Sentiment Inequality, Relative Performance of Firms, and the Stock Market

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Abstract:

This study shows that sentiment inequality, defined as the consumer sentiment difference between high- and low-income groups, is indicative of the future performance of high-end product firms compared with low-end product firms. High-market beta firms, which tend to sell high-end products, have relatively higher cash flows following sentiment inequality increases, while low-market beta firms, which tend to sell low-end products, have relatively higher cash flows following sentiment inequality decreases. These differences are not sufficiently priced in stock prices, and a trading strategy that uses knowledge of changes in sentiment inequality yields annual alphas in the range of 7%-16%, depending on whether the strategy is run unconditionally or conditional on the sentiment level in the economy. As a case study, we provide evidence of how changes in sentiment inequality predict the relative performance of fast-food versus casual dining firms. Finally, this study shows that the change in sentiment inequality is a leading indicator of systematic changes. When sentiment inequality increases, market value-weighted returns in the following months tend to increase, whereas the VIX index tends to decrease.

Keywords: Consumer Confidence Index, Leading indicator, Index of Consumer Sentiment, Sentiment, Sentiment inequality, Stock market, Systematic, VIX

JEL: D12, G10, G11, G14, G17

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Household spending on consumer goods and services is the central driver of a company's success. Therefore, firms spend much of their effort on understanding what drives consumer behavior. Firms' desire to understand consumer spending behavior is also evident in the development of academic research fields such as marketing science and consumer psychology. Consumer spending is crucial for the macroeconomy. In the US, it accounts for approximately two-thirds of GDP and is often used as a measure of an economy's productive success. Consequently, economists, managers, investors, and other market participants continuously follow consumers' outlook on their spending behavior. Two important numbers that are followed every month are the Consumer Confidence Index (CCI) and the Index of Consumer Sentiment (ICS), both of which are based on surveys that aim to understand the behavior and sentiment of American consumers. While the closely watched index scores are often used to predict spending behavior (e.g., Ludvigson, 2004), these aggregate numbers conceal a wealth of information that can be exposed at disaggregated levels (Dominitz and Manski, 2004; Souleles, 2004; Toussaint-Comeau and McGranahan, 2006).

In this study, we suggest that consumer sentiment[1] may differ by income, which should be indicative of the *relative spending* patterns of these groups.[2] Thus, the difference between the sentiment levels of high- and low-income groups, which we refer to as Sentiment Inequality (SI), should be informative for relative firm performance and asset prices. Our claim is simple: the consumption of high-end goods[3] and the performance of high-end goods firms predominantly depend on the sentiment of high-income groups, whereas the consumption of low-end goods and

[1] Consumer sentiment in this study follows the definition of CCI and ICS and refers to the overall health of the economy as determined by consumer opinion. It takes into account people's feelings toward their current financial health, the health of the economy in the short-term, and the prospects for longer-term economic growth. High (low) level of sentiment can be referred to as an optimistic (pessimistic) consumer feeling about their finances and the state of the economy.

[2] Relative spending rather than overall spending is analogous to relative valuation rather than fundamental valuation, which has been proven useful for predictions in a corporate finance setting (e.g., Boni and Womack, 2006; Da and Schaumburg, 2011).

[3] Throughout our paper, we refer to goods and services as goods for brevity.

the performance of low-end goods firms predominantly depend on the sentiment of low-income groups. When SI increases, high-income individuals are becoming relatively more confident than low-income individuals; when SI decreases, low-income individuals are becoming relatively more confident than high-income individuals. Consequently, relative changes in the sentiment of the high- and low-income groups can reflect the relative performance of high-end versus low-end goods firms. Of course, individuals are not fixed in their consumption choices, and a relatively low-income individual can buy high-end goods and vice versa. However, if the tendency to consume certain goods is not completely flexible and depends on income, changes in SI should have a significant effect on the relative performance of firms. For example, consider that low-income group individuals tend to own a Ford vehicle and high-income group individuals own a Porsche vehicle. One would think that when low-income consumers feel relatively more confident about their finances than high-income consumers, the purchase of a new Ford vehicle is more common than the purchase of a new Porsche vehicle. The opposite is true, and new Porsche vehicles are bought more often when high-income consumers are relatively more confident. Thus, the *SI hypothesis* posits that changes in SI reflect the future performance of high-end goods firms relative to low-end goods firms.

To test the SI hypothesis, we need to partition US firms based on the type of good they provide: high-end versus low-end. Although companies often produce both high- and low-end goods, we can rely on finance theory, which implies that, ceteris paribus, high-end goods firms tend to have a higher market beta than low-end goods firms. Because low-income groups have a large fraction of their disposable income devoted to necessities and a lower fraction of the income devoted to savings (Keynes, 1936), they are less flexible in changing their consumption based on the state of the economy, implying that the product they consume tend to have a low beta.

Additionally, the income of high-income groups is more sensitive to the stock market (Rubin and Segal, 2015). Assuming a positive correlation between changes in income and changes in consumption, high-end goods firms should be more cyclical. Indeed, continuing with our vehicle example, Porsche and Tesla tend to have a beta above 1.5, whereas lower-end automobile firms such as Ford, GM, and Toyota tend to have a lower beta. Additionally, we know that beta is useful for sorting industries according to consumer type. Luxury items, which are predominantly consumed by high-income groups, are typically bought during economic booms (e.g., Bils and Kenlow, 1998; Heffetz, 2011) and have high systematic risk. On the other hand, consumer staples or discount stores such as Walmart, where low-income individuals often spend their money, have relatively low systematic risk. Consequently, the SI hypothesis can be formulated as having implications for high-beta and low-beta firms. The hypothesis is that high-beta firms perform better than low-beta firms following SI increases and that high-beta firms perform worse than low-beta firms following SI decreases.

We analyze the cross-sectional performance of firms following SI changes in the 2001-2022 period. The study period follows the emergence of high-income inequality in the US (Piketty and Saez, 2006; Piketty and Goldhammer, 2014; Chancel et al., 2022) when the difference in consumption across income groups should be evident. [4] We partition firms based on their equity beta in the previous year and show that in the two quarters following SI increases, high-beta firms tend to have better cash flow performance than low-beta firms, and vice versa. The effect is stronger for the following quarter than the following second quarter, dissipating in the third quarter after the SI change. In addition, we find that high-beta firms are more sensitive to changes in SI

[4] The SI hypothesis has stronger implications when income groups differ more in their choices of product and services as that leads to consumer clientele effects that make product and service markets more segmented (Aguiar and Bils, 2015).

than low-beta firms. This may be attributed to an asymmetry in consumption patterns due to the higher saving rates of high-income groups than low-income groups (Keynes, 1936), making their spending more dependent on changing sentiment levels.

Next, we use the changes in SI at the monthly frequency to analyze whether it is predictive of the variation in returns across firms in the following months. Given that investors follow the sentiment level as well as many other variables in the economy, but are relatively unaware of SI, there is reason to believe that information on SI is not sufficiently priced in stock prices. The results show that, similar to the cash flow results, the stock returns of high-beta versus low-beta firms are positively correlated with changes in SI. Despite this predictability, a calendar-time one-month ahead trading strategy based on the sign of the change in SI provides 0.3%-0.4% monthly raw and abnormal returns (3.6%-4.8% annual), which are statistically insignificant. However, if one increases the holding period to two months following SI changes, one can generate a significant return of approximately 0.6% monthly (7.2% annually).

Next, we consider two types of strategies that condition on additional information. First, during times of low sentiment, both high- and low-income groups are close to the lower bound of the sentiment level, so SI is low. This is analogous to how income inequality is relatively small during economic downturns in the economy (Rubin and Segal, 2015). Consequently, SI increases during such times may be more informative, as it suggests that the market is getting out of the slump.[5] The opposite is true when the sentiment level is high and SI decreases. During such times, SI is high and consumer sentiment may be overly optimistic. A reduction in SI during such times is indicative of a cooling market. We call both these situations a Contrarian state (as the change in

[5] One possibility which is in line with this prediction is that the high-income individuals in the economy are more tuned to the state of the stock market and the value of real-estate than the lower-income individuals (see Rubin and Segal, 2015). Thus, when SI increases (decreases), it suggests that there is reason to believe that the market will outperform (underperform).

SI is contrary to the sentiment level) and find that during such times, trading strategies that use the SI change are highly profitable (a value-weighted abnormal return of 13% and equal-weighted return of 16%). A second strategy that we consider is to trade only when SI increases or decreases by a high absolute amount during the month. We call this strategy a large change in SI strategy. This latter strategy yields calendar-time trading strategies raw and equal-weighted abnormal return of 12-13% annually.

Throughout the study, our classification of high- and low-end goods is based on equity beta, which is probably a noisy measure for defining the income group of the representative consumer of the firm's goods. Therefore, we complement our analysis by conducting a case study of the restaurant business, where we can easily separate firms into high-end and low-end firms. We hand-collect all public firms in the US that can be considered as either fast-food chains or casual dining restaurants based on detailed information of their facilities and brand names. In this analysis, the high-end firms are all casual dining chains, and the low-end firms are fast-food chains. We repeat the analyses on cash flows and return predictability that we conduct for the full sample. The results are consistent with those of the full sample of firms: changes in SI are predictive of the relative performance of casual dining versus that of fast-food firms.

Finally, the predictions of the relative performance of high-versus low-beta firms naturally imply that changes in SI have implications for the future state of the macroeconomy. Because high-beta firms perform comparatively better during booms and low-beta firms perform comparatively better during busts, SI changes should be positively predictive of stock market movements. Thus, changes in SI are positively correlated with future economic changes. We show that SI changes are predictive of the next month's value-weighted return, after conditioning for known predictive variables in the literature. We also show that changes in SI are predictive of changes in the VIX index. These results imply that SI is predictive of systematic changes in the economy. A host of simple trading strategies (buying and shorting the market and trading the VIX) currently yield profitable returns using information on changes in SI.

In much of the finance literature, investor sentiment is defined as an optimistic or pessimistic belief of investors about the future that is not justified by the fundamental facts at hand (Baker and Wurgler, 2007).[6] However, this study proposes that SI has real cash flow implications for firms. We also note that SI does not lend itself to a market-wide temporary explanation because the difference in sentiment between the top- and bottom-income groups, by definition, wash away aggregate mood swings that affect the average investor in the economy.

This study is related to the literature that has shown that consumer sentiment indices affect consumer spending (Acemoglu and Scott, 1994; Carroll, Fuhrer, and Wilcox, 1994; Bram and Ludvigson, 1998; Batchelor and Dua, 1998; Ludvigson, 2004).[7] Previous research has also recognized that the distribution of income across households can play a role in the evolution and profitability of the economy (e.g., Murphy, Shliefer and Vishney, 1989; Matsuyama, 2002; Zweimüller and Brunner, 2005; Foellemi and Zweimüller, 2006). Our contribution can be considered as building on these two sets of literature, as we consider that consumer sentiment may

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[6] Investors' sentiment has been shown to temporarily affect prices because trading against changes in sentiment is risky and cannot be fully countered by arbitrageurs (e.g., De Long et al. ,1990; Shleifer and Summers, 1990; Barberies, Shleifer, and Vishney, 1998; Lemmon and Portniaguina, 2006; Da, Engelberg and Gao, 2015). However, investor optimism or pessimism can also be rational if these mood effects affect real outcomes, or, alternatively, be associated with a different underlying reason that correlates with the investor sentiment proxy (DeVault, Sias, and Starks, 2019).

[7] The permanent income hypothesis (Friedman, 1957) maintains that expenditure depends only on permanent income (wealth). Campbell and Mankiw (1990), however, conclude that half of the consumption can be attributed to liquidity constraints and precautionary savings motives (e.g., Shea, 1995; Alessie and Lusardi, 1997), which would imply that consumers are uncertain about their future income. If a reduction in sentiment reflects higher uncertainty, consumption today can drop (Acemoglu and Scott, 1994). Of course, sentiment can affect spending because of psychological reasons. John Maynard Keynes (1936) wrote that household consumption is influenced by “spontaneous optimism”, which can imply that households form their expectations about the future based on a host of issues such as preferences, technology, borrowing constraints, and subjective experiences, which sentiment indexes like the ICS and CCI summarize. Theoretical literature provides mechanisms for sentiment-driven business cycles (e.g., Angeletos and La’O 2013; Benhabib, Wang, and Wen 2015).

differ by income group, which translates to different spending behavior, which in turn matters for the cross-sectional performance of firms and the macroeconomy.

The remainder of this paper is organized as follows. In the next section, we provide a detailed description of SI and its evolution over time. In Section 3, we present other data sources used in this study. In Section 4, we provide the main empirical results that show that the change in SI is positively predictive of the relative performance of high-beta firms compared with low-beta firms. In Section 5, we present a case study of the restaurant business. In Section 6, we analyze the predictive ability of SI for the macroeconomy. Section 7 concludes.

2 Sentiment inequality

2.1 SI and sample period

The measure of sentiment inequality that we use throughout this paper is referred to as SI. It is the simple average of the sentiment inequality of the ICS index and the sentiment inequality of the CCI index, where the sentiment inequality of an index is the sentiment level of the upper- minus lower-income group of the respective index.[8]

Notably, only two organizations provide sentiment data based on the income group of individuals conducting the survey: the ICS, which is produced by the University of Michigan Survey Research Center, and the CCI, which is produced by the Conference Board. ICS cut-offs to three equal income groups (top, medium, and bottom) are based on respondent data, while CCI cut-offs to income groups are based on categories defined by a range of dollar income. Over the years, the income categories of the CCI have grown from three to nine. The CCI's bottom and top income categories are currently defined as household incomes below $15,000 and above $125,000,

[8] The results are robust to the usage of the principal component measure, which captures the common component of the two indices.

respectively. The ICS and CCI surveys poll households on their financial situation, expectations of the health and trajectory of the U.S. economy, and propensity to consume major household items. While both indices are highly correlated (Bram and Ludvigson, 1998; Ludvigson, 2004), they differ in terms of survey questions, sample size, and construction.

Michigan conducts its survey during most of the month, provides a preliminary mid-month release based on two-thirds of the sample, and provides final figures based on the full sample at the end of the month. The Conference Board provides its preliminary figures based on two-thirds of the sample on the last Tuesday of the survey month, and provides the final figures with the next month's preliminary figures. Despite this one-month lag in the release of the Conference Board's final figures, the revisions tend to be small and highly correlated with the final figures.[9]

Our analysis covers the period 2001-2022 because we would be missing most Compustat firm-level variables and the VIX index in earlier periods. In addition, theoretical and practical considerations make the post-2000 analysis suitable for our purpose. From a theoretical standpoint, if inequality in society is not large, individuals' income should have a minimal effect on the consumption of high-end versus low-end goods. Rather, what matters for the consumption of high-end versus low-end goods in relatively equitable economies is personal tastes. However, when income inequality is high, income becomes a major determinant of whether to consume high-end goods or low-end goods. By the early 2000s, income inequality in the US had reached its current high levels (e.g., Piketty and Saez, 2006; Piketty and Goldhammer, 2014; Chancel et al, 2022). Aguiar and Bils (2015) provide evidence that the increased income inequality observed at the turn of the century has materially shifted high-income households' consumption towards luxury goods

[9] The Conference Board survey is approximately six times larger than the Michigan survey, so its confidence interval on the preliminary figures should be relatively small. Ludvigson (2004) claims that the preliminary and final figures of the Michigan survey have a correlation of 0.99. Given the larger sample of the Conference Board, there is no reason to think that this correlation should be smaller for the Conference Board survey.

and low-income households' consumption towards necessities.[10] This increased segmentation in consumption makes the prediction of the SI hypothesis stronger in recent decades compared with the periods prior when income inequality was less severe. On the practical side, by the turn of the century, advances in computer technology have made it much easier to collect and process large amounts of historical data in real time; hence, the trading strategy results presented in this paper would have been available to the majority of the public in the post-2000 period. Thus, we consider the period 1980-2000 as a preliminary period, which is useful for understanding the distributional properties of SI but of limited value for real-time trading strategies.[11]

Figure 1 provides a schematic description of the timing of sentiment data release dates and out-of-sample prediction periods used in this study. The sentiment and SI of December would be based on surveys conducted in December. By the end of the month, the ICS has final figures for the month, but the CCI has only preliminary figures (based on two-thirds of the surveyed individuals). In an informal discussion with the Conference Board, we were told that adjustments made between preliminary figures and final figures are usually very small. It is important to note that throughout the paper, we generate SI from the final figures of ICS and CCI, which means that the trading profits for $t=0$ may marginally differ from what would be possible for a trader in real

[10] For example, during the years 2008-2010 compared to 1980-1982, the top income quintile increased spending on entertainment by 25 percent relative to that of food at home; by contrast, between the two periods, the bottom income quintile reported that entertainment expenditures declined by 40 percent relative to that of food. There is also evidence that the shrinking middle class lead to increased product market segmentation (Schwartz, 2014).

[11] Because sentiment data by income demographic is available starting in 1980, we can generate the SI starting in 1980. Almost all cross-sectional results reported in this paper are robust to the 1980-2020 period, however, the results are weaker and often insignificant when we consider the 1980-2000 alone. We note that a possibility for this lacking is the sentiment data by income reliability in the earlier period. Changes in technology such as mobile phone ownership (survey are conducted on phones), and the introduction of the internet have materially affected both the response rate to surveys and the distribution of incomes of household surveyed, so it is possible that the income groups were not well represented in earlier surveys. Lemmon and Portniaguina (2006) also find that the predictive power of consumer confidence is present only in the most recent 25-year of their sample and not earlier periods.

time. Nevertheless, because both ICS and CCI changes are based on the previous month, the economic and causal interpretation of our findings remains unchanged by this technical artifact.

2.2 Descriptive information on SI

Table 1 provides descriptive statistics for the main variables used in this study. Our sample covers the period from 2001 to 2021. As we rely on sentiment and SI distributional data for the 1980-2000 period for out-of-sample predictions, we also provide a comparison between the 1980-2000 and 2001-2021 periods in Panel A. A comparison between the two periods yields two interesting findings. First, the sentiment level decreased in the post-2000 period compared to that in the pre-2001 period. Thus, it appears that the average individual was more optimistic about the state of the economy before the turn of the century. Second, sentiment inequality has increased significantly after the turn of the century. Both findings may be related to the increase in income inequality that has emerged since the late 80s (e.g., Piketty and Saez, 2006) and may have caused the average sentiment level to drop and the average SI to increase. Next, we test whether there is a difference in the changes in sentiment and SI between the two periods. In the following rows, we provide distributional properties at the monthly and quarterly frequencies because sentiment data are provided at the monthly frequency and cash flow (financial statements) data are provided at the quarterly frequency. The difference of means tests show that we cannot reject the null hypothesis of a significant difference in the changes in the variables across the two periods.

In Figure 2, we provide the upper- and lower-group sentiment levels for 1980-2021 period. The upper figure provides the annual ICS of the upper- and lower-income groups and the bottom figure provides the annual CCI of the upper- and lower-income groups. The index levels are measured in December of each calendar year. It is apparent from the figure that upper-income individuals are almost always more optimistic than lower-income individuals, which is consistent with most studies that show that relative income and wealth matter for happiness (Rayo and Becker, 2007; Clark, Frijters and Shields, 2008). The sentiment levels of both groups tend to move together; however, the difference in sentiment level between the two groups, SI, which we analyze in this study, is continuously changing. For example, in the early 2000s, the difference was high. The difference drops with the collapse of the NASDAQ Index in 2000, and reaches a minimum during the financial crisis. We observed that the difference shrank again during the pandemic. There are two possible reasons why SI drops when the market contracts: first, the low-income group has a lower level of sentiment compared to the high-income group, so it is comparatively more bounded on how much further its sentiment can drop, leading to a reduction in SI during contractions in the economy; and second, it is plausible that the contemporaneous fall in the market inflicts more harm on the upper-income group than the lower-income group, as a large fraction of the upper-income group's income and wealth is derived from the value of the stock market (e.g., Favilukis, 2013; Rubin and Segal, 2015). Thus, on a comparative basis, the upper-income group is worse off during market contractions because its income and wealth are strongly tied to the stock market's value. Similarly, a buoyant stock market return increases income inequality and SI because it benefits high-income groups more than low-income groups do.

Next, in Figure 3, we examine the relationship of market returns with sentiment and SI at the quarterly frequency (end of a calendar quarter) from 2001 to 2021. The purpose of this figure is to visibly compare the variation in these measures with that of the value-weighted return. The LHS y-axis provides the value of the sentiment level (upper figure) and SI (bottom figure) at the end of the quarter, while the RHS y-axis provides the value-weighted return over the quarter. Although both series seem to correlate with the value-weighted return series, it is apparent that the sentiment series is less volatile than the stock market return or SI series. In conclusion, SI may capture aspects of the stock market's volatility that are not captured by sentiment series alone. If we consider that the sentiment level is followed by market participants continuously but SI is a novel construct introduced in this study, the evidence in Figure 3 suggests that changes in SI may be informative for stock market predictions.

3. Other sources of data

3.1 Firm-level variables

We use Compustat and CRSP data from January 2001 to December 2021. The sample includes all firms with common stocks (share code 11), excluding utilities and financial firms. To avoid small firm bias, we exclude firms with a market size of less than $50 million. Because we rely on the market beta to classify firms into high-end versus low-end type goods, we exclude firms that had less than 220 trading days in a calendar year and whose market beta, based on daily return in the calendar year, has a t-statistic of less than 2 (approximately 5.5% of firms). These criteria leave 5,799 unique firms during the sample period. Requiring a complete set of Compustat data reduces the sample by 28%. The final sample includes 4,182 firms with 122,005 firm-quarter observations during this period. Hence, the average firm appears in our sample over 7.5 years (30 quarters), with each quarter including an average of 2000 firms. Almost all S&P 1500 firms will be included in our sample.

Our empirical analysis aims to understand the impact of SI on cross-sectional firm performance. To measure firm performance, we use three measures: Operating Cash Flow (OCF), Return on Assets (ROA), and Profit Margin (PMI). OCF is income from operations before depreciation divided by total assets (Kaplan, 1989; Lang et al, 1991), ROA is income before extraordinary items (IB) divided by total assets (Hou, Xue, and Zhang, 2015 and 2020), and PMI is net income divided by sales (Fairfield and Yohn, 2001).

In the firm-level regressions, we control for the following firm characteristics: size, annual stock return volatility, market-to-book ratio, market leverage, dividend indicator, and capital expenditures. Firm size is the market value of a firm's equity (in billions of dollars) at the end of the calendar year. Volatility is the standard deviation of monthly stock returns over a year. Book-to-market ratio is the book value of equity divided by the market value of equity. Book equity is the book value of stockholders' equity plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of the preferred stock. Based on availability, we use the redemption, liquidation, or par value (in that sequence) to estimate the book value of the preferred stock (Davis, Fama, and French, 2000). Market leverage is the sum of long-term debt and current liabilities divided by the sum of long-term debt, current liabilities, and market value of equity (Denis and Mckeon, 2012). The dividend indicator equals one if the firm paid cash dividends, and zero otherwise. Capex is capital expenditure divided by book assets. The book-to-market ratio, market leverage, dividend indicator, and Capex are measured quarterly. All variables are winsorized at the 1st and 99th percentiles to minimize the effect of outliers.

Panel B of Table 1 provides firm-level descriptive statistics. The median OCF, ROA, and PMI are approximately 3%, 1.1%, and 4.2%, respectively, but their 99% confidence intervals are wide. The average firm has a market value of $6.15 billion. The median firm, however, is smaller than the average, with a market value of $1 billion. The average (median) firm stock return volatility is 13% (11%). The sample’s average (median) firm has a book-to-market ratio of 0.51 (0.42). Our sample’s average (median) firm has a market leverage of 20% (13%). Approximately

41% of firms in our sample pay quarterly dividends. The median firm in our sample has a capital expenditure of 1% of assets.

3.2 High-end versus low-end goods and market beta

The SI hypothesis posits that SI is predictive of firms' relative performance. When the top-income groups become comparatively more confident than the lower-income groups, we expect to see better performance by high-end goods firms compared to low-end firms. Similarly, when low-income groups become comparatively more confident than upper-income groups, we expect to see better performance of low-end goods firms compared to high-end firms. What remains is to determine how to empirically partition firms with high-end products to those with low-end products.

By definition, low-end goods have as consumers individuals that have a lower income than that of high-end goods. This implies that the consumption of high-income groups over time is more sensitive to market conditions than that of low-income groups for two reasons. First, low-income groups have a lower proportion of disposable income devoted to savings and higher proportion devoted to necessities than high-income groups (Keynes, 1936). The relatively low savings of low-income groups imply that they cannot easily defer or advance their consumption across time, which also makes their consumption less sensitive to the state of the economy.[12] Second, Rubin and Segal (2015) show that the income of low-income groups is less sensitive to market returns than that of high-income groups because a large fraction of the high-income groups is dependent on the return

[12] Assume, for example, that there are only two products, a high-end good which is bought solely by high-end consumers, and low-end good which is bought solely low-end consumers. Each type of consumers buys the goods based on necessity and inessential (i.e., sentiment) consumption. Consequently, because the necessity component is smaller for the high-income consumer, the high-end product is more sensitive to sentiment effects than the low-end product is. If sentiment is at least partially related to the state of the economy, we would expect high-end goods to have a higher beta.

of the stock market (pay-for-performance compensation, wealth-derived income from the value of their stock portfolio).[13] One would expect that the sensitivity of changes in income to market return will also triple down to consumption, resulting in low-end goods firms having a lower sensitivity to market returns than high-end goods firms. Thus, the fact that low-income groups have a lower saving rate, jointly with their income being less dependent on market returns, implies that low-end goods should be less sensitive to market returns.

This implies that high-income goods firms are associated with being more cyclical. Indeed, Bils and Klenow (1998) show that expenditures on luxuries and durables are cyclical, which is also widely known in practitioners' circles and the financial press (e.g., Deleersnyder, 2004; Daneshkhu and Simonian, 2009; Bain and Company, 2009; Danziger, 2022). Cyclical industries have higher market beta and risk premia than non-cyclical industries (e.g., Campbell and Mei, 1993; Fama and French, 1997; Gomes, Kohan and Yogo, 2009).

As an illustrative example of how market conditions play a role in the consumption of high- versus low-end goods, consider purchases in the car industry (Gavazza, Lizzeri and Roketskiy, 2014; Gavazza and Lanteri, 2021). High-income households tend to own new, high-quality cars, while low-income households tend to own older, low-quality cars. Suppose the economy is hit by a recession that affects both upper- and lower-income households. Because high-income households have better cars, it is easier for them to delay replacing their cars. That is, because their current cars are younger and of higher quality, they can afford to wait for a replacement decision. On the other hand, low-income individuals may be forced to scrap their cars despite the economic

[13] For example, in Table 3 of Rubin and Segal (2015), after controlling for GDP growth, the change in income of the top 1% has a beta of 0.275 with the market, which is highly significant; while the change in the income of the lowest group has a beta of 0.02, which is not significant.

downturn, because the cost of not replacing the car may be too high due to maintenance costs, or they may be forced to scrap the car by the regulator due to emission control policies.[14]

Thus, we choose the CAPM beta of a firm's equity as our proxy to differentiate between high-end and low-end good firms.[15] To measure a firm's beta, we use the daily return frequency and market model (CAPM) framework.[16] Our market proxy is the CRSP value-weighted index (including dividends). We partition all stocks each year (starting in the year 2000) into four portfolios according to the magnitude of their beta in the previous year ($\beta 1$ refers to the bottom quartile and $\beta 4$ the top quartile). In Panel A of Table 2, we have approximately 30,500 firm-quarter observations in each beta quartile. The mean beta of the top (bottom) quartile is 1.92 (0.75) with a standard deviation of 0.36 (0.2).

3.3 Other Variables

We employ macroeconomic variables used in the literature (e.g., Li, Ng, and Swaminathan, 2013) as controls in the market return and volatility analysis at a monthly frequency and measured in percent. The one-month T-bill rate and 30-year Treasury yield are from the CRSP database. The term spread is the difference between the AAA-rated corporate bond yields obtained from the Federal Reserve Bank of St. Louis (FRED) database and the one-month T-bill yield. The default

[14] Note that having a used-car market does not change the result that the high-income consumer is more flexible in the timing of the repurchase decision. All it would mean is that there is a continuum of alternatives, including purchasing a car in the used-car markets. Still, the higher the quality of the car a household possess, the more flexible it is in the replacement decision.

[15] According to financial theory, beta captures cyclicality in firms' performance, which can be related to many firm characteristics that are not related to the type of customers that buy the firm's good. Though we did try to adjust for various unrelated aspects of beta (such as operating and financial leverage), the results were minimally affected by such considerations. It seems that the large sample of firms, basically, all firms that have Compustat data, should have helped in eliminating the noise associated with choosing equity beta as a proxy.

[16] We use the CAPM rather than the four-factor, for example, because if we were to use the four-factor model, we would be getting a less suitable measure as aspects such as size and book-to-market, that are correlated with the high-end versus low-end scale, would take away from the ability of the market beta to capture the high-end versus low-end scale. This is similar to Berk and Demarzo (2020, pp. 487-488) discussion why we get better economic intuition about the company from the CAPM beta than the four-factor model.

spread is the difference between the BAA and AAA corporate bond yields for the last day of the month when both BAA and AAA daily yields exist, is obtained from the FRED. Inflation is the change in the consumer price index (CPI; all urban consumers, monthly, non-seasonally adjusted) obtained from the FRED. The earnings-to-price ratio and dividend-to-price ratio are calculated from the S&P 500 dividend, earnings, and price data on Robert Shiller's website[17]. Following Da, Engelberg and Gao (2015), we use the perceived economic policy uncertainty (EPU) which is a news-based measure provided by Baker, Bloom, and Davis (2016). The EPU change is the percentage change in the monthly average daily EPU for the month before the dependent variable's month. The CBOE (Chicago Board Options Exchange) Volatility Index (VIX) is from Wharton Research Data Services (WRDS).

4. Empirical Analysis

4.1 Univariate analysis

We begin by analyzing the major prediction of the SI hypothesis using univariate analysis. The prediction is that SI changes (ΔSI) positively predict the relative performance of high-end goods firms compared to that of low-end good firms. We use beta, estimated at the calendar year prior, as the measure of the good the firm produces on a low-end to high-end scale. We measure the change in firm performance as a seasonally adjusted quarterly change in OCF, ROA, and PMI (current quarter q minus the respective quarter in the previous year, *q-4*) and measure the ΔSI_{q-1} similarly, but one quarter prior, that is, the end of the previous quarter *(q-1)* minus that five quarters ago *(q-5)*.[18]

[17] Available at http://www.econ.yale.edu/~shiller/data.htm.
[18] The results are robust to quarterly change in SI (not seasonally adjusted).

Table 2 reports the mean performance of each beta quartile depending on whether ΔSI_{q-1}<0 (decrease in SI in previous quarter) or ΔSI_{q-1}>0 (increase in SI in previous quarter). The average performance decreases monotonically in beta when the ΔSI_{q-1} is negative. For example, the average one-quarter forward change in OCF is -0.09% for β1, -0.11% for β2, -0.16% for β3, and -0.36% for β4. These results strongly suggest that low-end good firms do comparatively better than high-ends good firms when ΔSI_{q-1} is negative. Contrary, the average performance increases monotonically in beta when the ΔSI_{q-1} is positive. For example, the average one-quarter forward change in OCF is -0.06% for β1, 0% for β2, 0.08% for β3, and 0.21% for β4. Thus, the results strongly suggest that high-end goods firms do comparatively better than low-end goods firms when SI increases in the previous quarter. Another way of showing that high-beta firms react differently than low-beta firms following changes in SI is to measure the difference for each beta quartile between quarters in which ΔSI_{q-1} is positive and those in which ΔSI_{q-1} is negative. Namely, this difference aggregates both sensitivities (following SI decreases and following SI increases) into one measure, reported in the Difference column. It is evident that this difference is increasing with beta quartile. It is 0.44% for β4 (highly significant) but only 0.03% for β1 (not significant).

Next, we conduct a difference-in-difference (DiD) analysis by comparing the performance difference following SI increases quarters and SI decreases quarters of β1 and β4. The DiD results can be considered a single aggregated test of the SI hypothesis. It captures variations following SI quarters (increases versus decreases) as well as variations across the type of goods the firm produces (proxied by the difference between betas). The last two rows of the Difference columns provide DiD results. The results show that the DiD of β4- β1 is 0.26% and that of (β4+ β3)- (β1+

β2) is 0.17%. The mean OCF (Table 1) is 2.3%; therefore, 0.26% represents a change of 11.3% in performance. Both the DiD results are highly economically and statistically significant.[19]

Moving to the one-quarter ahead change in ROA, the results are qualitatively the same as those of the change in OCF. There is a monotonic increase (almost monotonic decrease) in performance as we move from a low-beta quartile to a high-beta quartile following SI increases (decreases). There is a monotonic increase in the Difference column as we move from the low-beta to the high-beta quartile. The DiD results are similar in magnitude to those observed for the changes in OCF. Finally, the results for changes in PMI provide a similar interpretation, although the monotonicity property following SI decreases is not apparent, and it is also somewhat reduced in the Difference column. However, the DiD results are consistent with the SI hypothesis. Thus, we can conclude that the main prediction of the SI hypothesis, that high-beta firms perform comparatively better following quarters in which ΔSI_{q-1} is positive, and low-beta firms perform comparatively better following quarters in which ΔSI_{q-1} is negative, is consistent with the data.[20]

Table 2 also provides the results of the performance for two-quarter ahead following the change in SI. The results are mostly consistent with the SI hypothesis, although they are economically and statistically weak. For the two-quarter ahead change in OCF, monotonicity in difference (most LHS columns) exists and the DiD results are highly statistically significant. For

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[19] The difference between SI increases and SI decreases most naturally should be measured at the firm level. Thus, for each firm we want to compute the difference in performance between quarters that follow ΔSI_{q-1}<0 and those that follow ΔSI_{q-1}>0. However, because beta is measured at the annual frequency, firms can move from one beta-quartile to the other over the years. Thus, we are forced to measure the difference between quarters that follow ΔSI_{q-1}<0 and those that follow ΔSI_{q-1}>0 at the firm-year level. This means that years that do not have at least one quarter of increase in SI or decrease in SI are not included in the analysis, as during those years we cannot generate a measure. It also means that the DiD analysis is not a simple subtraction of the difference between columns β4 and β1. The former equal weights firm-year, while the later treats each firm-quarter the same. However, empirically, these technical aspects seem to matter little for the magnitude of the DiD percentage.

[20] In untabulated results we conduct a similar analysis on SALES (i.e., Sales/total assets), as one may claim that the SI hypothesis is most related to increased demand of consumers. The results with SALES are just as strong as with OCF.

the two-quarter ahead change in ROA and PMI, monotonicity generally exists, but is smaller than one-quarter ahead, making the DiD analysis insignificant. Overall, we interpret the results as supportive of the SI hypothesis for the one-quarter ahead performance and weakly supportive of the two-quarter ahead performance.

4.2 Multivariate analysis

The univariate analysis focuses on the two most important variables in the study (i.e., SI and beta quartile). However, it can fail to capture the various existing interactions. To determine whether changes in SI predict future firm cash flows, we estimate the following basic model:

$$\Delta P_{\ i,q} = \alpha_i + \theta_1\, \Delta SI_{q-1}\left(\beta_{i,\tau-1}\right) + \theta_2 \beta_{i,\tau-1} + \ \varphi_i + \Phi_t + \varepsilon_{iq} \qquad (1)$$

where $\Delta P_{\ i,q}$ is the quarterly (seasonally adjusted) firm performance in quarter q ($P_{i,q} - P_{i,q-4}$), ΔSI_{q-1} is the seasonally adjusted SI change in quarter *q-1*, that is, ($SI_{i,q-1} - SI_{i,q-5}$); $\beta_{i,\tau-1}$ is market beta measured based on daily return in the calendar year $\tau - 1$.[21] We include firm and month indicators, φ_i and Φ_t , respectively, to control for unmodeled heterogeneity across firms and months. For all the regression specifications, we cluster the standard errors at the firm level.

The coefficient of interest is that of the interaction term θ_1. Namely, a higher (lower) ΔSI_{q-1} is better for the relative performance of high-beta (low-beta) firms than for low-beta (high-beta) firms. Note that because ΔSI_{q-1} changes only in the time series, it is collinear with time-fixed effects; thus, so ΔSI_{q-1} affects the performance only through its interaction with beta. Thus, the implication of the SI hypothesis is that $\theta_1$is positive.

[21] Beta is measured in the calendar year prior to the time in which ΔSI_{q-1} is measured, this means that for performance measures in Q1, the beta is not from the calendar year prior, but rather two year prior.

Table 3 Panel A provides the estimation results from our regression specifications. The performance measures are changes in OCF, ROA, and PMI in the following quarter. In specification 1, 3, and 5 we provide the estimation of the basic model. The coefficient θ_1 is highly significant in all three specifications, indicating that the change in performance is positively correlated with $\Delta SI_{q-1}(\beta_{i,\tau-1})$, implying that a higher beta helps performance when SI_{q-1} is positive, but it hurts performance when SI_{q-1} is negative. For example, for one-quarter forward change in OCF (specification 1), the coefficient on the interaction is 0.019, which means that a one-point increase (decrease) in SI_{q-1} leads to an average 1.9 basis point increase (decrease) in performance for a firm whose beta is 1, but to an average 3.8 basis point increase (decrease) for a firm whose beta is 2. The results concerning the one-quarter forward change in ROA (specification 3) and change in PMI (specification 5) are similarly economically and statistically significant, with θ_1 equaling 2.2 basis point and 15.3 basis point, respectively.

Regression specifications 2, 4, and 6 in Panel A extend the basic model by including firm-level controls, interaction of each of the controls with ΔSI_{q-1}, and interaction of each of the controls with $\beta_{i,\tau-1}$. By including these controls and their interactions with the main variables of interest (change in SI and beta equity), we validate that our results are not driven by some artifacts that are not related to either the low-end versus high-end good scale that we proxy by beta or the previous quarter change in SI.

In specifications 2 and 4, the coefficients θ_1 are 0.017 and 0.020, respectively, representing a small 10% reduction compared with the base case in specifications 1 and 3, respectively. The drop in coefficient in specifications 6 to 12.3 basis points is a bit larger, representing a drop of 20% compared to specification 5. In any case, it can be concluded that the interaction between changes in SI and beta is hardly affected by other characteristics.

Next, in Panel B of Table 3, we evaluate the change in performance two- and three- quarters forward after the change in SI using the specification that includes all controls and their interactions with the change in SI and beta equity. For the two- and three-quarters ahead changes in OCF, the coefficient is economically weaker (1.3 basis point and 0.9 basis point, respectively) but statistically significant at the 1% level. For the forward change in ROA, the effect is weaker in magnitude and significance ($p<0.05$) and dissipates in the third quarter after the SI change. For the two- and three-quarters ahead changes in PMI, the interaction of beta and the change in SI is not statistically significant.

The results in Table 3 can be summarized as follows. The interaction between changes in SI and beta predicts the change in OCF up to three-quarter forward, the change in ROA up to two-quarter forward, and the change in PMI for the one-quarter forward. This finding is consistent with the univariate results shown in Table 2. Overall, we can conclude that the cash flow predictability results are consistent with our prediction that changes in SI interact with beta to positively affect future firm performance. These results are consistent with the SI hypothesis, which states that high-end goods firms outperform (underperform) low-end goods firms following SI increases (decreases).

4.3 SI predicting cross-sectional equity return

The cash flow predictions in the previous subsections support the economic predictions of the SI hypothesis. However, they do not imply any sort of inefficiency in equity markets. It is conceivable that the prices of company shares reflect the information embedded in SI changes. In this subsection, we analyze whether SI knowledge helps to predict cross-sectional stock returns. To study the relationship between changes in SI and firms' stock returns, we use the same beta quartiles as in the previous subsections, that is, estimated at the calendar year prior. Because information is expected to be embedded into prices rather quickly, our approach here is to make use of the most recent information on SI changes, so we measure the change in SI over the month (ΔSI_{t-1}), and analyze whether it is predictive of the returns of the firm in the following month, that is, $R_{i,t}$ (the return over month *t* as in Figure 1).

We are mindful that predicting the next month's return based on SI is a rather tough bar to cross, so we consider that not all changes in SI are informative for predictions. Thus, we consider the full sample period as well as two conditional samples to analyze the predictive ability of ΔSI_{t-1} on $R_{i.t}$. These samples are conditional on the sentiment level at t-1 and the magnitude of ΔSI_{t-1}; however, all strategies compare the average one-month ahead return of the β1 portfolio (referred to as low-beta) to that of the β4 portfolio (referred to as high-beta). Only the top and bottom quartiles are considered; however, if we were to partition the sample into above and below the median beta, the qualitative nature of the results would remain unchanged.

4.3.1. Average return in following month

We begin by providing univariate descriptive statistics in Panel A of Table 4. Specification 1 provides the average raw return in the following month depending on the beta (low or high) and the sign of ΔSI_{t-1}. When ΔSI_{t-1} is negative, low-beta stocks have an average return of 0.77%, and high-beta stocks have a significantly lower return of 0.28%. When ΔSI_{t-1} is positive, high- and low-beta stocks seem to perform similarly, with average returns of 2.09% and 2.16%, respectively. This relatively small difference in performance between high- and low-beta stocks when ΔSI_{t-1} is positive may be due to an asymmetry between the high- and low-income groups. Because high-income groups are more flexible in their consumption decisions than low-income individuals, they have two options to consider when they feel less confident (ΔSI_{t-1}<0): they can either wait with their decision to consume a high-end good, or alternatively, shift towards consuming a lower-end good. The latter suggests that SI decreases benefit (on a relative basis) low-end good stocks (i.e., low-beta stocks) because their clientele is comparatively more confident, and high-income groups may often consume low-end goods when they become less confident. Note that SI increases (ΔSI_{t-1}>0), however, do not lead to the same consumption shift in the other direction. Low-income groups do not shift towards high-income goods (high-beta stocks) when they are comparatively less confident. On the contrary, they are less confident on a comparative basis, so they continue to consume low-end goods (or not consume at all). That is, ceteris paribus, decreases in SI benefit low-beta stocks comparatively, but increases in SI do not hurt low-beta stocks as much, even on a comparative basis.

Next, we consider two types of samples, which consider the return on months in which the sentiment level at t-1 ($Sentiment_{t-1}$) and ΔSI_{t-1} passes a certain criterion. The first sample we consider is a *Contrarian state* sample. It considers that the sign of ΔSI_{t-1} is informative for future relative returns in two types of situations: when ΔSI_{t-1} is positive and $Sentiment_{t-1}$ is low, and when $\Delta SI_{t-1}$is negative and the $Sentiment_{t-1}$is high. This follows the business-cycle logic. When the economy is at a slump, the average sentiment level and SI are expected to be low. Under such circumstances, an increase in SI (i.e., positive ΔSI_{t-1}) means that the high-income groups, who are more tuned to the stock market (e.g., Rubin and Segal, 2015) are becoming more optimistic, which indicates that they expect the market to pull out of the slump. In contrast, an increase in SI is less informative when the sentiment level is high because the market may be overheated. The same reasoning follows for a decrease in SI (i.e., negative ΔSI_{t-1}): A decrease in SI is more informative when the sentiment level is high, as it suggests that the peak period for the stock market is expected to be over if, on a relative basis, the low-income group, whose income is less dependent on the stock market, is becoming relatively more optimistic. We call this sample the Contrarian state, as the change in SI is contrary to the sentiment level, and thus it refers to situations in which $Sentiment_{t-1}$is high and $\Delta SI_{t-1} < 0$, or $Sentiment_{t-1}$is low and $\Delta SI_{t-1} > 0$. In this sample, whether sentiment is deemed high or low depends on whether $Sentiment_{t-1}$ is higher or lower than the average sentiment level during the 1980-2000 period.

The second strategy that we consider concerns the magnitude of the change in ΔSI_{t-1}. Not all SI changes are the same; a one-point difference in SI is not the same as a ten-point difference in SI. We measure the monthly standard deviation change in SI during the 1980-2000 period and consider only the sample of months in which ΔSI_{t-1} is in absolute terms higher than two standard deviations. We call this second sample the *Large change* sample.

In the contrarian state sample, the difference between high- and low-beta returns, depending on whether ΔSI_{t-1} is negative or positive, is much greater than in the full sample. When ΔSI_{t-1} is negative, low-beta stocks' following month return is, on average, 1.71% higher than that of high-beta stocks; when ΔSI_{t-1} is positive, low-beta stocks' following month return is, on average, 0.46% lower than that of high-beta stocks. Both differences of mean tests are highly significant. In the large change sample, we learn that following large SI decreases, low-beta and high-beta stocks have negative returns of -1.05% and -1.44%, respectively, and following a large SI increase, low-beta and high-beta stocks have large positive returns of 3.32% and 5.10%, respectively. Thus, although low-beta stocks do better in SI decreases and the difference of 0.39% is similar to the 0.49% of the full sample, the lower power of the smaller sample does not allow us to reject the null hypothesis of no difference. However, following SI increases, high-beta stocks perform 1.79% better than low-beta stocks (highly significant). Overall, all samples are broadly consistent with the SI hypothesis, where low-beta stocks perform comparatively better following SI decreases and high-beta stocks perform comparatively better following SI increases. The Diff column analyzes the difference in the following month's mean returns between months in which ΔSI_{t-1} is positive and those in which ΔSI_{t-1} is negative. The difference of means tests yields statistically significant results throughout, implying that all stocks perform comparatively better following SI increases than when SI decreases. Evidently, this difference is higher for high-beta stocks than for low-beta stocks. In the full sample, it is 1.88% for β4 and 1.32% for β1. The magnitude of this difference is large in the contrarian state sample: 4.58% for β4 and 2.54% for β1. This larger spread for β4 compared to β1 indicates that high-beta stocks are more sensitive to SI changes compared to low-beta stocks, which, together with similar evidence in Table 2 concerning differences in spreads of cash flows, suggests that ΔSI_{t-1} may be positively correlated with future market-wide changes.

4.3.2. Trading strategy

The descriptive statistic falls short of providing evidence on profitable trading strategies because it is possible, for example, that the results of Panel A are driven by a few months. Under such circumstances, averaging returns across time and across firms may lead to biased estimates. The calendar-time approach addresses this potential bias in t-statistics (Mitchell and Staffard, 2000). By creating a portfolio of high-beta and low-beta stocks and moving forward in calendar time, we cluster stocks into long and short portfolios depending on whether SI increases or decreases in the previous month. Panel B shows the results for portfolios that are long low-beta stocks and short high-beta stocks when ΔSI_{t-1} is negative (i.e., when low-income groups are comparatively more confident), and are long high-beta stocks and short low-beta stocks when

$\Delta SI_{t-1}$is positive (i.e., when high-income groups are comparatively more confident). EW returns are equal weight returns, and VW (value-weighted) is based on the value of equity at the end of month *t-1*. We present both the raw returns and alpha. To calculate the alpha, we regress the excess returns (equal or value-weighted return minus the risk-free return) on the CAPM or the four-factor Fama-French (Fama and French, 1993) and momentum (Carhart, 1997) models. The reported alphas in Panel B (in %) are the intercepts of these regressions.

In the full sample of the entire time series, the trading strategy runs for a period of 21 years (252 months), yielding 0.30% and 0.25% monthly EW and VW raw returns, respectively, which are positive, but statistically insignificant. The alphas in the full sample are somewhat larger than the raw returns but are still statistically insignificant. The contrarian sample provides more impressive trading strategy results. This strategy runs after the 124 months, which are considered contrarian state months. The EW and VW raw returns are 1.19% (14.4% annual) and 1.09% (13.2% annual), respectively. Based on the CAPM and four-factor model, an investor holding an EW or VW portfolio in the contrarian state would earn similar magnitude alphas in the range of 1.09-1.30% (13.2-15.6% annual). For the large change state, the strategy runs for only approximately 10% of the months (24 months). It provides a similar magnitude of EW raw and alphas, but its VW performance is smaller and not significant.

Recall that our cash flow results (Tables 2 and 3) show that SI changes are predictive of cash flows up to three-quarter forward. Therefore, it is reasonable to consider that changes in SI are not necessarily incorporated into prices in the following month; rather, it may take time for the implications of the change in SI to be reflected in equity prices. Therefore, in Table 5, we analyze the alpha of calendar-time trading strategies for the full sample of months for a holding period of up to 12 months (months *t until t+11*), depending on whether ΔSI_{t-1} is positive or negative. Thus, the holding period starts, as before, based on information known at the end of *t-1* (Figure 1), but ends up to 12 months later. Note that there is an overlap in decision rules in each calendar month when the holding period is more than a month, so it is possible that a given security ends up having a long position of more than once, or alternatively, ends up not being in the portfolio at all. Consequently, there could be combinations of calendar months with a holding period month, in which the strategy is to hold nothing.[22] Both the raw and calendar-time portfolio alphas are presented in Table 5. Across columns 1-6, the monthly raw returns and alphas range from 0.22% to 0.65% (2.6% - 7.8% annual). Raw EW returns are significant from a four-month holding period and above, and the alphas are significant from a two-month holding period and above. Overall, the evidence in this section supports SI hypothesis. However, the predictability of the SI hypothesis for equity returns varies across samples and time length predictability. Following contrarian months, returns are highly predictive of the following month's equity returns. Following the large change in SI months, the predictability for the following month is somewhat reduced and significant only for the equal-weighted portfolio. In the full sample of months, there is evidence of predictability, but this is significant only for portfolio holdings of at least a two-month period.[23]

5. Case Study – Restaurant Business

[22] For example, consider a two-month holding period and that SI_{t-1} is positive and SI_{t-2} is negative. Under such circumstances, the trading rule is to buy high-beta and short low-beta stocks based on SI_{t-1} and short high-beta and long low-beta based on SI_{t-2}. If both months are in the same calendar year, beta quartiles are based on the same calendar year, so the overall effect is not to trade. Contrary to that, if both SI_{t-1} and SI_{t-2} are positive, the rule is to double the bet, and double the investment in high-beta stock and double the short position in low-beta stock. Note that with a longer holding period, the marginal effect of an additional month is small (for example, the trading rule is relatively unaffected when you move to a decision based on 11 months or 12 months), so eventually the alphas in Table 5 converge to a certain level.

[23] Somewhat interesting, trading strategy results are larger for abnormal return than raw return. This seems to be due to SI changes predictability of systematic changes (see Section 6), which should lead to more apparent abnormal return than raw return.

Throughout the study, our ability to test the SI hypothesis relies on two basic assumptions: (1) high-income groups tend to buy high-end products, while low-income groups tend to buy low-end products, and (2) the equity beta is a reasonable proxy for capturing the relative attribute of a good on the lower to upper end scale. In this section, we try to address this shortcoming by directly defining the income group of the representative consumer of the firm's good. Thus, we conduct a case study of a particular industry for which we do not need to rely on beta to partition its firms by their customers' income, that is, where it is comparatively simple to classify firms in that industry on the low-end to high-end scale and, as a result, on the income of its representative customer. The industry we chose is the restaurant business.

The total US food service industry is a significant part of the US economy, its revenues were about $876.33 billion in 2021 (Statista, 2022) and accounting for 4% of the GDP as of 2020. We partition public firms into those that own fast-food chains and those that own casual dining restaurants during the period 2001 to 2021. The defining issue of fast-food chains is that the average meal price is low ($4.72-10.00), and orders are self-administrated. In casual dining, average meal price is higher ($12–$88) and customers are served by a waiter. Casual dining is associated with a high-income elasticity of demand (Hiemstra and Kosiba, 1994; Heffetz, 2011) and is positively correlated with GDP (Lee and Ha, 2012). Both properties seem to fit the implications of SI well. The high-income elasticity implies that high-income individuals may decide not to go out or possibly switch to fast-fast eateries when their sentiment declines.[24]

[24] Compared to the fast-food restaurant sector, the casual dining restaurant sector suffers more severely from economic downturns (Lee and Ha, 2014). When household income is not increasing fast enough to keep up with the rising household costs, and as the disposable income drops, it constrains consumers' ability to keep eating at casual diners and results in reduced dining in casual dining restaurants (Lutz, 2015; Peltz, 2017). Some customers might switch from casual diners to fast-food restaurants during recessions. Other evidence indicates that fast-food restaurants showed significantly greater financial performance as compared to that of casual dining restaurants during recessions (Koh, Lee, and Choi, 2013; Zheng, Farrish and Wang, 2013).

We hand-collect detailed information about the facilities and brand names of all public firms in the US that can be considered as either fast-food chains or casual dining restaurants. Namely, in this analysis, compared to the full sample of the previous sections, the high-beta stocks are all casual dining chains, and the low-beta stocks are fast-food chains. The sample includes all public firms whose assets value was on average above $1 billion in the sample period and who had at least 80% of their operations classified as either fast-food or casual dining. These screens result in a sample of 16 restaurant firms (nine fast-food firms and seven casual dining firms). The results are presented in Table 6. We repeat the analyses on cash flows and return predictability that we conduct for the full sample. Panels B and C provide analyses of Tables 2 and 4 Panel B, respectively, for the restaurant sample.

Table 6 Panel A provides the brand names of the sample restaurant firms, their equity betas, and market value (in $billion as of December 2021). Beta is the coefficient of the market model based on daily returns. Beta (overall) is based on one regression per firm, and Beta (yearly) is the average beta of annual regression of a firm. As written above, fast-food restaurants stock prices should be less sensitive to the state of the economy (less pro-procyclical) compared to casual dining restaurants stock prices. Indeed, we estimate the beta of each stock in our sample and find that the fast-food restaurant stocks have an average market beta of 0.88, while the average market beta of casual dining stocks is 1.12. This difference is highly significant.

Next, we hypothesize that following positive changes in SI (i.e., high-income individuals are becoming comparatively more optimistic than low-income individuals), it reflects a comparatively better future for casual dining as opposed to fast-food. Panel B provides the mean performances of both casual dining and fast-food firms depending on whether ΔSI_{q-1} is negative or positive in the full and contrarian samples. As before, we analyze a one-quarter ahead (seasonally adjusted) change in the OCF, ROA, and PMI. When ΔSI_{q-1} is negative, the average one-quarter forward change in OCF is -0.20% for fast-food firms and -0.35% for casual dining firms. When ΔSI_{q-1} is positive, the average one-quarter forward change in OCF is 0.18% for fast-food firms and 0.05% for casual-dining firms. Thus, the results are mixed because the SI hypothesis implies that casual dining should perform better following SI increases. However, when we move to the one-quarter ahead change in ROA and PMI, the ordering of performance is consistent with the SI hypothesis. Fast food companies perform better following negative ΔSI_{q-1} , and casual dining performs better following positive ΔSI_{q-1}. The DiD analysis for each measure is presented in the last row of the Difference column. The results show that the DiD of Casual-Fast-food firms is 0.03% (not significant) for change in OCF, but it is significant for change in ROA (0.41%) and PMI (2.05%).

In the contrarian state, the results provide strong support to the SI hypothesis. When ΔSI_{q-1} is negative, the average one-quarter forward change in OCF is -0.06% for fast-food firms and -0.26% for casual dining firms. When ΔSI_{q-1} is positive, the average one-quarter forward change in OCF is -0.05% for fast-food firms and 0.22% for casual dining firms. The DiD results are significant, both economically (0.41%) and statistically. The ordering of performance and DiD also appears for the ROA and PMI analyses, and DiD results are statistically significant in the ROA analysis. Overall, the results show that fast-food firms perform better than casual dining firms following SI decreases, while the latter perform better following SI increases. Thus, we interpret the cash flow analysis as consistent with the SI hypothesis.

Next, we hypothesize and show that changes in SI are useful for portfolio decisions. Namely, following SI increases (decreases) during the month, one should go long (short) to a portfolio of casual dining stocks and short (long) to a portfolio of fast-food stocks. Panel C provides raw returns as well as the alpha of the various trading strategies, depending on ΔSI_{t-1} and the type of restaurant firm. In the full sample, the trading strategy earns 0.5% (0.6%) monthly EW (VW) raw returns over the252 months period, but it is statistically insignificant. Alphas in the full sample have similar magnitudes, but are mostly insignificant, probably due to the small sample size of firms. The contrarian strategy runs for 120 months and earns significant EW and VW raw returns, as well as significant alphas in the range of 1.06%–1.50% (13% – 18% annual). The large change strategy runs for 24 months and generates positive returns, but only the VW alphas are statistically significant in the range of 2.98-3.27% (36-38% annual).

Overall, the results are consistent with the full sample; changes in SI are predictive of the relative performance of casual dining versus that of fast-food firms. The evidence suggests that consumer income is a likely underlying mechanism driving the strong predictability of SI in the restaurant industry. The results also provide strong support for the use of the market beta in the full sample to proxy for the income level of the representative consumer of the firm.

6. Market level changes

6.1 SI and market returns

The previous section showed that changes in SI are indicative of the future performance of high-versus low-beta stocks. Given that high-beta stocks are more procyclical than low-beta stocks, one expects that changes in SI should also be predictive of the aggregate stock market. We measure the change in SI as in the prior sections with ΔSI_{t-1} $(SI_{t-1} - SI_{t-2})$ and analyze whether it is predictive of the market return in the following month, that is, $R_{m,t}$. We also include the change in sentiment level as a possible predictor. Table 7 reports the predictive ability of ΔSI_{t-1} on $R_{m,t}$ in the full sample period as well as in the two conditional samples. In specification 1, we find that the coefficient of $\Delta Sentiment_{t-1}$ is statistically insignificant. This finding implies that the change in sentiment over the month is not predictive of market returns in the following month. The next three specifications (2-4) show that the coefficient of ΔSI_{t-1} is significant at the 5% level and remains significant when we add $\Delta Sentiment_{t-1}$ and $R_{m,t-1}$ (past returns) as controls. The coefficient implies that a one-point increase in SI leads to a 10-basis point (0.1%) increase in the market return in the next month. In specification 5, the results control for various macroeconomic variables as of t-1. Specifically, we control for the monthly change in uncertainty related to economic policies, default spread, term spread, one-month T-bill yield, long-term T-bond yield, earnings-to-price ratio, dividend-to-price ratio, and inflation. The predictive ability of ΔSI_{t-1} remains unchanged. Finally, when considering only the months that are either a contrarian state or a large change (specifications 6 and 7, respectively), we find that ΔSI_{t-1} significantly predicts returns in the following month. The coefficient of ΔSI_{t-1} has a roughly similar magnitude for all the specifications. This unequivocally suggests that a change in SI is predictive of systematic changes, as reflected in changes in the value of the stock market. [25]

In the previous sections, we provide evidence of the predictive ability of change in SI on firm cash flows up to three quarters forward, but it is fair to say that most of the predictability concentrates on the following two quarters. Therefore, we test whether a change in SI is useful for predicting the market over a short horizon in both the full sample and subsample of the contrarian state and large change. Table 8 provides the additional cumulative return (in %) for holding the market when ΔSI_{t-1} is positive compared with when ΔSI_{t-1} is negative. The holding

[25] The results of Table 7 Panel B show that ΔSI_{t-1} dominates $\Delta Sentiment_{t-1}$ in predicting next month's market return. However, in untabulated analysis we find that $\Delta Sentiment_{t}$ dominates ΔSI_{t} in explaining concurrent monthly market return.

period starts, as before, based on information that is known at the end of *t-1* (see Figure 1), and ends in various months (up to six months after the publication of the sentiment indices).

In the full sample, the difference in market returns after positive ΔSI_{t-1} is significantly larger than after negative ΔSI_{t-1}returns, for the three- and four-month holding periods. For example, after a four-month period, an investor who buys the market following a positive ΔSI_{t-1} generates a 2.58% higher return than an investor who buys the market following a negative ΔSI_{t-1}. This result is significant at the 5% level. In the contrarian state subsample, the results are stronger in terms of their statistical significance and magnitude. The additional cumulative return following positive ΔSI_{t-1} compared with negative ΔSI_{t-1} is 4.29% (p<0.0.5) for the four-month holding period. The large change sample provides the most impressive results. Holding the market following large positive changes in ΔSI_{t-1} compared to holding the market following large negative changes in ΔSI_{t-1} yields an impressive additional return of 4.41% (t=2.04) for the one-month period and 16.59% (t=2.66) for the six-month period.

6.2 SI and market volatility

The results thus far are consistent with the SI hypothesis: increases in SI lead to relatively better performance of high-beta firms, and decreases in SI lead to relatively better performance of low-beta firms. As a result of this predictability, SI change is a useful indicator for predicting market movements. In this section, we analyze whether SI changes may have implications not only for market returns but also for market volatility.

According to the SI hypothesis, because high-income groups have a higher disposable income, their sentiment level is not only important for the consumption of high-end goods but also for investments. Ceteris paribus, an increase in SI reduces the risk to firms because more money is available for investment, which in turn could reduce the financial risk to firms, as they should find it easier to raise capital. The opposite prediction comes from the possibility that increases in SI imply increased tension between high- and low-income groups, which may lead to political tension, government intervention, and increased market volatility.[26] Regardless of the theoretical arguments of why SI changes may relate to changes in volatility, because SI changes positively predict market returns, it seems a worthwhile endeavor to analyze given that SI changes are predictive of market returns.

Thus, our objective in this subsection is to analyze whether SI changes are useful for predicting changes in next month's volatility, after controlling for known predictors, such as realized volatility and the VIX index. We start by visually observing the concurrent relationship between the VIX index and the SI measure in Figure 4. Given that the VIX predicts future volatility (based on the implied volatility of S&P 500 options), it seems worthwhile to see whether SI tracks the VIX. We observe a strong negative correlation between the SI measure and VIX index at a monthly frequency. When the VIX index increases (such as during a financial crisis), SI decreases, and vice versa. Next, to test whether changes in SI have explanatory value in predicting volatility, we estimate the following regression:

$$\Delta VOL_t = \alpha + \theta_1 \Delta SI_{t-1} + \theta_2 \Delta Sentiment_{t-1} + \theta_3 VIXret_{t-1} + \theta_4 \Delta VOL_{t-1} + \theta_5 VOL_{t-1} + \theta_6 R_{m,t-1} + \theta_7 \Delta Controls_{t-1} + \varepsilon_t \quad (2)$$

As volatility is persistent, our dependent variable is the change in market volatility, ΔVOL_t, defined as the month's *t* daily return standard deviation minus the month's *t-1* daily return standard

[26] We thus hypothesize that SI changes are analogous, at least to some extent, to income-inequality changes. Income inequality can increase growth due to the higher disposable income of high-income groups (i.e., higher savings and hence higher investment as in (Smith, 1776; Galor, 2000; Galor and Moav, 2004)), but income-inequality can create political-tensions (Esteban and Ray, 2011; Baker et. al., 2014). Stiglitz (2012a and 2012b) examines how inequality is both a cause and consequence of volatility.

deviation. All independent variables are determined one month prior. Additional controls refer to the macroeconomic variables used previously (Table 7, Panel B). The coefficient of interest is that of the ΔSI_{t-1}, that is, θ_1.

Panel A in Table 9 reports the estimation results. Because the major determinants of future volatility are lagged changes in the VIX, lagged changes in volatility, and lagged level of volatility, we include them in all specifications. The difference between specification 1-2 and 3-4 is that the latter also includes the $\Delta Sentiment_{t-1}$ as an additional control. In specification 1, a one-point increase in the ΔSI_{t-1} results in a 0.7 % ($p < 0.1$) decrease in the ΔVOL_t. Similar results are obtained for the other specifications. Overall, the results are both economically and statistically significant. The results for the other variables provide consistent interpretation. The VIX index return is positively predictive of the next month's volatility, and volatility is mean-reverting, as can be seen by the negative and significant coefficients of lagged volatility and lagged changes in volatility.

Because both the $VIXret_{t-1}$ and ΔSI_{t-1} are significant in explaining the next month's change in volatility, we next conduct a lead-lag (i.e., Granger, 1969) analysis to see which of the two ($VIXret_{t-1}$ or ΔSI_{t-1}) is more informative. In Panel B, the dependent variable is either $VIXret_t$ or ΔSI_t, and the independent variables are all of time *t-1*; we include the same set of controls as in Eq. (2). We find evidence that is consistent with the dominance of ΔSI_{t-1} over $VIXret_{t-1}$. We find that ΔSI_{t-1} is significant in explaining $VIXret_t$, while $VIXret_{t-1}$ is not significant in explaining ΔSI_t. A 1% increase in ΔSI_{t-1} decreases the $VIXret_t$ by 50 bps (specifications 1-4). The coefficient of $VIXret_{t-1}$ is not statistically significant in specifications 5 and 6. The results are also robust for the subsamples. The coefficients of the ΔSI_{t-1} are significant in the contrarian and just shy of significance (probably due to the small sample) in the large change sample (specifications 7 and 9, respectively), whereas the coefficient on $VIXret_{t-1}$ is statistically insignificant (specifications

8 and 10). Thus, because ΔSI_{t-1} is useful for predicting $VIXret_t$, but $VIXret_{t-1}$ is not useful for predicting ΔSI_t, it seems that changes in SI are sufficiently important to allow profitable trading strategies by trading the VIX index.

Thus, we study the profitability of utilizing ΔSI_{t-1} for a market-wide trading strategy. Panel C provides the returns of trading strategies that go long (short) on the VIX index at the end of month t-1 (and held until the end of month t), depending on whether ΔSI_{t-1} is negative (positive). Note that the strategy for going long is opposite in nature to what we have done prior. You go long the VIX index when ΔSI_{t-1} decreases because, after such changes, the VIX index and volatility tend to increase.[27] In the upper part of the panel, the results are provided for long or short positions in the VIX index ($VIXret_t$) minus the treasury bill (TB_t), as well as the VIX index ($VIXret_t$) minus the value-weighted return ($R_{m,t}$). The predictive ability of ΔSI_{t-1} is studied using the full sample and subsamples (contrarian and large changes). In the full sample, holding a long (short) position in $VIXret_t$ minus TB_t when ΔSI_{t-1} is negative (positive) yields a return of 1.85%, which falls below statistical significance. Even in the contrarian sample, where the long-short strategy yields a monthly return of 4.51%, falls short of significance due to the high volatility of the VIX index return. However, if the strategy is run only after a large change in ΔSI_{t-1}, it earns 19.72% over 24 months, which is significant at the 10% level. The $VIXret_t$ minus $R_{m,t}$ also generates positive excess returns for the large change strategy (22.95%, $p < 0.1$).

In the bottom part of the panel, we further explore the possibility of trading profits based on the changes in ΔSI_{t-1}. After all, our decision to concentrate only on months in which ΔSI_{t-1} is above two standard deviations of SI changes in the pre-2000 period is rather ad hoc. Therefore, we

[27] Thus, this can be considered a defensive strategy, it will tend to have a negative beta, as it will go up when the market goes down, and up when the market goes down.

analyze a spectrum of trading strategies by going long or short on the VIX index based on ΔSI_{t-1} cut-off values starting from zero and gradually increasing by 0.2 of a standard deviation of ΔSI_{t-1} based on the pre-2000 standard deviation of changes in SI. The trading rule, which varies across columns, is to go long the VIX index (and short the Treasury Bill) when ΔSI_{t-1} is below the threshold and to short the VIX index (and long the Treasury Bill) when ΔSI_{t-1} is above the threshold. All strategies provide both the long and short returns of the strategy as well as the overall performance of the long and short trading rules. We also provide the intercept (alpha) generated from a regression where the dependent variable is the trading strategy return and the independent variable is the market excess return (value-weighted return minus the risk-free rate) during the month when the trading strategy is active.

Several features of this part of the panel are noteworthy. First, as the threshold increases, there is an increase in long-short returns. Even the low threshold of 0.2sd is sufficient to increase the return from 1.85% (full sample) to 3.28%. Second, as we increase the threshold, both the magnitude of the long-short return and the alpha increase. The alpha becomes significant starting at a relatively low threshold of 0.4sd. Third, from a statistical point of view, although the long-short raw return seems high, it falls short of the significance level for most thresholds (the exceptions are specifications 7 and 10, with significance at the 10% level). Nevertheless, this strategy triumphs according to the market model, as we can see from its significant alpha. The implication is that a trading strategy that uses the ΔSI_{t-1} as a signal to switch between long and short VIX positions produces significant positive excess returns.

7. Conclusion

Substantial evidence suggests that income disparities in the US are higher in the 21st century than ever before. These increased disparities are accompanied by strong evidence of a shrinking middle class. As a direct result, stores and restaurants are chasing wealthy customers with a wide offering of high-end goods, or alternatively, focusing on providing rock-bottom prices to attract the expanding ranks of low-income consumers (Schwartz, 2014). However, households make purchasing decisions based not only on their income but also on their sentiment. Namely, the sentiment level of high-income groups matters for the consumption of high-end goods, and the sentiment level of low-income groups matters for the consumption of low-end goods.

This study tackles this phenomenon by hypothesizing that the changes in SI (the sentiment of the high- minus low-income groups) are important for the relative performance of high-end versus low-end firms. Namely, SI washes out common movements in sentiment that are held by the representative consumer, and further SI is a novel attribute of the economy that is probably not followed by market participants. We show that increases in SI have a significant predictive effect on both operating cash flows and stock returns of high-end versus low-end goods firms, which we proxy using their relative equity beta. A case study that analyses the performance of casual dining versus fast-food firms provides further evidence of the predictability of SI on their relative performance.

Though we use SI for the prediction of relative changes in firm performance, because high-end versus low-end good stocks are more procyclical, SI is also a useful indicator for predicting changes in the macroeconomy. We find that changes in SI are positively correlated with future monthly returns and negatively correlated with future volatility and changes in the VIX index. Thus, the SI hypothesis comes full circle, because change in SI predicts a change in the market, it is beneficial to use such changes and SI together with beta of the CAPM for predicting returns.

In total, the study provides evidence that sentiment inequality has real effects on a company's cash flow, is a useful predictor of asset prices, and is a leading indicator of systematic changes.

The following quotation is attributed to the well-known economist Benjamin Graham: "The intelligent investor is a realist who sells to optimists and buys from pessimists." While this statement is obviously correct, it has little practical value. It is difficult to know whether a would-be investor is overly optimistic or pessimistic, or whether the investor is simply informed about the prospects of the firm. This study shows that, in contrast to the complexity of incorporating investor sentiment levels in trading decisions, sentiment inequality has major implications for company performance and the state of the economy. To paraphrase the quote above, "The intelligent investor is a realist who buys shares of companies whose *consumers* are optimists and sells shares of companies whose *consumers* are pessimists."

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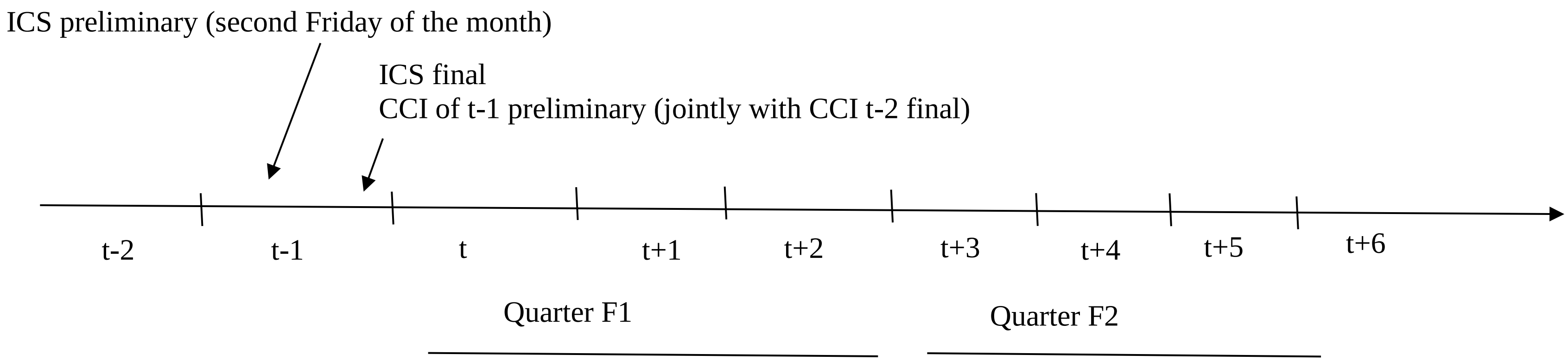
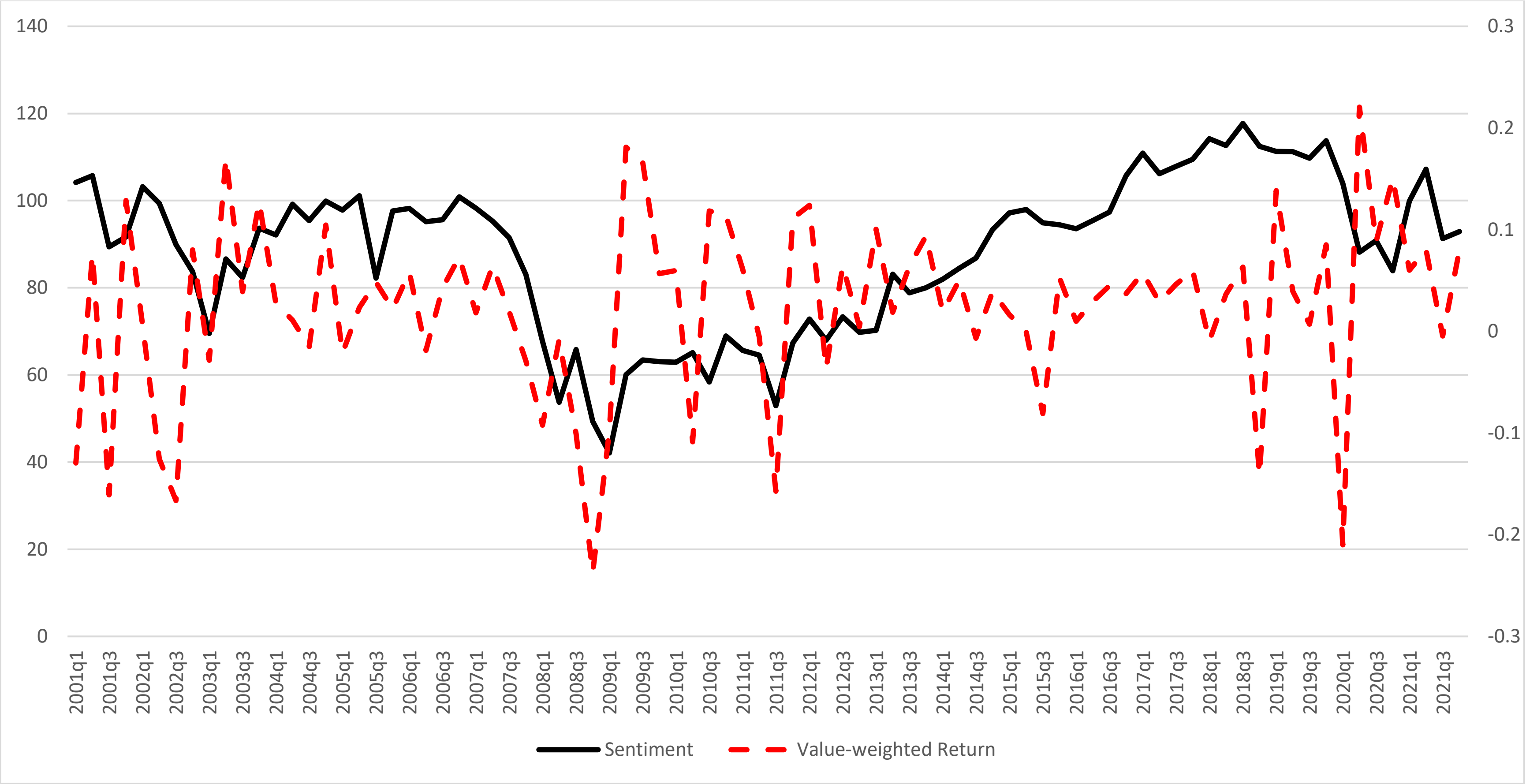


Figure 1: Schematic description of the timing of event and the results reported in this study
This figure presents the timing notation used in this study. The results reported in this study follow the changes in SI. What differs across the analyses is how ΔSI is measured (over the previous month ΔSI_{t-1} or the previous quarter ΔSI_{q-1}). The predictability of returns starts at t. Predictability in firm cash flows starts at t for quarter F1 and starts at t+3 for quarter F2 (t+3 until t+5). Although t follows the sentiment change period, only the preliminary CCI values are known at t-1.

Figure 2: Difference between the upper- and lower-income groups' sentiment

The upper figure provides the annual Consumer Sentiment Index (ICS) for the upper- and lower-income groups. The bottom figure shows the annual Consumer Confidence Index (CCI) of the upper- and lower-income groups. Sentiment is measured at the end of December of the calendar year.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60
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0.2
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2021q3
Sentiment
Value-weighted Return

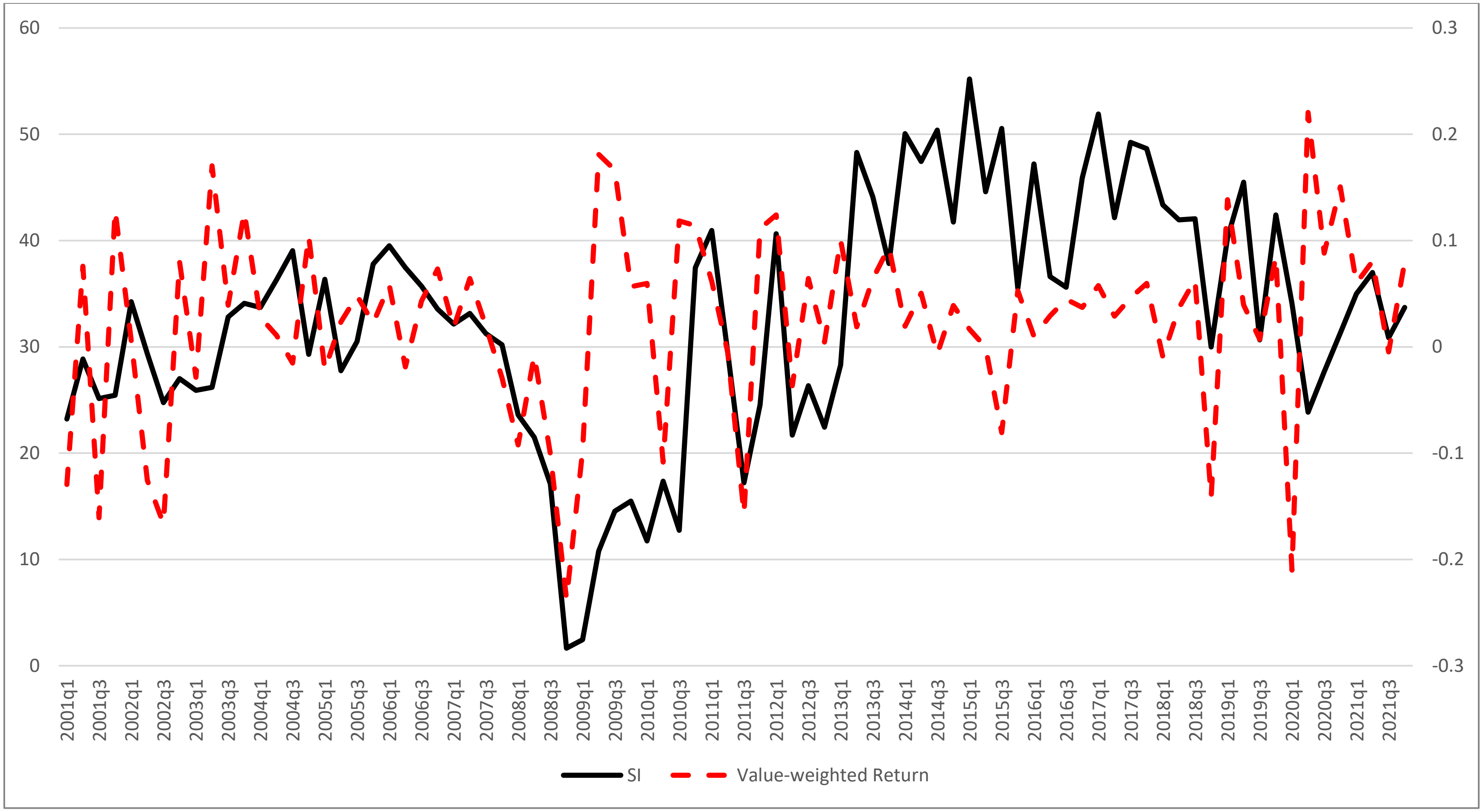

Figure 3: Sentiment, SI and market return

The upper figure shows the sentiment, and the bottom figure shows the SI. Sentiment is a simple average of the Consumer Sentiment Index (ICS) and Consumer Confidence Index (CCI). The sentiment inequality of an index is the sentiment level of the upper- minus lower-income group of the respective index. SI is the simple average of the sentiment inequality of the ICS index and the sentiment inequality of the CCI index. The right y-axis provides value-weighted returns over the calendar quarter.

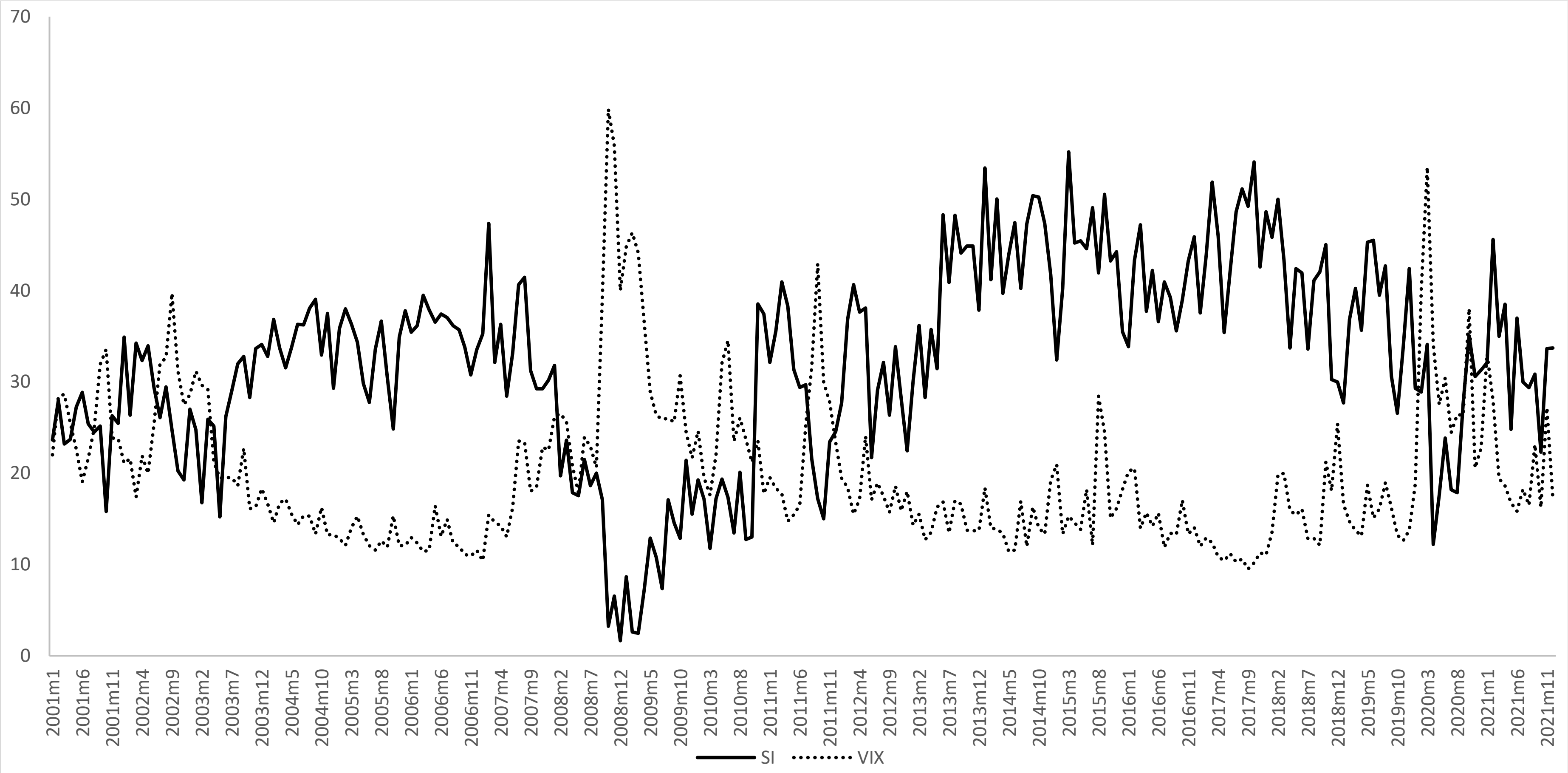

Figure 4: VIX and SI

The figure provides the VIX index and SI at the monthly frequency.

Table 1: Descriptive statistics

Panel A provides market-level data of Sentiment and SI, as well as monthly and quarterly changes in these variables. The two right-hand side columns provide the mean of the variables during the 1980-2000 period, as well as the difference of means between the 2001-2020 and 1980-2000 period, respectively. Panel B provides the main firm-level variables based on quarterly observations. Sentiment is the simple average of the Consumer Sentiment Index (ICS) and the Consumer Confidence Index (CCI). Sentiment inequality of an index is the sentiment level of the upper- minus the lower income group, of the respective index. SI is the simple average of the sentiment inequality of the ICS index and the sentiment inequality of the CCI index. OCF is income from operation before depreciation divided by total assets, ROA is income before extraordinary item (IB) divided by total assets, and PMI is net income divided by sales. Size is the market value of equity in billions of dollars. Volatility is the standard deviation of monthly stock returns during the year. Book-to-market is the book value of equity divided by the market value of equity. Market leverage is the sum of long-term debt and current liabilities divided by the sum of long-term debt, current liabilities, and the market value of equity. Dividend indicator equals one if the firm paid cash dividends and zero otherwise. Capex is capital expenditures divided by book value of assets. T-statistics is in parenthesis. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Market-level

	2001-2021						1980-2000	
	Obs.	Mean	Median	Std. Dev.	P1	P99	Mean	Difference
Sentiment	254	87.83	91.68	17.55	48.20	117.10	93.17	-5.34*** (-3.34)
SI	254	32.24	33.65	10.81	2.60	53.45	25.82	6.43*** (7.86)
Monthly ΔSentiment	254	-0.12	0.10	4.97	-15.10	10.85	0.15	-0.26 (-0.65)
Monthly ΔSI	254	0.03	0.02	6.60	-15.20	15.60	0.06	-0.03 (-0.05)
Quarterly ΔSentiment	84	-0.25	0.20	8.08	-18.90	17.95	0.54	-0.79 (-0.66)
Quarterly ΔSI	84	0.12	0.20	8.04	-18.95	24.70	0.10	0.02 (0.02)

Panel B: Firm-level

	Obs.	Mean	Median	Std. Dev.	P1	P99
OCF	122,005	0.023	0.030	0.045	-0.180	0.118
ROA	122,005	0.001	0.011	0.049	-0.239	0.085
PMI	122,005	-0.086	0.042	0.486	-2.164	0.237
Size	122,005	6.146	1.002	17.778	0.063	130.982
Volatility	122,005	0.125	0.107	0.071	0.035	0.415
Book-to-Market	122,005	0.510	0.416	0.452	-0.625	2.457
Market Leverage	122,005	0.196	0.130	0.212	0.000	0.875
Dividend indicator	122,005	0.409	0.000	0.492	0.000	1.000
Capex	122,005	0.012	0.008	0.013	0.000	0.078

Table 2: Change in cash flow, profitability and SI (DiD analysis)

The table reports the seasonally adjusted quarterly change (quarter minus the respective quarter in previous year, in firm performance (in %) depending on the sign of the change in SI (ΔSI_{q-1}), defined as the change in SI over the previous year (end of the quarter minus that four quarters ago). OCF, ROA, PMI are defined in Table 1. Beta quartiles are measured based on the daily return, at the calendar year prior to that in which performance is measured, β1 refers to lowest quartile and β4 the highest. Difference of means test t-statistics is provided in parenthesis. The difference of means is provided also for two quarters ahead. For DiD calculation, for each firm-year, we calculate the *performance difference* between the average change in performance when ΔSI_{q-1} increases to that when it decreases. We then conduct a t-test for the difference in performance *difference* between beta quartiles, i.e., β4- β1 or (β4+ β3)- (β1+ β2). $\boldsymbol{q}$, $\boldsymbol{q}$+1 refer to the forward 1 and 2 quarters, respectively. The RHS column provides difference of means (and DiD) for two quarters forward. *, **, *** is significance at the 1,5, 10% level, respectively.

Changes in OCF

	Beta quartile descriptive			$\Delta \boldsymbol{OCF}_{\boldsymbol{i,q}}$			$\Delta \boldsymbol{OCF}_{\boldsymbol{i,q+1}}$
Beta quartiles	N	Mean	Std. D.	ΔSI_{q-1}<0	ΔSI_{q-1}>0	Difference	Difference
β1	30,540	0.75	0.2	-0.09	-0.06	0.03	-0.04
						(1.05)	(-1.60)
β2	30,492	1.12	0.17	-0.11	0.00	0.12***	0.04
						(3.99)	(1.49)
β3	30,508	1.41	0.19	-0.16	0.08	0.24***	0.13***
						(7.15)	(3.66)
β4	30,465	1.92	0.36	-0.23	0.21	0.44***	0.16***
						(10.47)	(3.70)
(β4+ β3)- (β1+ β2)						0.17***	0.07***
						(9.72)	(4.04)
β4- β1						0.26***	0.12***
						(10.20)	(4.75)

Changes in ROA

	Beta quartile descriptive			$\Delta \boldsymbol{ROA}_{\boldsymbol{i,q}}$			$\Delta \boldsymbol{ROA}_{\boldsymbol{i,q+1}}$
Beta quartiles	N	Mean	Std. D.	ΔSI_{q-1}<0	ΔSI_{q-1}>0	Difference	Difference
β1	30,540	0.75	0.2	-0.15	-0.04	0.11***	0.09**
						(2.68)	(2.01)

β2	30,492	1.12	0.17	-0.12	0.02	0.15***	0.10**
						(3.36)	(2.12)
β3	30,508	1.41	0.19	-0.18	0.11	0.29***	0.16***
						(5.72)	(3.13)
β4	30,465	1.92	0.36	-0.25	0.29	0.54***	0.16**
						(8.62)	(2.48)
(β4+ β3)- (β1+ β2)						0.19***	0.01
						(7.30)	(0.39)
β4- β1						0.31***	0.05
						(8.26)	(1.39)

Changes in profit margin

	Beta quartile descriptive			$\Delta PMI_{i,q}$			$\Delta PMI_{i,q+1}$
Beta quartiles	N	Mean	Std. D.	ΔSI_{q-1}<0	ΔSI_{q-1}>0	Difference	Difference
β1	30,540	0.75	0.2	-0.87	-0.01	0.86***	0.15
						(2.81)	(0.49)
β2	30,492	1.12	0.17	-0.31	0.40	0.71**	0.02
						(2.09)	(0.06)
β3	30,508	1.41	0.19	-0.25	1.51	1.76***	0.26
						(4.47)	(0.65)
β4	30,465	1.92	0.36	-0.79	3.50	4.29***	0.61
						(8.14)	(1.14)
(β4+ β3)- (β1+ β2)						1.56***	0.12
						(7.50)	(0.58)
β4- β1						2.43***	0.17
						(8.03)	0.58

Table 3: Change in cash flow, profitability and SI

The table provides regression results where the dependent is the quarterly forward change in performance (in %). Control variables include size, volatility, book-to-market, market leverage, dividend dummy and Capex and are lagged compared to the period in which change in SI is measured. $\beta_{i,\tau-1}$ is measured based on daily return in the previous calendar year. All variables are defined in Table 1 and 2. q, q+1, q+2 refer to the forward 1, 2 and 3 quarters, respectively. Standard errors are clustered by firm. T-statistics is in parenthesis. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: One quarter forward

	$\Delta OCF_{i,q}$		$\Delta ROA_{i,q}$		$\Delta PMI_{i,q}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta SI_{q-1} \times \beta_{i,\tau-1}$	0.019***	0.017***	0.022***	0.020***	0.153***	0.123***
	(8.07)	(6.58)	(6.80)	(5.71)	(5.76)	(4.21)
$\beta_{i,\tau-1}$	0.006	-0.337***	0.068*	-0.467***	1.580***	-2.730**
	(0.18)	(-3.77)	(1.66)	(-3.94)	(4.28)	(-2.53)
Intercept	-0.322	-0.596	-0.461	-0.998*	-4.483	-10.037**
	(-1.24)	(-1.45)	(-1.08)	(-1.84)	(-1.49)	(-2.28)
Controls	No	Yes	No	Yes	No	Yes
Controls × $\beta_{i,\tau-1}$	No	Yes	No	Yes	No	Yes
Controls × ΔSI_{q-1}	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.020	0.028	0.029	0.037	0.020	0.028
Obs.	122,005	122,005	122,005	122,005	122,005	122,005

Panel B: Two and three quarters forward

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \boldsymbol{OCF}_{\boldsymbol{i,q+1}}$	$\Delta \boldsymbol{OCF}_{\boldsymbol{i,q+2}}$	$\Delta \boldsymbol{ROA}_{\boldsymbol{i,q+1}}$	$\Delta \boldsymbol{ROA}_{\boldsymbol{i,q+2}}$	$\Delta \boldsymbol{PMI}_{\boldsymbol{i,q+1}}$	$\Delta \boldsymbol{PMI}_{\boldsymbol{i,q+2}}$
$\Delta SI_{q-1} \times \beta_{i,\tau-1}$	0.013***	0.009***	0.009**	0.003	0.027	0.018
	(4.90)	(3.43)	(2.38)	(0.67)	(0.92)	(0.62)
$\beta_{i,\tau-1}$	-0.377***	-0.509***	-0.334***	-0.422***	-1.192	-2.841***
	(-4.35)	(-5.78)	(-2.83)	(-3.49)	(-1.12)	(-2.61)
Intercept	-0.385	-0.395	-0.725	-1.061*	-10.071**	-10.320*
	(-0.91)	(-0.99)	(-1.24)	(-1.83)	(-2.37)	(-1.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls × $\beta_{i,\tau-1}$	Yes	Yes	Yes	Yes	Yes	Yes
Controls × ΔSI_{q-1}	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.025	0.027	0.033	0.035	0.024	0.025
Obs.	115,798	110,532	115,798	110,532	115,798	110,532

Table 4: Returns, beta portfolios, and SI

Panel A provides monthly mean returns (in %) depending on ΔSI_{t-1} and the type of firm (High-beta/ Low-beta). High (low) beta refers to firms that had the highest (lowest) quartile beta in the previous calendar year. Contrarian state refers to situations in which sentiment is high and the $\Delta SI_{t-1} < 0$, or sentiment is low and $\Delta SI_{t-1} > 0$. Whether sentiment is high or low depends on the average sentiment during the 1980-2000 period. Sd refers to the standard deviation of the sentiment measure during the 1980-2000 period. The table reports the difference of means between the high-beta and low-beta firms. Panel B provides calendar time raw returns and alphas (in %) depending on ΔSI_{t-1} and the type of firm (High/ Low beta). Low quartile beta companies are held long (short) when ΔSI_{t-1} is negative (positive), and high quartile beta companies are held long (short) when ΔSI_{t-1} is positive (negative). The EW (VW) are equal weight (value-weighted, based on value at t-1) zero holding of (long-short) portfolios. For CAPM and 4-factor, the excess return of the portfolio (equal or value-weighted return minus the risk-free return) is run on the CAPM or four-factor model. The table provides the intercept of the regression (in %), and t-statistics are provided in parenthesis and are calculated with Newey-West standard errors (column 1) or robust standard errors (column 2-4). *, **, *** indicate significance at the 1,5, 10% level, respectively.

Panel A: Mean returns and sentiment inequality

Trading decision variable	(1) **Full sample**			(2) **Contrarian state**			(3) **Large change**		
	$\Delta SI_{t-1} < 0$	$\Delta SI_{t-1} > 0$	Diff	$\Delta SI_{t-1} < 0$	$\Delta SI_{t-1} > 0$	Diff	$\Delta SI_{t-1} < -2sd$	$\Delta SI_{t-1} > 2sd$	Diff
Low-beta quartile firms									
Mean return (L)	0.77	2.09	1.32***	0.22	2.63	2.41***	-1.05	3.32	4.37***
Observations	65,155	64,720		31,381	32,503		7,522	4,976	
High-beta quartile firms									
Mean return (H)	0.28	2.16	1.88***	-1.49	3.09	4.58***	-1.44	5.10	6.54***
Observations	65,185	64,620		31,385	32,456		6,958	4,974	
Diff H-L	-0.49***	0.07		-1.71***	0.46***		-0.39	1.79***	

Panel B: High and low quartile beta portfolios and SI

Trading decision Long low-beta and short high-beta (Short low-beta and long high-beta)	(1) **Full sample** $\Delta SI_{t-1} < 0$ ($\Delta SI_{t-1} > 0$)		(2) **Contrarian state** Sentiment high, $\Delta SI_{t-1} < 0$ (Sentiment low, $\Delta SI_{t-1} > 0$)		(3) **Large change** $\Delta SI_{t-1} < -2sd$ ($\Delta SI_{t-1} > 2sd$)	
	EW	VW	EW	VW	EW	VW
Number of months strategy is active	252		124		24	
Raw	0.30	0.25	1.19**	1.09*	0.98*	0.39
	(0.77)	(0.66)	(2.36)	(1.92)	(1.80)	(0.50)
CAPM	0.44	0.41	1.30**	1.14*	1.14*	0.72
	(1.10)	(1.07)	(2.37)	(1.83)	(1.92)	(0.96)
4-factors	0.42	0.33	1.33**	1.09*	1.25*	0.85
	(0.97)	(0.86)	(2.55)	(1.73)	(1.81)	(1.11)

Table 5: Special Trading Strategy- High/ Low beta portfolios and sentiment inequality

The table provides alpha of a trading strategy of holding periods 1-12 months, depending on whether ΔSI_{t-1} is positive or negative. For trading decision, top quartile beta companies are held long (short) when ΔSI_{t-1} is positive (negative), and bottom quartile beta companies are held long (short) when ΔSI is negative (positive). For CAPM and 4-factor, the excess return of the portfolio (equal or value-weighted return minus the risk-free return) is run on the CAPM or four-factor model. The reported alphas are the regression intercept (in %) and are estimated using robust standard errors. *, **, *** indicate significance at the 1,5, 10% levels, respectively.

	Raw (EW) (1)	Raw (VW) (2)	CAPM(EW) (3)	CAPM(VW) (4)	F4(EW) (5)	F4(VW) (6)
Holding months						
1	0.30	0.25	0.44	0.41	0.42	0.33
2	0.40	0.36	0.65**	0.65**	0.64**	0.57*
3	0.34	0.22	0.53**	0.50*	0.59**	0.48*
4	0.32*	0.22	0.47**	0.46*	0.53***	0.44*
5	0.28	0.22	0.40**	0.44*	0.46**	0.41*
6	0.29*	0.23	0.40**	0.42*	0.46***	0.40*
7	0.29*	0.25	0.39***	0.42*	0.44**	0.40*
8	0.29**	0.27	0.39***	0.44*	0.44***	0.42*
9	0.29**	0.28	0.37***	0.44*	0.43***	0.42**
10	0.29**	0.30	0.36***	0.44*	0.41***	0.42**
11	0.29**	0.31	0.35***	0.44*	0.40***	0.41**
12	0.29**	0.32	0.35***	0.45*	0.39***	0.42**

Table 6: Fast-food versus casual dining – cash flow and return predictability

Panel A provides the sample of 16 restaurant firms, the brand names of their restaurants, their equity betas, and market value (in $billion as of December 2021). Beta (overall) is based on one regression per firm (based on daily return), and Beta (yearly) is the average beta of annual regression of a firm (each based on daily return). The sample includes all public firms whose assets value was on average above $1 billion in the sample period, and who had at least 80% of their operations classified to either Fast-Food or Casual dining. Panel B and C provide the analyses of next quarter's cash flow and next month return for the sample of firms of Panel A, following SI changes, similar to Table 2 and 4 (Panel B), respectively. Definition of variables are in Table 1 and 2. *, **, *** indicate significance at the 1,5, 10% level, respectively. T-statistics are provided in parenthesis. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fast-food / casual dining Betas

Ticker	Name of Company	Brand names	Beta (overall)	Beta (yearly)	Market value
	Fast-food				
MCD	McDonalds	McDonalds – fast-food	0.59	0.60	200.3
CMG	Chipotle Mexican Grill	Chipotle – fast-food	0.94	0.97	49.2
YUM	Tricon Global Restaurants	KFC, Taco Bell, Pizza Hut, more	0.66	0.80	40.7
DPZ	Dominos Pizza	Dominos Pizza – fast-food/delivery	0.89	0.87	20.5
QSR	Restaurant Brands	Canadian-American multinational fast-food	1.01	0.98	19.1
WEN	Wendys Arbys	Wendys – fast-food	0.91	0.86	5.1
PZZA	Papa Johns	Papa Johns - pizza delivery	0.81	0.83	4.8
JACK	Jack In The Box	Jack in the Box- fast-food	1.07	0.93	1.8
TAST	Carrols Restaurant	Burger King and Popeyes franchisee.	1.01	0.96	0.1
	Average		**0.88**	**0.87**	38.0
	Casual dining				
DRI	Darden Restaurants	Olive Garden, LongHorn Steakhouse, more	0.96	0.87	19.6
TXRH	Texas Roadhouse	Texas Roadhouse, Bubba's 33, and Jaggers	0.97	0.97	6.2
CAKE	Cheesecake Factory	Casual, full-service dining: Cheesecake Factory.	1.10	0.97	2.0
DIN	Consorcio	Applebee's Neighborhood Grill + Bar and IHOP	1.11	0.92	1.3
DENN	Dennys	Dennys diner style restaurant	1.29	1.14	1.0
BJRI	Bjs Restaurants I	BJ's Restaurant & Brewery	1.23	1.10	0.8
RRGB	Red Robin Burgers	Red Robin	1.20	1.03	0.3
	Average		**1.12**	**1.03**	4.45
	Difference in Beta casual dining minus Beta fast-food		**0.24*** **	**0.13** **	
	T-statistic of difference of means		**(3.41)**	**(2.49)**	

Panel B: Future cash flow and change in SI

	$\Delta SI_{q-1} < 0$	$\Delta SI_{q-1} > 0$	Difference	$\Delta SI_{q-1} < 0$	$\Delta SI_{q-1} > 0$	Difference
	Full sample			**Contrarian state**		
$\Delta OCF_{i,q}$						
Fast-food	-0.20	0.18	0.38***	-0.06	-0.05	0.003
			(2.85)			(0.02)
Casual dining	-0.35	0.05	0.41***	-0.26	0.22	0.48***
			(3.57)			(3.45)
Casual-Fast	-0.15	-0.13		-0.21	0.27	
	(-1.19)	(-1.02)		(-1.19)	(2.08)	
DiD			0.03			0.49***
			(0.09)			(3.04)
$\Delta ROA_{i,q}$						
Fast-food	0.03	0.12	0.09	0.06	0.03	-0.03
			(0.74)			(-0.21)
Casual dining	-0.27	0.23	0.50***	-0.01	0.23	0.24
			(3.35)			(1.34)
Casual-Fast	-0.30**	0.10		-0.07	0.20	
	(-2.15)	(0.83)		(-0.40)	(1.52)	
DiD			0.41*			0.27**
			(1.79)			(1.96)
$\Delta PMI_{i,q}$						
Fast-food	0.43	0.37	-0.05	0.37	0.08	-0.29
			(-0.10)			(-0.42)
Casual dining	-0.92	1.10	2.02***	-0.21	0.49	0.71
			(3.12)			(0.82)
Casual-Fast	-1.35**	0.73		-0.58	0.41	
	(-2.31)	(1.23)		(-0.70)	(0.59)	
DiD			2.05***			0.96
			(2.94)			(1.10)

Panel C: Calendar time alpha- Fast-food / casual dining portfolios and SI

Trading Fast-food:	(1)		(2)		(3)	
	Full sample		**Contrarian state**		**Large change**	
Long portfolio	$\Delta SI_{t-1} < 0$		Sentiment high, $\Delta SI_{t-1} < 0$		$\Delta SI_{t-1} < -2sd$	
(Short portfolio)	($\Delta SI_{t-1} > 0$)		(Sentiment low, $\Delta SI_{t-1} < 0$)		($\Delta SI_{t-1} > 2sd$)	
	EW	VW	EW	VW	EW	VW
Number of months strategy active	252		120		14	
Raw	0.50	0.60	1.12**	1.37**	1.40	2.58
	(1.34)	(1.36)	(2.00)	(2.07)	(0.93)	(1.50)
CAPM	0.63	0.84*	1.19**	1.50**	1.17	3.27**
	(1.59)	(1.79)	(2.03)	(2.16)	(0.79)	(2.02)
4-factors	0.57	0.74	1.06*	1.29*	1.53	2.98*
	(1.44)	(1.55)	(1.84)	(1.86)	(0.79)	(1.73)

Table 7: Sentiment, SI and monthly market returns

Table 7 reports predictive regressions, where the dependent is the monthly value-weighted return (including dividend), and the independent variables are as of t-1. Sentiment and SI are defined in Table 1. Additional controls refer to the default spread, term spread, one-month T-bill yield, long term T-bond yield, earnings-to-price ratio, dividend-to-price ratio, EPU change, and inflation. In columns (6-7), we report the results depending on the contrarian state and large change being active (other months are excluded). T-statistics are provided in parenthesis and are calculated with Newey-West standard errors (columns 1-5) or robust standard errors (column 6 - 8). *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively

	Full Sample					Contrarian State	Large change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔSI_{t-1}		0.001**	0.001**	0.001**	0.001**	0.001**	0.001
		(2.04)	(2.12)	(2.15)	(2.39)	(2.14)	(1.62)
$\Delta Sentiment_{t-1}$	-0.000		-0.001	-0.001	-0.001	0.000	-0.002
	(-0.49)		(-0.89)	(-1.09)	(-1.24)	(0.35)	(-1.16)
$R_{m,t-1}$				0.111	0.157	0.101	0.155
				(1.29)	(1.65)	(0.62)	(0.78)
Intercept	0.008**	0.008***	0.008**	0.007**	-0.026	0.009	0.008
	(2.57)	(2.66)	(2.58)	(2.18)	(-1.10)	(0.27)	(0.14)
Additional Controls	No	No	No	No	Yes	Yes	Yes
Adjusted R^2	-0.003	0.001	0.011	0.019	0.028	0.033	0.522
Observations	252	252	252	252	252	124	24

Table 8: Holding the market portfolio depending on changes in SI

The table provides the additional cumulative return (in percentage) for holding the market (value-weighted portfolio) following months in which ΔSI_{t-1} is positive compared to months in which ΔSI_{t-1} is negative. $*$, $**$, and $***$ denote significance at the 1%, 5%, and 10% level, respectively.

Trading decision variable	(1) Full sample Depending on whether $\Delta SI_{t-1} < 0$ or $\Delta SI_{t-1} > 0$	(2) Contrarian state Depending on whether High Sentiment_{t-1}, $\Delta SI_{t-1} < 0$ or Low $\text{Sentimen}_{t-1} \Delta SI_{t-1} > 0$	(3) Large change Depending on whether $\Delta SI_{t-1} < -2sd$ or $\Delta SI_{t-1} > 2sd$
Holding months			
1	0.52	1.33*	4.41*
2	0.32	1.93*	3.39
3	2.23**	4.02***	10.13**
4	2.58**	4.29**	12.91**
5	1.50	2.87	14.53**
6	2.30	3.40	16.59**

Table 9: Change in volatility, VIX and SI

In Panel A, the dependent is the change in daily market return volatility over the month (current month's daily return standard deviation minus previous month's daily return standard deviation). Standard errors are calculated with Newey-West using three lags. In Panel B, the dependent variable is $VIXret_t$in specifications (1), (2), (3), (4), (7), (9) and ΔSI_t in specifications (5), (6), (8), (10). Specification (7)-(10) run on subsamples only. All independent variables are lagged compared to the dependent. All regressions include value-weighted market return (including dividends) measured at t-1. Additional controls refer to the default spread, term spread, one-month T-bill yield, long-term T-bond yield, earnings-to-price ratio, dividend-to-price ratio, EPU change, and inflation – all measured at t-1. Panel C provides the returns of trading strategies that go long (short) the VIX index at the end of month t-1 (and held till the end of month t), depending on whether ΔSI_{t-1} is negative(positive). In the upper part of the panel, the full sample and subsample (contrarian and large changes) results are provided for long or short position in the VIX index minus the treasury bill (TB), as well as VIX index minus the value-weighted return. In the middle and bottom part of the panel, the trading strategy is based on the concept of large changes in Δ SI, respectively. The trading rule, which varies across columns, is to go long the VIX index (and short the Treasury Bill) when ΔSI_{t-1} is below a certain threshold in standard deviation terms and to short the VIX index (and long the Treasury Bill) when $\Delta SI_{t-1}$is above the threshold. All strategies provide, both the long and short return of the strategy, as well as the difference between the long and short; as well as the intercept (alpha) generated from a regression where the dependent is the trading strategy return and the independent is the market excess return (value-weighted return minus the risk-free rate), during the month when the trading strategy is active. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Change in Volatility

	(1)	(2)	(3)	(4)
ΔSI_{t-1}	-0.007*	-0.009**	-0.008*	-0.010**
	(-1.72)	(-2.36)	(-1.78)	(-2.18)
$\Delta Sentiment_{t-1}$			0.008	0.005
			(0.97)	(0.61)
$VIXret_{t-1}$	0.954*	0.950*	0.941*	0.944*
	(1.92)	(1.86)	(1.91)	(1.86)
$\Delta Volatility_{t-1}$	-0.271***	-0.246***	-0.275***	-0.252***
	(-4.09)	(-3.53)	(-4.21)	(-3.52)
$Volatility_{t-1}$	-0.353***	-0.387***	-0.340***	-0.377***
	(-5.19)	(-6.20)	(-5.19)	(-5.71)
$R_{m,t-1}$	-1.086	-1.426	-1.207	-1.473
	(-0.82)	(-1.03)	(-0.91)	(-1.07)
Constant	0.342***	0.473***	0.331***	0.461***
	(5.14)	(3.09)	(5.17)	(2.95)
Additional Controls	No	Yes	No	Yes
Adjusted R^2	0.318	0.323	0.319	0.322
Observations	252	252	252	252

Panel B: VIX and SI- causality inference

	Full Sample						Contrarian		Large change	
Dependent variable:	$VIXret_t$				ΔSI_t		$VIXret_t$	ΔSI_t	$VIXret_t$	ΔSI_t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔSI_{t-1}	-0.005**	-0.005*	-0.005*	-0.005*	-0.367***	-0.388***	-0.006*	-0.304***	-0.013	-0.328***
	(-1.98)	(-1.89)	(-1.76)	(-1.71)	(-6.52)	(-6.98)	(-1.74)	(-4.52)	(-1.58)	(-3.50)
$\Delta Sentiment_{t-1}$			0.000	0.000	0.141	0.108	-0.002	0.137	0.014	-0.171
			(0.07)	(0.03)	(1.60)	(1.17)	(-0.47)	(1.43)	(0.69)	(-0.89)
$VIXret_{t-1}$	-0.162	-0.166	-0.163	-0.166	1.859	2.027	-0.003	1.269	0.571	-1.937
	(-1.10)	(-1.11)	(-1.12)	(-1.12)	(0.72)	(0.78)	(-0.02)	(0.42)	(0.75)	(-0.21)
$\Delta Volatility_{t-1}$	0.078**	0.091**	0.078**	0.091**	-1.019	-1.242	0.046	1.552	0.094	5.316**
	(2.42)	(2.29)	(2.38)	(2.22)	(-1.64)	(-1.65)	(0.71)	(1.08)	(0.87)	(2.23)
$Volatility_{t-1}$	-0.078***	-0.117***	-0.078***	-0.117***	-0.156	0.367	-0.028	0.845	0.041	0.706
	(-3.01)	(-3.16)	(-2.73)	(-2.96)	(-0.31)	(0.49)	(-0.91)	(1.06)	(0.38)	(0.47)
$R_{m,t-1}$	0.096	0.161	0.092	0.160	37.397***	29.914***	0.973	62.401***	3.102	75.071
	(0.21)	(0.31)	(0.21)	(0.32)	(3.56)	(2.72)	(1.23)	(3.24)	(0.99)	(1.45)
Intercept	0.106***	0.197**	0.105***	0.197**	-0.102	-0.050	0.033	-0.798	-0.104	-2.164
	(3.48)	(2.08)	(3.27)	(2.04)	(-0.17)	(-0.02)	(0.87)	(-0.77)	(-0.90)	(-0.99)
Additional Controls	No	Yes	No	Yes	No	Yes	No	No	No	No
Adjusted R^2	0.061	0.051	0.079	0.047	0.200	0.205	0.021	0.183	0.061	0.462
Observations	252	252	252	252	252	252	124	124	24	24

Panel C: Trading VIX depending on change in SI

The three samples

	$VIXret_t$ minus TB_t			$VIXret_t$ minus $R_{m,t}$		
	Full sample	Contrarian	Large	Full sample	Contrarian	Large
Return long (%)	3.06	2.62	6.55	2.78	2.84	6.80
Return short (%)	1.21	-1.89	-13.17	0.16	-3.24	-16.15
Long- short (%)	1.85	4.51	19.72*	2.62	6.09	22.95*

Various changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Long portfolio	ΔSI < -0.2sd	ΔSI < -0.4sd	ΔSI < -0.6sd	ΔSI < -0.8sd	ΔSI < -sd	ΔSI < -1.2sd	ΔSI < -1.4sd	ΔSI < -1.6sd	ΔSI < -1.8sd	ΔSI < -2sd
Short portfolio	ΔSI > 0.2sd	ΔSI > 0.4sd	ΔSI > 0.6sd	ΔSI > 0.8sd	ΔSI > sd	ΔSI > 1.2sd	ΔSI > 1.4sd	ΔSI > 1.6sd	ΔSI > 1.8sd	ΔSI > 2sd
Return long (%)	3.68	3.97	2.71	2.18	2.74	3.31	3.86	3.08	0.63	6.55
Return short (%)	0.40	-0.80	-0.72	-0.13	-3.67	-4.82	-5.72	-8.62	-8.59	-13.10
Long- short (%)	3.28	4.77	3.43	2.31	6.40	8.13	9.58*	11.70	9.22	19.75*
Intercept (alpha) (%)	2.42	3.79***	3.70**	3.44**	5.29***	5.64***	5.70***	5.86***	5.38***	5.45***
Months long portfolio	106	90	75	68	56	40	35	26	21	14
Months short portfolio	106	98	85	67	55	46	38	25	16	10