Social Sentiment and Asset Prices *

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Abstract – This paper shows that shifts in social sentiment affect stock prices. We use the Internet search volume on corporate social responsibility to capture investors' social sentiment shifts. Stocks with the most positive return sensitivity to social sentiment attract higher institutional demand and earn positive abnormal returns. A trading strategy that exploits the demand-based return predictability generates risk-adjusted returns of 0.46% per month. Further, the return predictability is stronger for stocks headquartered in regions with lower social sentiment. Social sensitivity does not predict firm profits. Overall, these results are consistent with the stock market mispricing stocks' social sensitivity.

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1. Introduction

Corporate social responsibility (CSR) has attracted increasing attention among academics as well as practitioners. According to the U.S. Forum for Sustainable and Responsible Investment (USSIF), the total U.S. domiciled assets under management using socially responsible investing (SRI) strategies have reached $12 trillion in 2018. Despite of a growing literature on CSR and finance, little is known on how the time-varying investor sentiment towards CSR affects asset prices.

In this paper, we construct a novel method to identify stocks that are likely to be more affected by investors' social sentiment. Our key innovation is to use the Internet search volume of CSR-related key words to measure investors' time-varying attitude towards CSR (i.e., social sentiment). Consequently, we estimate the return sensitivity of firms with respect to investors' internet search intensity on CSR-related keywords. These social sensitivity estimates capture stocks' social attributes perceived by the market: stocks have positive (negative) social sensitivity if their returns increase (decrease) during high social sentiment periods.

When investors update their beliefs about stocks' social attributes, they are likely to rebalance their portfolios and tilt investments toward firms with more positive social sensitivity. This trading behavior could generate predictable return patterns across stocks. Specifically, we conjecture that there will be predictable return patterns of socially sensitive firms that can be identified *ex-ante*. Stocks with stronger social sensitivity are likely to be mispriced in the short run.

Consistent with our conjecture, we find that returns of stocks with stronger social sensitivity are predictable. In particular, a trading strategy that goes long in a value-weighted portfolio of stocks with the most positive social sensitivity and goes short in a value-weighted portfolio of stocks with the most negative social sensitivity generates a characteristic-adjusted return of 0.46%

per month from 2006 to 2016, or 5.52% per year. This return predictability covers about 18% of total market capitalization, which is economically meaningful.

In addition to the time-series analyses, we also demonstrate that our social sensitivity estimate is able to predict cross-sectional stock returns using Fama-MacBeth regressions. Economically, after taking into account several factors that are known to explain cross-sectional stock returns, a one standard deviation increase in stock-level social sensitivity is associated with a 0.11% return increase in the following month.

In the next set of tests, we examine whether geographical differences in investors' CSR preference affect our predictability results. Specifically, the predictive power of social sensitivity estimates on stock returns could be different in regions with different CSR preferences. The existing literature demonstrates that asset managers and firm executives care more about CSR when they are politically leaning to Democrats (Hong and Kostovetsky, 2012; Di Giuli and Kostovetsky, 2014). Consistent with this finding, we also find that investors located in Democratic leaning states have higher search volume intensity in CSR.

Motivated by the above evidence, we construct double-sorted portfolios based on state-level CSR preference and stock-level social sensitivity. We measure state-level CSR preferences in two ways. First, investors located in U.S. states with higher search volume intensity are likely to have higher social sentiment. Second, we identify a state as having stronger social sentiment if a Democratic candidate won the most recent Presidential election in that state. We find that the social sentiment-induced mispricing is stronger in states with low *SVIs* or with a Republican political climate. This finding suggests that the mispricing is amplified for stocks headquartered in regions with low social sentiment.

Beyond these return-based tests, we further investigate the potential economic channel for our findings. In particular, we examine whether social sensitivity-induced mispricing can be explained by the investment choices of institutional investors using institutional trading data. If retail investors demand for stocks with the most positive social sensitivity, asset managers are likely to cater to their clients' demand. If institutional investors frequently update their portfolio holdings to include stocks with the most positive social sensitivity, their trading activity could generate mispricing on these stocks. Consistent with our hypothesis, we find that institutional investors have 1.4% higher net demand per month on firms with the most positive social sensitivity when compared with those with the most negative social sensitivity.

In the last set of tests, we examine the longevity of our return predictability results. We find that the predictive power of social sensitivity estimates declines as we increase the gap between social sensitivity estimation month and portfolio formation month. The alpha estimate of a long-short strategy that based on stale social sensitivity estimates becomes statistically insignificant after six months. This evidence suggests that the social sentiment-induced mispricing is likely to be corrected in about six months.

In addition, also we investigate whether our social sensitivity estimates predict future earnings. While social sensitivity is positively correlated with future operating performance, the relation is not statistically significant. Combining with the results of longevity tests, we interpret our findings as demand-induced mispricing.

We conduct several robustness checks for our baseline results. Our results are quantitatively similar after using longer social sensitivity estimate window or including the Baker and Wurger (2007) investor sentiment index as an additional control. In addition, our results remain robust to various conditional factor models that account for changes in business cycle over time. Third, the predictive power of social sensitivity estimates on stock returns is similar across firms with different sizes or institutional ownership. For further robustness, we also estimate social sensitivity of the 48 Fama and French (1997) industry portfolios and find similar results. A social sensitivity-based long-short strategy will generate a characteristic-adjusted return of 8.40% per year, which suggests that social sensitivity of firms in the same industry are positively correlated.

Taken together, our findings contribute to several strands of literature. First, we contribute to the emerging literature on corporate social responsibility. The existing literature has studied various perspectives on CSR such as Employee satisfaction and workplace safety (e.g., Edmans, 2011; Cohn and Wardlaw, 2016; Edmans, Li, and Zhang, 2016), environmental protection (e.g., Dowell, Hart, and Yeung, 2000; Konar and Cohen, 2001; Chava, 2014), corporate philanthropy (e.g., Masulis and Reza, 2015), customer satisfaction (e.g., Luo and Bhattacharya, 2006; Servaes and Tamayo, 2013), or corporate governance (e.g., Dimson, Karakas, and Li, 2015; Cheng, Hong, and Shue, 2016; Ferrell, Liang, and Renneboog, 2016). We extend the previous literature by focusing on the effect of investors' time-varying social sentiment on stock returns. Our key innovation is to identify the effect of time variation of social sentiment. In addition, we identify a profitable SRI trading strategy based on social sentiment.

Beyond the literature on CSR, our paper also contributes to the literature on return predictability. For example, Cohen and Frazzini (2008) show that consumer-supplier links can be used to identify predictable return patterns. In addition, Korniotis and Kumar (2013) find that local economic conditions predict local stocks returns. Similarly, Addoum and Kumar (2016) show that political sensitivity could also be used to identify predictable patterns in stock returns. Our paper provides evidence of return predictability along a new dimension, i.e., social sentiment dimension.

This paper is organized as follows. Section 2 discusses the data and methodology. Section 3 presents the empirical results. Section 4 concludes.

2. Data and methodology

2.1. Main datasets

We collect data from various sources. We obtain market excess return (*MKTRF*), the size factor (*SMB*), the value factor (*HML*), the momentum factor (*UMD*), the short term reversal (*STR*) and long-term reversal (*LTR*) factors, and monthly value-weighted returns of the 48 Fama and French (1997) industry portfolios from Kenneth French's website.[1] We obtain the liquidity factor (*LIQ*) from Lubos Pastor's website,[2] and U.S. business cycle data from National Bureau of Economic Research (NBER).

We obtain daily and monthly stock prices, stock returns, and shares outstanding from Center for Research on Security Prices (CRSP). We focus on all common stocks (i.e., share code equals to 10 or 11) in the CRSP universe and obtain relevant accounting information from Compustat. We use the historical Standard Industry Classification (SIC) codes from Compustat to assign all stocks into the 48 Fama and French (1997) industries. If the historical SIC code is not available, we use the SIC code from CRSP. We calculate book-to-market ratio for each firm using data from Compustat. Specifically, book-to-market ratio is calculated as the ratio of year-end stockholders' equity plus deferred taxes and investment tax credit minus preferred stocks to year-end market equity, as in Daniel and Titman (1997). We use the Daniel, Grinblatt, Titman, and Wermers (DGTW, 1997) method to generate characteristic-adjustment stock assignments and benchmark portfolio returns for the 2006 to 2016 period.[3]

[1] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] The liquidity factor is the main variable in Pastor and Stambaugh (2003) and is available at: http://faculty.chicagobooth.edu/lubos.pastor/research/.

[3] Following Daniel, Grinblatt, Titman, and Wermers (1997) DGTW returns are calculated as follows: First, we rank all stocks listed on NYSE, AMEX, or Nasdaq, at the end of June, by their market capitalization and form quintile portfolios using NYSE quintile size breakpoints. We then further divide each quintile portfolio into book-to-market quintiles based on their most recently available book-to-market ratio as of the end of the December immediately prior to the ranking year. Finally, each of the resulting 25 portfolios are further subdivided into quintiles based on the return in the past 12 months through the end of May of the ranking year. This procedure forms 125 portfolios with each having a distinct combination of size, book-to-market, and momentum characteristics. We reconstruct the 125 portfolios at the end of each June. We calculate value-weighted returns for each of the 125 portfolios. DGTW adjusted return is defined as the return difference between the stock and the corresponding portfolio of which that stock is a member. We verify the accuracy of our generated DGTW returns over the 2005 to 2011 period using the data from Russ Wermers' web site: http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

To examine the relation between our return-based social sensitivity measure and CSR scores, we obtain stock-level ratings of corporate social responsibility from KLD. This database covers the Russell 3000 stocks and is widely used in the CSR literature. We focus on six dimensions of corporate goodness rated by KLD: Community, Diversity, Employee Relations, Environment, Human Rights, and Product. KLD reports for each firm, its number of strengths and concerns across these six dimensions. Since the number of strength and concern indicators for most dimensions varies considerably each year, we follow Albuquerque, Koskinen, and Zhang (2018) to construct two normalized CSR measures to ensure comparability across years and dimensions. First, we divide both the aggregated strengths and concerns of each stock by the total number of strengths and concerns across all the six dimensions in each year. We then subtract the adjusted concerns from the adjusted strengths to obtain *KLD1*. Second, following Deng, Kang, and Low (2013), we divide the aggregated strengths (concerns) of each stock by the total number of strengths (concerns) in each year. We then construct *KLD2* as the difference between adjusted strengths and adjusted concerns.

As state-level political climate might affect local firms' CSR preferences (Di Giuli and Kostovetsky, 2014), we obtain state-level Presidential election outcomes in the 2004, 2008, 2012, and 2016 elections from Dave Leip's Atlas of U.S. Presidential elections. We classify a state as a Democratic (Republican) leaning state if a Democratic (Republican) candidate won the most recent Presidential election in that state.

To examine the institutional trading, we obtain transaction-level data of institutional investors for the 2005 to 2010 period from ANcerno Ltd. This dataset reports execution price, execution volume, side (i.e., buy or sell), and CUSIP for each transaction. As suggested by Puckett and Yan (2011), ANcerno institutions are larger than the typical institutions in the 13F universe and account for about 10% of all institutional trading volume. In addition, characteristics of stocks held and traded by ANcerno institutions are similar to those held by 13F institutions.

We obtain institutional ownership data provided by Ferreira and Matos (2008) from FactSet. We measure institutional ownership of a firm using its average quarterly total institutional ownership in the previous year.

2.2. CSR attention measure

Following Da, Engelberg, and Gao (2011, 2015), we use the search volume intensity (*SVI*) reported by Google Trends to directly capture investors' attention to CSR. Specifically, we use the *SVI* for the *topic* "corporate social responsibility". This time-series measure aggregates online search queries in different languages and different keywords if they are related to CSR.[4] The topic function in Google Trends is able to identify CSR-related searches even when a query does not explicitly contain the keyword "CSR".[5] As Google accounts for approximately 88 percent of all search queries in the U.S.,[6] high CSR attention reflects a market-level increase in social awareness (i.e., social sentiment). We restrict the search location to U.S. and measure the abnormal change in *SVI* (i.e., *ASVI*) as the log difference in *SVIs* between month t and month t-1, as in Da, Engelberg, and Gao (2011).

In addition, to examine the cross-sectional difference in CSR attention, we obtain annual cross-sectional *SVIs* of U.S. states during the 2004 to 2016 period using the "Interest by sub-region" function in Google. State-level *SVIs* report in which state the search topic was most popular during

[4] Google outputs an estimated time-series for each download. The time-series correlation between different downloads ranges from 89% to 93%. Our results remain robust if we download *SVI* on 10 different dates in different calendar months and take the average to measure investor attention to CSR.
[5] For example, if you input "capital of Japan", Google Trends will aggregate your search into the topic "Tokyo". Google Trends is available at: http://www.google.com/trends/.
[6] The market share of Google is measured as of 2018. Source: Statcounter.

the specified time frame. It ranges from 0 to 100. A higher cross-sectional *SVI* means a higher proportion of all searches, not a higher absolute search count. Therefore, the state-level *SVIs* are adjusted for state-level population.[7]

Figure 1 plots the time-series of *SVI* of the topic "corporate social responsibility". We find that the attention to CSR is time-varying. Peaks in the time-series coincide with major corporate scandals. For example, the highest point (Point A) corresponds to the largest CSR scandal in the U.S. history, the BP Oil Spill in April 2010. In addition, Point B corresponds to the Toshiba Accounting Scandal. Similarly, Point C corresponds to the Volkswagen emission scandal, and Turing Pharmaceuticals and Valeant Pharmaceuticals' scandals. Further, Point D relates to both Mylan's Epipen Scandal, Wells Fargo's fake accounts scandal, and Samsung's Note 7 recall scandal. Overall, Figure 1 suggests that negative CSR events draw more attention.

Table 1 reports the top five and bottom five states ranked by cross-sectional *SVIs* in CSR during the 2004 to 2016 period. We also report the popular vote differences between Democratic and Republican candidates in the 2004, 2008, 2012 and 2016 Presidential elections. We find that Democrats won all of the four Presidential elections in states with the highest *SVIs*. In contrast, Republican won all of the four Presidential elections in states with the lowest *SVIs*. This evidence is consistent with the existing literature, which shows that asset managers and firm executives who are politically leaning to Democrats care more about CSR (Hong and Kostovetsky, 2012; Di Giuli and Kostovetsky, 2014). Our finding suggests that political climate also affect local investors' preference for CSR. In particular, investors located in Democratic leaning states have stronger social sentiment.

2.3. Social sensitivity estimation and portfolio construction

[7] For example, a small state where 80% of the queries are for "CSR" will get twice the score of a large state where only 40% of the queries are for "CSR".

Using Google search volume to capture investor attention, we estimate the return-based social sensitivity for all common stocks (share code equals 10 or 11) in the CRSP universe. This return-based social sensitivity measure is motivated by the specifications used in Santa-Clara and Valkanov (2003) and Addoum and Kumar (2016). For example, Addoum and Kumar (2016) shows that industry-level return sensitivity to the political party in power is able to capture the market's attitude toward an industry in the recent period, which in turn could identify industries that are favored by investors in the current political climate. Similarly, we use return sensitivity of each stock to the national-level CSR attention in the U.S. to identify stocks that are more affected by investors' social sentiment ex-ante. Specifically, in each month and for each stock, we regress the excess returns during the past twelve months on the Carhart (1997) four factors and a CSR attention indicator.[8] In particular, we estimate the following time-series regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_1 (r_{mktrf} - r_f)_t + \beta_2 r_{smb,t} + \beta_3 r_{hml,t} + \beta_4 r_{umd,t} + \theta_i D_{CSR,t} + \epsilon_{i,t}. \tag{1}$$

In equation (1), the CSR attention indicator variable ($D_{CSR,\,t}$) is defined using expanding window medians. In particular, $D_{CSR,\,t}$ equals to 1 if $ASVI_{t-1}$ is larger than the median of all previous observations, or zero otherwise. We use the median of *ASVIs* in 2004 to define the first D_{CSR} in January 2005.

Our focus is on the θ_i estimate, which captures the social sensitivity of a stock after accounting for the market risk premium, size, book-to-market, and past returns. A positive θ_i estimate suggests that the stock earns higher average returns during high social sentiment periods. In contrast, a negative θ_i suggest that the stock earns lower average returns during high social sentiment periods. To allow for time-variation in both the magnitude and direction of the social sensitivity estimates,

[8] We use 12 months as the estimation window to ensure that our sample starts before the 2007 financial crisis. Our results remain quantitatively similar if we use 36 months as the estimation window.

we estimate θ_i with rolling window regressions. The estimation period for θ_i is from January 2005 to November 2016.

Using these social sensitivity estimates, we define five social sensitivity based stock portfolios as follows: in each month, we sort all stocks by θ_i in descending order and assign stocks to five social sensitivity quintiles. We form the Long (Short) portfolio using stocks in the top (bottom) social sensitivity quintile. The Long portfolio includes stocks with the largest return increase during high social sentiment periods, while the Short portfolio includes stocks with the largest return decrease during the same periods. We use stocks in the remaining three social sensitivity quintiles to form portfolios 2, 3, and 4. Portfolio returns are value-weighted by stock-level market capitalization in the previous month. We update stock sorting and portfolio construction on a monthly basis. The portfolio formation period (i.e., main sample period) is from January 2006 to December 2016.

2.4. Characteristics of portfolios sorted by social sensitivity

Table 2 reports the characteristics of the five portfolios sorted by the social sensitivity measure. Panel A reports the mean social sensitivity, number of stocks in each portfolio, size (log market capitalization), book-to-market ratio, return over the past six months and the average KLD scores using two different scaling methods. We calculate portfolio-level KLD scores by value weighting stock-level scores using stock market capitalizations in the previous month.

We find that social sensitivity increases monotonically from the Short to the Long portfolio while the five portfolios have similar number of stocks and book-to-market ratios. The Long and Short portfolios are smaller and have higher past returns than portfolios 2 to 4. In addition, although the Short portfolio has the lowest KLD scores, KLD scores do not increase monotonically from the Short to the Long portfolio. This result suggests that our return-based social sensitivity measure is different from the KLD measure. Stocks with higher social sensitivity not necessarily have better performance in CSR.

Next, we examine which industries have strong (positive or negative) social sensitivity. The existing literature on finance and economics suggests that investors have preconceptions about industry-level CSR performance. For example, retail-based industries are commonly perceived as socially responsible. Firms in these industries invest extensively in CSR marketing campaign since good CSR reputation could boost consumer demand, generate customer loyalty, support premium pricing, and serve as an alternative way to assure product quality (e.g., Besley and Ghatak, 2007; Castaldo, Perrini, Misani, and Tencati, 2009; Elfenbein, Fisman, and Mcmanus, 2012; and Albuquerque, Koskinen, and Zhang, 2018).

In contrast, industries involving in fossil fuel (i.e., coal, oil, and natural gas) and other natural resources (e.g., mining, precious metal) are commonly screened by SRI investors (Geczy, Levin, and Stambaugh, 2005). In addition, the USSIF also encourages all types of investors to divest from these industries to address climate changes risks.[9]

Panel B of Table 2 reports ten industries with the most positive and negative social sensitivity using the 48-industry classifications in Fama and French (1997). We value weight stock-level social sensitivity to industry level and report the median social sensitivity during our sample period. We find that sensitive industries are consistent with investors' preconception about social attributes. Specifically, retail-based industries (e.g., Apparel, Entertainment, and Consumer Goods) are more likely to have positive sensitivity while industries with controversial business operations (e.g., Mining and fossil fuel) are more likely to have negative social sentiment. In

[9] Source: http://www.ussif.org/climatereinvestment.

unreported results, we also find that mining and fossil fuel industries also have the lowest KLD scores during our sample period.[10]

3. Empirical results

3.1. Univariate sorting results

To investigate whether social sentiment affects stock returns, we first examine the performance of stock portfolios sorted by social sensitivity. Specifically, we examine the performance of the following portfolios: (i) the Short portfolio, which is a value-weighted portfolio of stocks with the most negative social sensitivity during the past twelve months, (ii) the Long portfolio, which is a value-weighted portfolio of stocks with the most positive social sensitivity in the past twelve months, (iii) the return differences between the Long and Short portfolios, and (iv-vi) portfolios 2-4, which are value-weighted portfolios of the middle three stock quintiles based on social sensitivity in the previous twelve months.

Table 3 presents the portfolio performance estimates. In Panel A, Columns (1) and (2) report the raw and DGTW returns for the full sample period from January 2006 to December 2016. The t-statistics reported in parentheses are computed using standard errors adjusted by the Newey and West (1987) method.

We find that portfolio excess returns increase monotonically from the Short to the Long portfolio. Stocks in the Short portfolio earn an average monthly excess return of 0.39%, while those in the Long portfolio earn an average monthly excess return of 1.08%. The monthly excess return difference between the Long and Short portfolios is 0.69% and is significant at the 1% level.

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[10] Panel B of Table 2 shows that tobacco industry also has positive social sensitivity. This is reasonable for two reasons. First, the overall KLD score for tobacco industry is positive during our sample period, which suggests that tobacco firms have more CSR strengths than concerns. Second, there are only 3 firms on average in this industry so the industry-level social sensitivity estimates could be very volatile. Relatedly, the alcohol industry also has positive median social sensitivity as well as positive KLD scores.

Further, the return pattern remains similar when we use DGTW returns to measure performance. After adjusting for size, book-to-market, and past performance, we find that the DGTW return difference between the Long and Short portfolios is 0.46%, which translates into an economically meaningful annualized return of 5.52%.

In our baseline specifications, we use twelve months as the estimation window for social sensitivity to ensure that our sample period starts before the 2007 financial crisis. For robustness, in Columns (3) and (4) of Table 3, we also report the portfolio return estimates by extending the social sensitivity estimation window to 36 months. As a result, the sample starts 24 months later (i.e., from January 2008). We find that the DGTW return difference between the Long and the Short portfolios translates into an annualized return of 0.481%×12=5.77%, which is quantitatively similar to our baseline results.

Next, we explicitly examine the riskiness of our social sensitivity based stock portfolios. In Panel B of Table 3, we find that both the Long and the Short portfolios have higher return standard deviations than the remaining portfolios. However, the Sharpe ratio increases monotonically from the Short to the Long Portfolio. The pattern remains similar when we use 36 months as social sensitivity estimation window.

In addition, we test whether our social sensitivity measure covers an economically meaningful segment of the market by examining the market share of the Long and the Short portfolios in the CRSP universe. In Panel C of Table 3, we report the average monthly market shares for social sensitivity sorted portfolios. Long - Short reports the combined market shares of the Long and Short portfolios. We find that for both excess and DGTW return measures, the Long - Short strategy covers about 18% of total market share in the CRSP universe. The results are similar when we extend the social sensitivity estimation window to 36 months. Overall, our social sensitivity based trading strategy covers an economically meaningful segment of the market.

To further ensure the robustness of our estimation results, Figure 4 plots the monthly DGTW return difference between the Long and Short portfolios for the 2006 to 2016 period. The bar chart shows that the Long portfolio outperforms the Short portfolio in 59% of the sample period. In addition, the average monthly outperformance magnitude (i.e., 1.85%) is larger than the average underperformance magnitude (i.e., -1.55%). Overall, these findings suggest that social sensitivity predicts future stock returns.

3.2. Factor model estimates

Our results based on excess and DGTW returns suggest that social sensitivity is positively correlated with future stock returns. In this section, we use various unconditional factor models to control for additional factors. Specifically, our unconditional factor models include different combinations of the following factors: the market excess return (*MKTRF*), the size factor (*SMB*), the value factor (*HML*), the momentum factor (*UMD*), short-term reversal (*STR*) and long-term reversal (*LTR*) factors, and the liquidity factor (*LIQ*). The sample period is from January 2006 to December 2016.

Table 4 reports the unconditional factor model estimation results. We find that our results remain robust across all specifications. In particular, even after including seven risk factors, the monthly alpha for the Long and Short portfolios are is 36 and -35 basis points, respectively. Both significant at the 5% level. The performance difference between the Long and Short portfolios converts into an annualized risk-adjusted return of 0.711%×12=8.53%, which is economically meaningful.

3.3. Fama-MacBeth regression estimates

In the last sets of our baseline tests, we estimate Fama and MacBeth (1973) regressions. The dependent variable is the monthly returns of each stock. The main explanatory variable is the lagged social sensitivity estimate (*CSR*$_{sensitivity}$). We also include the following explanatory variables that are commonly used to predict cross-sectional returns: the factor loadings of the Carhart (1997) four-factor model estimated by daily stock returns in the previous month (*Beta MKTRF*, *Beta SMB, Beta HML, Beta UMD*), return over the past six months (*Lag 6m Return*), log market capitalization in the previous month (*Size*), and book-to-market-ratio in the previous year (book-to-market). We also include year and industry fixed effects. The sample period is from January 2006 to December 2016. We report the time-series averages of monthly cross-sectional regression coefficients. The t-statistics reported in parentheses are computed using standard errors adjusted by the Newey and West (1987) method.

Table 5 reports the results. We find that stocks with more positive social sensitivity earn higher returns even after controlling for all commonly used factors in the literature. In economic terms, a one standard deviation increase in social sensitivity is associated with an additional return of 0.01×10.91=0.11% in the following month. Our results show that social sensitivity of stocks is an important factor in explaining the cross-sectional variation in returns and this effect is different from firm characteristics that are known to predict cross-sectional returns. This evidence further supports our main hypothesis.

3.4. Cross-sectional difference

In the next set of tests, we examine whether the predictive power of social sensitivity estimates on stock returns are different in regions with different CSR preferences. We construct double-sorted portfolios based on state-level *SVIs* and stock-level social sensitivity, or state-level political climate and social sensitivity. In each month, we classify a stock into high or low CSR attention group if the *SVI* in its headquarter state is above the median value across all U.S. states in the previous year. Similarly, we classify a stock into a Democratic or Republican political climate group if a Democratic or Republican candidate won the most recent Presidential election in that state. Within each attention (political climate) category, we further partition stocks in to high (low) social sensitivity group if the firm's social sensitivity is above (below) the top (bottom) tercile across firms.

Table 6 presents value weighted seven-factor adjusted alpha for the double-sorted portfolios. The t-statistics reported in parentheses are computed using standard errors adjusted by the Newey and West (1987) method. We find that social sensitivity has stronger predictive power in states with low SVIs or Republican political climates. The social sensitivity-based long-short strategy yields a 0.94% (1.04%) alpha estimate in states with high *SVIs* (Republican political climate), significant at 1% level. In comparison, the same strategy only yields a 0.42% (0.39%) alpha estimate in states with low *SVIs* (Democratic political climate). These findings suggest that the social sentiment-induced mispricing is larger in regions with lower social sentiment.

3.5. Institutional trading

Our baseline results demonstrate that perceived social attributes, as measured by social sensitivity, predict stock returns. In this section, we investigate a potential economic channel for this return predictability.

Specifically, we directly test whether investors' social sentiment generates institutional trading. We examine the actual transactions of institutional investors during the 2005 to 2010 period. Following Kumar and Lee (2006), we measure the excess demand for stocks with the most positive social sensitivity as the excess buy-sell imbalance (*EBSI*) defined as the difference in buy-sell imbalance between stocks in Long and Short portfolios.[11] This measure captures the changes in net demand for stocks in the Long portfolio relative to those in the Short portfolio. In addition, we also examine the *EBSI* between stocks in the Long and the middle three portfolios, and the *EBSI* between stocks in the Short and the middle three portfolios.

Table 7 presents the results. Consistent with our expectation, we find that the average *EBSI* between stocks in the Long and Short portfolios is 1.4% per month, significant at the 10% level. This evidence suggests that institutions have 1.4% more net purchases of stocks with the most positive social sensitivity relative to those with the most negative social sensitivity stocks during the 2005 to 2010 period. The excess buy sell imbalance is positive in 68% of the sample. In addition, institutions also have 1.8% net purchase of stocks in the Long portfolio relative to stocks in the middle three quintile portfolios. In contrast, the net demand for stocks in the Short portfolio and those in the middle three quintile portfolios are not significantly different. Overall, these findings suggest our return predictability results are likely to be driven by investor demand.

3.6. Longevity of return predictability

In this section, we study the longevity of the predictive power of our social sensitivity estimates. In particular, if it is driven by mispricing, then one might expect the perdition power of our social sensitivity estimates to decline if the gap between social sensitivity estimation month and portfolio formation month is widened. Our institutional trading results also suggest that institutional investors are likely to hold stocks with the most positive social sensitivity in the recent period.

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[11] The buy-sell imbalance (*BSI*) of portfolio *p* in month *t* is defined as $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$, where the *BSI* for stock *i* in month *t* is defined as $BSI_{it} = \frac{\sum_{j=1}^{D_t}(VB_{ijt} - VS_{ijt})}{\sum_{j=1}^{D_t}(VB_{ijt} + VS_{ijt})}$. Here, D_t is the number of days in month *t*. VB_{ijt} (VS_{ijt}) is the dollar buying (selling) volume of stock *i* on day *j* in month *t*, and N_{pt} is the number of traded stocks in portfolio *p* in month *t*.

Figure 3 plots the unconditional seven-factor adjusted alpha of the Long-Short portfolio when we vary the portfolio formation periods. We also include ±2 standard error bands. Consistent with the mispricing hypothesis, we find that the magnitude of seven-factor alpha gradually declines as we increase the gap between the social sensitivity estimation month and portfolio formation month. It becomes not significantly different from zero if we delay portfolio formation beyond six months. This evidence suggests that investors are likely to correct the social sentiment-induced mispricing in about six months.

3.7. Operating performance

In this section, we focus on cash flow channel and investigate whether return predictability and institutions' trading activities are driven by expectations about future operating performance. In particular, we examine whether our social sensitivity estimates predict earnings. We estimate the Fama and MacBeth (1973) type regressions. The dependent variable is the h-quarter ahead return on assets (*ROA*) of each stock. The main independent variable is the monthly average social sensitivity in the current quarter. Following Fama and French (2000), we include the following independent variables that are known to explain operating performance: the market to book ratio, an indicator variable for non-dividend-paying firms, and the ratio of dividends to book equity. In addition, following Vuolteenaho (2002) and Hou and Robinson (2006), we also include the current quarter *ROA* as an additional control variable. We report the time-series averages of the coefficient estimates of from quarterly cross-sectional regressions. The t-statistics reported in parentheses are computed using standard errors adjusted by the Newey and West (1987) method.

Table 8 reports the cash flow regression estimates. We find positive correlations between average social sensitivity in the current quarter and operating performance in the following two quarters. However, the results are only significant for return on assets 2-quarter ahead at the 10%

level. Together with disappearing return predictability shown in Figure 3, we interpret results in Table 8 as evidence for demand-based mispricing.

3.8. Robustness checks and further tests

In the last part of this paper, we conduct several robustness checks for our baseline results. First, we investigate the robustness of our factor model results. Our focus is the alpha estimate of a long-short trading strategy. In Column (1) of Table 9, we re-estimate the unconditional factor model by using a longer social sensitivity estimation period. We find that the alpha estimate is similar when we extend social sensitivity estimation window from 12 to 36 months. In Column (2), we include the Baker and Wurgler (2007) investor sentiment index to account for overall investor sentiment. Our results are quantitatively similar.

In addition, to ensure our results are not driven by improper adjustment for time-varying exposures to systematic risks, we use conditional factor models to address portfolio risks. In particular, we interact factors in unconditional models with macroeconomic variables to account for the U.S. business cycle. We include the following three macroeconomic variables: (i) NBER recession indicator (*REC*), (ii) the yield on the 90-day T-bill (*YLD*), and (iii) the term spread (*TERM*), defined as the difference between the yields of a constant maturity 10-year Treasury bond and a 90-day T-bill.

Columns (3) to (6) of Table 9 report the results. The interaction variable for each conditional factor model is indicated at the top of each column. We find that the alpha estimates remain economically significant (0.57% - 0.71%) when we use conditional factor model. These findings show that our results are robust to accounting for changes in business cycle over time.

Third, our institutional trading results suggest that institutional investors have net demand for stocks with the most positive social sensitivity. In the next set of tests, we examine whether our results remain robust across stocks with different sizes and institutional ownerships. The existing literature demonstrates that institutions prefer large stocks (e.g., Lakonishok, Shleifer, and Vishny, 1992; Gompers and Metrick, 2001). Therefore, we construct double sorted portfolios by firm size and social sensitivity, or by institutional ownership and social sensitivity. In each month, we classify all common stocks in the CRSP universe into large or small size group (high or low institutional ownership group) if its market capitalization (institutional ownership) is above or below the median value across all firms. Within each size (institutional ownership) category, we further partition stocks in to high (low) social sensitivity group if the firm's social sensitivity is above (below) the top (bottom) tercile across firms.

Table 10 presents the value weighted seven-factor adjusted alpha for the double-sorted portfolios. The t-statistics reported in parentheses are computed using standard errors adjusted by the Newey and West (1987) method. We find that social sensitivity-based long-short strategy has predictive power across different size and institutional ownership groups.

In the last set of our robustness tests, we examine whether our results hold at industry level. Specifically, if social sensitivities of firms within the same industry are correlated, the predictive power of social sensitivity on stock returns would also exist at industry level. To test this conjecture, we estimate social sensitivity for each of the 48 Fama and French (1997) industry portfolios using equation (1). In each month, we sort the 48 industries by θ_i in descending order. We use the top five industries to form the Long portfolio and use the bottom five industries to form the Short portfolio. We assign the remaining 38 industries into portfolios 2, 3, and 4. Portfolio returns are value-weighted by industry-level market capitalization in the previous month. We update industry sorting and portfolio construction on a monthly basis.

Panel A of Table 11 presents the industry-level portfolio performance estimates. Similar to stock-level sorting results, we find that the DGTW return difference between the Long and Short industry portfolios is 0.70% per month, significant at the 5% level. For further robustness, Columns (3) to (8) report the performance estimates when we vary the number of industries in the Long and Short portfolios. We find that even when we have ten industries in the two extreme portfolios, the return difference still translates into an annualized return of 0.541%×12=6.49%, which is both statistically and economically significant. In panel B of Table 11, similar to stock-level results, we find that the Sharpe ratio also increases from the Short to the Long Portfolio. In addition, the long short strategy covers 14% to 35% of the market share in the CRSP universe, which is economically meaningful. Overall, these findings suggest that social sensitivity also predict returns at the industry level.

4. Summary and conclusion

In this paper, we propose a novel measure to identify firms that are more affected by investors' social sentiment. Specifically, we use social sensitivity, defined as the return sensitivity to the aggregate attention to CSR, to capture stock-level social attributes perceived by the market.

We show that social sensitivity is different from overall CSR performance. Using social sensitivity estimates, we find that returns of market segments with stronger social sensitivity are predictable. A trading strategy that goes long in stocks with the most positive social sensitivity and goes short in stocks with the most negative social sensitivity generates a monthly DGTW return of 0.46%. Our return predictability evidence remains robust after controlling for a broad set of factors or observable characteristics, and becomes stronger in regions with lower social sentiment. In contrast, social sensitivity estimates do not predict operating performance.

Further, by investigating institutional trading, we demonstrate that social sentiment triggers institutional demand. This social sentiment-induced mispricing persists for six months after social sensitivities are estimated. Overall, our results suggest that social sensitivity affects stock returns.

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Table 1
Characteristics of state-level search interest in CSR

This table reports report characteristics of the top and bottom five states in terms of search interest for the topic "corporate social responsibility" from 2004 to 2016 period. Search interests are calculated on a scale from 0 to 100. A higher value means a higher proportion of all queries, not a higher absolute query count. Columns (3) to (6) reports the Popular vote differences (in percentage) between Democratic and Republican candidates in the U.S. President Elections in 2004, 2008, 2012 and 2016. A positive (negative) number suggests that Democrat (Republican) won the election in that state.

Panel A: States with the highest search interest in CSR

(1)	(2)	(3)	(4)	(5)	(6)
States	Search interest	Democrat - Republican			
		2004	2008	2012	2016
District of Columbia	100	79.84	85.93	83.63	86.77
Maryland	82	12.98	25.45	26.07	26.42
New Hampshire	78	1.37	9.61	5.58	0.37
Massachusetts	74	25.16	25.81	23.15	27.2
Rhode Island	71	20.75	27.8	27.46	15.51

Panel B: States with the lowest search interest in CSR

(1)	(2)	(3)	(4)	(5)	(6)
States	Search interest	Democrat - Republican			
		2004	2008	2012	2016
Wyoming	29	-39.79	-32.24	-40.82	-46.29
Alaska	36	-25.55	-21.53	-13.99	-14.73
North Dakota	37	-27.36	-8.65	-19.63	-35.73
Mississippi	37	-19.69	-13.17	-11.5	-17.8
Alabama	38	-25.62	-21.58	-22.19	-27.72

Table 2

Characteristics of social sensitivity based stock portfolios

This table reports characteristics of portfolios defined by social sensitivity. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. Stocks are sorted into quintiles based on social sensitivity in the past twelve months. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with the most positive (negative) social sensitivity. Long -Short reports the performance difference between the Long and Short portfolios. Panel A reports the mean social sensitivity, monthly average stock number, size (log market capitalization), book-to-market ratio, six months' cumulated return with a one-month lag, and KLD scores estimated using two different scaling methods for each quintile portfolio. Panel B reports the ten most sensitive (positive or negative) industries using the Fama and French (1997) 48 industries definition. Median sensitivity reports the median industry-level social sensitivity value-weighted from stock-level sensitivity. No. of stocks reports the monthly average number of stocks within each of Fama and French 48 industries. The sample period is from January 2006 to December 2016.

Panel A: Portfolio characteristics

Portfolio	Social sensitivity	No. of stocks	Size	Book to Market	Lag 6m Return	KLD1	KLD2
1 (Short)	-9.824	695	14.033	0.522	9.403	0.023	0.019
2	-3.481	700	15.131	0.519	6.100	0.030	0.021
3	-0.127	700	15.344	0.503	6.874	0.042	0.042
4	3.299	700	15.152	0.496	8.521	0.042	0.047
5 (Long)	9.035	696	14.182	0.525	12.061	0.032	0.036

Panel B: Median industry sensitivity

	Most positive			Most negative	
(1) Industry	(2) Median sensitivity	(3) No. of stocks	(4) Industry	(5) Median sensitivity	(6) No. of stocks
Apparel	2.000	42	Precious Metals	-1.481	6
Agriculture	1.941	8	Utilities	-1.254	95
Entertainment	1.233	42	Petroleum and Natural Gas	-1.096	129
Rubber and Plastic Products	0.922	17	Coal	-1.094	9
Tobacco	0.903	3	Automobiles and Trucks	-0.963	44
Healthcare	0.812	58	Steel Works	-0.846	38
Consumer Goods	0.705	44	Pharmaceutical Products	-0.714	241
Fabricated Products	0.662	7	Construction	-0.678	42
Textiles	0.659	8	Mining	-0.526	15
Real Estate	0.574	24	Medical Equipment	-0.525	111

Table 3
Performance of social sensitivity based stock portfolios

This table reports the performance of the five stock portfolios sorted by social sensitivity. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. Stocks are sorted into quintiles based on social sensitivity in the past twelve months. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with the most positive (negative) social sensitivity. Long -Short reports the performance difference between the Long and Short portfolios. Panel A reports the excess and DGTW returns during our sample period from January 2006 to December 2016. Excess returns are calculated as the difference between valued-weighted portfolio returns and the risk free rate. DGTW returns are calculated using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Columns (1) and (2) reports the excess and DGTW returns when we use twelve months as the estimation window for social sensitivity. For robustness, in Columns (3) and (4), we report the excess and DGTW returns when we use 36 months as the estimation window. Panel B reports the standard deviation of portfolio excess returns and the Sharpe ratio. Panel C reports the average monthly market share for the excess and DGTW return portfolios. We also report the total market share covered by the Long-Short trading strategy. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio performance estimates

	12 months		36 months	
	(1)	(2)	(3)	(4)
Portfolio	Excess return	DGTW return	Excess return	DGTW return
1 (Short)	0.386	-0.184	0.448	-0.250**
	(0.708)	(-1.468)	(0.782)	(-2.365)
2	0.392	-0.201**	0.533	-0.111
	(0.877)	(-2.225)	(1.034)	(-1.240)
3	0.631	-0.056	0.625	-0.087
	(1.596)	(-0.726)	(1.325)	(-0.985)
4	0.862**	0.154**	0.806	0.122
	(2.176)	(2.456)	(1.648)	(1.254)
5 (Long)	1.076**	0.273**	1.176**	0.231**
	(2.152)	(2.117)	(2.054)	(2.138)
Long - Short	0.690***	0.457**	0.728***	0.481***
	(2.904)	(2.461)	(3.987)	(2.933)
N months	132	132	108	108

Panel B: Portfolio performance characteristics

	12 months		36 months	
	(1)	(2)	(3)	(4)
Portfolio	Std. Dev	Sharpe ratio	Std. Dev	Sharpe ratio
1 (Short)	5.554	0.070	5.442	0.082
2	4.458	0.088	4.746	0.112
3	4.137	0.153	4.423	0.141
4	4.323	0.199	4.726	0.171
5 (Long)	5.148	0.209	5.714	0.206
Long - Short	2.850	0.242	2.283	0.319

Table 3 (Cont'd)

Panel C: Average monthly portfolio market share

	12 months		36 months	
	(1)	(2)	(3)	(4)
Portfolio	Excess return	DGTW return	Excess return	DGTW return
1 (Short)	8.412	8.347	7.485	7.718
2	25.094	25.026	25.820	25.632
3	31.058	31.001	32.010	31.450
4	25.522	25.404	25.165	25.488
5 (Long)	9.915	10.222	9.520	9.711
Long - Short	18.326	18.568	17.005	17.429

Table 4
Factor model estimation

This table reports factor model performance estimation of portfolios sorted by social sensitivity. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. Stocks are sorted into quintiles based on social sensitivity in the past twelve months. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with the most positive (negative) social sensitivity. Long -Short reports the performance difference between the Long and Short portfolios. The factor models include the following factors: the market excess return (MKTRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), short-term reversal (STR) and long-term reversal (LTR) factors, and the liquidity factor (LIQ). The sample period is from January 2006 to December 2016. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Factor	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
Alpha	0.353**	-0.404**	0.757***	0.362**	-0.357**	0.719***	0.361**	-0.350**	0.711***
	(2.369)	(-2.518)	(3.149)	(2.406)	(-2.311)	(2.962)	(2.402)	(-2.415)	(3.021)
MKTRF	1.061***	1.160***	-0.099	1.042***	1.096***	-0.054	1.046***	1.065***	-0.019
	(24.738)	(18.161)	(-1.030)	(21.198)	(18.017)	(-0.542)	(21.648)	(19.869)	(-0.209)
SMB	0.248***	0.283***	-0.035	0.253***	0.274***	-0.021	0.260***	0.223***	0.037
	(3.812)	(3.507)	(-0.282)	(3.803)	(3.541)	(-0.174)	(3.496)	(2.902)	(0.293)
HML	0.013	-0.117	0.130	-0.032	-0.198*	0.165	-0.036	-0.171*	0.135
	(0.226)	(-1.168)	(0.958)	(-0.462)	(-1.781)	(1.126)	(-0.521)	(-1.661)	(0.968)
UMD				-0.068	-0.057	-0.011	-0.065	-0.077**	0.013
				(-1.647)	(-1.592)	(-0.182)	(-1.544)	(-2.194)	(0.208)
STR				-0.002	0.173**	-0.174	-0.000	0.161**	-0.161
				(-0.029)	(2.191)	(-1.487)	(-0.003)	(2.134)	(-1.415)
LTR				0.001	0.032	-0.030	-0.009	0.109	-0.117
				(0.015)	(0.296)	(-0.188)	(-0.085)	(1.133)	(-0.763)
LIQ							-0.020	0.149**	-0.169*
							(-0.349)	(2.614)	(-1.784)
N months	132	132	132	132	132	132	132	132	132
Adj. R^2	0.891	0.884	0.006	0.891	0.891	0.015	0.891	0.898	0.044

Table 5
Social sensitivity and expected returns

This table reports estimates from Fama Macbeth (1973) regressions. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. The dependent variable is monthly stock return. Regressors include lagged social sensitivity loading, Carhart (1997) four-factor loadings estimated by daily returns over the previous month, cumulated stock return over the past six months (*Lag 6m Return*), lagged log market capitalization (*Size*), and lagged book-to-market ratio (*Book-to-market*). We report the time-series averages of monthly cross-sectional regression coefficients. The sample period is from January 2006 to December 2016. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Factor	(1)	(2)	(3)	(4)	(5)	(6)
CSR sensitivity	0.009**	0.009***	0.009***	0.010***	0.010***	0.010***
	(2.611)	(2.706)	(2.772)	(2.906)	(2.994)	(2.992)
Beta MKTRF	0.000	0.006	0.022	0.013	0.021	0.024
	(0.001)	(0.100)	(0.328)	(0.194)	(0.306)	(0.363)
Beta SMB		-0.056	-0.072*	-0.065	-0.068*	-0.064
		(-1.479)	(-1.772)	(-1.601)	(-1.697)	(-1.595)
Beta HML		0.005	0.019	0.011	0.016	0.013
		(0.173)	(0.531)	(0.312)	(0.465)	(0.363)
Beta UMD			-0.077	-0.048	-0.050	-0.045
			(-0.985)	(-0.706)	(-0.749)	(-0.696)
Lag 6m Return				-0.007*	-0.007*	-0.007*
				(-1.897)	(-1.864)	(-1.874)
Size					-0.076	-0.027
					(-1.629)	(-0.679)
Book-to-market						0.331***
						(3.411)
Constant	0.224	0.275	0.325	0.365	0.825	0.328
	(0.483)	(0.588)	(0.701)	(0.802)	(1.648)	(0.618)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	460,895	460,895	460,895	460,895	460,895	460,895
Avg. adj. R^2	0.095	0.099	0.103	0.107	0.111	0.114

Table 6

Performance of double sorted portfolios by search volume intensity or political climate

This table reports performance estimates of double sorted portfolios defined using social sensitivity and an additional firm characteristic. We use annual state-level *SVI* or political climate in each firm's headquartered state as an additional firm characteristic. Component returns are those of all common stocks (share code=10 or 11) in the CRSP universe. In each month, a stock is classified into low or high search volume intensity group if *SVI* in its headquartered state is above or below the median in the previous calendar year. Similarly, a stock is classified into Republican (Democratic) political climate group if Republican (Democrat) won the most recent Presidential election in its headquartered state. In addition, within a given social sentiment (political climate) group, a stock is further classified as being in the high (low) social sensitivity category if its social sensitivity is within the top (bottom) tercile. We report the alpha estimates using the seven-factor unconditional model. Panel A reports the alpha estimates of *SVI* and social sensitivity sorted portfolios while Panel B reports the alpha estimates of political climate and social sensitivity sorted portfolios. The sample period is from January 2006 to December 2016. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolios sorted by search interest and social sensitivity

Portfolio	Low interest	High interest	High - Low
1 (Low social sensitivity)	-0.434**	-0.219*	0.214
	(-2.563)	(-1.950)	(1.235)
2	-0.040	0.035	0.075
	(-0.438)	(0.514)	(0.550)
3 (High social sensitivity)	0.503***	0.197	-0.306
	(3.394)	(1.541)	(-1.630)
High - Low sensitivity	0.937***	0.416**	
	(4.190)	(2.051)	
N months	132	132	

Panel B: Portfolios sorted by political climate and social sensitivity

Portfolio	Republican	Democrat	Democrat - Republican
1 (Low social sensitivity)	-0.601***	-0.140	0.461**
	(-3.195)	(-1.310)	(2.232)
2	-0.064	-0.004	0.059
	(-0.684)	(-0.068)	(0.435)
3 (High social sensitivity)	0.442***	0.247**	-0.195
	(2.675)	(2.047)	(-1.032)
High - Low sensitivity	1.043***	0.387**	
	(4.144)	(2.073)	
N months	132	132	

Table 7
Institutional trading of stocks with different social sensitivity

This table reports the excess buy-sell imbalance (*EBSI*) of stocks with different levels of social sensitivity. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. Stocks are sorted into quintiles based on social sensitivity in the past twelve months. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with the most positive (negative) social sensitivity. *EBSI* reports the monthly difference in buy-sell imbalance between two groups of stocks. Columns (1) to (3) reports the EBSI between the Long and Short, Long and middle three, and the Short and middle three quintile portfolios. We also report the percentage of months when *EBSI* is positive. The sample period is from January 2006 to December 2016. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Long-Short	(2) Long-Middle	(3) Short-Middle
EBSI	1.436*	1.755**	0.319
	(1.712)	(2.581)	(0.366)
Positive EBSI	68%	68%	52%
N months	60	60	60

Table 8
Social sensitivity and operating performance

This table reports estimates from Fama Macbeth (1973) regressions. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. The dependent variable is return on asset (*ROA*) h-quarter ahead. Regressors include monthly average social sensitivity loadings in the current quarter, book-to-market ratio and dividend-to-equity ratio in the current quarter, following Fama and French (2000). We also include *ROA* in the current quarter as an additional regressor, as in Vuolteenaho (2002) and Hou and Robinson (2006). We report the time-series averages of monthly cross-sectional regression coefficients. The sample period is from January 2006 to December 2016 for regressor and is h-quarter ahead for the dependent variable. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) h=1	(2) h=2	(3) h=3	(4) h=4	(5) h=5	(6) h=6
Ave. sensitivity	0.020	0.021*	0.006	0.017	0.026	-0.014
	(1.547)	(1.956)	(0.990)	(1.637)	(1.400)	(-0.809)
Book-to-Market	-0.201	-0.374***	-0.596***	-0.810	-0.410***	-0.327***
	(-1.293)	(-4.250)	(-2.685)	(-1.618)	(-4.929)	(-6.311)
Dividend-to-Equity	0.157	0.369	0.246	0.386	-0.043	0.068
	(0.850)	(1.187)	(0.737)	(1.248)	(-0.135)	(0.158)
No Dividend	-0.309***	-0.414***	-0.460***	-0.371***	-0.677***	-0.301
	(-6.423)	(-10.079)	(-12.731)	(-8.001)	(-3.951)	(-0.942)
ROA	0.721***	0.620***	0.602***	0.618***	0.556***	0.499***
	(13.154)	(8.093)	(8.100)	(5.224)	(5.953)	(5.646)
Constant	1.130***	0.893**	0.966*	0.544	0.900	0.834
	(4.390)	(2.393)	(1.927)	(0.724)	(1.467)	(1.222)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	146,123	143,608	141,061	138,674	133,571	128,576
Avg. Adj. R^2	0.629	0.552	0.511	0.522	0.456	0.432

Table 9
Factor model estimation: Robustness

This table reports factor model risk-adjusted performance estimates. We focus on all common stocks (share code equals 10 or 11) in the CRSP universe. Stocks are sorted into quintiles based on social sensitivity in the past twelve months. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with most positive (negative) social sensitivity. The dependent variable is monthly return difference between the Long and Short portfolio. The factor models include the same factors as in Table 4. In Column (1), we estimate the factor model using social sensitivity constructed by a 36-month estimation window. In Column (2), we include the Baker and Wurgler (2007) investor sentiment index (SENT) as an additional control variable. In Columns (3) to (5), we interact each factor with one of the following interaction variables (INT): the recession indicator from the National Bureau of Economic Research (REC), the yield on the 90-day T-bill (YLD), and the term spread (TERM). The interaction variable used in each regression is indicated at the top of each column. In Column (6), we include interactions between all of the factors and interaction variables. The sample period is from January 2008 to December 2016 for Column (1), January 2006 to December 2014 for Column (2), and January 2006 to December 2016 for Columns (3) to (6). The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Interaction variable (INT)			REC	YLD	TERM	ALL
Alpha	0.707***	0.674***	0.577***	0.568**	0.705***	0.665**
	(3.744)	(2.708)	(2.710)	(2.148)	(2.749)	(2.203)
MKTRF	0.031	-0.072	0.047	0.001	-0.087	-0.057
	(0.485)	(-0.837)	(0.469)	(0.005)	(-0.852)	(-0.426)
SMB	0.019	0.080	-0.042	-0.026	0.004	0.064
	(0.153)	(0.634)	(-0.381)	(-0.194)	(0.036)	(0.523)
HML	0.002	0.211	0.023	0.228	0.196	0.066
	(0.017)	(1.180)	(0.159)	(1.382)	(1.177)	(0.392)
UMD	-0.002	0.004	0.020	-0.019	-0.002	-0.031
	(-0.028)	(0.068)	(0.203)	(-0.258)	(-0.033)	(-0.299)
STR	0.003	-0.210*	-0.132	-0.183	-0.030	-0.085
	(0.026)	(-1.876)	(-0.753)	(-1.240)	(-0.183)	(-0.387)
LTR	0.006	-0.061	-0.199	-0.145	-0.034	-0.174
	(0.051)	(-0.338)	(-1.235)	(-0.819)	(-0.229)	(-0.776)
LIQ	0.029	-0.108				
	(0.369)	(-1.194)				
SENT		0.457				
		(0.927)				
MKTRF×INT			-0.304*	-0.501	0.065*	
			(-1.936)	(-1.034)	(1.743)	
SMB×INT			0.058	0.147	-0.004	
			(0.165)	(0.160)	(-0.064)	
HML×INT			0.638***	-0.885	0.035	
			(3.547)	(-0.840)	(0.607)	
UMD×INT			-0.068	0.368	0.062**	
			(-0.524)	(0.632)	(2.584)	
STR×INT			-0.116	0.347	-0.032	
			(-0.526)	(0.421)	(-0.818)	
LTR×INT			0.193	1.125	-0.131**	
			(0.665)	(0.931)	(-2.189)	
N months	108	117	132	132	132	132
Adj. R^2	-0.059	0.063	0.089	-0.023	0.033	0.143

Table 10
Performance of double-sorted portfolios by size or institutional ownership

This table reports performance estimates of double sorted portfolios defined using social sensitivity and an additional firm characteristic. We use market capitalization or institutional ownership (IO) as an additional firm characteristic. Component returns are those of all common stocks (share code=10 or 11) in the CRSP universe. In each month, a stock is classified into large or small size group (high or low institutional ownership group) if its lagged market capitalization (average institutional ownership in the previous year) is above or below the sample median. In addition, within a given size (institutional ownership) group, a stock is further classified as being in the high (low) social sensitivity category if its social sensitivity is within the top (bottom) tercile. We report the alpha estimates using the seven-factor unconditional model. Panel A reports the alpha estimates of size and social sensitivity sorted portfolios while Panel B reports the alpha estimates of institutional ownership and social sensitivity sorted portfolios. The sample period is from January 2006 to December 2016. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolios sorted by size and social sensitivity

Portfolio	Small size	Large size	Large – Small size
1 (Low social sensitivity)	-0.338**	-0.318***	0.020
	(-2.206)	(-3.096)	(0.132)
2	0.098	0.043	-0.055
	(0.910)	(0.799)	(-0.440)
3 (High social sensitivity)	0.008	0.286***	0.278*
	(0.058)	(2.865)	(1.767)
High - Low sensitivity	0.345**	0.604***	
	(2.524)	(3.312)	
N months	132	132	

Panel B: Portfolios sorted by IO and social sensitivity

Portfolio	Low IO	High IO	High - Low IO
1 (Low social sensitivity)	-0.392*	-0.295***	0.097
	(-1.748)	(-3.030)	(0.467)
2	0.058	0.034	-0.024
	(0.502)	(0.706)	(-0.186)
3 (High social sensitivity)	0.193	0.285**	0.091
	(0.984)	(2.561)	(0.417)
High – Low sensitivity	0.585*	0.579***	
	(1.773)	(3.092)	
N months	132	132	

Table 11
Performance of social sensitivity based industry portfolios

This table reports the performance of the five industry portfolios sorted by social sensitivity. We focus on 48 Fama and French (1997) industries. The Long (Short) portfolio is a value-weighted portfolio of the five industries with the most positive (negative) social sensitivity in the past 12 months. Portfolios 2-4 are value-weighted portfolios of the remaining industries sorted into terciles based on social sensitivity during the same estimation window. Long-Short reports the performance difference between the Long and Short portfolios. Panel A reports the excess and DGTW returns during our sample period from January 2006 to December 2016. Excess returns are calculated as the difference between valued-weighted portfolio returns and the risk free rate. DGTW returns are calculated using the Daniel, Grinblatt, Titman, and Wermers (1997) method. Columns (1) and (2) reports the excess and DGTW returns when we use five industries to construct the Long and Short portfolios. For robustness, we also vary the number of industries in the Long and Short portfolios. In Columns (3) to (8), we report the excess and DGTW returns when we use three, seven, and ten industries to form the Long and Short portfolios. Panel B reports the standard deviation of portfolio excess returns and the Sharpe ratio. Panel C reports the average monthly market share for the excess and DGTW return portfolios. We also report the total market share covered by the Long-Short trading strategy. The t-statistics (reported in parentheses) are computed using standard errors adjusted by the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Portfolio performance estimates

	Baseline		3 industries		7 industries		10 industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio	Raw return	DGTW return	Raw return	DGTW return	Raw return	DGTW return	Raw return	DGTW return
1 (Short)	0.421	-0.160	-0.128	-0.669**	0.343	-0.186	0.418	-0.144
	(0.782)	(-1.154)	(-0.189)	(-2.179)	(0.643)	(-1.313)	(0.771)	(-1.147)
2	0.308	-0.203**	0.427	-0.134	0.446	-0.114	0.351	-0.154
	(0.674)	(-2.049)	(0.958)	(-1.411)	(1.015)	(-1.062)	(0.838)	(-1.390)
3	0.582	-0.160**	0.589	-0.135**	0.548	-0.175***	0.625	-0.126
	(1.292)	(-2.579)	(1.307)	(-2.148)	(1.207)	(-2.665)	(1.353)	(-1.654)
4	0.957**	0.203**	1.019**	0.226***	0.926**	0.188**	0.900**	0.174**
	(2.342)	(2.409)	(2.513)	(2.752)	(2.154)	(2.139)	(2.080)	(2.034)
5 (Long)	1.337***	0.541***	1.627***	0.810***	1.246***	0.423***	1.252***	0.397***
	(3.221)	(3.093)	(3.889)	(3.235)	(3.267)	(3.205)	(3.350)	(3.452)
Long - Short	0.915**	0.700***	1.754***	1.479***	0.903**	0.609***	0.835***	0.541***
	(2.311)	(3.020)	(3.137)	(3.369)	(2.528)	(3.237)	(2.738)	(3.145)
N months	132	132	132	132	132	132	132	132

Table 11 (Cont'd)

Panel B: Portfolio performance characteristics

	Baseline		3 industries		7 industries		10 industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio	Std Dev	Sharpe ratio	Std Dev	Sharpe ratio	Std Dev	Sharpe ratio	Std Dev	Sharpe ratio
1 (Short)	5.503	0.077	6.768	-0.019	5.386	0.064	5.276	0.079
2	4.828	0.064	4.784	0.089	4.727	0.094	4.706	0.075
3	4.560	0.128	4.533	0.130	4.570	0.120	4.606	0.136
4	4.360	0.220	4.381	0.233	4.453	0.208	4.574	0.197
5 (Long)	4.822	0.277	5.093	0.319	4.597	0.271	4.398	0.285
Long - Short	4.263	0.215	6.105	0.287	3.550	0.254	3.062	0.273

Panel C: Average monthly portfolio market share

	Baseline		3 industries		7 industries		10 industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Portfolio	Raw return	DGTW return	Raw return	DGTW return	Raw return	DGTW return	Raw return	DGTW return
1 (Short)	8.027	8.143	3.432	3.454	11.927	11.976	18.612	18.761
2	27.006	27.044	31.601	31.733	25.121	25.291	20.676	20.765
3	31.275	31.016	33.727	33.481	29.260	28.937	24.812	24.447
4	27.870	28.386	28.704	29.023	23.483	24.104	19.707	20.287
5 (Long)	5.821	5.411	2.535	2.310	10.209	9.692	16.193	15.740
Long - Short	13.849	13.554	5.968	5.763	22.137	21.668	34.805	34.502

Figure 1
Search volume intensity for CSR

This figure plots the time-series search volume intensity (*SVI*) for the topic "corporate social responsibility" in the U.S. region from January 2004 to December 2016. Source: Google Trends.

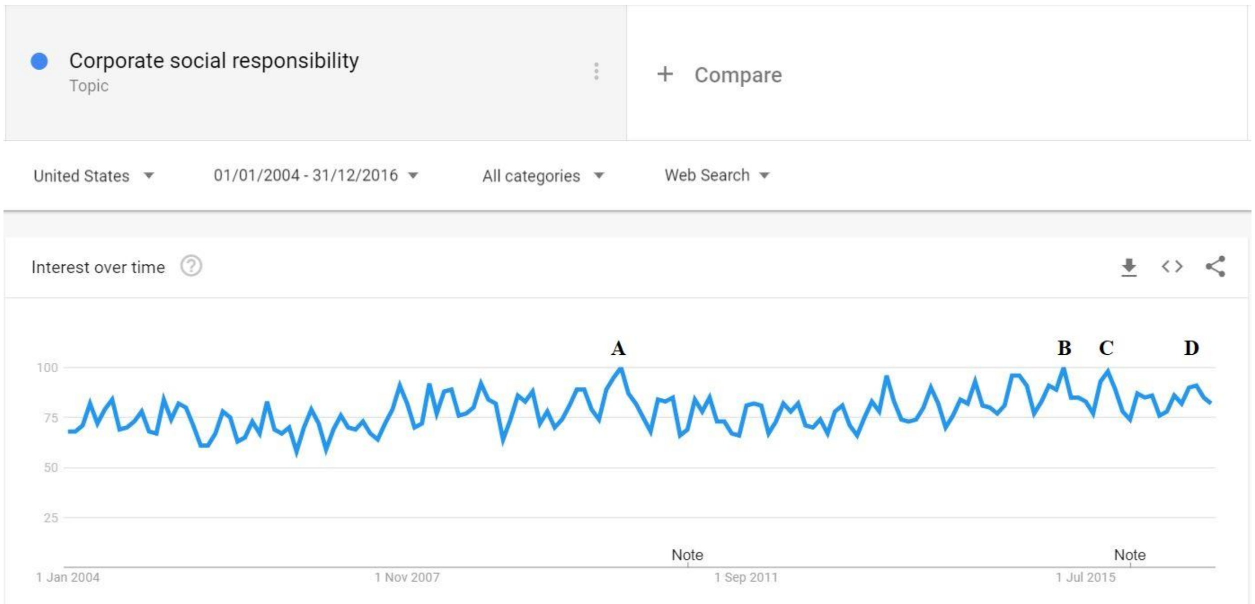

Figure 2
Social sensitivity based stock portfolios: DGTW returns

This figure plots the DGTW returns of the CSR sensitivity based Long-Short portfolio formed using all common stocks (share code equals 10 or 11) in the CRSP universe. The sample period is from January 2006 to December 2016.

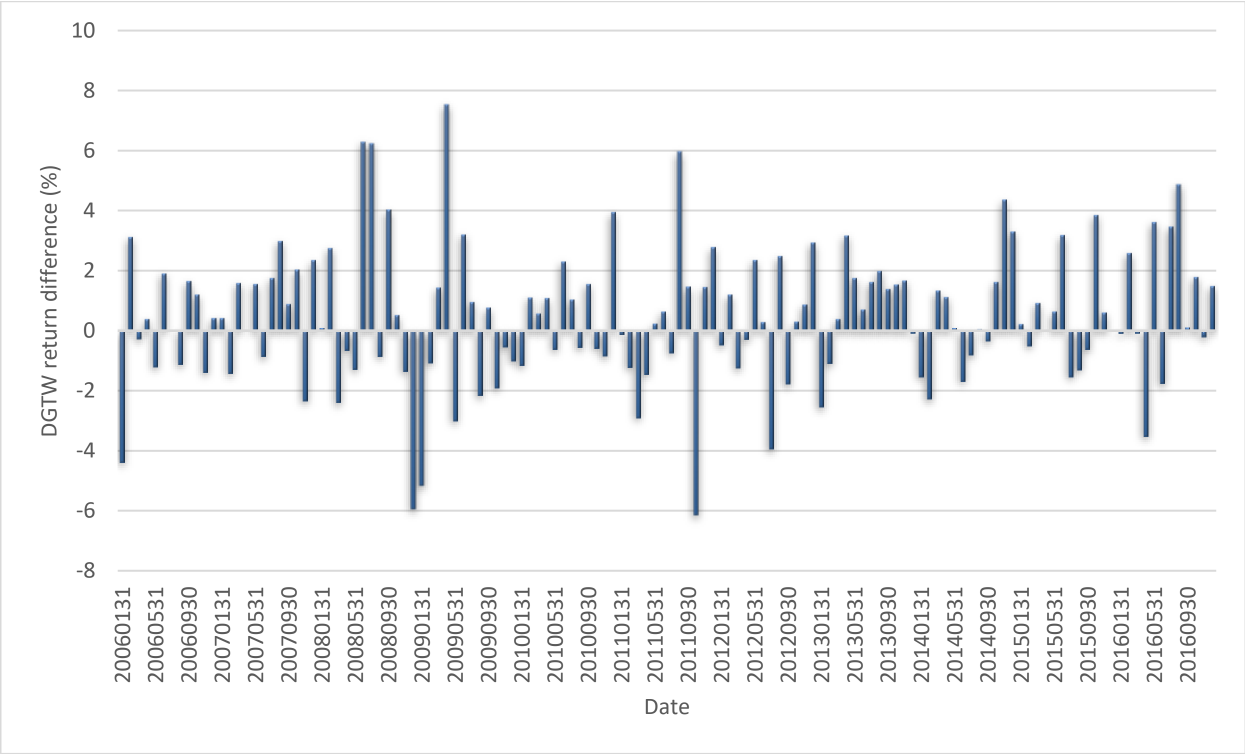

Figure 3
Social sensitivity based industry portfolios: DGTW returns

This figure plots the effect of varying portfolio formation periods on monthly seven-factor adjusted abnormal return (solid line) of portfolios sorted by social sensitivity. We focus on the performance difference between the Long and Short portfolios. The Long (Short) portfolio is a value-weighted portfolio of stocks in the quintile with most positive (negative) social sensitivity in the past twelve months. A positive shift in portfolio formation period corresponds to delayed formation of the Long and Short portfolios. We also report ±2 standard error bars (dashed lines). Standard errors are adjusted for auto-correlation using the Newey and West (1987) method. The sample period is from January 2006 to December 2016.