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

Ariadna Dumitrescu, Mohammed Zakriya

ESADE Business School and Ramon Llull University
Av. Pedralbes, 60-62, 08034 Barcelona, Spain

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Abstract

This paper shows that the relationship between corporate governance indices and stock returns has reappeared after a few years of its disappearance. We find that poor governance stocks have outperformed good governance stocks in recent years, indicating a directionally opposite relation to the one that existed in the past. To explain this puzzling reversal, we present a hypothesis that is characterized by the investors understanding governance risk, which other market participants –and markets at large (as proxied by common risk factors)– do not yet seem to understand and appreciate. Using a natural experiment that is set around an exogenous shock to governance information flow, we show that investors did potentially benefit through learning by better adjusting their returns expectations. Subsequent tests confirm that learning via *price* and *risk* channels may have helped investors recognize the uncertainty surrounding poorly governed firms' future earning power, hence, making them demand risk premia to mitigate increased information asymmetry.

Keywords:
Corporate governance, investor learning, antitakeover provisions, E-Index, managerial entrenchment

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Email addresses: ariadna.dumitrescu@esade.edu (Ariadna Dumitrescu), mohammed.zakriya@esade.edu (Mohammed Zakriya)

Introduction

Does corporate governance matter for stock returns? Can governance information be used by investors to implement investment strategies that outperform the market? In a recent paper, Bebchuk et al. (2013) answer these questions by showing that the correlation between stock returns and corporate governance indices ceased to exist beyond the year 2000. It is shown that while stock returns were associated with the G and E indices in the 1990s, subsequent disappearance of this association was due to “market participants gradually learning to appreciate the difference between firms scoring well and poorly on the governance indices”. Essentially, Bebchuk et al. (2013) points out that the governance-hedge portfolio as suggested in Gompers et al. (2003) cannot generate abnormal returns beyond the year 2000. In contrast, however, Core et al. (2006) show that bad governance portfolio outperformed the good governance one beyond 1990s which indicates possibilities of reversing the long/short strategy suggested in Gompers et al. (2003). In this regard, we contribute to the literature by investigating whether the disappearance of governance pricing anomaly only lasts till investors “learn” to appreciate the governance risks, subsequently allowing such alert investors to beat the markets.

In this paper, thus, we show that there are two structural changes in the stock returns and governance relationship, i.e. (a) existing association and then its disappearance, and (b) this disappearance followed by its reappearance beyond mid-2000s; and then using a natural experiment, we provide a possible explanation for the second structural break. While the Bebchuk et al. (2013) learning hypothesis does explain the first structural break and the disappearing returns – governance association, it does not shed light on the reappearance of this relation. To investigate the second break point, we present and explore the investor learning hypothesis. Under this hypothesis, after the initial learning as investors became more exposed to governance signals, they begin to further appreciate the differences in good governance and poor governance firms, so that their expectations of returns from poor governance firms change. This implies that, after a few years of *additional learning* beyond first structural break point, the governance – returns correlation reappears when investors begin incorporating governance risk in their investment decisions. Hence, investor learning effect is characterized by governance – returns relation that is directionally opposite to that seen in 1990s, with the poor governance stocks outperforming good governance ones.[1]

The relationship between corporate governance and stock returns is clouded by endogeneity concerns, as there may be questions both with regards to the direction of causality and the existence of confounding variables. This makes causal identification for investor learning phenomenon around the second structural break a big challenge. We overcome this by using a natural experiment that exogenously affected the flow of governance information to investors. This allows us

[1] Such hedge reversal was not captured in Bebchuk et al. (2013), since the investor learning was not visible in the sample timeframe considered therein.

to causally examine investors' learning in terms of the way stock prices and corresponding returns react to the governance information. In 2007, Institutional Shareholder Services (ISS) –a leading corporate governance data provider to institutional investors– changed its data collection and reporting methodology, which led to a faster distribution of governance data on annual basis unlike the previous years when governance data was made available to investors every 2 to 3 years. Since this exogenous shock occurs just before the second structural break in governance – returns relationship, it provides an ideal quasi-experimental setting to assess if investors do learn to recognize the riskiness of poorly governed firms. In its essence, our experimental test of investor learning hypothesis reflects the Grossman and Stiglitz (1980) theoretical model on informational inefficiencies, as we aim to understand how informed investors react to the quality of governance information and/or its noisiness (which, here, is proxied through information timeliness).

The change in ISS governance reporting methodology offers us a backdrop for good experimental setting to explore causality, and also allows us to additionally strengthen its validity by employing a long-run event study for both the control and treatment groups. First and foremost, the two groups are mutually exclusive ensuring that the treatment firms and the control firms are clearly earmarked. Secondly, considering that ISS issues governance data independently, both sets of treatment and control firms are largely unaware of which group they fall in. This would eliminate 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 would favour reporting some firms' governance provisions over others.[2] From investors' perspective as well, this would mean that they were largely unaware of which firms' information would be updated in 2007 and which would not. Third, as an extension of previous point, ISS's decision to cover a specific firm's anti-takeover provisions would largely have been independent of the firm's past returns. Fourth, although ISS was inconsistent in terms of the frequency and timing of releasing the governance data (which were issued either at 2 or 3 years intervals in the past), for the last three reports the timing and frequency remained consistent. This would have allowed the investors to plan their investment strategies around governance information with certainty. Lastly, the inconsistencies with reporting frequency in the past allows for possible placebo tests, which can strengthen the validity of our inferences.

To begin with, using the ISS governance provisions data for 26 years, we create governance-based hedge portfolios as employed in Gompers et al. (2003) and Bebchuk et al. (2009) to reaffirm the disappearance of governance indices and stock returns relation beyond 2000s.[3] Further exploration of this relation beyond the year 2001 reveals that another structural break exists in the year

[2] Nevertheless, we do tackle selection concerns by using propensity score matched groups as a robustness check.

[3] All out main results and additional analysis employs the E-Index as governance proxy, as this index can be reliably developed for the entire 26 years. The change in ISS data collection methodology beyond the year 2007 (that changed the number of anti-takeover provisions covered by ISS), makes replication of the G-Index difficult beyond 2006.

2008, whence the governance – returns association reappears, albeit in opposite direction. This finding suggests that the effect of investor learning, which allowed markets and its participants to completely understand the differences in good and poor governance practices, does not imply permanent market efficiency for governance information. While learning improved markets' understanding of the future profitability from well and poorly governed firms, additional wisdom after a few years (through superior learning) allowed the alert investors to further process differences in their riskiness. With superior riskiness of poor governance firms being appreciated by the investors, their market prices would have turned more volatile. We aim to capture this risk-induced effect through price informativeness, idiosyncratic volatility and stock price crash risk in subsequent analysis.

Once the two structural break points have been identified, we confirm them using Bai and Perron (1998) and Hatemi-j (2008) tests for two regime shifts, and proceed with the natural experiment designed around the changing ISS data collection methodology. We examine the abnormal returns for long good governance - short poor governance zero investment strategy surrounding the ISS data reporting change in 2007, and compare the abnormal returns for portfolios created using the firms whose information was not updated in 2007 (SLOW group) with the abnormal returns for those who had a new set of information in 2007 (FAST group). We find that investor learning effect (as proxied by information timing in Slow vs Fast groups) does exist for the second structural break point i.e. beyond January, 2008. Our findings are robust to selection bias controls using propensity score matching, and to multiple placebo tests.

Although the results from our natural experiment lends credence to the existence of investor learning phenomenon, it does not shed any light on the mechanism that drives such learning amongst the investors. How exactly does such governance information influence institutional investors' and/or other investors' expected returns? To answer this question, we further explore our investor learning hypothesis through two underlying learning mechanisms. First, exploiting Lee et al. (2016) findings that good governance is related with high information efficiency of prices, we study the information content of good and poor governance stocks' prices and the changes that their price informativeness experiences across the two structural break points. This captures investors' expectations of future firm growth rates and earnings prospects. Second, as Ross (1989) has shown that "no-arbitrage" condition does lead to a relation between information flow rate and stock price volatility, we examine the impact of governance on price non-synchronicity and idiosyncratic volatility across the two structural breaks. While the first mechanism characterizes the governance information that flows through the *price* channel across the different governance – returns association and disassociation periods, the second mechanism portrays *risk* channel as price volatility essentially reflects firm's riskiness.

To investigate the price channel, we analyze the differences between cross-sectional price informativeness for good governance and poor governance stocks. Our results support both the learning hypothesis for first structural break and the investor learning across second structural break. While price informativeness increased over the years in pre-2001 period for both the good and poor governance stocks (through learning effects), there is a different trend seen in the post-2008 period. Poor governance stocks show a distinctive decline in price informativeness beyond the second structural break point whereas the good governance stocks undergo an upward trend for the same. During the period of disassociation (i.e. between the two structural break points), price informativeness is statistically insignificant implying a stable information access across both the well and poorly governed firms. We complement the results from this cross-sectional measure of information content of prices by using firm-specific information flow proxies, and again find evidences supporting investor learning. Poor governance firms are seen to have greater information asymmetry, and also show comparatively lower trading activity beyond the second structural break.

We study the risk channel using firm's idiosyncratic volatility and complement it with measures of stock price crash risk. The results again support our investor learning hypothesis with poor governance firms being associated with higher idiosyncratic volatility in comparison to the good governance ones in the post-2008 period. Additionally, we find that while E-Index could not predict future stock price crash risk before 2008, subsequently there is a positive association between the two. This means that beyond the second structural break, poorly governed stocks with more entrenchment provisions have higher likelihood of crashes. Combined with the evidences from *price* channel tests, the results from *risk* channel tests support the Jin and Myers (2006) model to show that "limited information affects the division of risk bearing between inside managers and outside investors". In other words, investor learning increased the awareness of riskiness associated with poor governance firms, thus, forcing investors to wisely adjust their expectations of these firms' future earning power and associated risk premia as a result of increased information asymmetry.

Above and beyond just exploring and explaining the reassociation between governance indices and stock returns, our findings contribute to a broader body of literature that studies information-based trading strategies and/or long-run event studies. From asset pricing perspective, we draw attention to a possible "anomaly" and its reappearance (see Schwert, 2003). This is especially important as the anomaly in focus was shown to have disappeared beyond 1990s. While the disappearance of financial anomalies has been widely studied, very few papers have highlighted its possible reappearance. In some ways, our paper 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 recalibration of governance information by rational investors, additional uncertainties accompanying information asymmetry induces investor learning that creates arbitrage opportunities afresh. Additionally, we contribute to a larger market efficiency literature (see Fama, 1991). Our findings are consistent with Brown et al. (1988) as we show that investors' risk and returns do adjust to new information and more so for poor governance structures after the market prices have corrected for the differences in good and poorly governed firms (i.e. after the initial learning period). The resultant idiosyncratic risk and lower price informativeness in poorly governed firms may also be indicative of ambiguity premium (Epstein and Schneider, 2008).

The rest of this paper is organized as follows. Section 1 presents our investor learning hypothesis. Section 2 lays out the identification strategy to test this hypothesis and subsequently its underlying explanations. Section 3 describes the data. Next, Section 4 makes a case for the two structural breaks or regime shifts in governance – stock returns relationship. Section 5 applies the natural experiment design to identify the consequences of investor learning, and Section 6 explores the price and risk channels of such learning. Lastly, Section 7 summarizes our main results and concludes.

1. The investor learning hypothesis

Investors are constantly seeking information that can help them *beat* the markets (French, 2008). They are sensitive to managerial entrenchment or E-Index, as the presence of these anti-takeover provisions within the firms exposes them to possible information asymmetry when managers are better shielded from takeover threats (Bebchuk et al., 2009). When such scrutiny creeps into investment decisions, active investors who rely on governance data expect to be compensated for such additional governance risks. This is the underlying rationale behind the investor learning hypothesis. The term 'investor learning' here is used to emphasize the learning that investors undergo by being repeatedly exposed to governance signals so that they make more informed decisions than other market participants including analysts.

As the institutional investors (who are 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. While the markets returns at large do not really factor in these risks, at least in the period that immediately follows investors' learning, in the long run such governance-based opportunities should disappear with the market learning process eventually eliminating any systematic information asymmetry. Thus, while our investor learning hypothesis does dwell upon market inefficiency in short-run, it does not rule out possible return to efficient market conditions in the future.

From a different and more rational standpoint, our investor learning hypothesis does not necessarily assume market inefficiency nor suggest a purely investor-centric learning. Since we mimic the passive market portfolio by only controlling for a few well-known risk factors; such learning may even be a phenomenon experienced by investors and all other market participants alike, as long as they are able to factor in additional governance risk in their investment decisions.

We expect investor learning amongst the 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 become more prudent after the 2007-2008 financial crisis. Second, in the past, governance information was not made available to investors in a consistent and reliable manner. However, investment planning should have improved with ISS standardizing their governance reporting practices. Third, informed institutional investors are in a better position to react to newer information than the uninformed investors; and, hence, should demand higher returns when investing in high private information firms (Easley and O'hara, 2004). This would also entail that governance – returns relationship is affected with reliable information inflow.

2. Identification strategies and empirical models

This section details out the methodologies and identification strategies that we apply to (a) estimate the two structural breaks in governance – returns relation, (b) causally examine investor learning explanation for the second structural break and its consequential governance hedge reversal, and (c) investigate possible information channels through which learning may have aided investors in recognizing the governance-related risks. Thus, our analysis encompasses three broad empirical phases.

2.1. The structural breaks

In the first phase, using long-run event study methodology, we trace the governance hedge portfolio along with the two extreme governance portfolios (i.e. Democracy or Good Governance, and Dictatorship or Bad Governance) over a 25 year period. This allows us to locate the exact point (or points) of structural break (breaks) in the time-series for abnormal returns using the Quandt likelihood ratios (LR). We mainly use supremum of LR (sup-LR) estimation of unknown structural breaks (Andrews, 1993) in three stages. To begin with, we run sup-Wald test for the entire sample to identify the first break point. Next, we run the same test by restricting the sample months beyond the first break to locate the second break point. And last, we run confirmation tests using inputs from Clemente et al. (1998) and Bai and Perron (1998), specifically with Hatemi-j (2008) two structural break test.[4]

Put differently, we apply the Andrews (1993) tests for unknown structural breaks twice (for identifying each break) by running time-series regressions and looking for statistically significant breaks in 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 liquidity effects using (Pástor and Stambaugh, 2003) LIQ_t factor. Alternative asset pricing models, including the Fama and French (2016) five factors, are used for robustness checks.

$$R_t = \alpha + (\Delta\alpha) * POST + \beta_1 * RMRF_t + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * LIQ_t + \varepsilon_t \quad (1)$$

[4] We do not start with multiple structural break estimation techniques such as 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.

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

Additionally, for each governance-based hedge portfolio we estimate 36-months rolling abnormal returns or alphas, and identify (a) the month whence abnormal returns are statistically consistently insignificant, followed by (b) the exact month when abnormal returns are again consistently significant. While the statistical estimation using Quandt (1960) method identifies critical points of structural breaks or regime shifts, the rolling estimation methods pinpoint the last possible points for the two learning phases (Bebchuk et al., 2013).[5]

2.2. The investor learning experiment

The first structural break point can be explained either through learning hypothesis (Bebchuk et al., 2013) or using available investment and divestiture options across governance structures (Li and Li, 2016). However, since we show the second structural break in governance – returns relationship for the first time, there is a need to further understand the reappearance of this relation. One simple way to examine the explanations for this reappearance is to regress various outcomes or determinants of corporate governance on the governance measure (in our case, the E-Index) itself, and then compare the coefficients around the structural break point to determine if there are any systematic differences (Bebchuk et al., 2013; Li and Li, 2016). However, simple regression estimates are engulfed in endogeneity concerns whenever measures of governance are being studied (Wintoki et al., 2012). Thus, in this second empirical phase, we employ a cleaner identification using natural experiment to test the investor learning hypothesis and draw causal inferences for this investor learning explanation.

Our identification strategy exploits the changes in ISS data collection and reporting methodology from 2007 onwards. As the second structural break occurs just one year after this change, it provides us with an ideal setting to assess if investor learning does drive the reassociation between governance and returns. We proxy investor learning using ISS data reporting frequency that is a source of exogenous variation in governance information availability to the investors. The main underlying assumptions are that the investors are not aware of which firms' governance data will be reported for the year 2007, and that they do not plan their governance-based investment strategies in advance. However, it is also important to ensure that the ISS coverage in 2007 is independent of specific firm attributes such as size, profitability, age etc.

We consider the group of firms whose governance data was reported in 2006, and then updated soon after in year 2007, to be those firms with regards to whom investors' can experience higher learning through faster information turnarounds. We call this the $FAST$ group, which represents the treatment firms. In contrast, the firms that were covered by ISS in 2006 but were not reported for 2007 fall in the $SLOW$ group. In our setting, thus, this Slow group includes control firms that

[5] Assuming that the market learning or investor learning is completed within 3 years.

induces comparatively slower or no investor learning as their reporting frequency and accompanying investment strategy will be similar to the one employed with past ISS publications (i.e. portfolios being reset every 2 to 3 years). Since most of the firms reported by ISS in 2006 are updated with the new 2007 information, we find that the treatment group (2,469) is much larger in number than the control group (1,337). When we look at the extreme portfolios (i.e. *Democracy* with E-Index= 0, and *Dictatorship* with E-Index= 5 | 6) for each group, the total number of firms in treatment group (399) is more than double that in the control group (146).

On average, the Democracy stocks underperform the Dictatorship stocks in terms of raw returns. This difference is more pronounced in Fast group than in the Slow group, suggesting that learning investors do benefit from faster reporting of governance data. This variation in returns, in tandem with the long-run event study to obtain abnormal returns for governance hedge portfolios in each group, lays the basis for us to identify the causal estimates for governance-based investor learning on stock returns. The time window chosen for our experimental setting starts from January 2006 (when the *last* old ISS methodology-based governance data was 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 focuses on governance-based hedge portfolios over this 3 year window assuming a persistent investment strategy using the available governance data, we employ calendar-time portfolio approach to obtain the risk-adjusted or abnormal returns. This approach follows similar rationale as the long-run method in the previous empirical phase, but with the event window shortened to 3 years instead of 25 years.

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 hence, better information quality on stock returns; it does not provide any insights on the second structural break. Our investor learning hypothesis predicts that investors only learn to appreciate the governance risk of high E-Index firms beyond the second structural break point (i.e. January 2008). Hence, to capture the investor learning effect we divide the 36 month period into 24 months of pre-learning and 12 months of post-learning periods. With this, hence, we have an ideal backdrop for difference-in-differences (DiD) design that captures both the time trend (i.e. pre vs post) and the treatment effect.

2.2.1. Estimation model

In line with the arguments presented above, our natural experiment surrounding the change in ISS data collection methodology and how investors react to such a shock to governance information availability is modelled using DiD pooled regression that has the following specification:

$$R_{J,t} = \alpha + \pi_1 SB\_Dummy_t + \pi_2 Treat_J + \pi_3 SB\_Dummy_t * Treat_J + \gamma X_t + \varepsilon_t \qquad (2)$$

where $R_{J,t}$ denotes the hedge portfolio returns for a certain group J of firms in month t, SB_Dummy indicates the period after second break point or the months following investor learning, and $Treat$

is a dummy indicating if a portfolio is composed of firms from the Fast (treatment) or Slow (control) group. Our main coefficient in focus is, thus, π_3 that shows the DiD interaction effect i.e. the effect on the abnormal returns of the treated portfolio due to investor learning.

As in equation (1), 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 2.1, we include market, size, book-to-market, momentum and liquidity factors for X_t in our model.[6]

2.2.2. Internal validity

There are two potential threats to internal validity for our DiD inferences. a) As mentioned earlier, the control group is smaller in number than the treatment group, and there may also be possible selection biases driving our results. Selection biases confound the outcomes of an experiment when treatment and control firms have significantly different characteristics. For example, if size is such a factor, it could be that bigger firms are more likely to be covered in ISS governance publications (becoming treatment firms), and in turn, these firms may also have exaggerated influences from governance structures than the smaller-sized control firms. We account for the numerical differences in two groups by increasing the number of firms in control group using a median E-Index based classification of Democracy and Dictatorship firms.[7] We also tackle selection concerns by using 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). b) investor learning may not be a phenomenon unique to second structural break. Or, in other words, similar investor learning trends may exist in other time periods. We conduct placebo DiD tests to verify that this is not the case by first identifying a similar ISS reporting frequency centric control and treatment groups in another time period, and then running pre-post analysis across several alternative placebo break points.

2.3. The investor learning channels

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

First, we employ Bai et al. (2016) price informativeness measure that captures the ability of stock prices to predict future earnings. Under investor learning hypothesis, investors realize the inherent governance risk of poor governance firms vis-à-vis good governance ones. Thus, the focus with this earnings expectations or price channel is on information asymmetry within the firm when compared to the outsiders, or in our case, the investors. Such asymmetry would expectedly be larger for poor governance firms with more anti-takeover provisions (or higher managerial entrenchment).

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

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

In other words, we expect price informativeness of good governance stocks to be greater than that of poor governance stocks, and this difference to be driven by decreasing price informativeness of poor governance firms after the second structural break point. To compare the trends between these firms, we split our sample into two groups i.e. good governance and poor governance using median E-Index as 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 price informativeness values (under various investment horizons) for each group separately on the dummies representing the two structural breaks, so that we can examine the trends for each group. We additionally run a similar regression using differences in the price informativeness between the two groups as a dependent variable to quantify the differential trend.

While the price informativeness does give insights on trends in information asymmetry between the good and poor governance firm cross-sections, it does not provide any insights on firm-level changes. Thus, we complement the price informativeness tests with additional firm-based information flow measures. Since we are interested in essentially identifying whether the within firm governance changes potentially influence firms' information flow to investors, we employ fixed effects panel regression. This way, we are able to trace any systematic differences in the way changes in managerial entrenchment affects the information flow across the two structural breaks.

After assessing the price channel, we seek to identify if there are any 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 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 if, and in what direction, can E-Index predict firm-specific risk when the sample is broken down into three sub-samples around the two structural breaks.

2.3.1. Estimation models

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

We compute aggregate price informativeness PRI_t for each year across different horizons (see Section 2.3.2 for details), and then, run regressions of this price informativeness on two dummy variables each representing the pre-disassociation and the reassociation years. This essentially means that the 2001-2007 period (or the disassociation years) is captured by the constant term.

$$PRI_t = A_1 + B_1(SB\_Dummy\ 1_t) + C_1(SB\_Dummy\ 2_t) + \varepsilon_t \tag{3}$$

As an alternative specification, we again model 2001-2007 as the reference time period, but include a single SB variable that is assigned '-1' for pre-disassociation years and '+1' for the reassociation years. In this specification, we include an $E{-}Index\ Dummy$ that represents poor governance (above median E-Index based price informativeness).

$$PRI_t = A_2 + B_2(SB_t) + C_2(E{-}Index\_Dummy_t) + C_2(SB_t * E{-}Index\_Dummy_t) + \varepsilon_t \tag{4}$$

For the firm-based information flow measures $FPRI_{j,t}$ (that are either PIN or $TURN$ as defined in Section 2.3.2), we use the following specification:

$$FPRI_{j,t+1} = A_3 + B_3(E{-}Index_{j,t}) + C_3(X_{j,t}) + \varepsilon_{j,t} \tag{5}$$

where the $X_{j,t}$ includes all standard controls as suggested in Ferreira and Laux (2007) and Hutton et al. (2009).[8]

For insights on 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 i.e. idiosyncratic volatility (*IDIOSYN*, monthly) and crash risk (*CRASH*, yearly).

$$FR_{j,t+i} = A_4 + B_4(E{-}Index_{j,t}) + C_4(X_{j,t}) + \varepsilon_{j,t} \tag{6}$$

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

2.3.2. Price informativeness and information flow measures

The price informativeness measure is constructed using estimation procedures highlighted in Bai et al. (2016) by first regressing future earnings on market valuations for each of the years, with multiple time horizons (i.e. using future earnings at 1, 2, 3 and 5 year intervals). While the current period's earnings and industry sector controls are used to represent publicly available information set in Bai et al. (2016); it also helps us to account for industry booms and busts, hence, additionally controlling for alternative explanations that explore available investment opportunity sets for each firm (Li and Li, 2016).

$$\frac{E_{j,t+i}}{A_{j,t}} = a_{t,i} + b_{t,i} ln\left(\frac{MV_{j,t}}{A_{j,t}}\right) + c_{t,i}\frac{E_{j,t}}{A_{j,t}} + d_{t,i}S_{j,t} + \epsilon_{j,t,i} \tag{7}$$

[8] See Appendix I for the definitions of all these control variables.

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

$$PRI_{t,i} = b_{t,i} * \sigma_t \left(ln \frac{MV_{j,t}}{A_{j,t}} \right) \tag{8}$$

While this measure helps us trace the cross-sectional price informativeness amongst the good and poor governance firms from a holistic perspective, it does not reveal how information flows with in individual firms are influenced by governance structures. Thus, we also compute firm-specific information flow measures to see if any systematic difference exist across the second structural break indicating investor learning. We use two measures, namely, the share turnover (TURN) and the Easley et al. (2002) probability of informed trade (PIN) as used in Ferreira and Laux (2007).

2.3.3. 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 (such as institutional ownership, CEO stock options, percentage of outside directors with stock ownership and board size) can help predict future stock price crashes. To gather support for investor learning through risk channel, we assess if there are any differences pre and post the second structural break point in the relationship between E-Index and these two firm-specific risk measures.

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

$$r_{j,t} = \alpha_j + \beta_{a,j} * r_{m,t-2} + \beta_{b,j} * r_{m,t-1} + \beta_{c,j} * r_{m,t} + \beta_{d,j} * r_{m,t+1} + \beta_{e,j} * r_{m,t+2} + \epsilon_{j,t} \tag{9}$$

where a firm j's Wednesday-to-Wednesday return for week t is given by $r_{j,t}$, for same week the CRSP value-weighted market index return is $r_{m,t}$. One and two weeks 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 get firm-specific weekly return as $W_{j,t} = ln(1 + \epsilon_{j,t})$.

Our main crash risk measure (CRASH) indicates if a firm has experienced at least one crash week in a given year. These crash weeks are the ones in which the firm-specific $W_{j,t}$ declines more than 3.09 standard deviations below the average $W_{j,t}$ in that year.[9] Additional variable CRASHNUM is used to indicate number of crash weeks experienced by a firm in a given year. To test if the impact of governance is symmetrical on either side of average $W_{j,t}$, we construct a

[9] The 3.09 standard deviations threshold picks up 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.

complementary stock price up-movements measure (JUMP) as an indicator of if firm-specific $W_{j,t}$ rises 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 for robustness check i.e. negative conditional skewness (NCSKEW) and down-to-up volatility (DUVOL).

For idiosyncratic volatility, we try to capture more variation by considering monthly measures unlike the crash risk measures which are estimated on yearly basis. For each month, we run the estimation of a slightly modified version of Equation 9 considered for 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 monthly basis. As in previous literature (e.g. Ferreira and Laux, 2007), idiosyncratic volatility is then computed through a logistic transformation as:

$$IDIOSYN = ln\left(\frac{1-R^2}{R^2}\right) \tag{10}$$

3. Data

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

3.1. Governances data

We focus on governance data published by ISS (formerly IRRC-Riskmetrics), which reports anti-takeover provisions of S&P 500 and other large Fortune 500 companies to its customers i.e. institutional investors. ISS governance rankings and related data assess takeover protection mechanisms existing within the sample firms by using inputs from documents and forms filed with SEC, and other publicly available information from annual reports, proxy statements, etc. 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.[10] ISS governance data collection and reporting methodology, as well as its frequency, has changed over the years. Before 2007, almost 30 governance provisions and state-based statutes were reported for the sample firms every 2 to 3 years. From 2007 onwards, however, ISS publishes the anti-takeover provisions

[10] Anti-takeover provisions along with other governance characteristics such as ownership, board features and auditing requirements from ISS data are also used in Brown and Caylor (2006) to create Gov-Score as a measure of corporate governance. However, this data was made available by ISS for a limited time duration from 2001 onwards.

Table I: E-Index Across the Years

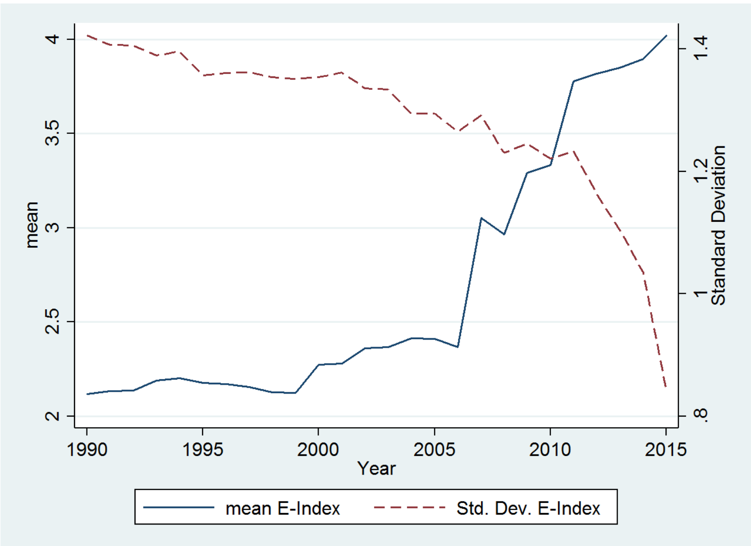
This table summarizes presence of entrenchment provisions (using E-Index) in our sample for each of ISS data publication years. Dual class stocks are left out. For details on each of the E-Index provisions, see Bebchuk et al. (2009). The dashed line indicates change in ISS data collection methodology.

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 whence the governance data was not issued by ISS. For example, the firms' E-Index scores in 1990 are replicated for 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 Table I, when governance data was not issued by ISS for a year, recent E-Index score for each firm is carried forward.



data annually and covers about 25 different provisions and state laws. Thus, to ensure comparison across the years, we use 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 from the ISS data.[11]

While Bebchuk et al. (2009) construct E-index as the managerial entrenchment subset from within the G-Index using pre-2007 ISS data, it can still be created for new ISS dataset as five of the six entrenchment provisions (i.e. staggered boards, limits to shareholder bylaw amendments, poison pills and golden parachutes) are retained even after 2007. The sixth provision on supermajority requirement for merger and charter amendment can also be included using additional details provided in the dataset.

Table I shows summary statistics for E-Index across our sample for each year of ISS governance data publication. We see that there is a distinctive trend for both the mean value of E-Index and its standard deviation across the years. This is clearly visible in Figure I, which plots the same. This plot is important because it shows that the change in ISS data collection methodology does have an impact on the visible trend as represented by the steepness of E-Index and its distribution beyond the year 2007. However, the monotonic trend of increasing average E-Index values and its declining cross-sectional variation is maintained before and after 2007. Over the entire 26 year period, our sample includes more than 36,500 firm year observations of the governance scores.

3.2. Other data

A large part of our analysis uses monthly returns obtained from CRSP for all the firms covered in the governance dataset from 1988 to 2016. Additional 2 years before and 1 year after the governance data timeframe is used to build additional controls (such as past returns) and/or to capture future portfolio performances. We additionally consider daily returns from CRSP for measures of crash risk (condensed to weekly returns) and idiosyncratic volatility. For all the sample firms, we also obtain requisite annual balance sheet data to measure price informativeness and other firm-specific controls.

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 present these statistics first for the full sample, and then, separately for the governance–returns association years (1990-2000), disassociation years (2001-2007) and reassociation years (2008-2015) as indicated on top of the table. Panel A covers all variables introduced to measure price informativeness as explained in Section 2.3.2. There is no visible trend for these variables seen across the three time periods. Panels B and C show all the firm-based information flow and risk measures. Whereas PIN (probability of informed trade) increases on an average over these three periods, the turnover activity or $TURN$ shows a declining trend on an average. Lastly, Panel

[11] Although we cannot construct G-Index across the entire sample period as the scale of such a measure would be different across the pre-2007 and post-2007 years, we do use a normalized G-Index score called *G-Proxy* to test the robustness of all our results.

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), disassociation years (2001-2007) and reassociation years (2008-2015) as indicated on top of the table. Panel A covers all variables introduced to measure price informativeness as explained in Section 2.3.2. 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 I for more details). Except for TURNOVER and IDIOSYN which are recorded at monthly frequency, all other variables are 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

.

D presents all the control variables. Many of the variables that are associated with firm size, show a characteristic rise over the years. This is expectedly because many of the firms in our sample are consistently reported by ISS, and have grown during these years.

4. The association, disassociation and reassociation of governance and returns: A case of two structural breaks

We start by estimating the first structural break using entire sample of 25 years data to identify that month whence the F-statistic for a break was biggest, using a 15% trimming. By design, the procedure identifies only the first structural break point as the first break usually gives the largest F-statistic due to the applied asymptotic distribution. Table III Panel A summarizes the identified break points from both Quandt method and the 36-month rolling method. Estimated break points for first structural break are very similar to those shown in Bebchuk et al. (2013) using the E-Index for both equal-weighted and value-weighted portfolios. To identify the second break point, we repeat the same 15% trimmed F-statistic test by excluding the time periods before the first structural break. The estimated second break points using both equal-weighted and value-weighted portfolios are just one month apart i.e. January 2008 and February 2008.

Next, following the assumption in Bebchuk et al. (2013) that learning is not a discrete event, we identify the possible "critical learning" point by using 36-month rolling alphas to determine when the gradual learning is complete (see Section 2.1). For investor learning as well, we apply similar gradual process assumption and determine the end point of investor learning using rolling estimation. Once again, the identified break points for first structural break are similar to Bebchuk et al. (2013). For the second structural break, interestingly, the estimated end points for investor learning are either July 2008 (for value-weighted portfolio) or December 2008 (for equal-weighted). This suggests that investor learning phenomenon is much quicker than the learning process. Note that our final estimate for first break point is January 2001, which is not the midpoint of start and end learning points identified from the two methods. This is done to ensure that the effects of learning are separated as early as possible in the returns time-series so that the investor learning point can be estimated within a larger window. For the second break point, we consider the earliest point in time from both the applied methods (across the two portfolios), as this point essentially identifies the first instance of investor learning and governance – returns reassociation in our sample.

We run confirmatory tests using Bai and Perron (1998) and Hatemi-j (2008) estimations (using slightly modified specifications of Equation 1 that allows multiple or two breaks) and find that the two structural breaks identified are very close to the ones that our previous analysis reveals.

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; which, as expected, appear a

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 Andrews (1993) Quandt tests (using Equation 1) and the 36-month rolling method. 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, on the other hand, reports abnormal returns (α s or alphas) by running Equation 1 with additional structural break (SB) variables. All estimations use White (1980) robust standard errors (in parenthesis). In 2 SB model, the disassociation period (2001-2007) is taken as benchmark, with each of the association and reassociation periods represented by SB Dummy 1 (for 1990-2000) and SB Dummy 2 (for 2008-2016) respectively. In 1 SB model, a single variable takes value of '-1' for pre-disassociation period and '+1' for post-disassociation 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

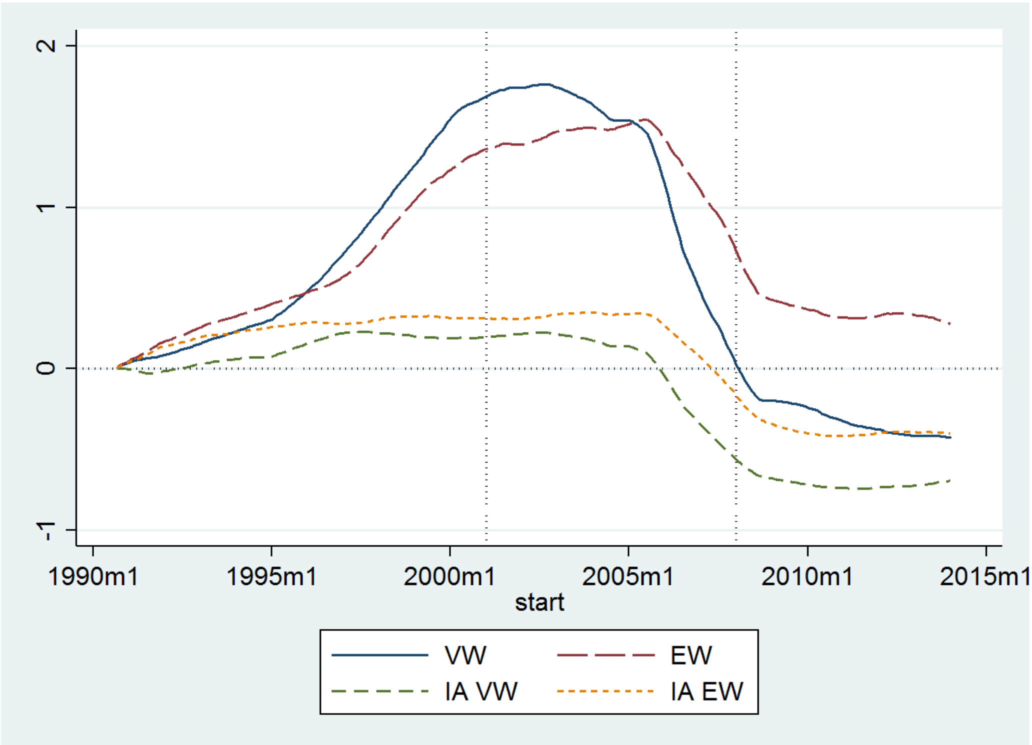
	1st break point		2nd break point	
	VW	EW	VW	EW
Quandt LR Method	July-2000	November-2000	January-2008	February-2008
36-month Rolling Method	February-2003	June-2002	July-2008	December-2008
Estimated point:	January-2001		January-2008	

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)
SB Dummy 1	0.0078**	0.0067*	-0.0147***	-0.0074***
	(0.004)	(0.004)	(0.004)	(0.002)
SB Dummy 2	-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

Figure II: Returns from Governance Trading Strategies

This figure shows the plots of cumulative excess returns generated from a long good governance / short bad governance hedge portfolio using the E-Index. For each month, the future 36-month average abnormal returns are computed using rolling five-factor regressions that account for the three Fama and French (1993) factors i.e. market ($RMRF$), size (SMB) and book-to-market (HML) along with the Fama-French momentum factor (MOM) and Pástor and Stambaugh (2003) liquidity factor (LIQ). These monthly abnormal returns are then compounded over the months beginning September 1990 and ending December 2015. The last 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 Fama and French (1997) 48 industry classification are also shown. Vertical dotted lines on the plot represent the two identified structural break points.



few months after the trend shifts, since these plots represent future returns. Along with the value-weighted (VW) and equal-weighted (EW) governance hedge portfolios, we additionally plot industry adjusted VW and EW returns by adjusting each stock's returns using Fama and French (1997) 48 industry mean. This helps us alleviate concerns about industry clustering driving the governance – returns relationship as expressed in Johnson et al. (2009) and Giroud and Mueller (2011). While the industry adjustment does drastically suppress the excess returns for EW and VW portfolios during the association and disassociation years, investor learning trend is consistent across all the portfolios. This suggests that investor learning hypothesis is in some ways robust to industry clustering and product market competition.

In Table III Panel B, we report two variations of Equation 1 that assess the changes in abnormal returns for the three time periods separated by aforementioned two structural break points i.e. 1990-2000, 2001-2007 and 2008-2016. In the first model, we consider 2001-2007 (or the disassociation years) as the benchmark and include two structural break (SB) dummies one indicating pre-disassociation period and other representing the reassociation years. In the second model, we again consider 2001-2007 as the reference period, but include a single SB variable that is assigned '-1' for pre-disassociation years and '+1' for the reassociation period. While both these estimations give us the differential abnormal returns for governance-based strategies over and above the zero alpha during disassociation 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 disassociation).

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

5. Investor learning and the reappearance of governance – returns association: The experiment

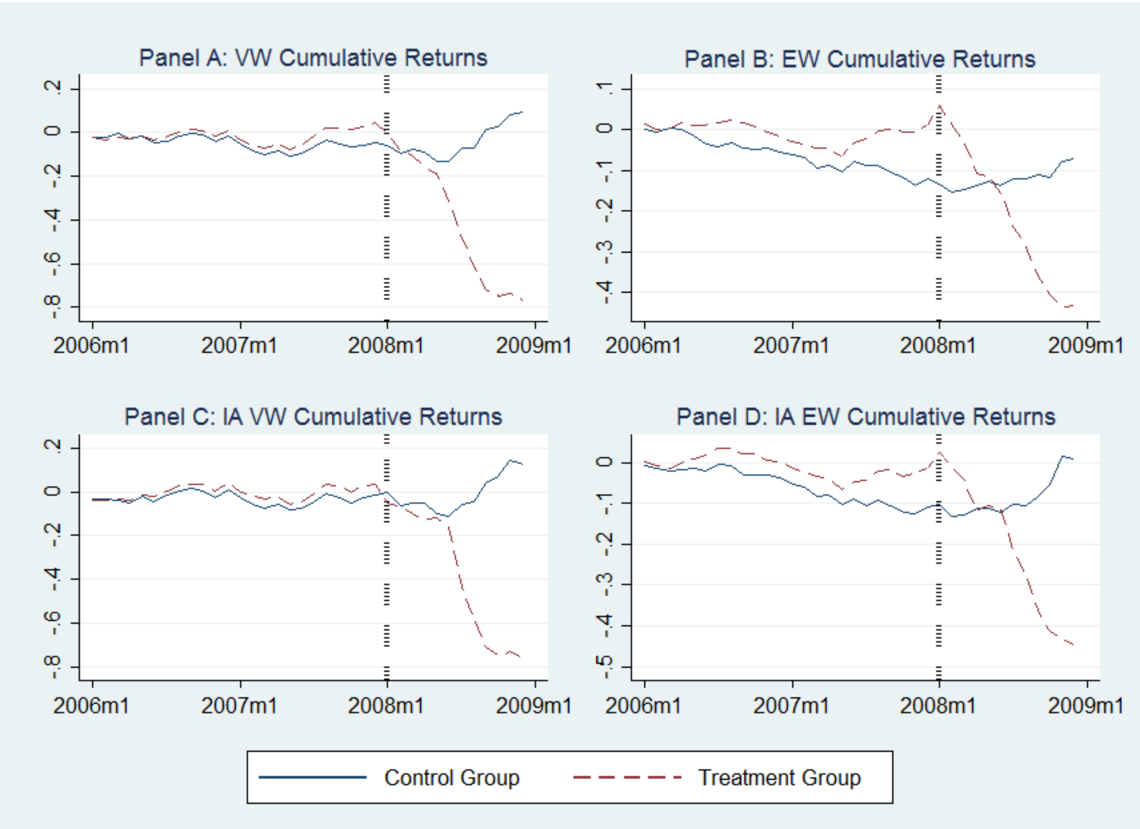
5.1. Experimental setting and preliminary evidence

We examine investor learning in terms of variations in the frequency of corporate governance reporting by ISS in our sample period. As the corporate governance provisions data became available to investors annually from 2007 onwards, how did they benefit from such timely dissemination of governance signals vis-à-vis pre-2007 years when governance data used to be made available every 2-3 years? In light of the argument made for the investor learning hypothesis, we expect institutional investors' learning experience to be higher when governance information is disseminated to them at a faster pace (in our setting, annual basis) than the older biennial or triennial ISS reporting practices. This means that, due to such learning, the institutional investors who only rely on the newer information must have an informational advantage leading to more premium-seeking behaviour for governance risks than those who continue using older information. This lays the main basis for our DiD estimation for investor learning effects.

Figure III provides a comparison of raw cumulative returns, using various long good governance - short bad governance portfolios, between the control (*Slow*) and treatment (*Fast*) group firms. Panels A and B show the value-weighted and equal-weighted E-Index governance hedge portfolios

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

This figure shows the plots of cumulative returns generated for control (*SLOW*) and treatment (*FAST*) group 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 starting January 2006 (the first month of our DiD period). Both last month market capitalization weighted or value-weighted (VW), and the equal-weighted (EW) portfolios are shown. Additionally, industry adjusted returns (IA) using Fama and French (1997) 48 industry classification are also shown to control for product market competition and industry clustering. Vertical dotted line on represents the critical investor learning point i.e. January 2008.



respectively, whereas Panels C and D show the same by adjusting each firm's returns with Fama-French 48 industry means to control for product market and related competitive clustering. Across all of the four plots, whilst cumulative hedge portfolio returns from control group remain almost flat and very close to zero; the same from treatment group shows a characteristic drop beyond the investor learning point (marked by the dotted vertical line in the figure). In fact, for some of the portfolio constructions, the trend is directionally opposite between the two groups with the control firms-based governance hedge showing positive and increasing returns. These plots support the validity of our experimental setting through and through.

5.2. Results

Regardless of the visual evidence in Figure III, we robustly study the changes around second structural break point to statistically test our investor learning hypothesis and eliminate possible biases from extraneous confounders. The main results from our DiD estimation are shown in Table IV. To test the validity of our experiment, we first run Model (1) which estimates only π_1 and π_2 ignoring the interaction term in Equation 2. In Panel A, we see that on an average, treatment group based portfolio generates significantly different abnormal returns than the control group one. This is indeed true for both equal-weighted and 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 investor learning phenomenon, as only the interaction term remains statistically significant.

In Panel B of Table IV, we correct for differences in the total number of firms in Democracy and Dictatorship portfolios between the treatment and control groups, by expanding the portfolio classification for control group firms using median E-Index. The results, especially when it comes to the DiD term, largely remain the same both in terms of the magnitude and statistical significance of the coefficient. Next, in Panel C, we ensure equivalent control and treatment firms in each portfolio by using nearest neighbor propensity score matching with a 0.001 calliper. The economic and statistical significance for matched DiD estimator is similar to the ones seen in Panels A and B.

For propensity score matching, the firms in control group are matched on size of assets, operating performance (i.e. return on assets) and leverage to obtain a comparable treatment group firm. Table V shows the summary of key characteristics of each group before and after matching. The three firm characteristics that we employ for matching seem to sufficiently balance the treatment and control groups even across additional dimensions as shown.[12] The matched

[12] Only the E-Index means are different between the two groups. However, this as shown by the mean values is higher for treatment group when compared to the control group, which shows that increased anti-takeover provisions within the 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 Investor Learning Drive the Governance – Returns Reassociation?

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 2 controlling for market, size, book-to-market, momentum and liquidity factors. Robust standard errors are shown in parenthesis. Structural Break (SB) Dummy represents the reassociation year (i.e. second SB or 2008). Treat is a dummy representing FAST group as defined in section 2.2. 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
SB Dummy	-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)
SB Dummy ∗ 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
SB Dummy	-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)
SB Dummy ∗ 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
SB Dummy	-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)
SB Dummy ∗ Treat			**-0.1734*** **	**-0.0507* **
			(0.035)	**(0.030)**
Observations	72	72	72	72
R-squared	0.15	0.08	0.43	0.11

Table V: Summary statistics for Unmatched and Matched DiD 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 I. Panel A considers the full DiD sample (i.e. all firms whose E-Index could be used by investors), whereas in Panel B, only the sub-sample that includes the Democracy and Dictatorship firms are shown for the treatment and control groups. 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 (2006–2008)

	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***

Table VI: Robustness for Investor Learning and Governance – Returns Reassociation

This table reports the robustness tests for the main Difference-in-Differences (DiD) estimation results shown in Table IV. 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 parenthesis. All models are estimated using Equation 1 controlling for market, size, book-to-market, momentum and liquidity factors. Structural Break (SB) Dummy represents the reassociation year (i.e. second SB or 2008) in Panel A, the placebo year (i.e. 2000) in Panel B, and the dissociation year (i.e. first SB or 2001) in Panel C. Treat is a dummy representing FAST group as defined in section 2.2. Panel A employs the PS matched sample while using the hedge portfolios defined around the median E-Index as in Table IV 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 IV Panel A (i.e. with the control group 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
SB Dummy	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)
SB Dummy ∗ 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
SB Dummy	-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)
SB Dummy ∗ 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
SB Dummy	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)
SB Dummy ∗ Treat			**-0.0485**	**-0.0068**
			(0.040)	**(0.032)**
Observations	96	96	96	96
R-squared	0.01	0.13	0.02	0.12

groups are equivalent for both the full DiD sample firms (Panel A Table V) and the extreme portfolio firms (Panel B).

We also confirm that our results are not driven by the applied five factor asset pricing model by using other alternative models. The coefficients for the investor learning effect remains stable across all these models (see Appendix II). Overall, Table IV indicates that the investor learning effect as well as the information advantage of faster dissemination does exist. Our main results do not change even when we account for selection biases and other possible cross-group differences.

5.3. Robustness and additional validity tests

Table V reports additional robustness tests for main results of DiD estimation shown in Table IV. While the results in Table IV Panels B and C, strengthen the validity of our results by increasing the power (Panel B - increased control group) and eliminating selection bias (Panel C - propensity matching with control group), we do not have a case of high power and low selection bias together. In table VI Panel A, we combine the wider median-based portfolios with the propensity score matching to overcome this. Once again, results support investor learning hypothesis, more so for the value-weighted portfolios. The loss of significance for equal-weighted portfolio can perhaps be explained by some of the matched characteristics explaining the variations in returns. The magnitudes of coefficients are also smaller, indicating that this is a much sterner test on our experiment understandable because the difference between Democracy and Dictatorship firms is much smaller with median-based division.

We run additional validity tests on our experimental setting by running a placebo DiD estimation as shown in Table VI Panels B and C. We first locate similar treatment and control group of firms at a different point of time (in this case taking 1998-2001 period, instead of 2006-2008). While the ISS report for 1995 lasted three years, the ISS governance report in 1998 was applicable for two years. We, thus consider the firms with newer information updated in the year 2000 as placebo treatment and the ones without new information as placebo control. Panel B considers a three year time frame as in all previous DiD estimation, considering an arbitrary investor learning year 2000. Panel C, on other hand, includes the returns for year 2001 (the learning structural break year) to see if similar investor learning effect, albeit, possible directional reversal existed. Across both the placebo test specifications, we see that the DiD terms are insignificant. This lays further credence to our main result as the investor learning from governance information was experienced only in the year 2008.

5.4. Abnormal returns from investor learning: The governance risk premium

We extend the findings from the DiD experiment to examine how a fully informed investor may potentially benefit from exploiting both the governance data and its timing, i.e. in other words, complete investor learning. We model this using the five factor model as shown in Equation 1, but taking the returns from information timeliness hedge of governance hedge portfolios. Alternatively

Table VII: Governance, Investor Learning and Returns

This table shows the coefficients and standard errors (in parenthesis) 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)

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 whence 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 investor 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 VII 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 Appendix II Table A.III). When the investment horizons are restricted to annual periods, in Table VII 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 investor learning premia are statistically significant beyond 5% levels.

6. The investor learning channels

6.1. Investor learning through price

In Figure IV, we compare price informativeness for our sample firms that are grouped into good and poor governance categories using the median E-Index in each year. The two groups are seen to follow similar trend of slightly positive price informativeness with 1 year earnings forecast horizon across all the three periods i.e. association, disassociation and reassociation years (these three periods are separated by vertical dotted lines in this figure). However, for remaining three horizons, a distinct common pattern emerges between the good and poor governance groups in the reassociation period (i.e. 2008-2015). We see that beyond second structural break, price informativeness for good governance stocks largely lies above the price informativeness of poor governance ones. Additionally, over the longer horizons of 3 and 5 years, poor governance stocks tend to show a visible declining trend in price informativeness after 2008. To gain more insights into this trend and the differences between these two groups, we run regressions as per Equations 3 and 4. The results are shown in Table VIII.

In panel A of Table VIII, we focus on the dummy variable representing years beyond second break point i.e. SB Dummy 2. While there is no difference in the relative price informativeness between good and poor governance firms over short horizon; when it comes to medium to longer horizons, a consistent trend appears. For all of the 2, 3 and 5 year horizons, it is seen that price informativeness during 2008-2015 for poor governance stocks has decreased whereas the same for

Figure IV: Governance and Price Informativeness

This figure compares price informativeness for good and poor governance firms grouped by the median E-Index cutoff for each year. For each groups, the price informativeness (PRI) is separately computed by first using the Equation 7 to get information coefficient (tracing $ln(MV/A)$) and then, substituting this coefficient in Equation 8 for each year. Each of the subplots represent different forecasting horizons considered (represented by i in Equation 8). The same are indicated on top of each subplot with the vertical dotted lines representing the two structural break points i.e. January 2001 and January 2008.

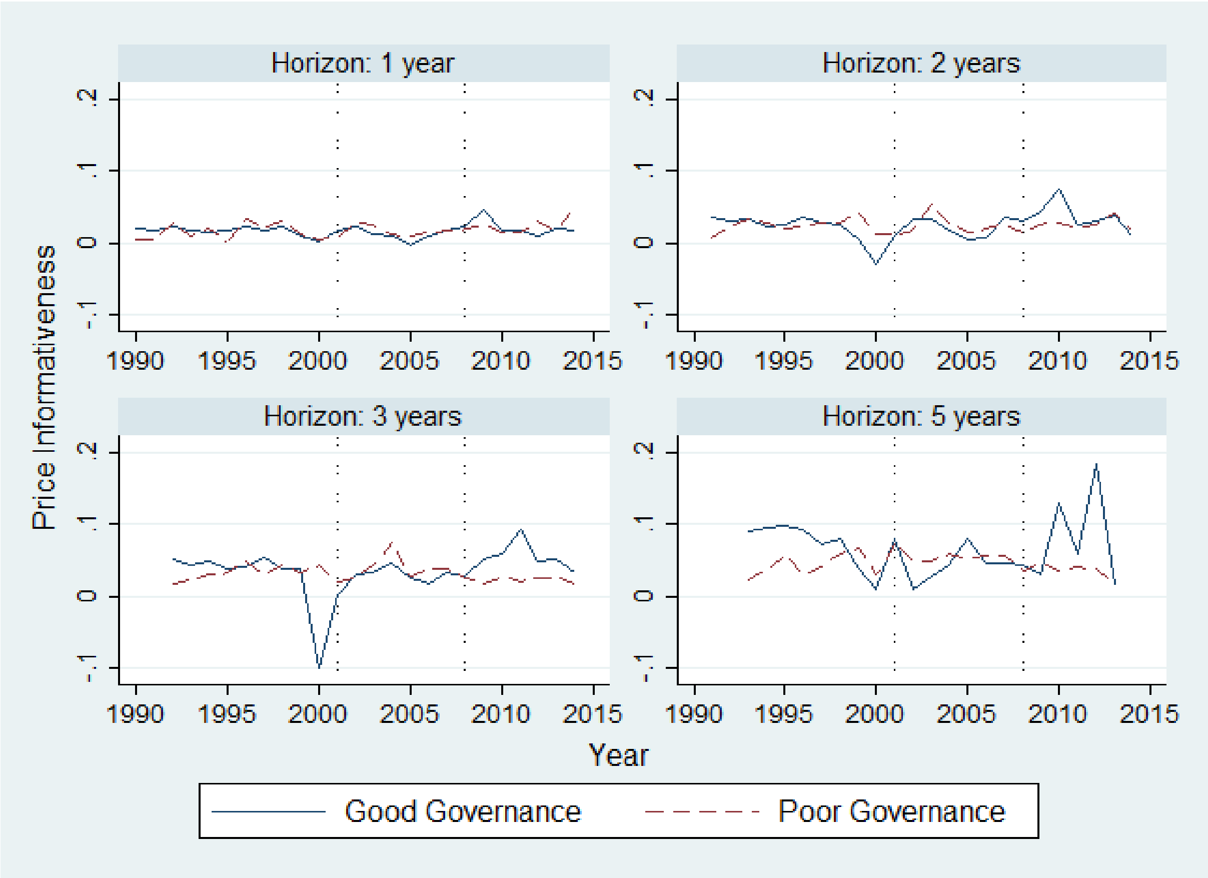


Table VIII: Price Informativeness Across the Two Structural Breaks

This table shows the coefficients and Newey and West (1994) standard errors (in parenthesis) 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-disassociation (1990-2000) and reassociation (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)
*SB Dummy*1	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)
*SB Dummy*2	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)
$E{-}Index\ Dummy$	0.0015	-0.0021	-0.0078	-0.0242***
	(0.002)	(0.003)	(0.006)	(0.008)
$SB * E{-}Index\ Dummy$	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

good governance ones has increased in comparison to the disassociation years. The differential effect (i.e good – poor PRI) for each of these horizons shows a monotonic increasing trend implying that price informativeness for poor governance stocks worsens in terms of future earnings predictability with longer horizons vis-à-vis good governance stocks. Results in Panel B confirm our findings in Panel A that much of the change in price informativeness is concentrated beyond the second structural break point. When we combine the two structural breaks into a single SB variable, only the price informativeness over 3 year horizon picks up consistent governance-based differential change across the two structural breaks.

To gather more fine-grained insights on price channel, next, Table IX reports firm-based information flow measures i.e. TURN and PIN in relation to E-Index across the two structural breaks. Model 1 uses simple OLS with industry fixed effects and Model 2 controls for firm heterogeneity by including firm fixed effects in a panel regression. Both for TURN and PIN, we see a distinctive shift in the E-Index coefficients across the second structural break, especially with firm fixed effects. Note that while TURN is measured monthly, PIN is taken on yearly basis. Whereas before investor learning, increasing E-Index would entail increased trading activity (TURN) for an average firm; the direction of this relationship reverses after investor learning. When it comes to probability of informed trade (PIN), the findings are directionally opposite to that for TURN. Increasing anti-takeover E-Index provisions, increases PIN after investor learning, in contrast to its effect on PIN before the second break point.

On the whole, the presence of a systematic difference between the disassociation years and the reassociation years for both aggregate price informativeness and firm-based information flow measures, indicates that information asymmetry has increased for investors within the poor governance firms. Market prices and trading activity does manage to communicate this difference to investors if they are alert and receptive to such signals.

6.2. Investor learning through risk

Although information flow and volatility have a very close relationship (Ross, 1989), they can be considered to be two distinctive channels for investors' learning. Thus, in this section, we examine and present results for the predictive ability of E-Index for firms' risk, and how it has evolved across the two structural break points (mainly, the second one).

In Table X, we report the results for pooled regressions (Model 1) as well as firm fixed effects panel regressions (Model 2) for the two main firm-specific risk measures i.e. $IDIOSYN$ and $CRASH$. To compare and contrast the predictive ability of governance or E-Index on these measures across the structural breaks, we subdivide the sample into three time periods i.e. 1990-2000, 2001-2007 and 2008-2016. In Panel A, the results for idiosyncratic volatility are shown. For both the pooled and fixed effects models, there is a peculiar change in the coefficients for E-Index before and after investor learning (i.e. around the second structural break point). During 1990-2000 and 2001-2007 periods, future idiosyncratic volatility is negatively associated with E-Index both

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, disassociation and reassociation 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 parenthesis. The coefficients for constant and industry dummies are omitted. See Appendix I for definitions of all controls. Significance levels at 10%, 5%, and 1% respectively are shown using *, **, and ***.

	Model 1			Model 2		
Panel A: TURN	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)
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
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	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)
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
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

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

This table shows results obtained for relative idiosyncratic volatility (IDIOSYN) and firm specific crash risk (CRASH) on E-Index across the association, disassociation and reassociation 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 (1) and panel firm fixed effects logit (2) models. 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 I for definitions of all control variables. *, **, and *** represent significance levels for 10%, 5%, and 1% respectively.

Panel A: IDIOSYN

	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)
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
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
Industry Fixed Effects	Yes	Yes	Yes	No	No	No
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
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

in cross-sectional terms (Model 1) and within firm terms (Model 2). However, this relationship turns positive for 2008-2016 period. Since *IDIOSYN* is a relative measure (see Equation 10), the coefficients for E-Index can be interpreted as a decline of idiosyncratic volatility by 10.31% (4.51%) for each extra adoption (cross-sectional change) of E-Index provision during the disassociation years. Investor learning opportunities get reflected in reassociation 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 period (i.e. across the first break point), the negative association with 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 E-Index from 2001-2007 to 2008-2016 period. Since *CRASH* is a dummy variable indicating stock price crash for a given year, in Table X Panel B, we apply pooled logit (Model 1) and panel logit with firm fixed effects (Model 2) regressions. During the disassociation years, the coefficients for E-Index are statistically insignificant indicating no relation with crash risk (for both regression models). On the contrary, E-Index shows statistically significant (at 1%) and positive relation with future stock price crash risk during the reassociation years. We estimate marginal effects for E-Index on future *CRASH* to establish the economic significance of the coefficients from 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). Lower effect for within firm adoption of anti-takeover provisions is understandably because, in our sample, the proportion of firms with changing E-Index values across time is much smaller than those with constant E-Index (especially when the sample is divided around the two structural breaks).

Just like idiosyncratic volatility, crash risk as well does not show any distinctive shifts around the first structural break. Furthermore, marginal effects during both the pre-disassociation (1990-2000) and the disassociation (2001-2007) periods are not statistically different from zero. This indicates that there is no learning-induced effects of E-Index on crash risk.

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

On the whole, our findings support the investor learning hypothesis and show that firm-specific risk is another possible channel through which alert investors may have learnt to appreciate

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)

governance risk difference between low and high E-Index firms.

7. Conclusion

In a 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 on investor learning hypothesis, to a certain extent, builds on this stock price overreaction / underreaction mechanism and shows that governance – returns anomaly is indeed fragile. This fragility is displayed by initial disappearance and then the reappearance of governance – returns association. We argue that, learning by market participants led to disappearance of returns – governance association only for a few years, following which it reappears albeit in opposite direction i.e. showing a possible hedge position reversal. Such hedge reversal was not captured in Bebchuk et al. (2013), since the investors' learning was not visible in the sample timeframe considered. In fact, this hedge reversal is more interesting to examine than just the reappearance of said association. Thus, in this paper, we explain why the abnormal return – governance indices association has reappeared and reversed in recent years.

The starting point for the investor learning phenomenon is the Bebchuk et al. (2013) learning hypothesis that explains disappearance of governance – returns correlation beyond 1990s.[13] We

[13] Alternatively, Li and Li (2016) show that governance – return relation across the years can be explained by

show that while this association did disappear beyond 2000s, it subsequently reappears in opposite direction from 2008 onwards. Thus, investor learning hypothesis is characterized by the investors understanding governance risk, which other market participants –and markets at large (as proxied through the common risk factors)– do not yet seem to recognize. Using a natural experiment that is set around an exogenous shock to governance information availability, we show that investors did potentially benefit through learning (beyond the second structural break point) by better adjusting their returns expectations.

Beyond the investor learning point (i.e. January-2008), we find evidence that supports possible communication of governance risk for poor governance firms vis-à-vis good governance ones through price information and risk channels. While medium and long run price informativeness declined for poor governance stocks beyond 2008, it showed a tendency to increase for good governance stocks. With respect to firm 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 firms risks were not visible expectedly in the pre-reassociation (i.e. the disassociation) period. Hence, we posit that alert investors would have gained additional wisdom beyond the first structural break point to identify such governance-based investment opportunities that appeared subsequently.

Daines et al. (2010) show that corporate governance rankings do not provide any useful information for shareholders (in the years 2005 through 2007). Our findings both support and contradict their result. It is true that during the disassociation years, there was no useful information provided to investors through governance data and rankings. However, we show that governance indices are indeed 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 returns consistently over and above some of the common risk factors. From this perspective, our results do not strictly indicate market inefficiency nor suggest solely investors' learning. Our passive investment strategy only controls for a few of the well-known risk factors, whereas market may yet be pricing the unobservable *governance risk* that we fail to account for as it has not been measured yet (Fama, 1998). However, as a word of caution, since corporate governance itself encompasses a wide variety of underlying monitoring and auditing mechanisms; it is highly unlikely that such governance risk does get completely priced by markets, thus, continually creating investment opportunities such as the one that we have documented.

economic states (i.e. booms or busts) that each firm's industry faces and, hence, the pre-2000s governance – returns anomaly is not robust when investment and divestiture options are accounted for. However, the hedge reversal and investor learning seems robust to such industry-wide factors. We do not directly test such economic states or investment options, but do control for them by adjusting returns for each firm by its industry's mean returns.

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Appendix I: Definitions of 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 months on CRSP database (measures 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 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 2.3.3) for a given firm over that year.
SIGMA: 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.

Appendix II: Alternative Asset Pricing Models

We check the robustness of all our main results that employ five factor model presented in Equation 1 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.I: 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 1 with additional structural break (SB) variables. All estimations use White (1980) robust standard errors (in parenthesis). 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)
SB Dummy 1	0.0107**	0.0054	-0.0107***	-0.0061**
	(0.005)	(0.004)	(0.004)	(0.002)
SB Dummy 2	-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)
SB Dummy 1	0.0092**	0.0059	-0.0112***	-0.0066**
	(0.004)	(0.004)	(0.004)	(0.003)
SB Dummy 2	-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)
SB Dummy 1	0.0079*	0.0045	-0.0129***	-0.0065**
	(0.004)	(0.004)	(0.004)	(0.003)
SB Dummy 2	-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)
SB Dummy 1	0.0082*	0.0052	-0.0110***	-0.0064**
	(0.004)	(0.003)	(0.003)	(0.002)
SB Dummy 2	-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)
SB Dummy 1	0.0072*	0.0041	-0.0126***	-0.0063**
	(0.004)	(0.004)	(0.004)	(0.003)
SB Dummy 2	-0.0185**	-0.0087		
	(0.008)	(0.005)		

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

This table summarizes results using alternative asset models for main DiD estimation result in Table IV (Panel A). White (1980) robust standard errors are shown in parenthesis. For variable definitions, see Table IV. Average main effects (Model 1) and average treatment effects (Model 2) are shown using either 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
SB Dummy	-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)
SB Dummy ∗ *Treat*			**-0.1275*** **	**-0.0565*** **
			(0.032)	**(0.014)**

Panel B: Fama-French 3 Factors

	Model 1		Model 2	
	VW	EW	VW	EW
SB Dummy	-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)
SB Dummy ∗ *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
SB Dummy	-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)
SB Dummy ∗ *Treat*			**-0.1275*** **	**-0.0566*** **
			(0.030)	**(0.014)**

Panel D: Fama-French 5 Factors

	Model 1		Model 2	
	VW	EW	VW	EW
SB Dummy	-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)
SB Dummy ∗ *Treat*			**-0.1275*** **	**-0.0566*** **
			(0.029)	**(0.014)**

Panel E: Fama-French 5 Factors + Liquidity Factors

	Model 1		Model 2	
	VW	EW	VW	EW
SB Dummy	-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)
SB Dummy ∗ *Treat*			**-0.1275*** **	**-0.0566*** **
			(0.029)	**(0.014)**

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

This table reports alphas (αs) when alternative asset pricing models are used in Table VII Panel A. For variable definitions and other details, see Table VII. 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)