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How social norms affect the corporate bond market: from a sinful perspective

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Abstract

I offer a comprehensive study on the existence and drivers of a Sin firm premium on the US corporate bond market. Using a sample of 7,499 non-financial bonds without any special features issued between 2000 and 2019, I provide statistically insignificant evidence that Sin firms pay a 23.3 bp higher credit spread compared to otherwise similar firms in non-Sin industries. This inflates the cost of corporate bonds for Sin firms by 7.9% relative to the 3.0% sample mean. The economic significance of the Sin firm premium is robust for different model specifications and Sin firm classifications. Like the literature I aim to supplement, I intend to attribute the Sin firm premium to neglect by norm-constrained institutional investors. Using time, Google trends and Republican electoral dominance as novel proxies for social norm intensity, I can only provide weak evidence for a relationship between social norms and the Sin firm premium. Also, I investigate whether the Sin firm premium is driven by idiosyncratic risk, liquidity, or sensitivity to market-wide illiquidity. I only find an indication for the latter, on which I build a suggestion for a liquidity neglect effect.

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1. Introduction

Ethical investing is hot. Public interest is stronger than ever and an increasing volume of assets under management is affected by ethical investment concerns (Kostigen, 2019). In the US, the size of the sustainable and responsible investment universe has eighteen-folded between 1995 and 2018. The assets affected by some social or sustainable investment screen has grown from 639 billion USD to a staggering 12 trillion USD. This amounts to over a quarter of total assets under professional management, of which institutional investors are responsible for 5.6 trillion. Their largest ESG screens are weapons (2.97 trillion) and tobacco (2.56 trillion) (US SIF Foundation, 2018). These developments are widely promoted by governments around the world (International Capital Markets Association, 2020). They regard sustainable finance as pivotal in the global shift towards a sustainable society (United Nations Environment Programme, 2016; European Union, 2018). The thought is that alignment of investor preferences with the public interest, incentivises firms in need of external financing to improve their social performance.

This thought is supported by Becker's (2010) theory of discrimination. He argues that discriminatory preferences can lead to a return disparity between discriminated and non-discriminated assets. Firms that face discrimination would then have higher financing costs. Akerlof (1980) and Romer (1984) recognise that it is unlikely that individual investor preferences affect aggregate prices. In response, they propose that social norms are able to sustain society-wide discriminatory preferences. They argue that social norm-violation leads to emotional or reputational cost, regardless of an agent's personal preferences. This inhibits social-norm neutral arbitrageurs to snatch up the price differences between discriminated and non-discriminated assets (Arrow, 1973). The theory, and vast amounts of affected assets under management, indicate that social norms against unethical investing are driving investment decisions to a magnitude that has the potential to significantly affect the capital markets.

Hong and Kacperczyk (2009) are amongst the first researchers to recognize this potential. In their seminal work, they investigate whether firms that operate in the alcohol, tobacco and gaming industries pay a premium on their cost of equity. They dub these firms 'Sin firms' and argue that their unequivocal unethical nature is a good and time-invariant proxy for the apparent social norms against unethical investing. Controlling for firm-specific risk and liquidity factors, they find evidence for a social norm-related Sin firm premium. They find that norm-constrained institutional investors (pension funds, banks, sovereign wealth funds and universities) shun Sin firms and explain the Sin firm premium along this altered investor base. Primarily, they point towards Merton's (1987) neglect effect. It poses that a smaller investor base leads an individual investor to take on more idiosyncratic risk, for which he demands compensation.

Hong and Kacperczyk's (2009) work is foundational for numerous subsequent studies. Different researchers study the relationship between various SRI, CSR or more ethics-based scores on the cost of different forms of capital.[1] On the equity market, authors find a consistent equity premium for firms that score poorly on SRI measures and Sin firm status (Geczy et al., 2005; Fabozzi et al., 2008; Renneboog et al., 2008; Chong et al. 2015). The CSR measure yields mixed results, but these measures may be noisy as they encompass a much wider range of information than a firm's ethical conduct (Kempf & Osthoff, 2007; El Ghoul et al., 2011). This provides further evidence for the notion that social norm-induced discrimination against firms with poor social performance increases their cost of capital.

Inflated equity cost for these firms may induce a flee to (potentially) cheaper debt. Hong and Kacperczyk (2009) find a 20% higher debt-equity ratio for Sin firms, substantiating this idea. Some papers further investigate this relationship between social desirability measures and the cost of debt capital. Most studies using SRI and CSR scores in relation to bond prices and bank loan interest find a similar premium as found on the equity market. Again, evidence from the noisy CSR measures is somewhat mixed (Menz, 2010; Goss & Roberts 2011; Chava, 2014; Kim et al., 2014; Oikonomou et al., 2014; Ge & Liu, 2015; Polbennikov et al., 2016).

Very few studies use Hong and Kacperczyk's (2009) Sin firm specification as a way to isolate the effect of social norms against unethical investing on the corporate debt market. Surprisingly, Chalabi et al. (2018) find a 43 to 57 bp discount for Sin firms on their bank loan interest rate. Their result is robust for superior accounting quality of Sin firms, relationship lending, hedging value of Sin firms' anti-cyclical nature and organisational structure. They find that including relationship lending, where banks engage in multiple subsequent loans to a Sin firm, mitigates the discount. They argue that long term relationships increase a bank's informational position, which reduces information risk. Goss and Roberts (2011) primarily study CSR measures but include Sin industry control variables in their study on bank loan interest. They offer contradicting evidence by finding a statistically significant premium on the interest charged to tobacco firms.

Both studies only evaluate the effect of social norms on the corporate debt market from the bank loan perspective. To my knowledge, no research exists on the relationship between social norms, proxied by Sin firm status, and the cost of corporate bonds. Therefore, my research question reads:

What is the effect of social norms on the price of publicly traded corporate bonds?

I formulate two hypotheses to investigate this question. Firstly, I expect to find a Sin firm premium on the corporate bond market due to the consistently found premium in the literature on publicly traded assets, and debt instruments in relation to SRI and CSR measures. I argue that Chalabi et al.'s (2018) peculiar results can be explained by the substantially different role of a bank as a delegated monitor (Diamond, 1984). They obtain much more information on their client and adjust interest rates accordingly. Therefore, I argue that a firm's social performance is a less important determinant.

[1] SRI is Socially Responsible Investment. CSR is Corporate Social Responsibility.

Secondly, I expect the Sin firm premium to be positively related to the intensity of the social norms against unethical investing. Multiple studies show that heterogeneity in social norm intensity, across investor groups or countries, indirectly affect asset holdings or directly affects asset prices (Kumar et al., 2011; Hong & Kostovetsky, 2012; Fauver & McDonald, 2014). As the literature suggests that the Sin firm premium is driven by social norms, I expect it to be affected by social norm intensity.

I study a potential social norm-driven Sin firm premium using OLS regressions on a large yearly panel dataset. My panel encompasses 7,499 corporate bonds without special features issued by 1,152 US non-financial firms over a 2000-2019 sample period. I obtain bond data from Mergent FISD and Refinitiv Datastream and add firm-level data from Compustat to form my core panel. I use this data to control for known firm and bond-specific risk and liquidity factors. I use several other datasets to perform additional analyses. Amongst those, I use Google trends data and US election data to proxy for social norm intensity. Also, I use a time-varying product relatedness scores provided by Hoberg and Philips (2016) to construct alternative lists of Sin and comparable firms to test for industry specification robustness.

I find evidence for a statistically insignificant Sin firm premium on the public corporate bond market. Despite the statistical insignificance, the observed Sin firm premium is economically significant. I show that Sin firms pay an average 23.3 bp higher credit spread on their publicly traded corporate bonds relative to otherwise similar firms in comparable, non-Sin industries. The premium translates to a 7.9% increase compared to the 3.0% sample mean credit spread. The economic significance of the Sin firm premium is robust for different model specifications and Sin firm classifications. These results fill the gap in the literature on the Sin firm premium in corporate financing.

My work is different from that of Hong and Kacperczyk (2009) in the sense that I am unable to attribute the Sin firm premium to social norm-induced shunning strategies by institutional investors. The opaqueness of the debt market does not allow me to study whether lower institutional ownership may induce a neglect effect. Therefore, I resort to several novel approximations for the intensity of social norms against unethical investing. Using time, Google Trends data and US election data, I offer somewhat consistent but statistically weak evidence for a relationship between the Sin firm premium and social norm intensity.

Using time as a proxy for increased investor attention, I find that the Sin firm premium is somewhat higher after 2005 and the financial crisis. This opposes Pereira (2018) and Gerard (2019), who state that the ESG effect on asset prices disappeared post-crisis. Moreover, I add to the literature on red and blue investing that aims to elicit the effect of republican or democratic electoral dominance on asset prices (Hong & Kostovetsky, 2012; Di Giuli & Kostovetsky, 2014). Again, I find weak statistical evidence for a relationship between social norms and the general Sin firm premium. Incited by Hong and Kostovetsky (2012), I further study the tobacco industry, as it is the most politically sensitive. I find evidence for a statistically significant tobacco firm premium of 80 bp, which is negatively related to republican electoral dominance.

My work does address Hong & Kacperczyk's (2009) suggestion that the Sin firm premium is driven by the neglect effect. I indirectly investigate the neglect effect by relating the Sin firm premium to crucial credit spread determinants. I use Longstaff et al.'s (2005) findings that corporate bond spreads are mostly determined by credit risk, firm-specific liquidity and sensitivity to market-wide illiquidity. I find no relationship for the first two determinants but show that the Sin firm premium is higher in years with restricted market liquidity. I argue that Sin firm's sensitivity to market-wide illiquidity can be explained by the neglect effect. It becomes especially hard to sell Sin assets if the market dries up if an investor is also unable to sell to a large fraction of other investors. Thereby, I suggest a sensitivity determinant to those found by Lin, Wang and Wu (2011). Moreover, I show that it is unlikely that the Sin firm premium is a persistent mispricing sustained by arbitrage impediments (Schleifer & Vishny, 1997). Nor can the premium be explained by the hedging value associated with Sin firms' anti-cyclical nature as suggested by Hong & Kacperczyk (2009).

Aside from contributions to existing literature, my work has practical implications for investors, legislators and managers. Investors may adjust their trading strategies based on the average premium, legislators may feel encouraged to further promote ethical investing as a means to improve firms' social performance, and Sin firm managers can take the bond premium into account when making corporate financing decisions.

I structure the remainder of my paper as follows. In section two, I review related literature and form my two hypotheses. Then, I describe my data gathering and manipulation process in section three. Subsequently, in section four I describe the OLS panel regression methodology I use. In section five, I present the results of my core and sub-analyses. Then, I discuss the implications of my findings in section six. Lastly, I offer a conclusion in section seven.

2. Theoretical Framework

2.1 Social norms and asset prices

In this section, I elaborate on the theoretical relationship between social norms and assets prices. Firstly, I demonstrate that social norms can sustain society-wide discriminatory preferences. Moreover, I address how a smaller and altered composition of the investor base for Sin firms theoretically affects the riskiness and returns of their assets. Also, I explain why the permanent social undesirability of Sin firms makes Sin firm status a useful proxy for social norms against unethical investing.

2.1.1 Discrimination theory

Academics have taken an interest in the sustenance and effects of discriminatory tastes and preferences by economic agents for a long time. In a seminal work, Becker (2010) argues that discriminatory preferences lead to a return disparity between a discriminated and non-discriminated group of resources or assets. For example, a manager would only hire a worker with attributes he discriminates against if this worker is substantially more productive than the non-discriminated against worker. He argues that an economic agent experiences stress from violating personal beliefs, so he only selects the option he discriminates against when the gain of that option more than offsets the incurred cost. Therefore, observing relative return differences within an asset class may illicit discriminatory preferences.

However, the preferences of a single manager are unlikely to cause observable differences in market wages or other aggregate measures. Discrimination needs to be more widespread to empirically find its impact. To this end, it is worth noting that individuals are not solely bound by personal beliefs and preferences. People are also subjected to social norms; (un)written rules that prescribe acceptable behaviour in a society. In this case, the employer not only considers his personal preferences in hiring decisions but must also account for societal preferences. Under the assumption that each manager is affected equally by a social norm, a social norm has the potential to sustain society-wide discrimination.

Academics have recognised that adhering to a limiting social norm seems irrational for an agent if the social norm does not overlap with the personal beliefs of that agent. If individuals exist that do not share the social norm, would they not violate it and nullify a potentially observable effect of discriminatory preferences of other members of society? Akerlof (1980) and Romer (1984) argue that it is rational to adhere to a social norm, even when it does not coincide with personal preferences, based on the cost of reputational loss or general emotional punishment associated with breaking the norm. Elster (1989) comes to a similar conclusion and states that social norms are self-perpetuating and self-reinforcing preference choice mechanisms that originate in a shared belief which are upheld by the emotional cost of norm violation.

Intuitively, in the case of the discriminated against worker, it would be beneficial to start a firm that only hires the cheaper and equally efficient group of discriminated against workers and gain a competitive advantage. Arrow (1973) addresses this intuitive response to discrimination theory by modelling the wages of discriminated and non-discriminated against workers under several sets of assumptions. He shows a persistent disparity in wages despite the absence of discrimination in some firms or inclusion of mitigating factors like competition and asset reallocation. He argues that discrimination consistently leads to reduced demand, resulting in negative price pressure.

Social norms affect all economic agents as norm-violation is associated with emotional or reputational cost, regardless of an agent's personal preferences. Therefore, social norms can sustain society-wide discriminatory preferences, in turn leading to price and return differences for assets. Economic agents only employ an asset if the cost of violation of the social norm against the use of that asset is compensated for. Arrow (1973) shows that arbitrageurs cannot fully exploit the disparity in asset or resource prices, even accounted for competition and asset reallocation. So, social norms against the employment of an asset or resource can have an observable effect on the relative price of assets or resources.

2.1.2 Sin as proxy for social norms

Like many authors who study the relationship between social norms and the cost of capital, I consider firms in the alcohol, tobacco or gaming industry to unequivocally and constantly manifest unethical firm behaviour (Fabozzi et al., 2008; Hong & Kacperczyk, 2009; Kim & Venkatachalam, 2011; Leventis et al., 2013; Novak & Bilinski, 2018). Sin firm unethical firm behaviour is unequivocal and constant because promoting human vice is inherent to their models and addiction and health risks are inherent to their products. For example, a tobacco firm cannot take away the health risks of their cigarettes like an oil company can reduce its climate impact by investing in greener technology. Hence, the social undesirability and unethical practices of Sin firms are constant over time and unrelated to firm investments into production process improvements.

Various papers substantiate my assumption on the existence of a social norm against investing in socially undesirable and unethical firms. Firstly, Hong and Kacperczyk (2009) find that norm-constrained institutional investors hold less Sin firm stocks than other institutional investors. Secondly, Kumar and Page (2011) find that sophisticated, norm-constrained investors earn – on average – a higher return on their Sin stock holdings. Indicating that norm-constrained investors only invest in Sin stocks when the cost of violating their norms is offset. My intuitive assumption is therefore backed by empirical evidence. As I address in section 2.3.2, the intensity of the social norm may vary over time. However, apparent unethical behaviour and the findings in the literature are strong indications that a social norm against investing in Sin assets is existent at all times.

Combining the permanence of unethical behaviour with the substantiated assumption of a societal norm against investing in unethical firms, allows me to equate Sin firm status with a social norm against unethical investing. In turn, this allows for an isolated study into the effect of social norms over a long timeframe.

2.1.3 Neglect effect

Socially Responsible Investing (SRI) investors generally follow a dual strategy according to Stratman and Glushkov (2009). They lean heavily on assets that perform well on social responsibility measures and shun assets of companies associated with tobacco, alcohol, gambling or other unbeneficial operations. In this subsection, I evaluate how this general strategy affects the investor composition for a company and in turn, how this affects the riskiness of their assets.

In their seminal work, Hong and Kacperczyk (2009) hypothesise that norm-constrained investors shun Sin firm equity assets because they face a social norm against investing in those firms. Norm-constrained investors are institutional investors who are sensitive to societal norms. They face public scrutiny of publicly available investment information by their diverse investor base. Reputational losses are large and likely to materialize if a norm-constrained investor violates a social norm. Examples of norm-constrained investors are pension funds, banks, endowment funds and insurance companies. Hong and Kacperczyk (2009) find evidence for their hypothesis. They find that Sin firm equity instruments have 24% lower institutional ownership relative to firms in comparable non-Sin industries.

Aside from Becker's (2010) costs associated with norm violation, the Sin firm premium may be explained by the effects of shunning strategies by norm-constrained institutional investors on the size and composition of the Sin firm investor pool. Merton (1987) focuses on the effect of the reduced investor base that arises by neglect of an asset by a subset of investors. He argues that neglected securities need to outperform their peers due to limited risk-sharing. He proposes that an individual investor is burdened by a larger share of idiosyncratic risk when this risk is shared amongst a smaller group of investors. Merton (1987) argues that investors demand compensation for the inflated risk associated with investing in a neglected security. He calls this the neglect effect.

Hong and Kacperczyk (2009) mention that the neglect effect is more pronounced for Sin stocks. They argue that Sin firms have a heightened litigation risk due to the nature of their business models. As litigation risk is idiosyncratic by definition, it is an important price driver for investors. Again, due to limited risk-sharing amongst investors for Sin firms, the heightened litigation risk has a relatively large impact on the expected returns by asset holders. In short, limited risk-sharing amongst a reduced investor pool increases expected returns. This effect is more pronounced for Sin firms due to the heightened litigation risk.

Not only the reduced size but also the altered composition of the investor base potentially affects asset performance. A shift in the investor base composition from institutional to retail investors may incite information asymmetries, for which investors demand compensation. Hong and Kacperczyk (2009) find that 21% fewer analysts follow Sin firms relative to non-Sin firms and argue that this is because analysts mostly cater to institutional investors. Doukas et al. (2005) argue that the number of covering analysts is a proxy for information asymmetry. Apart from firms with exorbitant numbers of analysts, they find a negative relationship between the number of covering analysts and information asymmetry. Therefore, Sin firms that are followed by fewer analysts, may pay a premium to compensate for information asymmetries.

Another potential driver of downward price pressure is reduced market liquidity for Sin stocks (Amihud & Mendelson, 1986; Datar et al., 1998). Liquidity is determined by the number of trades and the volume of shares traded. Since a smaller investor base is likely to make fewer trades, the reduced investor base resulting from the shunning of Sin firms is likely to lower market liquidity. Investors demand compensation for the risk that they cannot sell their assets for the market price at any time, which increases the expected returns.

In short, the shunning of Sin firm assets by norm-constrained institutional investors has various direct and indirect effects on asset prices. A smaller investor pool may induce the neglect effect and decrease asset liquidity. Moreover, the shift towards retail investors can enlarge information asymmetry and subsequent information risk.

2.2 Evidence from capital markets

A vast body of empirical literature has developed around the effect of various social norm specifications on asset prices. In this section, I review the current state of the empirical literature. I include studies into the relationship between the cost of capital and broadly specified Socially Responsible Investing (SRI) screens, Corporate Social Responsibility (CSR) scores and Sin firm status. First, I discuss literature on the equity side of corporate financing and thereafter the debt side.

2.2.1 Evidence from equity markets

Analysing SRI funds is perhaps the simplest way to study the relative performance of good and bad investments. For example, Geczy et al. (2005) compare U.S. mutual fund portfolios with an SRI objective to the universe of U.S. mutual funds. They show that adhering to SRI constraints imposes a cost of only a few up to as much as 30 bp per month. The level of incurred SRI cost depends on the belief in CAPM and managerial skill. The more belief is put in managerial skill, the higher the incurred cost. Renneboog et al. (2008) study the effect around the globe and find that SRI funds in the US, UK, many European and Asia-Pacific countries underperform the benchmark by 2.2-6.5%. Notably, the risk-adjusted returns of SRI are not statistically different for most countries. More recent studies reaffirm these results. Reboredo et al. (2017) find that alternative energy funds underperform their peers and a survey into the motivation for investors to hold SRI funds by Riedl and Smeets (2017) show that financial motives only play a secondary role.

Apart from SRI screens, investors can use constraints based on CSR performance. Empirical research contrasting well-performing and poor-performing firms on CSR measures yields contradicting evidence (Kempf and Osthoff, 2007; El Ghoul et al., 2011). However, a CSR score signals much more information than a firm's ethical behaviour. It encompasses ethical conduct, business model sustainability, better stakeholder relations and more. For example, the employee relations score only partly reflect ethical conduct towards employees. Better employee relations also improve employee-retention and thereby, for example, increase economies of learning. As CSR scores entail much more information, high CSR scores take away a lot of information asymmetry, reducing expected returns (Jensen and Meckling, 1979). Therefore, CSR scores are too noisy to study the effect of social norms on the capital markets directly.

As mentioned, Hong and Kacperczyk (2009) recognised this issue and incited a series of papers that attempt to isolate the effect of social norms by equating Sin firm status to unethical firm behaviour. They find evidence for a Sin firm premium of 25 to 33 bps per month over different sample periods between 1926 and 2006. They analyse Sin stock returns relative to a basket of similar firms in other industries and correct for market returns. Fabozzi et al. (2008) expand Hong and Kacperczyk (2009) work to 21 other equity markets during the period 1970 till 2007. As can be seen in exhibit 3 of their paper, they find an annual excess return between 11.15% and 13.70% for Sin firms at the portfolio level. Another affirmation is the continuing outperformance of the US Vice Fund compared to the S&P 500 and Domini social equity fund found by Chong et al. (2006). Altogether, researchers find consistent evidence for inflated equity returns for firms that score low on social desirability measures.

2.2.2 Evidence from debt markets

As firms generally finance themselves through both equity and debt, consistently inflated equity cost for unsocial firms may cause a flee to potentially cheaper debt. Hong and Kacperczyk (2009) find evidence for this phenomenon as they find that Sin firms have, on average, a 20% higher debt to equity ratio than their non-Sin counterparts. In this section, I review the empirical literature on the relationship between social norms and the cost bank loans and corporate bonds.

Some research has been conducted into the relationship between the interest on bank loans and various specifications of firm ethical behaviour. Goss and Roberts (2011) study the effect of CSR concerns on the cost of bank loans, based on thirteen CSR criteria. They offer two competing hypotheses; CSR spending either reduces firm risk or CSR spending wastes resources due to misspending. Goss and Roberts (2011) conclude that the first hypothesis primarily applies as they find that U.S. firms with CSR concerns pay a 7 to 18 bp premium compared to responsible firms. Concluding that CSR investments effectively reduce risk which results in lower interest rates on bank loans.

Kim et al. (2014) study the relationship between a self-constructed ethics score and the price of syndicated bank loans. Their ethics score is based on, amongst others, the level of disclosure of ethical behaviour and the existence of a corporate ethics policy. For a large sample of syndicated loans from 19 countries, they find that a one standard deviation increase in ethics score leads to a 24.8% reduction in mean loan spread. The difference is stronger when both borrower and lender adhere to similar ethical norms. Chava (2014) reaffirms these results. He finds that firms excluded by environmental screens pay an interest premium and that fewer banks participate in their loan syndicates. This is consistent with lower institutional ownership for unethical firms found in the equity market. Norm-constrained investors seemingly also shun unethical firms in lending decisions, yielding return disparities consistent with the neglect theory.

Again, CSR scores and self-constructed ethics measures face strong limitations as they (may) contain much more information. Therefore, Chalabi et al. (2018) directly investigate the relationship between social norms, measures by Sin firm status, and the cost of bank loans. Contrary to their own expectations, they find that Sin firms pay a consistently lower 42.71 to 57.2 bps spread than otherwise comparable firms. The Sin firm discount is robust for different explanations; superior accounting quality of Sin firms, reduced information asymmetry due to relationship lending, hedging value of Sin firm's anti-cyclical nature and organisational structure. Chalabi et al. (2018) conclude that banks profit from a Sin firm premium on the equity market by offering lower interest rates through their less transparent lending process.

Goss and Roberts (2011) find contradicting evidence in their aforementioned study on CSR and the cost of bank loans. They include exclusionary screen dummy variables for firms that operate in the Sin industries. Despite the fact that these dummies were not the objective of their analysis, they do yield an interesting insight. Tobacco firms pay an economically and statistically significant premium on their bank loan interest. Alcohol and gaming firms do not show such premia.

Fewer studies have been conducted on the relationship between ethical investing and the cost of corporate bonds. Firstly, studies using the noisy CSR measure yield inconclusive evidence. Ge and Liu (2015) find that higher CSR scores are associated with lower yield spreads. This relationship is stronger for firms with weak corporate governance and those that suffer high information asymmetries. Menz (2010) finds weakly statistically significant and contradicting results in a study on the relationship between CSR scores and European bond spreads. Secondly, studies using SRI measures find similar results as studies into bank loans. Oikonomou et al. (2014) find that good Corporate Social Performance is rewarded with lower credit spreads and poor performance punished by higher spreads. Polbennikov et al. (2016) study ESG measures and find that firms who score high on a composite ESG measure have slightly smaller spreads on their corporate bonds. This effect is most pronounced for the governance score but is modest for the social score.

To my knowledge, no studies have been conducted into the relationship between Sin firm status and corporate bond spreads. As a result, the potential flee by Sin firms to the debt market is only partly studied.

2.3 Social norm induced premium for corporate bonds

In this section, I translate the empirical literature and the theoretical relationship between social norms and asset returns into two hypotheses. I formulate my first hypothesis based on a comparison between the public debt and equity market and the implications of bond holder's limited monitoring role. I base my second hypothesis on studies exploiting known heterogeneities in social norm intensity.

2.3.1 The Sin firm premium

The previous paragraphs conclude that most publicly traded equity securities issued by firms who face some degree of a social norm against them, pay a premium on the cost of those securities. Only the noisy CSR measure yields mixed evidence. Assessment of the debt market for socially undesirable firms gives mixed results. On the one hand, poor CSR and SRI performers pay a premium on both publicly traded corporate bonds, as well as on the less transparent bank loans. On the other hand, Sin firms surprisingly receive a discount on their bank loans in one study and no research has been done into their cost of corporate bonds. I use two distinct characteristics to predict whether Sin firms pay a premium or receive a discount on their publicly traded corporate bonds. They may pay a premium like they do on their publicly traded equity securities or receive a discount as they do on their opaquer bank loans.

First, a distinction can be made along the debt or equity side of the asset. Equity capital providers may attach more value to ethical investing than investors in debt instruments. My review of empirical literature does not support this notion. Studies using SRI measures are most consistent, showing a premium for poor performers in equity markets and public bond markets. Nor is there a logical explanation that norm-constrained investors treat their debt and equity investments differently. Logically and empirically, it is unlikely that the neglect effect is different for public equity or debt instruments. Second, the studied assets are either publicly traded securities or privately issued bank loans. Banks may have a fundamentally different approach to the incorporation of social norms in their loaning decision than investors in their investment decision. To this end, I contrast a bank's crucial role as delegated monitor to the inferior monitoring role of a public corporate bondholder.

Diamond (1984) states that banks have a more important monitoring role than corporate bondholders because banks receive substantially more private information. The findings that poor CSR performers pay a bank loan premium by Goss and Roberts (2011) and Ge and Liu (2015) can then be explained a bank's use of its superior information position. A bank can customize loans directly to CSR performance. CSR underperformers pay a premium because of incurred agency costs and an increased risk profile. Meanwhile, bondholders have less information about a firm and cannot adjust their required return as well as banks can. Investors instead need to fare by publicly available information. Social norms against investing in an asset, that are part of the public information, then become a more important decision criterion.

Banks give a discount to Sin firms, which I explain using the inferior role of corporate bondholders as delegated monitors (Diamond, 1984; Chalabi et al., 2018). Otherwise, empirical literature consistently provides evidence that social norms induce a premium on the cost of debt and equity securities issued by socially undesirable firms. Therefore, I expect that social norms also lead to a Sin firm premium on the corporate bond market. This leads to my first hypothesis:

H1: Corporate bonds issued by firms that operate in Sin industries have higher credit spreads than corporate bonds issued by similar firms in comparable, non-sin industries

2.3.2 Cross & time variation in social norm intensity

A key assumption that I make is that social norms affect the propensity that (norm-constrained) investors hold a socially undesirable stock, which in turn affects asset prices through the neglect theory. However, asset prices are determined by myriad factors potentially explaining a Sin firm premium on corporate bonds. Longstaff et al. (2005) find that credit spreads are mostly determined by idiosyncratic credit risk, bond-specific illiquidity or sensitivity to market-wide illiquidity. So how can we distinguish between a social-norm driven difference in bond spreads from any other factor?

Luckily, social norms are heterogeneous over place and time. Where a 1900s doctor could carelessly smoke in the presence of his patients, that same act would nowadays be considered a disgrace. Similarly, alcohol consumption may be regarded as unhealthy and is somewhat frowned upon in the western world but is considered a sin in most Islamic cultures. This heterogeneity over time and place provides a quasi-experimental setting that some researchers exploited to study the relationship between social norm intensity and asset prices.

Hong and Kacperczyk (2009) and Chava (2014) consider reduced institutional ownership and fewer loan syndicate participants as evidence for the neglect theory. Hong and Kostovetsky (2012) use implied heterogeneity in social norms amongst republican and democratic investors to reaffirm this notion. They find that mutual fund managers that made donations to the democrats held less socially irresponsible stocks compared to managers who made donations to republicans. Similarly, Kumar et al. (2011) use geographic dispersion of Catholics and Protestants to study the effect of the social norm against gambling on the holding of lottery-type stocks. They assume that Catholics have a higher propensity to exhibit gambling-like behaviour than Protestants. A key finding is that more lottery-type stocks, with higher volatility and skewness, are bought in regions with a higher ratio of Catholic inhabitants. Both papers confirm the notion that asset holdings are influenced by social norm intensity.

Through the discrimination and neglect theory, heterogeneity in social norms then has the potential to affect asset prices. Fauver and McDonald (2014) find evidence for this by using geographic heterogeneity in social norms amongst 19 of the G20 countries. They link asset returns in these countries to social norms measures constructed by the World Values Survey. Controlling for other factors, they find that Sin stocks have a 1-2% lower equity valuation if a society strongly opposes such industries. This indicates that the premium on firms with poor social performance is dependent on the intensity of the social norm against investing in that industry.

Literature on heterogeneity in social norms substantiates my assumption that social norms affect asset holdings and returns. More intense social norms seemingly affect returns with greater impact. Therefore, if social norms drive a premium for Sin firms on the corporate bond market, I assume this effect to be larger when social norms are more intense. This translates into my second hypothesis:

H2: The Sin firm premium is positively related to the intensity of the social norm against investing in unethical firms

3. Data

3.1 Sample selection

I compile an initial sample of approximately 415,000 US bonds issued between Jan-2000 and Jul-2019 from the Mergent Fixed Income Security Database (FISD). I narrow down the total sample to a subsample of corporate bonds without any special features to enhance the quality of inferences drawn. Subsequently, I merge company and bond specific data to form my core sample. Lastly, I add economic and social variables necessary for separate analyses.

First, my paper's focus on the cost of corporate bonds requires that I delete all sovereign bonds from the sample. Then, I exclude bonds issued by financial firms because the high issue frequency by these firms would lead to overrepresentation in the sample. Moreover, financial firm bonds have other characteristics than ordinary corporate bonds because they are used to finance other loans. Subsequently, I follow Oikonomou et al. (2014) and exclude all non-standard and small bonds that are perpetual, zero-coupon, convertible, preferred security, exchangeable or a small bond with a nominal value below 100 million USD from my sample to the benefit of comparability. This selection yields 33,501 unique medium to large fixed coupon bonds without any special features, issued by 7,153 firms.

Second, I supplement the subsample of bonds with bond- and firm-level data to construct my core sample. I collect firm-level data from Compustat Fundamentals Annual database and use several sources for bond-level data. I find bond yield time series data on Refinitiv Datastream and use bond-level credit rating data from the Mergent FISD rating database. To compute credit spreads, I include US treasury yield data provided by Gürkaynak, Sack and Wright (2007). They estimate a smooth monthly yield curve for different maturities. I merge these datasets and drop bonds with missing observations on any of the aforementioned datasets. This procedure leaves a cross-sectional sample of 7,499 bonds issued by 1,152 firms.

Third, I transform the cross-sectional sample into monthly and yearly panel datasets and use the yearly panel dataset for my core analyses. A panel data structure allows and accounts for changing firm fundamental data or credit ratings over the lifetime of a bond. Each bond issue was duplicated for the number of months that it ran in the sample. I construct a yearly panel data by taking the 12-month mean of all variables, corresponding to a strategy applied by Oikonomou et al. (2014). The panel consists of 487,065 bond-months or 44,369 bond-years.

Last, I fuse two more firm-level and four general databases for supplemental analyses. I collect trends data from Google trends and US election data from USA.gov for my study of social norms heterogeneity.[2] Furthermore, I include IBES analyst coverage data, Thomson Reuters 13-F institutional equity ownership data and Relative Value Index data provided by Fontaine and Nolin (2019) for my liquidity analyses. And finally, I use FED economic data on a Bank of America Merrill Lynch A-rated corporate bond index to compute bond betas.

[2] Available on www.usa.gov/election-results, visited on 02-03-2020.

3.2 Data manipulation

3.2.1 Dependent variable: credit spread

I use the credit spread on corporate bonds as the dependent variable, which is the price of a corporate bond relative to a risk-free security. I calculate a bond's spread by subtracting the yield of a synthetic US treasury bond with equal maturity from its yield to maturity (Wang & Zhang, 2009). Thereby, the spread illuminates the risk premium that investors demand for lending out money to a firm. Simultaneously, this approach controls for market-wide interest fluctuations, as they also affect treasury bonds.

3.2.2 Independent variables

I perform a series of manipulations to my data to compute the variables that I use in my analyses. Appendix B lists those variables and their corresponding way of computation. Three variables require a more detailed description, which I provide in this subsection.

Credit ratings

I standardise S&P, Moody's and Fitch credit ratings provided by Mergent FISD by transforming them to a numerical rating scale. The highest AAA rating has the value 1 and the lowest D rating is 25. Appendix A shows the table used to construct ordinal credit ratings. For days with multiple credit ratings, I take the mean value and round off to the nearest integer. I repeat the procedure to find monthly and yearly mean credit ratings. If credit rating data is missing in a month, I use the last known (mean) rating. In a similar fashion, I compute an 8-point scale as proposed by Ashbaugh-Skaife et al. (2006).

Following the reasoning by Oikonomou et al. (2014), I use the credit ratings as a series of dummy variables as opposed to a continuous scale. They argue that the value of the slope coefficient would be devoid of meaning as a bond with a credit score of two is unlikely to have half the credit risk of a bond with credit rating one.

Google Trends data

Google Trends is a search trend feature that provides a monthly scale (1-100) on the monthly relative frequency that a search term or topic is entered into Google's search engine. This relative index is corrected for the site's total search volume. I collect US data on the three most related topics to ethical investing (ESG, Impact Investing and SRI) and most related search terms (ESG fund, impact investing and sustainable investing). This data is available from 2004-2019. I aggregate monthly scale data to a yearly measure and rescale the aggregate measures from 1-100.

Rolling bond beta

I compute a rolling bond beta to estimate a bond's sensitivity to a market index along the same line as Chalabi et al. (2018) and Hong and Kacperczyk (2009). First, I construct equal-weighted monthly returns for each Fama and French (1997) industry groups. Then, I apply a 60-month rolling window to regress industry-portfolio returns on an A-rated corporate bond index return compiled by Bank of America Merrill Lynch. I only keep rolling betas if at least 24 months of data are available for the regression.

3.3 Sin firm selection

3.3.1 Static industry screening

I select Sin firms following Hong and Kacperczyk (2009). I do an initial selection using Fama and French's (1997) 48 industry classification. I attribute smoke and tobacco companies with industry code 4 (SIC code 2080-2085), and beer or alcohol firms with industry code 5 (SIC codes 2100-2199) to the Sin firm group. Since the Fama-French classification does not specify gambling as an industry, I use a combination of NAICS and a single SIC code. I select firms with SIC code 7993 or NAICS codes 7132, 71312,713210, 71329, 713290, 72112, and 721120 as gaming firms and regard them as a part of the Sin firm group.

To include firms that run a Sin business unit in otherwise diversified operations, I supplement my Sin firm selection with a screening on the company segment level. I screen Compustat's company segment data using an identical SIC and NAICS code-based procedure as stated above and consider a firm to be Sinful when one of their segments falls in a Sin group. Subsequently, I supplement my Sin firm list with the one made available by Hong and Kacperczyk.[3] As a final step, I manually check each Sin firm for allocation errors.

Following Hong and Kacperczyk (2009), I also use SIC and NAICS codes to determine what firms belong to comparable, non-Sin industries. I attribute firms that belong the Fama and French (1997) industry groups 2 (food), 3 (soda), 7 (fun), and 43 (meals and hotels) as comparable to the Sin firms. For reasons elaborated on in Section 4.1, I assign all Sin firms to the comparable firm group.

My core sample lists 42 Sin firms that issue 472 bonds, totalling 2,523 Sin bond years in the panel dataset. Table 3.1 displays the aggregate distribution of total Sin bonds and per Sin category throughout my sample period. The number of Sin bonds increases over the years, which this corresponds to a larger number of corporate bonds in the whole dataset. Sin bonds are distributed fairly over the alcohol, tobacco and gaming industry.

[3] Available on www.columbia.edu/~hh2679/sinstocks.pdf, visited on 09-10-2019.

Table 3.1
Overview of the number of Sin bonds listed per year. Both the total number of Sin bonds are listed, as well as the number of Sin bonds per Sin sub-category. The last column displays the yearly total number of bonds in the sample.

Year	Sin bonds	Alcohol bonds	Tobacco bonds	Gaming bonds	Total bonds
2000	6	1	0	5	113
2001	64	27	7	30	1199
2002	77	31	9	37	1352
2003	93	36	13	44	1586
2004	110	38	13	59	1753
2005	110	34	13	63	1805
2006	122	34	20	68	1806
2007	125	42	28	55	1798
2008	99	14	31	54	1749
2009	120	23	39	58	2218
2010	131	34	39	58	2447
2011	147	44	44	59	2669
2012	165	61	51	53	2942
2013	189	72	58	59	3204
2014	186	70	61	55	3436
2015	200	79	73	48	3658
2016	211	85	87	39	3760
2017	198	91	65	42	3712
2018	170	73	61	36	3162

3.3.2 Time varying 10-k text analysis

Hoberg and Philips's (2016) construct yearly product relatedness scores for firm pairs based on 10-k filing text analysis. They list pairs that cross a relatedness threshold, resulting in a year-varying list of comparable firms for each firm. I use their list to construct a time-varying Sin and comparable firm list. Firstly, I find the comparable firms for each original Sin firm. Then, I attribute the three firms with the highest relatedness score to the new, time-varying Sin firm list. This operation yields 190 new Sin firms, with corresponding product relatedness scores to the original Sin firm list.[4]

Then, I compile a list of time-varying comparable firms. I start by extracting the comparable firms of the newly selected Sin firms from the H&B dataset. I refine this list by selecting the most frequently listed comparable firms. I select twice the number of comparable firms as Sin firms listed in any given year. For example, if a year has 30 listed Sin firms, I select the 60 most frequently listed

[4] 119 of the new Sin firms are listed as a comparable to an original Sin firm more than once. The maximum listing frequency of a firm is 45 and the mean listing frequency is 6.2 times. I assign the highest product related score to the new Sin firm if it is ranked in the top three for multiple original Sin firms.

comparable firms.[5] I include firms with the highest product relatedness score in case of equal frequency. These operations yield a list of 494 time-varying comparable firms.

Lastly, I assign each time-varying Sin firm to the time-varying comparable group for methodological purposes (see Section 4.1). All this yields 1,685 new Sin firm-years and 2,741 new comparable firm observations in the yearly panel.

3.4 Descriptive statistics

Table 3.2 provides descriptive statistics on the dependent variables, Sin and comparable firm dummies and key firm- and bond-level control variables. I winsorize accounting variables underlying the control variables at the 1% level to mitigate the effect of outliers. I list the mean, median, first and 99th percentile and the number of observations per variable. My core sample contains 44,369 bond-years. Institutional ownership, number of analysts and rolling bond beta are used in sub analyses and have slightly fewer observations. The mean credit spread is 2.96% on for all bond-year observations and had a large 3.439% standard deviation. Correspondingly, credit ratings have a similar standard deviation and a mean rating of 9.83 (close to BBB-). Sin firms are not significantly under- or overrepresented on the corporate bond market compared to the equity market. 5.7% of bond-years are classified as Sinful, whereas for example Kim and Venkatachalam's (2011) equity sample contains 4.8% Sin stocks.

[5] This would yield 3,620 comparable firms. I consider this too many as almost half of the firms in my core sample would be listed as comparable firms. For sake of comparability, I select a similar 1:2 ratio of Sin to comparable firms as in the main analysis. The average comparable firm in my time-varying list is listed as comparable 6.7 times each year.

Table 3.2
Descriptive statistics of all variables in the yearly panel data analyses. All accounting-based variables have been winsorized at the 1% level. For each variable, I show the mean, the median (p50), the standard deviation (SD), first percentile (p1), 99th percentile (p99) and the number of observations.

VARIABLES	Mean	p50	SD	p1	p99	N
Dependent variable						
Spread (bond - treasury)	2.956	1.775	3.439	0.245	20.69	44,369
Industry dummies						
Sin firm dummy	0.0569	0	0.232	0	1	44,369
Comparable dummy	0.111	0	0.315	0	1	44,369
Time-varying Sin firm dummy	0.0380	0	0.191	0	1	44,369
Time-varying comparable dummy	0.0618	0	0.241	0	1	44,369
Firm-level variables						
Altman's z-score	1.509	1.459	1.088	-1.718	4.486	44,369
Big4 dummy	0.971	1	0.167	0	1	44,369
Capex to sales ratio	0.0366	0.00641	0.220	-0.833	1.132	44,369
Free Cash Flow to assets ratio	0.0451	0.0485	0.0892	-0.318	0.274	44,369
Institutional ownership	0.701	0.762	0.245	0.000492	1	43,430
Interest coverage ratio	7.013	5.019	7.530	-6.318	38.70	44,369
Leverage ratio	0.321	0.296	0.160	0.0472	0.910	44,369
Market capitalisation	33,569	11,600	55,752	76.05	288,921	44,369
Market to book ratio	1.026	0.807	0.785	0.0532	4.079	44,369
Number of analysts	15.90	15.58	8.528	1	37.08	39,311
R&D to sales ratio	0.0207	0	0.0446	0	0.214	44,369
Return on assets	0.0903	0.0879	0.0697	-0.187	0.281	44,369
Total Assets	33,200	14,690	56,656	431.5	272,315	44,369
Bond-level variables						
Credit rating	9.832	9	3.848	2	21	44,369
Nominal bond value	554,316	400,000	697,348	100,000	2.500e+06	44,369
Remaining maturity (years)	8.757	6	7.715	1	30	44,369
Rolling bond beta	1.312	0.693	14.32	-1.708	11.40	44,342
Rule 144a dummy	0.188	0	0.391	0	1	44,369
Rule 414 dummy	0.535	1	0.499	0	1	44,369

4. Methodology

4.1 General methodology

My research question aims to elicit credit spread differences on the corporate bond market between Sin and non-Sin firms. I study the potential credit spread difference using an OLS panel regression model that I derive from studies with similar objectives (Hong & Kacperczyk, 2009; Oikonomou et al., 2014; Ge & Liu, 2015; Chalabi et al., 2018). My model measures the difference in credit spread between bonds issued by Sin firms and those issued firms in comparable non-Sin industries, controlling for bond and firm characteristics. I specify my model as follows:

$$Spread_{it} = \alpha + \beta_1 * Sin\ dummy_i + \beta_2 * Comparable\ dummy_{it} + \beta_3 * Firm\ control_{it} + \beta_4 * Bond\ control_{it} + Year\ indicator_t + \varepsilon_{it}$$

The Sin dummy takes on the value 1 if bond i is issued by a Sin firm and zero otherwise. The Comparable dummy is 1 if bond i is issued by a comparable or Sin firm. Firm control is a vector of firm characteristics. Bond controls is a vector of the following bond-level control variables. Year indicator is a dummy variable for each year in my sample. $\boldsymbol{\varepsilon_{it}}$ represents the error term.

The credit spread may be heavily reliant on the type of industry a firm belongs to as each industry faces typical risks or competitive environments. I address this by following the conservative model specifications of Hong and Kacperczyk (2009) and Chalabi et al. (2018). I aim to take out industry-specific determinants for Sin firms by comparing Sin yields to that of a natural comparable industry in one of Fama and French's (1997) consumer industry groups.[6]

To achieve an easy to interpret coefficient and test for significance, I follow Chalabi et al. (2018) and include all Sin firms in the comparable group. Because of this, a comparable firm has an average credit spread of β2. Meanwhile, a Sin firm has β1 + β2 mean spread. The average spread difference between Sin and comparable firms therefore equals to (β1 + β2) − β2 = β1. Significance of this coefficient signals a mean shift in credit spreads between Sin firms and firms in comparable non-Sin industries. Subsequently, an observed Sin firm premium cannot be explained by investor preferences for stable consumer industries.

Finally, I use the Year indicator to correct for year fixed effects because of the likelihood that credit spread variation is partly explained by variation over time. Moreover, I cluster standard errors at the firm level as the standard errors in an OLS panel regression model may be biased due to residual correlations (Petersen, 2009).

[6] Comparable industries are food (2), soda (3), fun (7), and meals (43).

4.2 Interaction effect

In some further analyses, I aim to find out the relationship between a certain risk, liquidity or social norm variable and the Sin firm premium. To that end, I add different variables as an interaction term to the Sin firm dummy. In those further analyses, my model is as follows:

$$\begin{aligned} Spread_{it} = {} & \alpha + \beta_1 * Sin\ dummy_i + \beta_2 * Sin\ dummy * Interaction\ var + \beta_3 \\ & * Comparable\ dummy_{it} + \beta_4 * Comparable\ dummy * Interaction\ var\ \beta_3 \\ & * Firm\ control_{it} + \beta_4 * Bond\ control_{it} + Year\ indicator_t + \varepsilon_{it} \end{aligned}$$

The above model is identical to the previous model, except for additional interaction terms to the bond and time-varying Sin and comparable dummies. I am interested in the joint effect between the interaction variable and Sin firm status. Therefore, I add a primary interaction term to the Sin firm dummy and a secondary one to the comparable dummy. As Sin firms are also represented in the comparable group, leaving out the interaction term with the latter would render the primary interaction term uninterpretable. As the interaction variables themselves only vary by year, I do not control for them separately. Their separate effect is already captured by the Year indicators.

5. Results

In this section, I explore the existence and drivers of a Sin firm premium on the public corporate bond market. Discussing hypothesis one in the first section shows that there is an economically significant but statistically insignificant Sin firm premium. In the later sections, I address drivers of the Sin firm premium. First, I aim to establish a connection between social norm intensity and the Sin firm premium level. Then, evaluate whether illiquidity or risk may explain an observed premium. Last, I perform several robustness checks, including a new Sin and comparable firm specification that allows for changing es in production over time.

5.1 The Sin firm premium

The results of a bare-bone analysis, only including year fixed effects, are depicted in column 1 of I display the dummy coefficients for each credit rating level in Appendix for the sake of parsimony. Conform expectations, high (low) credit ratings relate to spread discounts (premia). Strikingly, only the coefficients for the lower-rated bonds are statistically significant. Moreover, a credit
Table 5.1. The statistically insignificant comparable industry dummy coefficient indicates that Sin firms and their comparable industries jointly receive an average discount of 63.1 bp on their spread. The Sin firm dummy coefficient indicates a statistically insignificant 74.0 bp additional discount for Sin bonds relative to comparable, non-Sin industry bonds.

This result contradicts expectations raised by the literature. However, this bare-bone model neglects myriad corporate credit spread determinants uncovered by academics. In this section, I discuss the expansion of the bare-bone model to the formation of my fully specified core model. I sequentially include credit ratings as well as bond- and firm-level control variables that proxy for risk and liquidity (Oikonomou et al., 2014; Ge & Liu, 2015; Chalabi et al., 2018).

5.1.1 Credit ratings

Bond spreads are primarily determined by default risk (Longstaff et al., 2005). Credit Rating agencies approximate the default risk for an asset and assign a fitting credit rating, depending on the risk level of that asset. Therefore, I include bond-level credit ratings as control variables.

Column 2 of Table 5.1 shows the results of my bare-bone model including credit rating dummy variables. The comparable industry dummy is now statistically significant at the 1% level, indicating that the supergroup of Sin and comparable firms receive an average discount on their credit spreads. The Sin firm coefficient increases slightly to a 2.8 bp discount relative to the comparable group. The changing Sin-firm coefficient from column 1 to 2 elicits that credit rating variation partially explains credit spread differences between Sin and non-Sin comparable firms. Furthermore, the addition of credit ratings significantly adds to the model's explanatory power as the r-squared increases from 3.1% to 65.2%.

I display the dummy coefficients for each credit rating level in Appendix for the sake of parsimony. Conform expectations, high (low) credit ratings relate to spread discounts (premia). Strikingly, only the coefficients for the lower-rated bonds are statistically significant. Moreover, a credit

Table 5.1
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Sin firm dummy	-0.740	-0.0283	0.0231	0.223	0.233
	(0.530)	(0.235)	(0.226)	(0.224)	(0.225)
Comparable industry dummy	-0.631	-0.638***	-0.669***	-0.653***	-0.652***
	(0.438)	(0.175)	(0.171)	(0.164)	(0.164)
Nominal bond value (ln)			-0.306***		-0.282***
			(0.0464)		(0.0493)
Remaining maturity (ln)			0.0582**		0.0644***
			(0.0236)		(0.0233)
Rule 414 registration			-0.180***		-0.179***
			(0.0468)		(0.0461)
Rule 144a registration			0.153*		0.129
			(0.0857)		(0.0857)
Assets (ln)				-0.471***	-0.398***
				(0.0591)	(0.0623)
Return on assets				-3.950***	-3.897***
				(0.726)	(0.721)
Altman's z-score				-0.154**	-0.153**
				(0.0666)	(0.0660)
Leverage ratio				0.146	0.162
				(0.298)	(0.300)
Interest coverage rate				0.0136***	0.0131***
				(0.00448)	(0.00445)
Free Cash Flow to assets ratio				-0.543**	-0.574***
				(0.220)	(0.221)
Capex-sales ratio				-0.287***	-0.330***
				(0.0988)	(0.0998)
Market-to-book ratio				-0.147***	-0.156***
				(0.0424)	(0.0421)
Big4 accountant dummy				-0.319**	-0.308**
				(0.156)	(0.156)
R&D-sales ratio				-3.141***	-2.624**
				(1.124)	(1.104)
Constant	4.380***	2.108***	5.771***	7.696***	10.40***
	(0.274)	(0.277)	(0.620)	(0.718)	(0.773)
Observations	44,369	44,369	44,369	44,369	44,369
Number of firms	1,152	1,152	1,152	1,152	1,152
Rating	N	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

rating increase does not always correspond to reduced average spreads. For example, Fitch-equivalent AA rated bonds have a higher average credit spread than AA- rated bonds. These inconsistencies may be explained by the popular and empirically justified criticisms of inaccuracy and lack of impartiality by CRAs (Longstaff & Schwartz, 1995; Ammer & Packer, 2000; Cheng & Neamtiu, 2009).

Credit ratings are a useful control as they explain a lot of model variation and are widely acknowledged to proxy for default risk. As the measure is not perfectly accurate, I implement additional risk controls in the subsequent models.

5.1.2 Bond-level control variables

I add several bond-level control variables that literature finds to proxy for risk or liquidity. Firstly, I include bond maturity as Khurana and Raman (2003) find that bonds with longer maturity are deemed riskier than those with shorter maturities. Secondly, I control for issue size as economies of scale in the underwriting process make larger bonds less risky. Also, larger bonds tend to be issued by larger and thereby safer firms. Moreover, Whang and Zhang (2009) find that issue size proxies for bond liquidity as larger bonds are traded more frequently, which reduces liquidity risk.

Thirdly, I add SEC rule 144a and 415 registration dummy variables as proposed by Ge and Liu (2015). Rule 144a registration allows for the private placement of a bond amongst a select group of (institutional) investors. I expect a positive relationship with the spread due to the increased bargaining power of the institutions. Conversely, I expect a 415-registration bond, that can be shelved and issued at later and more favourable time, to have a lower spread because of timing benefits for the issuer.

Results of the OLS regression including bond-level control variables are depicted in column 3 of Table 5.1. The size, maturity and SEC registration dummy coefficients have expected signs and are statistically significant. The Sin firm premium notably changes to a positive, yet statistically insignificant 2.3 bp, while the comparable industry coefficient retains similar magnitude and statistical significance.

5.1.3 Firm-level control variables

The last step to my core model is the inclusion of firm-level control variables that literature finds to proxy for default risk. I control for firm size and profitability as larger and more profitable firms are less likely to default. Therefore, I expect negative coefficients for the amount of assets in a firm and its respective return on assets. Moreover, I use Altman's (1968) z-score as a control for a firm's financial stability. Altman develops an accounting variable-based measure which takes on a higher value for lower default risk, which leads me to expect a negative coefficient.

Then, I control for measures more directly linked to a firm's ability to service its interest payments as proposed by Ericsson et al. (2009). I control for leverage ratio as firms that carry more debt relative to their equity, are more prone to problems servicing their interest payments. Following analogous reasoning, I include the interest coverage ratio. Firms who spend a larger portion of their EBIT on interest payments have a smaller buffer for adverse times.

Additionally, I control for growth options. Fauver and McDonald (2014) conclude that growth options reduce default risk and that they are proxied by the free cash flow to assets ratio and capital expenditures to sales ratio. Moreover, they find that Sin firms have more growth options than comparable firms. Along the same reasoning, I add the market to book ratio, as Chen and Zhao (2006) find that firms with higher market to book ratios have lower debt financing costs.

Kim and Venkatachalam (2011) propose that Sin firms suffer from inflated information risk due to poorer financial reporting but find evidence to the contrary. Sin firms have superior accounting quality due to the higher predictability of earnings and timely loss recognition. They propose that accounting quality is proxied by the controlling accountant and state that the big4 is superior to other firms. Therefore, I add a big4 accountant dummy and expect its coefficient to be negative.

Lastly, I add research & development (R&D) intensity as a control variable. McWilliams and Siegel (2000) find that R&D intensity moderates the relationship between CSR and financial performance. They argue that exclusion of the risk associated with R&D investments biases results. As higher R&D intensity is riskier, I expect a positive coefficient.

Column 4 of Table 5.1 depicts the results of a bare-bone model including credit ratings and firm-level control variables. The Sin firm coefficient increases to a statically insignificant 22.3 bp premium. The comparable industry coefficient does not notably change. The size, profitability and Altman's financial stability coefficients comply with my expectations. A more sizable, profitable or stable firm pays statistically significant lower credit spreads. Moreover, both measures for the ability to service interest payments have expected positive coefficients. Unexpectedly, the leverage ratio lacks statistical significance. This is surprising as Myers (2003) names leverage as a vital driver of credit risk in his static trade-off theory.

The control variables for growth opportunities comply with my expectations. The free cash flow to assets ratio, market to book ratio and capital expenditures to sales ratio have expected negative coefficients. Also, the Big 4 dummy coefficient is consistent with Kim and Venkatachalam's (2011) theory. Firms that are audited by a Big 4 accountant receive a 31.9 bp discount on their corporate bonds. However, this coefficient may lack meaning in my model as 97.1% of firms in my sample are serviced by a Big 4 accounting firm.

Contrary to my expectations, the R&D intensity has a highly significant and negative coefficient (-3.141). Firms that spend a mean level on R&D (0.021) receive a 6.6 bp discount on their corporate bonds. Contrary to McWilliam and Sigel (2000), R&D expenditures seem to lower firm risk. This may be explained by McAlister et al.'s (2007) findings that R&D expenditures generate new growth opportunities. Earlier, I reviewed papers that find evidence for a reduction in default risk when a firm has more growth opportunities.

5.1.4 Hypothesis 1

Finally, I combine all relevant control variables in my core model and display the results in column 5 of Table 5.1. The positive Sin firm dummy coefficient indicates that Sin firms pay a 23.3 bp credit spread premium compared to firms in similar industries without a Sinful nature. The coefficient lacks statistical significance. Thus, I cannot reject the statistical null hypothesis of equal credit spread means for Sin and non-Sin firms associated with hypothesis 1. However, the coefficient does provide evidence for an economically significant Sin firm premium. Over a large sample, Sin firms pay an average 7.9% credit spread premium compared to the 3.0% sample mean spread.

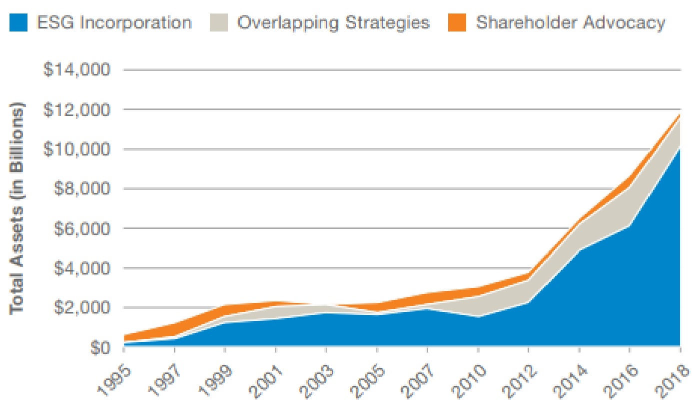
5.2 Proxies for social norm intensity

In this section, I investigate the hypothesis that the Sin firm premium is related to social norm intensity. Because social norms are inherently difficult to quantify, I use several novel proxies for the intensity of social norms against investing in Sin firms. I use time, Google trend analytics and investigate Sin firm premia under republican and democratic electoral reign. I conclude this section by rejecting my second hypothesis.

5.2.1 Time & SRI coverage

Firstly, I use time as a proxy for the intensity of social norms. Socially responsible investing has gained in importance over the years. Figure 1 shows that the assets under management by US money managers and institutional investors that fall under an SRI screen have grown from around $2 trillion in 2000 to $12 trillion in 2018. I assume that the increasing importance of SRI for investors is at least partially driven by intensifying social norms against socially undesirable investing. Therefore, I expect the effect of social norms on the bond market to intensify over time, which would result in an increasing Sin firm premium.

Figure 1
Asset volume under sustainable and responsible regimes by US money managers and institutional investors from 1995-2018.

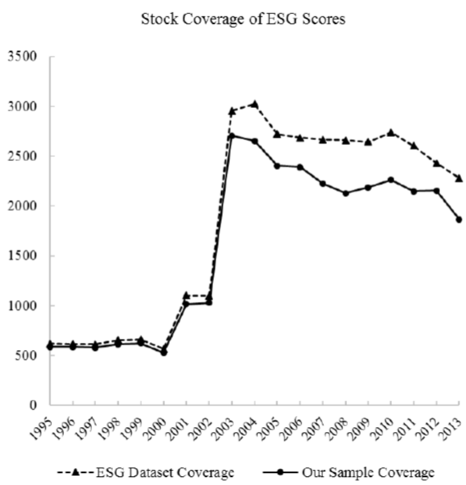


Source: US SIF foundation, 2018 Report on US sustainable, Responsible and Impact Investing Trends

I test this in a very simple model by adding a year interaction effect to the core model, while taking away the year fixed effects. This model is burdened by strong limitations as it assumes a linear relationship between time and the Sin firm premium, which is unlikely to be true. It is more likely that social norms changes are jerky since public opinion and legislative action comes in waves. Column 2 of Table 5.2 shows a negative interaction term between the year variable and Sin firm status. The small coefficient (0.004) indicates that the Sin firm premium slightly decreases over time. However, due to the simplicity and impactful limitations of this model, I investigate the relationship between the Sin firm premium and time in more detail.

I employ two other time variables. Firstly, I apply a similar sample period split as in Cao et al. (2019). They identify a shock in the number of firms covered in the Morningstar ESG database around 2005, depicted in Figure 2. Cao et al. (2019) argue that the sudden increase in covered firms shows that investors take a much larger interest in ESG investing from 2005 onwards. I generate a dummy variable for the sample period before and after 2005. The dummy takes on the value of 1 after 2005, which is the period with a higher interest in ESG investing. I keep year fixed effects to control for yearly variation and treat the threshold dummy for 2005 as an additional characteristic for the Sin firms. As I assume the attention of investors to proxy for the intensity of social norms, I expect a positive coefficient.

Figure 2
Number of stocks covered in the ESG database by financial analyst Morningstar from 1995-2013.



Source: Cao et al. (2018)

Secondly, I employ a pre- and post-crisis sample split. Contrary to my intuitive hypothesis on the relation between time and social norm intensity, Gerard (2019) concludes that the outperformance of excellent compared to poor ESG performers that was found in the 1990s, disappeared after the financial crisis. Pereira (2018) draws similar conclusions in his review of the relationship between CSR scores and bond performance in the EU. From these papers, I conclude that there is a break in the market's views on ESG investing before and after the financial crisis. Therefore, I include a dummy variable that takes on the value of 1 after the crisis (2009 and later) and 0 before the crisis (before 2007). I drop observations in the crisis in order to make a clean comparison.

Table 5.2
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. The year variable takes on a value of 1 in the first year of the sample (2000) and 20 for the last year of the sample (2019).

VARIABLES	(1)	(2)	(3)	(4)
Sin firm dummy	0.233	0.385	0.145	0.0995
	(0.225)	(0.396)	(0.295)	(0.291)
Comparable industry dummy	-0.652***	-0.749**	-0.813***	-0.740***
	(0.164)	(0.314)	(0.250)	(0.237)
Year*Sin dummy		-0.00372		
		(0.0253)		
Year*Com dummy		0.0148		
		(0.0209)		
Year		0.0268***		
		(0.00680)		
Sin*2005 split dummy(=1)			0.124	
			(0.232)	
Com*2005 split dummy(=1)			0.195	
			(0.203)	
Sin*pre/post crisis dummy(=1)				0.173
				(0.306)
Com*pre/post crisis dummy(=1)				0.206
				(0.250)
Constant	10.40***	10.66***	10.41***	10.30***
	(0.773)	(0.782)	(0.774)	(0.776)
Observations	44,369	44,369	44,369	36,157
Number of firms	1,152	1,152	1,152	1,142
Firmcontrol	Y	Y	Y	Y
Bondcontrol	Y	Y	Y	Y
Rating	Y	Y	Y	Y
Year FE	Y	N	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns 3 and 4 of Table 5.2 show the results of the model including the time-based sample split dummies. The interaction term between the 2005 sample dummy and the Sin dummy, displayed in Column 3, is 0.124. Meanwhile, the Sin firm premium decreases to 14.5 bp. It shows that the Sin firm premium is 12.4 bp higher after 2005. This result is in line with expectations and economically, but not statistically significant. Results displayed in column 4 reinforce this notion. It shows that the Sin firm premium is 17.3 bp higher after the financial crisis than before. Again, the interaction term is economically, but not statistically significant. The strongly reduced Sin firm coefficient (0.100) compared to column 1 (0.233) indicates that the Sin firm premium found in the core model is largely explained by post-crisis superior yields for Sin bonds.

These results fit Cao et al. (2019)'s hypothesis that increased attention for ESG by investors increases the importance of ESG scores for assets prices. They find that the impact of ESG measures on a subset of stock returns are more profound after 2005. On the contrary, my results do not match the conclusions of Pereira (2018) and Gerard (2019). However, incorporation of ESG measures in asset prices is different from incorporation of Sin firm status. ESG scores incorporate a broader array of return determining aspects, while Sin firm status isolates an ethical aspect as business processes cannot be made less Sinful.

Finally, these results are different from Hoe et al. (2017). They also find consistent outperformance of Sin funds before and after the financial crisis. But they find a higher pre-crisis premium than post-crisis premium. This may be instigated by the fact that their study focuses on Sinful mutual funds, and not on publicly traded corporate bonds.

Contrary to expectations raised by literature on pre-and post-crisis premia for poor ESG performers and Sin funds, my analyses indicate that the Sin firm premium has increased after the crisis. More importantly, the 2005 sample split results provide evidence for the notion that investor attention for SRI is positively related to the Sin firm premium. Under the assumption that investor attention is at least partially driven by social norms, this provides evidence for the hypothesis that social norms drive the Sin firm premium.

5.2.2 Google trend analytics

I also approximate the intensity of hard to quantify social norms by the relative attention for topics related to ethical investing on Google. I collect US data on the three most related topics (ESG, Impact Investing and SRI) and three most related search terms (ESG fund, impact investing and sustainable investing) from Google trend analytics. From this raw data, I create three aggregate measures: all topics, all search terms and a combination of all topics and search terms. I expect a more broadly specified measure to give a more accurate representation of the public interest in ethical investing, as it is unlikely that one measure perfectly represents the interest in ethical investing.

Again, I assume that increased attention for a subject by the public is at least partly instigated by intensifying social norms on the subject. Subsequently, I investigate whether the observed Sin firm premium is higher in years with a lot of attention to SRI related topics. I add separate interaction terms to my core model for each aggregate Google trend measure. I expect positive coefficients on the interaction terms as I expect the Sin firm premium to be more pronounced whenever there is more public interest in ethical investing.

Table 5.3 shows that the relationship between public interest in ethical investing and the Sin firm premium is only weakly backed by empirical evidence. One aggregate measure, the aggregate

Table 5.3
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. Sample runs from 2004 to 2019.

VARIABLES	(1)	(2)	(3)
Sin firm dummy	0.550	0.330	0.390
	(0.372)	(0.264)	(0.302)
Comparable industry dummy	-0.615***	-0.610***	-0.601***
	(0.236)	(0.181)	(0.203)
Topic interest scale*Sindum	-0.00203		
	(0.00784)		
Topic interest scale*Comdum	-0.00390		
	(0.00524)		
Search interest scale*Sindum		0.00475	
		(0.00497)	
Search interest scale*Comdum		-0.00481	
		(0.00396)	
Total interest scale*Sindum			0.00248
			(0.00610)
Total interest scale*Comdum			-0.00468
			(0.00452)
Constant	11.16***	11.14***	11.15***
	(0.855)	(0.854)	(0.854)
Observations	40,119	40,119	40,119
Number of firms	1,094	1,094	1,094
Firmcontrol	Y	Y	Y
Bondcontrol	Y	Y	Y
Rating	Y	Y	Y
Year FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

topic interaction term (column 1) is negative and statistically insignificant. The interaction terms of the aggregate search measure (column 2) and total interest scale (column 3) are positive and also statistically insignificant. Again, the coefficients do have some economic significance. According to the total interest scale model (column 3), the maximum theoretical difference of 100 points would result in a joint effect of public attention and Sin firm status on the credit spread of 24.8 bp. However, as my sample is a yearly average, the real maximum interest scale difference is much lower. At 55.5, the maximum impact of interest difference between the highest and lowest years accumulates to 13.8 bp.

This model is subjected to limitations as it is reliant on the selected topics and search terms in Google trends. Moreover, the assumption that Google trends accurately measures attention or the assumption that more public attention is related to social norm intensity, may not hold. Due to the weak statistical relationships and model limitations, my results only provide weak evidence for a relationship between social norm intensity, measured by google trends, and the Sin firm premium.

5.2.3 Red & blue investing

Lastly, I use democratic and republican electoral dominance as indicators for the intensity of social norms against unethical investing. I build this analysis on the assumption that democratic electoral dominance signals more fierce societal norms. Literature and surveys provide some evidence for this assumption. The 2007 National Consumers League conclude that more Democratic voters (96%) find it important that firms address social issues compared to Republican voters (65%). Additionally, Di Giuli and Kostovetsky (2014) finds that firms with Democratic founders have higher CSR scores relative to firms with Republican founders. Finally, Hong and Kostovetsky (2012) find that mutual fund managers who made donations to the Democratic party, hold less socially irresponsible stocks compared to managers who made donations to the Republican party.

I expand my core model with dummy variables for different types of republican dominance of US politics. I include a dummy that takes on the value of 1 (0) for a full year under Republican (Democratic) control. I leave out election years as their control sometimes changes mid-year. Furthermore, I include two republican election win dummies for the election year and post-election year. One dummy variable only has datapoints for presidential elections, while the other covers all years because it includes mid-term elections. I use the election and post-election year as I assume that the results of a directly upcoming or recent election are the most accurate approximation of societal norms. Of the three models, I consider the presidential election dummy to be the most insightful as public engagement and subsequent voter turnout in presidential elections is very high.[7]

The results depicted in Table 5.4 provide mixed and weak evidence for my hypothesis. Column 2 shows that the Sin firm premium is 7.4 bp lower during full years of Republican presidential control. Column 3 elicits that the Sin firm premium is 4.3 bp lower in presidential election years and post-presidential election years with a Republican win. Contrarily, the inclusion of mid-term elections changes the sign of the interaction term. This analysis gives a statistically insignificant 2.9 bp higher Sin firm premium in all (pre)election years with a Republican win. At best, these results provide weak evidence for a relationship between social norm intensity, measured by Republican electoral dominance, and the Sin firm premium. Moreover, this model has strong limitations as the election dummies that only vary by year may capture other effects entirely.

The previous model assumes that red & blue political views represent social norms against all types of unethical types of investments equally. However, assessing the campaign contributions to the Republican and Democratic party, displayed in Appendix E, makes it apparent that the tobacco industry has most to gain by a Republican win. The campaign donations by alcohol (Figure 4) and gaming

[7] www.usa.gov/election-results, visited on 02-03-2020.

(Figure 5) is somewhat equally spread over Republican and Democratic parties, while tobacco firms donate substantially more to the Republican party (Figure 3). Moreover, the study by Hong and Kostovetsky (2012) on stock holdings by Republican and Democratic mutual fund managers, names the tobacco industry as the most politically sensitive of the Sin firms. Subsequently, they find that tobacco firms are held significantly less by Democratic mutual fund managers.

Table 5.4
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. The republican control dummy takes on the value of 1 (0) for a full year under republican (democratic) control The republican (midterm) election win dummy takes on the value of 1 (0) for election and post-election years with a republican (democratic) win.

VARIABLES	(1)	(2)	(3)	(4)
Sin firm dummy	0.233	0.204	0.419	0.221
	(0.225)	(0.237)	(0.284)	(0.242)
Comparable industry dummy	-0.652***	-0.550***	-0.640***	-0.615***
	(0.164)	(0.178)	(0.173)	(0.175)
Republican control*Sindum		-0.0275		
		(0.253)		
Republican control*Comdum		-0.0721		
		(0.207)		
Republican election win*Sindum			-0.0481	
			(0.233)	
Republican election win*Comdum			-0.157	
			(0.142)	
Republican (mid) election win*Sindum				0.0157
				(0.0923)
Republican (mid) election win*Comdum				-0.0609
				(0.0653)
Constant	10.40***	10.82***	11.01***	10.40***
	(0.773)	(0.820)	(0.853)	(0.773)
Observations	44,369	37,240	22,455	44,369
Number of firms	1,152	1,135	1,132	1,152
Firmcontrol	Y	Y	Y	Y
Bondcontrol	Y	Y	Y	Y
Rating	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Consequently, the social norm against investing in tobacco firms may be more accurately measured by Republican political dominance than the norm against investing in other Sin industries. Therefore, I study the relationship between Republican political dominance and the Sin firm premium for tobacco firms separately. I exclude alcohol and gaming firms from my sample and list only companies belonging to the Fama-French 48 industry group food as comparable firms (Hong & Kacperczyk, 2009). In all other ways, my model is equal to my core model.

Table 5.5
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. The republican control dummy takes on the value of 1 (0) for a full year under republican (democratic) control The republican (midterm) election win dummy takes on the value of 1 (0) for election and post-election years with a republican (democratic) win.

VARIABLES	(1)	(2)	(3)	(4)
Tobacco firm dummy	0.803**	0.614	1.294***	0.809**
	(0.348)	(0.386)	(0.414)	(0.337)
Tobacco comparable dummy	-0.489***	-0.481**	-0.697***	-0.426**
	(0.178)	(0.221)	(0.143)	(0.180)
Republican control*Sindum		-0.0525		
		(0.160)		
Republican control*Comdum		0.362***		
		(0.117)		
Republican election win*Sindum			-0.247	
			(0.301)	
Republican election win*Comdum			0.151	
			(0.131)	
Republican (mid) election win*Sindum				-0.0155
				(0.0950)
Republican (mid) election win*Comdum				-0.103*
				(0.0550)
Constant	10.36***	10.77***	10.95***	10.35***
	(0.772)	(0.817)	(0.851)	(0.772)
Observations	44,369	37,240	22,455	44,369
Number of firms	1,152	1,135	1,132	1,152
Firmcontrol	Y	Y	Y	Y
Bondcontrol	Y	Y	Y	Y
Rating	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results depicted in Table 5.5 provide interesting insights. The Sin firm premium for tobacco firms in the core model (column 1) is economically and statistically significant at the 5% level. Tobacco firms pay an 80.3 bp premium compared to firms in the food industry. This constitutes a 27% tobacco firm premium relative to the mean sample spread. The tobacco comparable industry dummy has a statistically significant and expectedly negative coefficient. These results provide evidence for the notion that tobacco firms pay a social norm induced corporate bond premium compared to firms from a similar industry without a Sinful nature.

This time, the analyses including interaction terms with Republican political control provide consistent but weak evidence. All electoral dominance dummy interactions have expected, negative coefficients, indicating that the tobacco firm premium is lower during Republican electoral dominance. The effect is most pronounced for (pre-) presidential election years won by the Republicans. In those years, the tobacco firm premium is reduced by a statistically insignificant 24.7 bp. Inclusion of midterm elections reduces the electoral dominance interaction term to just 1.6 bp. The analysis on full years under Republican control (column 2) yields a negative but statistically insignificant coefficient of 5.3 bp tobacco firm premium reduction.

The consistently negative, but statistically insignificant coefficients on the electoral dominance dummies provide weak evidence for a reduced tobacco premium when support for the Republican party is high. However, this relation may not be purely driven by uncovered social norms against unethical investing. It may be caused by increased profitability due to laxer tobacco regulation under Republican control. Still, this relaxed approach by Republican leadership is chosen by the people and thereby at least partly represents the societal view on the tobacco industry.

5.2.4 Hypothesis 2

My investigations yield only weak evidence for a relationship between the intensity of social norms against unethical investing and the Sin firm premium. None of my tests using novel proxies for social norm intensity yield a statistically significant result. Therefore, I cannot reject the underlying null hypothesis of a correlation between social norm intensity and the Sin firm premium associated with hypothesis two. Despite the lack of statistical significance. my analyses do suggest a relationship between social norm intensity and the Sin firm premium level. Using time splits, Google Trends data and US election data, I offer somewhat consistent evidence.

5.3 Potential other drivers: Illiquidity & Risk

I use Merton's (1987) neglect theory to explain the observed premium on Sin firm bond spreads relative to non-Sin comparable bond spreads. However, the observed Sin firm premium may be driven by other factors. Longstaff et al. (2005) find that most of the credit spread can be explained by default risk. They state that the non-default aspect varies over time and is strongly related to firm-specific and market-wide illiquidity. As I aim to contribute a comprehensive study on the subject, I will address these other potential drivers in relation to the Sin firm premium in this section.

First, I assess whether Sin bonds are more or less sensitive to market-wide illiquidity. Then, I study the possibility that the Sin firm premium is random and merely sustained by impediments to arbitrage. Third, I investigate the implications of the popular anti-cyclicality theory for Sin assets. Last, I make some remarks on potential idiosyncratic risk drivers.

5.3.1 Sensitivity to market-wide illiquidity

Corporate bond spreads are partly determined by market-wide illiquidity (Longstaff et al., 2005). Investors want to be compensated for the risk of not being able to sell their assets at competitive market prices at the time of their preference. Lin, Wang and Wu (2011) find that bonds with high sensitivity to aggregate liquidity have 4% higher annual returns than firms with low sensitivities. Sin firms may be such firms with high sensitivities. This additional risk needs to be compensated for, which would (partly) explain the Sin firm premium. Alternatively, the Sin firm premium may be related to market-wide illiquidity through the neglect effect. As market liquidity dries up, an investor that wants to sell its Sin firm assets can only do so to the reduced investor base for Sin firms, inflating market-wide liquidity risk.

I test for Sin firm sensitivity to market-wide illiquidity using an aggregate illiquidity measure constructed by Fontaine and Nolin (2019). They improve a measure based on market noise constructed by Hu et al. (2013). Fontaine and Nolin infer market friction and transaction costs from the relative price levels of replicating bond portfolios (butterfly trades). They aggregate individual bond relative values to a Relative Value Index (RVI) for the US fixed-income market. A high RVI value corresponds to large average value differences and thereby high market-wide illiquidity. I add the RVI level as an

Table 5.6
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level.

VARIABLES	(1)	(2)
Sin firm dummy	0.233	0.0226
	(0.225)	(0.306)
Comparable industry dummy	-0.652***	-0.617***
	(0.164)	(0.214)
RVI*Sindum(=1)		0.0610
		(0.0633)
RVI*Comdum(=1)		-0.0113
		(0.0409)
Constant	10.40***	10.40***
	(0.773)	(0.774)
Observations	44,369	44,369
Number of firms	1,152	1,152
Firmcontrol	Y	Y
Bondcontrol	Y	Y
Rating	Y	Y
Year FE	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

interaction term with the Sin firm dummy to control for the sensitivity of market-wide illiquidity. A positive sign on the interaction term indicates that the Sin firm premium is higher when there is market-wide illiquidity.

Table 5.6 depicts the results of the standard model including all relevant control variables (column 1) and the model with the added RVI interaction term (column 2). Inclusion of market-wide illiquidity greatly reduces the magnitude of the Sin firm premium. The interaction term yields a positive but statistically insignificant coefficient (0.0694). This shows that the Sin firm premium is higher in periods with high market frictions. A one standard deviation increase (1.631) in RVI, increases the Sin firm premium by 11.3 bp. This is economically significant. The greatly reduced Sin firm premium and positive sign on the interaction term indicate that the Sin firm premium can be partially explained as compensation to investors for the sensitivity to market-wide illiquidity. Sin firms seemingly are sensitive to market-wide illiquidity, and investors demand higher yields in times with restricted market-wide liquidity.

5.3.2 Impediments to arbitrage

Differences in liquidity can also support another explanation. Persistent mispricing of Sin firm bonds may be unrelated to ethical investing and instead be sustained by arbitrage impediments (Schleifer & Vishny, 1997). Therefore, I use a two-sample t-test on known proxies for impediments to arbitrage to study whether Sin firms face inflated arbitrage impediments relative to their comparables. As arbitraging corporate bonds is mostly done OTC, little is known on indicators for impediments to arbitrage.

Asquith et al. (2013) use a proprietary dataset from an institutional investor to approximate the market for lending corporate bonds. They find that larger bond size and higher bond ratings negatively affect bond-lending costs. Furthermore, they conclude that borrowing stocks and bonds carries similar costs and are comparable in volume. Because of this similarity, I use two proxies for limits to arbitrage found in equity markets. Firstly, I use the negative relationship found between analyst following and arbitrage costs found by Zhang (2006). Secondly, I add institutional ownership of the publicly traded equity of the respective firm under the assumption that the ratio is similar for holdings of publicly traded corporate bonds. Nagel (2005) finds that short-sale constraints are likely to bind amongst stocks with low institutional ownership as they are the providers of loans.

Table 5.7 depicts the means comparison test between Sin and comparable firms. Contrary to findings by Hong and Kacperczyk (2009), Sin firms are on average followed by a statistically insignificant 0.529 more analysts than comparable firms.[8] Moreover, Sin bonds issued by Sin firms rank significantly higher on size. Sin firms also have a statistically significant lower credit rating, as a higher

[8] This striking result may be explained by the recent findings by Jo & Harjoto (2014) and Sharma & Song (2018). They respectively find that firms that engage more in CSR, have higher analyst following and that Sin firms conduct more CSR practices than non-Sin firms.

credit rating value corresponds to a lower rating. Lastly, sin firms have a statistically significant 4.0 per cent-point lower institutional ownership of their equity assets. This is in line with Hong and Kacperczyk (2009) and can be interpreted as an impediment to arbitrage as well as a clear indicator for shunning strategies by institutional investors. These results do not indicate that Sin firms are subjected to higher firm-specific impediments to arbitrage than comparable firms. Therefore, it is unlikely that the Sin firm premium is just random mispricing, that arbitrageurs fail to exploit.

Table 5.7
Mean comparison t-test between Sin and comparable firm-year observations on proxies for impediments to arbitrage.

	Sin & comparable	Sin firms	Comparable firms	Difference
	(1)	(2)	(3)	(4)
Spread (bond - treasury)	2.224	2.011	2.207	0.056
	2.287	1.924	2.223	
Size percentile	48.247	52.860	42.544	9.916***
	27.946	27.495	27.897	
Number of analysts	15.294	15.534	14.974	0.529
	6.888	5.441	8.428	
Credit rating	9.294	9.013	9.594	-0.553*
	3.613	3.761	3.312	
Institutional ownership	0.681	0.666	0.703	-0.040**
	0.182	0.149	0.209	
Observations	839	463	376	839

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3.3 Hedging value of anti-cyclical nature

A popular hypothesis in the literature is that Sin firms are less risky due to their anti-cyclical nature. The addictive nature of their products is theorized to make Sin firms less sensitive to the business cycle and thereby more recession-proof (Hong & Kacperczyk, 2009; Oikonomou et al., 2014; Chalabi et al., 2018). Investors may value this anti-cyclical nature as a market risk hedge and offer more favourable

Table 5.8
Mean rolling beta by Fama French 48 industry and separate gaming group. List of Sin and comparable industries.

Industry group	Rolling beta
Alcohol	0.711
Soda	0.771
Tobacco	0.943
Food	0.751
Gaming	0.587
Meals and hotels	0.724
Fun	0.550

loan terms. I investigate whether bonds issued by Sin firms have lower betas, and whether the inclusion of betas in my model affects the Sin firm premium. I expect a positive relationship between bond beta and credit spreads because investors want to be compensated for additional idiosyncratic exposure to market risk.

Table 5.8 shows no indication for systematically lower bond betas for bonds issued by Sin firms. Like in Hong & Kacperczyk (2009), the alcohol industry has a lower beta than the comparable soda industry. However, gaming and tobacco bonds do not have lower betas than bonds from comparable industries.

Table 5.9
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level.

VARIABLES	(1)	(2)
Sin firm dummy	0.233	0.229
	(0.225)	(0.225)
Comparable industry dummy	-0.652***	-0.653***
	(0.164)	(0.165)
Rolling bond beta		0.00567***
		(0.00123)
Constant	10.40***	10.41***
	(0.773)	(0.773)
Observations	44,369	44,342
Number of firms	1,152	1,145
Firmcontrol	Y	Y
Bondcontrol	Y	Y
Rating	Y	Y
Year FE	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column 2 of Table 5.9 shows similar results to Chalabi et al. (2018). The bond-level beta coefficient is positive and statistically significant at the 1% level. Also, adding bond beta as a control variable hardly affects the Sin firm premium. Suggesting that more cyclical firms pay higher credit spreads than less cyclical firms, while simultaneously suggesting that Sin firms are not less cyclical than comparable firms. The supposed hedging value caused by Sin firm's anti-cyclical nature does not offer an adequate explanation for the Sin firm premium, nor does the exclusion of bond betas lead to an underestimation of the premium.

5.3.4 Idiosyncratic risk

Differences in idiosyncratic risk between Sin and non-Sin firms can affect the credit spread as it is an important driver of expected returns (Longstaff et al., 2005). I want to mention several potential unobserved idiosyncratic risk factors that may drive the Sin firm premium. I do not study these factors empirically due to scope limitation and data availability issues.

Firstly, my analysis does not account for idiosyncratic return volatility. Malkiel and Xu (2002) find that idiosyncratic volatility partly explains cross-sectional expected returns. They build their argument on the premises that market participants cannot hold the entire market portfolio. Holding the market portfolio is a fundamental CAPM assumption as it allows investors to fully diversify away all idiosyncratic risk exposure. When this assumption is relaxed, investors cannot diversify sufficiently and must take on idiosyncratic risk. Investors want to be compensated for this additional risk, which explains part of the cross-sectional return variation.

This may be especially poignant for the Sin firm premium. Hong and Kacperczyk (2009) and I use Merton's (1987) neglect theory to explain the Sin firm premium. We argue that a significant portion of investors discriminates against Sin assets, resulting in risk-sharing amongst a smaller group of investors. Following Malkiel and Xu (2002) and Hong and Kacperczyk (2009), idiosyncratic risk exposure increases when more investors are limited in their portfolio choice, yielding higher asset return volatility. The observed Sin firm premium must then be explained as compensation for inflated idiosyncratic volatility instead of holding costs associated with unethical stocks.

Moreover, there may be unobserved differences in tail risk between Sin and non-Sin bonds. Kelly and Jiang (2014) conclude that stocks with a high tail risk loading outperform stocks with low tail risk loadings. Chava et al. (2014) confirm that bond investors also require compensation for tail risk by studying the bond premium and tail risk for financial institutions. Fatter tails for Sin firms relative to comparable firms may then explain the observed Sin firm premium in the corporate bond market.

Lastly, Sin firm risk relative to comparables may differ substantially over the business cycle. In the previous paragraph, I find that inclusion of bond betas does not alter the Sin firm premium. However, there may be other unobserved risk factors leading to differentiated risk profiles in times of economic expansion or downturn based on Matallín-Sáez et al. (2019). They find that the outperformance of non-SRI mutual funds is more pronounced in times of expansion than in economic downturn.

5.4 Robustness checks

Hong and Kacperczyk (2009), Oikonomou et al. (2014), Ge and Liu (2015) and Chalabi et al. (2018), all use slightly different model specifications, which may lead to different results using the same data. Moreover, my results may be sensitive to the way Sin and comparable firms are selected. Firstly, I address the Sin firm selection issue by employing a recently developed text-based industry classification. Also, I remove the comparison of Sin and comparables firms. Secondly, I evaluate the

Sin firm premium in a cross-sectional dataset at the moment of issue, as well as a monthly panel dataset. Lastly, I test the impact of alternative dependent variable and credit rating specification.

5.4.1 Industry classification

Comparison of Sin asset prices with assets from comparable, non-Sin firms is a cornerstone of the empirical literature I aim to supplement (Hong & Kacperczyk, 2009; Chalabi et al., 2018). However, previously found results on the Sin premium may be induced by erroneously choosing SIC code-based comparables. For example, asset returns of tobacco firms might not be comparable to that of food or alcohol to soft drinks. Therefore, I test the Sin firm premium without the comparable industry dummy. Instead, I include Fama-French 48 industry classification as fixed effects to account for industry-specific drivers of bond spreads.

Column 2 of Table 5.10 shows that the results are only slightly robust to the alternative model specification. The Sin firm coefficient remains positive and statistically insignificant but has greatly reduced magnitude (2.1 bp). Thereby, the economic significance of the Sin premium has nearly vanished, as Sin firms only pay a 0.7% premium on their corporate bonds compared to the sample mean. A similar result was found by Fabozzi et al. (2008), who forego a direct comparison with comparable industries for Sin equity assets and find a Sin firm premium. I expect the economic rationale for the model by Hong and Kacperczyk (2009) to add to the interpretability of the Sin firm coefficient. However, this analysis indicates that the Sin firm premium in my core model may be overstated if the selected comparables poorly resemble Sin firm characteristics.

My paper, and all other studies into the effect of Sin firm status on financial performance only use basic SIC and NAIC classifications to classify Sin and comparable firms. These classifications statically categorise firms by a broad product group. A firm is a member of a particular product group for its entire lifetime, despite possible changes in production or market circumstances. Moreover, this classification does not specify the degree of relatedness of firms, it merely identifies that firms belong to a group.

I combat this limitation by using a year-varying firm relatedness scores provided by Hoberg and Philips (2016) to construct a new list of Sin and comparable firms. Thereby, I allow for variation in product relatedness over time as businesses tend to (slightly) change over time. Hoberg and Philips use SEC 10-k filing text-analysis to determine product relatedness of firm pairs. They construct a yearly relatedness metric for each firm pair and list these pairs if the score crosses a threshold level. The newly comprised Sin and comparable firm list is time-varying and provides information on the degree of relatedness between firms.

I investigate the relationship between product relatedness with the original Sin firm list and the Sin firm premium for two reasons. Firstly, I test for the robustness of the Sin and comparable firm selection. Secondly, I investigate whether product relatedness to the original static Sin firms has a relationship with the magnitude of the Sin firm premium.

Table 5.10
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. Sin firm dummies in column 1 and 2 are based on static SIC/NAIC classification. Column two includes Fama-French 48 industry classification industry fixed-effects. Sin firm dummies in columns 3, 4 and 5 are based on 10-k text analysis. Columns 3, 4 and 5 have the same number of Sin firms.

	SIC/NAICS		Hoberg & Philips		
VARIABLES	(1)	(2)	(3)	(4)	(5)
Sin firm dummy	0.233	0.0201			
	(0.225)	(0.286)			
Sin comparable rank = 1			0.0617		
			(0.102)		
Sin comparable rank = 2				0.126	
				(0.115)	
Sin comparable rank = 3				0.0991	
				(0.0840)	
Sin product relatedness quintile 1				-0.0892	
				(0.186)	
Sin product relatedness quintile 2					0.106
					(0.138)
Sin product relatedness quintile 3					0.0357
					(0.108)
Sin product relatedness quintile 4					0.0609
					(0.116)
Sin product relatedness quintile 5					0.0186
					(0.167)
Comparable industry dummy					0.00888
					(0.389)
Constant	-0.652***		0.0618	0.0631	0.0576
	(0.164)		(0.0885)	(0.0894)	(0.0849)
	10.40***	9.939***	10.36***	10.36***	10.36***
Observations	(0.773)	(0.812)	(0.772)	(0.772)	(0.772)
Number of firms					
Firmcontrol	Y	Y	Y	Y	Y
Bondcontrol	Y	Y	Y	Y	Y
Rating	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	N	Y	N	N	N

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns 3, 4 and 5 of Table 5.10 display regression results with the time-varying Sin and comparable firm classification. Column 3 shows the results of the standard model specification and new industry classification. The Sin firm dummy remains positive and statistically insignificant, albeit with a smaller magnitude than in the standard static Sin classification model (column 1). So, firms with a high product relatedness score to the original Sin firm list, pay a premium on their corporate bonds. The time-varying group of Sin firms has a higher product relatedness score to the original Sin firms than the comparable group. Finding a premium for the time-varying Sin firms therefore provides evidence for a credit spread premium based on the degree of unethical business conduct.

In columns 4 and 5 of Table 5.10, I further investigate the relationship between a firms' product relatedness to the original Sin firms and their corporate bond spread. Hoberg and Philips (2016) only provide relatedness scores, which do not offer a clear-cut way to determine 'very relatable' firms. I test more restricted versions of the model presented in column 3 to test whether firms that have a higher product relatedness to the original static list pay a higher premium.

Column 4 shows that the Sin firm premium is largest for firms that were ranked highest on product relatedness to one specific original Sin firm (0.126), compared to those who were ranked second (0.099) and third (-.089). Strikingly, the coefficient for firms ranked third most comparable to a particular Sin firm is negative. This may be explained by the lack of an actual Sinful character for the third most relatable firm. This is supported by the data presented in Table 5.11, which shows that the share of time-varying Sin firms listed as Sin firms in the original static classification is decreasing as the relatedness rank is increasing. The highest-ranked firms were also a Sin firm in the Static list for 85.4% of the cases, while this is only the case for 66.1% of the third most relatable firms.

Table 5.11
Frequency of time-varying Sin firms also being listed as a Sin firm in the original static classification. Rank is determined by finding the first, second and third most comparable firm for each original Sin firm year based on Hoberg & Philips 10-k filing text analytics.

Product relatedness rank	Number of firm-years	% Sinful in static classification
Sinrank = 1	766	85.4%
Sinrank = 2	559	71.9%
Sinrank = 3	360	66.1%

In column 5, I display the results of an alternative product relatedness specification. For each year, I generate quintiles based on a firm's maximum product relatedness to a Sin firm in that given year. Quintile 1 (5) contains time-varying Sin firms with the highest (lowest) product relatedness score to an original Sin firm in that year. Across the different quintiles, I observe a statistically insignificant premium for Sin firms ranging from 0.9 to 10.63 bp from the lowest to the highest quintile. Like column 4, firms with the highest product relatedness to the original Sin firms pay the largest credit spread premia. Strikingly, there is no downward sloping premium for each higher quintile. Firms in quintile 2 pay a relatively lower premium to the other quintiles.

The results presented in columns 3, 4 and 5 show that the Sin firm premium is robust to an alternative, time-varying Sin and comparable firm classification. It also provides evidence for the relationship between the intensity of Sinful activities and the premium paid on corporate bond spreads. Firms whose products are more related to those of an originally listed and manually checked Sin firm pay a higher premium.

5.4.2 Cross-sectional & monthly panel data

Different studies use alternative data structures in their analyses. Chalabi et al. (2018) and Ge and Liu (2015) use a cross-sectional dataset of bank loan and bond issues respectively. Oikonomou et al. (2014) match the yearly frequency of their CSR statistic to monthly yield data and use a yearly panel dataset. Finally, Hong and Kacperczyk (2009) use a monthly panel in their analysis. In this paragraph, I study the effect of data structure on the Sin firm premium. Thereby, I discuss the choice for the yearly panel data structure used for the core analysis of my paper.

Table 5.12
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level. Column 1 contains purely cross-sectional data from the moment of issue of each bond. Column 2 and 3 contain yearly and monthly panel data respectively.

VARIABLES	(1)	(2)	(3)
Sin firm dummy	0.0610	0.233	0.0239
	(0.230)	(0.225)	(0.254)
Comparable industry dummy	-0.462***	-0.652***	-0.586***
	(0.148)	(0.164)	(0.202)
Constant	6.740***	10.40***	11.20***
	(0.955)	(0.773)	(0.958)
Observations	7,499	44,369	487,065
Number of firms	1,152	1,152	1,152
Firmcontrol	Y	Y	Y
Bondcontrol	Y	Y	Y
Rating	Y	Y	Y
Year FE	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.12 displays the OLS regression results for three different data structures. Column 1 depicts the results of the cross-sectional analysis of the moment of issue for bonds in my sample. Column 2 shows the results for the standard model specification I use in my paper and column 3 displays the results of the monthly panel. Each model specification has a positive but statistically insignificant Sin firm premium. The coefficient for the yearly panel data is the largest, with a Sin premium of 23.3 bp.

The cross-sectional dataset has the smallest coefficient with a statistically insignificant 6.1 bp Sin firm premium at the moment of issue. This effect has little economic significance, as Sin firms only pay a 2.0% premium compared to the sample mean spread. I expected to see a higher coefficient for the Sin premium at issue since bond issuance is a public process directly asking investors for their preferences. Norm-constrained investors might be less inclined to subscribe to new bonds because Sin firms do not try to place their bonds with them. The Sin firm premium is more observable for the yearly panel data, indicating that investors value the price of Sin more later in a bond's lifetime.

Analysis of the monthly data also yields a smaller Sin firm coefficient (0.024) than the yearly panel data. However, I believe that the yearly panel is more accurate as firm-level data is only available on a yearly basis. Like Oikonomou et al. (2014), I match the panel structure to the least frequently updated data.

5.4.3 Dependent variable & bond rating definition

As a last robustness check, I evaluate different specifications of the dependent variable and credit ratings. The dependent variable in my core model is the bond yield spread computed as the yield to maturity of the corporate bond minus the yield on a US treasury bond with equal maturity. This approach is shared by many authors (Jiang, 2008; Wang & Zhang, 2009; Ge & Liu, 2015; Chalabi et al., 2018). However, Oikonomou et al. (2014) take the natural logarithm of the computed spread to account for skewness in the bond yield spread distribution.

Table 5.13 displays various combinations of dependent variable and rating specifications. The first three columns depict the bond spread as I use in my core model. The latter three columns show the models using the natural logarithm of the spread as a dependent variable. In my core model (column 1), Sin firms pay a 23.3 bp premium, translating to a 7.9% premium relative to the mean spread. In the most comparable model using the natural logarithm of the spread (column 4), the coefficient of 0.0679 translates to a 7.0% premium relative to the mean. These similar results and the consistently positive Sin firm coefficient across all model specifications, indicate that my results are robust to the alternative spread computation.

Similarly, my results are robust for alternative implementations for credit ratings. My core model uses the 25-point scale constructed in accordance with Appendix A. Various other authors also use all available rating data, as more detailed rating information is a better proxy for default risk (Jiang, 2008; Chalabi et al., 2018). Conversely, Oikonomou et al. (2014) transform the available rating data to a 7-point ordinal scale and Ge and Liu (2015) use the logarithm of a 25-point scale as a continuous variable. Columns 2, 3, 5 and 6 show that the Sin firm premium is consistently positive and statistically insignificant. There are small differences in the magnitude of the Sin firm premium. However, I deem the 25-point scale specification to be superior as it includes more information.

Table 5.13
OLS regression result with bond spread as dependent variable in columns 1, 2 and 3. Dependent variable in columns 4, 5 and 6 is the natural logarithm of bond spread. Raw bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm specific credit ratings are included in three ways. Either as dummy variables on a scale of 1 to 25 (columns 1 and 4), as dummy variables from 1 to 7 (columns 2 and 5) or as the natural logarithm of the 7-point scale (columns 3 and 6). Standard errors are clustered at the firm level.

	Spread			Spread (ln)		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Rating (25)	Rating (7)	Rating (ln)	Rating (25)	Rating (7)	Rating (ln)
Sin firm dummy	0.233	0.152	0.115	0.0679	0.0360	0.0532
	(0.225)	(0.292)	(0.339)	(0.0624)	(0.0604)	(0.0541)
Comparable industry dummy	-0.652***	-0.709***	-0.601**	-0.165***	-0.158***	-0.146***
	(0.164)	(0.223)	(0.256)	(0.0424)	(0.0386)	(0.0332)
Rating (ln)			3.677***	0.952***		
			(0.579)	(0.0959)		
Rating scale 2/7		0.116			0.0152	
		(0.174)			(0.0447)	
Rating scale 3/7		0.309*			0.244***	
		(0.185)			(0.0493)	
Rating scale 4/7		1.463***			0.734***	
		(0.211)			(0.0555)	
Rating scale 5/7		2.228***			0.901***	
		(0.259)			(0.0607)	
Rating scale 6/7		6.168***			1.342***	
		(0.564)			(0.0753)	
Rating scale 7/7		0.500*			0.0212	
		(0.272)			(0.0808)	
Constant	10.40***	13.76***	8.193***	1.797***	3.228***	2.531***
	(0.773)	(0.984)	(1.749)	(0.396)	(0.213)	(0.226)
Observations	44,369	44,369	44,369	44,369	44,369	44,369
Number of firms	1,152	1,152	1,152	1,152	1,152	1,152
Firmcontrol	Y	Y	Y	Y	Y	Y
Bondcontrol	Y	Y	Y	Y	Y	Y
Rating	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

I investigate if and how social norms against unethical investing affect the US corporate bond market. My findings do not provide statistically significant evidence for a Sin firm premium on bond credit spreads. However, I do find such a Sin firm premium with economic significance, which is robust to alternative Sin firm selection and model specifications. I demonstrate that Sin firms pay an average 23.3 bp higher credit spread than otherwise similar firms in non-Sin industries. This makes debt financing through corporate bonds 7.9% more expensive for Sin firms relative to the 3.0% sample mean.

The economically significant Sin firm premium is in line with my first hypothesis and expectations raised by the literature. Many studies find a premium on debt and equity financing for socially undesirable firms based on SRI, CSR or Sin firm status. Surprisingly, Chalabi et al. (2018) find a discount for Sin firms on bank loans. In response, I use Diamond's (1984) suggestion that banks have a substantially more pronounced monitoring role than public bond investors. Banks determine loan spreads on much more (inside) information, causing social norms to be a smaller part of the equation. My theory is supported by my results. Like the premium on equity instruments found by Hong and Kacperczyk (2009), Sin firms pay a premium on publicly traded debt securities.

Fabozzi et al. (2008), Hong and Kacperczyk (2009) and Chong et al. (2015) explain the Sin firm premium by arguing that social norms affect holdings of investors, which in turn affects asset riskiness and/or liquidity. They provide ample evidence of Sin equity instruments being shunned by norm-constrained institutional investors. Through Merton's (1987) neglect theory, they explain how the shrunken investor base increases idiosyncratic risk taken on per investor. Subsequently, they argue that the Sin firm premium is investor compensation for taking on additional idiosyncratic risk. A major limitation of my paper is that I am unable to make similar inferences as I could not obtain corporate bond institutional ownership data.

Instead, I employ several novel public attention proxies to establish a relationship between the intensity of social norms against unethical investing and the Sin firm premium. I build these analyses on the assumption that increasing public attention is at least partly instigated by intensifying social norms. I can only provide weak and suggestive evidence for this notion, which forces me to reject my second hypothesis that predicts a positive relationship between social norm intensity and the Sin firm premium. These inferences are bound by another major limitation of my paper. I equate Sin firm status to social norms against unethical investments. Maybe, Sin firms do not face such social norms, maybe institution's bond holdings are unaffected by social norms or maybe my constructed proxies do not correctly resemble the social norm intensity. Regardless, I briefly discuss my three novel attention measures.

In time-based sample splits, based on Morningstar ESG coverage and assets under management affected by SRI screens, I find weak and statistically insignificant evidence for an increasing Sin firm premium over time. This contradicts literature that sees the disappearance of a premium for poor CSR performers after the financial crisis (Pereira, 2018; Gerard, 2019). However, as I propose on various occasions in my paper, CSR scores and Sin firm status are difficult to compare as CSR measures entail much more (non-ethics related) information.

Analyses using Google trends data on ethical investing related topics yield mixed evidence and face strong selection limitations. These analyses are sensitive to topic and search term selection and lack of evidence that these measures proxy for social norms. Still, the aggregate public opinion measure that I consider most insightful, explains up to 13.8 bp of the Sin firm premium.

Again, I find weak evidence when I proxy social norms against Sin industries by Republican electoral domination. I show that the Sin firm premium is reduced by a statistically insignificant 4.8 bp in years (leading up to) a presidential election won by Republicans. As campaign donations and Hong and Kostovetsky (2012) suggest that the tobacco industry is politically sensitive, I study it specifically. I find that the Republican election effect increases to 24.7 bp, confirming tobacco's inflated political sensitivity found in the literature. Moreover, I find that tobacco firms pay an average 80 bp credit spread premium relative to comparable firms in the food industry. This accidental finding incites further research into the Sin firm premium per industry, as each is affected by social norms in varying intensity. Also, this analysis is subject to limitations as my added variables only differ by year. These values might correlate with other unobserved factors.

I also investigate whether the Sin firm premium is driven by default risk, firm-specific liquidity or market illiquidity, which are the primary components of credit spreads (Longstaff et al., 2005). I find that inclusion of a market-wide illiquidity measure greatly reduces the Sin firm premium to a mere 2.3 bp. Moreover, I find a positive interaction term between market-wide illiquidity and the Sin firm premium, indicating that the Sin firm premium is higher in years with restricted market liquidity. These findings may be explained by Lin, Wang and Wu's (2011) findings that firms sensitive to market-wide illiquidity have higher returns than firms who are less sensitive.

Also, the positive interaction term provides an interesting insight related to Merton's (1987) neglect effect. I argue that a reduced investor base due to shunning strategies induces a sort of liquidity neglect effect. In a normal situation, investors want compensation for the risk that they are unable to sell their assets at the market price at any given time. A smaller investor base boosts this risk. If market liquidity dries up, the first affected firms are those with the fewest potential trading partners. Investors realise this and demand compensation for Sin firms' sensitivity to market-wide illiquidity. Unfortunately, I cannot provide evidence for this theory, as I am unable to obtain bond institutional ownership data. Besides, the RVI variable only varies by year, greatly increasing the risk of measurement error.

Furthermore, I do not find evidence for a popular theory that Sin firms are anti-cyclical. This hypothetically reduces their credit spreads as their market risk exposure diminishes. This is in line with Chalabi et al. (2018), who also find that their Sin firm coefficient is unaffected by inclusion of bond betas. Nor do I find evidence for the notion that the Sin firm premium is a random valuation error sustained by limits to arbitrage.

A last major limitation of my paper is that I am unable to study Sin specific idiosyncratic risk measures due to data availability and time constraints. I review literature that suggests that asset return volatility or tail risk distributions may drive the observed credit spread premium. Especially asset return volatility may shed light on the cause of the Sin firm premium. Malkiel and Xu (2002) find that investors who cannot hold a market portfolio, take on additional idiosyncratic risk in the form of asset return volatility. Since the neglect effect prescribes a smaller investor base, this effect may be more pronounced in Sin firms.

Further research can address limitations of my paper and shed light on the assumptions I make. Firstly, I recommend using a proprietary institutional investor dataset on corporate bond investments like Asquith et al. (2013) to find whether institutions actually shun Sin bonds. Moreover, Chalabi et al.'s (2018) work still suggest that Sin firms flee to more opaque markets and a proprietary dataset allows for studying of OTC trades. Secondly, I suggest constructing a more accurate measure for social norm intensity against investing in particular industries. This enhances my study into the relationship between social norm intensity and the Sin firm premium. Moreover, it allows for variation in social norm intensity between industries, something my static Sin firm status cannot. This addresses findings by Revelli and Viviani (2015), who point out that the outcome in SRI studies is heavily reliant on the used social desirability measure. Lastly, I want to suggest a similar comprehensive study on the European bond market. The EU's stakeholder-centric approach to governance may result in a more clearly observable effect than in the investor-centric US.

7. Conclusion

Recent political, public and investor interest in ethical sparks questions on the way social norms against unethical investing, in the form of shunning strategies, aide to achieve a sustainable future. My work addresses some of those questions. I study if and how social norms against unethical investing affect the cost of US corporate bonds. For this, I utilize the constant socially undesirable outcomes of alcohol, tobacco and gaming firms. Based on evidence in the literature, I assume that Sin firms are affected by social norms. I investigate this assumption in three manners. First, I determine whether Sin firms pay a credit spread premium on their corporate bonds while controlling for known risk and liquidity factors. Second, I try to establish a relationship between social norms and the Sin firm premium. Last, I address other risk or liquidity-based explanations.

I cannot provide statistically significant evidence for my first hypothesis that predicts a Sin firm premium relative to otherwise comparable firms. However, I do find a generally robust premium with economic significance. I show that Sin firms pay an average 23.3 bp higher credit spread than otherwise similar firms in non-Sin industries. This translates to a 7.9% inflated yield of corporate bonds relative to the 3.0% sample mean. My results are in line with literature that finds a neglect driven Sin firm premium on the equity market. With this finding, my paper complements a rich body of literature on the relationship between social desirability scores and the cost of capital.

Limited by data availability, I cannot study whether shunning of Sin firms by institutional investors drives the Sin firm premium. Instead, I use novel public attention proxies to attribute the Sin firm premium to social norm intensity. My second hypothesis predicts a positive relationship between the two. I find an indication that the Sin firm premium is 12.4 bp higher after a significant break in investor interest for ESG investing, measured by the number of firms covered in the Morningstar database. Also, the aggregate public opinion measure based on Google trends data explains up to 13.8 bp of the Sin firm premium. Another indication is that the Sin firm premium is 4.8 bp lower in (pre-) US presidential election years won by the Republicans, proxying social stance on ethical investing by republican electoral dominance. Unfortunately, these results are somewhat inconsistent and statistically insignificant. Therefore, I cannot further the literature by concluding that social norms drive the Sin firm premium.

As I fail to establish a relationship between social norm intensity and the Sin firm premium, I address other potential risk or liquidity-based drivers. Neither Sin firm anti-cyclicality or impediments to arbitrage sustain or mitigate the Sin firm premium. Sensitivity to market-wide liquidity seemingly explains a part of the Sin firm premium. However, this results also serves in support of a liquidity-based neglect theory. Lastly, scope and data availability inhibit empirical study of idiosyncratic asset return volatility or tail risk.

In conclusion, I find evidence for an economically significant but statistically insignificant Sin firm premium on the US corporate bond market. I cannot empirically establish a relationship between the Sin firm premium and the intensity of social norms against unethical investing, nor do I find another clear-cut driver. So, I cannot conclude what drives the Sin firm premium on the corporate bond market. Data on institutional ownership in equity studies points to the neglect theory as main the driver of the Sin firm premium. I find this credible for the corporate bond market too, as it is unlikely that norm-constrained institutional investors use vastly different SRI screens for stocks and bonds.

My inability to conclude what drives the Sin firm premium originates from my papers' three foremost limitations. Firstly, I build on the assumption that Sin firm status proxies for social norms against unethical investing. Secondly, I am unable to attribute the Sin firm premium to neglect by norm-constrained institutional investors as such data is unavailable. Lastly, I do not study Sin firm-specific idiosyncratic risk measures like asset volatility and tail risk. I encourage further research to tackle these issues.

Despite its limitations, my research adds to the literature on the relationship between social norms and Sin firms. It completes the research on financing costs for firms Sin firms specifically and adds to the literature on financing costs in relation to a firm's social performance more generally. Also, my findings are highly relevant for investors, legislators and managers. Investors can adjust their trading strategies based on the average premium, legislators may feel encouraged to further promote ethical investing as a means to achieve a sustainable society and Sin firm managers can take my research into account when making corporate financing decisions.

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Appendix

Appendix A
Table used to create the credit rating scale used in the core analysis. Bond level rating data was collected from Mergent FISD. If multiple ratings were available for a month, the mean rating scale was used. For the yearly panel, the mean rating scale was computed over the twelve months.

Rating scale	Fitch	S&P	Moody
1	AAA	AAA	Aaa
2	AA+	AA+	Aa1
3	AA	AA	Aa2
4	AA-	AA-	Aa3
5	A+	A+	A1
6	A	A	A2
7	A-	A-	A3
8	BBB+	BBB+	Baa1
9	BBB	BBB	Baa2
10	BBB-	BBB-	Baa3
11	BB+	BB+	Ba1
12	BB	BB	Ba2
13	BB-	BB-	Ba3
14	B+	B+	B1
15	B	B	B2
16	B-	B-	B3
17	CCC+	CCC+	Caa1
18	CCC	CCC	Caa2
19	CCC-	CCC-	Caa3
20	CC	CC	Ca
21	C	C	C
22			
23	DDD		
24	DD		
25	D	D	

Appendix B
Variables as named and used in the analyses. The variable description explains how the variable is computed, or on what basis values are assigned.

Variable name	Variable description
Spread	Yield to maturity – yield on a synthetic US treasury bond with equal maturity
Credit rating scale	Dummy variables for each level of S&P, Moody's and Fitch ratings. 1 = AAA, 25 = D
Nominal bond value (ln)	Natural logarithm of the nominal bond value in thousands of USD
Remaining maturity (ln)	Natural logarithm of remaining maturity in years

Rule 414 registration	Dummy variable, value of 1 if a bond has a 414 registration, 0 if not.
Rule 144a registration	Dummy variable, value of 1 if a bond has a 144a registration, 0 if not.
Assets (ln)	Natural logarithm of the issuing firms' assets in millions of USD
Return on assets	Earnings before interest and taxes (EBIT) divided by total assets
Altman's z-score	(1.2*Working capital ratio + 1.48*Retained earnings + 3.3*EBIT + 0.999*Revenue) / Total assets
Leverage ratio	Outstanding long-term debt divided by total assets
Interest coverage ratio	EBIT divided by interest and related expenses
Free cash flow to assets ratio	(Net income + net cash flow from operating activities + net cash flow from financing activities + net cash flow from investment activities) / Total assets
Capex to sales ratio	(Property plant and equipment [n] – Property plant and equipment [n-1]) / Total sales
Market to book ratio	Market capitalisation / Total assets
Big4 accountant dummy	Dummy variable, value of 1 if firm's accountant is a Big4 firm, 0 if not
R&D to sales ratio	Research and development expenses / Total sales
RVI	Relative Value Index
Number of analysts	Mean number of analysts issuing earnings forecasts for a firm over a given month or year
Institutional ownership	Mean share of a firm's outstanding equity held by institutional investors
Rolling bond beta	Bond's rolling return beta computed using a regression on the BAML A-rated corporate bond index

Appendix C
OLS regression result with bond spread as dependent variable. Bond spread is computed as bond yield minus the yield on a US sovereign bond with equal maturity. Firm-specific credit ratings are included as dummy variables on a scale of 1 to 25. Standard errors are clustered at the firm level.

VARIABLES	(1)	(2)	(3)	(4)	(5)
Sin firm dummy	-0.740	-0.0283	0.0231	0.223	0.233
	(0.530)	(0.235)	(0.226)	(0.224)	(0.225)
Comparable industry dummy	-0.631	-0.638***	-0.669***	-0.653***	-0.652***
	(0.438)	(0.175)	(0.171)	(0.164)	(0.164)
Credit rating = 2, AA+		-0.350***	-0.348***	-0.209**	-0.218**
		(0.0943)	(0.0708)	(0.0844)	(0.0941)
Credit rating = 3, AA		0.0841	0.0997	-0.237	-0.199
		(0.315)	(0.307)	(0.348)	(0.374)
Credit rating = 4, AA-		-0.238	-0.183	-0.413**	-0.338
		(0.224)	(0.208)	(0.201)	(0.251)

Credit rating = 5, A+		-0.117	-0.0711	-0.320*	-0.254
		(0.205)	(0.197)	(0.178)	(0.236)
Credit rating = 6, A		-0.117	-0.0917	-0.331*	-0.284
		(0.219)	(0.209)	(0.198)	(0.251)
Credit rating = 7, A-		0.0662	0.109	-0.198	-0.134
		(0.215)	(0.205)	(0.201)	(0.254)
Credit rating = 8, BBB+		0.205	0.258	-0.160	-0.0836
		(0.209)	(0.199)	(0.202)	(0.256)
Credit rating = 9, BBB		0.572***	0.626***	0.0794	0.158
		(0.211)	(0.201)	(0.216)	(0.268)
Credit rating = 10, BBB-		0.799***	0.851***	0.221	0.301
		(0.214)	(0.203)	(0.220)	(0.271)
Credit rating = 11, BB+		1.844***	1.865***	1.136***	1.204***
		(0.229)	(0.219)	(0.239)	(0.288)
Credit rating = 12, BB		2.293***	2.298***	1.472***	1.530***
		(0.236)	(0.227)	(0.251)	(0.299)
Credit rating = 13, BB-		2.531***	2.533***	1.625***	1.686***
		(0.246)	(0.239)	(0.266)	(0.313)
Credit rating = 14, B+		2.830***	2.834***	1.849***	1.922***
		(0.261)	(0.254)	(0.282)	(0.326)
Credit rating = 15, B		3.382***	3.386***	2.336***	2.410***
		(0.267)	(0.262)	(0.305)	(0.349)
Credit rating = 16, B-		4.124***	4.128***	2.988***	3.064***
		(0.285)	(0.279)	(0.317)	(0.358)
Credit rating = 17, CCC+		5.295***	5.311***	4.070***	4.160***
		(0.340)	(0.338)	(0.368)	(0.408)
Credit rating = 18, CCC		6.758***	6.778***	5.420***	5.515***
		(0.363)	(0.360)	(0.377)	(0.412)
Credit rating = 19, CCC-		11.33***	11.40***	9.728***	9.879***
		(0.806)	(0.805)	(0.783)	(0.805)
Credit rating = 20, CC		12.65***	12.70***	10.93***	11.07***
		(0.943)	(0.957)	(0.935)	(0.967)
Credit rating = 21, C		15.73***	15.78***	14.05***	14.21***
		(1.227)	(1.243)	(1.296)	(1.332)
Credit rating = 22, C-		15.02***	15.00***	13.80***	13.85***
		(0.831)	(0.822)	(0.910)	(0.909)
Credit rating = 23, DDD		19.05***	19.05***	17.40***	17.52***
		(1.524)	(1.519)	(1.509)	(1.516)
Credit rating = 24, DD		13.06***	13.02***	11.55***	11.63***
		(2.900)	(2.903)	(2.981)	(2.989)
Credit rating = 25, D		11.88***	11.89***	10.62***	10.75***
		(1.586)	(1.550)	(1.608)	(1.588)
Constant	4.380***	2.108***	5.771***	7.696***	10.40***
	(0.274)	(0.277)	(0.620)	(0.718)	(0.773)
Observations	44,369	44,369	44,369	44,369	44,369
Number of firms	1,152	1,152	1,152	1,152	1,152
Firmcontrol	N	N	N	Y	Y
Bondcontrol	N	N	Y	N	Y
Year FE	Y	Y	Y	Y	Y

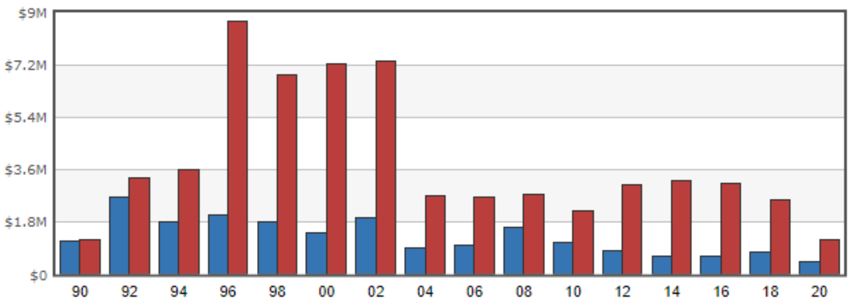
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D
Table used to construct dummy variables used in the analysis in paragraph 5.2.3. For the republican control dummy, full years under republican control have a value of 1, all full years under democratic control have value 0. Election years are left blank. For the republican election win dummies, only the election and post-election year are used. Again, a value of 1 (0) corresponds to a republican (democratic) win. The republican (midterm) election win dummy includes the results of the midterm elections, again assigning results based on the election year and post-election year.

Year	Republican Control dummy	Republican election win dummy	Republican (mid-term) election win dummy
2000	0	1	0
2001		1	0
2002	1		1
2003	1		1
2004	1	1	1
2005	1	1	1
2006	1		0
2007	1		0
2008	1	0	0
2009		0	0
2010	0		1
2011	0		1
2012	0	0	0
2013	0	0	0
2014	0		1
2015	0		1
2016	0	1	1
2017		1	1
2018	1		0
2019	1		0

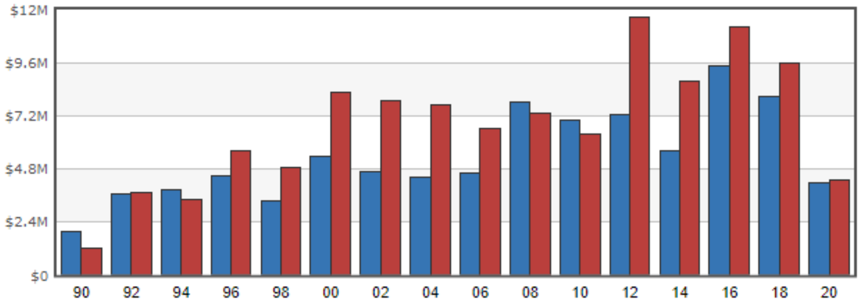
Appendix E
Campaign contributions to the democratic and republican party for mid-term and presidential elections from 1990-2020.

Figure 3
Aggregate campaign funding by firms in the tobacco industry in millions of US dollars, split by republican donations (red) and democratic donations (blue).



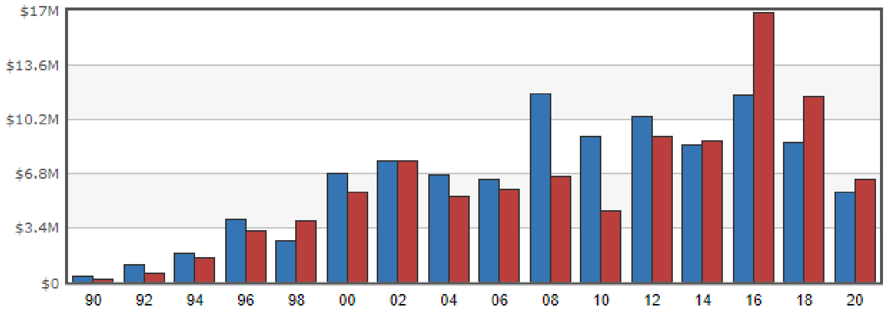
Source: Open secrets 2020
www.opensecrets.org/industries/indus.php?ind=N07

Figure 4
Aggregate campaign funding by firms in the alcohol industry in millions of US dollars, split by republican donations (red) and democratic donations (blue).



Source: Open secrets 2020,
https://www.opensecrets.org/industries/indus.php?ind=N07

Figure 5
Aggregate campaign funding by firms in the gambling industry in millions of US dollars, split by republican donations (red) and democratic donations (blue).



Source: Open secrets 2020,
https://www.opensecrets.org/industries/indus.php?ind=N07