Governance, Information Flow, and Stock Returns: Evidence from a Natural Experiment[☆]

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Abstract

We show that the poor governance stocks outperform good governance ones after 2008, implying that the disappearance of the relationship between governance indices and stock returns documented in Bebchuk, Cohen, and Wang (2013) is temporary. To explain this puzzling reappearance of abnormal returns, we hypothesize that learning helps sophisticated investors recognize governance risks and become more prudent after the global financial crisis. Exploiting an exogenous shock to the governance information flow, we find support for our hypothesis. Subsequent tests confirm that learning via the *price* and *risk* channels helped investors recognize the uncertainty surrounding poorly governed firms' future earnings powers.

Keywords: Learning, corporate governance, antitakeover provisions, institutional investors, E-Index

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Introduction

Does corporate governance matter for stock returns? Most investors would like to invest in good corporate governance stocks but perhaps not at the expense of shareholder returns. This issue is at the core of a recent debate about the role of corporate governance and corporate social responsibility in stock performance. On the one hand, firms with good corporate governance were associated with good stock performance (Gompers et al., 2003). On the other hand, Edmans and Ioannou (2019) state "[t]he idea that companies and investors can both do good and do well is finding ever greater traction among executives, shareholders and wider society." As a result, large institutional investors designed strategies to identify and invest in good corporate governance firms. The California Public Employees Retirement System (Calpers), for example, devised its own list of effective governance practices and also used social activism to improve the performance of its investments.[1] However, Gillers (2019) reports in the Wall Street Journal that "[d]oubts about the strategy rose as Calpers' funding situation worsened in the decade after the 2008 financial crisis. A key sign came in December 2016 as retirement-system officials recommended the board drop its tobacco ban, citing the potential money lost. Staying out of the investments for 16 years had cost the fund more than $3.5 billion, a fund consultant calculated." In a similar vein, did Calpers and other institutional investors realize the cost of ignoring poor governance stocks amid the funding crunch that accompanied 2008 crisis?

This paper reveals that indeed the importance of poor governance stocks cannot be ignored as they are under-priced in recent years (i.e., 2008 onward) leading to higher stock returns. This result is in contrast with previous empirical evidence that shows good corporate governance being under-priced prior to 2002 (Bebchuk et al., 2009). We conjecture that lower returns for good corporate governance firms after 2008 is consistent with prices reflecting the changing preferences of institutional investors toward corporate governance. Given the fact that the correlation between stock returns and corporate governance indices ceased to exist in the 2002-2008 period (Bebchuk et al., 2013), a profitable governance-based investment strategy as suggested in Gompers et al. (2003) was unimplementable after 2001.[2] However, the 2007-2008 financial

[1] Calpers is the largest public pension fund in the U.S. and is well known for creating the "Focus List," which contains companies with concerning or undesirable corporate governance practices. The fund worked with the listed companies to improve their performance creating a phenomenon known as the "Calper effect."

[2] This investment strategy involves buying good governance stocks and selling poor governance ones to form a zero-investment hedge portfolio.

crisis had differential impacts on the good and poor corporate governance firms (Erkens et al., 2012). So, an investment strategy that employs portfolios sorted on governance characteristics can generate as much as 2% monthly risk-adjusted returns after 2008, with poor governance stocks outperforming good governance ones. In other words, we show that both the disappearance of the governance pricing anomaly, and its directionality (i.e., good- outperforming poor-governance) are in fact temporary. The relationship between governance and returns undergoes two structural changes: (a) the existing association and then its disappearance and (b) the aforesaid disappearance followed by a reversed association. In the years following first structural break, we find that institutional investors recognize governance risks and understand that the other investors had adjusted their trading strategies to exploit the governance anomaly previously. However, they also realize the impact that crisis has on the governance structures. Consequently, they respond strategically taking into account the demand for corporate governance and adapt their investment strategies to beat the market.

Bebchuk et al. (2013) learning hypothesis explains the disappearing governance–returns association, but does not shed light on the reversal of this association and the appearance of a new governance-based investment strategy. Since the institutional investors play an important role in the governance of investee firms (Gillan and Starks, 2000; McCahery et al., 2016), we conjecture that they are the main drivers of the reversed association. Accordingly, we explore the sophisticated investor learning hypothesis. We hypothesize that the sophisticated investors understand that the increased volatility in the markets increases downside risk for poor governance firms, and they use this information together with corporate governance to design new investment strategies. In other words, sophisticated investors recognize that the corporate governance continues to be a reliable signal for good corporate governance firms, but not so for the poor governance ones. This implies that when *sophisticated learning* occurs after some years of the first structural break point, the governance–returns correlation reappears. Hence, the sophisticated learning effect is characterized by a governance–returns relation that is directionally opposite to that seen in the 1990s, with poor governance stocks outperforming good governance ones. Therefore, sophisticated investors can now use a reverse hedge (long poor governance and short good governance) to make profits.[3] To test the sophisticated learning

[3]This reverse hedge was not documented by Bebchuk et al. (2013), since sophisticated learning did not occur in the sample timeframe considered.

hypothesis, we use a natural experiment that captures the changes in institutional investors' governance preferences and its resultant impact on stock returns.

The intuition behind the sophisticated learning hypothesis can be explained as follows. Gompers et al. (2003) and Bebchuk et al. (2009) show that many market participants in the 1990s did not understand the importance of governance provisions, thus creating opportunities for institutional investors to obtain abnormal returns. Accordingly, Chung and Zhang (2011) find a positive relationship between institutional ownership and governance structures for the same period. However, increased attention toward these provisions over time resulted in the disappearance of abnormal returns from governance-based hedge portfolios (Bebchuk et al., 2013). Moreover, following the onset of the global financial crisis in 2007–2008, firms with better governance characteristics and higher institutional ownership performed poorly in terms of their stock returns (Erkens et al., 2012). This would have led to an increased prudence toward governance structures among informed institutional investors. Thus, the learning that accompanies such increased scrutiny should have created additional investment opportunities for these investors after the financial crisis. To gain further insights into the sophisticated learning phenomenon, we therefore examine two underlying learning mechanisms: price channel and risk channel.

The relationships among corporate governance, institutional investors, and stock returns are clouded by endogeneity concerns. This makes causal identification for the sophisticated learning phenomenon around the second structural break a major challenge. We overcome this using a natural experiment that exogenously affected the governance information flow to investors. In 2007, Institutional Shareholder Services (ISS)—a leading corporate governance data provider used by institutional investors—changed its data collection and reporting methodology, which led to the faster dissemination of governance data on an annual basis than in previous years when governance data were made available to investors every two or three years. Since this exogenous shock occurs just before the second structural break in the governance–returns relationship, it provides an ideal quasi-experimental setting within which to assess if investors learn to recognize the riskiness of poorly governed firms. In its essence, our experimental test of the sophisticated learning hypothesis builds on the Grossman and Stiglitz (1980) and Hellwig (1980) theoretical models on informational efficiencies, as we aim to understand how informed sophisticated investors react to the quality of governance information and/or its noisiness (which, here, is proxied through information timeliness).[4]

The change in ISS's governance reporting methodology offers us a good quasi-experimental setting that can isolate institutional investors' reaction to governance information, and comes with several advantages. First and foremost, firms whose information was not updated in 2007 (control firms, or Slow group henceforth) and those that had a new set of information in 2007 (treatment firms, or Fast group) are mutually exclusive, ensuring that the two groups are clearly categorized. Second, considering that ISS issues governance data independently, both sets of treatment and control firms are largely unaware of which group they fall into. This eliminates any potential intra-firm sources of endogeneity. Third, we can safely assume a roughly random assignment of firms to the two groups because there are no reasons to believe that ISS favors reporting some firms' governance provisions over others.[5] From the institutional investors' perspective, this also means that they were largely unaware of which firms' information was to be updated in 2007 and which was not. Fourth, as an extension of the previous point, ISS's decision to cover a specific firm's anti-takeover provisions should largely be independent of the firm's past institutional ownership and returns. Fifth, although the frequency and timing with which ISS released the governance data (which were previously issued at two- or three-year intervals) was inconsistent, the timing and frequency remained consistent for the last three reports. This would have allowed investors to plan their investment strategies using governance information with certainty. Lastly, the inconsistencies in past reporting frequency allows for possible placebo tests, which can strengthen the validity of our inferences.

Using the ISS governance provisions data, we first create governance-based hedge portfolios (see Gompers et al., 2003; Bebchuk et al., 2009) to reaffirm the disappearance of the governance–returns relation after the 1990s. The further exploration of this relation after 2001 reveals that another structural break exists in 2008, when the governance–returns association reappears, albeit in the opposite direction.[6] While learning improved markets' understanding of

[4]These models show that when it is costly to acquire information, prices cannot perfectly aggregate such information.

[5]Nevertheless, we do tackle selection concerns by using propensity-score-matched groups.

[6]All our main results and additional analysis employ the E-Index as a governance proxy, as this index can be reliably developed for the entire sample period. The change in ISS's data collection methodology after 2007 (that changed the number of anti-takeover provisions covered by ISS) makes the replication of the G-Index difficult after 2006.

the future profitability from well-governed and poorly governed firms, additional wisdom after a few years allowed alert institutional investors to further process differences in their riskiness. With the superior riskiness of poor governance firms being appreciated by investors, their market prices would have turned more volatile. We capture this risk-induced effect through price informativeness, idiosyncratic volatility, and stock price crash risk in subsequent analyses.

We identify the two structural break points using Bebchuk et al. (2013) approach, and use the Bai and Perron (1998) and Hatemi-J (2008) tests to confirm the two regime shifts. Then, we proceed with the natural experiment designed around the change in ISS's data collection methodology, and examine the changes in short- and long-term institutional ownership across the second structural break point using the Fast and Slow groups. While there is a significant decline in long-term institutional ownership among poor governance stocks, short-term institutional ownership increases for poor governance firms after the second break point. Our results support the idea that long-term investors choose good governance firms so that they can intervene through "voice," while they choose to "exit" when firms have poor governance structures (McCahery et al., 2016). In other words, the benefits from investing in good governance stocks arise in the form of lower monitoring costs, while foregoing short-term gains (Bebchuk et al., 2015).

Additionally, we employ the same quasi-experimental setting to assess the abnormal returns for the long good governance/short poor governance zero-investment strategy and compare the abnormal returns for portfolios created using the treatment and control firms. As with institutional ownership, we find that the sophisticated learning effect (proxied by the information flow for Slow vs. Fast groups) does exist—even with respect to abnormal returns for the second structural break point.

Although the results from our natural experiment lend credence to the existence of sophisticated learning, they do not shed light on the mechanisms that drive such learning among investors. How does governance information influence the risk-adjusted expected returns of institutional investors and/or other sophisticated investors? To answer this question, we further explore the sophisticated learning phenomenon through two underlying learning mechanisms. First, since good governance is related to the price informativeness (Lee et al., 2016), we study the information content of good and bad governance stocks' prices and the changes that their price informativeness experiences across the two structural break points. This captures the differences in investors' expectations of future firm growth rates and earnings prospects between well-governed and poorly governed firms. Second, since the "no arbitrage" condition leads to a relation between the information flow rate and stock price volatility (Ross, 1989), we examine the impact of governance on idiosyncratic volatility and price non-synchronicity across the two structural breaks. While the first mechanism reflects the sophisticated learning that is aided by information flows through the *price* channel, the second mechanism portrays the same experienced through the *risk* channel.

To investigate the price channel, we analyze the differences between the cross-sectional price informativeness of good and bad governance stocks. Our results support both the Bebchuk et al. (2013) learning hypothesis for the first structural break and sophisticated learning across the second structural break. While price informativeness increased in the pre-2001 period for both good and bad governance stocks (through learning effects), there is a different trend in the post-2008 period. Poor governance stocks show a distinct decline in price informativeness after the second structural break point, whereas well-governed stocks show an upward trend for the same period. During the period of dissociation (i.e., between the two structural break points), price informativeness is statistically insignificant, implying stable information access across both well-governed and poorly governed firms. We complement the results from this cross-sectional measure of the information content of prices using firm-specific information flow proxies, and again find evidence supporting sophisticated learning. More specifically, at the firm level, poor governance firms have greater information asymmetry and also show comparatively lower trading activity than well-governed ones after the second structural break.

We study the risk channel using the firm's idiosyncratic volatility and stock price crash risk. The results again support possible sophisticated learning, with bad governance firms being associated with higher idiosyncratic volatility in comparison with good governance ones in the post-2008 period. Additionally, we find that while the E-Index could not predict future stock price crash risk before 2008, there is a positive association between the two thereafter. This means that after the second structural break, poorly governed stocks with more entrenchment provisions have a higher likelihood of crashes. Combined with the evidence from the *price* channel tests, the results from the *risk* channel tests support the findings of Jin and Myers

(2006) that “limited information affects the division of risk bearing between inside managers and outside investors.” In other words, sophisticated learning increased the awareness of riskiness associated with poor governance firms, thus forcing investors to wisely adjust their expectations of these firms’ future earnings power and associated risk premia to counter increased information asymmetry.

In addition to merely exploring and explaining the negative association between governance and stock returns, our findings contribute to a broader body of the literature that studies information-based trading strategies and/or long-run event studies. From an asset pricing perspective, we draw attention to a possible “anomaly” (see Schwert, 2003). This is especially important as the anomaly in focus was shown to have disappeared after the 1990s. While the disappearance of financial anomalies has been widely studied, few studies have highlighted their possible reappearance. In some ways, our study also reflects the tensions and complementarities between the rational and behavioral theories of financial anomalies (Brav and Heaton, 2002). We show that while learning does involve the recalibration of governance information by rational investors, the additional uncertainties accompanying information asymmetry induce sophisticated learning, and this creates arbitrage opportunities afresh. Additionally, we contribute to the larger market efficiency literature (see Fama, 1991). Our findings are consistent with those of Brown et al. (1988), as we show that investors’ risk and returns adjust to new information, especially for poor governance structures after market prices have corrected for the differences between well-governed and poorly governed firms (i.e., after the initial learning period). Alternatively, the relatively high idiosyncratic risk and lower price informativeness of poorly governed firms after the second break point may also be indicative of the ambiguity premium (Epstein and Schneider, 2008).

The rest of this paper is organized as follows. Section 1 presents our sophisticated learning hypothesis. Section 2 describes the data and variables. Section 3 makes a case for the two structural breaks or regime shifts in the governance–returns relationship. Next, Section 4 applies the natural experimental design to first identify the short- and long-term institutional investor behavior toward governance information and then determine the abnormal returns from such sophisticated learning. Section 5 explores the price and risk channels, and Section 6 summarizes our main results and concludes.

1. The sophisticated learning hypothesis

Investors are constantly seeking information that can help them *beat* the markets (French, 2008). They are sensitive to managerial entrenchment (E-Index), as the presence of entrenching anti-takeover provisions within firms exposes them to possible information asymmetry when managers are better shielded from takeover threats (Bebchuk et al., 2009). The underlying rationale behind the sophisticated learning hypothesis is that the investors learn to better adapt to market conditions after financial crisis so that they make more informed decisions than other market participants.

As institutional investors (the main customers of ISS) have comparatively superior information-gathering and -processing power, they can identify potential sources of information asymmetries and agency risks faster. Accordingly, beyond the critical sophisticated learning point, short- and long-term institutional investors will react differently to governance signals. While the myopic view of short-term investors will make poor governance stocks lucrative for them, long-term investors will be attracted to good governance firms (Gaspar et al., 2005). From firms' perspective, stock prices are influenced by investors' liquidity needs (Chang et al., 2017). Thus, the impact of firms' governance structures on institutional ownership and subsequent liquidity pressures should jointly influence their stock returns. In other words, although governance risk may affect stock returns through liquidity risk (see Dumitrescu, 2015; Back et al., 2018), it is not captured through the same in its entirety. Hence, the markets at large may not really factor in governance risks. In the long run, however, such governance-based abnormal returns opportunities should disappear, with the market learning process eventually eliminating any governance-related information asymmetry. Hence, while our sophisticated learning hypothesis does dwell upon market inefficiency in the short run, it does not rule out the possible return to efficient market conditions in the future.[7]

We expect learning among institutional investors to be driven by either one or all of the following three conditions. First, investors' risk attitudes and returns expectations are known to change around financial crises (Weber et al., 2012). This implies that investors may have

[7]From a different and more rational standpoint, the sophisticated learning hypothesis does not necessarily assume complete market inefficiency or suggest purely investor-centric learning. Since we mimic the passive market portfolio by only controlling for some well-known risk factors, such learning may even be experienced by investors and all other market participants alike, as long as they can factor additional governance risk into their investment decisions.

become more prudent after the 2007–2008 financial crisis. Second, governance information was previously not made available to investors in a consistent and reliable manner. However, investment planning should have improved with ISS standardizing its governance reporting practices. Lastly, informed institutional investors are in a better position to react to newer information than uninformed investors and hence should demand higher returns when investing in high private information firms (Easley and O'Hara, 2004). This would also entail the governance–returns relationship being affected by a reliable information inflow.

The aforementioned effect of the financial crisis on investor behavior and stock prices cannot be ignored (Muir, 2017). In our tests of the sophisticated learning hypothesis, since our natural experiment focuses on investee firms, we can control for the 2007–2008 financial crisis under the assumption that it had similar impacts on both treatment and control firms. However, institutional investors must have readjusted their portfolios after the crisis. Two opposing catalysts drive these post-crisis readjustments: the improved accuracy of analysts' assessments of a firm's riskiness (Joos et al., 2016) and the decline in the accuracy of earnings forecasts (Sidhu and Tan, 2011). Moreover, Mondria and Quintana-Domeque (2013) and Bekaert et al. (2014) show that international investors pay more attention to "macroeconomic fundamentals" during a crisis period. In other words, the country's economic stability becomes more important than the individual firm's characteristics. Together, these factors would have contributed to sophisticated learning. While these are important explanatory drivers from investors' perspective, much of our analyses in this study aim to understand investees' firm-specific drivers.

2. Data and measurement

The data for our study were sourced from the ISS governance database (anti-takeover provisions), the Center for Research in Stock Prices (CRSP) database (stock returns, prices, and volumes), COMPUSTAT (firm-specific fundamentals and controls), and the Fama-French and Liquidity Factors database from WRDS. Additional data for the probability of informed trading (PIN), as used by Brown and Hillegeist (2007), were obtained from Stephen Brown's website. The main sample includes firms whose governance data are reported by ISS and excludes all firms with dual class stocks as these have governance structures that differ from single class stock firms (Gompers et al., 2009).

2.1. Governance data

We focus on the governance data published by ISS (formerly IRRC-Riskmetrics), which reports the anti-takeover provisions of S&P 500 and other large Fortune 500 companies to its customers (i.e., institutional investors). ISS's governance rankings and related data assess the takeover protection mechanisms in sample firms using the documents and forms filed with the U.S. Securities and Exchange Commission as well as other publicly available information from annual reports and proxy statements. Using these anti-takeover provisions as a proxy for the shareholder–manager relationship, Gompers et al. (2003) and Bebchuk et al. (2009) present the G-Index and E-Index, respectively.[8] ISS's governance data collection and reporting methodology as well as its frequency have changed over time. Before 2007, almost 30 governance provisions and state-based statutes were reported for sample firms every two to three years. Since 2007, however, ISS has published its anti-takeover provisions data annually, which cover about 25 provisions and state laws. Thus, to ensure comparison across the years, we use the E-index (Bebchuk et al., 2009) as our main corporate governance indicator, as it can be measured over the entire sample period from 1990 to 2015.[9]

While Bebchuk et al. (2009) construct the E-index as the managerial entrenchment subset from within the G-Index using pre-2007 ISS data, it can still be created for the new ISS dataset, as four of the six entrenchment provisions (i.e., staggered boards, limits to shareholder bylaw amendments, poison pills, and golden parachutes) were retained, even after 2007. The remaining provisions on the supermajority requirement for mergers and charter amendments are included by assessing the reported voting percentage requirements for these.

Table I shows the summary statistics for the E-Index across our sample for each year in which the ISS governance data were published. There is a distinct trend for both the mean value of the E-Index and its standard deviation across the years. We find that the average governance structures have worsened over time, supporting our argument for sophisticated learning as the institutional investors would have sought additional information after mid-2000s to overcome

[8] Anti-takeover provisions along with other governance characteristics such as ownership, board features, and auditing requirements from ISS data are also used by Brown and Caylor (2006) to create another measure of corporate governance (i.e., Gov-Score). However, these data have only been made available by ISS for a limited time since 2001.

[9] Although we cannot construct the G-Index across the entire sample period, as its scale would differ between the pre-2007 and post-2007 years, we do use a normalized G-Index score, or *G-Proxy*, to test the robustness of all our results.

the declining variations among the governance structures. Figure I also shows that the change in ISS's data collection methodology influenced the steepness of the E-Index and its distribution after 2007. However, the monotonic trend of the increasing average E-Index values and its declining cross-sectional variation is maintained before and after 2007. Over the 26-year period, our sample comprises more than 36,500 firm-year observations of governance scores.

2.2. Other data

Institutional ownership is obtained from Thomson Reuters institutional holdings 13f filings data, with the ownership proportions computed for short- and long-term investors separately. A large part of our remaining analysis uses monthly returns for 1988 to 2016 obtained from the CRSP for all the firms in the governance dataset. This ensures an additional two years before and one year after the governance data timeframe to compute the lagged controls (e.g., past returns) and/or capture future portfolio returns. We additionally consider daily returns from the CRSP to measure crash risk (condensed to weekly returns) and idiosyncratic volatility. For all the sample firms, we also obtain the requisite annual balance sheet data to measure price informativeness and other firm-specific controls.

2.3. Investment horizon measures

Using inputs from the recent literature (e.g., Harford et al., 2018), we identify short- and long-term institutional investors as follows. For each investor in a given year, we measure the proportion of each stock that is no longer held in the investor's portfolio in comparison to the amount of that stock held three years ago.[10] This turnover measure is in the interval of 0 to 1. Next, we compute a weighted average turnover measure for each investor based on its investment portfolio weights for that year. Finally, investors are classified into short- and long-term groups based on their average turnover. Corresponding approximately to the lowest quartile of the turnover distribution, investors with 35% or lower average turnover are categorized as long term, while the rest form the short-term investor group (for more details, see Nguyen et al., 2017).

2.4. Price informativeness and information flow measures

The price informativeness measure is constructed using the estimation procedures highlighted in Bai et al. (2016). We first regress future earnings on market valuations for each of

[10] In addition to three-year portfolio turnover, we employ two-year turnover in a robustness check.

Table I: E-Index Across the Years

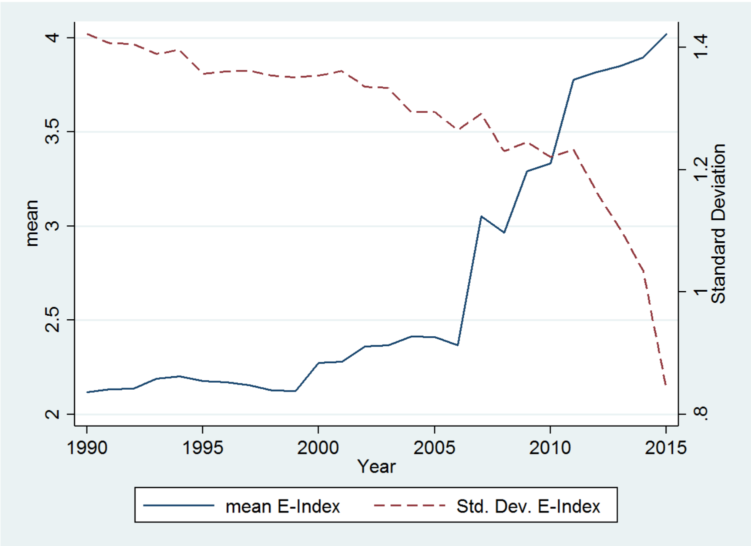
This table summarizes the presence of entrenchment provisions (using E-Index) in our sample for each of ISS data publication years. Dual class stocks are left out. For details on each of the E-Index provisions, see Bebchuk et al. (2009). The dashed line indicates change in ISS data collection methodology.

Year	Mean	SD	Minimum	Median	Maximum	Number
1990	2.2177	1.3826	0	2	6	1346
1993	2.3114	1.3548	0	2	6	1336
1995	2.2966	1.3420	0	2	6	1369
1998	2.2609	1.3245	0	2	6	1702
2000	2.4390	1.3055	0	2	6	1665
2002	2.4802	1.2877	0	3	6	1668
2004	2.5333	1.2457	0	3	6	1759
2006	2.4933	1.2354	0	3	6	1711
2007	3.0521	1.2923	0	3	6	1556
2008	2.9653	1.2303	0	3	6	1528
2009	3.2910	1.2456	0	3	6	1519
2010	3.3311	1.2214	1	3	6	1492
2011	3.7785	1.2331	1	4	6	1458
2012	3.8182	1.1627	1	4	6	1419
2013	3.8492	1.1038	1	4	6	1386
2014	3.8943	1.0347	1	4	6	1372
2015	4.0202	0.8416	1	4	6	1041
Full Sample$^+$	2.7711	1.4044	0	3	6	36705

$^+$The full sample here includes firms' last E-Index values for intermediate years when the governance data was not issued by ISS. For example, the firms' E-Index scores in 1990 are replicated for the years 1991 and 1992.

Figure I: Evolution of E-Index and its Cross-Sectional Variation Over Time

This figure shows the plots of average E-Index scores from 1990 to 2015 along with its standard deviations. As in the Table I, when governance data was not issued by ISS for a year, the previous E-Index score for each firm is carried forward.



the years, with multiple time horizons (i.e., using future earnings at one-, two-, three-, and five-year intervals). While the current period's earnings and industry sector controls are used to represent publicly available information as in Bai et al. (2016), this also helps us account for industry booms and busts. Hence, we additionally control for alternative explanations that explore the available investment opportunity sets for each firm (Li and Li, 2016):

$$\frac{E_{j,t+i}}{A_{j,t}} = a_{t,i} + b_{t,i} ln\left(\frac{MV_{j,t}}{A_{j,t}}\right) + c_{t,i}\frac{E_{j,t}}{A_{j,t}} + d_{t,i}S_{j,t} + \epsilon_{j,t,i}, \tag{1}$$

where $E_{j,t}$, $MV_{j,t}$, and $A_{j,t}$ are the annual earnings, market values, and total assets of firm j in year t, respectively. $S_{j,t}$ is a sector dummy using the one-digit SIC code. For each group of firms (i.e., good and poor governance), we obtain coefficients for each year t and time horizon i. Finally, price informativeness (PRI) is computed as a product of the cross-sectional standard deviation (σ_t) of the main regressor, namely, $MV_{j,t}/A_{j,t}$, and its coefficient's estimate from the above equation using:

$$PRI_{t,i} = b_{t,i} * \sigma_t\left(ln\frac{MV_{j,t}}{A_{j,t}}\right). \tag{2}$$

While this measure helps us trace the cross-sectional price informativeness of good and poor governance firms from a holistic perspective, it does not reveal how the information flows within individual firms are influenced by governance structures. Thus, we also compute firm-specific information flow measures to examine whether any systematic difference exists across the structural breaks. We use the two measures adopted by Ferreira and Laux (2007): share turnover ($TURN$) and the PIN following Easley et al. (2002).

2.5. Idiosyncratic volatility and crash risk measures

Ferreira and Laux (2007) show a persistent negative association between the G-Index and idiosyncratic volatility. Similarly, Andreou et al. (2016) show that a wide array of corporate governance mechanisms (e.g., institutional ownership, CEO stock options, percentage of outside directors with stock ownership, and board size) can help predict future stock price crashes. Thus, to gather support for sophisticated learning through the risk channel, we apply these two firm-specific risk measures: idiosyncratic volatility and stock price crash risk.

We begin by estimating firm-specific weekly returns W from the residuals obtained by regressing weekly firm returns in an expanded index model as suggested by Hutton et al. (2009):

$$r_{j,t} = \alpha_j + \beta_{a,j} * r_{m,t-2} + \beta_{b,j} * r_{m,t-1} + \beta_{c,j} * r_{m,t} + \beta_{d,j} * r_{m,t+1} + \beta_{e,j} * r_{m,t+2} + \epsilon_{j,t}, \quad (3)$$

where firm j's Wednesday-to-Wednesday return for week t is given by $r_{j,t}$; for the same week, the CRSP value-weighted market index return is $r_{m,t}$. One- and two-week lagged and forward market returns are introduced to control for infrequent trading. Next, we correct for the skewed residuals $\epsilon_{j,t}$ using logarithmic transformation to obtain firm-specific weekly returns as $W_{j,t} = ln(1 + \epsilon_{j,t})$.

Our main crash risk measure ($CRASH$) indicates whether a firm has experienced at least one crash week in a given year. These crash weeks are those in which the firm-specific $W_{j,t}$ declines by more than 3.09 standard deviations below the average $W_{j,t}$ in that year.[11] An additional variable, $CRASHNUM$, is used to indicate the number of crash weeks experienced by a firm in a given year. To test whether the impact of governance is symmetrical on either side of the average $W_{j,t}$, we construct a complementary stock price up-movements measure as an indicator of whether firm-specific $W_{j,t}$ rises by more than 3.09 standard deviations above the average $W_{j,t}$ in that year. Using inputs from Chen et al. (2001), we compute two alternative measures of stock price crashes as a robustness check: negative conditional skewness and down-to-up volatility.

For idiosyncratic volatility, we aim to capture more variation by considering monthly measures unlike the crash risk measures, which are estimated on a yearly basis. For each month, we run the estimation of a slightly modified version of Equation (3) considered for the crash risk measures. In this case, we consider daily stock returns $r_{j,t}$ for each firm without the lead and lag market returns, and estimate R^2 on a monthly basis. As in the literature (e.g., Ferreira and Laux, 2007), idiosyncratic volatility is then computed through a logistic transformation as

$$IDIOSYN = ln\left(\frac{1 - R^2}{R^2}\right). \quad (4)$$

[11]The 3.09 standard deviation threshold picks up the lowest 5% of $W_{j,t}$ for any year. We use 10% or 1% thresholds as a robustness check and see no difference in our main findings for $CRASH$.

Table II: Descriptive Statistics

This table presents the mean, standard deviation (SD), median and the number of observations (N) for all of the main variables and controls. The summary statistics are reported first for the full sample, and then, separately for the governance–returns association years (1990-2000), dissociation years (2001-2007) and negative association years (2008-2015) as indicated on top of the table. Panel A covers all variables introduced to measure price informativeness as explained in Section 2.4. Panels B and C show all the firm-based information flow and risk measures, whereas Panel D presents all the control variables. All variables are computed from COMPUSTAT Annual and CRSP daily/monthly data (see Appendix A for more details). Except for *TURNOVER* and *IDIOSYN* which are recorded at monthly frequency, all other variables are observed on annual basis.

		Full Sample				1990-2000				2001-2007				2008-2015			
		Mean	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**	**Mean**	**SD**	**Median**	**N**
Panel A: Variables for Price Informativeness																	
Earnings Over Asset	E_t/A_t	0.075	0.134	0.078	52034	0.075	0.138	0.081	25158	0.065	0.139	0.071	13499	0.084	0.118	0.077	11215
1 Year Future Earnings Over Assets	E_{t+1}/A_t	0.091	0.186	0.086	47875	0.091	0.231	0.090	24031	0.086	0.129	0.079	12178	0.096	0.111	0.082	9537
2 Year Future Earnings Over Assets	E_{t+2}/A_t	0.108	0.364	0.093	43910	0.108	0.485	0.098	22874	0.105	0.147	0.086	10995	0.111	0.130	0.090	7950
3 Year Future Earnings Over Assets	E_{t+3}/A_t	0.130	0.569	0.101	40105	0.135	0.755	0.106	21726	0.125	0.176	0.096	9892	0.123	0.158	0.096	6431
5 Year Future Earnings Over Assets	E_{t+5}/A_t	0.185	1.409	0.121	32875	0.203	1.817	0.128	19387	0.158	0.248	0.112	7973	0.145	0.278	0.109	3587
Market Value Over Assets (in logs)	$\ln(MV_t/A_t)$	-0.224	1.117	-0.136	51956	-0.232	1.185	-0.175	25118	-0.145	1.019	-0.049	13486	-0.242	1.047	-0.125	11196
Panel B: Firm-based Information Flow Variables																	
Monthly Share Turnover	TURN	0.163	2.592	0.104	624461	0.115	3.806	0.060	288332	0.182	0.204	0.125	183321	0.229	0.243	0.171	152808
Probability of Informed Trade*	PIN	0.162	0.084	0.145	38938	0.190	0.086	0.175	19623	0.142	0.071	0.127	15548	0.100	0.052	0.093	3767
Panel C: Firm Risk Variables																	
Idiosyncratic Volatility (in logs)	*IDIOSYN*	1.834	2.176	1.383	439621	2.952	2.262	2.490	156982	1.570	1.907	1.160	138769	0.868	1.734	0.558	143870
Crash Risk	*CRASH*	0.256	0.437	0	64806	0.209	0.407	0	32068	0.299	0.458	0	18990	0.308	0.462	0	13748
Price Jump	JUMP	0.268	0.443	0	64806	0.257	0.437	0	32068	0.254	0.436	0	18990	0.311	0.463	0	13748
Negative Conditional Skewness	NCSKEW	0.051	1.130	0.030	64601	0.018	1.053	-0.002	31940	0.104	1.181	0.073	18935	0.054	1.223	0.055	13726
Down-to-Up Volatility	DUVOL	0.014	0.441	0.016	64449	0.006	0.428	0.006	31856	0.027	0.451	0.029	18888	0.015	0.455	0.021	13705
Panel D: All Control Variables																	
Return on Equity	ROE	0.291	0.896	0.011	48864	0.223	0.789	0.010	24926	0.336	0.995	0.012	13396	0.394	0.983	0.016	10542
36 Months Variance for ROE	vROE	0.016	0.059	0.000	49936	0.010	0.045	0.000	22982	0.022	0.069	0.001	14587	0.020	0.065	0.001	12367
Leverage	LEV	0.189	0.200	0.146	53593	0.185	0.199	0.138	28354	0.189	0.202	0.142	14024	0.200	0.201	0.168	11215
Market Value (in logs)	SIZE	6.904	1.723	6.838	52030	6.373	1.670	6.296	27358	7.327	1.548	7.201	13476	7.696	1.603	7.576	11196
Market to Book (in logs)	MB	4.229	2.724	3.538	46151	3.982	2.630	3.303	23767	4.627	2.854	3.908	12009	4.333	2.720	3.711	10375
Return on Asset	ROA	0.110	0.133	0.114	53593	0.112	0.139	0.120	28354	0.099	0.131	0.102	14024	0.118	0.118	0.115	11215
Dividend Dummy	DD	0.479	0.500	0.000	56483	0.518	0.500	1.000	26925	0.412	0.492	0.000	16470	0.483	0.500	0.000	13088
Age (in logs)	AGE	4.930	1.092	5.159	54738	4.712	1.182	4.970	25554	4.961	0.997	5.050	16193	5.321	0.890	5.438	12991
Share Turnover YOY Difference	DIFTURN	0.404	9.957	0.145	58240	0.399	5.495	0.116	26933	0.593	15.855	0.345	17828	0.164	5.954	-0.119	13479
Average Return	AVG	-0.002	0.013	-0.002	64806	-0.003	0.014	-0.002	32068	-0.002	0.014	-0.001	18990	-0.001	0.009	-0.001	13748
Return Volatility	SIGMA	0.057	0.039	0.046	64707	0.062	0.041	0.052	31999	0.055	0.040	0.044	18967	0.047	0.031	0.039	13741
Opacity	OPQ	0.214	0.193	0.180	58462	0.222	0.178	0.165	22147	0.214	0.221	0.690	14132	0.214	0.218	0.176	11261

* The full sample for probability of informed trade (PIN) spans 1993-2010 as obtained from Stephen Brown's Database

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2.6. Summary statistics

Table II summarizes the mean, median, standard deviation, and total number of available observations for each of the main variables other than stock returns, market returns, and related risk factors. We first present these statistics for the full sample and then separately for the governance–returns association years (1990–2000), dissociation years (2001–2007), and negative association years (2008–2015), as indicated at the top of the table. Panel A covers all the variables introduced to measure price informativeness. There is no visible trend for these variables across the three time periods. Panels B and C show all the firm-based information flow and risk measures. Whereas PIN increases on average over these three periods, turnover activity ($TURN$) shows a declining trend on average. Lastly, Panel D presents all the control variables. Many of the variables associated with firm size show a characteristic rise over the years. This is expected because many of the firms in our sample are consistently reported by ISS and have grown during these years.

3. The association, dissociation, and negative association of governance and returns: A case of two structural breaks

3.1. Identification strategy

Using the long-run event study methodology, we trace the two extreme governance portfolios (i.e., Democracy or Good Governance with E-Index = 0, and Dictatorship or Bad Governance with E-Index = 5 | 6) along with the governance hedge portfolio (long Democracy/short Dictatorship) over a 26-year period.[12] This allows us to locate the exact point (points) of the structural break (breaks) in the time series for abnormal returns using Quandt likelihood ratios. To estimate unknown structural breaks, we use the supremum of the likelihood ratios (Andrews, 1993) in three stages. We first run the sup-Wald test for the entire sample to identify the first break point. Next, we run the same test by restricting the sample months after the first break to locate the second break point. Lastly, we run confirmation tests using inputs from Clemente et al. (1998) and Bai and Perron (1998), specifically with the two structural break tests of Hatemi-J (2008).[13]

[12]When the minimum E-Index for any year is not '0', the next lowest value i.e., '1' is used to identify the Democracy stocks.

[13]We do not start with multiple structural break estimation techniques such as in the Bai and Perron (2003) procedure because they seek structural breaks for both slopes and trends in multivariate cases, whereas we seek to identify breaks only in the alphas or constants. Nevertheless, we apply these estimations as a more stringent robustness check to detect the second structural break.

Put differently, we apply the Andrews (1993) tests for unknown structural breaks twice (to identify each break) by running time-series regressions and looking for statistically significant breaks in the αs or risk-adjusted returns. Like Bebchuk et al. (2013), we account for monthly $RMRF_t$ (market factor), SMB_t (size factor), HML_t (book-to-market factor), and MOM_t (momentum factor). In addition, we control for the liquidity effects using the LIQ_t factor (Pástor and Stambaugh, 2003). Alternative asset pricing models, including the Fama and French (2016) five factors, are used for the robustness checks. Thus, main specification is as follows:

$$R_t = \alpha + (\Delta\alpha) * POST + \beta_1 * RMRF_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * LIQ_t + \varepsilon_t, \quad (5)$$

where R_t is the governance-based hedge portfolio return for month t. This model allows us to statistically locate the exact points in time when the two regime shifts occur for α.

Next, following the assumption in Bebchuk et al. (2013) that learning is not a discrete event, we identify the possible "critical learning" point using 36-month rolling alphas to determine when gradual learning is complete. For sophisticated learning, we apply a similar gradual process assumption and determine the end point of sophisticated learning using a rolling estimation. For each governance-based hedge portfolio, we estimate the 36-month rolling abnormal returns or alphas and identify (a) the month in which abnormal returns are consistently statistically insignificant and (b) the exact month in which abnormal returns are again consistently significant. While the statistical estimation using the Quandt (1960) method identifies the critical points of the structural breaks or regime shifts, the rolling estimation method pinpoints the last possible points for the two learning phases (Bebchuk et al., 2013).[14]

3.2. Results

We start by estimating the first structural break, which is the month in which the F-statistic for a break was the largest in the entire sample of 26 years. By design, with 15% trimming applied, the procedure identifies only the first structural break point, which usually provides the largest F-statistic because of the approximated asymptotic distribution. Panel A in Table III summarizes the first break points identified by both the Quandt method and the 36-month rolling returns method. The estimated break points for the first structural break in the table

[14]Assuming that market learning and sophisticated learning is completed within three years.

Table III: The Two Structural Breaks in Governance – Returns Association

In this table, Panel A reports the two break points in governance – returns relationship as identified using the Andrews (1993) Quandt tests and the 36-month rolling methods. The results follow both equal-weighted (EW) and value-weighted (VW) governance hedge (long Democracy/ short Dictatorship) portfolios wherever indicated. Hedge portfolios are rebalanced whenever new data is made available by ISS. Monthly portfolio returns are loaded on five factors capturing market (RMRF), size (SMB), book-to-market (HML), momentum (MOM) and liquidity (LIQ). Our final estimates for each break point are also shown. Panel B, alternatively, reports abnormal returns (α s or alphas) by running Equation (5) with additional structural break (SB) variables in place of POST. All estimations use White (1980) robust standard errors (in parentheses). In the 2 SB model, the dissociation period (2001-2007) is taken as the benchmark, with each of the association and negative association periods represented by SB1 Dummy (for 1990-2000) and SB2 Dummy (for 2008-2016) respectively. In the 1 SB model, a single variable takes the value of '-1' for pre-dissociation period and '+1' for post-dissociation years. The benchmark remains the same as before. Significance levels at 10%, 5%, and 1% are shown using *, ** and *** respectively.

Panel A: The break points				
	1st break point		2nd break point	
	VW	EW	VW	EW
Quandt LR Method	July-2000	November-2000	January-2008	February-2008
36-month Rolling Method	February-2003	June-2002	July-2008	December-2008
Estimated point:	January-2001		January-2008	

Panel B: Alphas and the two structural breaks				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	0.0010	0.0004	-0.0037	0.0003
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0078**	0.0067*	-0.0147***	-0.0074***
	(0.004)	(0.004)	(0.004)	(0.002)
SB2 Dummy	-0.0211***	-0.0093*		
	(0.007)	(0.005)		
Observations	304	304	304	304
R-squared	0.31	0.32	0.30	0.30
p-Value	0.00	0.00	0.00	0.00

are similar to those shown by Bebchuk et al. (2013) for both the equal- and the value-weighted portfolios. To identify the second break point, we repeat the same 15% trimmed F-statistic test by excluding the time period before the first structural break. The estimated second break points using the equal- and value-weighted portfolios are just one month apart (i.e., January 2008 and February 2008).

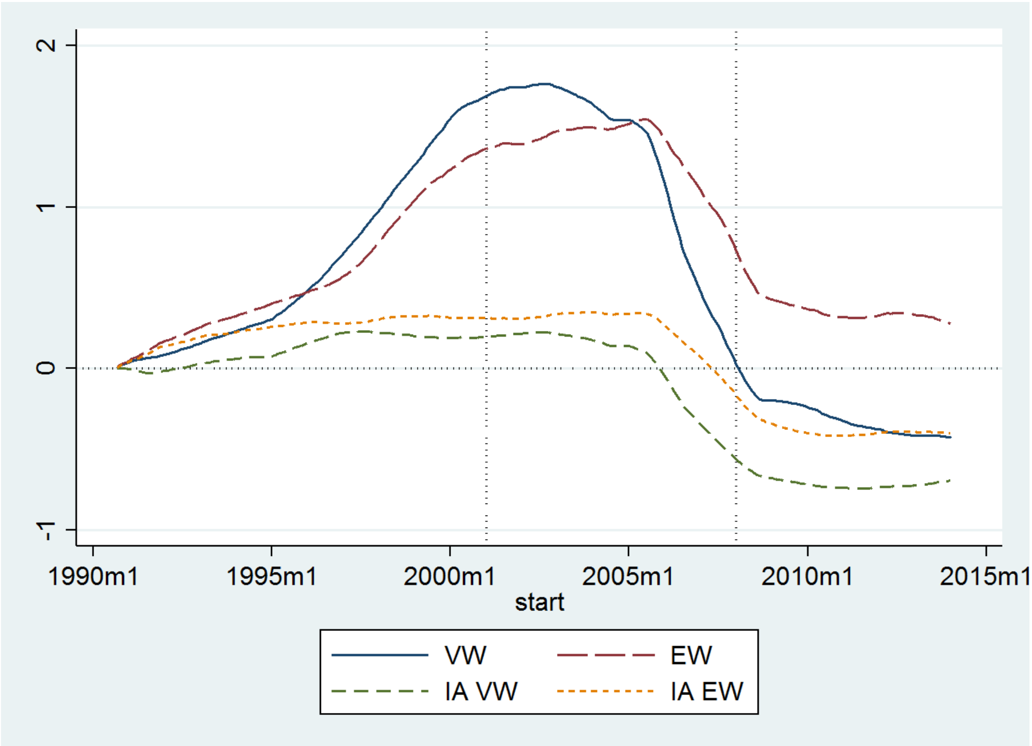
Using the 36-month rolling returns method as well, the identified break points for the first structural break are similar to those of Bebchuk et al. (2013). For the second structural break, interestingly, the estimated end points for sophisticated learning are either July 2008 (for the value-weighted portfolio) or December 2008 (for the equal-weighted portfolio). This suggests that sophisticated learning is much quicker than the Bebchuk et al. (2013) learning during the first structural break. Our final estimate for the first break point is January 2001, which is not the midpoint of the starting and end learning points identified from the two methods, to ensure that the effects of learning are separated as early as possible in the returns time series so that the sophisticated learning point can be estimated within a larger window. For the second break point, we consider the earliest point in time found by both the applied methods (across the two portfolios), as this point essentially identifies the first instance of sophisticated learning and the governance–returns' negative association in our sample. Confirmatory tests using the Bai and Perron (1998) and Hatemi-J (2008) estimations—with the slightly modified specifications of Equation (5) that allow for multiple breaks—show that the second structural break is close to that in our previous analysis.

Figure II confirms our two structural break hypothesis by showing that there are indeed three distinct phases in the evolution of average 36-month future abnormal returns: (a) a monotonically increasing trend, (b) an almost flat trend, and (c) a decreasing trend. The dotted vertical lines superimposed on this figure are the two structural break points. As expected, these appear a few months after the trend shifts, since the plots represent future returns. Along with the value- and equal-weighted governance hedge portfolios, we additionally plot the industry-adjusted value- and equal-weighted returns by adjusting each stock's returns using the 48-industry mean of Fama and French (1997) classification. This helps us alleviate concerns about industry clustering driving the governance–returns relationship, as expressed by Johnson et al. (2009) and Giroud and Mueller (2011). While the industry adjustment does drastically suppress the excess returns for the equal- and value-weighted portfolios during the association and dissociation years, the sophisticated learning trend is consistent across all the portfolios. This suggests that the sophisticated learning hypothesis is in some ways robust to industry clustering and product market competition.

Panel B of Table III reports the two variations of Equation (5) that assess the changes in abnormal returns for the three time periods separated by the two aforementioned structural break points: 1990–2000, 2001–2007, and 2008–2016. In the first model, we consider 2001–2007 (or the dissociation years) to be the benchmark and include two structural break (SB) dummies: one indicating the pre-dissociation period and the other representing the negative association years. In the second model, we again consider 2001–2007 to be the reference period, but include a single structural break variable coded -1 for the pre-dissociation years and +1 for the post-

Figure II: Returns from Governance Trading Strategies

This figure shows the plots of the cumulative excess returns generated from a long good governance/ short bad governance hedge portfolio using the E-Index. For each month, future 36-month average abnormal returns are computed using rolling five-factor regressions that account for the three Fama and French (1993) factors, namely, market, size, and book-to-market, along with the Fama-French momentum factor and Pástor and Stambaugh (2003) liquidity factor. These monthly abnormal returns are then compounded over the months beginning September 1990 and ending December 2016. The previous month market capitalization-weighted or value-weighted (VW), and the equal-weighted (EW) portfolios are both considered. Additionally, to account for product market competition, industry-adjusted returns (IA) using the 48-industry classification of Fama and French (1997) are shown. The vertical dotted lines on the plot represent the two identified structural break points.



dissociation period. While both these estimations provide the different abnormal returns for the governance-based strategies over and above the zero alpha during the dissociation years, the first variant breaks them down into two components and the second one measures the average excess alphas during the two association periods (i.e., both pre- and post-dissociation).

Using the two structural break variables, we find that the E-Index-based value-weighted (equal-weighted) hedge portfolio alphas are statistically significant, producing +78 (+67) basis points and almost -2% (-1%) monthly risk-adjusted returns in the pre- and post-dissociation periods, respectively. Expectedly, the reference period alpha is statistically insignificant, confirming the dissociation between governance and returns. The negative abnormal returns for our governance hedge point out the reversal of the long/short positions (i.e., long Dictatorship and short Democracy) to generate zero-investment gains in the post-dissociation years. The second estimation in Panel B of Table III, with one structural break variable, shows the net association effect across the two governance–returns association periods. For the value-weighted (equal-weighted) portfolio, this is 147 (74) basis points, statistically significant at 1%. Even when we use alternative asset pricing models instead of the five factors shown in Equation (5), the coefficients retain their statistical and economic significance (see Appendix C).

4. Sophisticated learning and the appearance of a negative governance–returns association: The experiment

The first structural break point can be explained either through the learning hypothesis (Bebchuk et al., 2013) or using the available investment and divestiture options across governance structures (Li and Li, 2016). However, we need to provide more insights on the second break point. This could be done by simply regressing the various outcomes or determinants of corporate governance on the governance measure (in our case, the E-Index) itself, and then comparing the coefficients around the second structural break point to determine if systematic differences exist (Bebchuk et al., 2013; Li and Li, 2016). However, simple regression estimates are affected by endogeneity whenever measures of governance are studied (Wintoki et al., 2012). Thus, we employ a cleaner identification using a natural experiment to test the sophisticated learning hypothesis and draw causal inferences for this explanation.

4.1. Identification strategy

Our identification strategy exploits the change in ISS's data collection and reporting methodology in 2007. Although IRRC (the governance data provider) was taken over by ISS in 2005, its methodology was not immediately affected. Subsequently, with ISS introducing new specifications for collecting the data on takeover defenses, which required annual reviews of firms' charters and bylaws, a newer methodology was adopted in 2007. Thus, we proxy for sophisticated learning using the change in ISS's data reporting frequency, which is a source of exogenous variation in the governance information available to institutional investors. With respect to stock returns, this shock allows us to further strengthen the validity of our inferences using a long-run event study for both control and treatment groups. The main underlying assumptions are that investors are not aware which firms' governance data will be reported for 2007 and do not plan their governance-based investment strategies in advance. It may be argued that if some institutional investors do actively seek governance information to plan their trading strategies, they may obtain such information on their own—even before it is provided by ISS. If this is indeed true, then these investors will trade on governance information beforehand, thereby eliminating any potential gains from the informational advantage that ISS's new data reporting methodology provides. In other words, the attenuation accompanying such pre-shock trading makes it harder for us to observe the sophisticated learning effect (because of relatively conservative estimates), thus enhancing our identification.

We consider the group of firms whose governance data were reported in 2006 and updated in 2007 to be the group with which institutional investors can experience superior learning through a faster information turnaround. As mentioned earlier, we call this the Fast group, which represents treatment firms. By contrast, firms covered by ISS in 2006 but not reported in 2007 are allocated to the Slow group. In our setting, the Slow group thus includes control firms that induce comparatively slower or no sophisticated learning, as their reporting frequency and accompanying investment strategy are similar to those employed with past ISS (or, IRRC) publications (i.e., portfolios being reset every two to three years). Since most firms covered by ISS in 2006 are updated with the 2007 information, we find that the treatment group (2,086) is much larger than the control group (395).[15] When we look at the number of firms in extreme portfolios (i.e., *Democracy* with E-Index = 0 and *Dictatorship* with E-Index = 5 | 6) for each group, the trend remains the same (i.e., 399 firms in the treatment group and 55 in the control group). Importantly, we also ensure that the ISS coverage in 2007 is independent of firm-specific attributes such as size, profitability, and age by using propensity score matching.

To assess if and how institutional investors adjust their investment portfolios based on governance structures, we focus on short- and long-term institutional ownership during the experimental window (2006 to 2009). Overall, institutional ownership has increased on average over the years. However, since our experimental setting centers on a shock to the governance information flow, we seek to identify how short- and long-term institutional investors across the treatment and control groups react differently to changes in the frequency and quality of governance reporting. Short-term investors tend to seek mispriced stocks (Derrien et al.,

[15]The governance index scores change little over time. Within the treatment group, only 505 firms (i.e., 25% of the sample) E-Index scores change in the treatment period from 2006 to 2007. This proportion is slightly higher than the past governance updates from ISS (approximately 21% of firms E-Index scores changed in the governance datasets of 2004 and 2006). However, it is still much smaller than the proportion of changes observed for 2010 (51%) and 2015 (74%).

2013). Thus, we expect these investors to aggressively invest in poor governance stocks to maximize their short-term gains after the second break point. On the contrary, long-term investors actively intervene in their portfolio firms (McCahery et al., 2016). Hence, they will prefer to exit poor governance firms and stay invested in good governance ones to maximize their long-term performance after the same point.[16] To capture this different behavior for each group of institutional investors across the treatment and control firms, we segregate the four-year experimental window into pre- and post-learning periods of two years each. We then estimate the overall treatment effect on short- and long-term institutional ownership (termed SIO and LIO, respectively) using triple difference (DDD) analysis.

With respect to abnormal returns, the time window chosen for our experiment lasts from January 2006 (when the *last* old IRRC methodology-based governance data were published) to December 2008 (which covers the end date of possible investment strategy using the *first* set of new ISS methodology-based governance data). Since our identification strategy for returns focuses on governance-based hedge portfolios over this three-year window, while assuming a persistent investment strategy using the available governance data, we employ the calendar-time portfolio approach to obtain the risk-adjusted abnormal returns. This approach follows a similar rationale to the long-run method in Section 3, but with the event window shortened to three years instead of 26 years. We find that, on average, Democracy stocks underperform Dictatorship stocks in terms of raw returns. This difference is more pronounced in the Fast group than in the Slow group, suggesting that learning investors benefit from the faster reporting of governance data. This variation in returns, in tandem with the long-run event study used to obtain abnormal returns for the governance hedge portfolios in each group, lays the basis for us to identify the causal estimates for governance-based sophisticated learning on stock returns. While testing for differences in raw returns or abnormal returns for governance portfolios across the treatment and control groups can identify the effect of reporting frequency and better information quality on stock returns, it does not provide any insights into the second structural break. Our sophisticated learning hypothesis predicts that investors only learn to appreciate

[16] It is important to note that our classification of short- and long-term investors applies three-year investment horizon (see Section 2.3), whereas subsequent tests on abnormal returns consider monthly returns for portfolios that are rebalanced annually. However, as the investor classification considers a continuum of proportions of long-term shares held (i.e., 0 to 1), both sets of investors, in principle, can invest in the governance-hedge that we use to assess abnormal returns.

the governance risk of high E-Index firms after the second structural break point (i.e., January 2008). Hence, to capture the sophisticated learning effect, we divide the 36-month period into a 24-month pre-learning period and 12-month post-learning period. With this, we thus have the ideal backdrop for a difference-in-differences (DiD) design that captures both the time trend (i.e., before vs. after) and the treatment effect in the interaction term.

4.1.1. Estimation models

In line with the arguments presented above, our natural experiment of the change in ISS's data collection methodology and how investors react to this shock to governance information availability is modeled using either DDD (for institutional ownership) or DiD (for abnormal returns) pooled regressions.

To subdivide the sample into good and poor governance firms, we employ the dummy variable EI indicating the above- and below-median E-Indices for each year t. Two additional dummy variables, $SB2$ and $Treat$, represent the post-learning period (2008 onward) and treatment firms, respectively. The institutional ownership variable IO is either SIO or LIO depending on the investment horizon:

$$\begin{aligned} IO_{j,t} = A_0 + B_{0,1} * EI_{j,t} + B_{0,2} * SB2_{j,t} + B_{0,3} * Treat_{j,t} + B_{0,4} * EI_{j,t} * SB2_{j,t} \\ + B_{0,5} * EI_{j,t} * Treat_{j,t} + B_{0,6} * SB2_{j,t} * Treat_{j,t} \\ + B_{0,7} * EI_{j,t} * SB2_{j,t} * Treat_{j,t} + C_0 * X_{j,t} + \epsilon_{j,t}. \end{aligned} \tag{6}$$

We aim to identify how SIO and LIO react to changes in EI for treatment firms compared with control firms after the second structural break. Accordingly, the interaction of EI with $SB2$ and $Treat$ gives us the DDD coefficient of interest (i.e., $B_{0,7}$). The controls $X_{j,t}$ include size (market capitalization), age, leverage, return on assets, Tobin's Q, dividend yield, share price, monthly turnover, past returns, and volatility following Yan and Zhang (2007) and Chung and Zhang (2011).

For abnormal returns, the DiD design has the following specification with observations for each month:

$$R_{J,t} = \alpha + \pi_1 SB2_t + \pi_2 Treat_J + \pi_3 SB2_t * Treat_J + \gamma F_t + \varepsilon_t, \tag{7}$$

where $R_{J,t}$ denotes the hedge portfolio returns for a certain group J of firms in month t, $SB2$

indicates the period after the second break point or the months following sophisticated learning, and $Treat$ is a dummy indicating if portfolio J is composed of firms from the Fast (treatment) or Slow (control) group. Our main coefficient for this model is thus π_3, which shows the DiD interaction effect, namely, the effect on the abnormal returns of the treated portfolio due to sophisticated learning. As in Equation (5), we control for some of the common risk factors that can explain the time series of a market or passive portfolio returns. Similar to Section 3.1, we include the market, size, book-to-market, momentum, and liquidity factors for F_t in this model.[17]

4.1.2. Internal validity

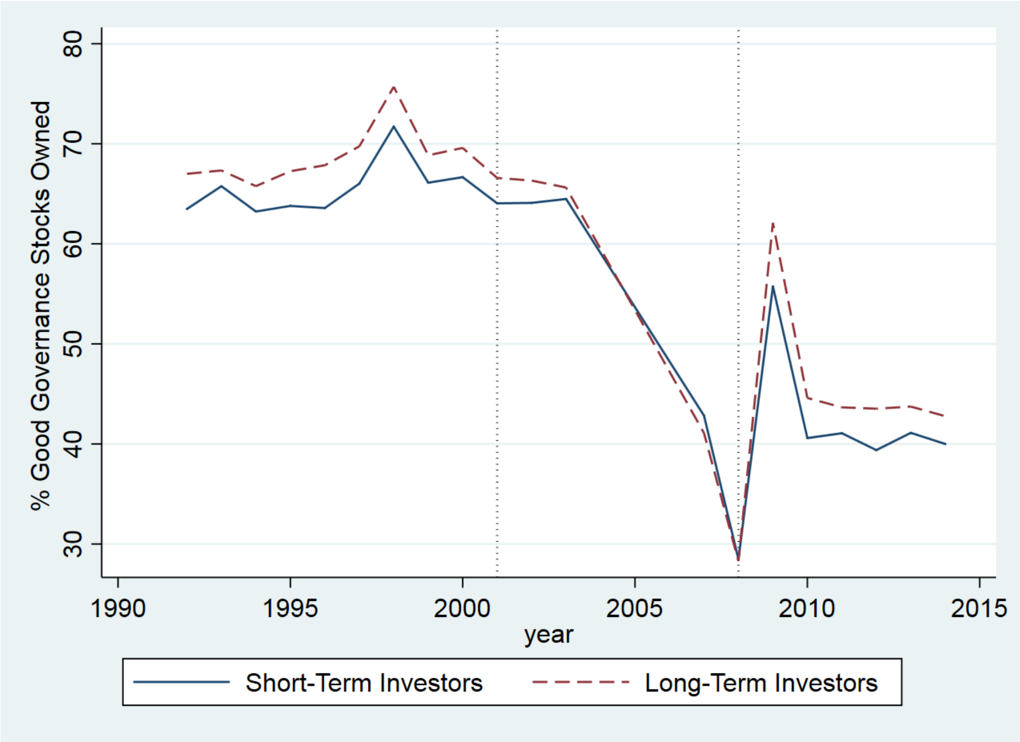
There are two potential threats to the internal validity of our experimental inferences. First, as mentioned earlier, the control group is smaller than the treatment group (especially when abnormal returns are considered using extreme portfolios) and selection biases, which confound the outcomes of an experiment when treatment and control firms have significantly different characteristics, may also drive our results. For example, if size is such a factor, larger firms may be more likely to be covered by ISS's governance publications (becoming treatment firms), and in turn these firms may also have exaggerated influences from governance structures than smaller control firms. For abnormal returns, we account for the numerical differences in the two groups by increasing the number of firms in the control group using a median E-Index-based classification of Democracy and Dictatorship firms.[18] For both institutional ownership and abnormal returns, we also tackle selection concerns using a propensity-score-matched treatment group that identifies comparable firms for each control group firm matched on size (log of total assets), profitability (return on assets), and leverage (debt to assets). Second, sophisticated learning may not be unique to the second structural break. In other words, similar sophisticated learning trends may exist in other periods. We conduct placebo DDD and DiD tests to verify that this is not the case by first identifying similar ISS reporting frequency-centric control and treatment groups in another period and then running a pre-post analysis across alternative placebo break points.

[17]Other asset pricing models are again used for the robustness checks.

[18]Using such broad criteria, Democracy firms are redefined as $E - Index \leq 3$ and Dictatorship firms as those with $E - Index > 3$. This results in an almost equal number of firms in both the Fast and the Slow groups.

Figure III: Institutional Investors and the Two Structural Breaks

This figure shows the plots of the proportion of good governance stocks held by short- and long-term institutional investors. All the sample firms were grouped into good and poor governance stocks around the median E-Index for each year. For each institutional investor, the proportion of good governance stocks in its portfolio is then computed as the total good governance stock value divided by the total portfolio value at the end of each year. Finally, the cross-investor value-weighted mean proportions are computed for each of the two investor types. The two structural break points are represented using vertical dotted lines.

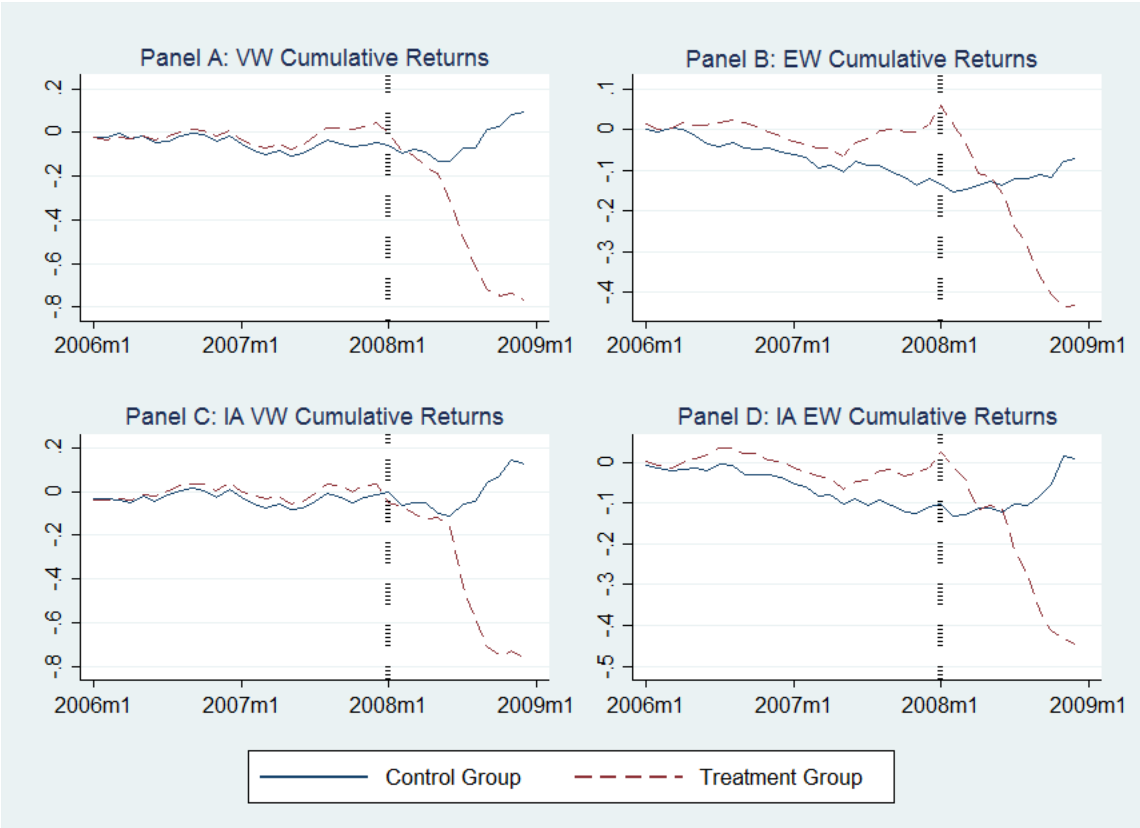


4.2. Preliminary evidence

When the corporate governance provision data became available to institutional investors annually from 2007 onward, how did they adjust their investments to the more timely dissemination of governance signals than before 2007? The sophisticated learning hypothesis predicts that institutional investors' learning experience is higher when governance information is disseminated to them at a faster pace (in our setting, annual basis) than the older IRRC reporting practices (biennial or triennial). Owing to such learning, institutional investors (both short- and long-term ones) would have readjusted their investment portfolios to benefit from the subsequent informational advantage. As shown by Yan and Zhang (2007), we expect this informational advantage to be better exploited by short-term investors. For abnormal returns, we expect investors who only rely on the newer information to have an informational advantage, leading to more premium-seeking behavior for governance risks than those who continued to use older information.

Figure IV: Returns from Governance Trading Strategies Around the Second Structural Break

This figure shows the plots of the cumulative returns generated for control (Slow) and treatment (Fast) firms using various long good governance/ short bad governance hedge portfolios constructed with the E-Index. For each month, we compute compounded hedge portfolio returns from January 2006 (the first month of our DiD period). Both value-weighted (VW)and equal-weighted (EW) portfolios are shown. Additionally, industry-adjusted returns (IA) using the Fama and French (1997) 48-industry classification are shown to control for product market competition and industry clustering. The vertical dotted lines on the plots represent the critical sophisticated learning point (i.e., January 2008).



To show the differences in preferences for governance structures between short- and long-term institutional investors, Figure III compares the cross-investor average proportion of good governance stocks held by each investor type for each year in our sample period. We divide firms into good and poor governance stocks by considering the median E-Index cutoff for each year. The plots indicate a general trend of long-term investors preferring more good governance stocks than short-term ones. While the average preferences for both investor types overlap between the two structural breaks, the difference reappears after the second structural break. Interestingly, while both short- and long-term investors had the majority of their investment in good governance stocks before the first structural break, they both show much lower average propensities for the good governance stocks after the second structural break. Between the two breaks, there is a sharp decline in the institutional ownership of good governance stocks, seemingly driven by two factors. First, learning-induced rebalancing makes good governance stocks less attractive to investors. Accordingly, investors' choices are independent of the governance characteristic (50%) around 2006. Second, a further decline accompanies the increased investor prudence during the crisis years (see Section 1).

Figure IV, meanwhile, compares the raw cumulative returns, using various long good governance/short bad governance portfolios, between control (Slow) and treatment (Fast) firms. Panels A and B show the value-weighted and equal-weighted E-Index governance hedge portfolios, respectively, whereas Panels C and D show the same by adjusting each firm's returns using the Fama-French 48-industry means to control for product market competition and industry clustering. Across all four plots, whereas cumulative hedge portfolio returns from the control group remain almost flat and close to zero, those from the treatment group drop after the sophisticated learning point (marked by the dotted vertical line in the figure). Indeed, for some of the portfolio constructions, the trend between the two groups is directionally opposite, with the governance hedge portfolios of control firms showing positive and increasing returns. These plots support the validity of our experimental setting.

Despite the preliminary evidence presented in Figures III and IV, there is a need to statistically examine the sophisticated learning phenomenon for the experimental period. Thus, we next employ Equations (6) and (7) to study the changes around the second structural break point while eliminating possible biases from extraneous confounders.

4.3. Institutional ownership

Table IV shows the results for the DDD estimations using firms' institutional ownership classified into short and long term based on their investment horizons (Panels A and B use three- and two-year turnover periods, respectively). All the DDD estimations use the E-Index dummy (EI) coded 1 when the E-Index score for a firm is greater than or equal to the cross-sectional median scores in that year and 0 otherwise.[19] The baseline results show that while short-term institutional investors increase their ownership (SIO) of poor governance stocks on average after the second structural break point, the long-term institutional ownership (LIO) of

[19]The statistical significance of the DDD terms remains the same when the true E-Index scores are used in place of the E-Index dummy. However, we prefer to report the results for EI in Table IV to allow us to interpret and compare good and bad governance firms.

poor governance stocks decreases after the same point. This is reflected by the coefficients of the DDD terms, which are statistically significant for both SIO and LIO, but in the opposite directions.

Next, we ensure equivalent control and treatment firms using nearest neighbor propensity score matching with a 0.001 caliper. Firms in the control group are matched based on size of assets, operating performance (i.e., return on assets), and leverage to obtain a comparable treatment firm. Panel A in Table V summarizes the key characteristics for each group before and after the matching. The three firm characteristics used sufficiently balance the treatment and control groups, even across the additional dimensions, as shown in Table V.[20] The economic and statistical significance of the matched DDD estimators remains the same as in the baseline estimations.

We additionally test the validity of our experiment using placebo sophisticated learning points, as shown in Table IV. We first locate similar treatment and control firms at a different point in time (in this case, taking the 1998–2001 period instead of 2006–2009). While the IRRC report for 1995 lasted three years, the IRRC governance report in 1998 was applicable for two years. We thus consider firms with information updated in 2000 to be the placebo treatment and those without such new information to be the placebo control. Both the DDD terms for SIO and LIO are statistically insignificant for this test (placebo DDD 1). Lastly, we check if a similar sophisticated learning effect is visible across the first structural break by including 2001 as the learning year within the same experimental setting as placebo DDD 1. For this test (placebo DDD 2), there is again no significant changes for SIO, whereas LIO has a DDD coefficient with the opposite sign to that in the baseline DDD. However, the positive influence of the E-Index on LIO has to be interpreted with caution, as the application of placebo learning in 2001 affixes the E-Index for four consecutive years (1998 to 2001) for control firms.

Overall, the results in Table IV support the existence of the sophisticated learning effect through the informational advantages that accompany faster information dissemination. Our results indicate a preference for poor governance stocks among short-term investors after 2008. Meanwhile, long-term investors prefer to exit poor governance stocks after the same year. This

[20]Only the E-Index means are different between the two groups. The mean value is higher for the treatment group than the control group, which shows that increased anti-takeover provisions within firms did not necessarily prevent these firms from making such information available to ISS. Additionally, the median E-Index across both these groups is the same.

Table IV: Does Sophisticated Learning Affect the Institutional Ownership?

This table reports the triple difference (DDD) estimation results for short- and long-term institutional ownership (shown as SIO and LIO respectively) for the experimental period 2006 to 2009. Panels A and B show the results for both SIO and LIO with the institutional ownerships categorized using three- and two-year portfolio horizons respectively. All models are estimated using Equation (6) controlling for size (log of market capitalization), age (in logs), leverage, return on assets (ROA), Tobin's Q, dividend yield, share price, monthly turnover, past returns (in logs) and volatility. See Appendix A for further details on control variables. Robust standard errors, clustered by firms, are shown in parentheses. Structural Break Dummy (SB2) represents the post-dissociation years in the baseline and propensity score (PS) matched DDD models. Placebo DDD 1 employs the year 2000 as a dummy structural break and placebo DDD 2 applies the first structural break year 2001. PS matched DDD employs nearest-neighbor logit using a 0.001 calliper to match one treatment firm for each control firm in each of the years in our experimental period. Significance levels for 10%, 5%, and 1% are shown using *,**, and *** respectively.

Panel A: Investor horizons defined using past three year portfolio turnover

	Baseline DDD		PS Matched DDD		Placebo DDD 1		Placebo DDD 2	
	SIO	LIO	SIO	LIO	SIO	LIO	SIO	LIO
EI	0.2520	0.7722	0.2763	0.8537	-0.0094	0.0101	0.0034	0.0428**
	(0.250)	(0.779)	(0.278)	(0.866)	(0.013)	(0.025)	(0.010)	(0.020)
$SB2$	0.0196	-0.1016**	0.0109	-0.1193**	-0.0009	-0.0227	-0.0175	-0.0155
	(0.016)	(0.047)	(0.020)	(0.059)	(0.007)	(0.015)	(0.012)	(0.031)
$Treat$	0.0031	-0.0262	0.0168	0.0318	-0.0068	-0.0101	-0.0053	-0.0084
	(0.013)	(0.038)	(0.028)	(0.086)	(0.006)	(0.012)	(0.004)	(0.008)
$EI * SB2$	0.0488***	-0.0665***	0.0458***	-0.0696**	0.0097	0.0449	-0.0031	0.0220
	(0.009)	(0.021)	(0.011)	(0.028)	(0.013)	(0.031)	(0.031)	(0.047)
$EI * Treat$	0.0131	0.0167	0.0168	0.0316	0.0038	0.0246*	0.0056	0.0301**
	(0.010)	(0.026)	(0.018)	(0.052)	(0.007)	(0.014)	(0.006)	(0.012)
$SB2 * Treat$	0.0214*	-0.1202***	0.0327***	-0.0921***	-0.0009	-0.0164	-0.0038	0.0415***
	(0.013)	(0.035)	(0.011)	(0.030)	(0.006)	(0.013)	(0.004)	(0.009)
$\boldsymbol{EI * SB2 * Treat}$	**0.0369*** **	**-0.0813** **	**0.0395*** **	**-0.0701** **	**0.0094**	**0.0201**	**0.0055**	**0.0618** **
	(0.012)	**(0.034)**	**(0.011)**	**(0.029)**	**(0.008)**	**(0.016)**	**(0.006)**	**(0.013)**
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3480	3480	2685	2685	2549	2549	2596	2596
R-squared	0.010	0.010	0.012	0.012	0.159	0.283	0.159	0.309

Panel B: Investor horizons defined using past two years portfolio turnover

	Baseline DDD		PS Matched DDD		Placebo DDD 1		Placebo DDD 2	
	SIO	LIO	SIO	LIO	SIO	LIO	SIO	LIO
EI	0.1843	0.5228	0.2017	0.5733	-0.0132	0.0139	0.0014	0.0478**
	(0.165)	(0.519)	(0.182)	(0.572)	(0.009)	(0.025)	(0.007)	(0.020)
$SB2$	0.0512***	-0.1003**	0.0451**	-0.1193*	-0.0077	-0.0213	-0.0224***	-0.0014
	(0.016)	(0.050)	(0.020)	(0.063)	(0.006)	(0.016)	(0.008)	(0.032)
$Treat$	0.0101*	-0.0140	0.0155	0.0158	-0.0090*	-0.0014	-0.0028	-0.0055
	(0.006)	(0.018)	(0.012)	(0.036)	(0.005)	(0.013)	(0.003)	(0.009)
$EI * SB2$	0.0701***	-0.0665***	0.0677***	-0.0770**	-0.0009	0.0551*	0.0041	0.0261
	(0.009)	(0.025)	(0.011)	(0.032)	(0.010)	(0.032)	(0.036)	(0.061)
$EI * Treat$	0.0204***	0.0090	0.0253**	0.0211	-0.0001	0.0356**	0.0062	0.0368***
	(0.006)	(0.017)	(0.011)	(0.032)	(0.005)	(0.016)	(0.004)	(0.013)
$SB2 * Treat$	0.0494***	-0.1149***	0.0587***	-0.0972***	-0.0068	-0.0152	-0.0050	0.0528***
	(0.011)	(0.035)	(0.010)	(0.028)	(0.005)	(0.014)	(0.003)	(0.009)
$\boldsymbol{EI * SB2 * Treat}$	**0.0612*** **	**-0.0722** **	**0.0635*** **	**-0.0708** **	**0.0007**	**0.0270**	**0.0027**	**0.0732** **
	(0.012)	**(0.036)**	**(0.011)**	**(0.033)**	**(0.006)**	**(0.017)**	**(0.004)**	**(0.013)**
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4561	4561	3584	3584	2549	2549	2596	2596
R-squared	0.008	0.008	0.010	0.009	0.173	0.280	0.174	0.307

Table V: Summary Statistics for Unmatched and Matched Samples

This table reports the averages of important firm characteristics for the treatment and control group firms along with the differences in their means. For definitions of each of these characteristics, see Appendix A. Panel A considers the full E-Index sample employed for short- and long-term institutional ownerships, whereas Panel B includes only the sub-sample consisting of Democracy and Dictatorship firms used for assessing the abnormal returns. The propensity score and matching employs log of assets, return on assets (ROA) and leverage (LEV). For the mean differences, significance levels at 10%, 5%, and 1% are represented using *,**, and *** respectively.

Panel A: Full E-Index Sample (2006–2009)

	Unmatched			Matched		
	Control	Treatment	Difference	Control	Treatment	Difference
ln(assets)	6.979	7.865	-0.886***	7.295	7.308	-0.013
ROA	0.053	0.116	-0.064***	0.099	0.097	0.002
LEV	0.227	0.185	0.043***	0.211	0.222	-0.011
Tobin's Q	2.096	2.115	-0.019	1.984	2.023	-0.039
CAPEX/TA	-3.681	-3.65	-0.031	-3.576	-3.631	0.056
R&D/TA	0.742	0.093	0.649***	0.052	0.055	-0.003
Annual Returns	-0.081	-0.044	-0.037**	-0.062	-0.061	-0.001
Propensity Score	0.744	0.824	-0.080***	0.786	0.786	0.001
E-Index	1.938	2.784	-0.846***	1.906	2.758	-0.851***

Panel B: Democracy & Dictatorship Sample (2006–2008)

	Unmatched			Matched		
	Control	Treatment	Difference	Control	Treatment	Difference
ln(assets)	7.338	8.22	-0.882***	7.361	7.629	-0.268
ROA	0.099	0.115	-0.016	0.101	0.094	0.007
LEV	0.221	0.193	0.027	0.201	0.196	0.005
Tobin's Q	1.889	1.956	-0.068	1.901	1.889	0.012
CAPEX/TA	-3.564	-3.641	0.077	-3.546	-3.678	0.132
R&D/TA	0.027	0.031	-0.004	0.025	0.039	-0.014
Annual Returns	-0.02	-0.102	0.082	-0.028	-0.104	0.076
Propensity Score	0.787	0.836	-0.049***	0.792	0.802	-0.01
E-Index	0.407	4.064	-3.656***	0.423	4.215	-3.792***

finding is consistent across the two short- and long-term institutional investor classifications.[21]

4.4. Abnormal returns

Table VI shows the main results of our DiD estimation for abnormal returns. To test the validity of our experiment, we first run Model 1, which estimates only π_1 and π_2; that is, it ignores the interaction term in Equation (7). Panel A shows that the treatment group-based portfolio generates significantly different abnormal returns than the control group one on average for both the equal-weighted and the value-weighted portfolios. Additionally, there is a statistically significant change in returns across the second structural break for both these portfolios. In Model 2 with the DiD term included, the estimation results strongly support the existence of the sophisticated learning phenomenon, as only the interaction term remains statistically significant.

In Panel B of Table VI, we correct for the differences in the number of firms in the Democracy and Dictatorship portfolios between the treatment and control groups by expanding the portfolio classification for control group firms using the median E-Index. The results, especially when it comes to the DiD term, remain largely the same in terms of both the magnitude and the statistical significance of the coefficient. Next, in Panel C, we ensure equivalent control and treatment firms in each portfolio using nearest neighbor propensity score matching with a 0.001 caliper. As was the case for institutional ownership, the matched groups are equivalent for extreme portfolio firms as well (see Panel B in Table V). The economic and statistical significance of the matched DiD estimator is similar to the baseline DiD estimate.

Table VII reports additional robustness tests for the main results of the DiD estimation shown in Table VI. While the results in Panels B and C of Table VI strengthen the validity of our results by increasing the power (Panel B: increased control group) and eliminating selection bias (Panel C: propensity matching with the control group), we do not have a case of high power and low selection bias together. In Panel A of Table VII, we combine the wider median-based portfolios with propensity score matching to overcome this. Once again, the results support the sophisticated learning hypothesis, especially for the value-weighted portfolios. The loss of significance for the equal-weighted portfolio may be driven by some of the matched

[21] In an unreported analysis, we also apply the classification of short- and long-term investors proposed by Yan and Zhang (2007) using the portfolio turnover in the last four quarters and obtain similar results to those reported in Table IV.

Table VI: Does Sophisticated Learning Drive the Negative Governance–Returns Association?

This table reports the Difference-in-Differences (DiD) estimation results for average main effects (Model 1) and average treatment effects (Model 2) using various governance-based hedge portfolios excess returns. All models are estimated using Equation (7) controlling for market, size, book-to-market, momentum and liquidity factors. Robust standard errors are shown in parentheses. Structural Break (SB2) Dummy represents the post-dissociation year 2008. Treat is a dummy representing Fast group as defined in Section 4.1.1. Baseline estimation in Panel A considers extreme portfolios in the Fast (treatment) and Slow (control) groups by hedging long Democracy (E-Index=0) short Dictatorship (E-Index=5|6). Panel B augments the results of Panel A by ensuring larger control group whereby the two extreme portfolios are redefined around the median E-Index=3 (included in the Dictatorship portfolio). To correct for the possible selection bias, Panel C employs nearest-neighbor logit propensity score (PS) matching using a 0.001 calliper to match one treatment firm for each control firm. Here, hedge portfolios are defined as in Panel A. Lastly, Panel D employs the PS matched sample while using the hedge portfolios defined around the median E-Index as in Panel B, but for both control and treatment groups. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: Baseline Difference-in-Differences (DiD) estimation

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0426***	-0.0183*	0.0211	0.0100
	(0.015)	(0.010)	(0.018)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0058
	(0.013)	(0.006)	(0.007)	(0.004)
$\boldsymbol{SB2 * Treat}$			**-0.1275***	**-0.0566***
			(0.030)	**(0.013)**
Observations	72	72	72	72
R-squared	0.25	0.15	0.49	0.40

Panel B: DiD estimation with median-based control group portfolios

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0283*	-0.0212**	0.0495***	0.0068
	(0.016)	(0.010)	(0.017)	(0.010)
$Treat$	-0.0400***	-0.0183***	0.0119*	0.0004
	(0.014)	(0.006)	(0.008)	(0.004)
$\boldsymbol{SB2 * Treat}$			**-0.1555***	**-0.0560***
			(0.028)	**(0.016)**
Observations	72	72	72	72
R-squared	0.22	0.16	0.56	0.37

Panel C: DiD estimation with propensity score (PS) matched treatment group

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0353	-0.0029	0.0514***	0.0225
	(0.023)	(0.018)	(0.018)	(0.022)
$Treat$	-0.0359**	0.0075	0.0219	0.0244
	(0.017)	(0.014)	(0.014)	(0.016)
$\boldsymbol{SB2 * Treat}$			**-0.1734***	**-0.0507***
			(0.035)	**(0.030)**
Observations	72	72	72	72
R-squared	0.15	0.08	0.43	0.11

characteristics explaining the variations in returns. The magnitudes of the coefficients are also smaller, indicating that this is a much sterner test of our experiment because the difference between Democracy and Dictatorship firms is much smaller with the median-based division.

We carry out additional validity tests in our experimental setting by running placebo DiD estimations (see Panels B and C of Table VII). Panel B considers a three-year timeframe as in all the previous DiD estimations, considering arbitrary sophisticated learning in 2000 within an estimation period from 1998 to 2000. Panel C, on the contrary, includes the returns for 2001 (the learning structural break year) to assess whether a similar sophisticated learning effect exists, albeit with a possible reversal of direction. Across both placebo test specifications, the DiD terms are insignificant, providing further credence to our main result that sophisticated learning from governance information was experienced only in 2008.

We run a supplementary analysis to test whether a combined governance and information timeliness (double-sorted) hedge portfolio could generate abnormal returns, and obtain results supportive of a possible premium (see Appendix B for the details). Lastly, we also confirm that our results are not driven by the applied five-factor asset pricing model using other alternative models. The coefficients of the sophisticated learning effect remain stable across all these models (see Appendix C).

5. Sophisticated learning channels

After identifying that sophisticated learning does drive the negative association between governance and returns, we investigate the possible channels of information flow through which investors learn to recognize governance risk. We look at two broad channels.

First, we employ the price informativeness measure of Bai et al. (2016) that captures the ability of stock prices to predict future earnings. Under the sophisticated learning hypothesis, investors realize the inherent governance risk of bad governance firms compared with good governance ones. Thus, the focus of this earnings expectation or price channel is on information asymmetry between the firm and its investors. Such asymmetry would expectedly be larger for poor governance firms with more anti-takeover provisions (or higher managerial entrenchment). In other words, we expect the price informativeness of good governance stocks to be greater than that of poor governance stocks and this difference to be driven by the decreasing price informativeness of poor governance firms after the second structural break point. To compare

Table VII: Robustness for Sophisticated Learning and Negative Governance–Returns Association

This table reports the robustness tests for the main Difference-in-Differences (DiD) estimation results shown in Table VI. The average main effects (Model 1) and average treatment effects (Model 2) using various governance-based hedge portfolios excess returns are shown accordingly with robust standard errors given in parentheses. All models are estimated using Equation (7) controlling for market, size, book-to-market, momentum and liquidity factors. Structural Break Dummy represents the post-dissociation year (SB2 or 2008) in Panel A, the placebo year (2000) in Panel B, and the dissociation year (SB1 or 2001) in Panel C. Treat is a dummy representing Fast group as defined in Section 4.1.1. Panel A employs the PS matched sample while using the hedge portfolios defined around the median E-Index as in Table VI Panel B, but for both control and treatment groups. For the placebo tests, i.e. Panels B and C, hedge portfolios are defined exactly as in Table VI Panel A (i.e. with the control group's extreme portfolios divided around the median E-Index=3). The significance levels at 10%, 5%, and 1% are represented using *,**, and *** respectively.

Panel A: DiD estimation with PS matched treatment group using median-based portfolios

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	0.0156**	0.0055	0.0357***	0.0081
	(0.007)	(0.005)	(0.012)	(0.008)
$Treat$	-0.0036	-0.0047	0.0098*	-0.0030
	(0.005)	(0.003)	(0.005)	(0.003)
$\boldsymbol{SB2 * Treat}$			**-0.0402*****	**-0.0052**
			(0.012)	**(0.009)**
Observations	72	72	72	72
R-squared	0.30	0.18	0.43	0.17

Panel B: Placebo DiD estimation

	Model 1		Model 2	
	VW	EW	VW	EW
$PlaceboSB$	-0.0174	0.0123	0.0021	-0.0003
	(0.016)	(0.017)	(0.028)	(0.028)
$Treat$	0.0334*	-0.0058	0.0465**	-0.0142
	(0.017)	(0.015)	(0.022)	(0.016)
$\boldsymbol{PlaceboSB * Treat}$			**-0.0392**	**0.0252**
			(0.035)	**(0.034)**
Observations	72	72	72	72
R-squared	0.10	0.26	0.11	0.26

Panel C: Placebo DiD estimation around first structural break (2001)

	Model 1		Model 2	
	VW	EW	VW	EW
$SB1$	0.0155	0.0018	0.0397	0.0052
	(0.021)	(0.019)	(0.038)	(0.033)
$Treat$	0.0213	-0.0075	0.0334*	-0.0058
	(0.016)	(0.013)	(0.017)	(0.015)
$\boldsymbol{SB1 * Treat}$			**-0.0485**	**-0.0068**
			(0.040)	**(0.032)**
Observations	96	96	96	96
R-squared	0.01	0.13	0.02	0.12

the trends between these firms, we split our sample into good governance and poor governance firms using the median E-Index as the cutoff for each year. We then compute the welfare-based price informativeness measure for each group separately over different expectation horizons. The final empirical testing involves regressing the time series of the price informativeness values (under various investment horizons) for each group separately on the dummies representing the two structural breaks to examine the trends for each group. We additionally run a similar regression using the differences in price informativeness between the two groups as a dependent variable to quantify the differential trend.

While price informativeness does shed light on the information asymmetry trends between good and bad governance firms, it provides no insights into firm-level changes. Thus, we complement the price informativeness tests with additional firm-based information flow measures. Since we are interested in identifying whether within-firm governance changes influence firms' information flow to investors, we employ a fixed effects panel regression to find any systematic differences in the way changes in managerial entrenchment affect the information flow across the two structural breaks.

After assessing the price channel, we seek to identify systematic differences in firms' riskiness based on governance changes across the two structural breaks. The empirical models here apply similar fixed effects regressions as those used for the firm-based information flow measures. We consider two main measures of risk (i.e., idiosyncratic volatility and crash risk) to assess how the E-Index relates to these measures across the two structural break points. In other words, our empirical models aim to establish whether (and if so, in what direction) the E-Index can predict firm-specific risks when the sample is divided into three subsamples around the two structural breaks.

5.1. Estimation models for the two sophisticated learning channels

As mentioned above, we run two complementary tests to assess sophisticated learning through the information-in-price channel. First, we compare the aggregate price informativeness of good governance firms with that of bad governance ones. Second, we focus on the firm-specific information flow measures to reaffirm that sophisticated learning through price is not merely an aggregative process.

We compute aggregate price informativeness (PRI_t) for each year across different horizons (see Section 2.4 for the details) and then run regressions of this price informativeness on two dummy variables representing the pre-dissociation ($SB1$) and post-dissociation years ($SB2$). This means that the 2001–2007 period (or the dissociation years) is captured by the constant term. This model is run separately for the price informativeness of good and bad governance firms:

$$PRI_t = A_1 + B_1(SB1_t) + C_1(SB2_t) + \varepsilon_t. \tag{8}$$

As an alternative specification, we again model 2001–2007 as the reference time period, but include a single SB variable coded -1 for the pre-dissociation years and +1 for the post-dissociation years. In this specification, we include a dummy EI that represents poor governance (above the median E-Index):

$$PRI_t = A_2 + B_2(SB_t) + C_2(EI_t) + C_2(SB_t * EI_t) + \varepsilon_t. \tag{9}$$

For the firm-based information flow measures ($FPRI_{j,t}$), which are either PIN or $TURN$ as defined in Section 2.4, we use the following specification:

$$FPRI_{j,t+1} = A_3 + B_3(E\text{–}Index_{j,t}) + C_3(X_{j,t}) + \varepsilon_{j,t}, \tag{10}$$

where $X_{j,t}$ includes all the standard controls suggested in Ferreira and Laux (2007) and Hutton et al. (2009).[22]

For insights into the risk channel, we use two main measures of firm-specific risk ($FR_{j,t}$) for each firm j in a given year or month t, namely, idiosyncratic volatility (*IDIOSYN*, monthly) and crash risk (*CRASH*, yearly):

$$FR_{j,t+i} = A_4 + B_4(E\text{–}Index_{j,t}) + C_4(X_{j,t}) + \varepsilon_{j,t}. \tag{11}$$

For *IDIOSYN*, the firm-specific controls $X_{j,t}$ are similar to those used for the firm-based information flow measures using inputs from Ferreira and Laux (2007), whereas for *CRASH* we identify the controls from Hutton et al. (2009), An and Zhang (2013), and Kim et al. (2016). For idiosyncratic volatility, we consider 12-month forward values or $i = 12$, whereas for crash risk, $i = 1$. We additionally control for accounting opacity in both these firm risk regressions. With the annual *CRASH* measure, the year fixed effects are also taken to help control for

[22] See Appendix A for the definitions of all these control variables.

unobservable time trends.

5.2. Sophisticated learning through price channel

Figure IV compares the price informativeness of our sample firms grouped into good and poor governance categories using the median E-Index in each year. The two groups follow a similar trend of slightly positive price informativeness with the one-year earnings forecast horizon across all three periods (i.e., association, dissociation, and negative association), which are separated by the vertical dotted lines in this figure. However, for the remaining three horizons, a common pattern emerges between the good and poor governance groups in the post-dissociation period (i.e., 2008–2015). After the second structural break, the price informativeness of good governance stocks largely lies above that of poor governance ones. Additionally, over the longer horizons of three and five years, poor governance stocks tend to show declining price informativeness after 2008. To gain more insights into this trend and the differences between these two groups, we run regressions as per Equations (8) and (9).

In Panel A of Table VIII, we focus on the dummy variable representing the years after the second break point (i.e., $SB2$). While there is no difference in the relative price informativeness of good and poor governance firms over the short horizon, a consistent trend appears for the medium to long horizons. For the two-, three-, and five-year horizons, the price informativeness of poor governance stocks during 2008–2015 decreases, whereas that of good governance ones increases in comparison to the dissociation years. The differential effect (i.e., good – poor PRI) for each of these horizons shows a monotonic increasing trend, implying that the price informativeness of poor governance stocks worsens in terms of future earnings predictability with longer horizons compared with good governance stocks. The results in Panel B confirm our findings in Panel A that much of the change in price informativeness is concentrated after the second structural break point. When we combine the two structural breaks into a single structural break variable, only price informativeness over the three-year horizon picks up the consistent governance-based differential change across the two structural breaks.

To gather more fine-grained insights into the price channel, Table IX reports the firm-based information flow measures (i.e., $TURN$ and PIN) in relation to the E-Index across the two structural breaks. Model 1 uses simple ordinary least squares (OLS) with industry fixed effects and Model 2 controls for firm heterogeneity by including firm fixed effects in a panel

Figure IV: Governance and Price Informativeness

This figure compares the price informativeness of good and poor governance firms grouped by the median E-Index cutoff for each year. For each group, price informativeness (PRI) is separately computed by first using Equation (8) to obtain the information coefficient (tracing $ln(MV/A)$) and then substituting this coefficient into Equation (9) for each year. Each of the subplots represents the different forecasting horizons considered (represented by i in Equation (9)). The same are indicated at the top of each subplot, with the vertical dotted lines representing the two structural break points (i.e., January 2001 and January 2008).

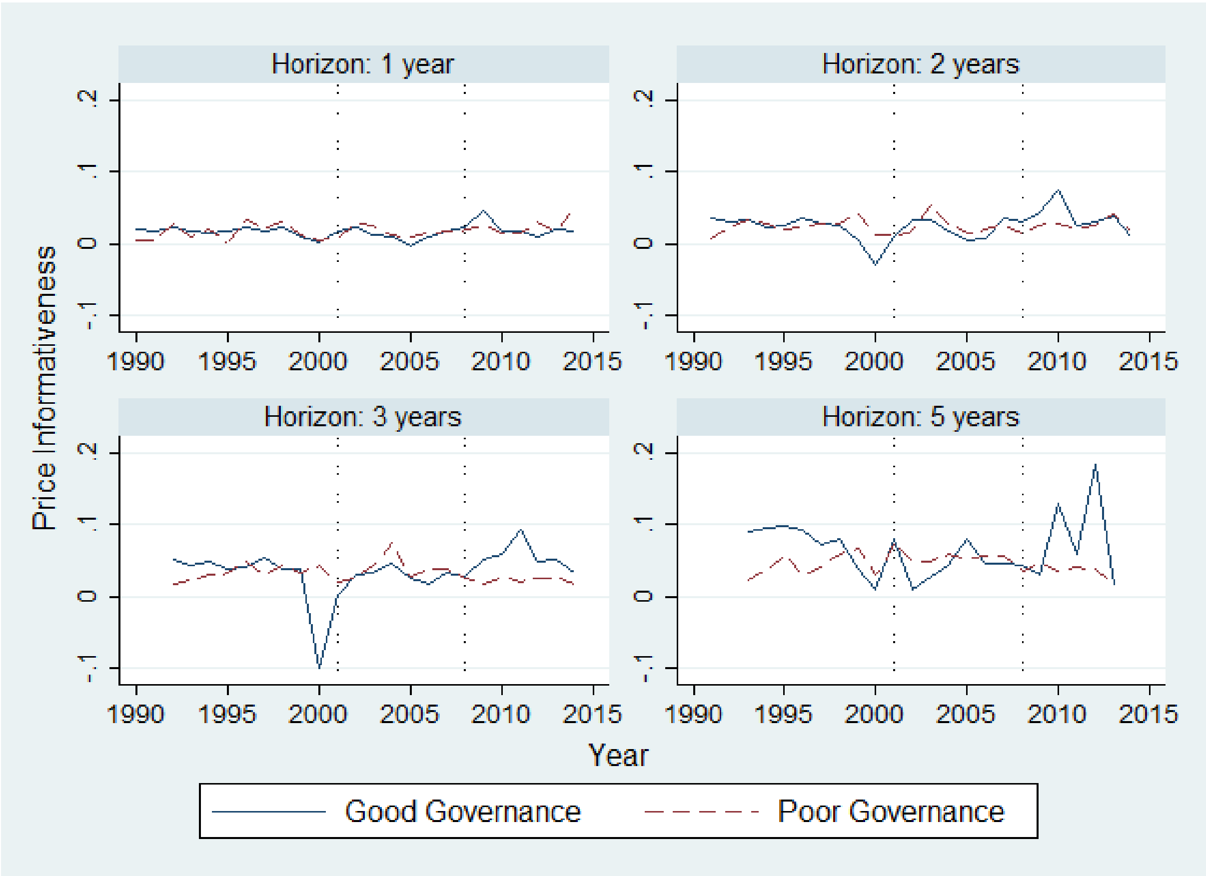


Table VIII: Price Informativeness Across the Two Structural Breaks

This table shows the coefficients and Newey and West (1994) standard errors (in parentheses) with five lags for time series regressions of price informativeness around the two structural breaks. In Panel A, Bai et al. (2016) price informativeness measure is computed separately for good governance and poor governance firms separated by the median E-Index (=3 for years ¡ 2010, and 4 otherwise). Additionally the difference in price informativeness between good and poor governance firms is also taken for each year and regressed over the two structural break (SB) variables each representing the pre-dissociation (1990-2000) and post-dissociation (2008-2015) periods. Panel B considers pooled regressions of price informativeness for good and poor governance firms by applying a single structural break variable that is defined as in Table III. Statistical significance at 10%, 5%, and 1% respectively are denoted by *, **, and ***.

Panel A: Price informativeness and governance using two structural break (SB) variables

Horizon	1 year			2 years			3 Years			5 Years		
	Good	Poor	Good - Poor	Good	Poor	Good - Poor	Good	Poor	Good - Poor	Good	Poor	Good - Poor
Constant (2001 to 2007)	0.0129***	0.0164***	-0.0036**	0.0232***	0.0247***	-0.0016	0.0336***	0.0382***	-0.0046	0.0599***	0.0497***	0.0102
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)	(0.006)	(0.003)	(0.008)
$SB1$	0.0041	-0.0010	0.0051	-0.0033	-0.0018	-0.0015	-0.0075	-0.0061	-0.0014	0.0037	-0.0024	0.0061
	(0.003)	(0.002)	(0.003)	(0.007)	(0.003)	(0.006)	(0.011)	(0.004)	(0.011)	(0.012)	(0.004)	(0.015)
$SB2$	0.0087***	0.0078**	0.0008	0.0142**	0.0020	0.0122*	0.0242***	-0.0145***	0.0387***	0.0261*	-0.0166***	0.0427***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.006)	(0.005)	(0.005)	(0.007)	(0.013)	(0.004)	(0.013)
Observations	25	25	25	24	24	24	23	23	23	21	21	21
R-squared	0.14	0.13	0.04	0.15	0.02	0.09	0.14	0.17	0.18	0.04	0.14	0.10
p-Value	0.03	0.03	0.30	0.06	0.11	0.15	0.00	0.00	0.00	0.15	0.00	0.01

Panel B: Price informativeness and governance using a single structural break (SB) variable

Horizon	1 year	2 years	3 Years	5 Years
Constant (2001 to 2007)	0.0174***	0.0269***	0.0392***	0.0684***
	(0.001)	(0.003)	(0.005)	(0.008)
SB	0.0019	0.0083*	0.0148**	0.0076
	(0.002)	(0.004)	(0.007)	(0.009)
EI	0.0015	-0.0021	-0.0078	-0.0242***
	(0.002)	(0.003)	(0.006)	(0.008)
$SB * EI$	0.0023	-0.0064	-0.0177**	-0.0123
	(0.003)	(0.004)	(0.007)	(0.010)
Observations	50	48	46	42
R-squared	0.08	0.10	0.11	0.11
p-Value	0.08	0.02	0.00	0.02

Table IX: Firm-based Information Flow Measures Across the Two Structural Breaks

This table lists the results obtained for regressions of trading activity proxy (TURN) and information asymmetry proxy i.e. probability of informed trade (PIN) on E-Index. The full sample period is segregated around the two structural breaks and separate regressions are run for each of the association, dissociation and negative association periods shown in the table by their respective time periods. For both TURN (Panel A) and PIN (Panel B), we report OLS (Model 1) and firm fixed effects (Model 2). Standard firm-based controls as suggested in Ferreira and Laux (2007) are included. Additional industry-wide controls using Fama and French (1997) 48 industry classification are present in Model 1 with firm clustered standard errors shown in parentheses. The coefficients for constant and industry dummies are omitted. See Appendix A for definitions of all controls. Significance levels at 10%, 5%, and 1% respectively are shown using *, **, and ***.

Panel A: TURN	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2015	1993 - 2000	2001 - 2007	2008 - 2015
E-Index	**0.0004***	**0.0058*****	**-0.0019*****	**0.0005**	**0.0069*****	**-0.0040*****
	(0.000)	**(0.000)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
ROE	-0.8050***	0.3710***	0.0005	0.3330***	-0.4670***	0.0052
	(0.109)	(0.010)	(0.001)	(0.006)	(0.008)	(0.009)
vROE	0.0022***	0.0011***	0.0021***	-0.0005***	0.0010***	0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEV	-0.0174***	0.0218***	0.0976***	0.0068**	0.0357***	0.0632***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)
MB	0.0075***	0.0058***	-0.0009**	-0.0008**	0.0038***	-0.0005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
SIZE	0.0120***	0.0164***	0.0098***	0.0214***	0.0483***	-0.0403***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
AGE	-0.0165***	-0.0180***	-0.0061***	0.0083***	0.0286***	-0.0080***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
DD	-0.0685***	-0.0719***	-0.0586***	-0.0172***	-0.0050**	-0.0178***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	141681	116929	125242	141681	116929	125242
R-Squared	0.246	0.164	0.087	0.008	0.014	0.006
Number of Groups				2023	2356	1537
Panel B: PIN	Model 1			Model 2		
	1993 - 2000	2001 - 2007	2008 - 2010	1993 - 2000	2001 - 2007	2008 - 2010
E-Index	**-0.0036*****	**-0.0034*****	**-0.0038*****	**-0.0052*****	**-0.0029*****	**0.0037****
	(0.000)	**(0.000)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.002)**
ROE	0.2100	-0.2540***	-0.0001**	-0.0080	0.2270***	-0.1390
	(0.132)	(0.007)	(0.002)	(0.158)	(0.008)	(0.161)
vROE	0.0001	0.0000	0.0001	0.0000	-0.0002*	0.0002
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
LEV	-0.0046	0.0045	-0.0024	-0.0201***	0.0128**	-0.0109
	(0.005)	(0.004)	(0.005)	(0.008)	(0.005)	(0.018)
MB	-0.0052***	-0.0012***	-0.0006	-0.0054***	-0.0038***	-0.0020*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
SIZE	-0.0291***	-0.0269***	-0.0179***	-0.0286***	-0.0231***	0.0065***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
AGE	-0.0004	0.0010	-0.0000	-0.0182***	-0.0256***	-0.0027
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.006)
DD	0.0080***	0.0015	0.0016	0.0061*	-0.0007	-0.0041
	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.008)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	8551	8426	2076	8551	7234	2076
R-Squared	0.416	0.558	0.440	0.361	0.426	0.217
Number of Groups				1683	1829	1341

regression. For both $TURN$ and PIN, we see a distinct shift in the E-Index coefficients across the second structural break, especially with the firm fixed effects. While $TURN$ is measured monthly, PIN is taken on a yearly basis. Whereas before sophisticated learning, an increasing E-Index would entail increased trading activity ($TURN$) for an average firm, the direction of this relationship reverses after sophisticated learning. For PIN, the findings are directionally opposite to those for $TURN$. Increasing anti-takeover E-Index provisions increases PIN after sophisticated learning in contrast to its effect on PIN before the second break point.

The systematic differences between the dissociation and post-dissociation years for both aggregate price informativeness and the firm-based information flow measures indicate an increase in information asymmetry for poor governance firms after 2008. Market prices and trading activity can communicate this change to investors if they are alert and receptive to such signals.

5.3. Sophisticated learning through risk channel

Although information flow and volatility have a close relationship (Ross, 1989), they can be considered to be two distinct channels for sophisticated learning. The investors' portfolios are not only sensitive to the earnings information in price (Hamburger and Kochin, 1972), but also to the stock price volatility (Ferreira and Laux, 2007). Thus, in this section, we examine the ability of the E-Index to predict firms' risk and show how it evolved across the two structural break points (mainly the second one).

While relative idiosyncratic volatility (*IDIOSYN*) captures firm-specific risk by accounting for the covariance of a firm's stock returns with market returns, stock price crash risk (*CRASH*) captures the skewness of returns distributions through the presence of extreme negative outliers. Stock price crashes are generally a result of managerial bad news hoarding (Jin and Myers, 2006). In the short run, managers have the freedom to choose to hide or divulge firms' bad performance, and they tend to show a preference toward withholding it (Kothari et al., 2009). However, when the downside risk exposure grows beyond managers' control in consecutive bad periods, the sudden release of accumulated bad news results in a crash.

Table X reports the results of the pooled regressions (Model 1) and firm fixed effects panel regressions (Model 2) for our two main firm-specific risk measures (i.e., *IDIOSYN* and *CRASH*). To compare and contrast the predictive ability of governance or the E-Index on these measures across the structural breaks, we subdivide the sample into three periods: 1990–2000, 2001–2007, and 2008–2016. Panel A shows the results for idiosyncratic volatility. For both the pooled and the fixed effects models, there is a peculiar change in the coefficients of the E-Index before and after sophisticated learning (i.e., around the second structural break point). During 1990–2000 and 2001–2007, future idiosyncratic volatility is negatively associated with the E-Index both in cross-sectional terms (Model 1) and within firm terms (Model 2). However, this relationship turns positive for 2008–2016. Since *IDIOSYN* is a relative measure (see Equation (4)), the coefficients of the E-Index can be interpreted as a decline in idiosyncratic volatility by 10.31% (4.51%) for each extra adoption (cross-sectional change) of the E-Index provision during the dissociation years. sophisticated learning opportunities are reflected in the post-dissociation years with idiosyncratic volatility increasing by 9.49% (4.74%) for each E-Index differential change within (across) firms. From 1990–2000 to 2001–2007 (i.e., across the first break point), the negative association with the E-Index is persistent for idiosyncratic volatility and increases in magnitude for both Models 1 and 2.

Similarly, even crash risk shows a distinct shift in relation to the E-Index from 2001–2007 to 2008–2016. Since *CRASH* is a dummy variable indicating a stock price crash in a given year, we apply pooled logit (Model 1) and panel logit with firm fixed effects (Model 2) regressions in Panel B of Table X. During the dissociation years, the coefficients of the E-Index are statistically insignificant, indicating no relation with crash risk (for both regression models). On the contrary, the E-Index shows a statistically significant (at 1%) and positive relation with future stock price crash risk during the post-dissociation years. We estimate the marginal effects of the E-Index on future *CRASH* to establish the economic significance of the coefficients from the pooled logit and panel logit models by fixing all control variables at their means. Every additional E-Index provision is found to increase crash likelihood by 1.21% ($p < 0.01$) in cross-sectional terms (Model 1) and 0.05% ($p < 0.10$) for within-firm changes (Model 2). The lower effect for the within-firm adoption of anti-takeover provisions is understandable because, in our sample, the proportion of firms with changing E-Index values over time is much lower than those with a constant E-Index (especially when the sample is divided around the two structural breaks).

Just as for idiosyncratic volatility, crash risk also shows no distinct shifts around the first

Table X: Idiosyncratic Volatility and Crash Risk Around the Two Structural Breaks

This table shows results obtained for relative idiosyncratic volatility (*IDIOSYN*) and firm specific crash risk (*CRASH*) on E-Index across the association, dissociation and negative association years as indicated by their respective time periods. In Panel A, we report results for *IDIOSYN* using OLS (Model 1) and firm fixed effects (Model 2) with all controls similar to those used in Table VIII, and an additional control for opacity (OPQ) introduced (Hutton et al., 2009). Panel B reports results for *CRASH* using logit (Model 1) and panel firm fixed effects logit (Model 2). When firm fixed effects are not considered (i.e. Model 1), we control for industry characteristics using Fama-French 48 industry classification dummies and use firm clustering to report standard errors and corresponding z or t statistics. The coefficients for constant and industry/year dummies are left out. See Appendix A for definitions of all control variables. *, **, and *** represent significance levels for 10%, 5%, and 1% respectively.

Panel A: Idiosyncratic Volatility	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2015	1990 - 2000	2001 - 2007	2008 - 2015
E-Index	**-0.0222*** (0.006)**	**-0.0451*** (0.005)**	**0.0474*** (0.004)**	**-0.0625*** (0.019)**	**-0.1031*** (0.010)**	**0.0949*** (0.007)**
ROE	0.0001 (0.000)	-0.0000 (0.000)	-0.0001** (0.000)	-0.0001 (0.000)	0.0002* (0.000)	-0.0002** (0.000)
vROE	0.0000* (0.000)	0.0000 (0.000)	-0.0000 (0.000)	0.0000** (0.000)	-0.0000*** (0.000)	-0.0000*** (0.000)
LEV	0.1161** (0.054)	0.2287*** (0.038)	0.1999*** (0.030)	0.0503 (0.108)	-0.1071 (0.076)	0.4769*** (0.065)
MB	-0.0448*** (0.005)	-0.0185*** (0.003)	0.0117*** (0.003)	-0.0329*** (0.011)	-0.0356*** (0.008)	-0.0259*** (0.006)
SIZE	-0.3526*** (0.006)	-0.1969*** (0.004)	-0.1382*** (0.004)	-0.2384*** (0.015)	-0.2398*** (0.015)	0.1166*** (0.012)
AGE	-0.0680*** (0.013)	-0.0521*** (0.009)	-0.0599*** (0.007)	-0.2963*** (0.031)	-0.3534*** (0.032)	0.3596*** (0.020)
DD	0.1146*** (0.022)	-0.1717*** (0.015)	-0.1848*** (0.012)	0.0336 (0.053)	0.1374*** (0.035)	0.1120*** (0.026)
OPQ	0.0367*** (0.004)	0.0219*** (0.002)	0.0435*** (0.005)	0.0624*** (0.002)	0.0506*** (0.002)	0.0208*** (0.001)
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	78098	91747	116669	78098	91747	116669
R-Squared	0.082	0.079	0.065	0.051	0.030	0.013
Number of Clusters / Groups	1271	1975	1460	1271	1975	1460
Panel B: Crash Risk	Model 1			Model 2		
	1990 - 2000	2001 - 2007	2008 - 2015	1990 - 2000	2001 - 2007	2008 - 2015
E-Index	**0.047* (0.027)**	**0.022 (0.023)**	**0.059*** (0.020)**	**0.087 (0.090)**	**-0.016 (0.082)**	**0.087*** (0.033)**
DIFTURN	0.044** (0.017)	0.021*** (0.006)	0.028*** (0.005)	0.036*** (0.012)	0.016** (0.006)	0.026*** (0.005)
AVG	12.765** (5.316)	15.705*** (4.384)	1.002 (4.065)	-12.187 (7.501)	-13.217** (5.501)	-22.361*** (4.526)
SIGMA	3.005* (1.688)	0.140 (1.398)	2.870** (1.328)	-4.829 (3.033)	-4.229** (1.990)	0.362 (1.683)
LEV	0.384* (0.220)	0.194 (0.179)	-0.204 (0.135)	0.022 (0.521)	-0.293 (0.373)	0.011 (0.288)
SIZE	0.045* (0.026)	-0.047** (0.022)	0.004 (0.018)	0.506*** (0.098)	0.417*** (0.093)	0.694*** (0.071)
MB	0.048*** (0.018)	0.025** (0.012)	0.008 (0.009)	-0.018 (0.051)	0.001 (0.035)	0.006 (0.022)
ROA	0.711* (0.384)	0.488* (0.267)	0.977*** (0.254)	1.244 (0.811)	0.508 (0.548)	0.515 (0.411)
NCSKEW	0.022 (0.046)	0.094*** (0.033)	0.057** (0.026)	-0.251*** (0.053)	-0.207*** (0.036)	-0.115*** (0.025)
OPQ	0.062*** (0.002)	0.051*** (0.002)	0.021*** (0.001)	0.041*** (0.001)	0.026*** (0.002)	0.012*** (0.001)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Industry Fixed Effects	Industry	Industry	Industry	Firm	Firm	Firm
Number of observations	5265	6295	9360	4131	5436	9867
Pseudo R-Squared	0.361	0.426	0.217	0.0378	0.0233	0.0273
Number of Clusters / Groups	928	1366	1454	587	988	1277

Table XI: Alternative Firm Risk Measures Across the Two Structural Breaks

This table presents the coefficients and standard errors (robust/clustered by firms as in Table X Models 1 and 2) using alternative firm risk measures i.e. negative conditional skewness (NCSKEW - Panel A), down-to-up volatility (DUVOL - Panel B), number of CRASHes experienced by a firm in a year (CRASHNUM - Panel C) and an indicator if the firm specific weekly return shows a price jump (JUMP) in a year. All controls in Table X are used. Additionally, for DUVOL and NCSKEW, past three years values of the same are included to partially control for autocorrelation and reverse causality. Model 1 in Panels A and B apply OLS regressions, with Panel C using Tobit regression and Panel D employing Logit regression. Model 2 controls for firm heterogeneity by including firm-fixed effects. *, **, and *** represent significance levels for 10%, 5%, and 1% respectively.

Model 1			Model 2		
1990–2000	2001–2007	2008–2015	1990–2000	2001–2007	2008–2015
Panel A: NCSKEW					
0.0106	0.0059	0..0487***	0.0248	0.0121	0.0712***
(0.011)	(0.011)	(0.010)	(0.042)	(0.039)	(0.018)
Panel B: DUVOL					
0.0045	-0.0046	0.0191***	0.0034	-0.0067	0.0273***
(0.004)	(0.004)	(0.004)	(0.016)	(0.014)	(0.006)
Panel C: CRASHNUM					
0.0346	0.0174	0.0423***			
(0.021)	(0.017)	(0.014)			
Panel D: JUMP					
-0.0313	-0.0140	-0.0024	-0.0309	-0.0503	-0.0438
(0.026)	(0.023)	(0.018)	(0.087)	(0.094)	(0.032)

structural break. Furthermore, the marginal effects during both the pre-dissociation (1990–2000) and the dissociation (2001–2007) periods are not statistically different from zero. This indicates that there is no learning-induced effect of the E-Index on crash risk.

Robustness check: We apply alternative measures of crash risk as a robustness check (Table XI) and find that our previous result indicating the predictive ability of the E-Index for future price crashes after second break point remains consistent across all these alternative measures. Additionally, we test whether the effect of the E-Index is symmetrically observed across price crashes and jumps. Using the price $JUMP$ indicator, we see that the E-Index does not show a similar marginal effect as on $CRASH$. This indicates that while poor governance (Model 1) as well as deteriorating governance structures (Model 2) do marginally influence future stock price crash risk in recent years, the opposite is not true; in other words, good governance and improving governance structures do not explain stock price jumps.

Overall, our findings support the sophisticated learning hypothesis and show that firm-specific risk is another possible channel through which alert investors may have learnt to appreciate the governance risk difference between low and high E-Index firms.

6. Conclusion

In his seminal paper, Fama (1998) examines several asset pricing anomalies and shows that "anomalies are chance results" and "apparent overreaction of stock prices to information is about as common as underreaction." Our tests of the sophisticated learning hypothesis, to a certain extent, build on this stock price overreaction/underreaction mechanism and show that the governance–returns anomaly is indeed fragile. This fragility is displayed by the initial disappearance of the governance–returns association and then its reappearance when institutional investors with different investment horizons learn to adapt their investment strategies by considering governance-related risks.

The starting point for the sophisticated learning phenomenon is the learning hypothesis of Bebchuk et al. (2013) that explains the disappearance of the governance–returns relation.[23] We show that while this association did disappear after 2000, it subsequently reappeared in the opposite direction (i.e., showing a reversal of the hedge position) from 2008 onward. Thus, the sophisticated learning hypothesis is characterized by institutional investors understanding governance risk, which other market participants as well as the markets at large do not yet seem to recognize. Using a natural experiment set around an exogenous shock to governance information availability, we show that investors may have benefited from learning (after the second structural break point) by better adjusting their investment portfolios and corresponding returns expectations. Our results indicate that firms' corporate governance structures influence the heterogeneity of their institutional investors. In other words, when we look at firms' ownership patterns, the proportion of short-term investors increases in poorly governed firms after the critical sophisticated learning point. Long-term investors are known to reduce managerial rent extraction and improve governance (Harford et al., 2018). This, along with our findings on their recently revitalized preference for well-governed firms, suggests a reinforcing mechanism that benefits these investors through lowered monitoring costs. On the contrary, trading profits seem to attract short-term investors to poor governance stocks in lieu of forgoing the long-term monitoring benefits. Our results from the governance-based hedge portfolios reaffirm the possi-

[23] Alternatively, Li and Li (2016) show that the governance–returns relation over time can be explained by the economic conditions (i.e., booms or busts) faced by each firm's industry. Hence, the pre-2000s governance–returns anomaly is not robust when investment and divestiture options are accounted for. However, hedge reversal and sophisticated learning seem robust to such industry-wide factors. We do not directly test such economic conditions or investment options, but do control for them by adjusting the returns of each firm by its industry's mean returns.

ble trading benefits from poor governance stocks, as the portfolio of these stocks (Dictatorship) consistently outperforms the good governance portfolio (Democracy) after the sophisticated learning point (i.e., January 2008). Both our findings on institutional ownership and hedge portfolio returns remain robust to selection bias controls with propensity score matching as well as to multiple placebo tests.

We also find evidence that supports the possible communication of governance risk for poor governance firms compared with good governance ones through the price information and risk channels. While medium- and long-run price informativeness declined for poor governance stocks after 2008, it tended to increase for good governance stocks. With respect to firms' risk measures, we find that poor governance stocks are more likely to face future stock price crashes and have higher future idiosyncratic volatility. Both these trends with regards to price information flows and firm risks were not visible in the dissociation period as expected. Hence, we posit that alert investors would have gained additional wisdom after the first structural break point to identify such governance-based investment opportunities that subsequently appeared.

Daines et al. (2010) show that corporate governance rankings do not provide any useful information for shareholders (in 2005–2007). Our results confirm that indeed during the dissociation years, no useful information was provided to investors through governance data and rankings. However, we also find that governance indices can be informative for investors and that this information content changes across the two identified structural breaks. In fact, such governance information can be used by investors to develop investment strategies that can generate abnormal returns after 2008. From this perspective, our results neither strictly indicate market inefficiency nor suggest sophisticated learning solely for the institutional investors. Our passive investment strategy only controls for some of the well-known risk factors, whereas the market may yet be pricing the unobservable *governance risk* that we fail to account for as it has not yet been measured (Fama, 1998). However, as a word of caution, since corporate governance itself encompasses a variety of underlying monitoring and auditing mechanisms, it is highly unlikely that such governance risk becomes completely priced by markets, thus continually creating investment opportunities such as the one documented herein.

Appendix A: Definitions of the control variables

SIZE: The market value of equity (in logs) either for each month or year.

ROE: Net income divided by the book value of common stock i.e. the sum of book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

vROE: Variance of ROE over last 36 months.

Age: Log transformation of firm age measured as the months that firm is listed on CRSP database (as per the end of each calendar year).

Leverage: Long term debt (Compustat data item 9) / Total assets (Compustat data item 6). Alternative measure of leverage (Long term debt/ Total equity) was used for robustness check.

Market-to-Book: Log of the ratio of the CRSP market value of common equity to its book value. Book value of common equity is the sum of book value of common equity (Compustat item 60) and deferred taxes (Compustat item 74).

Dividend Dummy: A dummy variable indicating if the firm pays dividends.

ROA: Return on Assets calculated as the operating income divided by end of the year total assets (Compustat data item 6). We use operating income before depreciation (Compustat data item 13) in the numerator.

DIFTURN: It is the difference of mean monthly share turnover for current year t and the mean monthly share turnover of prior year $t-1$. For each firm-month, the monthly share turnover is the ratio of corresponding trading volume to the total shares outstanding.

AVG: The average firm specific weekly return $W_{j,t}$ (see Section 2.5) for a given firm in a year.

SIGMA/ Volatility: Volatility or standard deviation of specific weekly return $W_{j,t}$ for a given firm over that year.

OPAQUE: Discretionary accruals that indicate opacity as measured by Hutton et al. (2009) using a three year moving sum of the absolute value of discretionary accruals calculated with modified Jones model.

Tobin's Q: Using inputs from Bebchuk et al. (2009), computed as market value (MV) of assets divided by book value (BV) of assets (Compustat data item 6) with the MV of assets being: (BV of assets + MV of common stock) – (BV of common stock + deferred taxes). Corresponding industry-adjusted (SIC 2-digit) values are obtained using industry median Tobin's Q values.

Monthly Turnover: Measures liquidity using the volume of trade for the firm's common equity recorded in the calendar year divided by 12 (in logs).

Share Price: Firm's share price as on the last trading day of a calendar year.

Appendix B: Abnormal returns from sophisticated learning: The governance risk premium

As a supplementary analysis, we extend the findings from the DiD experiment (see Section 4.4) to examine how a fully informed investor may potentially benefit from exploiting both the governance data and its timing, or in other words, complete sophisticated learning. We model this using the five factor model as shown in Equation (5), but taking the returns from information timeliness hedge of the governance hedge portfolios. Alternatively put, our hypothetical investment strategy involves going long Slow governance hedge (Democracy – Dictatorship) and shorting the Fast one. In some ways, this strategy mimics double-sorted portfolio hedging when the stocks are sorted both by their E-Index values and its availability (or frequency). Hence, we expect the abnormal returns from such a strategy to essentially represent the sophisticated learning premium, especially beyond the second structural break point. As a word of caution, the proposed investment strategy is actually impractical in our DiD experimental period as the investors were unaware in advance as to which stocks' governance data will be updated for the year 2007. For this reason, the premium measures using abnormal returns from our double-sorted hedge may be inflated by informational biases.

Table A.I presents possible premia for investors' learning using both the value-weighted and equal-weighted portfolios. In Panel A, we see that a long Slow governance hedge and short Fast one would have generated 4.38% (26 bps) premium for value-weighted (equal-weighed) portfolios. These results are robust to alternative asset pricing models (see Table A.IV). When the investment horizons are restricted to annual periods, in Table A.I Panel B, we find that much of the governance risk premium is generated soon after the second structural break i.e. in the year 2008. For both the value-weighted and equal-weighted portfolios, such sophisticated learning premia are statistically significant beyond 5% levels.

Table A.I: Governance, Sophisticated Learning and Returns

This table shows the coefficients and standard errors (in parentheses) of five-factor regression using three factors of Fama and French (1993) i.e. market (RMRF), size (SMB), book-to-market (HML) along with the momentum factor (UMD) and Pástor and Stambaugh (2003) liquidity factor (LIQ). The dependent variable is monthly returns from an information-based hedge on governance-based portfolios i.e. long Slow information governance hedge / short Fast information governance hedge. The governance hedge is set up through zero-investment trading strategy that buys good governance stocks and shorts bad governance ones. For the Fast stocks, portfolios get reset in the beginning of each year when new governance data is available, while the Slow stocks employ governance information of year 2006 as ISS did not report updated governance data for this group. Panel A considers the full DiD horizon period, whereas Panel B consider annual investment horizons. *,**, and *** respectively represent significance levels at 10%, 5%, and 1%.

Panel A: Full DiD horizon (2006 to 2008)

Portfolios	α	$RMRF_t$	SMB_t	HML_t	MOM_t	LIQ_t	R^2
Value-weighted							
Slow	0.0131	-0.2603	0.4403	-1.4691***	-0.0909	-0.6047	0.330
	(0.009)	(0.222)	(0.517)	(0.506)	(0.269)	(0.366)	
Fast	-0.0307***	0.5675*	-1.6650**	-1.7338***	-0.2836	0.4351	0.462
	(0.011)	(0.316)	(0.653)	(0.613)	(0.387)	(0.404)	
Slow – Fast Hedge	0.0438***	-0.8278*	2.1053**	0.2648	0.1927	-1.0398	0.298
	(0.016)	(0.409)	(0.964)	(0.959)	(0.518)	(0.646)	
Equal-weighted							
Slow	-0.0107	-0.5234	1.0687*	-1.3621*	-0.3394	0.2853	0.120
	(0.013)	(0.335)	(0.622)	(0.721)	(0.443)	(0.340)	
Fast	-0.0132**	0.0314	-0.1183	-0.5257*	-0.3731	0.3583	0.153
	(0.005)	(0.174)	(0.286)	(0.304)	(0.224)	(0.243)	
Slow – Fast Hedge	0.0026	-0.5547	1.1869*	-0.8364	0.0337	-0.0730	0.093
	(0.014)	(0.393)	(0.653)	(0.792)	(0.481)	(0.458)	

Panel B: Annual investment horizons

Portfolios	2006	2007	2008
Value-weighted			
Slow	0.0477	0.0286	0.0621***
	(0.027)	(0.026)	(0.016)
Fast	-0.0123	-0.0124	-0.0836**
	(0.007)	(0.010)	(0.031)
Slow – Fast Hedge	0.0601*	0.0410	0.1458***
	(0.025)	(0.023)	(0.043)
Equal-weighted			
Slow	-0.0224	0.0125	0.0090
	(0.028)	(0.035)	(0.016)
Fast	-0.0052	-0.0065	-0.0578***
	(0.005)	(0.006)	(0.020)
Slow – Fast Hedge	-0.0172	0.0189	0.0668**
	(0.030)	(0.315)	(0.029)

Appendix C: Alternative asset pricing models

We check the robustness of all our main results that employ five factor model presented in Equation (5) by using alternative asset pricing models. We apply capital asset pricing model (CAPM), the three-factor model (Fama and French, 1993), the five-factor model (Fama and French, 2016) and the variations of these Fama-French (FF) models with the Pástor and Stambaugh (2003) liquidity factor included. The Cremers et al. (2009) takeover factor was also considered, but left out due to lack of data availability for recent years.

Table A.II: Robustness Check for Table III using Alternative Factor Models

This table summarizes results when alternative asset models are considered in Table III Panel B by running different factors and factor combinations in Equation (5) with additional structural break (SB) variables. All estimations use White (1980) robust standard errors (in parentheses). For variable definitions, see Table III. Significance levels at 10%, 5%, and 1% are shown using *, ** and *** respectively.

Panel A: CAPM				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	-0.0055	-0.0015	-0.0056	-0.0020
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0107**	0.0054	-0.0107***	-0.0061**
	(0.005)	(0.004)	(0.004)	(0.002)
SB2 Dummy	-0.0109*	-0.0068		
	(0.006)	(0.005)		
Panel B: Fama-French 3 factors				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	-0.0022	-0.0009	-0.0037	-0.0014
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0092**	0.0059	-0.0112***	-0.0066**
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0133*	-0.0072		
	(0.007)	(0.005)		
Panel C: Fama-French 3 factors + liquidity factor				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	-0.0008	0.0004	-0.0046	-0.0010
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0079*	0.0045	-0.0129***	-0.0065**
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0182**	-0.0085		
	(0.008)	(0.005)		
Panel D: Fama-French 5 factors				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	0.0003	0.0013	-0.0017	0.0004
	(0.003)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0082*	0.0052	-0.0110***	-0.0064**
	(0.004)	(0.003)	(0.003)	(0.002)
SB2 Dummy	-0.0138*	-0.0077		
	(0.007)	(0.005)		
Panel E: Fama-French 5 factors + liquidity factor				
	2 SB Variables		1 SB Variable	
	VW	EW	VW	EW
Alpha	0.0015	0.0024	-0.0026	0.0008
	(0.004)	(0.003)	(0.003)	(0.002)
SB1 Dummy	0.0072*	0.0041	-0.0126***	-0.0063**
	(0.004)	(0.004)	(0.004)	(0.003)
SB2 Dummy	-0.0185**	-0.0087		
	(0.008)	(0.005)		

Table A.III: Robustness Check for Table VI using Alternative Factor Models

This table summarizes results using alternative asset models for main DiD estimation result in Table VI (Panel A). White (1980) robust standard errors are shown in parentheses. For variable definitions, see Table VI. Average main effects (Model 1) and average treatment effects (Model 2) are shown using either the equal-weighted (EW) or value-weighted(VW) governance-based hedge portfolios. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

Panel A: CAPM

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0561***	-0.0162*	0.0077	0.0120*
	(0.019)	(0.009)	(0.014)	(0.006)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275*** **	**-0.0565*** **
			(0.032)	**(0.014)**

Panel B: Fama-French 3 factors

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0421***	-0.0184*	0.0216	0.0099
	(0.015)	(0.010)	(0.018)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.007)	(0.004)
$SB2 * Treat$			**-0.1275*** **	**-0.0565*** **
			(0.030)	**(0.014)**

Panel D: Fama-French 3 factors + liquidity factor

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0425***	-0.0181*	0.0212	0.0101
	(0.014)	(0.010)	(0.017)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0058
	(0.013)	(0.006)	(0.007)	(0.004)
$SB2 * Treat$			**-0.1275*** **	**-0.0566*** **
			(0.030)	**(0.014)**

Panel D: Fama-French 5 factors

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0329*	-0.0180	0.0309	0.0103
	(0.018)	(0.011)	(0.020)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275*** **	**-0.0566*** **
			(0.029)	**(0.014)**

Panel E: Fama-French 5 factors + liquidity factor

	Model 1		Model 2	
	VW	EW	VW	EW
$SB2$	-0.0299*	-0.0158	0.0338	0.0124*
	(0.016)	(0.011)	(0.021)	(0.007)
$Treat$	-0.0389***	-0.0131**	0.0036	0.0057
	(0.013)	(0.006)	(0.006)	(0.004)
$SB2 * Treat$			**-0.1275*** **	**-0.0566*** **
			(0.029)	**(0.014)**

Table A.IV: Robustness Check for Table A.I using Alternative Factor Models

This table reports alphas (αs) when alternative asset pricing models are used in the Panel A of Table A.I. For variable definitions and other details, see Table A.I. Abnormal returns from long / short strategies based on governance information (Fast vs Slow) on the E-Index hedge (long Democracy short Dictatorship) using both equal-weighted (EW) and value-weighted (VW) portfolios are shown. Levels of significance at 10%, 5%, and 1% are indicated by *,**, and *** respectively.

VW			EW		
Slow	Fast	Slow − Fast	Slow	Fast	Slow − Fast
Panel A: CAPM					
0.0072	-0.0314**	0.0344*	-0.0089	-0.0126**	0.0036
(0.010)	(0.012)	(0.018)	(0.012)	(0.005)	(0.013)
Panel B: Fama-French 3 factors					
0.0069	-0.0285***	0.0311*	-0.0102	-0.0123**	0.0021
(0.009)	(0.010)	(0.018)	(0.011)	(0.006)	(0.012)
Panel C: Fama-French 3 factors + liquidity Factor					
0.0128	-0.0315***	0.0446***	-0.0116	-0.0143**	0.0026
(0.009)	(0.010)	(0.016)	(0.013)	(0.005)	(0.013)
Panel D: Fama-French 5 factors					
-0.0003	-0.0160*	0.0159*	-0.0186	-0.0063	-0.0122
(0.008)	(0.009)	(0.013)	(0.011)	(0.005)	(0.011)
Panel E: Fama-French 5 factors + liquidity Factor					
0.0056	-0.0212**	0.0294**	-0.0175	-0.0087*	-0.0088
(0.008)	(0.009)	(0.013)	(0.013)	(0.005)	(0.012)

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