxy as we can hope to find.

For Japan and the UK we used Datastream's respective total return indices as our market return proxy. The Japanese risk free rate was based on the short term call rate from the Bank of Japan. However, they only provide data for this measure back to July 1985, so the Japanese target policy rate found in Datastream is used in the preceding period. For the UK, the monthly discount rate of three month Treasury Bills from the Bank of England was used as the risk free rate proxy.

4. Time Series analysis

In this section, we will use time series analysis to test our hypothesis of whether sin stocks are associated with a return premium. The basis for the analysis is a zero investment portfolio that is long the sin portfolio and short the portfolio of comparable companies. The return of this portfolio at time t, Y_t, can be expressed as the difference between the return of the sin portfolio, $r_{s,t}$ and the comparable portfolio, $r_{c,t}$:

$$\left(r_{s,t} - r_{c,t}\right) = Y_t$$

If the return on this portfolio is significantly larger than zero when controlling for the return factors detailed in section 2, we can reject our null hypothesis of no sin premium. Our tests begin with the naïve approach of assuming that the comparable portfolio completely matches the sin portfolio in every way, except for the fact that the comparable stocks are not perceived as sinful. With this at the assumption, it is clear that any difference between the two is either a result of the sin factor, or simply random noise, thus it can be modelled as:

$$Y_t = \alpha_t + v_t \tag{4.1}$$

where α_t is the return stemming from the sin factor and v_t is a random error term. However, as we mentioned in the methodology section, we have reason to believe that the relevant factors of return vary somewhat between the sin stocks and the comparable companies over time. Seeing as we in this section are estimating differences between aggregate portfolios where some stocks get listed as others get delisted, there is all the more reason to believe in this type of variation. We gradually add return factors, starting with an equation that includes beta differences (the "CAPM model"), moving to one that takes into account differences regarding the Fama-French factors (the "Fama-French model"), and

finally taking into account the momentum factor (the "Carhart model"). The last one can be expressed as:

$$Y_t = \alpha_t + \beta_{M,t} MrktPrem_t + \beta_{SMB,t} SMB_t + \beta_{HML,t} HML_t + \beta_{MOM,t} MOM_t + v_t \quad (4.2)$$

where $\beta_{x,t}$ ($x = \{1,2,3,4\}$) is the coefficient of the respective return factor at time t, the return factor being the return of a portfolio seeking to emulate one of the relevant factors. α_t and v_t have the same interpretation as in equation (4.1), thus checking the significance of α is still our focus.

4.1 Time-series specific data

In addition to the data detailed in section 3, the time series regressions require data for the size, value and momentum factors on the portfolio level. For the US, this was simply downloaded using the database of Kenneth French[21], which has ready-made portfolios in accordance with Fama and French (1993). The SMB factor is calculated based on six portfolios, three for small market cap stocks and three for large companies. Small and large companies are split into value, growth, and a neutral portfolio in order to control for the value effect and avoid correlation between the two. Similarly the HML factor is calculated based on four portfolios, large and small cap value and growth portfolios in order to control for the size factor when calculating the value factor. Additionally, French has calculated a momentum factor, MOM, using six portfolios based the last 2-12 months of returns. Stocks are divided into one of three categories depending on whether their return is short of the 30th percentile of the NYSE, above the 70th percentile, or in between. Furthermore they are divided based on their market cap. The factor is then calculated as a portfolio long the large and small high performing portfolios, and short the large and small low performing portfolios. Note that the value effect is not strictly controlled for this way.

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[21] URL: < http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>

For the UK we also have readily downloadable SMB, HML and MOM factors, as created by Gregory, Tharyan and Huang (2009) in their effort to make a UK equivalent of Kenneth French's data library. All the factors are thus constructed as in Fama French (1993), based on the FTSE 350, excluding financials. Unfortunately, Gregory et al. only provides factor data from October 1980 until year end 2008, thus we had to shorten our time period accordingly when including these factors in the UK analysis.

For Japan the HML factor was readily available from the Kenneth French's data library, but the data were only provided up until the end of 2007, thus the time period of our analysis has to be shortened accordingly upon adding this factor. SMB and MOM are not provided on the website, however. A proxy SMB factor was constructed using a portfolio short the Russell/Nomura large cap index, and long the corresponding small cap indices. The large cap index constitutes the 350 largest securities with values of over 148.3 billion yen, totaling approximately 85% of the total market cap, while the small cap index constitutes the remaining 1350 securities. Unfortunately, the data for the index only reach back as far as March 1980 in Datastream, thus shortening the time span of the Fama-French model in the other end. We were not able to construct a satisfactory momentum factor given the time constraints when writing this paper, so the three factor model was the most complicated model tested for Japan.

4.2 Rolling regressions

The question is how one should go about testing models such as equation (4.1) and (4.2), seeing as a standard OLS regression does not allow the loadings of the coefficients to change over time. In the time-series analysis section of their article, Hong and Kacperczyk (2009) perform rolling OLS regressions with 36 month estimation windows, on the grounds that the factor loadings of the different portfolios should change over time. This means that the first regression runs from months t to t+36, while the next regression runs from months t+1 to t+37, and so on. The output of a rolling regression takes the form of a new time series, namely the series of coefficients from all individual 36 month time series regressions. Hong

and Kacperczyk (2009) then take the time-series average and standard deviation of this time-series of single regression coefficients, and use this to calculate Newey-West standard errors. In a similar manner, we have performed 381 rolling OLS regressions on our dataset ranging from 1975-2009, using unconditional versions of equation (4.2). The time series of the intercept coefficient α is graphed in figure 4.2.1.
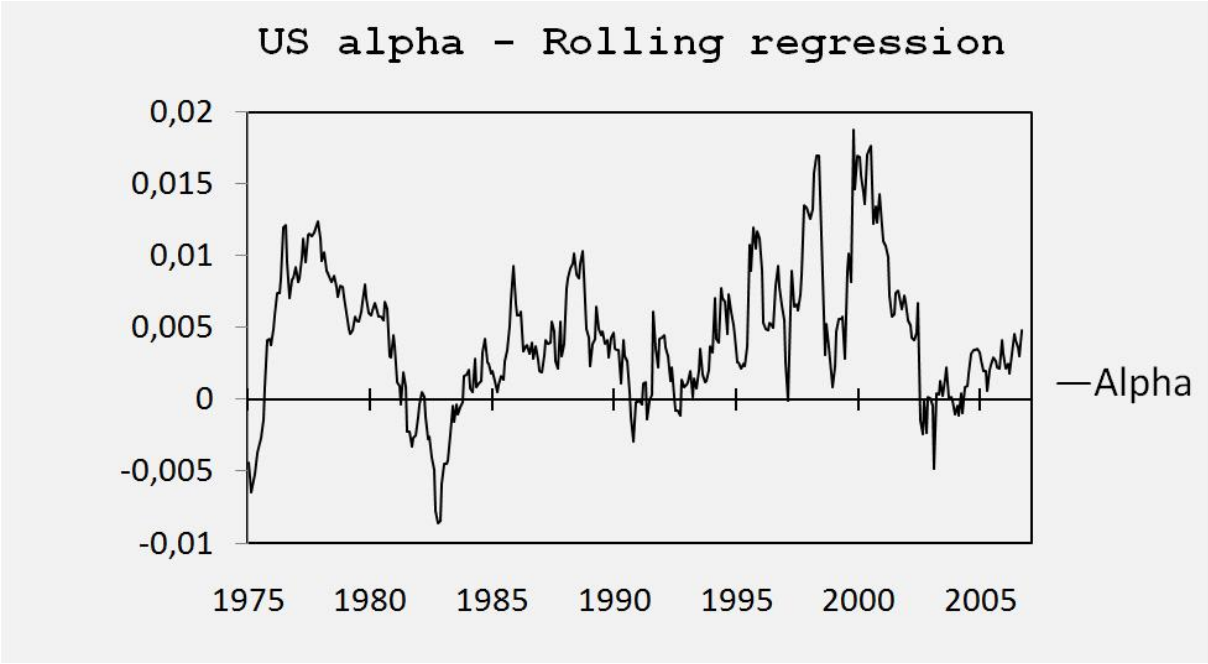

Fig 4.2.1: US α, calculated by rolling regressions on overlapping windows of 36 months.

In Fig 4.2.1 we can observe how the sin premium to holding sin stocks has fluctuated over the course of our sample. The coefficients of the control variables are less interesting, because they only relate to the differences between sin stocks and their comparables. Unlike Hong and Kacperczyk (2009), we have not presented the coefficients' mean and standard errors. When using the time-series means and standard errors of coefficients from rolling regressions, problems can arise because you have knowingly introduced significant serial correlation in the time-series you want to test. If for instance the intercept coefficient from a regression ranging from month t to t+36 is strongly positive, it is almost certain that the same coefficient from the regression ranging from t+1 to t+37 is also positive. The question is whether this may significantly underestimate the standard errors used to test the results for the rolling regression as a whole, even when using Newey-West standard errors. In this part of their paper, Hong and Kacperczyk (2009) present extraordinary significant sin stock

performance (i.e. the average of all alpha coefficients are significantly larger than zero). If the same exercise is performed on our sample, the results also indicate sin stock outperformance of great significance. However, we have instead concentrated the time-series section of our sin stock analysis on the Kalman filter.

4.3 Why the Kalman filter?

It is sensible to assume that the differences between the sin portfolio and the comparable portfolio with regards to the return factors change in a random fashion, as they are hit by asymmetric shocks from e.g. new regulation. There have been proposed many different methods for estimating this type of stochastic processes. In financial academia, the estimation of beta as this type of stochastic process has especially garnered much attention. One of the most popular tools for modelling this type of process is the Multivariate Generalized Autoregressive Conditional Heteroskedasticity test (M-GARCH) of Bollerslev (1990), which forecasts the conditional coefficient based on the conditional variance. It has been used for beta estimation by for example Braun, Nelson and Sunier (1995) and McClain, Humphreys and Boscan (1996). An alternative is the so-called Kalman filter of Kalman (1960), used by among others Black, Fraser and Power (1992) and Wells (1994). Along with other alternatives, these two methods have been the subject of several comparative studies, the majority of which favors the Kalman filter method with a random walk parameterization, see e.g. Faff, Hillier and Hillier (2000), Mergner and Bulla (2008) and Choudhry and Wu (2008 and 2009). Even though we are not attempting to estimate beta, it thus seems sensible to choose the Kalman filter, seeing as we want to estimate a similar stochastic process on financial return data as these papers used.

4.4 The Kalman Filter Method

Pioneered by Rudolf E. Kalman in his groundbreaking paper (Kalman 1960), state space models and the Kalman filter were for a long time only utilized in the field of engineering. The first papers using state space models for time series analysis appeared in the 1970's, with e.g. Akaike (1974) and Harrison and Stevens (1976). Since then, the method has become increasingly popular, now verging on becoming a mainstay tool within the fields of economics and finance. By using this method, the coefficients can be calculated on a

monthly basis, while at the same time taking into account all the available data from the entire data set. This way we can capture when and how the differences between the sin and the comparable portfolio occur in a fashion that is theoretically sound. The special form of state space model we will be applying, called dynamic linear models (DLM), can be seen as a generalization of a linear regression model that allows for time varying coefficients. The way DLMs are specified makes it possible to estimate the conditional coefficients by way of a recursive process on the basis of some initial prior distribution.

All of our state space computations were done in the computer language R (R Development Core Team 2009), with the help of the R package developed by Giovanni Petris (2010), as well as the supplementary book by Petris, Petrone and Campagnoli (2009). In the following section we will go more in depth as to how this process works, and what modifications we have made to suit our data set. Starting with a mathematical introduction to the model, we move on to how we specified the relevant return factor models. The section after that details maximum likelihood estimates for the variances, before we treat the filter/smoother algorithm. The casual reader, or one well versed in the methodology, can skip to the final section, where the results from our R computations are presented.

4.5 State space form and dynamic linear models

The state space form lets the user interpret time series as the output of a combination of several components, in a dynamic system where random disturbances play a part. It is a framework that allows for extensive customization, which easily accommodates our desire to interpret the excess return data as a product of time-varying predictors of stock return. In the following, we will attempt to explain the state space method in relation to our dynamic linear models. For a more in depth and general treatment of this methodology for time series analysis, see for example Durbin and Koopman (2001). In our discussion of state space models we use a similar notation to that of Petris (2009), both because of its more economical use of Greek letters for the error terms than alternatives like Durbin and Koopman (2001), and the fact that we use Petris' R package for our computations.

4.5.1 Introduction to dynamic linear models

A dynamic linear model is a special case of the state space model with linear and Gaussian properties. A DLM can be seen as a generalized version of the linear regression model; one which allows for time variation in the regression coefficients. In a state space model the observable time series vector Y_t is seen as an imperfect measure of an unobservable underlying process θ_t, called the state process. In the early applications in aviation, θ_t would be e.g. the position and/or speed of an aircraft, with Y_t being a radar observation. Every observation $t \geq 1$ in our DLM's can be described by a set of two equations:

$$Y_t = F_t * \theta_t + v_t, \qquad \overset{\text{iid}}{v_t \sim N_m(0, V)} \qquad\qquad (K.1a)$$

$$\theta_t = G_t * \theta_{t-1} + w_t, \qquad \overset{\text{iid}}{w_t \sim N_p(0, W)} \qquad\qquad (K.1b)$$

$$t = 1, \dots, T$$

Y_t is an m-dimensional vector, representing the observed return of the Sin-Comp portfolio at time t. θ_t is a p-dimensional vector, representing the state of the system at time t. In our case, θ_t denotes the unknown parameters that affect stock return, such as the β-differences between the sin portfolio and the comparable portfolio. F_t is an $m \times p$ matrix where known time series data that corresponds to the relevant parameters we want to estimate in θ are inserted. For example, the market premium for month t is inserted into F_t, in order to compute the beta difference at time t in θ_t. G_t is known $p \times p$ matrix that is used to specify the movement of θ_t over time. v_t and w_t are serially independent Gaussian error terms with mean zero and variance V and W respectively. V is an $m \times m$ matrix, and W a $p \times p$ matrix, and both are assumed to be diagonal in order for the error terms to be identically distributed. The error terms are further assumed to be independent of each other.

(K.1a) is referred to as the observation equation and specifies the relationship between Y_t and θ_t. Since F_t is a real number, the model assumes that $Y_1, \dots, Y_T$ are conditionally independent and identically distributed given θ, with each Y_t solely dependent on θ_t as illustrated in 4.5.1 below:

$$
\begin{array}{ccccccc}
\theta_0 & \rightarrow & \theta_1 & \rightarrow & \theta_2 & \rightarrow & \dots & \rightarrow & \theta_T \\
& & \downarrow & & \downarrow & & & & \downarrow \\
& & Y_1 & & Y_2 & & & & Y_T
\end{array}
\qquad (4.5.1)
$$

In other words, $Y_t|\theta_{0:t} = Y_t|\theta_t$

(K.1b) is called the state equation and denotes how θ_t evolves over time. θ_t has a linear relationship with the observation immediately preceding it, θ_{t-1}, the known trend component G_t and the Gaussian error term w_t, called the evolution variance. In all our DLMs, G_t is set as a simple identity matrix to achieve a random walk parameterization for the $\theta's$. Finally, the DLM is fully specified by the addition of a prior distribution for the p-dimensional state vector when the time, t, is equal to zero. It is normally distributed with a mean of m_0 and variance C_o:

$$
\theta_0 \sim N_p(m_0, C_o) \qquad (K.1c)
$$

m_0 is our "guess" for the value of θ_0, and will serve as the starting point for the prediction of $\theta_t \geq 1$. A high value for C_o implies that we are very uncertain about our guess for the mean, and will increase our propensity to change our opinion about θ_t as we start to factor in the observed corresponding Y_t's, as we will show later. The prior distribution is assumed to be independent of the error terms v_t and w_t.

4.6 Model specification

We now have the framework for constructing the four models we wish to test. In all models, we have assumed that the sin premium, α, as time-varying along with the other return coefficients. It seems reasonable to assume that this premium does not necessarily stay constant over the years; investors notion of how problematic it is to invest in the three sin industries may vary over time, just like the relative weight of a certain sin industry will vary as some companies go bankrupt while others thrive. One could hypothesize that the movement of the α also had a trend component, perhaps increasing as more investors adopt

negative screening processes. However, we do not have adequate historical data to base this on, and have thus modelled α as a random walk in all our models.

4.6.1 "Random walk plus noise"

Equation (4.1), the most naïve of our models, is also the easiest one to construct. The model is a form of *random walk plus noise model*, also referred to as a local level model. Here the return of the Sin-Comp portfolio, Y_t, is modelled simply as a noisy observation of the level α_t, the sin effect, which itself is subject only to random changes. In specifying this model, (K.2), we simply use (K.1), setting $\theta_t = \alpha_t$, $F_t = 1$ and $G_t = 1$ to ensure a random walk parameterization.

$$Y_t = \alpha_t + v_t, \qquad \overset{\text{iid}}{v_t \sim N_m(0, V)} \qquad (K.2a)$$

$$\alpha_t = \alpha_{t-1} + w_t, \qquad \overset{\text{iid}}{w_t \sim N_p(0, W)} \qquad (K.2b)$$

$$\alpha_0 \sim N_p(m_0, C_o) \qquad\qquad\qquad (K.2c)$$

$$t = 1, \dots, T$$

4.6.2 "The CAPM DLM"

Expanding the model to correct for beta differences between the two portfolios requires us to complicate the formula somewhat. We expand the state to include the coefficient denoting the return effect of beta differentials, β_t, so that $\theta_t = (\alpha_t, \beta_t)$. will need to be altered by inserting the time series data for the relevant market premium at time t into F_t, making $F_t = [1, Mrktprem_t]$. The model then ends up looking like (K.3):

$$Y_t = \alpha_t + Mrktprem_t * \beta_t + v_t, \qquad \overset{\text{iid}}{v_t \sim N_m(0, V)} \qquad (K.3a)$$

$$\alpha_t = \alpha_{t-1} + w_{\alpha,t}, \qquad \overset{\text{iid}}{w_{\alpha,t} \sim N_p(0, W_\alpha)} \qquad (K.3b)$$

$$\beta_t = \beta_{t-1} + w_{\beta,t}, \qquad \overset{\text{iid}}{w_{\beta,t} \sim N_p(0, W_\beta)} \qquad (K.3c)$$

$$\theta_0 \sim N_p(m_0, C_o), \qquad\qquad (K.3d)$$

$$t = 1, \dots, T$$

4.6.3 The three- and four factor models

Using the same techniques as above, the DLM can be further expanded to include the Fama-French factors, by setting $F_t = [1, Mrktprem_t, SMB_t, HML_t]$, $\theta_t = (\alpha_t, \beta_{M,t}, \beta_{SMB,t}, \beta_{HML,t})$. $\beta_{n,t}$ denotes the loading of factor n, with $\beta_{M,t}$ being the loading of the market premium etc. Finally the momentum factor can be taken into account by including MOM_t in F_t and $\beta_{HML,t}$ in θ_t, creating a form of four factor Carhart model, as seen in (K.4) below.

$$Y_t = \alpha_t + Mrktprem_t * \beta_{M,t} + SMB_t * \beta_{SMB,t} + HML_t * \beta_{HML,t} + \cdots$$

$$\dots + MOM_t * \beta_{MOM,t} + v_t, \qquad v_t \overset{iid}{\sim} N_m(0, V) \tag{K.4a}$$

$$\alpha_t = \alpha_{t-1} + w_{\alpha,t}, \qquad w_{\alpha,t} \overset{iid}{\sim} N_p(0, W_\alpha) \tag{K.4b}$$

$$\beta_{n,t} = \beta_{n,t-1} + w_{\beta_n,t}, \qquad w_{\beta_n,t} \overset{iid}{\sim} N_p(0, W_{\beta_n}) \tag{K.4c}$$

$$n = \{M, SMB, HML, MOM\}$$

4.7 Maximum likelihood estimation of the variances

After specifying our models we need an estimate for the unknown observation variance, V, and evolution variances, W_x[22] before we can use the Kalman filter to estimate θ_t. There are several ways of doing this, including maximum likelihood estimation (MLE) and Bayesian analysis. We chose MLE, due to its comparative simplicity in execution and more widespread use. The likelihood function allows us to estimate the unknown variances based on known observations. The estimation assumes that the initial state of the system is normal and that the error terms are jointly normal and uncorrelated.

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[22] e.g. x=$\{\alpha, \beta_M, \beta_{SMB}, \beta_{HML}, \beta_{MOM}\}$ for the four factor model

Using R, we compute the maximum likelihood estimates for the variances by minimizing the negative loglikelihood of the model (the formulation can be found in Petris et. al 2009). The optimization is based on a version of the relevant regression model where the variances are parameterized on a log scale, to stop the optimizer from considering negative variances. After the optimization we check that the convergence command yields a zero, to make sure convergence to a minimum has been successfully achieved. A weakness of the MLE method is that it cannot distinguish between local and global minimums, thus the process has to be run multiple times from different arbitrary starting points to be reasonably certain of reaching the true global minimum.

4.8 Using the Kalman filter and smoother

Having found the maximum likelihood estimates of the variances, we can apply the filter and smoother. In the following we explain the steps in the recursive Kalman filter algorithm for calculating the state for a given month, θ_t. For a more in depth treatment with mathematical proof, see for example Petris et. al. (2009) or Durbin and Koopman (2001).

Simply put the Kalman filter works in three steps that are repeated recursively. First it makes a prediction for the value θ_t, which in turn is used to make a prediction for Y_t. The estimated Y_t is then compared to the actual Y_t, computing an error term according to the difference between them. This error term is then used for an updated estimate of θ_t, that is then used for the prediction of θ_{t+1} which is then computed in the same recursive fashion. The Kalman filter builds on the conditional independence and Gaussian nature of the DLMs. Since the random vectors $[\theta_t]$ and $[Y_t]$ have a Gaussian distribution for every $t \geq 1$, it follows that their marginal and conditional distributions are Gaussian as well, and it is thus sufficient to calculate their mean and variance.

Let us first define the conditional distribution of θ_{t-1} given $Y_{1:t-1}$ as $\sim N(m_{t-1}, C_{t-1})$. The first step of the filter algorithm is to calculate the so-called one step ahead predictive distribution of the state vector θ_t given $Y_{1:t-1}$, outputting the minimum mean-square linear

estimate (MMSLE) of the conditional coefficients in the following period. The distribution has a mean a_t and covariance matrix R_t:

$$a_t = E(\theta_t | Y_{1:t-1}) = G_t m_{t-1}$$

$$R_t = Var(\theta_t | Y_{1:t-1}) = G_t C_{t-1} G_t' + W$$

This way, starting from the initial values m_0 and C_o given by the model, we can make predictions for the following θ_t, $t \geq 1$. As already noted, seeing as we are using a simple random walk parameterization with G_t as an identity matrix, it is easy to see that our one step ahead estimate of θ_t is in fact θ_{t-1}, as we would expect. These predictions are then used to give us predictions as to the corresponding values of Y_t. This is done by computing the one step ahead predictive distribution of Y_t given $Y_{1:t-1}$, has a mean of f_t and covariance matrix Q_t:

$$f_t = E(Y_t | Y_{1:t-1}) = F_t a_t$$

$$Q_t = Var(Y_t | Y_{1:t-1}) = F_t R_t F_t' + V$$

Note that this way we only predict that $Y_t = Y_{t-1}$ if $F_t = F_{t-1}$, which is true only for the random walk model that simply calculates the value of α_t. In the models that control for more return factors, the market premium, fama-french and momentum portfolios will play a part here. f_t is then used to find the forecast error, $e_t = Y_t - f_t$, denoting the discrepancy between our prediction for Y_t and the actual value of Y_t, the return of the portfolio long sin stocks and short comparable companies, in month t. In the final step of the recursive algorithm, e_t is incorporated into the filtering process with a weight given by the so-called Kalman gain matrix, $K_t = R_t F_t' Q_t^{-1}$. The way the Kalman gain is specified, the weight a new observation is given depends to a large extent on the ratio between the observation variance, which is a part of Q_t, and the evolution variance, which can be found in R_t. This ratio is often referred to as the "signal to noise ratio". If observation variance is high relative to evolution variance, the new observation is given little weight, since the noise affecting the observation is likely to be large. On the other hand, a relatively high evolution variance

("strong signal"), means that we have to update our estimate of m_t more frequently to reflect the changes in the state. A local level model with variance V=0 would yield a K_t=1, so that the forecast error is given 100% weight, and thus the prediction for the next month is given by the current month. This follows intuitively from there being no noise affecting the observation. Correspondingly, as V increases in relation to W, the Kalman gain decreases towards zero. e_t and K_t are incorporated in the so-called filtering distribution, that is used to update our estimate of θ_t given $Y_{1:t}$ with this new information. The distribution has a mean of m_t and covariance matrix C_t:

$$m_t = E(\theta_t|Y_{1:t}) = a_t + K_t e_t$$

$$C_t = Var(Y_t|Y_{1:t})R_t - K_t F_t R_t$$

These new values, m_t and C_t, can then be computed into the one step ahead predictive distribution of θ_{t+1} given $Y_{1:t}$, starting the process all over again until one reaches the end of the sample period.

Since we use the DLMs as a means of retrospectively reconstructing the behavior of the system, we need to refine the filtered data by a smoothing procedure. The aim of the filtering process is to find the best possible estimate for the current value of the unobservable state, θ_T, but we want estimates for the historical states, $\theta_{1:T-1}$. The smoother basically does the same as the Kalman filter, only backwards. The backwards recursive algorithm lets us base our estimates (of the loadings of the stock return predictors) on the knowledge inherent in the entire data set in a more balanced fashion.

As straightforward as the above algorithm might seem, it does suffer from some numerical instability in its calculation of variances (Petris et. al. 2009). Both non-symmetric and negative variance matrices might result from it, and to correct for this Petris' R-package uses the so-called singular value decomposition (SVD), believed to be more stable based on the research of Oshman and Bar-Itzhack (1986) and Wang, Liber and Manneback (1992). A

practical problem with the SVD is that it decomposes the variance into parts that cannot be readily used for creating confidence bands, but Petris' R package also provides a tool for reassembling the variance-covariance matrices. Finding confidence bands for the individual factors can then be done simply by extracting the relevant time-varying variance from these matrices, calculating the standard deviations and subtracting the relevant number of standard deviations from the factor.

4.9 Return effects of sin stocks – results from the Kalman filter method

Using the Kalman filter and smoother we find estimates for α based on four different models: a random walk plus noise model, a simple conditional CAPM function, a three factor Fama-French model, and a four factor Carhart model. With these models we test whether the alpha (sin stock premium) is significantly larger than zero, after correcting for differences in progressively more return factors between the sin and comparable portfolio. Estimations were done on the stock markets of the United States, the United Kingdom and Japan.

Since the filtered values are far from independent, aggregating them is not a trivial matter. Instead we analyze them on a disaggregate basis, computing lower confidence bands for the individual alpha-observations. Thus the monthly output from the Kalman filter estimation procedure is illustrated in graphs showing the movement of the smoothed α_t coefficient in relation to a confidence band. If the confidence band stays above zero for the majority of the time period, that is a strong argument for the existence of a sin premium. The α-coefficients were first checked against a 95% one-sided lower confidence band, and expanded to a one-sided 90% confidence band if the first band was below zero in more than one in twenty observations. For each of the graphs the y-axis denotes monthly basis points, while the x-axis denotes years. The solid line shows the smoothed alpha coefficients, while the dotted line is the confidence band.

4.9.1 United States

As previously noted, the United States has the most extensive amount of data, making it possible to use all models for the entire time interval from January 1975 to September 2009. Starting off from the simple random walk plus noise model (fig. 4.9.1.1), the Kalman method yields an α-coefficient of around 33 basis points on a monthly basis. The α is nearly constant, advancing only ever so slightly over the course of the 35 years (in Fig.4.9.1.1, the line looks constant, if the y axis is magnified, we can see that it has a slight curve). The 95% confidence band exceeds zero for every single month; a very strong indication that the α is indeed larger than zero, given that the model captures all other differences between the two portfolios.
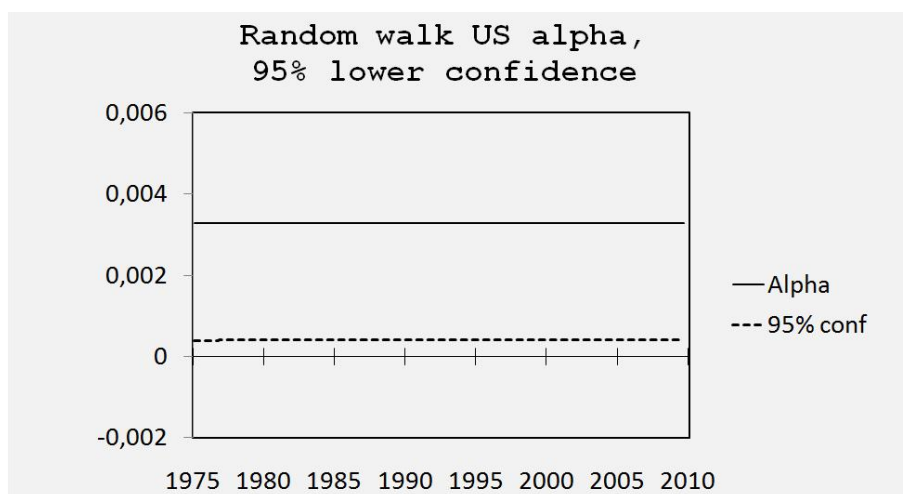

Fig. 4.9.1.1: US α, calculated by the Kalman method in accordance with a random walk model.

However, as we have mentioned, it is highly unlikely that the comparable portfolio perfectly matches the sin portfolio in every aspect except for the perceived sinfulness of their business activities. There might be other factors of stock return that can explain the significant over performance of the sin portfolio. In order to examine this, we first expand our model to a form of conditional CAPM model (fig. 4.9.1.2.). This model attempts to account for any differences in the betas of the two portfolios. As we can see from figure 4.9.1.2, taking beta into consideration does very little to the overall picture. The α drops only approximately a single basis point on average, and the 95% confidence band still exceeds zero for every single month. Overall this can be interpreted as a sign that the systematic risk component is very similar for the two portfolios we are comparing.
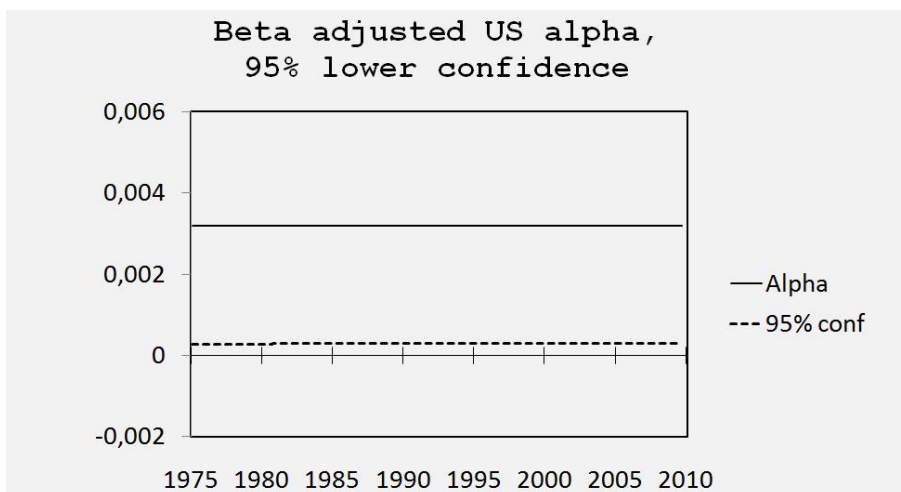
Fig. 4.9.1.2: US α, calculated by the Kalman method in accordance with a time-varying CAPM model.

Figure 4.9.1.3 shows that the two portfolios may indeed differ when it comes to other factors of stock return. Including the SMB and HML factors of Fama and French (1993), the α-coefficient falls to about 28 basis points on average, and the individual observations are now only significantly larger than zero at the 10 percent level. This may be a sign that the outperformance of sin stocks over comparable companies in the US is partly attributable to the value and size effects.

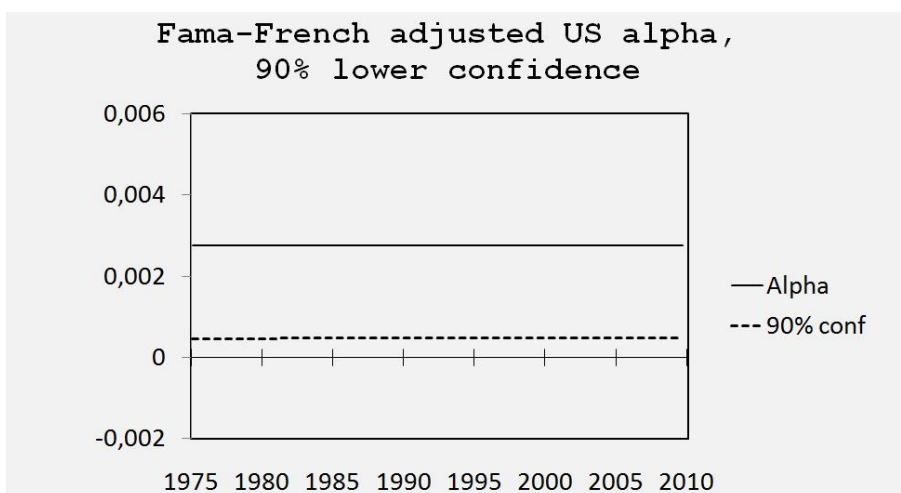**Fig. 4.9.1.3:** US α, calculated by the Kalman method in accordance with the three factor Fama-French model.

Expanding the model with a momentum factor to create a form of four-factor Carhart model (fig. 4.9.1.4.), the α-coefficient springs right up again. This may indicate that the momentum factor favors the comparable companies more than the sin stocks, thus understating the sin

premium before the factor was controlled for. The 37 basis point α in this model is the highest of the four, and the α is significantly larger than zero at the five percent level in every month in the interval.
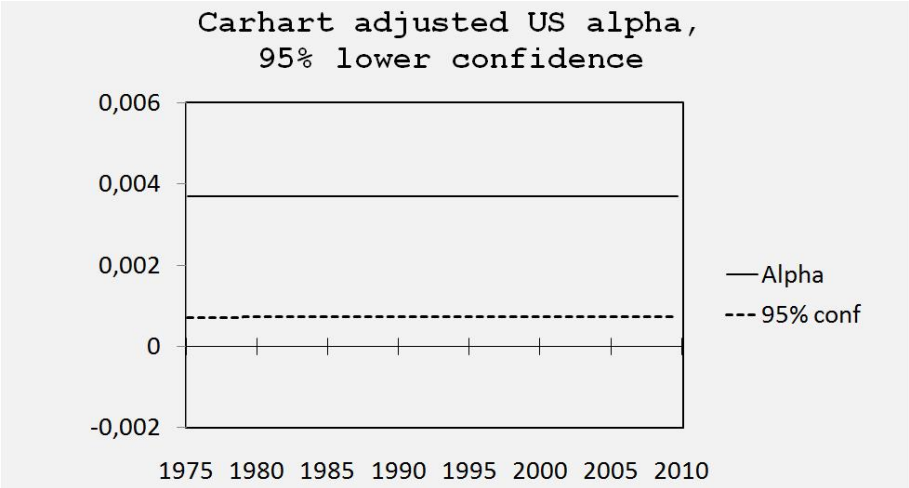
Fig. 4.9.1.4: US α, calculated by the Kalman method in accordance with the four factor Carhart model.

4.9.2 United Kingdom

Moving our attention to the United Kingdom, the results are far less conclusive. Our analysis is also somewhat hampered by the fact that we only have data for the SMB, HML and MOM factors from October 1980 until year end 2008. The simple random walk model (fig. 4.9.2.1) produces an α that, while on average positive, varies greatly. It has a negative coefficient at the beginning of the time period, but a fairly stable positive α from the November 1982. As the figure shows, the coefficient is not even close to being significantly larger than zero in any of the relevant months, even at the 10 percent level.
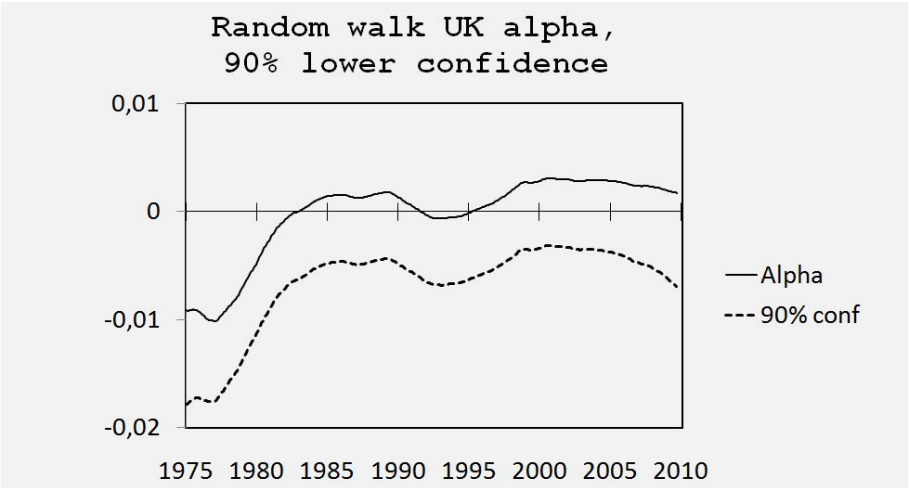
Fig. 4.9.2.1: UK α, calculated by the Kalman method in accordance with a random walk model.

Expanding the model to account for the beta factor, we see from figure 4.9.2.2 that much of the initial negative reaction has been absorbed as beta difference. On the other hand, the period of negative alphas now lasts until December 1989. While the confidence band has crept a lot closer to the zero mark, it is still very far from crossing, so the results are inconclusive.
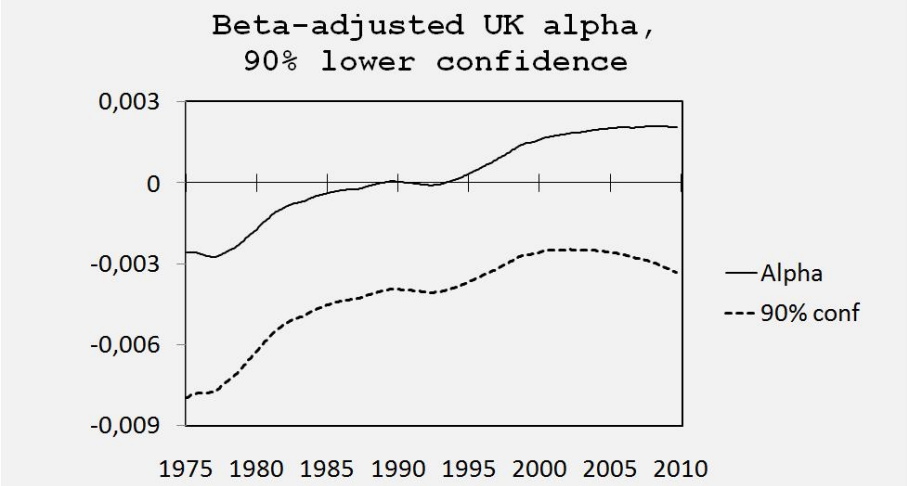
Fig. 4.9.2.2: UK α, calculated by the Kalman method in accordance with a time-varying CAPM model.

As previously stated, when adding the Fama French factors we lose the first few years of our sample. This may explain the different form of the coefficient, with a very high value for alpha at the beginning of the period. We can see from figure 4.9.2.3 that the observations for the better part of the 1980's are significantly larger than zero at the 90 percent level, but that for the later months the confidence band crosses over into negative terrain. All in all the results must be considered inconclusive.
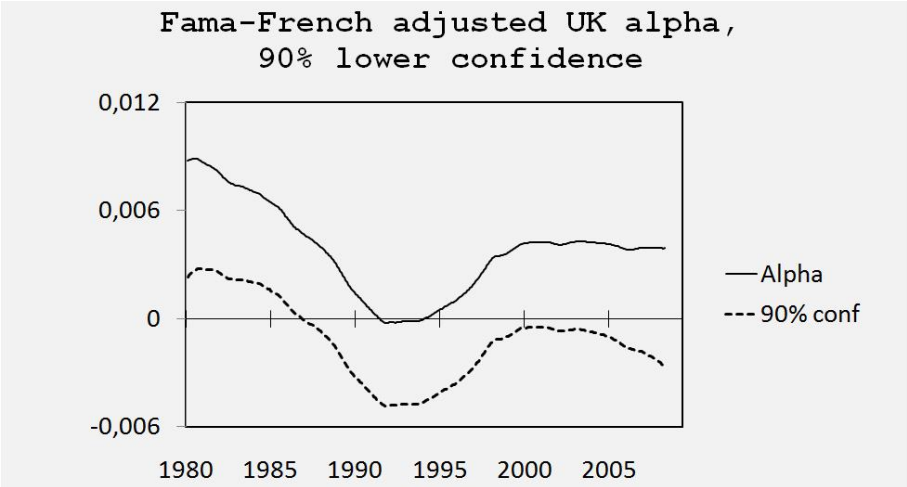
Fig. 4.9.2.3: UK α, calculated by the Kalman method in accordance with the three factor Fama-French model.

As we can see from figure 4.9.2.4, the differences upon adding the momentum factor are miniscule, with the alpha significantly larger than zero in approximately the same period of time. In other words, the UK sin and comparable portfolios seem to be very closely matched in terms of exposure to the momentum effect.
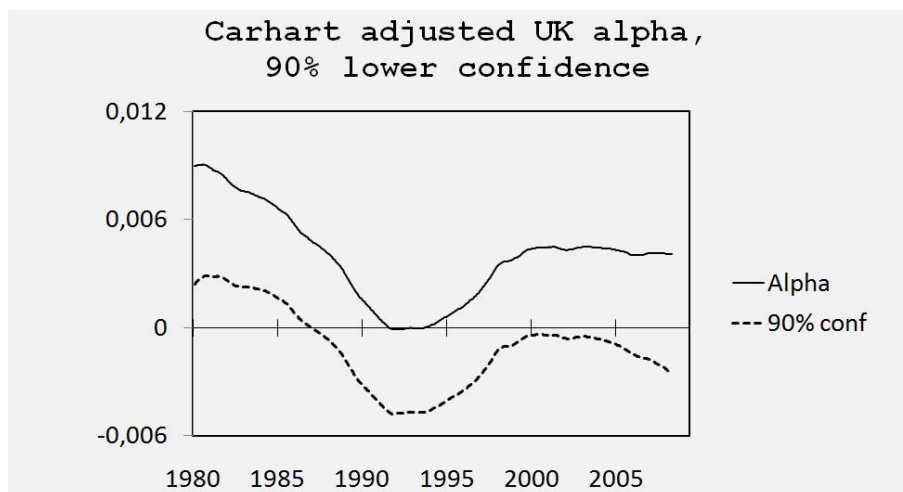
Fig. 4.9.2.4: UK α, calculated by the Kalman method in accordance with the four factor Carhart model.

4.9.3 Japan

Finally, we used the method on the Japanese data. As stated before, we unfortunately do not have any good momentum data for Japan, so our analysis of the Japanese market does not include the four factor Carhart model. Starting from the Random Walk model (fig. 4.9.3.1.), the alphas start out far into positive terrain at around 60 basis point, but fall to around 20 basis points. A large standard deviation means that the alpha is only significantly larger than zero at the 90% level till into the early 1980's, thus not giving strong evidence that the null hypothesis is false.
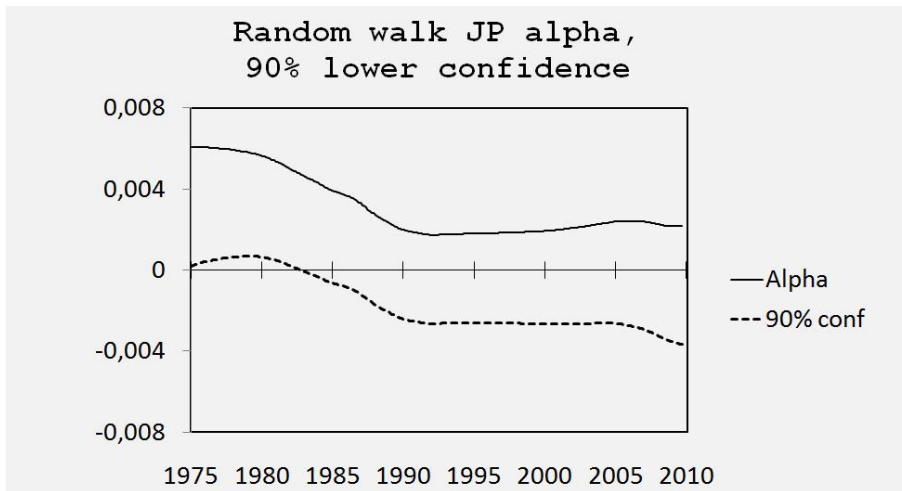
Fig. 4.9.3.1: Japanese α, calculated by the Kalman method in accordance with a random walk model.

As we can see from figure 4.9.3.2, adding a beta factor to the equation drastically cuts down on the variation in the estimated alpha, making it almost completely stationary at 18 basis points. The standard deviations of the individual estimates are still too large, with the 90% confidence band consistently subzero.
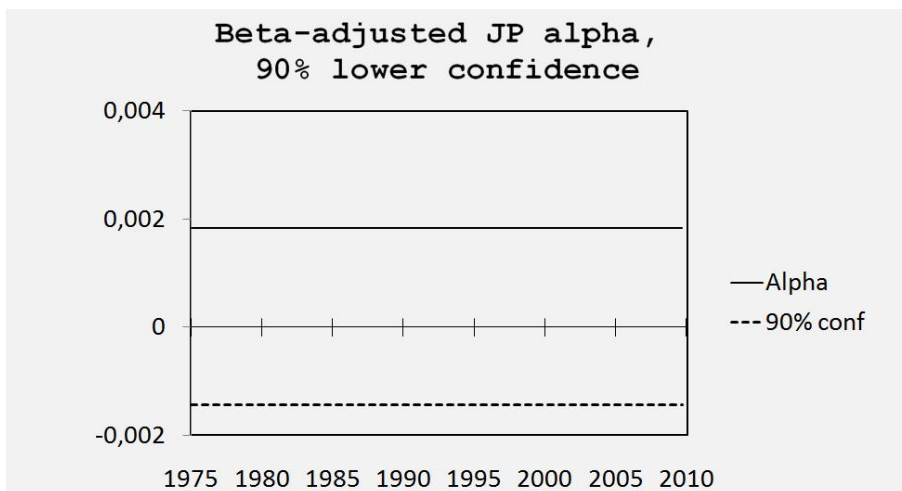
Fig. 4.9.3.2: Japanese α, calculated by the Kalman method in accordance with a time-varying CAPM model.

Estimating the alpha in a three factor Fama-French setting (fig. 4.9.3.3) the monthly alpha estimates does little to change the overall picture does not change. The alphas increase by approximately 0.9 basis points on average but, as the figure shows, none of the observations are significantly larger than zero.
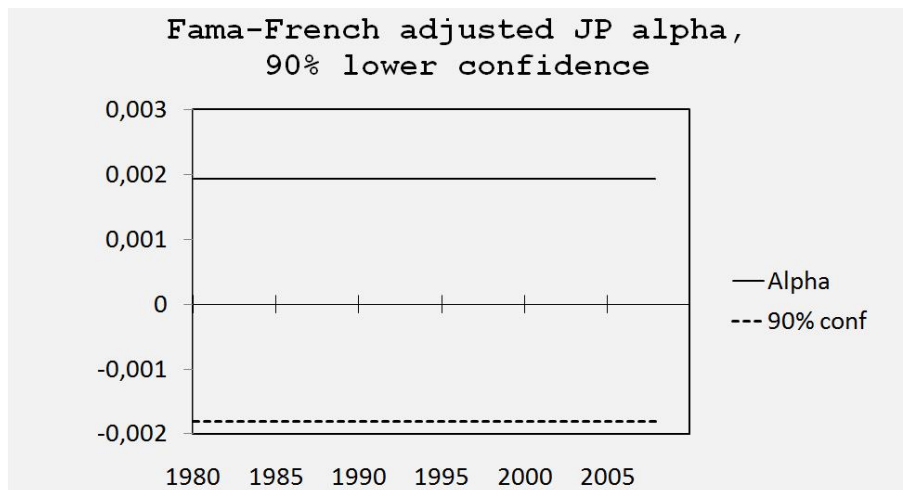
Fig. 4.9.3.3: Japanese α, calculated by the Kalman method in accordance with the three factor Fama-French model.

4.9.4 Summary of findings

All in all, the Kalman method gives a strong indication that there indeed is a sin premium in the United States (and a large one at that). However, for the United Kingdom or Japan our analysis does not give sufficient grounds to reject the null hypothesis of no **(or negative)** sin premium.

4.10 Robustness

The R package we use for the Kalman method does not really have this type of hypothesis testing as its main objective; hence it is not an easy task to extract variables like the evolution error for the models. However, the observation error is fairly ease to calculate based on the known values Y_t, the smoothed coefficients and their corresponding risk factor portfolios. Computing the residuals for the models after the other factors are accounted for, we can test whether these observation variances are in fact normal. As we can see from Appendix 3, much can actually be gleaned from a simple histogram. As it turns out, the distribution is not completely normal for any of the models, with some degree of fat tails, as is usually the case with stock return data. As we pointed out in section 4.3, the Kalman filter have proved to be one of the best tools for modeling similar stochastic process on financial return data, so we have reason to believe that the assumptions still are sufficiently met, if not completely.

5. The Fama-MacBeth regressions

The cross sectional regression methodology of Fama and MacBeth (1973) has been an important and popular tool in empirical finance. Notably, it has been employed in a number of empirical tests of financial theory such as the CAPM and APT (Arbitrage Pricing Theory), as well as other factor models aiming to explain the returns of securities. As previously mentioned, the hypothesis we want to test is whether sin stocks are associated with a return premium, and employing the Fama-MacBeth procedure gives us an indication of whether the results are sensitive to the choice of methodology. In cross sectional regressions, we can control for the same predictors of stock returns as in the time-series regressions. Although, now we include variables for company characteristics directly instead of using portfolios designed to highlight the returns of companies with the same characteristics. For instance, as input we will use a stock's market capitalization or market-to-book value, instead of the return on a SMB or HML portfolio.

In general, cross-sectional regression involves running a single regression on the cross section of assets. This provides a way of testing how different company characteristics affect the returns of stocks within a given time period. We can do a cross-sectional regression for a single day, a month, or even for several years. Inconveniently, when running only a single cross-sectional regression, the method does not allow the loadings of the coefficients to change during the time period of estimation. We would also need to have the same stocks in the sample over the whole interval. When doing only a cross-sectional regression over a single month, this does not represent a major issue; the problem arises when we want to see what factors affect stock performance over several years. Over the course of years, it is not unreasonable to expect that stocks may experience somewhat changing characteristics. Market capitalizations can move up or down, financial decisions and changes in leverage can affect a stock's market Beta, and market-to-book values can fluctuate as investors revise their assessment of the value of assets. A way of incorporating time-varying company characteristics is to pool time-series of different cross-sections together. We would still run only one regression, but each stock would now be represented several times over the

sample, each time for a different interval of time (depending on whether we have weekly, monthly or annual data frequency). The problem with such a pooled cross-sectional regression is, as Cochrane (2001) points out, that cross-sectional correlation of the error terms at any given time is likely to be great, i.e. if one stock experiences abnormal returns in a certain month, another stock's return is likely to be affected also. An example could be if an exogenous shock such as a strike among airport employees affected the return on an airline stock in a given month, other airlines would likely be affected by the same strike. This breach of the assumptions behind OLS regression could still generate consistent estimates. However, the size of the standard errors could be significantly underestimated because the distribution theory is now erroneous.

5.1 The Fama-MacBeth cross-sectional regression technique

Similar to the pooled time-series cross-sectional regression, a Fama-MacBeth regression contains both a time-series and a cross-sectional element. However, in addition to accounting for time-varying company characteristics, Fama-MacBeth represents a method of correcting for cross-sectional correlation in panel data. Fama-MacBeth regression involves making a series of regressions on the cross-section of stocks. For monthly data, this requires one regression for each month in the sample. To generate Fama-MacBeth regression coefficients and standard errors, we collect the coefficients from every monthly cross-sectional regression and subsequently take their time-series averages and standard deviations. With an ordinary t-test we find whether we can reject the null hypothesis that the mean of the cross-sectional coefficients, i.e. the Fama-MacBeth coefficient, is zero.

We can illustrate the procedure by considering a situation in which the Fama-MacBeth technique is applied to test the relationship between stock returns and the CAPM beta. This involves estimating the CAPM beta for each stock prior to running the cross-sectional regressions, thus making this a two-pass regression analysis. We can estimate a trailing beta for any month in the sample, or we can use a full sample beta. In this example, and for the rest of this paper, we use a beta estimated from time-series market model regressions with 3 year estimation windows. While a common rule of thumb seems to be the use of a five

year window, we have chosen a 3 year window in accordance with the best performing procedure found in Groenewold and Fraser (2000). The three year window was also chosen by Hong and Kacperczyk (2009), on which we have modeled several elements of this paper. The regression equation for a single cross-sectional regression in any given month can be expressed as (5.1),

$$\left(Ret - r_f\right)_i = c_0 + c_B Beta_i + \varepsilon_i \tag{5.1}$$

$$i = 1,2,\dots N$$

where $\left(Ret - r_f\right)_i$ denotes the return of stock i in excess of the risk free rate, c denotes the regression coefficients, and *Beta* refers to the market beta of stock i, estimated through time-series market model regression. With a sample length of T months, regression (5.1) is repeated T times, allowing the estimated Beta to vary across time. Accordingly, the Fama-MacBeth regression equations become (5.2).

$$\left(Ret - r_f\right)_{i,t} = c_{0,t} + c_{B,t} Beta_{i,t} + \varepsilon_{i,t} \tag{5.2}$$

$$t = 1,2,\dots,T \quad i = 1,2,\dots,N$$

Using the time series of cross-sectional regression coefficients ($c_{x,t}$), we take the averages (which become the Fama-MacBeth regression coefficients) and calculate standard errors similar to equations (5.3) and (5.4) respectively.

$$\bar{c}_x = \frac{1}{T} \sum_{t=1}^{T} \hat{c}_{x,t} \tag{5.3}$$

$$\hat{\sigma}(\bar{c}_x) = \frac{1}{T(T-1)} \sum_{t=1}^{T} (\hat{c}_{x,t} - \bar{c}_x)^2 \tag{5.4}$$

$$t = 1,2,\dots,T \quad x = \{0,B\}$$

We use (5.3) and (5.4) to find the t-stat (5.5), with which we can test whether the Fama-MacBeth coefficients are significantly different from zero.

$$\hat{t}(\bar{c}_x) = \frac{\bar{c}_x}{\hat{\sigma}(\bar{c}_x)} \tag{5.5}$$

In the example with testing CAPM, we would expect to see that c_0 would equal zero and that c_1 is greater than zero. However, in the context of this paper, we are not primarily concerned with beta, but rather with the performance of our sin stocks. The complete model we use in the Fama-MacBeth regressions is an expansion of equation (5.2), on which we will elaborate in section 5.2.

There are some issues with the Fama-MacBeth regressions that need to be addressed. By doing a simple t-test on the mean of coefficients, we assume that the time series of coefficients are independent and identically distributed, something that might not always be the case. First of all, there is a potential error-in-variable problem caused by the fact that the beta values used as regression input are also estimated, and the Fama-MacBeth procedure does not account for its potential measurement errors. Shanken (1992) points out that this can lead to the independence assumption not being strictly satisfied. Like Fama and MacBeth (1973), we assume that these errors are small; moreover, it can be argued that the issue is greater when dealing with specific tests of the CAPM. We previously mentioned that Fama-MacBeth corrects for the fact that error terms might be correlated across firms in a given time period, but what if the error terms are correlated across time for a given firm? Petersen (2005) notes that this is most likely to happen in studies were one persistent dependent variable is regressed on other persistent independent variables, such as whether a firm pays a dividend regressed on characteristics such as market-to-book value, earnings-to-assets ratio and relative firm size. The literature on capital structure is another example mentioned by Petersen (2005) as being prone to firm effects that could potentially bias the Fama-MacBeth standard errors downwards, causing researchers to falsely reject the null hypothesis that the coefficient is actually zero. Nonetheless, as both Petersen (2005) and

Cochrane (2001) point out, the issue seems to be greater when corporate finance data are regressed, and as noted by Cochrane (2001), the correlation is usually less among asset return data. Thus, with regards to the methodology used in this paper, we have not adjusted the Fama-MacBeth standard errors, we will however return briefly to this issue when the regression results are discussed.

5.2 Variables of the cross-sectional regressions

The underlying data for the cross sectional regressions have been extracted using Datastream, and have subsequently been transformed into a format suitable for regressions. For the United States, the United Kingdom and Japan, the following variables have been downloaded: share price, market value, market-to-book value, turnover, and dividend yield. The variables have been downloaded for all dead and alive stocks (excluding financial stocks), ranging for the 419 months from January 1975 to November 2009.

The response variable for a regression in a given month is the realized returns in this month for all the different stocks in the sample. A dummy variable separates alcohol, gambling and tobacco stocks from all other stocks. The regressions include control variables that attempt to pick up return differences attributable to differences in stock and company characteristics. Emphasis is placed on predictors of stock returns that have been popular in other studies, and are considered important in financial empirics. The first control variable is the market beta from the capital asset pricing model. Although the empirical and theoretical discussions on CAPM are mixed, the market beta is still the most commonly accepted determinant of stock returns. Further, we include variables for size and market-to-book values, which are approximations to the factors of stock returns detailed in Fama and French (1992, 1993). A variable for past performance can capture momentum effects as found in Jegadeesh and Titman (1993) and Carhart's (1997) four factor model. Similar to Brennan et al (1998), we have also included variables for stock turnover and dividend yield. Stock turnover can reflect differences in risks associated with the liquidity of a certain stock, for instance whether illiquid stocks offer a return premium. Dividend yield can be an interesting variable because of both tax and demand aspects, as pointed out by Miller and Scholes

(1982). Tax regimes that seemingly favor dividend payouts over capital gains could provide investors in high dividend yielding stocks with a return premium due to the added tax cost incurred. The effects of tax differentials are argued theoretically by Brennan (1970). On the other hand, there is also a popular belief that market participants prefer income in the form of dividends, and that large dividend payouts are interpreted as a sign of financial health. This interpretation would suggest an opposite hypothesis, namely a return premium on low dividend yielding stocks. The final control variable is included in the fashion of Hong and Kacperczyk (2009): an additional dummy variable branding both sin and comparable companies. This dummy variable will attempt to distinguish the pure sin effect from a more general industry effect. If sin stock over-performance is simply due to industry specific characteristics rather than the sin effect; this variable will make this separation. To sum up, we are left with the Fama-MacBeth regression equations (5.6).

$$\left(Ret - r_f\right)_{i,t} = c_{0,t} + c_{SD,t}SinDum_i + c_{B,t}Beta_{i,t} + c_{S,t}LSize_{i,t} + c_{M,t}LMTBV_{i,t}$$
$$+ c_{R,t}Ret12_{i,t} + c_{T,t}TurnOver_{i,t} + c_{D,t}DivYield_{i,t} + c_{CD,t}CompDum_i \quad (5.6)$$

The variables in equation (5.6) have been calculated as follows. The response variable $\left(Ret - r_f\right)$ is the return of stock i in month t, net of the risk free rate. **SinDum** is a dummy variable branding the sin stocks, and is fundamental to the analysis. This variable equals 1 if stock i is identified as a tobacco, alcohol or gambling company, otherwise the variable equals 0. **Beta** is the slope of a 36 month regression, ranging from months t-37 to t-1, of stock i on the market index. Betas are estimated provided that more than 13 months of data is available; thus newly introduced stocks will have betas that are estimated with less than 36 month samples. In the event that, for a given month, a beta estimate (or any other variable) for a company is missing, the company would not be included for that month in a Fama-MacBeth regression where this variable is utilized. Thus the beta estimation procedure is chosen in order to not have to discard too many data points, and there would obviously be compromise between this and reducing the likelihood of errors in the estimation of beta. **LSize** is the natural logarithm of the dollar denominated market capitalization of stock i in month t-1. **LMTBV** is the natural logarithm of the market-to-book value of stock i in month t-1. **Ret12** is the arithmetic average returns of stock i over the last 12 months leading up to

and including month t-1. The exclusion of month t in these variables is important to avoid a situation where the value of the explanatory variables will be dependent on the value of the response variable, in which case the regression estimates will have no meaning. *TurnOver* is the monthly trading volume divided by the number of shares outstanding in month t-1[23]. *DivYield* is the annual dividend payout per share as a percentage of a company's share price in month t-1. *CompDum* is a variable aimed at separating the effect of sin from other exogenous effects that might be related to the broader industry in which the sin stocks operate. This variable equals 1 if stock i is identified as either a tobacco, alcohol or gambling company, or a company within food producers, beverages, or travel and leisure industry groups. Otherwise, this variable equals 0.

5.2.1 Removing outliers

Inherent in the Fama-MacBeth procedure, all stocks in the sample carries equal weight. Because of the possibility of insignificant stocks acting erratic or otherwise small errors in the database, we include cutoff points on certain variables to remove outliers that could contribute noise to the analysis. The primary cutoff is the same as in the time series analysis; companies with market values less than 20 million US dollars are removed from the sample. Furthermore, a stock is only allowed to have a market beta between 40 and minus 40. The natural logarithm of the market-to-book value cannot be greater than 6. The average 12 month return variable cannot be larger than 100 (9900%), and not below -1 (-100%). The monthly turnover of a stock cannot exceed 30 times its market value, and lastly, a stock's dividend yield cannot exceed 100%. These cutoff points might appear rather unrestricting, but they work to sort out the most erratic or erroneous data points that, due to the equal weighting nature of the Fama-MacBeth method, is in danger of moving the coefficients one way or another.

5.3 Return effects of sin stocks – results from cross-sectional regressions

To test our hypothesis of whether sin stocks are associated with a return premium, we have completed Fama-MacBeth cross-sectional regressions for the United States, United Kingdom

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[23] Actually calculated as: unadjusted volume/(market value/unadjusted price)

and the Japanese market. Sin stock outperformance is tested with a range of control variables, including a variable for comparable companies. In relation to our hypothesis, the most interesting coefficient to observe is c_{SD}, the coefficient for the *SinDum* variable in equation (5.6). This variable marks the tobacco, alcohol and gambling companies, and will indicate whether investors receive a premium by holding these allegedly sinful stocks. A summary of the Fama-MacBeth regression findings for the three markets are found in tables 5.2.1, 5.2.2 and 5.2.3 below, and the coefficients for *SinDum* are accentuated with a blue background. The tables display the output from the Fama-MacBeth regressions with different control variables included. This is done to show the development of the coefficients when additional variables are added. The data for company market-to-book value were only available from February 1980, thus for the sake of comparison, all Fama-MacBeth regressions in tables 5.2.1, 5.2.2 and 5.2.3 are the output from taking the time series averages and standard deviations of coefficients from 357 monthly cross-sectional regressions ranging from March 1980 to November 2009.

The output tables show the Fama-MacBeth regression coefficients while the parentheses contain the p-values. The null hypothesis inherent in the regressions is that the regression coefficients are zero. The p-value represents the likelihood of incorrectly rejecting the null hypothesis given the available data. For instance, a p-value of 0.05 indicates that we would expect to observe a coefficient of this magnitude with a probability of 5%, even though the coefficient is actually zero and the null hypothesis is valid. The p-values for the coefficients are calculated using two-sided t-tests, except for the *SinDum* and *Beta* coefficients where the tests are one-sided. This is appropriate because our hypothesis states that sin stocks provide investors with a premium in return for exposure to the sin element (or for overweighting sin stocks in their portfolio, cf. the arguments put forward in section 1.3).

5.3.1 United States

Table 5.2.1 provides the regression summary for the United States market. When all control variables are included, the *SinDum* coefficient is positive and significant at the 10% level, not far from the 5% threshold. The magnitude of the coefficient is quite large, suggesting sin

stock over-performance of almost 27 basis points per month. These results indicate that sin stocks have been subject to a return premium in the United States. However, looking at the level of significance, we see that there is a non-negligible probability that the over-performance we observe is just a matter of coincidence. Regarding the control variables, the *Beta* coefficient is positive and significant at the 5% level, something we would expect to see from traditional asset pricing theory. *LSize* is positive, suggesting that larger companies experience higher returns than smaller, although the coefficient is not statistically significant (the sign of the coefficient is actually the opposite of what we would expect to see based on Fama and French's four factor model, namely that small companies outperform larger due to a risk premium related to holding small cap companies). *LMTBV* has the expected effect. High market-to-book stocks do far worse than low market-to-book stocks, supporting the conviction that value stocks outperform growth stocks. The coefficient is negative, with a large magnitude, and statistically significant even at the 1% level. Furthermore, the results in table 5.3.1 also support that stock momentum is a determinant of stock returns, since the *Ret12* coefficient (denoting performance over the last 12 months) is strongly positive and statistically significant at the 1% level. *TurnOver* is negative and significant at the 5% level, suggesting a possible liquidity premium. The *DivYield* coefficient is also negative and significant at the 5% level, implying that high dividend yielding stocks provide lower returns than lesser yielding stocks. The comparable dummy, *CompDum*, is negative but not statistically significant. Accordingly, it could seem like the returns from companies exposed to several of the same industry factors as alcohol, tobacco and gambling were somewhat on the low side. When we loosen the control variables to include other specifications of the model (table 5.3.1 second row and below), we see that the *SinDum* coefficient is reduced, although it is still significant at the 10% level. This is the same pattern as found by Hong and Kacpercyk (2008), suggesting that the effect of sin is more easily identified when other return effects are controlled for. As shown in table 5.3.1, the *SinDum* coefficient is significant at the 10% level for all specifications of the model until we remove the variable for market-to-book values (*LMTBV*)[24].

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[24] Often bivariate coefficients are the strongest, and by adding control variables, the coefficient weakens. That the opposite happens here suggest that there is a relationship between SinDum and stock returns that is initially "suppressed" by one or several of the control variables, but that comes to light once these control variables are included in the regression equation.

Table 5.3.1 United States data 1980-2009   Fama-MacBeth cross-sectional regressions

Coefficient

(p-value)   *10%; **5% ; ***1% significance

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	TurnOver	DivYield	CompDum
0,009193	0,002671	0,003760	0,000053	-0,010148	0,102473	-0,011737	-0,041559	-0,000065
(0,0076)***	(0,0558)*	(0,0376)**	(0,9041)	(0,0000)***	(0,0000)***	(0,0213)**	(0,0119)**	(0,9510)
0,009231	0,002603	0,003697	0,000055	-0,010143	0,103305	-0,011299	-0,041957	
(0,0069)***	(0,0779)*	(0,0808)*	(0,9009)	(0,0000)***	(0,0000)***	(0,0267)**	(0,0107)**	
0,008520	0,002762	0,004073	-0,000055	-0,009959	0,104262	-0,010574		
(0,0107)**	(0,0668)*	(0,0573)*	(0,9049)	(0,0000)***	(0,0000)***	(0,0407)**		
0,008759	0,002640	0,003834	-0,000123	-0,009910	0,101715			
(0,0092)***	(0,0702)*	(0,0770)*	(0,7857)	(0,0000)***	(0,0000)***			
0,008539	0,002595	0,004264	-0,000146	-0,008443				
(0,0128)**	(0,0778)*	(0,0464)**	(0,7522)	(0,0000)***				
0,000775	0,002131	0,003153	-0,000065					
(0,8192)	(0,1141)	(0,0559)*	(0,8752)					
0,000474	0,002225	0,003326						
(0,7867)	(0,1042)	(0,0444)**						
0,004573	0,001480							
(0,1112)	(0,2192)							

5.3.2 United Kingdom

5.3.2 United Kingdom

The corresponding regression output for the United Kingdom market is presented in table
5.3.2 below. Sin stocks exhibit comparable behavior to that of the United States market. In
the full specification of the model (table 5.3.2, top row) the results indicate a premium to
holding sin stocks, with the *SinDum* coefficient nearing almost 34 basis points per month.
The coefficient lies within 10% significance, and similar to the United States regressions, it is
just shy of the 5% significance level. As for the control variables, the role of *Beta* for stock
returns is less clear in the United Kingdom than in the US market. The coefficient is positive,
but not statistically significant. Similar to the US, company size (*LSize*) is not statistically
significant (however, unlike the US market, the sign of the coefficient is negative, as we

would expect it to be based on the works of Fama and French). Market-to-book value (*LMTBV*), past stock performance (*Ret12*), and share liquidity (*TurnOver*) prove to be important determinants of stock return in the United Kingdom, paralleling the results from the United States; value outperforms growth stocks, past performers outperform past losers, and less liquid stocks are associated with a return premium. Contrary to the United States however, the dividend yield (DivYield) is not statistically significant in the UK. Finally, and unlike the US, the comparable dummy is significant at the 10% level in the UK. The size of the coefficient is substantial, suggesting that stocks similar to sin stocks, but lacking the sin element, underperform by almost 21 basis points per month. Discussing possible reasons for this underperformance is beyond the scope of this paper; but it is highly likely that the negative performance by the comparable companies has an effect on the perceptible return of sin stocks. With a model with fewer variables, excluding the *CompDum* variable, the return premium for sin stocks is substantially reduced, and no longer significant (table 5.3.2, second row).

Table 5.3.2   UK data   1980-2009   Fama-MacBeth cross-sectional regressions

Coefficient
(p-value)   *10%; **5% ; ***1% significance

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	TurnOver	DivYield	CompDum
0,003670	0,003392	0,001649	-0,000021	-0,008042	0,250651	0,000341	-0,003142	-0,002078
(0,3158)	(0,0502)*	(0,2982)	(0,9647)	(0,0000)***	(0,0000)***	(0,0005)***	(0,8852)	(0,0572)*
0,003492	0,001667	0,001742	-0,000065	-0,007931	0,250830	0,000340	-0,002517	
(0,3323)	(0,2042)	(0,2873)	(0,8911)	(0,0000)***	(0,0000)***	(0,0006)***	(0,9075)	
0,003304	0,001792	0,001506	-0,000074	-0,007794	0,258566	0,000350		
(0,3363)	(0,1855)	(0,3150)	(0,8766)	(0,0000)***	(0,0000)***	(0,0004)***		
0,002309	0,001581	0,002036	0,000326	-0,007650	0,250980			
(0,4924)	(0,2185)	(0,2575)	(0,4724)	(0,0000)***	(0,0000)***			
0,001814	0,001319	0,002206	0,000467	-0,005005				
(0,6150)	(0,2561)	(0,2362)	(0,3352)	(0,0000)***				
-0,002053	0,001327	0,001971	0,000407					
(0,5312)	(0,2456)	(0,2526)	(0,3589)					
-0,000019	0,002127	0,002005						
(0,9919)	(0,1400)	(0,2462)						
0,001447	0,000934							
(0,6137)	(0,3270)							

5.3.3 Japan

Table 5.3.3 shows the cross-sectional regression results for the Japanese market. Differing from the previous results we have discussed, Japanese sin stocks do not exhibit any statistically significant return premium when controlling for the full specification of the model (table 5.3.3, top row). Like in the UK and US markets, the *SinDum* coefficient is positive, but it is not statistically significant. When we relax the controls in the model and remove the CompDum variable, the SinDum coefficient increases in magnitude, and becomes significant at the 10% level (table 5.3.3, second row). Thus inclusion of the comparable companies explains excess returns previously allocated to the sin stocks. This indicates that, for Japan, the excess returns of sin stocks is not related to risk (or other) factors associated with sin stocks, but rather to broader, industry-specific factors not specified by the model. With regard to the control variables, the *Beta* coefficient is not

significant for any specification of the model (similar to the UK, but not the US). The coefficient for market-to-book value (*LMTBV*) is negative and statistically significant at the 1% level. The effects of *Ret12* and *DivYield* are not statistically significant, hence momentum and dividend yield do not appear to explain stock returns in the Japanese market. The effect of *Size* is statistically significant at the 1% level when we include only *SinDum*, *Beta* and *LSize* in the regression (table 5.3.3, fifth row). The coefficient is negative, as we would expect to see based on the factor models of Fama and French: indicating that smaller companies outperform larger. However, when we expand the model to include the variable for market-to-book values (*LMTBV*), the magnitude of the coefficient is reduced and it is no longer statistically significant.

Table 5.2.3   Japan data   1980-2009   Fama-MacBeth cross-sectional regressions

Coefficient
(p-value)   *10%; **5% ; ***1% significance

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	DivYield	CompDum
0,007251	0,001136	0,004862	-0,000937	-0,007419	-0,027552	0,094558	0,001862
(0,1622)	(0,2855)	(0,1386)	(0,1428)	(0,0000)***	(0,3294)	(0,1986)	(0,0653)*
0,007725	0,002774	0,004546	-0,000937	-0,007362	-0,025004	0,091657	
(0,1333)	(0,0884)*	(0,1669)	(0,1413)	(0,0000)***	(0,3785)	(0,2103)	
0,008555	0,002558	0,004670	-0,000967	-0,007532	-0,023185		
(0,0859)*	(0,1064)	(0,1567)	(0,1305)	(0,0000)***	(0,4136)		
0,010005	0,002367	0,005027	-0,001081	-0,007807			
(0,0490)**	(0,1255)	(0,1327)	(0,1033)	(0,0000)***			
0,012460	0,002348	0,003396	-0,002035				
(0,0056)***	(0,1043)	(0,2558)	(0,0006)***				
0,001535	0,000991	0,002240					
(0,3962)	(0,3024)	(0,4496)					
0,003973	0,001837						
(0,1468)	(0,1658)						

5.3.4 Discussion of findings

Using the Fama-MacBeth procedure, we find indications of a sin stock premium in the US and UK, but not in Japan. The results suggest that the sin stock premium is large, in the range of 27 and 34 basis points per month for the US and UK respectively. For both countries, the results are significant at the 10% level. As we recall, the significance tests we employ assume that the series of coefficients from the monthly cross-sectional regressions are independent from each other across time. Appendix 4 shows a correlogram over the US time-series of *SinDum* coefficients (the coefficients we are most interested in testing), and we can see that the sample seems to be relatively free of autocorrelation.

The *SinDum* coefficient for the United States can be compared to the results of Hong and Kacperczyk (2009), who recorded sin stock outperformance of 29 basis points per month in their cross sectional regressions (with statistical significance at the 5% level). Their methodological approach was somewhat similar to the methodology employed in this chapter, at least in broad strokes; but the results cannot be compared directly. Hong and Kacperczyk (2009) used a different screening methodology for identifying sin stock, and they used CRSP/Compustat to extract data. Their sample spanned the period from 1965 to 2006, and included slightly different control variables, such as the inclusion of company age instead of dividend yield, and somewhat different comparable companies. Compared to our results, their choice of comparable companies actually had a negative coefficient of greater magnitude. Nonetheless, the coinciding results indicate that the sin stock return premium in the US is relatively robust to differences in sample periods, data sources and stock screening methodology. For added comparison with Hong and Kacperczyk's (2009) paper, we have performed cross sectional regressions with a sample ending at the end of 2006 (the end of their sample). This sample does not include the turmoil of the financial markets in the last couple of years, which may have impacted on the regression results. The results are displayed for United States, United Kingdom and Japan in table 5.3.4 below. Only the full specification of the model is included.

Table 5.3.4　　　　　　**US data 1980-2006**　　**Fama-MacBeth cross-sectional regressions**
Coefficient
(p-value)　　　　　　　　　　　　　　　　　　　　　　*10%; **5% ; ***1% significance

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	TurnOver	DivYield	CompDum
0,010703	0,003142	0,004115	-0,000071	-0,010084	0,118015	-0,012613	-0,045088	-0,000164
(0,0018)***	(0,0268)**	(0,0227)**	(0,8724)	(0,0000)***	(0,0000)***	(0,0190)**	(0,0086)***	(0,8717)

UK data 1980-2006　　**Fama-MacBeth cross-sectional regressions**

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	TurnOver	DivYield	CompDum
0,005228	0,002889	0,002408	-0,000268	-0,007679	0,276179	0,000283	0,008874	-0,001335
(0,1490)	(0,0772)*	(0,2055)	(0,5606)	(0,0000)***	(0,0000)***	(0,0028)***	(0,6697)	(0,2113)

Japan data 1980-2006　　**Fama-MacBeth cross-sectional regressions**

Constant	SinDum	Beta	Lsize	LMTBV	Ret12	DivYield	CompDum
0,009765	0,001616	0,005860	-0,001188	-0,007259	-0,027316	0,098413	0,001451
(0,0716)*	(0,4356)	(0,0693)*	(0,0738)*	(0,0000)***	(0,3421)	(0,2036)	(0,1626)

For the United States, the *Sindum* coefficient increases by limiting the time period to 1980-2006, and indicates a sin stock premium in excess of 31 basis points. This is statistically significant at the 5% level. The result for the US sin stock premium is remarkably similar to Hong and Kacperczyk's (2009) 1965-2006 cross sectional sample (29 basis points). The effects of the other variables are also quite similar to their results, both in magnitude and significance, except for the *Beta* and *Size* coefficients. In our analysis, the *Beta* coefficient is significant while the *Size* coefficient is not; in Hong and Kacperczyk (2009) the *Size* coefficient is significant while the *Beta* coefficient is not. As previously mentioned the results are by no means directly comparable, as both the time interval and even certain variables are different (they include age instead of dividend yield, as well as comparable companies being somewhat different). Indirectly, the results from the 1980-2006 sample show that the events of the last few years have made the US return premium on sin stocks less clear, since the effect is weaker in table 5.3.1. As for the United Kingdom and Japan, the 1980-2006 samples goes in the opposite direction than for the US, the *SinDum* coefficients are reduced.

Nevertheless, the UK regression still shows a sin stock premium that is statistically significant at the 10% level. The Japanese effect is still not statistically significant.

6. Implications of findings

Both the Kalman filter and the Fama-Macbeth method suggest that there indeed exists a sin premium in the United States. This is in line with the previous research on the subject; in particular Hong and Kacperczyk's study (2009). For the United Kingdom the Fama-Macbeth method found a significant sin premium only if all control variables were included in the regression, while the Kalman filter was inconclusive. In Japan neither the Fama-Macbeth method nor the Kalman filter method found any statistically significant sin stock premium.

The existence of a sin premium in some markets has several implications for investors considering whether or not they should employ a negative screen when picking stocks. Knowing more about the costs of screening, investors have a better footing for weighing the costs and benefits. At the same time, the existence of a sin premium is also a sign that negative screening has an effect. Investors with Akerlof (1980) style preferences may well think that not breaking the norms against investing in certain industries is still worth the cost. An investor that gains utility from changing or hurting unethical firms has a somewhat more complicated calculation to make. In addition to weighing the costs and benefits of investing versus screening, he should also consider whether the cost he incurs from screening would be better put to use with an alternative approach to a similar socially responsible objective.

Keep in mind that the existence of a sin premium does not necessarily imply that a mean-variance maximizing investor should overweight sin stocks either. Merton's model (1987) is perhaps the strongest theoretical foundation for a sin premium, and it states that the premium stems from a portion of investors having to bear otherwise diversifiable risk. Taking on this extra risk without a return premium would only be rational if you already have a high exposure to a negatively correlated risk factor, for example if your human capital was correlated with the success of an anti-tobacco tort law firm (but in that case, by overweighting the portfolio towards tobacco one might risk a substantial Akerlof-style backlash).

As regards to what the specific causal mechanisms for the existence of a sin stock premium are, the data does not give us any definite answers. However, the fact that we found differences between countries may take us some way towards tentatively differentiating between the hypotheses for why there exists a sin premium. One possible explanation for the difference between countries has to do with the proportion of investors conducting socially responsible investing in each market, and thus the degree of market segmentation in accordance with Merton (1987). As we recall from section 2, SRI funds had the largest market share in the US, followed by the UK, and less than 0.01 percent market share in Japan (ASrIA 2003). The statistical significance of the sin factor thus seems to be somewhat correlated with the presence of SRI funds in the market, and how long that presence has been felt, which seems very reasonable.

However, this may beg the question why SRI funds have such a small market share in Japan. It may simply be a time-lag effect, i.e. the US is a leader and Japan more of a latecomer when it comes to implementing SRI[25]. If so, we would expect the sin stock premium in Japan to rise across time, as SRI investors become more numerable and Japan "cathes up" with SRI leaders. Alternatively, the different performance of sin stocks may reflect deep-seated differences in underlying values; differences less likely to change across time. Perhaps

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[25] The first Japanese SRI mutual fund, the Nikko Eco Fund, was launched as late as August 1999, while the first pension fund to change to SRI practices was the Mutual Aid Association for Tokyo Metropolitan Teachers and Officials in March 2003.

Japanese mainstream culture does not have the same "Puritan" relationship to alcohol, tobacco and gaming as in the US or UK[26]. We argued in chapter 1 that a strong norm was one possible basis for a sin premium. This type of norm would in general need to be shared by a fairly large part of the populace. Perhaps Japanese culture, based on Buddhist and/or Shinto traditions, have different perceptions in this regard compared to (traditionally mainly Protestant Christian) US and UK. In this context, it is intriguing to notice that Salaber (2007, referred in chapter 1) found differences between (traditionally) Protestant and (traditionally) Catholic European countries with regard to sin stock returns. At least according to cultural stereotypes, Protestants are supposedly more concerned with Puritan virtues than Catholics[27]. Although very speculative, maybe there is a larger population group that can be mobilized for SRI investments in traditionally Protestant countries (including the US and UK). We must strongly emphasize here that although cultural hypotheses are fascinating, they are difficult to test empirically; nor has this been the intention in this paper. We mention this possible "cultural" explanation here mainly as an interesting topic for future research. Another related topic worthy of attention is whether a sin premium also exists in the bond markets, seeing as these markets are far less transparent than most stock markets.

7. Conclusion

In this paper we have examined whether a premium exists for alcohol, tobacco and gaming stocks. This was done by analyzing historical stock returns of these sin stocks and correcting for common return predictors and industry effects. To see whether the results are sensitive to different methodologies, we have employed both the Fama-Macbeth regression technique and the Kalman filter. We also wanted to see whether results were robust across different countries, thus we performed the analysis for United States, United Kingdom, and

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[26] "Because Japan has a different religious background, there is no consensus on what anti-social business is", claims Japan Research Institute, in a text explaining why they did not include questions on this matter in their CSR questionnaire (ASrIA 2003). This is echoed by Eiichi Takeda, founder of the Nikko Eco Fund: "Many Japanese are conservative and do not consider cigarettes, nuclear power, gambling and weapons production as "anti-social"", he said in an interview with SocialFunds.com. For this reason, most of SRI in Japan is primarily directed at environmental issues, which seems more important to the general populace. The interview can be found at URL: <http://www.socialfunds.org/news/article.cgi/1151.html>

[27] After all, the term "Puritan" originates from the English Protestants of the 16th century.

for Japanese data. The strongest evidence of a sin stock premium was found for the United States market with both the Kalman procedure and the Fama-MacBeth regressions indicating sin stock outperformance when correcting for a host of control variables. However, for the United Kingdom the results are less clear. The Fama-MacBeth regressions indicated the presence of a sin stock premium, but this result was not supported by the Kalman filter, which came out inconclusive. For Japan, neither the Kalman filter nor the Fama-MacBeth regressions picked up significant evidence for a return premium. Thus the results indicate that the sin stock premium is not fully robust to different methodologies, and it may differ across countries. Presence of a sin stock premium indicates that there is a cost associated with socially responsible investing. The aim of this paper has not been to pass any judgment on SRI itself. However, research such as this should prove valuable for investors, both individual and institutional, considering whether or not to employ a negative screen in their investment decisions.

8. Literature

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9. Appendices

Appendix 1: Merton's market segmentation model

Merton's (1987) model for market segmentation was first used to illustrate the effects of negative screening by James and Rivoli (1997), who set it up as follows:

$$\lambda_k = \frac{(1 - q_k)}{q_k} \times x_k \times \delta \times \sigma^2$$

λ_k denotes the increase in the cost of capital stemming from investors abstaining from invest in the firm[28], while q_k is the fraction of investors willing to invest in the firm. x_k is the weight of the stock in the market portfolio, δ is a factor capturing risk aversion and σ the idiosyncratic risk of the firm.

Merton (1987) states that a risk aversion, δ, og two is reasonable, based on empirical results. With that given, one can alter the other variables to fit the case. James and Rivoli exemplifies by using a firm with an idiosyncratic risk of 40 percent, and a weight in the market portfolio of 1 percent. This specification yields the following illustration on the effect of a negative screening by a certain percentage of investors:
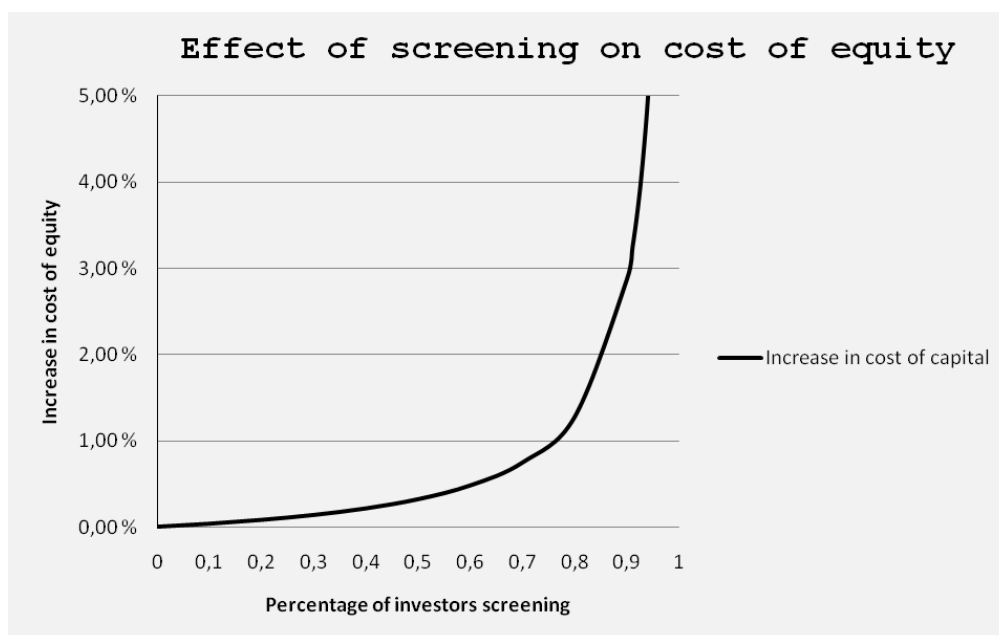

Fig. A.1.1: Example effect of screening on a large company

As can be seen from figure A.1.1, more than 76 percent of investors have to refuse to invest in the stock in order for the firms cost of capital to increase by more than one basis point. A 1 percent weight in the market portfolio is incredibly large, though, and even a large firm would be hard pressed to take up more than 0.1 percent of a well specified market proxy.

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[28] Merton's model was originally intended to show the effects of incomplete information, and thus called λ_k the "shadow cost" associated with not knowing about a certain stock. However, he pointed out that a similar effect could arise from market segmentation.

Changing x_k to this yields an even more depressing result for those who wish to hurt firms through negative screening:
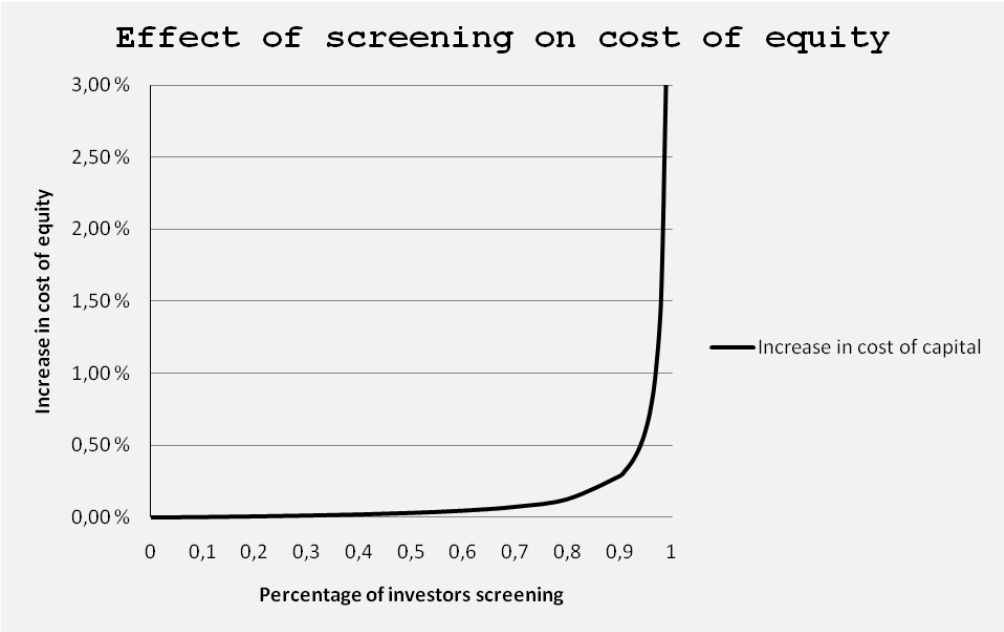

Effect of screening on cost of equity

Fig. A.1.2: Example effect of screening on a smaller company

Figure A.1.2 shows that approximately 94 percent of investors need to refrain from investing should the cost of capital increase by 0.5 basis points. Bear in mind though, that this holds for equity markets that otherwise holds the assumptions of the CAPM. Other factors the negative screening might affect, like the stocks liquidity, are not taken into account. Thus, the final impact on cost of capital may indeed be greater. It is also worth noting that even small increases in cost of capital may be painful for a company with a high growth rate, which can be illustrated by any time-discounting valuation model. On the other hand, a company with low or negative growth can stomach a fairly high cost of capital, by comparison.

Appendix 2: Movements of smoothed coefficients

Figure A.2.1 shows the movement over time of the smoothed coefficients for the US DLM that incorporates all the four factors of the Carhart model, as well as the sin premium.
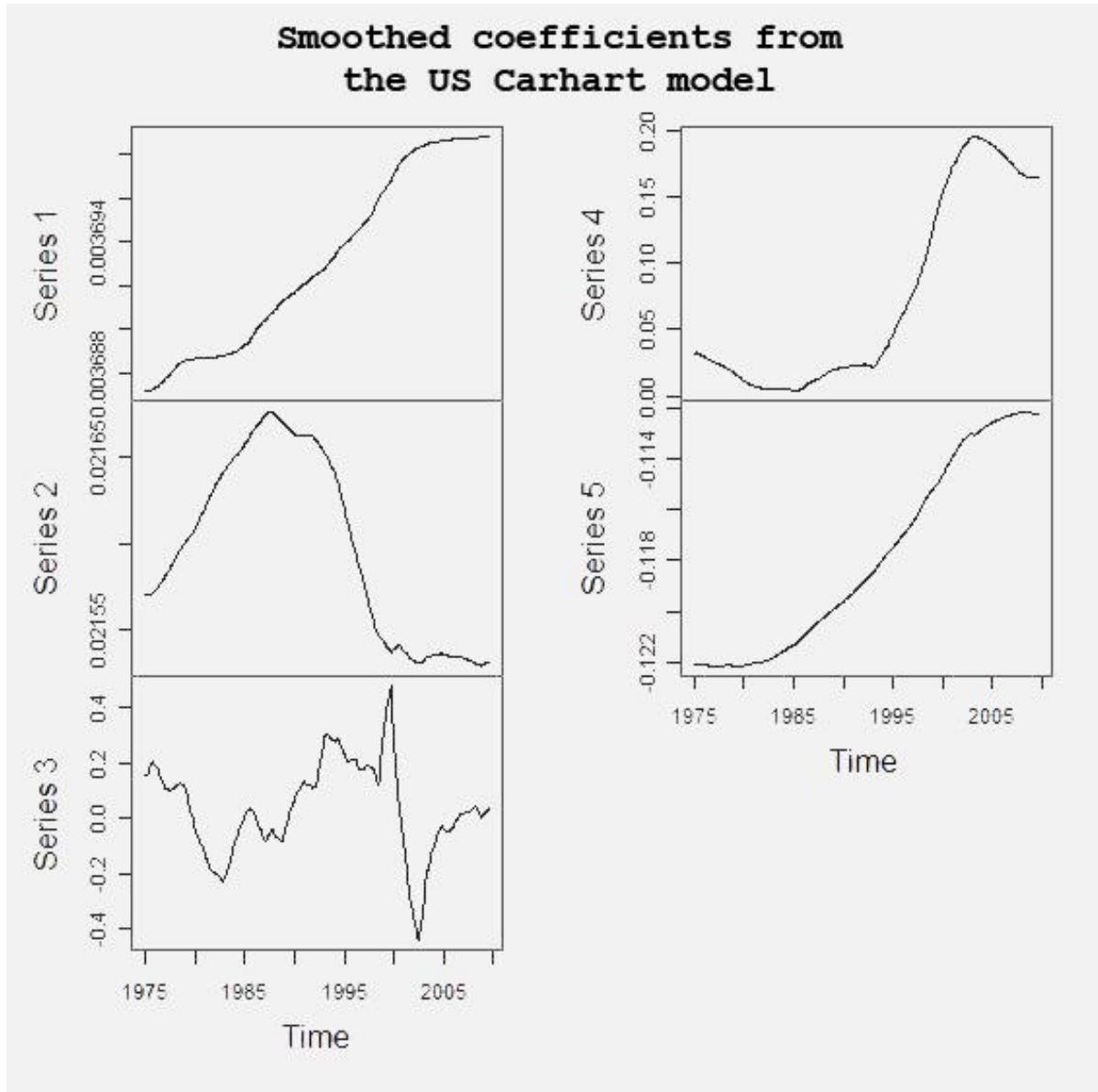

Fig. A.2.1: Kalman smoothed coefficients for the Carhart model for the US.

Series 1 shows α_t, Series 2 shows $\beta_{M,t}$, Series 3 shows $\beta_{SMB,t}$, Series 4 shows $\beta_{HML,t}$, while Series 5 shows $\beta_{MOM,t}$. Note that the y-axis while the coefficients all share a common x-axis the values on the y-axis vary wildly in accordance with the standard preset of R. $\beta_{M,t}$ does not change by much more than one basis point over the entire sample period, and α_t even less so (thus it appears completely time-invariant in fig. 4.9.1.4). $\beta_{MOM,t}$ varies a great deal more than these first two, put nothing compared to the wild swings of $\beta_{SMB,t}$, and $\beta_{HML,t}$. The latter two seem to explain most of the variation in return over time for the portfolio long sin stocks and short their comparables.

Appendix 3: The Normality of the Observational Variance

Figure A.3.1 is an example of the histogram plots of the observational variance we have done to check the normality assumption.
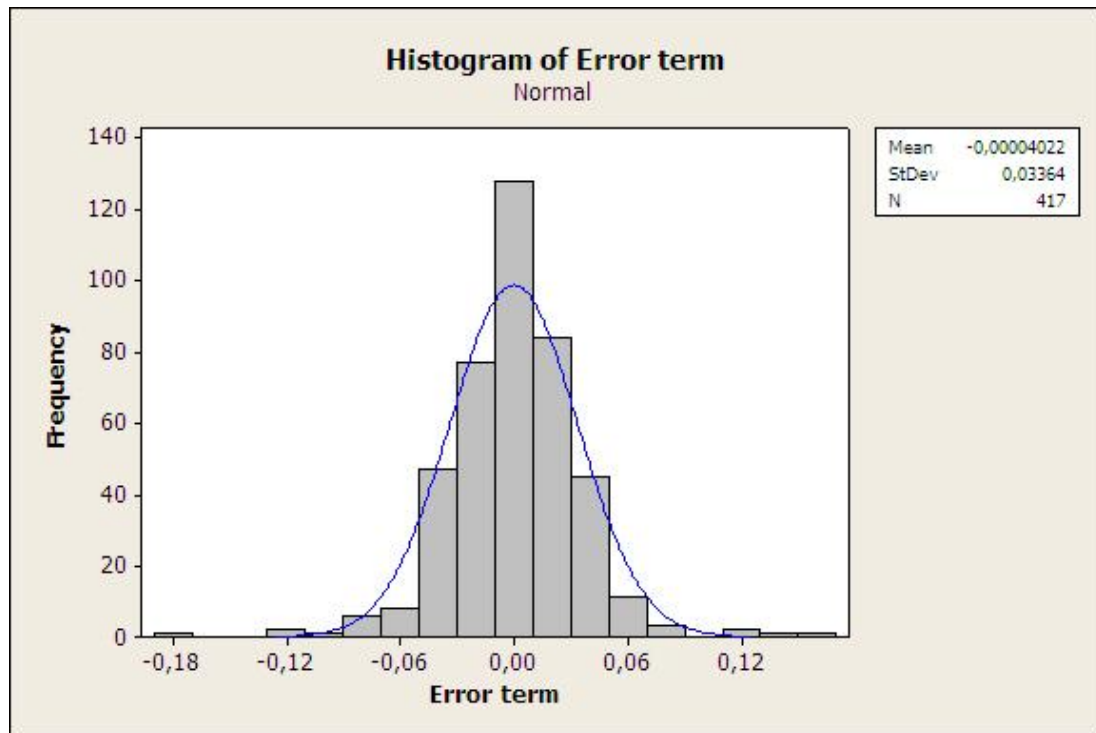

Fig. A.3.1: Histogram for observation error terms of the US Carhart DLM

Notably, all other histograms yield similar results, with somewhat fatter tails than the normal distribution would indicate. The fat tails are to be expected, since we are working with stock return data prone to black swans and their positive equivalents. Most also exhibit some slight positive skewness, which is also natural, seeing as a stock can increase by a near infinite number, but never fall more than 100 percent. All in all, we can conclude that none of them are strictly normal just from looking at the histograms.

Appendix 4: Serial Correlation in Fama-MacBeth

Figure A.4.1 is a correlogram for the time series of cross-sectional regression coefficients used to calculate means and standard errors in the US Fama-MacBeth regressions.
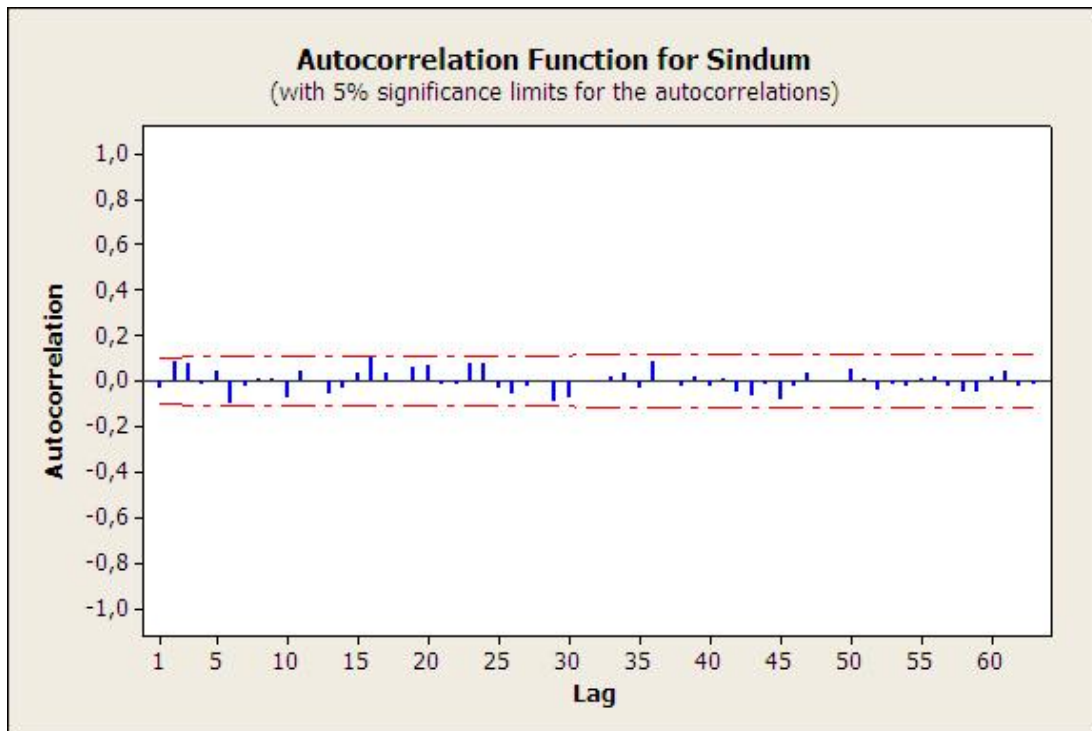

Fig. A.4.1: Correlogram for US Fama-Macbeth