Essays Exploring the Impact of Socioeconomic and Political Factors on Corporate Performance

by

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Abstract

This thesis comprises three studies exploring the impact of income inequality on firm performance and political influence on gender parity within Canadian corporate boards. The issues addressed here are varied but connected to highlight "How socioeconomic and political transitions affect the corporate outcomes?". The following are the brief summaries of three studies:

In the first study, Sentiment Inequality (SI) is introduced to capture the difference in consumer sentiment between high- and low-income groups. It is hypothesized that SI can be used to predict the relative performance of high-end versus low-end product firms. A case study illustrates how variations in SI can predict the comparative performance of casual dining versus fast-food companies. Across the economy, it is hypothesized and shown that more cyclical firms in the industry or across the economy, which typically serve the relatively higher-income groups, outperform or underperform non-cyclical firms following SI increases or decreases, respectively.

The second study examines the SI implications for the stock market performance. An increase in SI indicates a rise in market return, reinforcing SI's predictive value for firms' performance dynamics. There is evidence that SI possesses superior informational value compared to changes in aggregate sentiment and conventional predictive variables. Due to the interrelated nature of these two studies, they are presented as a single chapter in this thesis.

The last study examines the impact of Canadian governmental gender parity on the appointment of women to corporate boards. Trudeau's commitment to gender parity within the Canadian government exemplifies a national leader's effort to structurally transform women's leadership by setting a personal example. The paper shows that following Trudeau's gender parity initiative, Canadian firms saw a more significant increase in the proportion of women on their boards compared to their U.S. counterparts and the period before Trudeau's ascendance to leadership. Additionally, the increased presence of women on boards during this time not only correlated with but also appears to have causally contributed to a reduction in Canadian stock return volatility.

Keywords: Consumer Confidence Index; Inattention; Leading indicator; Index of Consumer Sentiment; Sentiment inequality; Stock market; Systematic; VIX; Board of Directors; Gender diversity; Female Directors; Firm volatility

Dedication

This thesis is dedicated to my late grandmother, who always dreamed of seeing "Doctor" before my name.

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I want to acknowledge an important group of people who supported me through my doctoral journey and made this work possible. To *Amir*, I am proud and honored to have been your student. You have enormously shaped my perspective not only on research but also on life goals and values. Thank you for your dedication to my professional and personal development. Your patience and understanding made it possible for me to preserve and reach a positive conclusion in my Ph.D. studies. To my *family*, your unlimited love and infinite patience sustain me and motivate me to try harder and do a little better every day.

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List of Acronyms

2SLS	Two-stage least square
CAPM	Capital Asset Pricing Model
CBOE	Chicago Board Options Exchange
CCGG	Canadian Coalition for Good Governance
CCI	Consumer Confidence Index
CRSP	Center for Research in Security Prices
DID	Difference-in-difference
EB	Entropy Balance
EPU	Economic Policy Uncertainty
ESG	Environmental, Social, and Governance
FE	Fixed effect
FRED	Federal Reserve Bank of St. Louis
GDP	Gross Domestic Product
ICS	Index of Consumer Sentiment
IV	Instrumental variable
NDP	New Democratic Party
OECD	Organization for Economic Co-operation and Development
OSC	Ontario Securities Commission
PM	Prime Minister
PSM	Propensity Score Matching
ROA	Return on Assets
SB	Senate Bill
S.D.	Standard Deviation
SI	Sentiment Inequality
S&P	Standard and Poor's
TSX	Toronto Stock Exchange
VIX	Volatility Index
WRDS	Wharton Research Data Services

Executive Summary

As we navigate unprecedented socioeconomic shifts and financial complexities, my thesis is grounded in understanding the forces influencing firm performance, market behavior, and governance structure. In this dissertation, I study the critical dimensions of income inequality, political influence, and gender diversity in shaping organizational outcomes. My research is motivated by the intersection of corporate finance with two contemporary issues: rising consumption inequality and the permeability of firms to political influence and leadership.

Financial economists are interested in survey-based indices like the Confidence Index (CCI) and the Index of Consumer Sentiment (ICS) because they provide insights into individuals' financial well-being and economic expectations, demonstrating predictive power for spending behavior (Acemoglu and Scott, 1994; Carroll, Fuhrer, and Wilcox, 1994; Batchelor and Dua, 1998; Bram and Ludvigson, 1998; Ludvigson, 2004). However, these surveys have not been able to predict cash flow performance so far because the mapping from macro-level cash flow to firm cash flow is non-trivial.

The mounting evidence and varied scholarly interpretations of the decline of the middle class in the U.S. (Acemoglu and Autor, 2011; Piketty, 2014; Song et al., 2019; Auten and Splinter, 2023) serve to motivate the first two chapters of the thesis. This transformation has led several businesses to strategically shift their focus towards either the wealthier clientele or people lower on the income ladder who spend a large share of their income on necessities. This expanding divide in consumption patterns calls for a more in-depth exploration of consumption inequality across various income groups and its implications for economic outcomes. To uncover the dynamics of income inequality, the study uses consumer sentiment data segmented by income levels. The thesis introduces a new construct that is intuitively appealing, which captures Sentiment Inequality (SI). It is defined as the difference in sentiment levels between high- and low-income groups.

The first two studies examine the consumer channel through which SI affects the corporate landscape, so they are integrated into a single chapter. This combined analysis first addresses the impact of SI on firm performance. Then, it explores its macroeconomic implications, demonstrating how changes in SI influence the trajectory of the US stock market.

The first study posits that firms cater to different income groups of their end-consumers, which significantly influences their performance. Therefore, it demonstrates that changes in SI can predict the relative performance of high-end versus low-end product firms. It starts by illustrating this with a case study of how variations in SI can predict the comparative performance of casual dining versus fast-food companies in terms of cash flow and returns, implying that the market is unaware or inattentive to the economic significance of SI shifts. Then, the paper explores this intuition across the broad US economy. Because there is evidence that relatively more cyclical firms in the industry and across the economy tend to serve the high-income groups, they should outperform or underperform non-cyclical firms following SI increases or decreases, respectively. This is robustly confirmed across various analyses. The main findings are further substantiated by showing the predictive potential of SI in anticipating the future performance disparities between consumer staples and luxury goods firms.

The second study shifts focus to the broader macroeconomic implications of changes in SI. It examines the comparative advantage of using changes in SI relative to changes in aggregate consumer sentiment and other predictive indicators used in the finance and economics literature to predict changes in the macroeconomy. The research finds that an increase in SI predicts an increase in the next month's market return, underscoring the importance of analyzing sentiment differences among income groups to understand economic and market dynamics. The study shows that the predictability of SI changes extends to forecasting market trends over short horizons, such as four months. This finding is consistent with the idea that shareholders are not mindful of how SI reflects shifts in consumption of high-end versus low-end groups. Additionally, it reveals a negative correlation between SI changes and stock market volatility. A lead-lag (i.e., Granger, 1969) analysis supports these findings. The implications of this relationship are demonstrated through various trading strategies: using changes in SI as a signal to switch between long and short VIX positions generates significant positive excess returns.

The third chapter explores a different socioeconomic variable: gender. Gender diversity in corporate leadership has become a more ubiquitous concern in recent years. Decades of research are unequivocal that gender equality is the foundation for a liberal-equal society. Regions lacking gender parity often experience high instability and are more likely to host autocratic, corrupt governments. Treating women equally and integrating them meaningfully into institutions and decision-making represents a noble objective and significantly promotes sustainable equality and security. Trudeau's dedication to gender equality within his government offers a unique case study on the impact of leading by example. His emphasis on gender balance and visibly prioritizing women in government leadership could have influenced how organizations approach diversity and inclusion. This study investigates whether political commitment to gender parity influences corporate board composition.

Trudeau's ascent to Liberal Party leadership in April 2013 and ascendence to the PM role in October 2015 led to an increase in female board participation in Canadian corporations, which could have led to a positive shift in the gender dynamics of corporate boards. Consistent with this, it is found that female board participation in Canadian firms significantly increased during 2014-2015, paving the way for a more gender-balanced future. The study conducts a difference-in-difference analysis comparing the changes in the female director ratio in Canadian firms to US firms before and after the ascendence of Trudeau to leadership. Next, the study utilizes the increased participation of women on Canadian boards to analyze whether that affected the riskiness of corporations. The study finds a significant and negative association between the proportion of females on boards and changes in firm volatility.

Overall, the three papers in my dissertation contribute to understanding how firm outcomes are affected in the context of evolving socioeconomic and political landscapes. First, the conceptualization of SI is valuable in understanding how income inequality, mediated through sentiment variation, impacts corporations and the market. Second, the study suggests a more tangible method of leveraging sentiment analysis into financial market outcomes. Lastly, I provide evidence of the causal impact of political leadership on corporate decision-making in advancing gender equality and the subsequent benefits that ensue. The findings highlight the importance of proactive measures to promote gender equality within governmental and corporate spheres, signaling a promising step toward more inclusive and resilient business environments. From the cumulation of knowledge in each study, each chapter ends with practical implications.

Chapter 1. Consumer Sentiment Inequality and the Relative Performance of Firms[1]

1.1. Introduction

Consumer spending plays a crucial role in macroeconomic dynamics, acting as a key driver of economic growth and advancement. In the United States, it accounts for approximately two-thirds of the Gross Domestic Product (GDP), making it a widely employed indicator of a nation's economic well-being. Recognizing its significance, methodologies have been developed to measure the sentiment of American consumers. Notably, survey-based indices like the Confidence Index (CCI) and the Index of Consumer Sentiment (ICS) aim to understand individuals' perspectives on their personal financial well-being and long-term economic expectations. These indices have demonstrated predictive power for future spending behavior (e.g., Ludvigson, 2004).

Firms are also highly concerned with consumer sentiment because their customers' spending behavior is a primary driver of their success. However, a measure of aggregate consumer sentiment does not provide comprehensive information for companies since their customer base varies by income group. Certain firms cater to high-income consumers, while others focus on low-income groups, with distinct lifestyles and social pressures. Hence, fluctuations in aggregate consumer sentiment might not accurately reflect how sentiment changes within each income group.[2] Consequently, relying solely on monitoring aggregate sentiment numbers might obscure valuable insights when predicting shifts in

[1] This chapter was co-authored by my supervisor, Dr. Amir Rubin.

[2] Events on a macroeconomic scale can affect diverse income groups in unpredictable and varied ways. For instance, in a financial crisis, although low-income groups might seem to be more exposed, individuals with higher incomes could face greater challenges in upholding their lifestyle, complicating predictions about which group's sentiment suffers more significantly. A divergence in average sentiment between high- and low-income groups can occur even without external shocks because of the inherent economic disparities. For example, high-income individuals might experience positive sentiment due to investment growth or real estate appreciation, i.e., areas in which they are more likely to have significant stakes. In contrast, low-income groups, whose financial well-being is more tied to job stability or cost of living, could experience less positive or even negative sentiment changes unless these factors do not improve concurrently with the assets' appreciation.

spending patterns among various income groups. Such insights can have significant implications for relative valuation in the corporate landscape.[3]

This study hypothesizes that consumer sentiment may exhibit variations across income groups, reflecting divergent spending patterns among these groups. Therefore, the difference in sentiment levels between high- and low-income groups, defined as Sentiment Inequality (SI), is expected to provide valuable information regarding *relative* firm performance and asset prices. Our argument is simple: the consumption of high-end goods[4] and the performance of high-end goods firms primarily depend on the sentiment of high-income consumers, whereas the consumption of low-end goods and the performance of low-end goods firms depend on the sentiment of low-income consumers. Consequently, relative changes in the sentiment of high- and low-income consumer groups can reflect the relative performance of high- versus low-end goods firms.[5] For example, consider that low-income group individuals tend to own a Ford vehicle, and high-income group individuals own a Porsche vehicle. One might assume that, regardless of the aggregate sentiment level in the economy and its impact on overall automobile demand, when low-income consumers become relatively more confident about their finances compared to high-income consumers, there would be a greater increase in demand for new Ford vehicles compared to new Porsche vehicles. The opposite is observed when high-income consumers become relatively more confident, as the demand for new Porsche vehicles exhibits a stronger growth than that for Ford vehicles. The shift in demand creates a domino effect that influences not just Ford and Porsche but extends to their suppliers and customers across the automotive sector, which indirectly is affected by the sentiment of low- and high-income groups, respectively. Consequently, the SI hypothesis posits that the distribution of income among end-consumers shapes the entire economy.

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[3] Previous studies that provide analysis from disaggregating consumer sentiment by demographics include Das, Kuhn, and Nagel (2019), Dominitz and Manski (2004), Souleles (2004), and Toussaint-Comeau and McGranahan (2006).

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

[5] Relative spending rather than overall spending should be easier to gauge. This is similar to the benefits of relative valuation compared to fundamental valuation, which has been proven useful for predictions in a corporate finance setting (e.g., Boni and Womack, 2006; Da and Schaumburg, 2011).

We begin with an illustration of the implications of the SI hypothesis and analyze publicly traded companies within the restaurant industry. These companies are relatively straightforward to categorize according to the income levels of their end consumers. We distinguish between fast-food companies, primarily serving lower-income consumers, and casual dining establishments, which tend to attract consumers from higher income brackets. Our findings indicate that after an increase in SI, representing a relative rise in the sentiment of high-income individuals compared to those with lower incomes, casual dining firms outperform fast-food; on the other hand, following SI decreases, fast-food firms outperform casual dining. This trend persists in both changes in cash flow and returns, indicating that market prices do not fully incorporate shifts in SI.

Analyzing the effects of the SI hypothesis across the entire US population of firms requires us to rank companies from low- to high-end, a task that becomes complex because many companies serve end-consumers that consist of both low and high-income groups. To address this, we turn to finance theory, which indicates that the income and consumption patterns of high-income individuals are more cyclical compared to those of low-income individuals.[6] Our method involves partitioning firms on a scale from low to high according to their cyclicality attribute. This is determined by equity beta or comparing their equity beta to the industry average, referred to as the Industry-Adjusted (Ind-Adj) beta.[7] Our findings indicate that after a rise in SI, companies characterized by high beta and high Ind-Adj beta demonstrate a more favorable change in cash flow performance in

[6] Low-income individuals allocate a larger portion of their disposable income to necessities and less to savings (Keynes, 1936), and therefore, exhibit less flexibility in altering consumption based on economic conditions. Empirical evidence indeed suggests that the more affordable goods, compared to the luxury goods, tend to be less cyclical and have a lower sensitivity to market return (Ait-Sahalia, Parker, and Yogo, 2005; Baker, Baugh, and Kueng, 2021). Additionally, there is evidence that the income of high-income individuals is more cyclical as it is much more sensitive to stock market return than the income of low-income individuals (Parker and Vissing-Jorgensen, 2010; Rubin and Segal, 2015). This too should lead to high-income individuals' consumption being more cyclical compared to low-income individuals.

[7] We utilize equity beta and Ind-Adj equity beta as our measures for partitioning firms on the low to high-end goods scale. We recognize that equity beta may be affected not only by the cyclicality of sales but also by operating and financial leverage, which could compromise our ability to precisely reflect the SI hypothesis's forecasts for the sales of low- to high-end goods. To evaluate the importance of modifying beta for a more accurate depiction of sales cyclicality, we assess how our sales predictions are impacted by employing asset beta instead of equity beta as our measure of cyclicality. The results are not materially different. The pros and cons of making such leverage adjustments are further explained in the text and the Supplemental Materials for chapter, section S1.

comparison to their counterparts with low beta and low Ind-Adj beta, respectively, over the following two quarters. On the other hand, following a decline in SI, companies with low beta and low Ind-Adj beta surpass those with high beta and high Ind-Adj beta in terms of their cash flow performance improvement. The effect is stronger in the first quarter than in the second quarter and dissipates in the third quarter after the SI change.

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. The results show that the difference between stock returns of high-beta or Ind-Adj beta firms and low-beta or Ind-Adj beta firms are positively correlated with changes in SI. If one increases the holding period to three months following SI changes (until the publication of the next earnings figures), one can generate a statistically significant abnormal return of approximately 0.6% monthly (7.2% annually).

We also consider a Contrarian strategy to refine our findings using additional information. During times of low aggregate sentiment, both high- and low-income groups are close to the lower bound of sentiment levels, 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 relatively more informative, as they suggest that the market is getting out of the slump and entering a boom period. Similarly, SI decreases are relatively more informative when the aggregate sentiment level is high. During such times, SI is also high, so a reduction in SI during such times is indicative of an expectation of a cooling stock market.[8] We call both these situations a Contrarian strategy (as the direction of the change in SI is contrary to the aggregate sentiment level) and find that, during such times, trading strategies that use the SI change are particularly profitable (a value-weighted abnormal return of 13.7% and equal-weighted abnormal return of 15.6%).

[8] One possibility consistent with this prediction is that the high-income individuals in the economy are more tuned to the state of the stock market than the lower-income individuals and, hence, are more responsive to economic news when the economy is expected to enter a boom or a bust period (Rubin and Segal, 2015; Das, Kuhn, and Negal, 2019).

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 stock market. Since firms with high beta values typically outperform during periods of market expansion, and those with low beta values fare better during market contractions, shifts in SI are likely to offer positive predictions about stock market trends.[9] Our findings demonstrate that changes in SI provide predictive power for the market (the value-weighted return) in the following month after accounting for aggregate sentiment and established predictive variables in the existing literature, and this predictability persists for up to four months. Furthermore, we establish that increases in SI predict reductions in the VIX index. While we control for past market movements and volatility, as well as a comprehensive array of potential predictor variables encompassing both aggregate sentiment and economic factors, we exercise caution in drawing causal conclusions in the traditional sense. We explicitly avoid claims that relative changes in SI directly cause market movements because there remains a possibility that changes in consumer sentiment among different income groups may respond to the overall business cycle. Consequently, we claim that SI possesses superior informational value compared to changes in aggregate sentiment and conventional predictive variables.

This paper makes significant contributions in two primary areas. Firstly, it advances the finance literature by investigating the impact of sentiment on corporate behavior and performance.[10] Secondly, it enriches the macroeconomic literature by demonstrating that sentiment heterogeneity across income demographics can predict market movements.

In finance literature, the CCI and the ICS are commonly utilized as proxies for investor sentiment, capturing the temporary mispricing of securities driven by investor

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[9] We demonstrate market predictability, highlighting that SI information is not factored into prices, thus offering profitable trading opportunities. Additionally, we note that SI is a superior predictor of monthly real sales growth rate compared to aggregate sentiment.

[10] Prior studies have documented the influence that investor sentiment can have on investment decisions, the issuance of equity versus debt, dividend payments, and merger decisions. Some of the notable studies addressing these topics include: Baker and Wurgler, 2000, 2002, 2004; Baker, Stein, and Wurgler, 2003; Chirinko and Schaller, 2001; Gilchrist, Himmelberg, and Huberman, 2005; Lamont and Stein, 2006; Polk and Sapienza, 2009; Campello and Graham, 2012; Arif and Lee, 2014; Huang, Keskek and Sanchez, 2022; Li, Hoque and Liu, 2023.

optimism or pessimism (e.g., Baker and Wurgler, 2006, 2007). In contrast, the current study posits that while consumer sentiment may be related to investor sentiment, it distinctly influences consumer demand, thereby impacting corporate profitability.[11] Macroeconomists are interested in using survey-based indices like the CCI and the ICS because they offer valuable insights into individuals' financial well-being and are effective for predicting aggregate consumption patterns. The current paper utilizes disaggregated data of the indices across income groups to develop and test the SI hypothesis. As such, it extends the literature that shows that the macroeconomic cycle is influenced by changes in demographics such as age, income, and fertility (Jaimovich and Siu, 2009, Yoon, Kim, and Lee, 2014; Aksoy et al., 2019). What is unique about this study is that, even if income distribution does not undergo changes, it still plays a crucial role due to the dynamic nature of sentiment variation across different income groups. The study demonstrates that in unequal economies, sentiment differences based on income have predictive power for market-level outcomes.

In essence, the study utilizes existing evidence on the rise of income inequality (e.g., Cutler and Katz, 1991; Krueger and Perri, 2003; Acemoglu and Autor, 2011; Piketty, 2014; Song et al., 2019; Auten and Splinter, 2024), in conjunction with the documented increased income and consumption cyclicality among high-income groups relative to low-income groups (Parker and Vissing-Jørgensen, 2009, 2010; Rubin and Segal, 2015), to develop and test the SI hypothesis. These insights are valuable for academics and corporate managers who aim to understand how income inequality, mediated through sentiment variation, impacts corporations and macroeconomic dynamics.

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[11] Therefore, in the current study, CCI and ICS are indicators for future spending behavior, rather than indirect measures of investors' mood. Consistent with this approach, CCI and ICS show little correlation with proxies of investor sentiments. For example, in the period 1980-2021 for which we have overlapping data, the correlation between the CCI and CSI indices is above 0.8, while their correlation with the index of Baker and Wurgler (2006) index is below 0.2. This suggests that measures capturing investors' mispricing of securities and sentiment based on consumer purchasing decisions may differ significantly. Our findings suggest that the observed phenomena, where the effect of consumer sentiment (or mood) can predict firm performance, is not driven by investors' mood but rather by their inattention (Hirshleifer, Lim, and Teoh, 2009; Gilbert et al., 2012; Gabaix, 2019), as market participants may not be aware of SI or its implications.

1.2. Illustration – restaurant industry

In this section, we illustrate the SI hypothesis and its implication in the restaurant industry during the period 2001-2021.[12] 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 aspect of fast-food chains is that the average meal price is low ($4.72-10.00), and orders are self-administered. In casual dining, the average meal price is higher ($12–$88), and customers are served by a waiter.

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. The sample includes all public firms whose asset 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). Table 1.1 Panel A provides the brand names of the sample restaurant firms. On average, since fast-food restaurant companies cater to individuals with lower incomes, their stock prices are expected to be less cyclical compared to the stock prices of casual dining restaurant companies, which target individuals with higher incomes. Indeed, we estimate the beta of each stock in our sample and find that the fast-food restaurant stocks have an average equity beta of 0.88, while the average equity beta of casual dining stocks is 1.12. This difference is highly statistically significant.

In Panel B, we analyze the ability of SI changes (ΔSI_{q-1}) and aggregate sentiment changes ($\Delta SENT_{q-1}$) to predict changes in operating cash flow (ΔOCF) and return on assets (ΔROA) next quarter. ΔSI_{q-1} and $\Delta SENT_{q-1}$ are defined as the change in SI and aggregate sentiment, respectively, over the previous quarter. In the LHS of the panel, we provide the average future change in performance depending on the sign of ΔSI_{q-1}. The SI hypothesis posits that when ΔSI_{q-1} is negative, i.e., the low-income group becomes

[12] The total US food service industry is a significant part of the US economy, with revenues of about $876.33 billion in 2021 (Statista, 2022) and accounting for 4% of the GDP as of 2020.

relatively more confident compared to high-income group, the performance of fast-food should be comparatively better than casual dining. Indeed, following ΔSI_{q-1} decreases, the ΔOCF is -0.03% for fast-food and -0.29% for casual dining, with the difference of 0.26% tabulated in the Casual-Fast row being significant at the 5% level. As predicted by the SI hypothesis, the ordering in performance between the two types of firms flips following quarters in which ΔSI_{q-1} is positive. The fast-food firms underperform with an average of 0.03% increase in OCF compared with the 0.14% of casual dining firms, though this difference of 0.11% falls short of significance. The Difference column offers an alternative and potentially more robust econometric approach to understanding the implications of the SI hypothesis. Specifically, since fast-food out-perform casual dining when ΔSI_{q-1} is negative and under-performs when ΔSI_{q-1} is positive, the spread between the positive and negative ΔSI_{q-1} quarters is smaller for fast-food (0.06%) compared to casual dining firms (0.43%). Thus, the SI hypothesis posits and it is confirmed that as we move from low-end to high-end goods, the spread between performance following SI increases and decreases increases. To fully assess the implications of the SI hypothesis, we undertake a triple difference (DID) analysis (highlighted in bold in Panel B), which subtracts the fast-food spread from the casual dining spread. Our analysis reveals that the DID results yield a 0.37% difference, representing the spread between casual dining and fast-food.[13] Similarly, the findings related to ΔROA carry interpretation akin to that of ΔOCF, enhancing our confidence in their reliability.

While the SI hypothesis is agnostic to aggregate sentiment changes, it is plausible that changes in SI and aggregate sentiment are correlated. This correlation could arise if, for instance, the high-income group disproportionately influences changes in aggregate

[13] The DID result of 0.37% is also obtainable by calculating the differences in the Casual-Fast row, i.e., 0.11 - (-0.26) = 0.37. However, the sequence of differencing—whether across columns, representing the change in ΔSI_{q-1} in terms of increases versus decreases; or across rows, between types of firms—plays a critical role in unequal panels due to the need to choose the unit of difference for distribution analysis. Differencing across rows means your primary unit of observation is a quarter, and the number of firms in each category (low-end versus high-end) may vary significantly from one quarter to the next. Conversely, differencing across columns allows for a difference measure for each firm (provided the firm remains in the same category), offering a broader population for analysis. Therefore, although for the restaurant industry analysis this distinction is not important—as all firms are present throughout the entire panel and maintain their categories—the spread method proves more practical and suitable for deriving the DID result in the population.

sentiment within the economy. In the quarterly sample, the correlation between ΔSI_{q-1} and $\Delta SENT_{q-1}$ is 0.31. Therefore, a legitimate question is whether the SI hypothesis can predict future cash flows better than aggregate sentiment. The RHS of Panel B reports the average performance based on whether $\Delta SENT_{q-1}$ is positive or negative. We can see that the performance of fast-food and casual-dining firms is better following $\Delta SENT_{q-1}$ increases compared to decreases, but the DID result is insignificant, implying that aggregate sentiment is not useful for relative performance predictions. The only significant results in RHS are the better OCF performance of casual dining and the whole industry after positive $\Delta SENT_{q-1}$ (compared to negative $\Delta SENT_{q-1}$), but this too is not robust as it does not hold for ROA.

Overall, the results show that a change in SI is a better predictor of future cash flows than a change in aggregate sentiment, emphasizing the importance of relative sentiment changes for the cross-section predictability of cash flows. We also learn that SI changes have predictability for the whole industry, as the change in SI is positively correlated with its performance. The performance differences across the whole industry for OCF and ROA are 0.21% and 0.19% higher for positive compared to negative ΔSI_{q-1}, respectively. This amounts to roughly half the disparity observed in the triple DID, which stands at 0.37% and 0.39%, respectively. This suggests that about half of the predictability in cash flow observed in the DID results is attributable to the relative performance within the industry, while the other half stems from predictability at the industry-wide level.

Next, the SI hypothesis posits that changes in SI may be useful for portfolio decisions, as the market may not be aware of SI or does not continuously follow SI and incorporate it into prices. Based on the sign of the change in SI during period *t-1* (ΔSI_{t-1}), one may be able to create profitable trading strategies. Namely, if $\Delta SI_{t-1} > 0$ ($\Delta SI_{t-1} < 0$), one should hold a portfolio of casual dining (fast-food) firms and short a portfolio of fast-food (casual dining) for month *t*. Given the positive correlation between changes in future cash flow and SI in the restaurant industry, as observed in Panel B, we also implement a trading strategy that is long (short) for all firms in the restaurant industry based on the sign of SI. Additionally, to show the added value of using SI changes compared to aggregate sentiment changes for trading, we run both strategies depending on the sign of $\Delta SENT_{t-1}$.

The calendar-time approach addresses the potential shortcoming if a certain trend in fast-food and/or casual dining occurred during our sample period, as averaging returns across time and firms may lead to biased estimates in t-statistics (Mitchell and Stafford, 2000). We put fast-food and casual-dining stocks into long and short portfolios depending on whether SI (or aggregate sentiment) increased or decreased in the previous month. To calculate the alpha, we regress the excess returns (equal or value-weighted return minus the risk-free return) in the CAPM or the four-factor Fama-French (Fama and French, 1993) and momentum (Carhart, 1997) models. The reported alphas in Panel C (in %) are the intercepts of these regressions.

Panel C provides raw returns and the alphas. In column 1, we see that the trading strategy earns 0.5% (0.6 %) monthly EW (VW) raw returns over 252 months, but given the relatively small sample of firms, these results are statistically insignificant. Alphas are 25% larger for VW portfolios than EW portfolios and are significant at the 10% level in the CAPM specification. As expected, the trading strategy provides no value if we use the sign of $\Delta SENT_{t-1}$ instead of ΔSI_{t-1} (column 2). Next, because we saw that both changes in SI and sentiment are positively correlated with future industry cash flow, we also analyze the possibility that they may be useful for predicting the overall return within the industry in columns 4 and 5. The result is that ΔSI_{t-1} has high raw and alpha predictability for overall performance in the EW sense (significant at the 10% level), but the VW predictability falls short of statistical significance. In column 5, we learn that $\Delta SENT_{t-1}$ is not predictive of the restaurant industry performance.

Finally, in columns 3 and 6, we conduct an additional analysis that refines our trading strategies regarding the usage of the sign of ΔSI_{t-1}. We run our strategy in a subsample of the months in which the aggregate sentiment level at *t-1* ($SENT_{t-1}$) passes a certain criterion. 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 $SENT_{t-1}$ is low and when $\Delta SI_{t-1}$is negative and the $SENT_{t-1}$is high. In this strategy, whether aggregate sentiment is deemed high or low depends on whether $SENT_{t-1}$ is higher or lower than the average aggregate sentiment level during the pre-period of 1980-2000, which ensures the strategy is out-of-sample. In column 3, across all EW and VW strategies, the alphas range between 1.01% - 1.42% per month (which is 12.12% - 17.04% annually), statistically significant at the 5% to 10% level. Implementing the Contrarian strategy for buying or shorting all firms depending on the sign of SI, as presented in column 6, is highly profitable for EW performance and significant at the 10% level for VW performance.

Overall, the results show the relevance of the SI hypothesis across three important dimensions, which we next analyze for the population of US firms. First, SI is useful for relative performance evaluation of high-end versus low-end firms, showing predictability in both cash flow and return. Second, SI is especially useful when combined with knowledge of the aggregate sentiment level in the economy, in the Contrarian strategy. Third, SI can predict the overall performance of the restaurant industry, so it may be useful for predicting fundamental systematic changes.

1.3. Sentiment inequality

1.3.1. SI and sample period

Only two organizations provide sentiment data based on the income group of individuals conducting the survey: the ICS, produced by the University of Michigan Survey Research Center, and the CCI, produced by the Conference Board. ICS determines the cut-off level of three equal income groups (top, medium, and bottom) based on respondent data, while CCI income group cut-off values are based on categories defined by a range of dollar income. Over the years, the CCI income categories have increased from three to nine. We use the lowest and highest income categories for our SI measure. The CCI's bottom- and top-income categories are currently defined as household incomes below $15,000 and above $125,000, respectively. The ICS and CCI surveys poll households on their financial situation, the propensity to consume major household items, and expectations of the health and trajectory of the U.S. economy. While both indices are highly correlated (Bram and Ludvigson, 1998; Ludvigson, 2004), they differ in terms of the survey questions, sample size, and construction.

The measure of sentiment inequality that we use throughout this study is the simple average of the sentiment inequality of the ICS index and the sentiment inequality of the CCI index,[14] where the sentiment inequality of an index is the sentiment level of the upper- minus lower-income group of the respective index. We also point out that SI, by its definition, is not determined by overall mood shifts affecting the representative consumer in the economy; rather, it concerns the relative mood changes between the two representative consumers, the high-income versus the low-income representative consumer. It is important to note that shifts in sentiment within only the high-income or low-income group do not yield the findings detailed in this paper because each group's sentiment is highly correlated with aggregate sentiment, which is continuously monitored by the market and likely already priced in.

Our study covers the period 2001-2021 because from a theoretical standpoint, if inequality in society is not large, individuals' income should have a small effect on the consumption of high-versus low-end goods. Rather, personal preferences matter for the consumption of high-end versus low-end goods in relatively equitable economies. However, when income inequality is high, income becomes a major determinant of whether to consume high- 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, 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 and low-income households' consumption towards

[14] Using the measure of sentiment inequality by comparing the highest and lowest income groups has distinct advantages over a Gini-type measure. It offers simplicity and clarity, making it easy to compute and interpret while directly highlighting the disparity between the extremes, and it avoids diluting inequality, providing a sharper picture by focusing on the most and least advantaged groups, which is particularly useful for policy-making and public communication. The results are robust to the usage of the principal component measure of the two indices. Also, if we use only one of the measures (ICS or CCI), most of the results still hold, but the significance is reduced. This may be because each of the measures alone is noisier than a measure that combines both indices together.

necessities.[15] This increased segmentation in consumption makes the prediction of the SI hypothesis possibly stronger in recent decades compared to the periods prior when income inequality was less severe. On the practical side, to find inefficiency in equity prices in our sample period would be a hard bar to pass as during the last two decades it has become 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 public.[16]

Figure 1.1 provides a schematic description of the timing of sentiment data release dates and out-of-sample prediction periods used in this study. Both Michigan and the Conference Board conduct their surveys throughout the month. Michigan provides a preliminary mid-month release based on two-thirds of the sample and provides month-end final figures based on the full sample. 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. Therefore, 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. In an informal discussion with the Conference Board, we were told that adjustments made between preliminary figures and final figures are usually very small.[17] Since we generate SI from the final figures of ICS and CCI, the trading profits may marginally differ from what would be possible for a trader in real time. However, in our analysis, both ICS and CCI changes rely on the previous month's data. Therefore, the economic interpretation that alterations in the relative spending patterns between high- and

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[15] 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).

[16] 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 1980-2022 period, however, the results are weaker and often insignificant when we consider the 1980-2000 alone. This could be due to the reduced income inequality in the earlier period, or less representative SI data in the earlier period.

[17] The Conference Board survey is approximately six times larger than the Michigan survey, so the confidence interval on its 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.

low-income groups are the causal explanation for our cross-sectional findings remains unaltered by this technical artifact.

1.3.2. Descriptive information on SI

Table 1.2 provides descriptive statistics for the main variables used in this study. Our sample covers the period 2001 to 2021, but we also rely on the mean aggregate sentiment level and the standard deviation of SI in the 1980-2000 period as benchmarks for our out-of-sample predictions in the post-2000 years. In Panel A, we compare sentiment and SI data in the 1980-2000 and 2001-2021 periods. The comparison between the two periods yields two interesting findings. First, the aggregate sentiment level decreased in the post-2000 period compared to that in the pre-2001 period (from a mean of 93.2 to a mean of 87.8). Second, SI has increased significantly since the turn of the century (from a mean of 25.8 to a mean of 33.7). Auten and Splinter (2023) suggest that when accounting for taxes and in-kind transfers, U.S. income inequality may have not increased as previously believed. Nevertheless, in terms of sentiment, our findings align with the notion of increasing income inequality since the late 80s, as proposed by Piketty and Saez (2006), as that would likely lead to an increase in SI. Next, we test whether there is a difference in the changes in aggregate sentiment and SI between the two periods. In the following rows, we provide distributional properties of aggregate sentiment and SI 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. Thus, although it seems that the aggregate sentiment and SI levels have changed between the pre- and post-2000 periods, the monthly and quarterly differences in these variables can be considered stationary.

In Figure 1.2, we provide the upper- and lower-group sentiment levels of ICS for the 1980-2021 period. The upper figure shows the ICS of the upper- and lower-income groups, and the bottom figure shows the CCI of the upper- and lower-income groups. The index levels are measured in December of each calendar year. The figure shows 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).

Next, in Figure 1.3, we plot SI with aggregate sentiment at the quarterly frequency (end of a calendar quarter) from 2001 to 2021. The LHS y-axis provides the value of the aggregate sentiment level and the RHS y-axis provides the SI level. Although both series correlate (the correlation is 0.31), SI is more volatile and continuously changing. For example, SI dropped by much during the financial crisis. 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). Overall, the fluctuations in SI highlight a dimension that is notably distinct from the aggregate sentiment level, underscoring the necessity to delve deeper into the SI hypothesis to uncover its potential impacts on economic dynamics.

1.4. Other sources of data

1.4.1. 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 daily return to estimate beta and classify firms into high-end versus low-end type goods, we exclude stocks that had fewer than 220 trading days in a calendar year and whose beta, based on daily returns 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, which are not utilities or financial, are included in our sample.

We use two measures of firm performance: Operating Cash Flow (OCF) and Return on Assets (ROA). OCF is the income from operations before depreciation divided by total assets (Kaplan, 1989; Lang et al, 1991), and ROA is the income before extraordinary items (IB) divided by total assets (Hou, Xue, and Zhang, 2015 and 2020).

In the firm-level regressions, we control for firm characteristics: Firm size is the market value of a firm's equity (in billions of dollars) at the end of a calendar year. Volatility is the standard deviation of the 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 firm-level variables are winsorized at the 1st and 99th percentiles to minimize the effect of outliers.

Panel B of Table 1.2 provides the firm-level descriptive statistics. The median OCF and ROA are approximately 3% and 1.1%, respectively, but their 99% confidence intervals are wide. The average firm has a market value of $6.1 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 12.5% (10.7%). 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 the firms in our sample pay quarterly dividends. The median firm in our sample has a capital expenditure of 1.2% of assets.

1.4.2. High-end versus low-end goods and market beta

The consumption patterns of high-income groups are more cyclical compared to low-income groups due to two primary reasons: low-income individuals allocate a higher portion of their income to necessities and have lower savings, limiting their consumption flexibility in response to economic changes (Keynes, 1936). Additionally, their income is less tied to financial market returns compared to high-income individuals, whose earnings are significantly influenced by stock market performance and pay-for-performance schemes (Parker and Vissing-Jorgensen, 2010; Rubin and Segal, 2015).18 Consequently, firms serving high-income clientele are likely, on average, to exhibit greater cyclicality compared to those serving low-income individuals. This phenomenon is observable within industries, where firms manufacturing premium, high-priced goods aimed at high-income consumers tend to experience more pronounced cyclical variations than those producing goods for the lower end of the market. Furthermore, this pattern extends across industries, given that low-income individuals constitute a relatively larger segment of the consumer base for staple goods as opposed to durable goods.[19] Indeed, the evidence is that high-end goods, including luxury and more pricey durable products, typically exhibit higher cyclicality across and within industries, a phenomenon well-documented in the literature (Ait-Sahalia et al., 2004; Baker, Baugh, and Kueng, 2021; Bils and Klenow, 1998; Yogo,

[18] 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. Parker and Vissing-Jorgensen (2010) document that the rise in the high-income group share of aggregate income coincides with it also being more cyclical.

[19] Engel's Law posits that with the rise in household income, the share of income dedicated to purchasing food (a staple category) declines, whereas spending on non-essential products, like durable goods, increases. This trend suggests that, holding other factors constant, firms specializing in staple goods disproportionately serve low-income segments, in contrast to durable goods companies, which cater more to high-income demographics. Note that this fact also has an empirical implication. In an additional analysis, we use the S&P 500 Consumer Staples Sector Index and the U.S. firms in S&P Global Luxury Goods Index to construct a sample of luxury firms and consumer staples firms. The results are consistent with the SI hypothesis prediction and are of similar magnitude to that of the full sample (these results are presented in the Supplemental Materials for Chapter 1, section S2).

2006; Gomes et al., 2009) and recognized in the financial press (Deleersnyder, 2004; Daneshkhu and Simonian, 2009; Bain and Company, 2009; Danziger, 2022).20 The relationship between cyclicality and customer income, both within industries and across the economy respectively, suggests that since the Ind-Adj beta and the beta (using the Capital Asset Pricing Model, CAPM) reflect a firm's cyclicality, they are capable of indicating a firm's position on the spectrum from low-end to high-end goods within the industry and across the economy, respectively.

To measure beta, we use the daily return frequency and the CRSP value-weighted index (including dividends) as our market proxy. We use the CAPM to estimate beta rather than the four-factor model, 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 cyclicality, would take away from the ability of the market beta to capture cyclicality. This follows the discussion in Berk and Demarzo (2020, pp. 487-488) of why we get better economic intuition about the company from the CAPM beta than the four-factor model.

We define the Ind-Adj beta as the firm's equity beta minus the mean equity beta in the industry (two-digit SIC code).21 Throughout the paper, we partition all stocks each year (starting in 2001) into four portfolios according to the magnitude of their beta (or Ind-Adj beta) in the previous year (β1 refers to the bottom quartile and β4 the top quartile).

1.4.3. 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 percentages. 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-

[20] We note that though the cyclicality of income and consumption of high-income groups is evident in the financial economic literature and the data (for example, high-end luxury good tend to have high beta, and staples good tend to have low beta), the macro literature tends to compare consumption over long period of time, and in that regard, the cyclicality argument is less clear (see Krueger, Metti, and Perri, 2006).

[21] The industry-adjusted results that we report in this study for the two-digit SIC code and the qualitative nature of the results is similar if we use three-digit, four-digit, or Fama and French 49 industries instead.

rated corporate bond yields obtained from the Federal Reserve Bank of St. Louis (FRED) database and the one-month T-bill yield. The default 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, and 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.[22] 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).

1.5. Empirical analysis

1.5.1. Univariate cash flow analysis

It is unclear where the predictions of the SI hypothesis are greater: at the industry level as we have done for the restaurants, or across industries. Throughout our analysis, we provide results both when using the Ind-Adj beta, as well as unadjusted beta (for briefness, we refer to it as beta). We measure the change in firm performance as a seasonally adjusted quarterly change in OCF and ROA (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)*.[23]

Table 1.3 Panel A reports the mean changes in OCF of each beta quartile depending on whether ΔSI_{q-1}<0 (decrease in SI in the previous quarter) or ΔSI_{q-1}>0 (increase in SI in the previous quarter). The average performance decreases monotonically in Ind-Adj beta when the ΔSI_{q-1} is negative. For example, the average one-quarter forward change in OCF is -0.11% for β1and β2, -0.17% for β3, and -0.20% for β4. These results suggest that

[22] Available at http://www.econ.yale.edu/~shiller/data.htm.

[23] The results are robust to using quarterly changes in SI that are not seasonally adjusted.

low-end good firms do comparatively better than high-end good firms when ΔSI_{q-1} is negative. Contrary, the average performance increases monotonically in Ind-Adj beta when the ΔSI_{q-1} is positive. The Difference column measures how each Ind-Adj beta quartile performs following SI increases compared to decreases. This difference is increasing with higher quartiles. It is 0.10% for β1 and 0.32% for β4. For beta-based quartiles (lower part of the panel), it is 0.03% for β1 and 0.44% for β4.

Next, we conduct a difference-in-difference (DID) analysis by comparing the change in performance following SI increases quarters and SI decreases quarters of top and bottom quartiles. The last two rows of the Difference columns provide DID results, where β4- β1 is 0.08% and that of (β4+ β3)- (β1+ β2) is 0.06%. The mean OCF (Table 1.2) is 2.3%; therefore, 0.08% represents a change of 3.5% in performance.[24]

In Panel B of Table 1.3, we repeat the analysis using the one-quarter ahead change in ROA and the results are qualitatively the same as those for the change in OCF. For both Ind-Adj beta and beta, 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). Similarly, 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 changes in the OCF.

Table 1.3 Panels A and B also provide the Difference column results for two-quarter ahead following the change in SI. The results are economically and statistically strong for OCF, but not significant for ROA. 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.

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[24] The difference between SI increases and SI decreases naturally should be measured at the firm level. Thus, for each firm we want to compute the difference in performance between quarters that follow $\Delta SI_{q-1}<0$ and those that follow $\Delta SI_{q-1}>0$. However, because beta and Ind-Adj beta are 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 $\Delta SI_{q-1}<0$ and those that follow $\Delta SI_{q-1}>0$ 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 these years we cannot generate a measure. It also means that the DID analysis is not a simple subtraction of the difference between rows β4 and β1.

After illustrating the implications of the SI hypothesis on changes in OCF and ROA, it's reasonable to argue that we could similarly explore its effects on sales figures, given that sentiment shifts are presumed to directly influence sales, while impacts on OCF and ROA are indirect. Repeating the analysis in Table 1.3 for sales changes (changes in sales/assets) indeed yields significant outcomes as predicted (The Supplemental Materials for Chapter 1, section S1). This introduces another point for consideration. We do not adjust our equity beta (or Ind-Adj equity beta) for operating and financial leverage effects, potentially obscuring the direct impact of SI shifts on sales changes. We do so for good reasons as both OCF and ROA are influenced by operating leverage's multiplicative effect on sales, so adjusting equity beta to exclude this influence may offer a more accurate measure for assessing SI's effect on sales yet this adjustment compromises the relationship between sales and ROA or OCF. Similarly, analyzing returns (which represent the shareholders' stake in the company) and removing the effect of financial leverage to derive asset beta can aid in forecasting sales based on SI shifts but can weaken the mapping from sales to stock returns, which is our goal in subsequent analyses. To gauge the significance of adjusting beta for a refined measure of sales cyclicality, we examine the impact on our sales forecasts when we use asset beta over equity beta as our measure of cyclicality. The findings, detailed in Supplemental Materials S1, reveal minimal differences, indicating that these adjustments for leveraging effects are not crucial for sales predictions in the context of the SI hypothesis.

1.5.2. Multivariate analysis

The univariate analysis focuses on the two most important variables in the study (i.e., SI and Ind-Adj beta/beta quartiles). However, it can fail to capture the various existing interactions of SI or beta with other firm characteristics. To determine whether changes in SI predict future firm performance, we estimate the following basic model:

$$\Delta P_{i,q} = \alpha_i + \theta_1 \, \Delta SI_{q-1}\left(\beta_{i,\tau-1}\right) + \theta_2 \beta_{i,\tau-1} + \varphi_i + \Phi_t + \varepsilon_{i,q} \qquad (2)$$

where $\Delta P_{i,q}$ is the quarterly (seasonally adjusted) firm performance (ΔOCF or ΔROA) 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 the Ind-Adj beta or beta in the calendar year $\tau - 1$. 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 and quarter levels.

The coefficient of interest is that of the interaction term, θ_1. Specifically, 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. Thus, the SI hypothesis predicts that $\theta_1$is positive. Note that because ΔSI_{q-1} changes only in the time series, it is collinear with time-fixed effects; thus, ΔSI_{q-1} affects performance only through its interaction with beta.

Table 1.4 provides the estimation results for our regression specifications using both Ind-Adj beta and beta. Specifications 1 and 3 provide an estimation of the basic model (eq. 2). Regression specifications 2 and 4 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 integrating these controls and their interplay with the key variables (SI changes and Ind-Adj beta/beta), we ensure that our results reflect the SI predictions on the impact of the low- versus high-end goods scale depending on past changes in SI, rather than being influenced by firm characteristics that are associated with beta or the change in SI from the prior quarter.

The coefficient θ_1 is positive and highly significant in all four specifications, indicating that the change in performance is positively correlated with $\Delta SI_{q-1}(\beta_{i,\tau-1})$, implying that a higher Ind-Adj beta and beta helps performance when SI_{q-1} is positive but hurts performance when SI_{q-1} is negative. For example, in the Ind-Adj beta, for a one-quarter forward change in OCF (specification 1), the coefficient of the interaction is 0.013, which means that a one-point increase (decrease) in SI_{q-1} leads to an average 1.3 basis points increase (decrease) in performance for a firm whose Ind-Adj beta is 1, but to an average 2.6 basis points increase (decrease) for a firm whose Ind-Adj beta is 2. The results concerning the one-quarter forward change in ROA (specification 3) are also economically and statistically significant, with θ_1 equaling 2.0 basis points. In specifications 2 and 4, the coefficients θ_1 are 0.014 and 0.020, respectively, representing no reduction compared to the base case in specifications 1 and 3, respectively. It can be concluded that the interaction between changes in SI and Ind-Adj beta is hardly affected by the other characteristics.

Next, in specifications 5-8 of Table 1.4, 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. Interestingly, the results become marginally stronger for Ind-Adj beta in terms of OCF, but the ROA predictability in the beta analysis reveals weaker predictability.

The results in Table 1.4 can be summarized as follows. The interaction between changes in SI and Ind-Adj or beta predicts the change in OCF up to three-quarters forward and the change in ROA up to two-quarters forward. This finding is consistent with the univariate results presented in Table 1.3. Overall, we can conclude that high-end goods firms have improved (reduced) performance compared to low-end goods firms following SI increases (decreases).

1.5.3. SI predicting cross-sectional returns

We next analyze whether SI knowledge helps predict cross-sectional stock returns, which would imply that the market is unaware or inattentive concerning information embedded in SI. To study the relationship between changes in SI and firms' stock returns, we use the same Ind-Adj beta and beta quartiles as in the previous subsections, that is, estimated at the calendar year prior.

Trading strategy

Given the expectation that information is rapidly incorporated into prices, our approach 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 LHS of Table 1.5 shows the results for portfolios that are long low Ind-Adj beta stocks (β1 portfolio) and short high Ind-Adj beta stocks (β4 portfolio) when ΔSI_{t-1} is negative (i.e., when low-income groups are comparatively more confident) and are long high Ind-Adj beta stocks and short low Ind-

Adj beta stocks when ΔSI_{t-1} is positive (i.e., when high-income groups are comparatively more confident). In the full sample, the trading strategy runs for 21 years (252 months[25]), yielding 0.22% and 0.21% monthly EW and VW raw returns, respectively, which are positive but not statistically significant. The alphas in the full sample are somewhat larger than the raw returns but are still statistically insignificant.

The Contrarian strategy, on the other hand, provides significant trading strategy results. This strategy runs for 124 months, which are considered the Contrarian months. The EW and VW raw returns are 0.89% (10.7% annual) and 1.02% (12.2% annual), respectively. Based on the CAPM and four-factor model, an investor holding an EW or VW portfolio in the Contrarian strategy would earn similar magnitude alphas in the range of 0.92-1.05 (11-12.6% annual). The RHS presents the results using beta quartiles instead of Ind-Adj beta quartiles. The results are not much different in statistical significance, but the Contrarian strategy performs approximately 20% better with beta compared to Ind Adj beta.[26]

Recall that our cash flow results (Tables 1.3 and 1.4) show that SI changes are predictive of cash flows up to three quarters forward. Therefore, it is reasonable to consider that changes in SI may take more than one month for the cash flow effect due to the change in SI to be reflected in the stock price. Therefore, in Table 1.6, we analyze the raw and alpha of calendar-time trading strategies of Table 1.5 for holding periods of up to 6 months (months *t until t+5*). Note that there is an overlap in the decision rules in each calendar month when the holding period is more than a month, so a given security may end up having a long position of more than once, or alternatively, ends up not being in the portfolio

[25] We note that the number of months in which we have ΔSI_{t-1} drops from 253 (Table 2) to 252 because we rely on lagged changes.

[26] In untabulated analyses, we investigate which SI changes contribute most significantly to the results. SI changes are divided into three categories: when sentiments of both low and high-income groups decrease, when sentiments of both income groups increase, and when they diverge. The monthly data is distributed relatively evenly among these scenarios. The greatest trading profits occur in months where the sentiments of low- and high-income groups move in opposite directions, followed by months where sentiments of both groups decrease. Although the analysis has limited power, it highlights that SI becomes particularly informative in periods when aggregate sentiment remains relatively stable.

at all. Consequently, there could be combinations of calendar months with a holding period month in which the strategy is to hold nothing.[27]

We also take the opportunity to provide more analysis and robustness in Table 1.6, by considering the industry-adjusted raw return performance (subtract the industry's equal-weighted (EW) average return and the industry's value-weighted (VW) return from the raw EW and VW returns, respectively), as well as five-factor model and the Betting Against Beta (BAB) factor (Frazzini and Pedersen, 2014; Novy-Marx and Velikov, 2022) as our procedure sorts firms based on beta equity.[28] Finally, we use our knowledge to create a Dynamic trading strategy. Instead of going long and short high and low beta stocks, respectively, we assign a weight for the holding position that depends on whether you are in a Contrarian month or not, giving more weight to Contrarian months than non-Contrarian months. This allows the trading strategy to be active in the full-time series.[29]

Table 1.6 presents the results. The left-hand side of the table reports results with Ind-Adj beta, while the right-hand side reports results with beta. The upper part of the table displays results for the full sample, the middle part displays results for the Contrarian sample, and the bottom part displays results for the Dynamic strategy. It is evident that all abnormal returns reach a maximum after three months, which would be consistent with the

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[27] 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 1.6 would converge to a certain level. Note that as the holding period increases, one expects the alpha (per-month) to decrease because the effect of a change in $SI_{t-\mathrm{k}}$ on the portfolio's alpha should decrease as k increases, but for statistical significance the increased time allows for a larger and less volatile portfolio, which has the benefit of reducing the variance of the portfolio.

[28] The BAB factor in asset pricing outlines a strategy of purchasing low-beta assets and shorting high-beta assets to leverage the lower risk-adjusted returns of high-beta stocks, attributed to heightened demand for high-beta stocks due to borrowing constraints. The SI hypothesis, focusing on trading stocks conditional on SI shifts, is conceptually unrelated to the BAB factor. However, due to our sorting of stocks by equity beta, it may be judicious to control for the BAB factor in our analysis.

[29] The weight is a linear function depending on how far you are from the mid-point of the aggregate sentiment level. The further you are, the signal of the sign in SI is considered more informative, especially in Contrarian months. The average weight in any month remains one, so the results are comparable to the full sample results.

publication of next quarter's financial statements. This reflects that SI shifts are priced once their tangible effects is revealed to market participants. The range of raw and abnormal returns for the full sample after three months is 0.39%-0.44% for Ind-Adj beta, and it is 0.44%-0.62% for beta. These translate to a modest abnormal return of approximately 6% in the full sample. The Contrarian strategy yields more impressive results throughout all holding periods and reaches a range of 11.8-18.6% (annually) after a three-month holding period. The Dynamic strategy is the most impressive and almost always provides significant raw and alpha returns. Overall, the evidence in Table 1.6 suggests that information on SI changes is not fully embedded into asset prices, and there is a range of periods and procedures to achieve profitable trading by incorporating the predictions of the SI hypothesis.[30]

Fama-Macbeth regressions

We next conduct Fama-MacBeth regressions (Fama and MacBeth, 1973). Given our finding that it takes up to three months for prices to reflect the information embedded in SI, we measure the change in SI over the previous quarter (ΔSI_{q-1}), and analyze whether it predicts the firm's returns in the following month. Note that we run the regressions for all months, so the independent is overlapping—similar to the approach in Table 1.6 for a three-month holding period trading strategy. The results are presented in Table 1.7. Specifications 1-4 provide the regression estimates for the full sample, and specifications 5-8 provide the regression estimates for the Contrarian sample.

All specifications reveal a positive and statistically significant coefficient for the interaction term alongside a non-significant coefficient for the standalone Ind-Adj beta and beta. Considering the average change in ΔSI_{q-1} is 6 points for positive shifts in SI and -6 for negative shifts in SI, a rudimentary calculation offers insight into the economic implication of these findings. For instance, in specification 3, firms with a beta value of 1 experience an average return of -0.06% in months that follow a quarter with no change in SI, -1.08% (i.e., 0.0017× (-6)-0.0006 = -0.0108) in months that follow SI decreases, and

[30] The outcomes of trading strategies show greater abnormal returns compared to raw returns, with alphas being more substantial when utilizing equity beta over industry-adjusted beta. This appears to be because changes in SI are predictive of systematic variations, as discussed in Section 6.

0.96% in months following SI increases. For firms with a higher beta value of 2, the return following each of these three states would double (i.e., -0.12%, -2.16%, and 1.92% following no change in SI, negative change in SI, and positive change in SI, respectively). All specifications for Table 1.7 allow for similar interpretation, with an apparent stronger economic implication for months following Contrarian months.

1.6. Market level changes

1.6.1. SI and market returns

We have shown that on a relative basis, increases in SI benefit high-beta stocks compared to low-beta stocks. Because high-beta stocks are expected to do better than low-beta stocks when the market goes up (and worse when the market goes down); it is expected that increases (decreases) in SI hypothesis should be related to positive (negative) future movements of the stock market. In the previous sections, we presented evidence that is consistent with this. Table 1.1 Panel B and Table 1.3 demonstrate that the performance differential between SI increases and decreases is positive across all beta quartiles, with a more pronounced spread observed for high-beta stocks compared to low-beta ones. This finding suggests that SI changes forecast future shifts in market-wide cash flows. The results concerning the ability of SI to predict returns of high relative to low beta stocks further enhance this impression. However, these findings fall short of a formal test, which is the focus of this section.

In this section, we analyze whether changes in SI predict changes in the stock market. We measure the change in SI as in the previous 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 changes in the aggregate sentiment level as a possible predictor. In addition to the full sample period and the Contrarian sample, we consider the possibility of our results being driven by only a few months in which the ΔSI_{t-1} is especially large. 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 Table 1.8, specification 1, we find that the coefficient of $\Delta SENT_{t-1}$ is statistically insignificant, suggesting that aggregate sentiment does not predict market returns. 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 $\Delta SENT_{t-1}$ 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, we use various macroeconomic variables as of *t-1* as control variables. Specifically, we control for the monthly change in EPU-, 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 with either a Contrarian strategy or a Large Change (specifications 6 and 7, respectively), we again find that ΔSI_{t-1} predicts returns in the following month. The coefficient of ΔSI_{t-1} has a similar magnitude across all the specifications. This unequivocally suggests that a change in SI is predictive of systematic changes, as reflected by changes in the value of the stock market. [31]

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 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 the subsamples of the Contrarian and Large Change strategies. Table 1.9 presents the additional cumulative return (in %) earned from holding the market when ΔSI_{t-1} is positive, as opposed to holding the market when ΔSI_{t-1} is negative. The holding period starts, as before, based on information known at the end of *t-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 that 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

[31] The results of Table 1.8 show that $\Delta Sentiment_{t-1}$ is not correlated with next month's market return. However, in untabulated analysis we find that $\Delta Sentiment_{t}$ is correlated with concurrent monthly market return.

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}. In the Contrarian sample, the results are stronger in terms of statistical significance and magnitude. The additional cumulative return following positive ΔSI_{t-1} compared to negative ΔSI_{t-1} is 4.29% 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 with holding the market following large negative changes in ΔSI_{t-1} yields an impressive additional return of 4.41% for the one-month period and 16.59% for the six-month period.

1.6.2. SI and market volatility

We next 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 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 may suggest that 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 the high- and low-income groups, which may lead to political conflicts, government intervention, and increased market volatility.[32] Regardless of the theoretical arguments on why SI changes may relate to changes in volatility, because SI changes positively predict market returns and because VIX is known to be negatively correlated with the market, it seems worthwhile to analyze whether SI changes are predictive of market volatility.

We analyze whether SI changes are useful for predicting changes in the next month's volatility after controlling for known predictors, such as realized volatility and the VIX index. We begin by visually observing the concurrent relationship between the VIX and the SI measure in Figure 4. Both measures align in their levels and variations, allowing

[32] We 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), and 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.

them to be depicted on a unified y-axis. We observe a negative correlation between the SI measure and VIX 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 changes in volatility, we estimate the following regression:

$$\Delta VOL_t = \alpha + \theta_1 \Delta SI_{t-1} + \theta_2 \Delta SENT_{t-1} + \theta_3 VIXret_{t-1} + \theta_4 \Delta VOL_{t-1} + \theta_5 VOL_{t-1} + \theta_6 R_{m,t-1} + \theta_7 \Delta Controls_{t-1} + \varepsilon_t \quad (3)$$

The change in stock market volatility, ΔVOL_t, is defined as the month's t daily return standard deviation minus the month's t-1 daily return standard deviation. All independent variables are determined one month prior to the dependent. Additional controls refer to the macroeconomic variables used previously (Table 1.8). The coefficient of interest is that of ΔSI_{t-1}, that is, θ_1 of eq. (3).

Panel A of Table 1.10 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 the specifications. The difference between specifications 1-2 and 3-4 is that the latter set also includes the $\Delta SENT_{t-1}$ 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 three specifications as well. 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 determine 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, the independent variables are all of time t-1, and we include the same set of controls as in eq. (3). We find that ΔSI_{t-1} is significant in explaining $VIXret_t$, but $VIXret_{t-1}$ 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 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 large variance of the small sample as the coefficient is more than twice as large compared to specifications 1-4) in the Large Change sample (specifications 7 and 9, respectively), whereas the coefficient of $VIXret_{t-1}$ 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. The implication, which is analyzed in the Supplemental Materials for Chapter 1 section S3, 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.

1.7. Conclusion

As the 21st century progresses, evidence points to a growing gap between the affluent and the less fortunate, with the middle class—the traditional pillar of economic stability—facing a noticeable decline (Schwartz, 2014). This socioeconomic shift has prompted businesses, including stores and restaurants, to strategically pivot towards serving either the high-end luxury market or the low-end price-sensitive segment of the population. This growing gap in consumption trends sets the stage for a deeper investigation into the dynamics of consumer sentiment across different income groups and its impact on economic outcomes.

This research presents the construct of Sentiment Inequality (SI), defined as the disparity in sentiment between high- and low-income groups, as an overlooked yet significant element affecting the performance of companies serving these end-consumers demographic segments. The study posits that SI significantly affects the relative success of firms. The analysis suggests that fluctuations in SI can predict the operational and financial performance of companies, offering a novel perspective on how sentiment disparities across income groups play out in the financial performance of firms and the trajectory of the US stock market.

In the context of investment strategies, Benjamin Graham's assertion, "The intelligent investor is a realist who sells to optimists and buys from pessimists," highlights the importance of discerning market sentiment. However, applying this principle to investment decisions is challenging due to the difficulty in accurately assessing individual investor sentiment. We propose a nuanced perspective: "The intelligent investor is a realist who buys shares of companies whose consumers are optimists and sells shares of companies whose consumers are pessimists." This approach suggests a more tangible method of leveraging sentiment analysis into financial market outcomes.

Figures and Tables

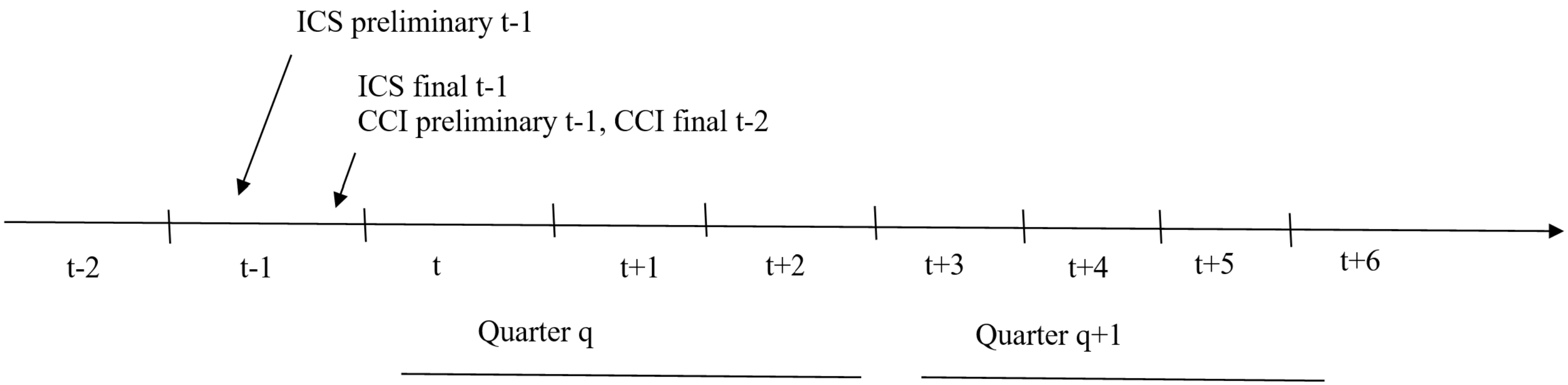

Figure 1.1. Schematic description of the timing of ICS and CCI publication and the results reported in this study
The results reported in this study follow the changes in SI. What differs across the analyses is how ΔSI is measured (over the previous month ΔSI_{t-1} or previous quarter ΔSI_{q-1}). The predictability of cash flows and returns start at t, after the publication of ICS final figures and CCI preliminary figures of *t-1*.

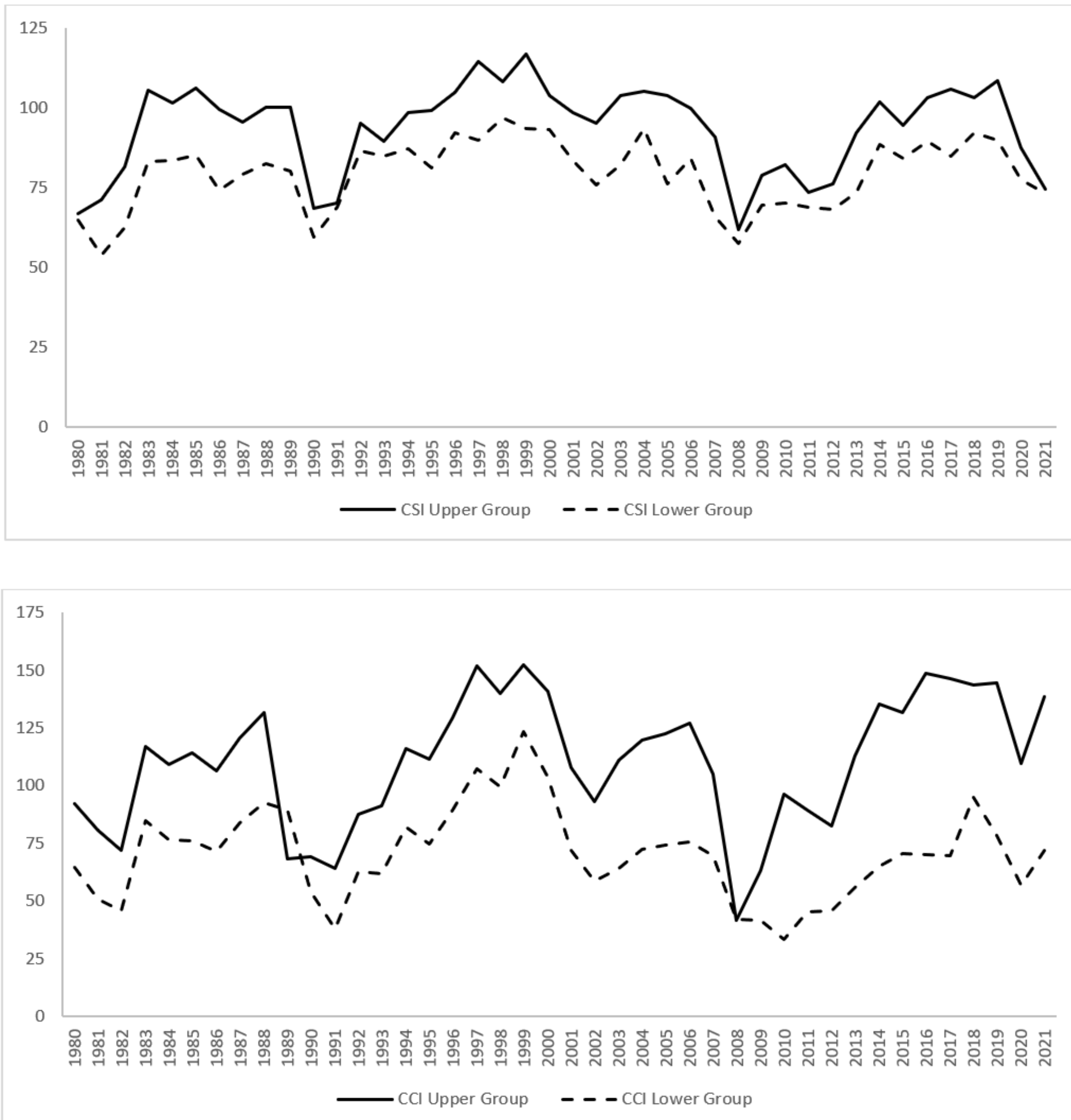

Figure 1.2. Difference between the upper- and lower-income groups' sentiment
The upper figure shows the annual Consumer Sentiment Index (ICS) for the upper- and lower-income groups. The bottom figure shows the annual Consumer Confidence Index (CCI) of the upper- and lower-income groups. These are measured at the end of December of the calendar year.

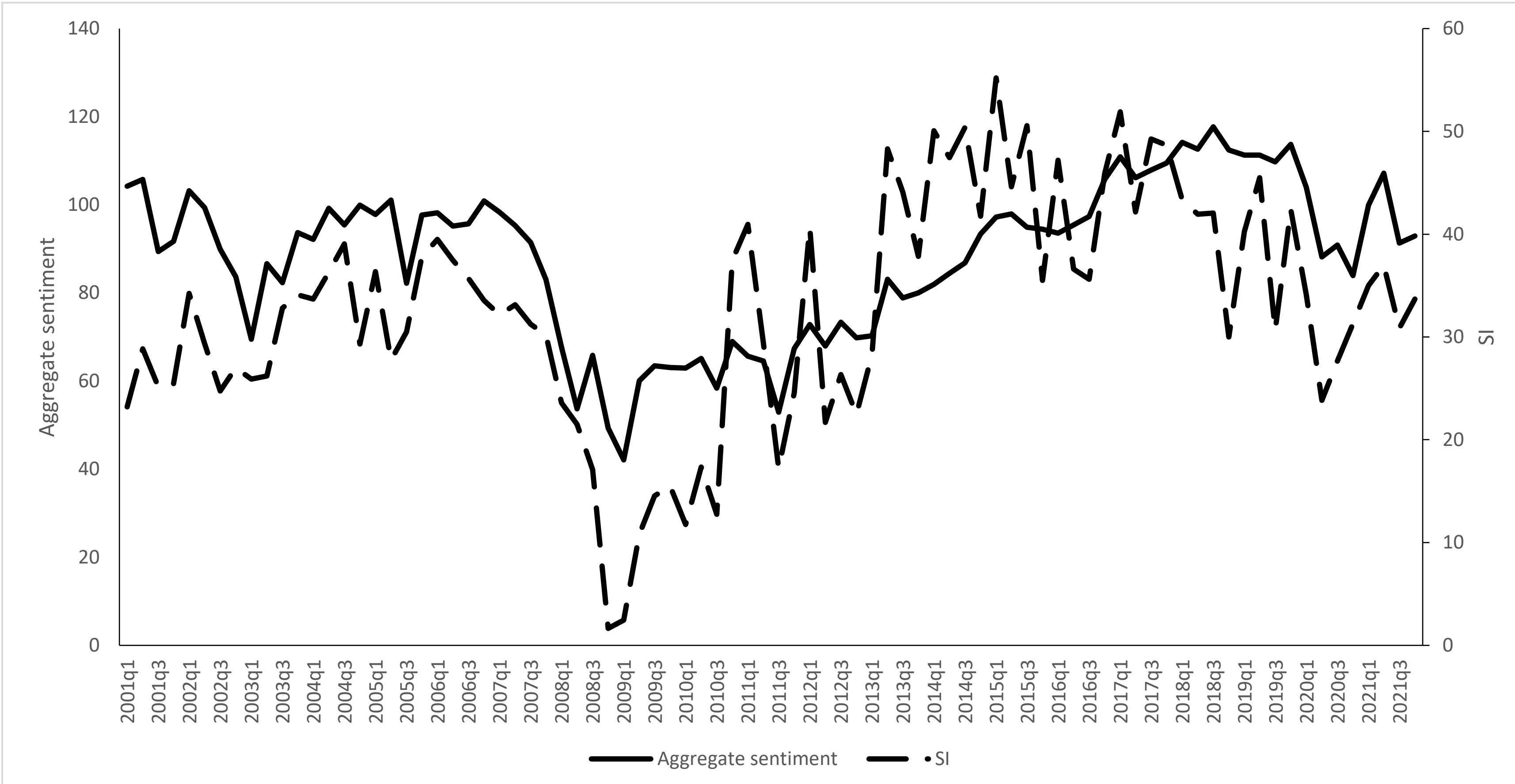

Figure 1.3. Aggregate sentiment and SI

The figure shows the aggregate sentiment and SI. Sentiment is the 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.

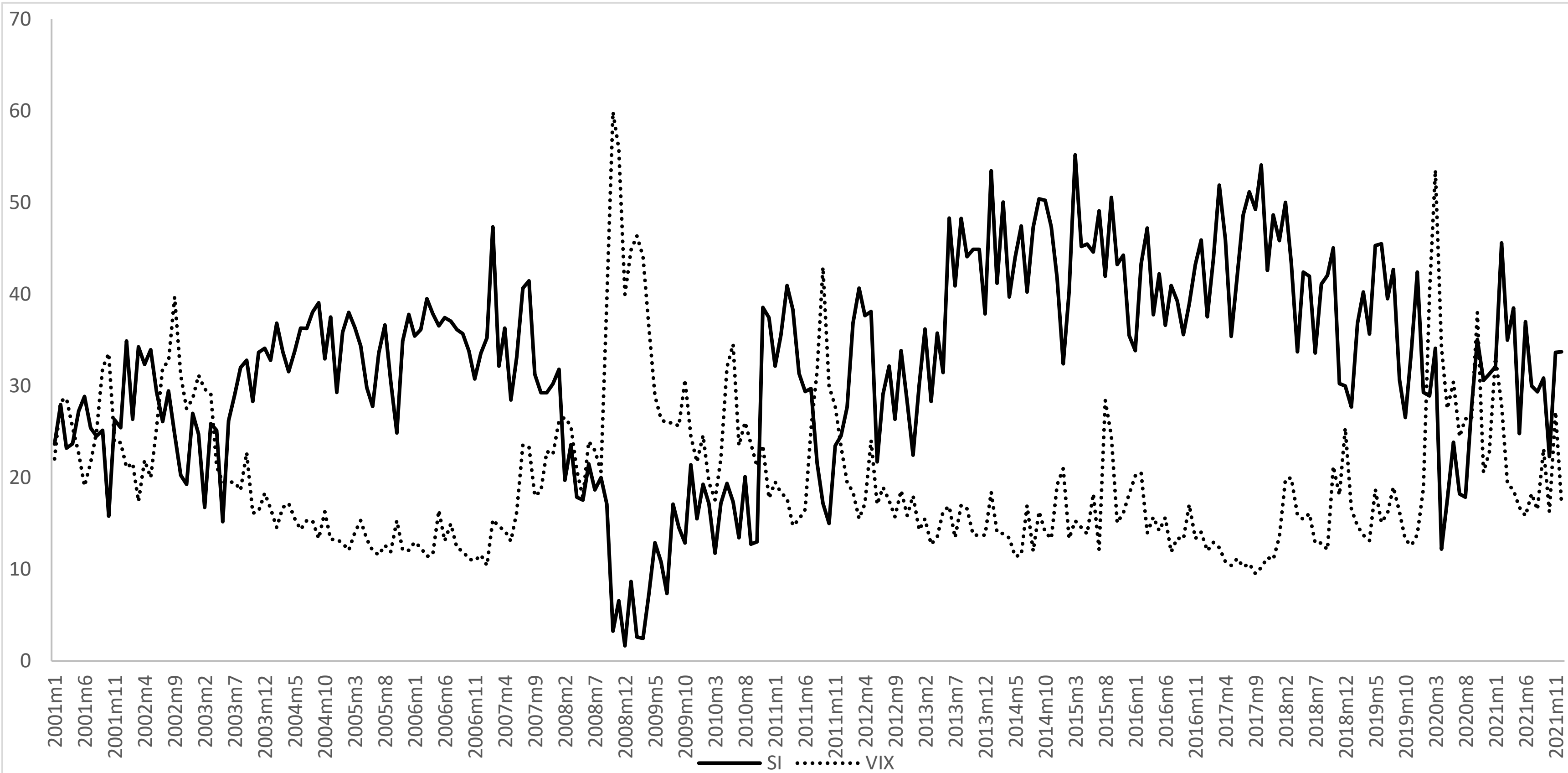

Figure 1.4. VIX and SI

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

Table 1.1. 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 is based on one regression per firm for the entire time series. Panels B and C provide the analyses of next quarter's cash flow and next month's calendar-time raw returns and alphas A. **In Panel B**, ΔSI_{q-1} and $\Delta SENT_{q-1}$ are the change in SI and the change in aggregate sentiment during quarter *t-1*, respectively. OCF is income from operation before depreciation divided by total assets, and ROA is income before extraordinary item (IB) divided by total assets. The ΔOCF, ΔROA is the difference in OCF and ROA, respectively, during quarter q. For triple DID analysis (highlighted in bold), we first measure for each company the difference in performance between increases and decreases of SI. We then conduct a t-test for the difference between Casual dining and Fast-food firms. **In Panel C**, we provide calendar time raw returns and alphas (in %) depending on the sign of ΔSI_{t-1} or $\Delta SENT_{t-1}$ during month *t-1*, and create a long/short portfolio to hold in month *t* depending on its type (casual dining/fast-food). We also run a long/short portfolio for the whole industry (i.e., all 16 firms) depending on the sign of ΔSI_{t-1} or $\Delta SENT_{t-1}$. The EW (VW) are equal weight (value-weighted, based on value at *t-1*) of these 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 %), which is run over 252 months during the period 2001-2021 in the full sample, and over 124 months for the Contrarian strategy. T-statistics are provided in parentheses and are calculated with Newey West (columns 1, 2, 4, 5) and robust (column 3, 6) standard errors in Panel C. *, **, 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	Market value
	Fast-food			
MCD	McDonalds	McDonalds – fast-food	0.59	200.3
CMG	Chipotle Mexican Grill	Chipotle – fast-food	0.94	49.2
YUM	Tricon Global Restaurants	KFC, Taco Bell, Pizza Hut, more	0.66	40.7
DPZ	Dominos Pizza	Dominos Pizza – fast-food/delivery	0.89	20.5
QSR	Restaurant Brands	Canadian-American multinational fast-food	1.01	19.1
WEN	Wendys Arbys	Wendys – fast-food	0.91	5.1
PZZA	Papa Johns	Papa Johns - pizza delivery	0.81	4.8
JACK	Jack In The Box	Jack in the Box- fast-food	1.07	1.8
TAST	Carrols Restaurant	Burger King and Popeyes franchisee.	1.01	0.1
	Average		**0.88**	**38.0**

	Casual dining			
DRI	Darden Restaurants	Olive Garden, LongHorn Steakhouse, more	0.96	19.6
TXRH	Texas Roadhouse	Texas Roadhouse, Bubba's 33, and Jaggers	0.97	6.2
CAKE	Cheesecake Factory	Casual, full-service dining: Cheesecake Factory.	1.10	2.0
DIN	Dine Brands Global, Inc.	Applebee's Neighborhood Grill + Bar and IHOP	1.11	1.3
DENN	Dennys	Dennys diner style restaurant	1.29	1.0
BJRI	BJ's Restaurants Inc	BJ's Restaurant & Brewery	1.23	0.8
RRGB	Red Robin Burgers	Red Robin	1.20	0.3
	Average		**1.12**	**4.45**
	Difference in Beta casual dining minus Beta fast-food		**0.24*****	
	T-statistic of difference of means		**(3.41)**	

Panel B: Next quarter cash flow predictability based on SI and aggregate sentiment changes

	$\Delta SI_{q-1} < 0$	$\Delta SI_{q-1} > 0$	Difference	$\Delta SENT_{q-1}$<0	$\Delta SENT_{q-1}$ >0	Difference
ΔOCF						
Fast-food	-0.03	0.03	0.06	-0.10	0.10	0.21
			(0.44)			(1.56)
Casual dining	-0.29	0.14	0.43***	-0.23	0.08	0.32***
			(3.91)			(2.89)
Casual-Fast	-0.26**	0.11	**0.37*****	-0.12	-0.02	**0.09**
	(-2.08)	(0.83)	**(3.06)**	(0.96)	(-0.17)	**(0.55)**
Whole industry	-0.14	0.07	0.21**	-0.16	0.09	0.26***
			(2.54)			(2.91)
ΔROA						
Fast-food	0.03	0.05	0.02	0.04	0.03	-0.01
			(0.19)			(-0.06)
Casual dining	-0.21	0.19	0.40***	-0.09	0.08	0.17
			(2.87)			(1.22)
Casual-Fast	-0.24*	0.14	**0.39****	-0.13	0.05	**0.18**
	(-1.73)	(1.21)	**(2.42)**	(-0.99)	(0.39)	**(1.29)**
Whole industry	-0.08	0.11	0.19**	-0.02	0.06	0.08
			(2.16)			(0.84)

Panel C: Calendar time alpha- fast-food/casual dining portfolios

	Positive – Long casual dining/ short fast-food Negative – Long fast-food/short casual dining			Positive – Long both types of firms Negative – Short both types of firms		
	(1)	(2)	(3)	(4)	(5)	(6)
Trading signal	ΔSI_{t-1}	$\Delta SENT_{t-1}$	ΔSI_{t-1} (Contrarian)	ΔSI_{t-1}	$\Delta SENT_{t-1}$	ΔSI_{t-1} (Contrarian)
Number of months strategy is active	252	252	124	252	252	124
			Equal-weighted (EW)			
Raw	0.50	0.08	1.01*	1.37*	-0.36	2.70***
	(1.34)	(0.22)	(1.84)	(1.88)	(-0.36)	(2.82)
CAPM	0.63	0.02	1.09*	1.33*	-0.39	2.47**
	(1.59)	(0.05)	(1.96)	(1.72)	(-0.37)	(2.49)
4-factors	0.58	0.07	1.01*	1.09	-0.26	2.26**
	(1.44)	(0.19)	(1.78)	(1.36)	(-0.23)	(2.25)
			Value-weighted (VW)			
Raw	0.60	-0.17	1.26**	0.42	-0.12	0.90*
	(1.36)	(-0.44)	(2.02)	(1.15)	(-0.34)	(1.69)
CAPM	0.84*	-0.28	1.42**	0.58	-0.13	0.97*
	(1.79)	(-0.56)	(2.22)	(1.38)	(-0.31)	(1.67)
4-factors	0.74	-0.26	1.23*	0.56	-0.12	1.01*
	(1.55)	(-0.52)	(1.89)	(1.33)	(-0.29)	(1.76)

Table 1.2. Descriptive statistics

Panel A provides data of aggregate 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 periods, respectively. Aggregate sentiment (SENT) is the simple average of the aggregate 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. **Panel B** provides the main firm-level variables based on quarterly observations. OCF is income from operation before depreciation divided by total assets, and ROA is income before extraordinary item (IB) divided by total assets. 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 are provided in parentheses. *, **, 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
SENT	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 ΔSENT	253	-0.08	0.10	4.95	-15.10	10.85	0.15	-0.26 (-0.65)
Monthly ΔSI	253	0.03	0.05	6.61	-15.20	15.60	0.06	-0.03 (-0.05)
Quarterly ΔSENT	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
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 1.3. Change in cash flow, profitability, and SI (DID analysis)

This table reports the seasonally adjusted quarterly change (quarter minus the respective quarter in the previous year) in firm performance (in %) depending on the sign of the change in SI (ΔSI_{q-1}). ΔSI_{q-1} is defined as the change in SI over the previous year (end of the previous quarter minus that five quarters ago). OCF and ROA are defined in Table 1.2. Betas are measured based on the daily return, at the calendar year before that in which performance is measured. These betas are then partitioned into four quartiles, where β1 refers to the lowest quartile and β4 the highest. **Panel A** provides the results for OCF and **Panel B** for ROA. Ind-Adj beta is calculated by subtracting from the annual beta measure the average beta across all stocks in the same two-digit SIC industry in that year. Difference of means test t-statistics are provided in parentheses. For DID calculation ((β4+ β3)- (β1+ β2) and β4- β1), for each firm-year, we first calculate the spread between the average change in performance when ΔSI_{q-1} increases to that when it decreases. We then conduct a t-test for the spread difference between beta quartiles, i.e., β4- β1 or (β4+ β3)- (β1+ β2). q, q+1 refer to the forward 1 and 2 quarters, respectively. The RHS column provides the difference of means (and DID) for two quarters forward. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: OCF

					$\Delta OCF_{i,q}$	$\Delta OCF_{i,q+1}$
Beta quartiles	N	Mean Beta	ΔSI_{q-1}<0	ΔSI_{q-1}>0	Difference	Difference
Ind-Adj beta						
β1	30,542	-0.47	-0.11	-0.02	0.10***	-0.04
					(3.11)	(-1.34)
β2	30,498	-0.12	-0.11	0.01	0.13***	0.00
					(4.42)	(0.09)
β3	30,499	0.12	-0.17	0.10	0.27***	0.16***
					(8.16)	(4.64)
β4	30,466	0.55	-0.20	0.13	0.32***	0.17***
					(8.36)	(4.25)
(β4+ β3)- (β1+ β2)					0.06***	0.06***
					(4.28)	(3.79)
β4- β1					0.08***	0.06***
					(3.62)	(2.77)
Beta						
β1	30,540	0.75	-0.09	-0.06	0.03	-0.04
					(1.05)	(-1.60)
β2	30,492	1.12	-0.11	0.00	0.12***	0.04
					(3.99)	(1.49)
β3	30,508	1.41	-0.16	0.08	0.24***	0.13***
					(7.15)	(3.66)
β4	30,465	1.92	-0.23	0.21	0.44***	0.16***
					(10.47)	(3.70)
(β4+ β3)- (β1+ β2)					0.09***	0.05***
					(5.95)	(3.25)
β4- β1					0.13***	0.08***
					(6.02)	(3.59)

Panel B: ROA

			$\Delta ROA_{i,q}$			$\Delta ROA_{i,q+1}$
Beta quartiles	N	Mean Beta	ΔSI_{q-1}<0	ΔSI_{q-1}>0	Difference	Difference
Ind-Adj beta						
β1	30,542	-0.47	-0.14	0.00	0.15***	0.04
					(3.26)	(0.91)
β2	30,498	-0.12	-0.14	0.05	0.19***	0.05
					(4.18)	(1.17)
β3	30,499	0.12	-0.17	0.11	0.28***	0.20***
					(5.80)	(3.95)
β4	30,466	0.55	-0.25	0.22	0.47***	0.21***
					(7.74)	(3.35)
(β4+ β3)- (β1+ β2)					0.05**	0.04*
					(2.22)	(1.82)
β4- β1					0.08***	0.04
					(2.48)	(1.18)
Beta						
β1	30,540	0.75	-0.15	-0.04	0.11***	0.09**
					(2.68)	(2.01)
β2	30,492	1.12	-0.12	0.02	0.15***	0.10**
					(3.36)	(2.12)
β3	30,508	1.41	-0.18	0.11	0.29***	0.16***
					(5.72)	(3.13)
β4	30,465	1.92	-0.25	0.29	0.54***	0.16**
					(8.62)	(2.48)
(β4+ β3)- (β1+ β2)					0.09***	0.02
					(3.88)	(0.69)
β4- β1					0.13***	0.01
					(4.05)	(0.22)

Table 1.4. Change in cash flow, profitability and SI

The table provides regression results where the dependent is the quarterly forward change in performance (in %). $\beta_{i,\tau-1}$ is measured based on daily return in the previous calendar year. ΔSI_{q-1} is defined as the change in SI over the previous year (end of the previous quarter minus that five quarters ago). Control variables include size, volatility, book-to-market, market leverage, dividend dummy, and Capex, defined in Table 1.2. The control variables are lagged compared to the period in which performance is measured. The top of the table reports results with Ind-Adj beta, followed by results with beta. q, q+1, q+2 refer to the forward 1, 2 and 3 quarters, respectively. Standard errors are clustered by firm and quarter. T-statistics are provided in parentheses and all specifications include an intercept. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

	One quarter forward				Two and three quarters forward			
	$\Delta OCF_{i,q}$		$\Delta ROA_{i,q}$		$\Delta OCF_{i,q+1}$	$\Delta OCF_{i,q+2}$	$\Delta ROA_{i,q+1}$	$\Delta ROA_{i,q+2}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Ind-Adj beta (a)				
$\Delta SI_{q-1}\times\ \beta_{i,\tau-1}$	0.013***	0.014***	0.020***	0.020***	0.015***	0.015***	0.014***	0.011**
	(3.73)	(3.75)	(3.76)	(3.58)	(4.92)	(4.68)	(2.96)	(2.31)
$\beta_{i,\tau-1}$	0.013	-0.248**	0.035	-0.468***	-0.203*	-0.236*	-0.283*	-0.243
	(0.34)	(-2.20)	(0.63)	(-2.86)	(-1.83)	(-1.92)	(-1.83)	(-1.35)
				Beta (b)				
$\Delta SI_{q-1}\times\ \beta_{i,\tau-1}$	0.018***	0.017***	0.021***	0.020***	0.013***	0.009**	0.009	0.003
	(3.73)	(3.92)	(3.65)	(3.52)	(2.92)	(2.43)	(1.56)	(0.52)
$\beta_{i,\tau-1}$	0.030	-0.337***	0.068	-0.467***	-0.377***	-0.509***	-0.334**	-0.422**
	(0.54)	(-3.23)	(1.00)	(-3.42)	(-3.39)	(-3.82)	(-2.38)	(-2.43)
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Controls × $\beta_{i,\tau-1}$	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Controls × ΔSI_{q-1}	No	Yes	No	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2 (a)	0.020	0.058	0.029	0.052	0.061	0.066	0.051	0.055
Adjusted R^2 (b)	0.021	0.058	0.029	0.051	0.062	0.066	0.051	0.055
Obs.	122,005	122,005	122,005	122,005	115,798	110,532	115,798	110,532

Table 1.5. Calendar time alpha- stock returns and change in SI

The table provides calendar time raw returns and alphas (in %) of trading strategies depending on the sign of ΔSI_{t-1} and the type of firms (high/low Ind-Adj beta in (1) and (2), and high/low beta in (3) and (4)). ΔSI_{t-1} is defined as the change in SI over the previous month. 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 the 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 %). T-statistics are provided in parentheses and are calculated with Newey-West standard errors (columns 1 and 3) or robust standard errors (columns 2 and 4). *, **, *** indicate significance at the 1,5, 10% level, respectively.

	Ind-Adj beta				***Beta***			
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 strategy** $High\ SENT_{t-1}, \Delta SI_{t-1} < 0$ $(Low\ SENT_{t-1}, \Delta SI_{t-1} > 0)$		(3) **Full sample** $\Delta SI_{t-1} < 0$ $(\Delta SI_{t-1} > 0)$		(4) **Contrarian strategy** $High\ SENT_{t-1}, \Delta SI_{t-1} < 0$ $(Low\ SENT_{t-1}, \Delta SI_{t-1} > 0)$	
	EW	VW	EW	VW	EW	VW	EW	VW
Number of months strategy is active	252		124		252		124	
Raw	0.22	0.21	0.89**	1.02*	0.30	0.25	1.19**	1.09*
	(0.75)	(0.61)	(2.25)	(1.97)	(0.77)	(0.66)	(2.36)	(1.92)
CAPM	0.34	0.35	0.97**	1.05*	0.44	0.41	1.30**	1.14*
	(1.15)	(0.96)	(2.29)	(1.84)	(1.10)	(1.07)	(2.37)	(1.83)
4-factors	0.31	0.25	0.95**	0.92	0.42	0.33	1.33**	1.09*
	(0.99)	(0.68)	(2.33)	(1.62)	(0.97)	(0.86)	(2.55)	(1.73)

Table 1.6. Long-term trading strategies based on the sign of SI

The table provides alpha of trading strategies of holding periods 1-6 months, respectively, depending on whether ΔSI_{t-1} is positive or negative. For trading decisions, top quartile beta companies are held long (short) when $\Delta SI_{t-1}$is positive (negative), and bottom quartile beta companies are held long (short) when $\Delta SI_{t-1}$is negative (positive). The upper part of the table displays results for the full sample, the middle part presents results for the Contrarian strategy subsample, and the bottom part presents results for the Dynamic strategy that runs throughout the sample period but assigns more weight to Contrarian months compared to non-Contrarian months. The Ind-Adj EW (VW) Raw return is the monthly raw return minus the industry's equal-weighted) average return or the industry's value-weighted return, respectively. The reported alphas are the regression intercept (in %) where the portfolio's excess return is run on the various factor models (F4, F4+BAB, F5). Standard errors are estimated with Newey-West standard errors for full sample and Dynamic strategy and robust standard errors for Contrarian strategy. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ind-Adj beta						***Beta***					
Holding months	1	2	3	4	5	6	1	2	3	4	5	6
					Full sample							
Equal weight												
Raw	0.22	0.03	0.39**	0.28**	0.17	0.21*	0.30	0.07	0.55**	0.38*	0.26	0.29*
Ind-Adj Raw	0.21	0.02	0.38**	0.27*	0.17	0.20	0.15	0.03	0.28**	0.20**	0.13	0.16**
CAPM	0.34	0.07	0.40***	0.29**	0.17*	0.19**	0.44	0.12	0.56***	0.39**	0.26*	0.27*
F4	0.31	0.10	0.44***	0.33***	0.21*	0.24**	0.42	0.16	0.62***	0.45**	0.32*	0.34**
F4+BAB	0.27	0.12	0.47***	0.35**	0.24*	0.29**	0.39	0.22	0.66***	0.48**	0.37*	0.40**
F5	0.24	0.07	0.47***	0.36***	0.23*	0.24**	0.32	0.13	0.66***	0.48**	0.35*	0.34**
Value weight												
Raw	0.21	0.00	0.33	0.29	0.19	0.16	0.25	0.12	0.44	0.35	0.25	0.20
Ind-Adj Raw	0.34	0.07	0.37	0.27	0.20	0.14	0.11	0.11	0.21	0.19	0.14	0.07
CAPM	0.35	0.12	0.39*	0.34*	0.20	0.16	0.41	0.25	0.50**	0.41**	0.27	0.19
F4	0.25	0.05	0.36*	0.33*	0.20	0.16	0.33	0.20	0.48**	0.40**	0.28	0.21
F4+BAB	0.19	0.00	0.32*	0.26	0.14	0.12	0.25	0.17	0.45**	0.32*	0.22	0.17
F5	0.15	-0.09	0.28*	0.26	0.11	0.07	0.27	0.09	0.42**	0.33*	0.19	0.11

Contrarian strategy

Equal weight												
Raw	0.89**	0.95***	1.05***	0.86***	0.67**	0.62**	1.19**	1.33***	1.48***	1.26***	1.03***	0.97***
Ind-Adj Raw	0.90**	0.96***	1.06***	0.87***	0.68**	0.63**	0.59**	0.68***	0.72***	0.59***	0.47***	0.45***
CAPM	0.97**	1.02***	1.09***	0.92***	0.70**	0.65**	1.30**	1.43***	1.55***	1.35***	1.08***	1.02***
F4	0.95**	0.99***	1.05***	0.89***	0.71***	0.68***	1.33**	1.42***	1.51***	1.33***	1.10***	1.06***
F4+BAB	0.99**	1.00***	1.06***	0.93***	0.76***	0.72***	1.34**	1.38***	1.46***	1.32***	1.12***	1.07***
F5	0.77**	0.84***	0.92***	0.83***	0.69***	0.62***	1.03**	1.18***	1.34***	1.23***	1.05***	0.97***
Value weight												
Raw	1.02*	0.88*	0.98**	0.75*	0.55	0.47	1.09*	1.05**	1.17**	0.95**	0.77*	0.67
Ind-Adj Raw	1.19**	1.04**	1.16***	0.89**	0.75**	0.69*	0.47	0.34	0.42	0.26	0.22	0.15
CAPM	1.05*	0.91*	0.97*	0.77	0.52	0.42	1.14*	1.10*	1.18**	0.99*	0.75	0.63
F4	0.92	0.77	0.87*	0.68	0.47	0.41	1.09*	1.01*	1.11**	0.94*	0.74	0.66
F4+BAB	0.68	0.51	0.64	0.43	0.21	0.21	0.81	0.70	0.82	0.65	0.44	0.42
F5	0.71	0.66	0.69*	0.63	0.45	0.34	0.85	0.87*	0.91*	0.85*	0.68	0.57
Dynamic strategy												
Equal weight												
Raw	0.77**	0.60**	0.89***	0.72***	0.51***	0.49***	1.03**	0.84***	1.24***	0.99***	0.75***	0.72***
Ind-Adj Raw	0.78**	0.61**	0.91***	0.74***	0.53***	0.51***	0.53**	0.41**	0.62***	0.50***	0.37***	0.36***
CAPM	0.91**	0.64**	0.91***	0.74***	0.53***	0.49***	1.21**	0.90**	1.27***	1.02***	0.77***	0.71***
F4	0.89**	0.68**	0.93***	0.76***	0.55***	0.52***	1.20**	0.97***	1.30***	1.06***	0.80***	0.75***
F4+BAB	0.87**	0.64**	0.87***	0.69***	0.52***	0.52***	1.18**	0.93**	1.22***	0.97***	0.77***	0.75***
F5	0.70*	0.53**	0.85***	0.71***	0.52***	0.47***	0.93*	0.77**	1.22***	1.00***	0.77***	0.70***
Value weight												
Raw	0.85*	0.64*	0.89**	0.80**	0.61**	0.57*	0.90*	0.82**	1.08***	0.92***	0.73**	0.65**
Ind-Adj Raw	0.99**	0.71**	0.98***	0.84***	0.71**	0.65**	0.36	0.38	0.49*	0.44	0.37	0.32
CAPM	0.97*	0.75*	0.96**	0.85**	0.64*	0.58	1.05*	0.95**	1.17***	0.98**	0.77*	0.67*
F4	0.88	0.68*	0.91**	0.81**	0.61*	0.56*	0.99*	0.91**	1.13***	0.96**	0.75**	0.66*
F4+BAB	0.72	0.47	0.69**	0.55*	0.38	0.35	0.80	0.70*	0.89**	0.67**	0.50*	0.45
F5	0.62	0.39	0.66**	0.58**	0.39	0.33	0.74	0.58	0.86**	0.72**	0.52*	0.42

Table 1.7. Stock returns and change in SI: Fama-MacBeth method

This table reports the result of Fama-MacBeth regressions of stock returns in month *t* on ΔSI_{q-1} and firm characteristics. ΔSI_{q-1} is the change in SI over the previous quarter. Additional control variables include volatility, market leverage, dividend dummy, and Capex, defined in Table 1.2. The intercept is included in all regressions. T-statistics are provided in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent: $\boldsymbol{R_{i,t}}$							
	Full sample				Contrarian strategy			
	Ind-Adj beta		***Beta***		***Ind-Adj beta***		***Beta***	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta SI_{q-1} \times \beta_{i,\tau-1}$	0.0014*	0.0011**	0.0017**	0.0015**	0.0024**	0.0015**	0.0027**	0.0020**
	(1.95)	(2.06)	(2.07)	(2.39)	(2.55)	(2.25)	(2.40)	(2.37)
$\beta_{i,\tau-1}$	0.0001	0.0005	-0.0006	0.0001	-0.0008	0.0001	-0.0013	-0.0004
	(0.03)	(0.63)	(-0.51)	(0.03)	(-0.47)	(0.00)	(-0.69)	(-0.27)
$Size_{q-1}$	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001*	-0.0001**	-0.0001**	-0.0001**
	(-1.00)	(-1.02)	(-1.23)	(-1.14)	(-1.93)	(-2.25)	(-2.16)	(-2.15)
$Book\text{-}to\text{-}market_{q-1}$	0.0039**	0.0080***	0.0035*	0.0077***	0.0029	0.0069***	0.0028	0.0067***
	(1.97)	(5.19)	(1.84)	(5.11)	(1.15)	(3.56)	(1.15)	(3.54)
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	448,385	448,385	448,385	448,385	239,024	239,024	239,024	239,024
R-squared	0.026	0.057	0.034	0.062	0.026	0.056	0.033	0.060
Number of months	249	249	249	249	134	134	134	134

Table 1.8. Sentiment, SI and monthly market returns

The dependent is the monthly value-weighted return (including dividend), and the independent variables are as of *t-1*. ΔSI_{t-1} and $\Delta SENT_{t-1}$ are the change in SI and aggregate sentiment (defined in Table 1.2) in month *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. In specifications (6-7), we report the results depending on the Contrarian and Large Change strategies (other months are excluded). A Large Change month is identified as a month where the absolute value of ΔSI_{t-1} exceeds two standard deviations from the mean, using the standard deviation of ΔSI_{t-1} calculated over the years 1980 to 2000. T-statistics are provided in parentheses and are calculated with Newey-West standard errors (specifications 1-5) or robust standard errors (specifications 6-7). All specifications include an intercept. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

	Full Sample					Contrarian Strategy	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)
$\Delta SENT_{t-1}$	-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 1.9. Holding the market portfolio depending on changes in SI

The table provides the additional cumulative return (in %) 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.

	(1)	(2)	(3)
Trading decision variable	Full sample Depending on whether $\Delta SI_{t-1} < 0$ or $\Delta SI_{t-1} > 0$	Contrarian strategy Depending on whether $High\ SENT_{t-1}$, $\Delta SI_{t-1} < 0$ or $Low\ SENT_{t-1}, \Delta SI_{t-1} > 0$	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 1.10. Change in volatility, VIX and SI

In **Panel A**, the dependent variable is the change in daily market return volatility over the month (the current month's daily return standard deviation minus the previous month's daily return standard deviation). 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). Specifications (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*. T-statistics are provided in parentheses and are calculated with Newey-West standard errors (Panel A and Panel B specifications 1-6) or robust standard errors (Panel B specifications 7-10). All specifications include an intercept. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Change in Volatility

	$\Delta Volatility_t$	$\Delta Volatility_t$	$\Delta Volatility_t$	$\Delta Volatility_t$
	(1)	(2)	(3)	(4)
ΔSI_{t-1}	-0.007*	-0.009**	-0.008*	-0.010**
	(-1.72)	(-2.36)	(-1.78)	(-2.18)
$\Delta SENT_{t-1}$			0.008	0.005
			(0.97)	(0.61)
$VIXret_{t-1}$[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)
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)
$\Delta Sent_{t-1}$			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)
$VIXret_{t-1}$[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)
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

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Supplemental Materials for Chapter 1

S1. Change in Sales and SI

This supplemental section aims to determine whether adjusting equity beta for financial leverage significantly enhances the accuracy of the SI hypothesis predictions about sales fluctuations. The SI hypothesis concerns the comparative performance of firms in response to the sentiment changes of high- versus low-income groups. Our empirical analysis involves the cash-flow performance of firms, examining OCF and ROA, as well as stock return performance. We rely on Industry-Adjusted equity beta as our principal metric for cyclicality relative to the average in the industry yet acknowledge that it is influenced by operating and financial leverage, which might affect its applicability in measuring the low- to high-end scale of the good. However, as mentioned in the main text, our ultimate objective is to evaluate equity return, which is influenced by the combined effects of sales changes and both types of leverages. Although using equity beta (or Industry-Adjusted equity beta) might not precisely measure the direct impact of SI on sales, it is beneficial to consider the compounded effects of leverage for our final goal. Therefore, this analysis aims to assess how critical the leverage consideration is for predicting sales. We conduct a similar analysis to that in Table 1.3, but instead of predicting changes in ROA and OCF, we investigate the influence of SI changes on changes in SALES. SALES is defined as sales divided by total assets. We present the triple DID results for four types of beta measurements (Ind-Adj beta equity, beta equity, Ind-Adj beta assets, and beta assets). The findings, showing consistent DID results across all measures, suggest that leverage concerns—even for SALES, where they might most challenge the SI hypothesis—do not significantly alter the outcomes.

Table S1.1 Change in sales and SI (DID analysis)

The table reports the seasonally adjusted quarterly change (quarter minus the respective quarter in the previous year, in sales (in %) depending on the sign of the change in SI (ΔSI_{q-1}). ΔSI_{q-1} is defined as the change in SI over the previous year (end of the previous quarter minus that five quarters ago). SALES is defined as sales divided by total assets. Betas are measured based on the daily return, at the calendar year before that in which performance is measured. These betas are then partitioned into four quartiles, where β1 refers to the lowest quartile and β4 the highest. Ind-Adj beta is calculated by subtracting from the annual beta measure the average beta across all stocks in the same two-digit SIC industry in that year. Asset beta is the unlevered equity beta., which equals equity beta divided by (1+D/E), where D is the book value of firm debt and E is the firm's equity market value. Ind-Adj asset beta is calculated by subtracting from the annual asset beta measure the average asset beta across all stocks in the same two-digit SIC industry in that year. Difference of means test t-statistics are provided in parentheses. For DID calculation ((β4+ β3)- (β1+ β2) and β4- β1), for each firm-year, we first calculate the spread between the average change in performance when ΔSI_{q-1} increases to that when it decreases. q, q+1 refer to the forward 1 and 2 quarters, respectively. The table also provides the difference of means (and DID) for two quarters forward. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Quartiles	***Ind-Adj beta***				***Beta***		***Ind-Adj asset beta***		***Asset beta***	
	$\Delta SALES_{i,q}$			$\Delta SALES_{i,q+1}$	$\Delta SALES_{i,q}$	$\Delta SALES_{i,q+1}$	$\Delta SALES_{i,q}$	$\Delta SALES_{i,q+1}$	$\Delta SALES_{i,q}$	$\Delta SALES_{i,q+1}$
	ΔSI_{q-1} <0	ΔSI_{q-1} >0	Difference	Difference	Difference	Difference	Difference	Difference	Difference	Difference
β1	-0.51	-0.12	0.40***	0.07	0.24***	-0.09	0.36***	0.03	0.44***	0.02
			(5.97)	(0.96)	(3.51)	(-1.36)	(5.61)	0.45	(6.80)	(0.23)
β2	-0.59	0.04	0.63***	0.26***	0.50***	0.19***	0.61***	0.27***	0.55***	0.18***
			(9.69)	(3.94)	(7.85)	(2.92)	(9.44)	(4.16)	(8.53)	(2.81)
β3	-0.74	0.04	0.78***	0.45***	0.81***	0.49***	0.90***	0.43***	0.86***	0.48***
			(11.60)	(6.49)	(11.89)	(6.94)	(13.73)	(6.52)	(13.09)	(7.11)
β4	-0.64	0.46	1.11***	0.62***	1.36***	0.81***	1.05***	0.66***	1.06***	0.72***
			(15.49)	(8.59)	(19.32)	(11.43)	(13.99)	(8.64)	(14.22)	(9.49)
TRIPLE DID										
(β4+ β3)- (β1+ β2)			0.08**	0.08**	0.13***	0.11***	0.13***	0.07**	0.12***	0.12***
			(2.39)	(2.23)	(3.96)	(3.26)	(3.78)	(2.04)	(3.70)	(3.35)
β4- β1			0.16***	0.10**	0.24***	0.19***	0.16***	0.13**	0.20***	0.19***
			(3.24)	(2.03)	(5.01)	(3.86)	(3.38)	(2.70)	(4.00)	(4.06)

S2. Luxury goods versus consumer staples

In this supplemental section, we conduct the same analyses as for the full sample but restrict our sample to luxury goods and consumer staples firms. We construct our sample by using the S&P 500 Consumer Staples Sector Index and the U.S. firms in the S&P Global Luxury Goods Index. We drop the firms with a market value of less than one billion as of December 2021. There are 58 consumer staples firms and 17 luxury goods firms. The average yearly beta of luxury goods firms is 1.30, and that of consumer staples is 0.69. Their difference is highly significant. The results are presented in Table S2. Both in the full sample and Contrarian strategy subsample, the luxury goods firms' ROA and OCF are significantly lower (higher) than those of consumer staples firms following SI decreases (increases). The spread between decreases and increases in SI is significant for consumer staples and highly significant for luxury goods. The one-month trading results are similar in magnitude to that of the full sample.

Table S2.1 Luxury goods versus consumer staple– cash flow and return predictability

Panel A and B provide the analyses of next quarter's cash flow and next month's return for the sample firms, following SI changes, similar to Tables 1.3 and 1.5, respectively. The sample includes all public firms whose asset value was above $1 billion as of December 2021. The definition of variables is in Table 1.2. T-statistics are provided in parentheses. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Future cash flow and change in SI

	Full sample			Contrarian strategy		
	$\Delta SI_{q-1} < 0$	$\Delta SI_{q-1} > 0$	Difference	$\Delta SI_{q-1} < 0$	$\Delta SI_{q-1} > 0$	Difference
$\Delta OCF_{i,q}$						
Staples	-0.04	-0.05	-0.01	-0.07	-0.34	-0.27***
			(-0.24)			(-3.59)
Luxury	-0.27	0.14	0.41***	-0.01	0.37	0.38***
			(4.54)			(4.64)
Luxury-Staples	-0.23***	0.19***		0.06	0.71***	
	(-3.84)	(3.40)		(1.29)	(5.51)	
DID			0.33			0.70***
			(1.61)			(3.31)
$\Delta ROA_{i,q}$						
Staples	0.01	0.03	0.01	0.06	0.12	0.06
			(0.26)			(0.87)
Luxury	-0.12	0.20	0.32***	-0.17	0.43	0.61***
			(2.91)			(3.87)
Luxury-Staples	-0.13*	0.17**		-0.23**	0.32***	
	(-1.84)	(2.53)		(-2.13)	(3.44)	
DID			0.47**			1.14***
			(2.05)			(3.28)

Panel B: Calendar time alpha- luxury goods/ consumer staples portfolios and SI

Trading Fast-food:	(1) Full sample		(2) Contrarian strategy	
Long portfolio (Short portfolio)	$\Delta SI_{t-1} < 0$ ($\Delta SI_{t-1} > 0$)		$High\ SENT_{t-1}$, $\Delta SI_{t-1} < 0$ ($Low\ SENT_{t-1}$, $\Delta SI_{t-1} < 0$)	
	EW	VW	EW	VW
Number of months strategy active	252		124	
Raw	0.16	0.01	1.11*	0.78
	(0.40)	(0.03)	(1.86)	(1.41)
CAPM	0.41	0.22	1.21**	0.85
	(1.04)	(0.58)	(1.99)	(1.52)
4-factors	0.27	0.06	1.04*	0.63
	(0.70)	(0.15)	(1.77)	(1.11)

S3. Trading VIX depending on change in SI

In this supplemental section, we study the profitability of utilizing ΔSI_{t-1} for a market-wide trading strategy. Table S3.1 provides the returns of trading strategies that go long (short) on the VIX index[33] 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 to what we have done previously. We go long the VIX index when ΔSI_{t-1} decreases because, after such changes, the VIX index and volatility tend to increase.[34]

Panel A provides the results 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 Change). 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 because of 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 Panel B, we further explore the possibility of trading profits based on the changes in ΔSI_{t-1}. We 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 the 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

[33] The VIX itself is not directly tradable like a stock. However, investors can gain exposure to the VIX through various financial instruments.

[34] 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.

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 during the month when the trading strategy is active.

Several features of this part of the panel are noteworthy. First, as the threshold increases, the long-short returns increase. 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 alpha increase. 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 columns 7 and 10, with significance at the 10% level). Nevertheless, this strategy triumphs according to the market model, as can be seen 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.

Table S3.1 Trading VIX depending on change in SI

Table S3 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 **Panel A**, the full sample and subsamples (Contrarian and Large Change) results are provided for long or short positions in the VIX index minus the treasury bill (TB), as well as the VIX index minus the value-weighted return. In Panel B, the trading strategy is to trade depending on the absolute magnitude change in ΔSI, respectively. The trading rule, which varies across columns, is to go long the VIX index (and short the Treasury Bill) when $\Delta SI_{t-1}$is below a certain threshold in standard deviation terms 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 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. All specifications include an intercept and are estimated using robust standard errors. *, **, and *** indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: The three samples

	$VIXret_t$ minus TB_t			$VIXret_t$ minus $R_{m,t}$		
	Full sample	Contrarian	Large Change	Full sample	Contrarian	Large Change
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*

Panel B: 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

Chapter 2. The Influence of Trudeau on Gender Parity within Canadian Corporate Boards

> Interviewer: "*I understand one of the priorities for you was to have a cabinet that was gender balanced. Why was that so important to you?*"
>
> Justin Trudeau: "*Because it's 2015*."
>
> - Nov 4, 2015, Rideau Hall, Ottawa.

2.1. Introduction

Justin Trudeau's commitment to gender parity and head-on approach to addressing disparities within his government present an interesting case for investigating the influence of "leading by example." After winning a strong majority on the first ballot in 2013, he became the leader of the Liberal Party and made gender equality one of his key objectives. His campaign was marked by a commitment to addressing issues such as pay equity, equal opportunities for women, and combating gender-based marginalization and violence. His commitment was evident in his pledge to achieve gender parity in government, which he implemented upon becoming Prime Minister, garnering significant media attention. By prioritizing gender-balanced cabinet appointments[35], he sent a clear message about the importance of inclusivity and equal representation at the highest levels of government.

Could Trudeau's efforts significantly influence gender representation on Canadian corporate boards, demonstrating how leadership and advocacy can shape institutional practices? Political science literature shows that women's political and government advancements often precede their advancements in the private sector (e.g., Skjeie, 1991; Seierstad and Opsahl, 2011; Chizema et al., 2015; Seierstad et al., 2017). This finding supports our main hypothesis that political leaders can serve as an invisible hand in disintegrating gender stereotypes. Bandura's

[35] Sweden was the first country to achieve gender-balanced representation in its cabinet in 1996. The Nordic countries have a long history of endorsing and mainstreaming gender equality, which is deeply embedded in their social, political, and economic structures. In the 2000s, initiatives to achieve gender parity on corporate boards began gaining momentum in Europe. Meanwhile, during this period, Canada and the United States lagged in achieving similar levels of gender balance in their cabinets and broader political and corporate leadership roles.

(1977) work highlights the significance of role models and their influence on behavior. We can learn behaviors, values, and attitudes by observing and imitating role models. The above finding also shows that change in one part of society could catalyze social change in other areas. In this context, more women in top government positions will likely encourage firms to follow suit and increase board diversity.

Firms are permeable to political influence, and Trudeau's emphasis on women in government leadership sets a precedent for more female directors on Canadian corporate boards. Our main conjecture is that Trudeau's focus on gender parity represents a shift towards more equitable corporate governance in Canada. We integrate insights from political behavior and corporate decision-making to quantify Trudeau's impact on corporate governance, reflecting firms' responsiveness to political transitions.

We start by conducting cross-country comparisons between the USA and Canada to assess the effectiveness of gender parity initiatives. We analyze this by contrasting the period before Trudeau's rise to prominence (before 2014) with the period that followed. Our findings indicate that Trudeau's ascent to Liberal Party leadership in April 2013 and ascendence to the PM role in October 2015 led to an increase in female board participation in Canadian corporations, marking a positively significant shift in the gender dynamics of corporate boards. Before Trudeau's rise, the representation of women on boards in our sample averaged around 12% and 15% for Canada and the U.S., respectively, from 2005 to 2014. This increased to 26% for Canada and 21.5% for the U.S. after 2014, paving the way for a more gender-balanced future.

Estimates from difference-in-differences (DID) regressions indicate that the average fraction of female directors on Canadian boards increased by two percentage points more in the post-Trudeau period, representing approximately a 12% increase relative to the unconditional sample mean. Next, we use a matched sample where each Canadian firm is paired with a U.S. control firm based on identical Fama-French industry classification and the closest Female ratio in fiscal year 2009. In cases of multiple exact matches, the U.S. firm with the closest market size is selected. The matched DID analysis suggests a causal effect of Trudeau's impact on the percentage of female directors in Canadian firms.

Subsequently, we adopt a year-by-year approach to better isolate the effect of Trudeau's emphasis on gender parity by examining its impact on female board representation in the years surrounding his rise. Through this analysis, we identify a strong correlation between a firm's country of headquarters and its enhanced board gender diversity in 2014-2015. To further assess this impact, we analyze the year-on-year changes in the percentage of female board members. Our results reveal a statistically significant increase in the year-over-year changes in the percentage of female directors among Canadian firms after 2014, confirming the presence of a "Trudeau break" in the trend of females on boards.

A potential identification concern is that the increase in female board participation might not be causally linked to Trudeau's ascendance to power but could instead reflect the broader liberal rise in Canada during that period. To address this, we use PM approval ratings in each province as a proxy for Trudeau's popularity and likeability. These approval ratings serve as a variable that captures Trudeau's following in the province while we also control for the province's liberal voting share.

The empirical results align with the prediction that higher approval ratings for Trudeau positively affected the female ratio on boards. We apply entropy balancing as a robustness check to ensure that the relationship between PM approval ratings and the increase in female directors is not confounded by underlying firm-level characteristics. By using an entropy-matching estimator, we reduce the risk that differences in these characteristics could bias our results, making it more likely that the observed relationship is attributable to Trudeau's popularity rather than other firm-level factors. The findings reinforce that firms headquartered in provinces with higher PM approval ratings experienced more significant increases in female directors than in provinces with lower approval ratings.

Next, we examine the firm-level outcome, to shed light on the relative benefit of this gender-diverse board.[36] The systematic increase in the female board ratio in Canada compared to the U.S. may or may not have had financial effects on Canadian corporations. Our approach in the

[36] We note that many consider increasing gender and racial diversity in corporate boardrooms a vital endeavor, regardless of whether it contributes to the financial bottom line or other outcomes.

study is to analyze a particular angle that has received much attention in the literature.[37] Research in psychology and economics has long documented that women generally exhibit a higher aversion to risk than men (e.g., Niederle and Vesterlund, 2007; Croson and Gneezy, 2009; Flory, Leibbrandt, and List, 2015). However, this risk aversion may diminish among women who have shattered the glass ceiling and acclimated to a male-dominated culture (e.g., Deaves et al., 2009; Adams and Funk 2012; Matsa and Miller, 2013). Therefore, women on boards may not represent the "average" female experience, making broad generalizations difficult. This study represents an interesting case to see whether the evidence of the "average" women being more risk-averse than the average male aggregates to the board, which represents well-accomplished women, but perhaps not the extreme right-tail as in the case of CEOs.

The systemic changes in women's roles during Trudeau's leadership in Canada underscore the need to explore further the link between female board representation and firm volatility. This study applies empirical findings to extrapolate the impact of board gender diversity on firm volatility. Prior studies suggest that boards matter for firm risk-taking behavior (e.g., Cheng, 2008; Pathan, 2009). However, very few studies have explored the influence of female board representation on firm risk-taking behavior, and consensus is lacking. This gap in research highlights the urgency and importance of our study.[38] It's important to note that the observed

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[37] Corporate boards' roles can be broadly categorized into monitoring and resource provision. Boards mitigate the agency problems that arise from the separation of ownership and control. Directors supervise and curtail managerial attempts to extract private benefits and hurt the interests of dispersed shareholders. Additionally, directors provide access to resources critical to the company’s success, such as counsel, advice, reputational capital, and human connections.

The impact of gender diversity on board effectiveness and firm performance remains a significant focus in corporate finance research. Gender diversity can enhance decision-making by introducing new skills and broadening expertise (Hoogendoorn et al., 2013; Kim and Stark, 2016) but may also complicate consensus-building (Bernile et al., 2018). Empirical evidence is mixed, suggesting that more women on boards do not harm corporate performance, with some studies showing potential benefits in specific contexts (Adams and Ferreira, 2009; Green and Homroy, 2018; Bennouri et al., 2018).

[38] Some studies suggest that female directors lead to positive outcomes, such as increased board activity, fewer financial reporting mistakes, and enhanced monitoring (Levi et al., 2013; Schwartz-Ziv, 2017; Wahid, 2019; Boutchkova et al., 2020; Cardillo et al., 2021). Conversely, other studies report increased portfolio risk (Berger et al., 2014), no significant impact on equity risk (Sila et al., 2016), or suggest that female directors may self-select into lower-risk firms (Farrell and Hersch, 2005).

discrepancies in previous studies are likely due to factors such as the sample under consideration (e.g., U.S. rather than European firms) and variations in econometric techniques and study periods.

To analyze the time-varying responses of firm volatility to the female board representation, we use stock return volatility and idiosyncratic volatility measures. Our baseline regressions find a significant negative association between the proportion of females on boards and change in our volatility measures. These findings indicate that female directors tend to reduce firms' risk.

We conduct further analyses to quantify the extent of this effect using the state—or province-level wage gap in the firm's headquarters location as an instrument for female board participation. This variable captures the prevailing cultural and normative differences between men and women in the province. Terjesen and Singh (2008) argue that smaller gender pay gaps are correlated with better representation of women in boardrooms. Complementing this, Thams et al. (2018) find that firms headquartered in states with progressive policies (e.g., protection from discrimination, availability of emergency contraception, and public abortion funding) have a higher share of women directors on their boards. Therefore, one might assume that provinces already implementing pay parity would be more inclined to appoint women to the board (high pool of candidates and more liberal-leaning).[39] Noteworthy, there is no reason to suspect that the wage gap in the province is related to changes in volatility, so the variable meets the exclusionary restrictions. While firm-level policies and performance might influence internal gender dynamics, the broader state-level wage gap is driven by various macroeconomic and social factors that are generally outside the control of any single firm. Thus, it satisfies the exogeneity condition. We observe that firms experience lower volatility in regions with narrower gender wage gaps, a trend attributed to increased female representation on corporate boards. These findings corroborate our argument that gender diversity initiatives drive the mitigating effect on firm volatility, as demonstrated in the baseline analysis.

After that, we show that we can derive similar results by considering the "Trudeau's Break" as an instrument. Thus, if we consider Canadian firms in the post-2014 period as being exposed to

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[39] Importantly, as in most Western countries, women are expected to be paid similarly to men; however, practical challenges arise due to career-life interruptions, which women are more likely to experience. Therefore, the wage gap may not necessarily indicate discrimination but could reflect women's tendency to stay at home or the availability of professional women in the province.

the treatment of the Trudeau gender parity lead, we find that these firms have a high Female ratio that leads to a reduction in volatility in these firms.

Lastly, we propose a mechanism to explain why volatility may decrease when women are appointed to boards. We conjecture that increasing female representation on boards may lead to a greater propensity to hedge, which, in turn, reduces volatility. We suggest that women may be more inclined to employ hedging strategies to minimize the firm's exposure to earnings risk, exchange rate risk, and the various costs associated with highly volatile cash flows. Our probit regression results from a sample of non-financial firms indicate that a higher female ratio increases the probability of hedging in the following year. These findings are consistent with OLS estimates from the full and matched samples of non-financial firms, even after controlling for industry and firm fixed effects.

The lack of gender diversity in the highest echelon of corporate leadership, the board, has sparked intense public debate over the past few decades, leading to several interventions worldwide. Consequently, the factors influencing board gender diversity remain an actively researched topic.[40] To the best of our knowledge, our study is the first to analyze the impact of a political leader on gender equality on boards. The paper makes two significant contributions.

First, this paper demonstrates the importance of political leadership leading by example in corporate governance practices.[41] Second, this paper's findings complement the emerging literature on understanding the benefits of gender diversity in corporate leadership and add to the growing literature on board diversity. As discussions intensify globally regarding the impact of female

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[40] For instance, countries with higher representation of women in senior management, smaller gender pay gaps, and shorter periods of political representation of women tend to see more women in boardrooms (Terjesen and Singh, 2008). Institutional investors' campaigns (Gormley et al., 2021) and public attention to gender equality (Giannetti and Wang, 2023) also correlate with increased board gender diversity. Most of the existing empirical literature on board gender quota law or comply-or-explain governance mechanisms mainly examines European contexts. While a handful of studies evaluate the effectiveness of gender quotas and principles-based approaches in promoting gender equality on corporate boards in North America (Dhir et al., 2022; Bakke et al., 2023; Bian et al., 2023), our study research diverges in its focus.

[41] The existing empirical literature documenting political influence on firm decision-making, which can affect corporate governance and state-owned enterprises (SOEs), has predominantly drawn upon data from China (Clarke, 2003; Bai et al., 2006; Qu and Wu, 2014; Clarke, 2016).

leadership and participation on corporate and societal outcomes, our research has implications for both public and private policies and practices promoting gender diversity in competitive domains.

The remainder of the paper is organized as follows. Section 2 describes the data, and Section 3 provides the background. Section 4 describes the research design and provides the empirical results. Section 5 explores possible benefits, and Section 6 investigates a potential mechanism behind the relationship to explain the results. The final section concludes.

2.2. Sample formation and overview

2.2.1. Sample formation

We use Compustat and CRSP data from January 2005 because Refinitiv's ESG data is relatively sparse prior to 2005. Our sample ends in December 2021, as that is the most recent data available (it takes two years to include data in Refinitiv). The sample includes all firms with common stocks (share code 11). We exclude firms with a market size of less than $50 million to avoid small firm bias. We obtain firm-level board data from Refinitiv. Because we rely on Refinitiv for board gender composition, we remove any observations with missing values for the variable of interest. Our sample consists of 17,408 firm-country-year observations from 2,370 Canadian and U.S. firms after merging the Compustat and Refinitiv ESG databases. The state-level wage data are sourced from Statistics Canada and the U.S. Census Bureau. We provide variable definitions used in the baseline regressions and their sources in the Supplemental Materials for Chapter 2, section S1.

2.2.2. Sample overview

Table 2.1 reports the sample characteristics. Panel A provides the distribution of the main variables used in this study. We measure all variables at the annual frequency and winsorize all continuous variables at the 1st and 99th percentiles to minimize the effect of outliers. Supplemental Materials S1 contains the definition of all variables. The primary variable of interest is the Female ratio, defined as the percentage of female directors on the corporate board. The sample's average (median) Female ratio is 19.58% (18.18%). The median board size is 10 members, with a mean of 9.92. The median change in board size is 0, while the mean change is 0.06.

The sample comprises mostly large firms with a mean market capitalization of $18.18 billion. The median firm, however, is smaller than the average, with a market value of $4.44 billion. An average (median) firm has a book-to-market ratio of 0.49(0.39), a market leverage ratio of 26% (21%), and a ROA of 3% (4%). Approximately 65% of the firms in the sample pay dividends. The average (median) firm stock return volatility is 2.43% (2.01%), while idiosyncratic volatility is 5.51 (2.77).

In Panel B, we inspect the distribution of companies across different industries using the Fama-French industry classifications (17 industries) based on SIC codes, encompassing both U.S. and Canadian firms. The sample reflects a higher proportion of firms in the financial, retail, and manufacturing sectors. However, our sample has no Canadian firm in the steelworks sector.

We also examine the average Female ratio for these industries for the 2005-2014 and 2015-2021 periods. First, we estimate the mean Female ratio at the firm level, averaging across the years for both the U.S. and Canada. Next, these firm-level means are averaged to calculate the average Female ratio for each industry. The difference column provides the difference in the means for each industry between Canada and the USA in each period. In the pre-2015 period, Canadian industries exhibit a lower female ratio than their U.S. counterparts. The last row indicates that, on average, the female ratio of Canadian industries was 3.59% lower than that of U.S. industries, with this difference being significant at the 1% level. There is a noticeable shift across industries in the post-2014 period. In aggregate, the mean female ratio of Canadian industries is 3.98% higher than that of U.S. industries, with this difference significant at the 1% level.

The final Difference-in-Differences (DID) column reports the t-test results for the difference in the female ratio between the two periods. This column considers only firms with observations in the pre-2015 and post-2014 periods. For the analysis, we only retain those firms for which the female ratio was reported consistently across both periods. Overall, there has been a significant increase in the representation of females on corporate boards across most industries from pre-2015 to post-2014. The aggregate difference in the mean female ratio between these periods is 5.62, with a p-value of 0.00.

To visually analyze the effect of Trudeau's initiatives on the percentage of female directors on Canadian corporate boards, we plot the Female ratio for both U.S. and Canadian firms. Figure

2.1 Panel A illustrates the female board ratio of Canadian and U.S. firms from 2005 to 2021 for the full sample. The blue line represents the Female ratio of Canadian firms, while the red line indicates that of U.S. firms.

Several observations can be made from the figure. Firstly, the graph demonstrates a trend of increased Female ratio with occasional dips between 2005 and 2021. Secondly, U.S. firms have a higher female ratio before 2014. Thirdly, there is an apparent break that seems to emerge around 2014. After Trudeau's rise to power, there was a shift in the female ratio, which was consistently higher for Canadian corporate boards than for U.S. corporate boards. Lastly, we observe that the average Female ratio is picking up in the US after 2016, which is beyond the scope of this paper to explain but can be attributed to various reasons. For example, it is possible that the US followed the trend worldwide, especially given the large change in Canada in previous years. The "Me Too" movement gained global prominence in 2017 and could have also contributed to this. The movement initially focused on women's status, perception, and sexual harassment. Then, it also ignited broader discussions about gender inequality and the need for increased female representation in leadership roles, including corporate boards. In response to public pressure and advocacy from organizations promoting board gender diversity[42], firms increased their efforts to improve gender diversity on their boards (e.g., Heminway, 2019; Miazad, 2020; Giannetti and Wang, 2023; Gormley et al., 2023).

Panel B depicts the matched sample's Female ratio of Canadian and U.S. firms. Each Canadian firm is paired with a U.S. counterpart based on identical Fama-French industry classification and the closest Female ratio in fiscal year 2009. In cases of multiple exact matches, the U.S. firm with the closest market size is selected. The figure clearly shows a break in the trajectory of the Female ratio on Canadian corporate boards compared to the matched U.S. firms around Trudeau's rise to power.

[42] In 2017, the three major institutional investors, State Street Global Advisors, Blackrock, and Vanguard, launched campaigns to increase gender diversity on corporate boards.

2.3. Background

Justin Trudeau won the 2013 Liberal leadership in a landslide first-ballot victory. Equality and diversity were the key agendas in the Liberal plan draft under Trudeau's leadership. The Liberal plan focused on ensuring equitable economic opportunities for everyone while upholding and advancing freedom and diversity. In June 2013, the Minister of Finance, Charles Sousa, and the Minister Responsible for Women's Issues, Laurel Broten, requested that the OSC (Ontario Securities Commission) undertake a public consultation process regarding disclosure requirements for gender diversity. Both these ministers who led the introduction of the 'Comply or Explain' rule to enhance diversity transparency in Canada belonged to the Liberal Party. This request followed when the Ontario provincial government (Liberal Party member and Ontario premier Kathleen O'Day Wynn) included the diversity statement in its May 2, 2013, budget.

The "comply or explain" rule[43] was enacted in December 2014 in Canada. The OSC amendment did not require firms to increase the gender diversity of their boards, but rather, it required firms to disclose their policies regarding board representation. On October 19, 2015, Trudeau guided his party to victory, securing a majority government with representation in every province and territory. The voter turnout was 82.16% of all registered voters, and he was sworn in on November 4, 2015. In 2015, the Canadian Coalition for Good Governance (CCGG) also introduced an initiative to support disclosure procedures for Canadian corporations.

During Trudeau's campaign and subsequent election in 2015, he emphasized a strong commitment to gender equality. His political career has been marked by a strong stance on gender issues. His government made several initiatives in this regard, including amendments to domestic

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[43] Comply-or-explain disclosure and quotas rules represent important paths forward in promoting gender diversity on corporate boards. Comply-or-explain disclosure rules offer a lighter regulatory approach by encouraging transparency and accountability without imposing strict numerical requirements. At the same time, quotas can be seen as the force of heavy regulation, providing clear mandates for gender representation. The comply-or-explain rules do not ensure that specific representation levels are achieved within specific timeframes. While quota-based systems are certainly a more robust and effective form of regulatory change to achieve gender balance on the boards (e.g., Bertrand et al., 2019; Bennouri et al., 2020), it is also the case that quotas present implementation challenges (Ahern and Dittmar, 2012) in addition to political and legal viability issues. For instance, on May 13, 2022, the California Court overturned Senate Bill 826, a pivotal legislation to implement gender quotas for the female board representation of publicly traded companies based in California.

violence laws, women entrepreneurs support programs increased parental leave benefits, etc. [44] Furthermore, he has been an outspoken advocate for women's rights and empowerment on the global stage.

His focus on the gender balance served as a reference point to initiate change in the Canadian corporate governance landscape. Essentially, suppose the Prime Minister visibly prioritizes women in government leadership roles. In that case, it sends a powerful signal to women's appointments in leadership positions outside government, most notably in Canadian corporate boards. This represents a significant turning point, leading to increased corporate board female representation.

Bakke et al. (2023), conducting a cross-country analysis similar to ours, find that Canadian firms subject to the regulation increased their fraction of female directors relative to U.S. firms in the control group. However, without appropriate political intervention or regulatory oversight, the comply-or-explain approach risks allowing firms excessive leeway to define what it means to comply (e.g., Jackman, 2015; Lepore et al., 2018; Dhir et al., 2022). Various studies highlight the low quality of explanations provided under comply-or-explain mechanisms in corporate governance and non-financial reporting regulations (e.g., Shrives and Brennan, 2015; Cuomo et al., 2016; MacNeil and Esser, 2022). Hence, the effectiveness of comply-and-explain mechanisms can vary depending on factors such as political environment, enforcement bodies, corporate culture, and societal norms. The political landscape is pivotal in influencing corporate board gender diversity, where government policies, regulations, and initiatives advocate for greater inclusion of women.

Therefore, we contend that Trudeau's active and vocal advocacy for diversity played a crucial role in shaping the normative dimensions of comply-or-explain rules and promoting increased diversity on corporate boards. We argue that this development is partly due to the successful positioning of women in cabinet roles, which encourages organizations to promote women for board seats.

[44] See the timeline in the Supplemental Materials for Chapter 2, section S2.

This impact is illustrated in Figure 2.2, which compares the percentage of female directors in Canada to that in a control group, as determined by Statistics Canada, for the years 2009 and 2016. In 2009, the percentage of female directors in Canada was just above 5%, significantly below the OECD average of 10%. By 2016, Canada had surpassed all countries in the control group in terms of female board representation.[45]

2.4. Main Results

2.4.1. The DID regressions

To investigate the effect of Trudeau's rise to power and active advocacy of gender parity on corporate board female representation, we employ a DID specification as follows:

$$Female\ ratio_{i,t} = \beta_0 + \beta_1 CAN_i \times Post_{i,t} + \beta_2 CAN_i + \beta_3 Post_{i,t} + \beta_4 Firm\ controls_{i,t-1} + Firm\ FE + Year\ FE + \varepsilon_{i,t} \quad (1)$$

The observations are at the firm-year level, with *i* indexing firms and *t* indexing calendar years. The dependent variable $Female\ ratio_{\ i,t}$ is the annual percentage of women on board in year *t*. CAN is an indicator variable that takes the value of one if firm *i* is headquartered in Canada and zero is headquartered in the U.S. $Post_{\,i,t}$ is an indicator variable that takes the value of one in the year after Trudeau's rise (after 2014) and zero otherwise. The interaction term *CAN* × *Post* captures Trudeau's break. The standalone indicators, CAN and $Post$, are absorbed by our inclusion of time and firm fixed effects. The control variables, including size, book-to-market, market leverage, ROA, and a dividend dummy, are lagged compared to the period in which the dependent variable is measured. Firm and year fixed effects (FE) are included to control for time-invariant firm characteristics and temporal trends, respectively.

Table 2.2 Panel A presents the results examining the effect of Trudeau's rise on female board representation. We show that the coefficient on the interaction term *CAN* × *Post* is positive and significant. This implies that following Trudeau's rise, Canadian firms experienced an increase

[45] It should be noted that in 2015, Japan introduced the comply-or-explain principle, while Germany implemented a gender quota for corporate boards. The U.K. first introduced the comply-or-explain principle in 1992, and it was reinforced and updated as part of the U.K. Corporate Governance Code in 2010.

in Female ratio 5 percentage points more, on average, than U.S. firms during the same period relative to before 2014. In terms of economic significance, using column (1) as an example, the Female ratio of the treated firms (headquartered in Canada) increases by 27% (5.302/19.5) relative to the mean of the control firms (headquartered in the U.S.). Across columns (2) and (3), we include a lagged female ratio and change in the controls to equation (1). As a result, the coefficient of the interaction term is reduced in magnitude, but it remains statistically significant at a 1% level. The coefficient of 2.364 in column (3) implies that Canadian firms experience around a 12% increase in the percentage of female directors relative to the unconditional sample mean.

We repeat the DID analysis using U.S. firms matched to Canadian firms in terms of industry, Female ratio, and size in the fiscal year 2009. We show that the coefficient on the interaction term *CAN* × *Post* significantly differs from zero, indicating a significant increase in female board directors for Canadian firms post-2014. However, the last column is merely non-significant, with a t-statistic of 1.64.

Overall, the DID analysis suggests a causal effect of Trudeau's approach on the firm-level representation of female directors in Canadian firms. The results reported in Table 2.2 Panel A validate the statistical significance of the patterns presented graphically in Figure 2.1.

2.4.2. Using the year-by-year approach

Next, we use a year-by-year approach to better isolate Trudeau's effect by examining the evolution of the changes in board composition of Canadian firms in the years surrounding Trudeau's rise. We conduct multivariate analysis to investigate potential relations between the Female ratio and the years of Trudeau's rise in both full and matched samples. The prediction is that Canadian firms experienced a surge in the percentage of female directors on corporate boards compared to U.S. firms during 2014-2015. To test this prediction, we estimate the following general form panel regression model:

$$Female\ ratio_{i,t} = \beta_0 + \sum_{k=1}^{t} \beta_k CAN_i \times year_k + Year\ FE + \varepsilon_{i,t} \quad (2)$$

where $Female\ ratio_{i,t}$ is the annual percentage of women on board in year *t*. The primary independent variables are the interaction between *CAN* and the year indicators ($CAN \times year_t$), where *CAN* is an indicator that equals one if the firm is Canadian, and $year_t$ equals one if the dependent observation is of year *t*.

The coefficient of interest is that of the interaction term, $CAN \times year_t$. Specifically, a higher estimate is better from 2014 onwards, indicating that the coefficient is positively significant for the years following Trudeau's rise to Liberal Party leadership. Table 2.2 Panel B provides the estimation results for our regression specifications using full and matched samples. Specifications (1) and (2) provide an estimation of the basic model (eq. 1). In specification (1), the coefficient of $CAN \times year_t$ is negative and significant up till 2013. Then it becomes positive and highly significant from 2016 onwards in the full sample. The coefficient for CAN2016 is 3.204, with a t-statistic of 5.19. This indicates that, in 2016, Canadian firms experienced around a 16% increase in the percentage of female directors relative to the unconditional sample mean.

In specification (2), we re-estimate the equation using the matched sample. We extend the basic model by including paired FE. This approach includes only the matched pairs, meaning if one firm drops from the sample after 2009, we also drop the matched firm. We interact each control variable with year *t* to affirm that the results are not a consequence of using U.S. firms as a control group. Interacting controls with year ensures that our results reflect the impact of the gender parity initiatives associated with Trudeau's rise to office rather than being confounded by firm-specific characteristics. The coefficients for the interaction terms CAN2014 and CAN2015 are 2.306 and 3.091, respectively. This indicates that, on average, Canadian firms had female board percentages 2.306 and 3.091 percentage points higher than their matched U.S. firms in 2014 and 2015, respectively. Both results were statistically significant at the 1% level. These findings suggest a notable increase in the female board percentage for Canadian firms relative to U.S. firms during these years.

Next, to verify the statistical significance of Trudeau's break further, we examine the year-on-year change in the Female ratio sample period by estimating the following regression specification:

$$\Delta Female\ ratio_{i,t} = \beta_0 + \sum_{k=1}^{t} \beta_k CAN_i \times year_k + Year\ FE + \varepsilon_{i,t} \quad (3)$$

The dependent variable is the percentage point change in the percentage of female board directors between the current year, *t*, and the previous year, *t-1*.

Specification (3) in Panel B provides the estimates for the basic model (eq.3), and the coefficients on the interaction terms CAN2014 and CAN2015 are positively significant. Specification (4) extends specification (3) by including the interaction of each control variable with year *t* and industry fixed effects (FE) to control for unobserved industry heterogeneity. The coefficients for CAN2014 and CAN2015 remain positive and highly significant.

In specification (5), we repeat the analysis for the matched sample, including paired fixed effects and the interaction of control variables with the years. The matched pairs analysis of changes in the female ratio enables a more precise identification of the timing of the transition. The results indicate that the coefficient on the interaction term $CAN \times year_t$ becomes significantly positive during 2014-2015. The coefficient for 2014 and 2015 is even higher in magnitude compared to the full sample. These results reinforce our argument that female representation in Canadian boardrooms increased following Trudeau's rise to Liberal Party leadership.

Using this approach, we identify that CAN2014 and CAN2015 are positively and significantly associated with both levels and changes in the Female ratio. This suggests a high correlation between a firm's country of headquarters and its enhanced board gender diversity in that period. This finding aligns with the time-series Female ratio trends illustrated in Figure 2.1.

The key result of this study is that Canadian-headquartered firms increased the percentage of female directors following Trudeau's gender parity initiatives.

2.4.3. PM approval rating and Female ratio

This subsection explores the extent to which female board percentages change with political preferences about gender equality. One concern is that events occurring in 2014 and 2015 in the U.S. and Canada, unrelated to Trudeau, such as a shift toward more liberal policies, might influence these changes. To address this, we employ a unique identification strategy to demonstrate a positive correlation between Trudeau's leadership and the increase in female directors.

Specifically, we use Prime Minister Justin Trudeau's approval ratings by province as a proxy for his popularity.

The Prime Minister's approval rating by province serves as a variable to distinguish between firms more inclined to emulate Trudeau's policies and initiatives and those that are not, providing cross-sectional variation across different provinces. This reflects a 'follow-the-leader' mindset, where individuals who like the leader are likelier to follow in their footsteps. Therefore, firms headquartered in the provinces with higher approval ratings of the Prime Minister are expected to demonstrate a greater propensity to increase the female board ratio compared to firms headquartered in provinces with lower approval ratings. Additionally, we control for overall liberal leanings in the province by using the percentage of votes secured by the Liberal Party, which is correlated with the Prime Minister's approval ratings, as evidenced by a correlation of 0.80 observed during the 2015 election year. By controlling for the level of liberalism in the province, we isolate the additional explanatory power provided by Prime Minister approval ratings, which can be attributed to Trudeau.

We obtain these PM approval ratings from the Angus Reid Institute.[46] This analysis is limited to Canadian firms and spans from 2015 to 2021. We average the PM approval rating by province each year to measure the PM's provincial approval rating. We partition all Canadian firms each year (starting in 2015) into terciles according to the magnitude of the PM approval rating of the province in which they are headquartered. Then, we run the following lead-lag panel data regression model:

$$Female\ ratio_{i,t} = \beta_0 + \beta_1 High\ PM\ approval_{p,t-1} + \beta_2 Firm\ controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (4)$$

where $Female\ ratio_{i,t}$ is the annual percentage of women on board in year *t*. Our primary measure is the High PM approval, which takes the value of one if a firm is headquartered in a

[46] The Angus Reid Institute conducts all its polling online. The Angus Reid Forum includes sufficient individuals from each major demographic group to draw randomized samples that represent the overall population. To ensure their online research accurately reflects the public's demographics and attitudes, their surveys use representative samples from each panel, randomized and statistically weighted according to the latest demographic and regional voting data.

province *p* that has high levels of PM approval in the preceding year (i.e., the top tercile of the provincial PM approval rating) and zero for low level (the bottom tercile).[47] The middle tercile is excluded from this analysis. Our control variables are similar to those in the previous analysis, and we cluster standard errors at the firm level. We also include industry and year FE to control for time-invariant industry unobservables and time trends that might drive the board's female representation.

Table 2.3 presents the results of the regressions. Specification (1) shows a positive association between the High PM approval and the percentage of female directors, with significance at the 5% level after controlling for the lagged Female ratio. The economic magnitude of the effect is nontrivial. We show that *ceteris paribus*, a high PM approval rating in the firm's headquartered province, is associated with a 1.23% increase in the Female ratio, around a 6% increase relative to the unconditional sample mean of Canadian firms. This baseline result is subject to potential endogeneity concerns if the popularity of the Liberal Party drives the increase in board diversity. To help alleviate such concerns, we control for Liberal Party popularity through the percentage of votes secured by the party at the provincial level and re-estimate the equation (2) using a binary indicator "Liberalism," which is set to one if the province's percentage of votes for the Liberal Party in the preceding year exceeds the median percentage and zero otherwise. The coefficient on High PM approval decreases in magnitude by roughly 2% to 1.21% yet remains statistically significant at the 10% level. In contrast, the coefficient on Liberalism is not statistically significant.

We consider a battery of additional tests that help strengthen our inferences. First, we re-estimate specifications (1) and (2) by incorporating firm fixed effects. The difference between specifications (3) and (4) is that specification (4) controls for liberalism. In both specifications, the coefficient for High PM approval remains statistically significant at the 5% level. Secondly, using an entropy-matching estimator, we re-estimate the relationship between the female board ratio and the Prime Minister's provincial approval rating. In this approach, we match firms headquartered in

[47] It is important to note that the results are robust if we use the PM provincial approval rating as a continuous variable instead of a High PM approval binary variable. While entropy-matching analysis helps sharpen our inferences, it limits us to use the High PM approval variable as it matches on a discrete (i.e., non-continuous) treatment measure. We provide additional results with the PM approval rating in the Supplemental Materials for Chapter 2, section S3.

provinces with high levels of PM approval to peers headquartered in provinces with lower levels of PM approval but that are otherwise similar across observable characteristics. Recent studies (e.g., Hainmueller, 2012) suggest entropy matching is generally more effective than simple or propensity score matching. This is attributed to its ability to achieve a high degree of covariate balance across multiple moments of the covariate distribution, dependence on fewer restrictive assumptions, and preservation of more information by allowing weights to vary smoothly across observations more flexibly.

We match firms on the first two moments (i.e., mean and variance) of the control variables (e.g., size, book-to-market, market leverage, ROA, and dividend dummy) following Hainmueller and Xu (2013). Specifications (5) to (8) report the results from the entropy-matching procedure. In specifications (7) and (8), we match based on the Female ratio and the control variables. Our inferences are unchanged across all these tests, suggesting that time-invariant firm heterogeneity does not explain the association between Trudeau's popularity and female board representation. Regarding economic significance, we show that *ceteris paribus*, a High PM approval rating in the previous year, increases the Female ratio in the 1.09% to 3.55% range. The results are consistent with the prediction that Trudeau's high approval positively affected the Female ratio.[48]

In summary, our results in Table 2.3 highlight PM Trudeau's importance in attenuating gender differences in board composition, supporting our hypothesis.

2.5. The Volatility Analysis

Our main finding in the previous section is that Trudeau's initiatives helped attenuate the gender board representation gap during the 2014-2015 period. In this section, we explore the possible gains from these increases in the percentage of female directors. More specifically, we contend that firms that increased their female board representation would benefit from reduced

[48] In untabulated results, we compare the approval ratings of former PM Stephen Harper with those of PM Justin Trudeau at the federal level to address whether the PM approval rating is merely affecting the female board percentage or reflects superior leadership under Trudeau. Our findings indicate that Trudeau's approval rating is positively associated with female representation on Canadian boards in our sample, while PM Harper's is not. The results suggest that the effects generated by Trudeau's approval ratings are distinct from those of Harper. For PM Harper, the approval ratings are only available from 2013-2015, resulting in a smaller sample size, hence not reported.

firm volatility. To assess this prediction, we conduct a host of tests to determine whether firms decrease their volatility by enhancing board gender diversity. To analyze the time-varying responses of firm volatility to the Female ratio, we rely on two measures of volatility: stock return volatility and idiosyncratic volatility. Supplemental Materials for Chapter 2, section S1 contains the definition of all variables.

2.5.1. Baseline regressions

We begin by investigating the effect of the female ratio on the change in firm volatility. To test whether a lagged Female ratio is useful for predicting the change in firm volatility in both the full and matched samples, we use the following panel data regression specification:

$$\Delta FirmVol_{i,t} = \beta_0 + \beta_1 Female\ ratio_{i,t-1} + \beta_2 \Delta Female\ ratio_{i,t} + \beta_3 FirmVol_{i,t-1} + Industry\ FE + Year\ Fe + \varepsilon_{i,t} \quad (5)$$

where $\Delta Firm\ Vol_{\ i,t}$ is a measure of the annual change in firm volatility in year *t*. The main independent variables are the Female ratio at year *t-1* and ΔFemale ratio at year *t*. The main coefficient of interest is that of the Female ratio, that is, β_1. We also include the lagged volatility as the explanatory variable. We include industry and year FE to control unmodeled heterogeneity across industries and years. For all regression specifications, we cluster standard errors at the firm level.

Table 2.4 reports the estimation results of equation (5). The dependent is the change in stock return volatility (ΔVolatility) in the first four specifications. Specifications (1–2) report the estimates for the full sample, and specifications (3–4) for the matched sample. Specification (1) provides the results for the basic model. Both β_1 and β_2 estimates are negative and statistically significant. The estimates for β_1, and β_2 are -0.6 bps and -0.4 bps, respectively, significant at the 1% level. This finding suggests that females on boards have a strong dampening effect on the firm volatility. In specification (2), we extend the basic model (eq.5) by including lagged controls and changes in controls. The coefficient of the $Female\ ratio_{t-1}$ remains highly significant, although its magnitude is somewhat reduced. Meanwhile, the coefficient of $\Delta Female\ ratio_t$ declines in both magnitude and significance, becoming significant only at the 5% level. The following two specifications for the matched sample demonstrate that a higher lagged Female ratio significantly predicts a decrease in volatility (p-value <0.01). However, the estimates of β_2 are statistically very weak.

In Specifications (5-8), we repeat the tests with the change in idiosyncratic volatility (ΔIvol) as the dependent and derive similar results. Taken together, the coefficient of the *Female ratio$_{t-1}$,* β_1, is consistently negative and significant at a 1% level across all four specifications. The estimates range from -0.023 (t-stat = -5.01) in Specification (6) to -0.057 (t-stat = -4.39) in Specification (7). This suggests that a lagged Female ratio is predictive of lower firm volatility. The coefficient of Δ*Female ratio$_{t}$,* β_2, is highly significant in the full sample but not in the matched sample.

In summary, the findings consistently indicate a significant and negative association of the proportion of females on boards across both volatility measures. The dampening effect persists even when accounting for additional factors and is robust across different specifications and matched sample.

2.5.2. The instrumental variables approach

While we have established that the country of headquarters and the 2014-2015 period play an essential role in driving the Female ratio, and there is a negative relationship between the Female ratio and firm volatility, the causal inferences of this link may be subject to endogeneity concerns. To circumvent such a problem, we exploit the state-level gender wage gap as a source of exogenous variation in diversity. We define the Wage gap as the percentage difference in average earnings between males and females in the state or province where the firm's headquarters are located. We contend that firms in states with higher diversity consciousness, proxied by a lower gender Wage gap, should have more substantial incentives to have more females on board.

The wage gap reflects cultural and normative differences regarding gender in the province. Consequently, we anticipate that states/provinces with smaller wage gaps, indicative of better pay parity, are more likely to appoint women to boards due to a larger pool of qualified candidates and more progressive attitudes. Conversely, states with more significant wage gaps, suggesting less progress in pay equity, are expected to see fewer female board appointments. Hence, the state wage gap is correlated with the proportion of female board directors.

It is important to note that the state-level/provincial wage gap is unlikely to influence changes in firm volatility, thus meeting the exclusion restriction criterion. The state wage gap should affect firm volatility primarily through its impact on the gender composition of the workforce and, by extension, the pool of eligible and qualified women for board positions. It is not likely to directly impact firm volatility other than through its effect on the availability and inclusion of female directors. The state wage gap can be considered exogenous to the specific characteristics of individual firms. While firm-level policies and performance might influence internal gender dynamics, the broader state-level wage gap is driven by a variety of macroeconomic and social factors that are generally outside the control of any single firm. Thus, it is unlikely to be correlated with the idiosyncratic shocks or error terms affecting a specific firm's board composition. Therefore, it satisfies the exogeneity condition.

To test this prediction, we conduct the instrumental variable (IV) tests with the state-level gender Wage gap as an instrumental variable. Table 2.5 Panel A presents the results of the first and second stages of the instrumental variables analysis. The endogenous variable is the ΔFemale Ratio, and the dependent variable is ΔVolatility in specifications (1-2) and ΔIvol in specifications (3-4). Each model incorporates additional exogenous variables in both stages, including the lagged Female ratio, the lagged level of the dependent variable, and lagged firm controls (such as size, book-to-market, market leverage, ROA, and a dividend dummy). We also add concurrent changes in firm-level controls in specifications (2) and (4). All regression specifications include industry and year FE.

The first stage results are presented in the upper part of the panel. To evaluate the instrument's strength, we note that the Sanderson-Windmeijer F-statistic allows us to reject the null of weak instruments. This shows that the instrumental and control variables have significant explanatory power. We observe that the coefficient on the wage gap is negative and significant across four specifications. This suggests that the gender earnings gap hurts the percentage change in women on corporate boards.

The lower part of the panel presents the second-stage results with the change in firm volatility as the dependent variable. The results show that the coefficients on the predicted ΔFemale Ratio are negative and significant in all four specifications. Importantly, we fail to reject the null hypothesis that a higher Female ratio significantly negatively affects firm volatility. Specifically, the findings indicate that firms experience lower volatility in regions with narrower gender wage gaps, a trend attributed to increased female representation on corporate boards. These findings corroborate our argument that gender diversity initiatives drive the mitigating effect on firm volatility, as demonstrated in the baseline analysis presented in Table 2.4. We conduct further analyses in the following subsection to quantify the extent of this effect.

2.5.3. Using the Trudeau break

To further analyze the relationship between volatility and the proportion of female directors, we use the Trudeau break in Canada in 2014. This breakpoint allows us to investigate how shifts in political focus on equal gender representation around that time may have influenced the representation of women on boards and associated firm volatility. Using Trudeau's break in a two-stage least-squares (2SLS) setting, we study whether the Female ratio reduces firm volatility in the post-2014 period. The variable "Trudeau's break" is an indicator that equals one if the firm is Canadian and the period is post-2014 and zero otherwise. CAN is an indicator that equals one if the firm is Canadian.

Panel B of Table 2.5 presents the results of this analysis. The endogenous variable is the ΔFemale Ratio, and the dependent variable is ΔVolatility in columns (1–2) and ΔIvol in columns (3–4). Each model incorporates additional exogenous variables in both stages, including the lagged Female ratio, the lagged level of the dependent variable, and lagged firm controls (such as size, book-to-market, market leverage, ROA, and a dividend dummy). We add concurrent changes in firm-level controls in columns (2) and (4). All regression specifications include industry and year FE.

In the upper part of the panel, we present the first-stage results. Consistent with the multivariate results in Table 2.2, we find that the coefficients on Trudeau's break are positive and significant at the 1% level in all four specifications. Although the magnitude of this coefficient decreases when accounting for concurrent changes in control variables, its statistical significance remains robust. The results provide evidence of the positive shift in the Female ratio in Canada post-2014.

The lower part of the panel presents second-stage results for firm volatility. The predicted changes in the Female ratio have significant negative effects across both firm volatility measures. The coefficient on the predicted ΔFemale Ratio is statistically significant at the 5% level across all four columns, indicating that firms with positive change in female board representation realize lower volatility. These results indicate the strong effects of increasing the Female ratio on firm volatility post-2014. Regarding economic magnitude, there is a reduction of 9.3 bps (column (2)) in volatility after controlling for concurrent change in firm-level controls. Similarly, for idiosyncratic volatility, the point estimates range from 89.3 bps to 68.9 bps in columns (3) and (4), respectively. The results show that Canadian firms post-2014 increased the ΔFemale ratio, thereby reducing the change in firm volatility. These results collectively offer evidence supporting that diversity initiatives in Canada, particularly those implemented in the 2014-2015 period, have a causal impact on the interplay between a firm's board gender diversity and volatility.

We find evidence consistent with the results in Table 2.4, showing that an increase in female board members is associated with reducing firm volatility. Although one must exercise caution in making a causality statement, the regression results in both panels of Table 2.5 support the idea that board gender diversity may decrease firm volatility.

2.6. The Channel Analysis: Hedging for Non-Financial Firms

So far, the results demonstrate that country headquarters plays a vital role in firms' increase in female representation on corporate boards. In this section, we explore the possible source of reduction in firm volatility arising from these responses. We intend to enhance the findings on the Female ratio and volatility by incorporating empirical evidence related to improvements in hedging.

In practice, imperfections within capital markets offer a rationale for mitigating the volatility of cash flows and earnings through hedging. Two classes of theories explain the reasons managers engage in risk management activities. The first revolves around maximizing shareholder value (e.g., Leland, 1998; Haushalter, 2000; Allayannis and Weston, 2001; Pérez-González and Yun, 2013; Dudley et al., 2022). The second centers on owners' diversification motives or managers' personal utility maximization (e.g., Smith and Stulz, 1985; DeMarzo and Duffie, 1995;

Chava and Purnanandam, 2010). According to the shareholder maximization perspective, firms hedge to alleviate the costs associated with highly volatile cash flows. Froot et al. (1993) discuss how firms use hedging strategies to smooth out cash flows and to coordinate their investment and financing decisions better.

To examine the relationship between the Female ratio and hedging, we test the hedging propensity for a subsample of nonfinancial firms from our primary sample. We delete financial entities (SIC codes 60 to 69) since they are both users and providers of risk management products. Though detailed data on derivative use are unavailable for a large panel of nonfinancial firms, Compustat reports information on gains/losses associated with using derivatives for all publicly traded firms. Following Bonaimé et al. (2014) and Giambona and Wang (2020), we use this information to build an indicator for whether firms hedge. We categorize a firm as a hedging firm if either Compustat item aocidergl - "Accumulated Other Comprehensive Income- Derivative Unrealized Gain/Loss" or cidergl - "Comprehensive Income- Derivative Gains/Losses" are nonzero.

The additional control variables are defined following risk management studies. Purnanandam (2008) models the ex-post hedging incentives of firms in financial distress. For firms facing financial distress, the provision of hedging instruments should increase. Therefore, following Giambona and Wang (2020), we also control for a firm's financial distress using Altman's (1968) z-score, cash, and tangibility. Financial distress is an indicator with an Altman z-score < 1.81.[49] A z-score lower than 1.81 characterizes financial distress. Cash is the ratio of cash and marketable securities to book assets, and tangibility is the ratio of property, plant, and equipment to book assets.

Table 2.6 presents the results of this analysis. Since the dependent variable is an indicator, the regression is estimated using binary estimation techniques such as probit. Panel A reports the results for the nonfinancial firms in the full sample. Columns (1) and (5) provide the results from the probit regressions predicting the hedging indicator. The main coefficient of interest is the

[49] The results remain robust when we use the Altman Z-score as a continuous variable. Additionally, the results hold when we include the Whited-Wu Index (Whited and Wu, 2006) as a proxy for the firm's financial constraints (Adam, Dasgupta, and Titman, 2007).

Female ratio in year *t-1*. The results show that the coefficient on *Female ratio*$_{t-1}$ is highly significant (p-value<0.01) in both specifications, indicating that firms with a higher Female ratio have a higher marginal probability of hedging. For example, our subsample's unconditional probability of hedging is approximately 50% (the mean of Hedging1 and Hedging2 is 0.53 and 0.52, respectively). According to columns (1) and (5), accounting for the Female ratio in the previous year increases this likelihood by approximately 1%. The economic magnitude of the Female ratio on the proportion of hedging, compared to this unconditional probability, is approximately 2% for measures of hedging (0.010/0.50=0.02).

We provide OLS regression estimates for the sample to examine whether the female ratio predicts the hedging and explain our findings on reduced volatility. The results are statistically significant. Under both definitions of hedging, we observe a positive and significant relationship between the hedging indicator and the lagged Female ratio.

We repeat the analyses using the matched subsample, and the results are provided in Panel B of Table 2.6. The results provide evidence of a strong to moderately significant influence of the lagged female ratio on the propensity to hedge in 7 out of 8 columns. The economic magnitude of the lagged female coefficient is higher in the matched sample than in the full sample.

Hence, an uptick in the Female ratio in the preceding year positively influences the likelihood of hedging. [50]

2.7. Conclusion

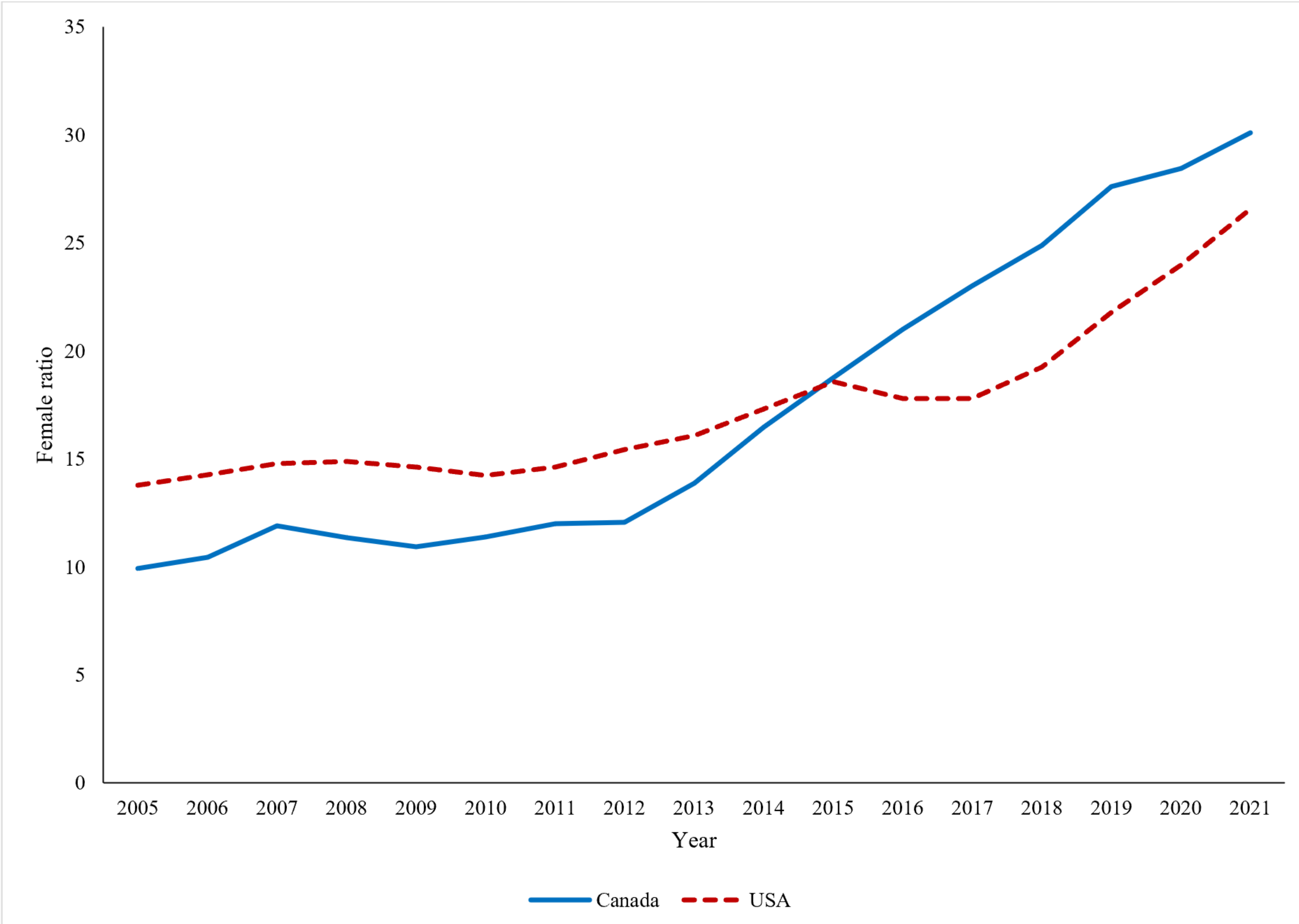
Decades of research have shown that gender equality is the foundation for a more equitable world. Regions lacking it will likely experience high instability and foster autocratic and corrupt governments. Ensuring women are treated equally and integrating them meaningfully into institutions and decision-making are important goals and crucial for achieving sustainable peace.

[50] Our results are robust to excluding the financial crisis and including non-hedging firms with missing values for derivative gains and losses.

By examining the permeability of Trudeau's gender parity initiatives on Canadian corporate boards, the study highlights the significant role of political leadership in driving corporate change. The observed increase in female representation on Canadian boards following Trudeau's rise to prominence is a testament to the influence of leadership and advocacy in shaping corporate governance practices. Furthermore, the association between increased female representation and reduced volatility in Canadian firms post-2014 hints at the potential benefits of gender diversity in enhancing corporate stability. The study explains the findings on female directors and reduced volatility by incorporating empirical evidence related to improvements in hedging.

The findings have implications for proactive efforts to advance gender equality in government and corporate settings, marking progress toward more inclusive and resilient business environments. Recently, regulators have broadened their focus on board composition to include diversity beyond gender. Thus, firms must adopt a broader perspective to enhance shareholder value and societal impact.

Figures and Tables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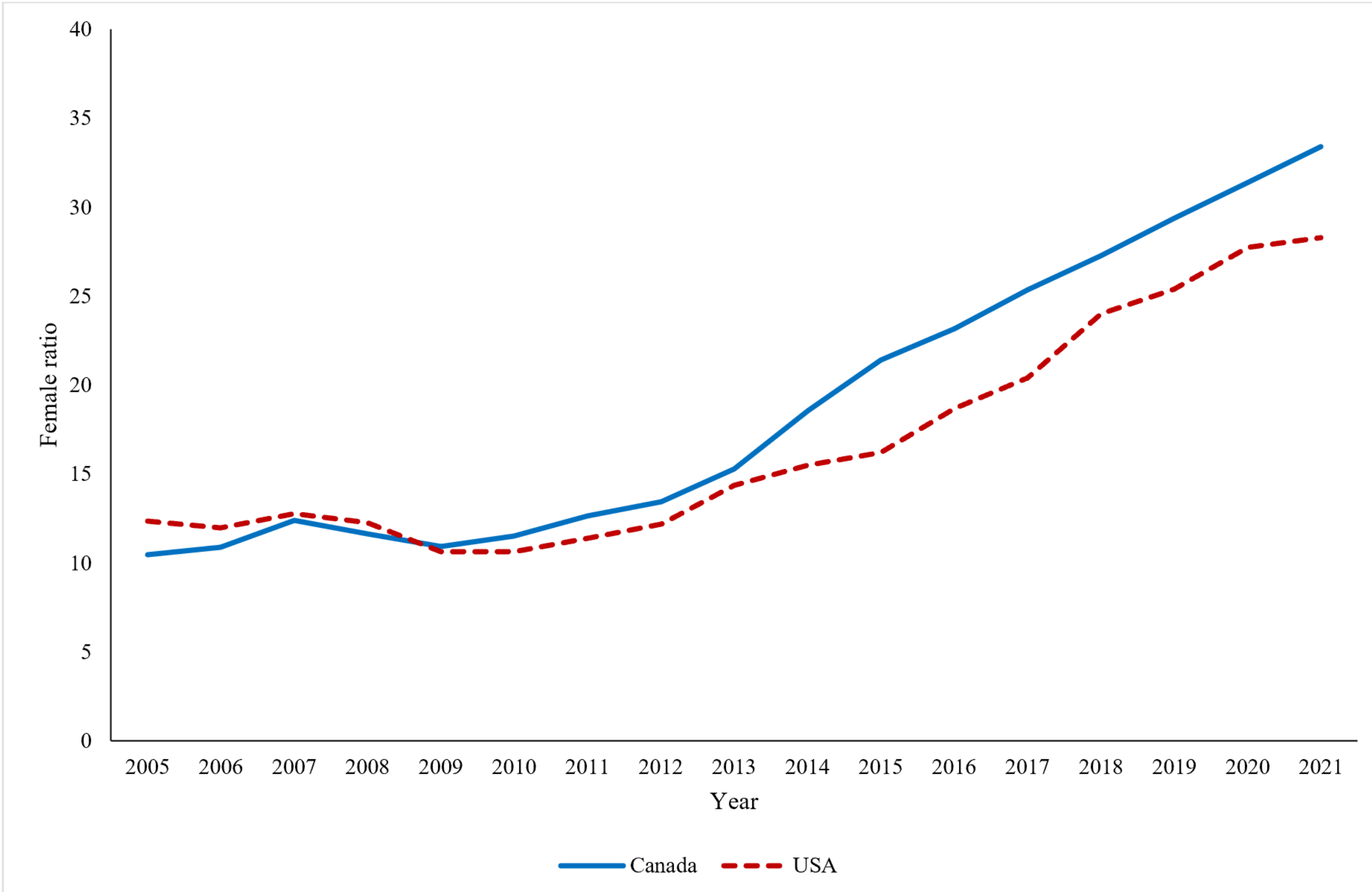

Figure 2.1. Female ratio over the years

Panel A illustrates the average female board ratio over the years for the full sample and Panel B for the matched sample (one-to-one). A Canadian firm is matched with a US firm based on having the same Fama-French industry and the closest Female ratio at fiscal year 2009. In multiple exact-matches cases, the closest market size US firm is selected.

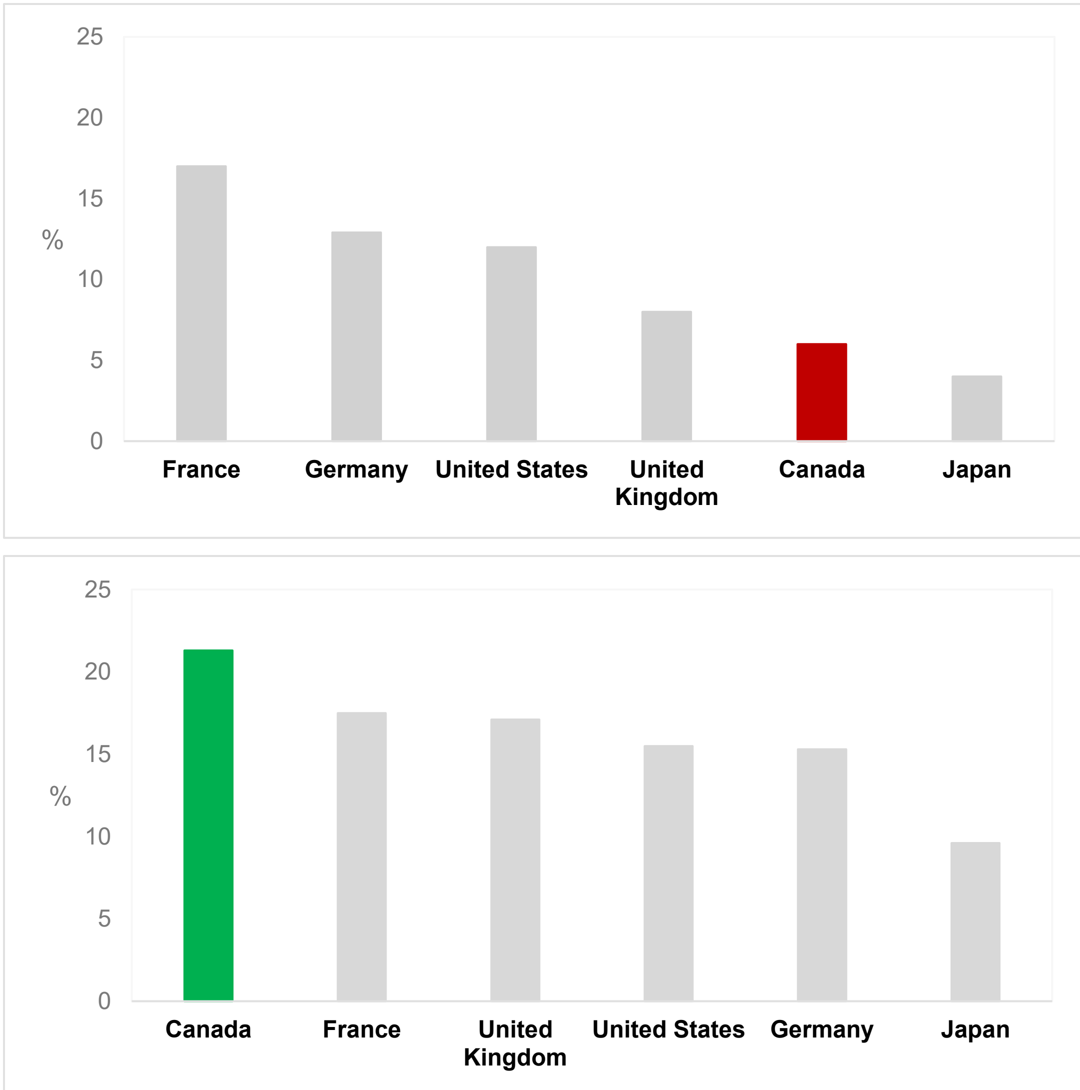

Figure 2.2. Female ratio by selected country of control

Panel A shows the share of women on corporate boards by country, in order of greatest share to lowest in 2009 (Status of Women Canada, 2015), and Panel B shows it for 2016 (Statistics Canada, 2016).

Table 2.1. Sample Characteristics

Panel A provides descriptive statistics of the main variables based on annual observations from 2005 to 2021. Female ratio is the percentage of females on the board and ΔFemale ratio is the change in the percentage of females on the board. Board size is the total number of board members at the end of the fiscal year and ΔBoard size is the change in the number of board members. Size is the market value of equity in billions of dollars. 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. ROA is income before extraordinary items divided by total assets. Dividend Indicator equals one if the firm paid cash dividends during the year and zero otherwise. Volatility (expressed in %) is the standard deviation of daily stock returns during the year. Ivol refers to idiosyncratic volatility and is the mean sum of squared error (multiplied by 10000) from a firm-year regression where the dependent is the daily return of the firm's share. The independent variable is the value-weighted return. Panel B presents, by industry, the total count of companies in our sample, encompassing both US and Canadian firms, and the average Female ratio for these firms for the 2005-2014 and 2015-2021 periods. In this panel, the mean Female ratio for either US or Canadian firms is first determined at the firm level, averaging across the years. Subsequently, these firm-level means are averaged to calculate the average Female ratio for each industry. Based on SIC codes, industries are partitioned according to the Fama-French industry classifications (17 industries). The difference column provides the difference of means between Canada and the USA Female Ratio for each industry in each period. The DiD column reports the t-test results for the difference in the Female ratio between these two periods. T-statistics (or z-statistics in cases with few observations for Canadian firms) are in parenthesis. *, **, *** indicate significance at the 1,5, 10% level, respectively.

Panel A: Descriptive statistics

	Mean	Median	Std. Dev.	P1	P99	Obs.
Board-level variables						
Female ratio	19.58	18.18	11.34	0	50	17408
ΔFemale ratio	1.84	0	5.61	-11.11	20	14972
Board size	9.92	10	2.66	5	17	17408
ΔBoard size	0.06	0	1.50	-3	3	14972
Firm-level variables						
Size	18.18	4.44	60.95	0.10	218.22	17408
Book-to-Market	0.49	0.39	0.41	-0.20	2.28	17408
Market Leverage	0.26	0.21	0.21	0	0.85	17408
ROA	0.03	0.04	0.11	-0.53	0.26	17408
Dividend Indicator	0.65	1	0.48	0	1	17408
Volatility	2.43	2.01	1.44	0.78	7.50	17408
Ivol	5.51	2.77	7.48	0.43	45.49	17408

Panel B: Industry constituents

Industry	#firms	Female ratio: Pre-2015 Canada	USA	Difference (a)	Post-2014 Canada	USA	Difference (b)	DID (b)-(a)
Food	51	18.03	22.40	-4.37 (-0.84)	25.17	25.48	-0.30 (-0.08)	13.72* (2.09)
Mining and Minerals	69	5.66	9.49	-3.83 (-1.46)	21.69	18.21	3.48 (1.64)	2.31 (0.90)
Oil and Petroleum Products	92	4.89	9.03	-4.14** (-2.29)	19.84	15.07	4.77** (2.21)	3.79* (1.82)
Textiles, Apparel & Footware	34	28.45	21.63	6.81 (0.85)	25.28	23.80	1.47 (0.26)	8.80 (1.27)
Consumer Durables	44	10.63	20.18	-9.54 (-1.27)	21.43	23.79	-2.36 (-0.36)	2.70 (0.63)
Chemicals	47	18.39	13.15	5.25 (0.61)	33.07	20.85	12.22*** (3.48)	5.17 (0.98)
Drugs, Soap, Perfumes, Tobacco	75	9.78	19.79	-10.01 (-1.50)	22.55	21.04	1.51 (0.37)	-0.09 (0.08)
Construction and Construction Materials	92	6.18	12.62	-6.44 (-1.57)	26.25	17.84	8.42*** (2.97)	6.60* (2.00)
Steel Works Etc.	22	-	13.35	-	-	22.14	-	
Fabricated Products	19	5.20	10.80	-5.60 (-0.89)	22.44	16.53	5.91 (1.24)	11.96***(5.46)
Machinery and Business Equipment	228	7.26	12.99	-5.73 (-1.45)	22.07	19.56	2.52 (0.82)	4.52 (1.51)
Automobiles	33	17.10	11.06	6.04 (1.11)	27.82	18.78	9.04 (1.40)	0.75 (0.18)
Transportation	87	8.58	11.48	-2.90 (-0.94)	26.56	18.85	7.70*** (2.99)	9.41*** (4.20)
Utilities	82	20.03	18.38	1.66 (0.48)	33.46	25.86	7.60** (2.58)	5.32* (1.73)
Retail Stores	114	13.20	17.18	-3.98 (-1.23)	24.42	27.33	-2.92 (-0.96)	1.45 (0.50)
Banks, Insurance, and Other Financials	505	14.51	14.33	0.18 (0.09)	27.09	21.23	5.86*** (4.64)	5.52*** (3.98)
Other	776	13.76	14.57	-0.82 (-0.45)	26.03	21.46	4.58*** (2.91)	5.60*** (3.26)
Total	2370	11.05	14.63	-3.59*** (-4.38)	25.18	21.20	3.98*** (6.11)	5.62***(8.30)

Table 2.2. Board female percent- levels and changes in multivariate analysis

Panel A examines the increase in female directors using a DID approach in the full and matched samples. A Canadian firm is matched with a US firm based on having the same Fama-French industry classification and the closest Female ratio in fiscal year 2009. In multiple exact-matches cases, the closest market size US firm is selected. CAN is an indicator variable that takes the value of one if the firm is headquartered in Canada and zero is headquartered in the U.S. Post is an indicator variable that takes the value of one in the year after Trudeau's rise (after 2014) and zero otherwise. The key variable of interest is the interaction between CAN and Post. **Panel B** provides regression results where the dependent is the Female ratio in specifications (1-2) and the ΔFemale ratio in specifications (3-5) for the full sample and matched pairs of US and Canadian firms. Specifications (2) and (5) include only the matched pairs, so if one of the matched pairs drops from the sample after 2009, we also drop the matched firm. The main independent variable is the interaction between the Canada dummy and year indicator (CAN×year *t*), where CAN is an indicator that equals 1 if the firm is Canadian, and year *t* equals 1 if the dependent observation is of year *t*. Control variables include size, book-to-market, market leverage, ROA, and dividend dummy and are lagged compared to the period in which the dependent variable is measured. Firm-level variables are defined in Table 2.1. Standard errors are clustered by firm. T-statistics are in parenthesis; all specifications include year fixed-effects (FE) and an intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

Panel A: DID Regressions

	Dependent: ***Female ratio***					
	Full sample			Matched sample		
	(1)	(2)	(3)	(4)	(5)	(6)
CAN × Post	5.302***	2.355***	2.364***	2.603**	2.818***	0.899
	(6.79)	(5.35)	(5.40)	(2.58)	(2.82)	(1.64)
Female ratio$_{t-1}$		0.544***	0.544***			0.600***
		(41.51)	(41.50)			(23.87)
Firm FE	Yes	Yes	Yes	Yes	No	Yes
Paired FE	-	-	-	No	Yes	No
Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
ΔControls	No	No	Yes	No	No	Yes
Observations	14,972	14,972	14,972	2,409	2,409	2,409
Adjusted R^2	0.725	0.803	0.803	0.767	0.687	0.845

Panel B: Year-on-year increases in the Female ratio

Dependent	***Female ratio***		***ΔFemale ratio***		
	Full sample	Matched pairs	Full sample		Matched pairs
	(1)	(2)	(3)	(4)	(5)
CAN2006	-3.797***		1.087	1.065	
	(-2.87)		(1.39)	(1.33)	
CAN2007	-2.860**		0.804	0.633	
	(-2.16)		(1.29)	(1.02)	
CAN2008	-3.518***		-0.493	-0.468	

Panel B: Year-on-year increases in the Female ratio

Dependent	*Female ratio*		*∆Female ratio*		
	Full sample	Matched pairs	Full sample		Matched pairs
	(1)	(2)	(3)	(4)	(5)
	(-3.04)		(-0.77)	(-0.73)	
CAN2009	-3.696***		0.445	0.433	
	(-3.25)		(0.81)	(0.78)	
CAN2010	-2.848**	0.583	0.249	0.302	0.551
	(-2.56)	(0.88)	(0.47)	(0.57)	(0.86)
CAN2011	-2.627**	0.471	0.419	0.412	0.290
	(-2.50)	(0.70)	(0.88)	(0.86)	(0.45)
CAN2012	-3.361***	0.435	-0.056	-0.039	0.222
	(-3.08)	(0.64)	(-0.14)	(-0.09)	(0.30)
CAN2013	-2.206**	0.146	0.453	0.453	-0.082
	(-2.00)	(0.19)	(1.02)	(1.00)	(-0.10)
CAN2014	-0.823	2.306***	1.913***	1.968***	2.142**
	(-0.77)	(2.69)	(3.24)	(3.11)	(2.24)
CAN2015	0.194	3.091***	1.678***	1.593***	2.264***
	(0.19)	(4.16)	(3.10)	(2.89)	(2.66)
CAN2016	3.204***	0.622	0.422	0.559	-0.648
	(3.07)	(0.73)	(0.81)	(1.00)	(-0.77)
CAN2017	5.207***	1.572*	0.924*	0.936*	0.451
	(5.19)	(1.85)	(1.85)	(1.77)	(0.50)
CAN2018	5.643***	-0.951	-0.336	-0.174	-2.335**
	(6.60)	(-0.98)	(-0.65)	(-0.33)	(-2.24)
CAN2019	5.823***	0.834	-0.135	0.063	0.044
	(7.65)	(0.84)	(-0.27)	(0.12)	(0.04)
CAN2020	4.491***	0.393	-0.265	0.037	-0.381
	(6.12)	(0.49)	(-0.53)	(0.07)	(-0.45)
CAN2021	3.527***	2.392**	-0.342	-0.078	1.539
	(4.89)	(2.22)	(-0.81)	(-0.18)	(1.38)
Female ratio$_{t-1}$		0.731***			
		(40.06)			
Industry FE	No	No	No	Yes	No
Paired FE	-	Yes	-	-	Yes
Controls$_{t-1}$ × Year	No	Yes	No	Yes	Yes
Observations	17,408	2,304	14,972	14,972	2,304
Adjusted R^2	0.160	0.843	0.026	0.029	0.028

Table 2.3. PM approval ratings and female on board

Table 2.3 provides regression results where the dependent is the Female ratio. The sample includes Canadian firms over the period 2015–2021. The variable "High PM Approval" is a binary indicator set to one if the province's Prime Minister approval rating is in the top tercile and zero if the rating is in the bottom tercile (the middle tercile is not included in the analysis). The variable "Liberalism" is a binary indicator set to one if the province's percentage of votes for the Liberal Party is above the median and zero otherwise. In columns (5)-(8), we provide the results based on the EB procedure-based regression results. We match firms headquartered in provinces with High and Low PM approval ratings on the control variables' first two moments, mean and variance. Columns (7) and (8) include the lagged Female ratio for matching along with controls. Control variables include size, book-to-market, market leverage, ROA, and dividend dummy – all measured at t-1. Definitions of variables are in the Supplemental Materials for Chapter 2, section S1. Standard errors are clustered by firm. T-statistics are in parenthesis; all specifications include year FE and an intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

	Dependent: ***Female ratio***							
	Full Sample				Matched			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High PM approval$_{t-1}$	1.228**	1.208*	1.896**	2.000**	3.548***	3.310***	1.170*	1.086*
	(2.02)	(1.95)	(2.31)	(2.43)	(2.84)	(2.79)	(1.85)	(1.69)
Liberalism$_{t-1}$		-0.090		-1.822		-1.208		-0.455
		(-0.15)		(-1.05)		(-0.76)		(-0.68)
Female ratio$_{t-1}$	0.776***	0.776***	0.310***	0.309***			0.768***	0.768***
	(34.07)	(34.04)	(6.14)	(6.13)			(26.30)	(26.24)
Firm FE	No	No	Yes	Yes				
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	682	682	682	682	682	682	682	682
Adjusted R^2	0.734	0.733	0.437	0.438	0.339	0.340	0.744	0.744

Table 2.4. Firm volatility and female on board

Table 2.4 provides regression results where the dependent is ΔVolatility in specifications (1–4) and ΔIvol in specifications (5–8) for both full and matched samples. The full sample spans 2005 to 2021, while the matched sample covers 2010 to 2021. Control variables include size, book-to-market, market leverage, ROA, and dividend dummy – all measured at t-1. Definitions of variables are in Table 2.1. Standard errors are clustered by firm. T-statistics are in parenthesis; all specifications include the year FE and intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

Dependent	*ΔVolatility*				*ΔIvol*			
	Full sample		Matched sample		Full sample		Matched sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female ratio$_{t-1}$	-0.006***	-0.004***	-0.009***	-0.009***	-0.038***	-0.023***	-0.057***	-0.054***
	(-6.58)	(-4.22)	(-4.81)	(-4.84)	(-8.21)	(-5.01)	(-4.39)	(-4.49)
ΔFemale ratio	-0.004***	-0.003**	-0.006*	-0.005	-0.029***	-0.023***	-0.029	-0.026
	(-2.77)	(-2.53)	(-1.69)	(-1.63)	(-3.46)	(-3.09)	(-1.45)	(-1.35)
Volatility$_{t-1}$	-0.366***	-0.511***	-0.543***	-0.528***				
	(-17.43)	(-19.44)	(-12.19)	(-11.96)				
Ivol$_{t-1}$					-0.412***	-0.568***	-0.686***	-0.667***
					(-28.75)	(-35.18)	(-16.20)	(-16.88)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls$_{t-1}$	No	Yes	Yes	Yes	No	Yes	Yes	Yes
ΔControls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	14,972	14,972	2,409	2,409	14,972	14,972	2,409	2,409
Adjusted R^2	0.674	0.719	0.681	0.715	0.477	0.554	0.531	0.574

Table 2.5. 2SLS regressions to analyze the volatility-female ratio relation

Panel A presents the results from the first and second stages of four instrumental variable (IV) regression models. In these models, the endogenous variable is the change (Δ) in the Female Ratio, and the dependent variable is either a change in Volatility or a change in Ivol. The instrumental variable used in all models is the state-level gender Wage gap, defined as the percentage difference in average earnings between males and females in the state or province where the firm's headquarters are located. **Panel B** presents the results from the first and second stages of four two-stage least-squares (2SLS) regression models. In these models, the endogenous variable is the change (Δ) in Female Ratio, and the dependent variable is either a change in Volatility or a change in Ivol. The instrumental variable used in all models is Trudeau's break. The variable Trudeau's break is defined as an indicator that equals one if the firm is Canadian and the period is post-2014 and zero otherwise. CAN is equal to one if the country of headquarters is Canada. Each model incorporates additional exogenous variables in both stages, including the lagged Female ratio, the lagged level of the dependent variable, and lagged or changing firm controls (such as size, book-to-market, market leverage, ROA, and a dividend dummy). The definitions for firm-level variables are provided in Table 2.1. Standard errors are clustered at the firm level, and t-statistics are presented in parentheses. All specifications include the year FE and intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

Panel A: IV regression: Using the male-female wage gap for the volatility-female ratio relation

	(1)	(2)	(3)	(4)
1st Stage	ΔFemale ratio	ΔFemale ratio	ΔFemale ratio	ΔFemale ratio
Wage gap	-2.017***	-2.031***	-2.024***	-2.040 ***
	(-6.36)	(-6.39)	(-6.40)	(-6.64)
F-statistic (Sanderson-Windmeijer)	40.40	40.79	40.96	41.45
P-value (rejecting null of weak instruments)	0.000	0.000	0.000	0.000
2nd Stage	ΔVolatility	ΔVolatility	ΔIvol	ΔIvol
ΔFemale ratio	-0.209***	-0.229***	-0.795***	-0.887***
	(-5.05)	(-5.36)	(-4.36)	(-4.77)
Female ratio$_{t-1}$	-0.038***	-0.041***	-0.152***	-0.166***
	(-5.45)	(-5.73)	(-5.02)	(-5.37)
Volatility$_{t-1}$	-0.511***	-0.521***		
	(-19.31)	(-18.51)		
Ivol$_{t-1}$			-0.562***	-0.568***
			(-32.02)	(-31.53)
Industry FE	Yes	Yes	Yes	Yes
Controls$_{t-1}$	Yes	Yes	Yes	Yes
ΔControls	No	Yes	No	Yes
Observations	14,972	14,972	14,972	14,972

Panel B: Using the 2014 structural break in Canada for the volatility-female ratio relation

	(1)	(2)	(3)	(4)
1^{st} Stage	ΔFemale ratio	ΔFemale ratio	ΔFemale ratio	ΔFemale ratio
Trudeau's break	4.494^{***}	0.802^{***}	4.582^{***}	0.805^{***}
	(6.53)	(3.13)	(6.63)	(3.13)
F-statistic (Sanderson-Windmeijer)	42.63	9.77	43.96	9.82
P-value (rejecting null of weak instruments)	0.000	0.000	0.000	0.000
2nd Stage	Δ*Volatility*	Δ*Volatility*	Δ*Ivol*	Δ*Ivol*
ΔFemale ratio	-0.125^{**}	-0.093^{**}	-0.893^{**}	-0.689^{**}
	(-2.29)	(-1.98)	(-2.49)	(-2.22)
Female $ratio_{t-1}$	-0.024^{***}	-0.018^{**}	-0.168^{***}	-0.132^{***}
	(-2.64)	(-2.35)	(-2.83)	(-2.58)
$Volatility_{t-1}$	-0.513^{***}	-0.522^{***}		
	(-20.46)	(-19.95)		
$Ivol_{t-1}$			-0.562^{***}	-0.569^{***}
			(-31.24)	(-33.11)
CAN	-0.110^{**}	-0.150^{***}	-0.127	-0.345
	(-2.12)	(-3.19)	(-0.40)	(-1.21)
Industry FE	Yes	Yes	Yes	Yes
$Controls_{t-1}$	Yes	Yes	Yes	Yes
ΔControls	No	Yes	No	Yes
Observations	14,972	14,972	14,972	14,972

Table 2.6. Hedging for nonfinancial firms with a high Female ratio

Panel A reports the probit model predicting the hedging indicator in columns (1) and (5) and OLS estimations from hedging regressions in the remaining columns. The sample includes nonfinancial firms from 2005–2021. The dependent variables Hedging1 and Hedging2 are indicator variables equal to 1 if Compustat items aocidergl "Accumulated Other Comprehensive Income - Derivative Unrealized Gain/Loss" and cidergl "Comprehensive Income - Derivative Gains/Losses" are nonzero, respectively. **Panel B** reports the probit model predicting the hedging indicator in columns (1–2) and (5–6) and OLS estimations from hedging regressions in the remaining columns. The sample includes matched nonfinancial firms from 2009–2021. A Canadian firm is matched with a US firm based on having the same Fama-French industry and the closest Female ratio in fiscal year 2009. In multiple exact-match cases, the firm with the closest market size in the US is selected. The dependent is Hedging1 in columns (1–4), whereas Hedging2 is in columns (5–8). Additional controls include financial distress, cash, and tangibility– all measured at t-1. Control variables include size, book-to-market, market leverage, ROA, and dividend indicator, and are lagged compared to the period in which the dependent variable is measured. All variables are defined in the Supplemental Materials for Chapter 2, section S1. The probit coefficients are reported as marginal probability effects. All models include the year FE and intercept. Standard errors are clustered by firm. z-statistics for probit models and t-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full sample

Dependent	***Hedging1***				***Hedging2***			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female $ratio_{t-1}$	0.010***	0.003***	0.003***	0.002*	0.010***	0.003***	0.003***	0.001
	(3.29)	(3.03)	(2.96)	(1.84)	(3.30)	(3.05)	(2.98)	(0.93)
ΔFemale ratio		-0.000	-0.000			-0.000	-0.000	
		(-0.27)	(-0.19)			(-0.06)	(-0.00)	
Industry FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Firm FE	-	No	No	Yes	-	No	No	Yes
Additional $Controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Controls_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ΔControls	No	No	Yes	No	No	No	Yes	No
Observations	10,115	10,115	10,115	10,115	10,403	10,403	10,403	10,403
Adjusted R^2	.	0.219	0.220	0.0143	.	0.216	0.217	0.014

Panel B: Matched sample

Dependent	*Hedging1*				*Hedging2*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female ratio$_{t-1}$	0.047***	0.030**	0.010***	0.001	0.046***	0.028**	0.009**	0.005*
	(4.82)	(2.51)	(2.70)	(0.26)	(4.48)	(2.37)	(2.53)	(1.77)
ΔFemale ratio			0.001				0.002	
			(0.45)				(0.92)	
Industry FE	No	Yes	Yes	No	No	Yes	Yes	No
Paired FE	-	-	No	Yes	-	-	No	Yes
Additional Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,235	1,151	1,235	1,235	1,300	1,216	1,300	1,300
Adjusted R^2	-	-	0.355	0.580	-	-	0.306	0.561

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Supplemental Materials for Chapter 2

S1. Variable definitions

Variable	Source	Definition
Female ratio	Refinitiv	Percentage of female directors on the board
ΔFemale ratio	Refinitiv	Change in the Female ratio
Board size	Refinitiv	the total number of board members at the end of the fiscal year
CAN	Compustat	CAN is equal to one if the country of headquarters is Canada
Size	Compustat	Firm size is the market value of a firm's equity (in billions of dollars) at the end of a calendar year
Book-to-market	Compustat	The 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, I 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	Compustat	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).
Return on Assets	Compustat	The ratio of income before extraordinary items to the book value of total assets (Hou, Xue, and Zhang, 2015).
Dividend indicator	Compustat	The dividend indicator equals one if the firm paid cash dividends and zero otherwise.
Volatility	CRSP	Volatility (expressed in %) is the standard deviation of daily stock returns during the year.
Ivol	CRSP	Iidiosyncratic volatility is the mean sum of squared error from a firm-year regression where the dependent is the daily return of the firm's share, and the independent variable is the value-weighted return.
Post	Compustat	Post is equal to 1 for the post-2014 period and 0 otherwise.
Hedging 1	Compustat	An indicator variable equal to 1 if the Compustat item aocidergl "Accumulated Other Comprehensive Income - Derivative Unrealized Gain/Loss" is nonzero.
Hedging 2	Compustat	An indicator variable equal to 1 if the Compustat item cidergl "Comprehensive Income Derivative - Gains/Losses" is nonzero
High PM Approval	Angus Reid Institute	A binary indicator set to one if the province's Prime Minister approval rating is in the top tercile and zero if the rating is in the bottom tercile
Liberalism	Elections Canada	The variable "Liberalism" is a binary indicator set to one if the province's percentage of votes for the Liberal Party is above the median and zero otherwise.
Trudeau's Break		A binary indicator that equals one if the firm is Canadian and the period is post-2014 and zero otherwise.
Cash	Compustat	Cash is the ratio of cash and marketable securities to book assets.

Variable	Source	Definition
Financial distress	Compustat	Financial distress is an indicator with an Altman z-score < 1.81.
Tangibility	Compustat	Tangibility is the ratio of property, plant, and equipment to book assets.

S2. Timeline of Trudeau's rise to power and gender initiatives

This subsection aims to provide information about some gender parity initiatives under Trudeau's leadership.

April 2011	Justin Trudeau is re-elected as a member of Parliament for Papineau.
April 2013	Trudeau is elected leader of the Liberal Party of Canada.
May 2013	The Ontario provincial government ((Liberal Party member and premier Kathleen O'Day Wynn) included the diversity statement in its May 2, 2013, budget.
June 2013	The Minister of Finance, Charles Sousa, and the Minister Responsible for Women's Issues, Laurel Broten, requested that the OSC (Ontario Securities Commission) undertake a public consultation process regarding disclosure requirements for gender diversity.
October 2015	Trudeau leads the Liberal Party to victory in the federal election, becoming Prime Minister of Canada.
November 2015	Trudeau and his cabinet are sworn in, marking the beginning of his tenure as Prime Minister. Trudeau appoints Canada's first gender-balanced cabinet "because it's 2015."
March 2016	Canada's budget under Trudeau's government includes significant investments in gender equality, including childcare and support for survivors of gender-based violence.
June 2017	Trudeau announced Canada's Feminist International Assistance Policy, which focuses on gender equality and empowering women and girls in developing countries.
June 2017	Canada's Strategy to Prevent and Address Gender-based Violence (the federal GBV Strategy)
November 2017	Canada announced the Elsie Initiative for Women in Peace Operations during the Vancouver UN Peacekeeping Defence Ministerial Conference in November 2017.
October 2017	The launch of Canada's five-year action plan on Women, Peace and Security (2017-2022). This action plan aimed to advance gender equality and women's empowerment in peace and security contexts.
October 2018	Canada hosts the first-ever Women Foreign Ministers' Meeting, bringing female foreign ministers worldwide to discuss global issues.
December 2018	In 2018, the Canadian federal government established the position of Minister for Women and Gender Equality as part of the Budget Implementation Act, 2018, No. 2. This role was introduced along with the creation of the Department for Women and Gender Equality.

June 2019	Canada hosts the Women Deliver Conference, the world's largest conference on gender equality and girls and women's health, rights, and well-being.
2019-2020	Canada served as the lead of the Call to Action and launched the current 2021-2025 Roadmap. The Call to Action is a collective of states, UN organizations, and civil society organizations that aim to address the increased risk of gender-based violence (GBV) in humanitarian emergencies.
March 2020	Canada's budget includes funding for gender equality initiatives, including support for women entrepreneurs and investments in childcare.
January 2021	The declaration of the National Action Plan to End Gender-Based Violence, which builds on the federal Gender-Based Violence Strategy announced in 2017. The goal is to make Canada free of gender-based violence in 10 years.
February 2021	Feminist Response and Recovery Fund calls for proposals totaling $100 million to fund projects tackling systemic barriers for marginalized or underrepresented women.
June 2021	Launched in June 2021, the Federal Pathway to Address Missing and Murdered Indigenous Women, Girls, and 2SLGBTQQIA+ People outlines the Government of Canada’s commitments to addressing the root causes of violence against Indigenous women, girls, and 2SLGBTQI+ people.
2022	Canada led the Elimination of Violence Against Women and Girls resolution at the United Nations Human Rights Council in 2022.
October 2023	Canada’s National Action Plan on Women, Peace and Security (2023-2029). It includes more commitments at the domestic level than previous action plans. It also seeks to maintain the country’s leadership through meaningful action at an international level.

S3. Robustness check

S3.1 Univariate analysis

In this subsection, we conduct the robustness check using univariate analysis, which involves comparing the average Female ratio and ΔFemale ratio (the change in the female ratio) for each year between Canada and the US from 2005 to 2021. The prediction is that Canadian firms experienced a surge in the percentage of female directors on corporate boards compared to U.S. firms during 2014-2015. The following table reports the results of the univariate analysis. The panel's left-hand side (LHS) presents the results for the Female ratio, while the right-hand side (RHS) shows the results for the ΔFemale ratio, both in the full and matched samples. In both the full and matched samples, the difference in mean ΔFemale ratio is statistically insignificant from 2006 to 2013. However, the difference in means becomes statistically significant in 2014 and 2015. The findings of univariate analysis are consistent with multivariate analysis in the main text and the visual evidence presented in Figure 2.1.

Table S3.1. Board female percent levels and changes - Univariate analysis

This table reports the mean Female ratio and change (Δ) in the Female ratio for the full sample and matched pairs of US and Canadian firms. A Canadian firm is matched with a US firm based on having the same Fama-French industry and the closest Female ratio in fiscal year 2009. In multiple exact-match cases, the firm with the closest market size in the US is selected. Additionally, we include descriptive information for matched pairs that align in the same year and extend backward to before 2009. T-statistics are in parenthesis. *, **, *** indicate significance at the 1,5, 10% level, respectively.

	Female ratio				***ΔFemale ratio***			
	Full Sample			Matched pairs	Full Sample			Matched pairs
Year	Canada	US	Difference	Difference	Canada	US	Difference	Difference
2005	9.93	13.77	-3.85*** (-2.60)	-2.62 (-0.92)				
2006	10.47	14.26	-3.80*** (-2.89)	-0.16 (-0.07)	1.46	0.32	1.14 (1.17)	2.35 (1.62)
2007	11.92	14.78	-2.86** (-2.17)	-0.45 (-0.21)	1.54	0.73	0.80 (1.03)	-0.88 (-0.53)
2008	11.35	14.87	-3.52*** (-3.17)	-0.02 (-0.01)	-0.10	0.40	-0.49 (-0.79)	-0.13 (-0.12)
2009	10.94	14.64	-3.70*** (-3.60)	0.31 (0.22)	0.72	0.27	0.45 (0.78)	0.22 (0.34)
2010	11.39	14.23	-2.85*** (-2.83)	0.65 (0.44)	0.53	0.28	0.24 (0.56)	0.34 (0.56)
2011	12.00	14.63	-2.63** (-2.64)	0.85 (0.58)	0.99	0.58	0.42 (0.94)	0.20 (0.35)
2012	12.07	15.44	-3.36*** (-3.37)	1.34 (0.91)	0.84	0.90	-0.06 (-0.13)	0.21 (0.37)
2013	13.88	16.08	-2.21** (-2.25)	0.94 (0.66)	1.19	0.74	0.45 (1.07)	-0.41 (-0.59)
2014	16.48	17.30	-0.82 (-0.85)	2.93** (2.00)	3.11	1.20	1.91*** (3.89)	1.98** (2.44)
2015	18.76	18.57	0.19 (0.21)	5.36*** (3.70)	3.04	1.37	1.68*** (3.23)	2.22*** (3.22)
2016	21.02	17.81	3.36*** (3.52)	4.17*** (2.68)	1.72	1.30	0.42 (0.84)	-0.63 (-0.86)
2017	23.02	17.81	3.20*** (3.32)	4.82*** (3.18)	2.46	1.54	0.92* (1.95)	0.47 (0.61)
2018	24.88	19.24	5.21*** (5.46)	2.99** (2.24)	2.23	2.56	-0.34 (-0.65)	-1.98** (-2.33)
2019	27.62	21.80	5.64*** (6.28)	3.67*** (2.68)	2.78	2.92	-0.13 (-0.26)	0.50 (0.65)
2020	28.46	23.97	5.82*** (6.87)	3.60*** (2.88)	2.29	2.55	-0.26 (-0.54)	-0.33 (-0.40)
2021	30.11	26.58	3.53*** (4.72)	5.33*** (3.72)	2.42	2.77	-0.34 (-0.72)	1.75* (1.85)

S3.2 Alternative matching sample

The purpose of this supplemental subsection is to conduct a robustness check by using an alternative matching sample to verify the consistency of our results. We use 2012 for matching to ensure that the comparisons are not influenced by Trudeau's rise, which began in 2013, and to establish a baseline that precedes any potential changes driven by his leadership.

In this approach, we match firms based not only on identical Fama-French industry classifications and the closest Female Ratio in the fiscal year 2012 but also on the political leaning of their headquarters location. Specifically, Canadian provinces with Conservative party governments are paired with U.S. states governed by Republicans, while provinces with Liberal or New Democratic Party (NDP) governments are matched with Democratic states. The NDP advocates for social justice, environmental protection, and enhanced public services, which align more closely with the liberal and progressive policies of the Democratic Party. In cases where multiple exact matches are found, the U.S. firm with the closest market size is selected.

Figure S3.2 illustrates the annual percentage of female directors on firms' boards from 2005 to 2021. The graph shows a noticeable increase in the slope around 2014 for Canadian firms, indicating that these firms responded to Trudeau's initiatives by adding female directors at a higher average rate despite having the same political leaning. Additionally, this increased rate continues for the rest of the sample period. This figure aligns with the figures presented in the main text and further reinforces our confidence that Trudeau's advocacy drove the inflection point in the trajectory for Canadian firms.

Table S3.2 examines the increase in female directors on board using the DID approach. We show that the coefficient on the interaction term *CAN* × *Post* is positive and significant across all columns. This suggests that Canadian firms increased their female director ratios by 1 to 3 percentage points more than the paired US firms. The coefficients are statistically significant at the 1%-5% level. The results are consistent with the DID analysis in Panel A of Table 2.2.

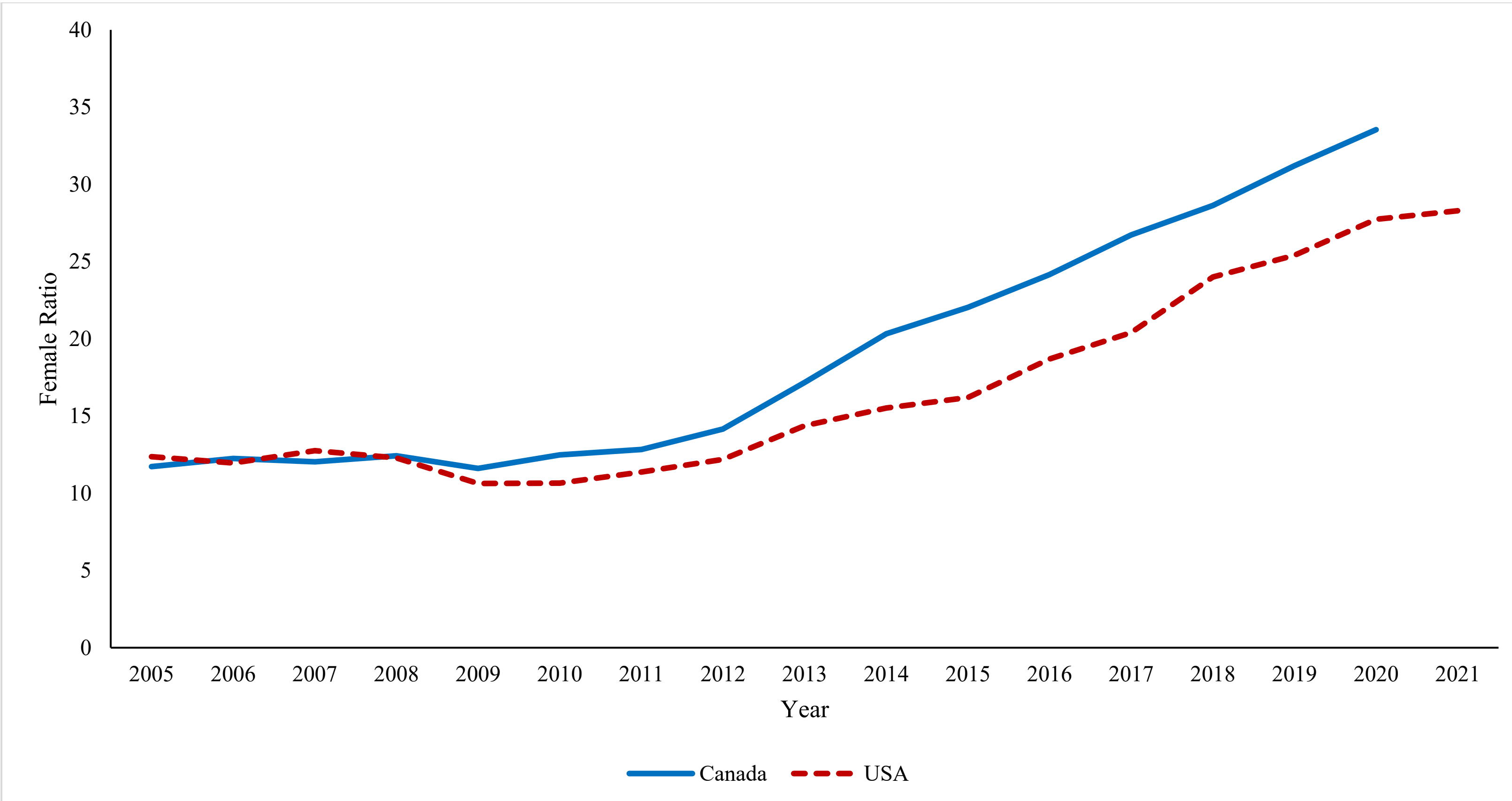

Figure S3.2. Female ratio over the years

Figure S3.2 illustrates the average female board ratio for the matched sample (one-to-one) over the years. A Canadian firm is matched with a U.S. firm based on having the same Fama-French industry classification, the closest Female Ratio, and the political leaning of their respective headquarters' state or province in the fiscal year 2012. In multiple exact-match cases, the firm with the closest market size in the US is selected.

Table S3.2. Increase in females on boards– pre- and post-2014 analysis

Table S3.2 examines the increase in female directors using a DID approach in the matched sample. A Canadian firm is matched with a U.S. firm based on having the same Fama-French industry classification, the closest Female Ratio, and the political leaning of their respective headquarters' state or province in the fiscal year 2012. In multiple exact-match cases, the firm with the closest market size in the US is selected. The key variable of interest is the interaction between CAN and Post. CAN is an indicator variable that takes the value of one if the firm is headquartered in Canada and zero is headquartered in the U.S. Post is an indicator variable that takes the value of one in the year after Trudeau's rise (after 2014) and zero otherwise. Control variables include size, book-to-market, market leverage, ROA, and dividend dummy and are lagged compared to the period in which the dependent variable is measured. Firm-level variables are defined in Table 2.1. Standard errors are clustered by firm. T-statistics are in parenthesis; all specifications include year fixed-effects (FE) and an intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

	Dependent: ***Female ratio***					
	2005-2021			2010-2021		
	(1)	(2)	(3)	(4)	(5)	(6)
CAN × Post	3.233***	1.034**	1.119**	3.199***	0.983**	1.118**
	(3.40)	(2.59)	(2.43)	(3.27)	(2.43)	(2.31)
Female ratio$_{t-1}$		0.690***	0.629***		0.688***	0.616***
		(37.11)	(26.61)		(37.84)	(26.56)
Firm FE	Yes	Yes	Yes	Yes	No	Yes
Controls$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
ΔControls	No	No	Yes	No	No	Yes
Observations	3,178	3,178	3,178	2,787	2,787	2,787
Adjusted R^2	0.747	0.836	0.840	0.754	0.835	0.841

S3.3 PM approval ratings and year-on-year increases in the Female ratio

In this subsection, we examine the impact of PM Trudeau's approval ratings by province year-by-year on the percentage of women on board. This analysis addresses the concern that the PM ratings experienced fluctuations during our study period. In 2015, he began his tenure as PM with a strong public mandate and high approval ratings. He maintained his approval ratings due to his progressive agenda, which included promoting gender equality. However, between 2017 and 2018, his approval ratings declined due to issues such as the SNC-Lavalin affair handling, the Trans Mountain pipeline approval, and the electoral reform plan abandonment. In 2019, despite the drop in ratings, he managed to win re-election. In 2020, his ratings increased due to the COVID-19 pandemic handling and the introduction of economic relief measures like the Canada Emergency Response Benefit (CERB). However, by mid-2021, his ratings dropped again due to ongoing pandemic restrictions and controversies such as the WE Charity scandal.

Table S3.3 presents regression results with the female ratio as the dependent variable for Canadian firms from 2015 to 2021. The main independent variable is the interaction between the PM approval rating by province and the year indicator (PM approval ×year *t*), where year *t* equals one if the dependent observation is from year *t*. The results indicate that the coefficient of the interaction between the PM approval rating and year is statistically significant in the years when the rating was high. The most robust and significant results are observed for the year 2016.

Table S3.3. PM approval ratings and year-on-year increases in the Female ratio

Table S3.3 provides regression results where the dependent is the Female ratio. The sample includes Canadian firms over the period 2015–2021. The main independent variable is the interaction between the PM approval and year indicator (PM approval ×year *t*). PM approval is the PM approval rating by province and year *t* equals one if the dependent observation is from year *t*. The variable Liberal Party is the province's percentage of votes for the Liberal Party. Control variables include size, book-to-market, market leverage, ROA, and dividend dummy – all lagged relative to the dependent. Firm-level variables are defined in Table 2.1. Standard errors are clustered by firm. T-statistics are in parenthesis; all specifications include year FE and an intercept. *, **, *** indicate significance at the 1,5, 10% level, respectively.

Dependent	***Female ratio***				
	(1)	(2)	(3)	(4)	(5)
PM approval×2015	0.323*	0.259	0.413	0.431*	0.430*
	(1.91)	(1.52)	(1.63)	(1.71)	(1.66)
PM approval×2016	0.359***	0.280***	0.367***	0.387***	0.387***
	(3.84)	(2.92)	(2.65)	(2.77)	(2.66)
PM approval×2017	0.240**	0.181*	0.275*	0.269*	0.334**
	(2.18)	(1.70)	(1.72)	(1.70)	(2.00)
PM approval×2018	0.292**	0.233*	0.357*	0.368*	0.380**
	(2.42)	(1.75)	(1.92)	(1.97)	(2.04)
PM approval×2019	0.207*	0.116	0.289	0.288	0.285
	(1.84)	(0.90)	(1.34)	(1.37)	(1.35)
PM approval×2020	0.058	0.023	0.140	0.156	0.157
	(0.81)	(0.27)	(0.97)	(1.09)	(1.07)
PM approval×2021	0.115	0.090	0.199	0.230	0.211
	(1.42)	(0.95)	(1.30)	(1.52)	(1.36)
Liberal Party			-0.114	-0.097	-0.094
			(-0.92)	(-0.80)	(-0.78)
Industry FE	No	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Controls* Year	No	No	No	No	Yes
Observations	1,031	1,031	1,031	1,031	1,031
Adjusted R^2	0.138	0.246	0.247	0.307	0.301