Essays on Corporate Governance and Firm Performance

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Declaration

I hereby declare that this thesis entitled "Essays on Corporate Governance and Firm Performance" and the work presented in it are my own and have not been submitted in substantially the same form for the award of a higher degree elsewhere.

A further developed working paper which is based on Chapter 2 is circulated under the title "The Benefit of the Friendly Board". The paper is co-authored with Prof. Sudipto Dasgupta and Prof. Tao Shu.

Chapter 3 is being circulated as a working paper with the same title. This paper is co-authored with Dr. Li He and Prof. Toni Whited.

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Abstract

This thesis contains two studies that examine the interaction between corporate governance and firm performance.

In the first study, I examine whether board friendliness reduces crash risk. I measure friendliness by the Political Homophily Index (*PHI*), which captures the similarity of political orientations of managers and directors. We find that firms' crash risk decreases in political homophily. The results are robust when we instrument the change in *PHI* by the change in local political homogeneity. Our results suggest that better alignment in political orientations facilitates information sharing, including information on bad outcomes in a timely manner. The effect is more pronounced when firms have stronger corporate governance mechanisms and directors have a stronger incentive to acquire information.

In the second study, I examine how the use of relative performance evaluation (RPE) affects industry competition. Using data from the U.S. airline industry, we estimate a dynamic game of competition with heterogeneous firms in an oligopolistic market with the presence of RPE contracts. As is standard, RPE makes CEO compensation less sensitive to market conditions. Therefore, the CEO's propensity to operate in a given market is determined by a trade-off that arises between the reduction in compensation based on market conditions and the gain from being compared to competing agents. The estimation results show that the use of RPE decreases a firm's tendency to be active under bad market conditions by 10.1%. Conversely, the tendency to be active rises in good market conditions by 12.4%. These effects are stronger for firms with lower fixed operating costs.

Chapter 1

Introduction

Corporate governance has been believed to be critical to ensure that activities and policies of management are in line with shareholders' interests. However, the practice of corporate governance is complicated. In this thesis, I study two important aspects of corporate governance and examine their effect on firm performance: the characteristic of independent directors and the contracting of CEO compensation.

As pointed out in Adams and Ferreira (2007), there is a trade-off between the monitoring role and the advisory role played by independent directors. The independent directors have the responsibility to discipline the CEO from not behaving in the best of shareholders' interest. However, tougher in monitoring makes independent directors harder to acquire firm-specific information from the CEO, especially in bad situations. Therefore, in theory, a friendly board may benefit the firm by facilitating information sharing between the CEO and directors.

In Chapter 2, I empirically examine the benefit of friendly boards. Particularly, we construct measures of individual political orientation using their donations to candidates during Federal Election cycles. The similarity between individual political orientation can serve as an ideal instrument for the friendliness between CEO and independent directors: the more similar political orientation is, the more friendly are the independent directors towards to CEO. Using the measure of political similarity, we then develop and test hypotheses on the benefit of a friendly board. Firstly, we find that higher political similarity between the CEO and independent directors significantly associates with lower crash risk in firm stock prices. The effect is stronger for firms with stronger corporate governance mechanisms. Secondly, we find evidence that the insider trading from independent directors is more informative when they share similar political orientation with the CEO. In addition, our results are robust when we instrument the change in political similarity by the change in local political homogeneity. Our findings provide strong support to the argument that the friendly board may benefit the firm.

Another practice to align the CEO's behavior with shareholders' interest is to set up an incentive compatible compensation contract. Especially, people believe that the best practice should only award CEO based on his/her attribution. That is why the Relative Performance Evaluation (RPE) is widely regarded in the literature on optimal contracts as an efficient tool to incentivize CEO effort. However, the evidence of RPE in practice is largely mixed. The reason is that the use of RPE greatly affects the strategic interaction within the industry. Therefore, it is questionable both theoretically and empirically that to what extend the use of RPE is optimal.

In Chapter 3, we examine how the use of RPE affects industry competition. We develop a parsimonious dynamic game of competition with heterogeneous firms in an oligopoly market where CEOs make entry-exit decisions to maximize their expected discounted inter-temporal utilities, taking as given their expectations about competitor actions. In this setting, we find that the use of RPE has an asymmetric effect on competition depending on market conditions. When the market condition is good, the use of RPE encourages CEO to take more competition. However, if the market condition is bad, the use of RPE decreases the probability of a firm being active in a certain market.

Furthermore, we use data from the US airline industry to estimate the model. The information on quantities, prices, and route entry-exit decisions between the 50 largest U.S. metropolitan statistical areas provides an ideal set-up of an oligopoly industry. The estimated model is able to match key features of the market structure and dynamics. Our estimation results confirm the existence of Relative Performance Evaluation. In addition, the use of RPE depends also on the firm's comparative advantage relative to its peers, suggested from the estimated operating cost.

Lastly, Chapter 4 concludes the thesis and summarizes my findings.

Chapter 2

The Effect of Politically Alignment Between the CEO and the Board on Firm's Crash Risk

2.1 Introduction

The pace of change has accelerated dramatically in the business world due to the rapid emergence of technologies, presenting boards with an ever more challenging environment. At the same time, boards face growing pressure from a variety of stakeholders, ranging from institutional investors to proxy advisory firms and shareholder activists. As stated in the speech by the former SEC Commissioner, Luis A. Aguilar, at the 12th Annual Boardroom Summit and Peer Exchange in 2015, their fiduciary responsibility requires boards to ensure that they possess necessary skills and judgment, to foresee opportunities and problems that lie ahead, and to apply their expertise to help navigate their firms.[1]

However, meeting this high standard is not an easy task, especially when there is a rising trend in demand for independence. To effectively discipline, independent directors need to be least connected to the firm so that they are willing to stand up

[1] Source: https://www.sec.gov/news/speech/important-work-of-boards-of-directors.html

to protect shareholders' interests. By selection, such directors are likely to have inferior information to corporate insiders and may lack of knowledge when their firms face negative shocks.[2] Therefore, it is increasingly critical for the outside directors to acquire information for them to be competent stewards.

In this chapter, we study whether board friendliness lowers the firm's crash risk by encouraging managers to share private information with independent directors. Since many board members have full-time jobs in other corporations, they rely on the chief executive and the company's management to provide them with relevant firm-specific information (Adams and Ferreira (2007)). The better the information the CEO provides, the better is the board's advice. Therefore, the "friendliness" should be an important characteristic for the board to incentivize the CEO to share their private information. However, the concept of friendliness has not been well defined in the literature and it may contain multi-dimensional interpretation. It is very challenging to find a proper measure for friendliness in the setting of CEO-board relationship.

Ideally, we need a measure of friendliness which satisfies three criteria. First, the measure can map the multi-dimensional concept of friendliness into a linear space so that we can easily use the measure to investigate the impact of friendliness on firm's performance. Second, this measure should at its best to capture the friendliness but not the friendship, since the latter characteristic apparently hurts board independence. Last but not least, the measure should be regarded to be correlated with people's intentions for collaboration. A such measure should be believed to be connected with better communication and information sharing, which is the channel that we propose to benefit the value of the firm.

In particular, we examine "friendliness" in terms of political similarity. Our hypothesis is that similarity in the political orientation of the CEO and board helps facilitate information sharing and reduces crash risk. The measure of "friendliness"

[2]For example, on February 2, 2018, the Federal Reserve issued an enforcement action against Wells Fargo, which, among other things, publicly censured directors for the failures of risk oversight and "lack of inquiry and lack of demand for additional information". See https://www.federalreserve.gov/newsevents/pressreleases/files/enf20180202a2.pdf.

in terms of political similarity certainly satisfies the first criterion, since we can easily map the political orientation into a linear space in which Republic-leaning posits on the one end and Democratic-leaning posits on the other end. This measure also satisfies the second criterion, since sharing similar political leaning does not necessarily mean that they also share physical friendship in real life. In addition, we control for social relationships in our tests to further isolate the effect of personal connection. For the third criterion, in psychology, sociology, and political science literature, it is well documented that sharing similar political orientation could enhance cooperation. For example, Huber and Malhotra (2017) document that people evaluate potential dating partners more favorably and are more likely to reach out to them when they have similar political characteristics. In Banda, Carsey and Severenchuk (2019), authors find that partisans evaluate objects linked to the opposing party less favorably than otherwise identical nonpartisan objects. In the broader context, political ideology is one critical component to form social identification, and there is widely established research documented the positive effect of in-group social identification on promoting cooperation in social dilemmas (De Cremer and Van Vugt (1999)). Individuals favor the in-group to which they belong which they define against a relevant out-group, and political leaning is one of the key elements to form such social identity (Greene (2002)).

Moreover, political leaning may be directly linking to the preference of corporate decisions. As shown in Hutton, Jiang and Kumar (2014), political preferences of managers influence corporate policies.[3] When managers and boards have similar political orientation, they will cooperate more and jointly formulate policies that are in conformity with their common political priors. This suggests more information sharing, including information on bad outcomes in a timely manner. Also, "friendly" boards are more willing to share the blame for bad outcomes since policies are set jointly. In this case, a friendly board reduces the costs of the CEO for sharing information. So the investors could process the information gradually and it is less likely to have an unexpected negative shock for the firm. Thus, we should

[3]Specifically, they find that Republican managers who are likely to have conservative personal ideologies adopt and maintain more conservative corporate policies.

also expect that the crash risks of the firm with a friendly board is lower.

Using the political leaning of the CEO and that of the directors, we can measure the similarity of the political orientation of the CEO and the board. We define it as the Political Homophily Index (*PHI*). For each individual (a CEO or a director), we capture her(his) political leaning using a Republican Index constructed with her(his) contributions made to Republican and Democratic candidates and committees. The underlying assumption is that political contributions made by individuals can largely be viewed as consumptions of political good (Gordon, Hafer and Landa (2015)) rather than political investments, and can largely reflect an individual's political leaning (Lee, Lee and Nagarajan (2014)). Therefore, the relative (dollar) amounts of political donations made to the two parties could capture which direction the person's political ideology tilts towards.[4] We then take the average of political orientations of all independent directors for a given firm-year and construct the *PHI* as the similarity between the Republican Index of the CEO and that of the independent directors.[5]

To test the prediction that political similarity between the CEO and board reduces crash risk, we regress two measures of crash risk on our measure of political alignment, *PHI*. We find that both the Negative Coefficient of Skewness (*NCSKEW*) and down-to-up volatility of the firm (*DUVOL*) are negatively associated with the political alignment between the CEO and the board. The results are obtained after controlling for firm fixed effects, year fixed effects, and factors that also affect the negative skewness of the stock returns (including *Board Size, 1-year lagged ROA Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*). The effect is also economically significant. For one standard deviation increase in political alignment, the firm's negative skewness of stock returns is

[4]The Republican Index is the difference between the dollar amounts of political donations made by individual i in year t to the Republican and that to the Democratic candidates and committees in the federal elections, scaled by the total amount to both parties. A positive (negative) value of *Rep* indicates that the individual's political orientation is more conservative (liberal). We discuss the measures in detail in Section 2.2.2.

[5]*PHI* takes a value between $[0, 1]$, where a value of one (zero) indicates that the independent directors share most (least) similar political orientation with the CEO, and are more (less) friendly to the CEO.

reduced by 0.002, whereas the sample mean of *NCSKEW* is only around 0.001. Our results are robust if we further control for the cases when both CEO and independent directors make 0 political contribution.

Important to note that, the composition of the board is not exogenous. While we control for firm fixed effects, year fixed effects, firm characteristics, and connections between the CEO and board, certain (unobserved time-varying) factors or shareholder preferences may drive both the political alignment and the crash risk of the firm. In this case, we would obtain a correlation between *PHI* and the crash risk even when PHI does not affect the crash risk. To mitigate the endogeneity problem, we construct an instrumental variable for the change in firm *PHI* and perform a two-stage least squares estimation to verify our results.

We instrument the change in firm *PHI* by the change in local political homogeneity (*Local PHI*). Since independent directors are likely to be selected from the local business community (Knyazeva, Knyazeva and Masulis (2013)), we expect the political leaning of the the local population to affect the expression of political leaning of independent directors. We measure the local political homogeneity (*Local PHI*) by the absolute difference between the votes received by the two major parties in a federal election cycle and regress the change of *PHI* on the change of *Local PHI* for the first stage. We allow the effect to differ between "Safe States" and "Swing States",[6] since higher discrepancy in political ideology are likely to follow unexpected electoral outcomes, which can be affected differently by the change in *Local PHI* in safe states and swing states.[7] We also include lagged *PHI* to control for the mechanical reversal of *PHI* since it is bounded between $[0, 1]$. We include

[6]Safe states are defined as states in which *Local PHI* is above the median and swing states are defined as states with a *Local PHI* below the median.

[7]Specifically, a decrease in Δ*Local PHI* predicts a decrease in firm's Δ*PHI* in safe states because a decrease in *Local PHI* in safe states implies a less safe position for the dominating party and higher uncertainty in the forthcoming election (Lindbeck and Weibull (1987), Duffy and Tavits (2008)). In this situation, voters have a higher tendency to participate as the prior belief that their votes are pivotal is increased, leading to less predictable electoral outcomes and greater discrepancy in political ideology among people. For swing states, however, unexpected electoral outcomes are more likely to occur when *Local PHI* increases (i.e., one party gains a more dominating position). Thus, an increase in Δ*Local PHI* leads to higher voter participation and a decrease in firm's Δ*PHI* in swing states.

the same set of control variables as in the baseline regressions.

The results from our first-stage regression are consistent with predictions. An increase in Δ*Local PHI* (indicating higher uncertainty in electoral outcomes in swing states and lower uncertainty in safe states) leads to a decrease in firms' Δ*PHI* in swing states, and an increase in firms' Δ*PHI* in safe states, which is consistent with studies in political science. So the change in the local political environment does significantly affect the firm-level political similarity. Moreover, although it is possible that election outcomes affect the local economy since different parties have different preference over inflation and unemployment rate (see Garfinkel and Review (1994)), it can not explain why the effect of Republican (Democratic) gaining votes on firm crash risk is asymmetric in different states. Therefore, it is less likely that the change in local political homophily, Δ*Local PHI*, directly correlates with the change in crash risk and have an opposite effect in safe and swing states. Based on these arguments, we believe that our instrument variable satisfies the exclusion conditions. After conducting the two-stage least squares estimation, we obtain very consistent results to our baseline model.

Overall, we find very consistent results that crash risk is reduced when the CEO and independent directors are better aligned in their political orientations. When independent directors are more friendly towards the CEO, the CEO would be less hesitant to reveal negative information, leading to lower negative skewness in stock returns. If, however, the CEO withholds information from the board, when piles up, negative information is eventually going to be reflected in the stock prices. In contrast, having prior (social) connections with the board may be mainly associated with less monitoring of the manager and cannot prevent bad outcomes from happening. In line with this prediction, we find that connections between the CEO and the directors do not help reduce crash risk.

We also empirically examine whether better alignment in political orientation is associated with higher firm value. Political alignment, if impeding board independence, would hurt firm value (Lee, Lee and Nagarajan (2014)). However, if the lower crash risk can be priced, then we would expect board friendliness to be associated with higher firm value. To answer this question, we run our baseline regression with *Q* as the dependent variable. While the coefficients for *PHI* is significantly negative, the coefficient becomes significantly positive when we additionally control for the case that *PHI* equals to one because of the 0 political contributions. The coefficient of *Q* is also insignificant under the IV 2SLS regression. So the evidence is largely mixed and it is possible that the negative effect of *PHI* on firm value is due to the cases when both CEO and independent directors make 0 political contribution.

A natural question that appears is how the effect of political alignment on crash risk and firm value interacts with corporate governance mechanisms. On the one hand, directors receive heavier pressure from shareholders under stronger governance and may have a higher incentive to acquire information from the CEO. On the other hand, stronger corporate governance structures may deter the CEO's willingness to share information with the board. Therefore, it is not emphex ante clear whether we see a stronger effect under stronger or weaker corporate governance structures. We split the firms into subsamples based on three dimensions: whether a staggered board is adopted or not, whether the firm adopts both a staggered board and poison pill, and whether the percentage of institutional ownership is high. The staggered board is commonly viewed as a weak corporate governance structure. Faleye (2007) and Bebchuk and Cohen (2005) find that classified boards are associated with less director effectiveness and more management entrenchment. Faleye (2007) find that management is entrenched the most when combining staggered board and poison pill since blending the two provisions ensures that a firm can only be the consent of its directors. Cremers, Litov and Sepe (2017), however, argue that staggered boards enhance the incentive of directors to build a stable relationship with executives. We find that the effect of political alignment on crash risk is more pronounced for firms without a staggered board. The magnitude of the effect is doubled to what we obtained from the whole sample. When the board is staggered (and when the firm adopts both a staggered board and poison pill), the coefficient is not statistically significant and the magnitude is much smaller. Similarly, institutional investors have been argued to be one of the most important party who undertake monitoring over executives and also directors. We find that the negative association between *PHI* and crash risks only presents for firms with higher than average institutional ownership. Therefore, these findings suggest that a friendly board can only benefit the firm when the governance structure is strong so that directors have a stronger incentive to acquire information.

Finally, we examine the returns of insider tradings by the CEO and the independent directors to further test if political alignment ease information sharing between the CEO and the independent directors. Open market tradings made by the CEO and the independent directors are believed to be informative. Ravina and Sapienza (2010) find that both executives and independent directors earn positive substantial abnormal returns when they purchase their company stock. Moreover, executives on average earn more than independent directors when they make open market purchases, indicating that there is a gap between the information held by the CEO and the independent directors. Using data from the TFN Insider Filing, we empirically test if a higher political alignment between the CEO and the independent directors is associated with a smaller gap between the trading returns of open market purchases made by CEO and independent directors. We find that mimicking the CEO's long position yields a 7.5% market-adjusted return in 60 days and independent directors earn less abnormal returns comparing to CEOs. The coefficients of *PHI* are not statistically significant, indicating that having a friendly board does not widen the information gap between insiders and the market. Finally, the triple interaction of *PHI* with *Trade Size* and *ID* has a positive coefficient for the 60, 90, and 180 trading days horizon and is statistically significant, which confirms that political alignment between the CEO and the independent directors does increase the quantity of information acquired by independent directors. This is consistent with the conjecture that a friendly board is more desired when directors have a stronger incentive to acquire information from the CEO.

This chapter relates to the literature on the friendly board. It has been much debated in the previous research that to what extend board independence benefits shareholders' value.[8] Adams and Ferreira (2007) hypothesize that the CEO faces a trade-off when s/he decides whether to disclose information with the board or not. If the CEO shares information to the board, s/he is able to gain better advice. However, sharing private information imposes costs to the CEO as a more informed board would monitor the CEO more intensively. Our results support the view that sharing common ideology between the CEO and independent directors facilitates information sharing and lower the risk of catastrophe. An important takeaway of our results is that board friendliness in itself does not imply weak governance and less board independence. On the contrary, when combines with strong shareholder protections and less management entrenchment, the friendly board can facilitate information sharing and reduces crash risk. Moreover, for firms with stronger governance, the effect of *PHI* on *Q* is positive and significant. This distinction sets board friendliness apart from board dependence measures. To this end, this chapter provides guidance on how information sharing can be enhanced without compromise the directors' independence.

The rest of the chapter is organized as follows. Sections 2.2 describes the sample and variable constructions. Section 2.3 develops hypotheses and shows our main empirical findings. Section 2.4 presents additional results on insider tradings. Section 2.5 concludes.

2.2 Data Sources and Variable Construction

2.2.1 Individual Contributions

We collect individual political contribution records from the *Federal Election Commission* (FEC). In each federal election cycle, contributions made by individuals must be reported to FEC if exceeding the amount of $200. Information contained in the reporting file includes the donor's name, employer, occupation, state, city, and zip code, which can be used to identify the donors. The original dataset con-

[8] See Byrd and Hickman (1992), Cotter and Shivdasani (1997), Aggarwal et al. (2009), among others.

tains 22,074,387 contributions from individuals during the period between 1980 and 2012. Recipients who accept individual contributions can be classified into five categories: (i) candidate, or candidate committee, (ii) political action committee (PACs), (iii) state, district & local party committee, (iv) national party committee, and (v) additional national party committee accounts.[9] Using the committee linkage file provided by FEC, we assign a political leaning of Republican, Democratic, or other to each receiver. We exclude the contributions to PACs which we may not able to label with political leaning, such as those connected with corporations, labor unions, etc. Furthermore, for PACs connected with ideology groups with missing partisan information in FEC, we obtain the political leaning of such PACs from the Center for Responsive Politics.

We obtain the information on firm executives is from *Compustat*'s *Execucomp* database. The initial dataset contains 6,951 unique CEOs working for 3,397 firms during the period 1992-2013. The data of directors are obtained from two sources. The primary source is the July 2010 data dump provided by *BoardEx*,[10] including 6,322 unique firms for the period 2000 to 2009 with 74,533 unique directors. We further complement the directors' data from the second data source *RiskMetrics* (through ISS Governance Services, and the database is maintained by IRRC before 2005), adding 449 more firms that are not covered by *BoardEx* for the period 2000 to 2009. We then merge the data from *Execucomp* with that from *BoardEx* and RiskMetrics, and keep those firms which have information on both CEO and independent directors. Our sample contains 2,688 firms for the period from 2000 to 2009.

Next, we use individual names and employment history records to match the individual contribution data with the sample of CEO and directors. Since the names

[9]Individual contributions to each receiver are subject to different limits. For example, in the election cycle 2003-2004, an individual may contribute to each candidate or candidate committee not more than $2000 per election and national party committee not more than $25,000 per calendar year. To state, district & local party committee, this number decreases to $10,000 per calendar year. However, Independent-expenditure-only political committees, often referred to as "super PACs", may accept unlimited contributions, from corporations and labor organizations after 2010.

[10]After 2010, the full dump of *BoardEx* is no longer allowed, and the names of the director/officer are not identifiable within the database

and employment information are self-reported to the FEC, the quality of the data is not flawless. For example, people may report abbreviated names instead of full names. They may also report a different employer than the one recorded in *BoardEx* or *RiskMetrics* since there is no strict reporting standard required by FEC. Therefore, we first re-code all the abbreviations reported in the FEC individual contribution data to be their full name equivalents. Then we match the individual contribution data to the CEO and directors sample using only first names and last names. For the linked sample, we calculate the Jaro-Winkler distance score between the employer's name in the individual contribution data and individual's name in the CEO and directors sample. The Jaro-Winkler distance score measures the similarity of two strings and varies from 0 to 1, whereas the value of 0 means two strings are very different, and 1 means two strings are exactly the same. For the individuals who have multiple employment positions, we calculate all the pairwise scores and keep the highest one. We keep the matched pairs with Jaro-Winkler score higher than 0.8 and drop the matching pairs with a Jaro-Winkler score lower than 0.6. All matching pairs with a Jaro-Winkler score between 0.6 and 0.8 are carefully manually examined in order to keep the correct match. In the final sample, we are able to identify $59,288$ contribution records from $2,711$ CEOs and $49,982$ contribution records from $3,809$ independent directors.

2.2.2 Political Variables

We measure the political leaning of individuals using the political leaning of the recipients to whom they made contributions. The underlying assumption is that political contributions made by individuals can largely be viewed as consumptions of political good (Gordon, Hafer and Landa (2015)), rather than political investments. Similar to Lee, Lee and Nagarajan (2014), we construct a Republican Index (*Rep*) using the individual contributions made to Republican and Democratic candidates and committees:

$$Rep_{it} = \frac{R_{it} - D_{it}}{R_{it} + D_{it}} \tag{2.1}$$

where R_{it} (D_{it}) denotes the total dollar amounts of political donations made by individual i in year t to the Republican (Democratic) candidates and committees in the federal elections. By definition, the political orientation index Rep_{it} takes value in the range of $[-1, 1]$. If an individual only contributes to Republican (Democratic) candidates or committees, the corresponding Rep would take the value 1 (-1). Therefore, the Rep index helps us map the individual political ideology into a continuous liberal-conservative spectrum, whereas a positive (negative) value of Rep indicates that the individual's political orientation is more conservative (liberal).

We do not consider the total amount of political contribution made by individuals in our Rep index. It is common to think that total political contribution may reflect the intensity of political involvement, which could potentially bias our measure of individual political orientation. There are two reasons that we only consider the simple fraction of contributions to the Republicans in our Rep index. First, the individual contribution limit (around $5,000$\$) is very low compare to the income of the managers of the firms. The individual political contribution made by such people is usually considered as the "ticket" for lobbying, so the amount of contribution is not correlated with the intensity of political involvement. Second, it is hard to obtain data on individual wealth. So it is problematic to measure political involvement without adjusting for personal wealth.

Our individual political orientation measure, Rep_{it}, is allowed to vary over time. This is consistent with the revisionist views that the conception of partisanship is a running tally of party utilities that is updated continuously according to the positions of parties on different issues and personal evaluations of party performances (Bonica (2014) Berry et al. (1998)).[11] The time-varying characteristic of individual political orientation provides important benefit in identification: it helps us distinguish our effect of friendliness board from the channel of personal connection between CEO and independent directors, since personal connections, once formed, are stable and

[11]In Lee, Lee and Nagarajan (2014), the authors assume that the individual political orientation is either time-invariant or only adjusts smoothly from previous political orientation. This follows the static view of individual political orientation common in early political science research.

persistent over time.[12]

Using individual political orientation Rep_{it}, we construct the political homophily index (PHI) of the firm as follows:

$$PHI_{it} = 1 - \frac{|Rep_{it}^{CEO} - Rep_{it}^{ID}|}{2} \tag{2.2}$$

where Rep_{it}^{CEO} is the political orientation index of the CEO of firm i in fiscal year t, and Rep_{it}^{ID} is the equal-weighted simple average of political orientation indices of all independent directors of firm i in fiscal year t. By construction, PHI takes a value between [0, 1], where a value of one (zero) indicates that the independent directors share most (least) similar political orientation with the CEO, and are more (less) friendly to the CEO. Similar to *Rep* index, we do not consider the total amount of political contribution made by the all managers in *PHI* index. The political involvement of the firm is usually taken through the corporate political action committee (PAC) but not from individual donations. So the total amount of contribution is less correlated with the similarity between the individual political orientation of the CEO and the board [13]

It is worth pointing out that the *PHI* measure (as well as Rep^{CEO} and Rep^{ID}) is less accurate when both the CEO and independent directors make 0 political contribution. By our construction, such a case would yield a value of 1 for *PHI* since both Rep^{CEO} and Rep^{ID} would have a value of 0. However, it is still possible that they have strong political leaning but lack of incentive to engage in political activities, such as making political donations. Zero political contribution is also likely to happen if the information reported in the FEC file is unrecognizable so that we failed to match it to the CEO or director. In either case, the CEO and the independent directors may not have precisely the same political orientation, although the value of *PHI* indicates so. To address this concern, we include a *Weak*

[12]The baseline results are robust if we use political orientation measures following which in Lee, Lee and Nagarajan (2014), i.e. assuming that individual political orientation is persistent over time. We report the results using the robustness measures of individual political orientation in A.1

[13]The intensity of the political involvement may have impacts on the effect of *PHI* on crash risks. We report the test for the effect of the political involvement of the firm in section A.2.

PHI Dummy, which takes a value of 1 if both the CEO and independent directors make 0 political contribution in our data, and 0 otherwise.

In Panel A of Table 2.1, we report the summary statistics of individual political contributions and political indices. On average, a CEO spends $\$2,078$ per contribution, and an independent director spends $\$2,349$, both are significantly higher than the minimum reporting threshold \$200. The amount per contribution is slightly higher to Democratic candidates and committees comparing to Republicans. In terms of their political leaning, CEOs tend to be slightly conservative, with the average Rep_{it}^{CEO} to be 0.12. The political orientation of independent directors is more balanced distributed. The average Rep_{it}^{ID} of independent directors of each firm is 0.02. The average PHI of the firms is around 0.81, which indicates that the political orientation of CEOs and independent directors are overall very similar, consistent with the findings in Lee, Lee and Nagarajan (2014).

2.2.3 Financial variables, board characteristics

The financial variables of the firm are based on the data from *Compustat* and *CRSP* databases. The main variables of our interest is the crash risk. Following Chen, Hong and Stein (2001), we construct two measures of crash risk using daily returns obtained from *CRSP* database.

The first measure is the negative coefficient of skewness (*NCSKEW*), which is calculated as:

$$NCSKEW_{it} = -(n(n-1)^{\frac{3}{2}} \sum R_{it}^3)/((n-1)(n-2)(\sum R_{it}^2)^{\frac{3}{2}}) \tag{2.3}$$

where R_{it} is the sequence of the market-adjusted returns to stock i during the year t, and n is the number of observations on daily returns during the year t.

We use the down-to-up volatility of the firm (*DUVOL*) as an alternative measure of crash risk. It is constructed as:

$$DUVOL_{it} = log\{(n_u - 1) \sum_{down} R_{it}^2 / ((n_d - 1) \sum_{up} R_{it}^2)\} \tag{2.4}$$

where "down" indicates the days when the returns are below the mean of year t, and "up" indicates the days when the returns are above the mean of year t. n_u (n_d) is the number of up (down) days. *DUVOL* also measures the negative skewness of the distribution of returns, but does not involve third moments and is less likely to be extremely biased by few extreme days.

Both NCSKEW and DUVOL measure the asymmetries of returns. A higher value of NCSKEW and DUVOL corresponds to a more left-skewed (negatively-skewed) distribution and a higher risk of crashes.

The firm valuation Q is constructed as the ratio of the firm's market value of assets to its book value. Other financial variables we use in the following sections are: return on assets (*ROA*), the market leverage ratios, capital expenditures (*CAPX*), the natural logarithm of the book value of assets ($log(Assets)$), and research and development (*R&D*). All the financial variables and measures of crash risks are winsorized at the 1% and 99% levels. The summary statistics are reported in Panel B of Table 2.1. The figures of our financial variables are comparable to other research which uses *BoardEx* firms, such as Knyazeva, Knyazeva and Masulis (2013), Lee, Lee and Nagarajan (2014), among others.

We obtained the corporate governance data regarding institutional ownership, the adoption of poison pills and staggered board, from the *ISS* database. We calculate the Board Size as the number of total directors using the information from *BoardEx*. Similar to the social connection measure used in Dasgupta, Zhang and Zhu (2015), we construct the CEO-Directors Connection Strength as the fraction of directors who have any social connection with the CEO identified using the biographic information provided by the *BoardEx* database. If the CEO has one of the following two types of social connections with any director, we establish a social connection between the CEO and that director: (1) they studied at the same institution during an overlapped period; (2) they worked for the same employer other than the current firm at least five years before the first year they have been reported working in the current firm.

In Panel C of Table 2.1, we report the summary statistics of board characteristics. In our sample, the average board has 10 directors. Around 48.9% of boards adopt poison pills, and 57.3% of boards adopt staggered classes. The average institutional ownership is around 75.5%. More than 80% of the firms have no directors socially connected with the CEO, resulting in the average CEO-Directors Connection Strength to be only 4.2%.

2.3 Results

2.3.1 Political alignment and crash risk

We first study the effect of political alignment on crash risk. We hypothesize that political alignment between CEO and independent directors facilitates communication between them, especially when the firm faces negative shocks. When managers and boards have similar political orientation, they will cooperate more and jointly formulate policies that are in conformity with their common political priors. Moreover, boards are more willing to share the blame for bad outcomes since policies are set jointly. If, however, independent directors are less friendly towards the CEO and tougher in monitoring, then the CEO would hesitate to reveal negative information in order to avoid board discipline. Since the CEO cannot withhold the information forever, when the negative information is accumulated to be able to generate large impact or when the market suffers from significant declines, negative information is eventually going to be reflected into the stock prices. Therefore, the lack of disclosure, especially about negative information, leads to negatively skewed stock returns. If the alignment in political orientation makes independent directors more friendly to the CEO so that the CEO is more willing to disclose negative information, we would expect the returns of the firm to be less negatively skewed.

To test this prediction, we regress crash risk on our measure of political alignment *PHI*. We first use *NCSKEW*, the Negative Coefficient of Skewness, to measure crash risk.

$$NCSKEW_{i,t} = a_0 + a_1 PHI_{i,t-1} + Controls + \varepsilon_{it} \tag{2.5}$$

The results are reported in Table 2.2. We control for firm fixed effects and year fixed effects in all specifications, and cluster standard errors at the firm level. As shown in Column 1, the coefficient of *PHI* in the regression is around −0.015 and statistically significant at the 5% level. We include *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength* in the regression to control for factors that also affect the negative skewness of the stock returns. The result suggests that better alignment of political orientation is associated with lower crash risk (equivalently, less left-skewed stock returns). The effect is also economically significant. For one standard deviation increase in *PHI*, crash risk, measured by *NCSKEW*, is reduced by 0.002, whereas the sample mean of *NCSKEW* is only around 0.001. However, the total explanatory power for the cross-sectional variation of skewness is very low, since the adjusted R squared is only 0.02. This is because the prediction power of the skewness of stock returns mostly comes from time series variation. The explanatory power of our model with *PHI* for cross-sectional variation of skewness is comparable to the findings in Chen, Hong and Stein (2001).

In Column 2, we further include the *Weak PHI Dummy* to control for the case that *PHI* equals to one because both CEO and independent directors make 0 political contribution. Ideally, CEO and the board should have the highest political alignment when $PHI = 1$. However, when individuals make no contribution in that year, their political orientation are mechanically labeled as neutral, which could be potentially biased. It is possible that individual does have political leaning, but (s)he did not make any political contribution in the given year, or we simply could not match her(his) information with the position in the firm. Therefore, for those cases, the true political similarity is not as high as indicated in the *PHI* and the *Weak PHI Dummy* captures the noisy part of *PHI*. We do find that the effect of *PHI* become stronger after controlling for *Weak PHI Dummy* as reported in Column 2. The economic significance of the effect of *PHI* on the crash risk increases by almost 63%.

We then test our prediction with *DUVOL*, our second measure for crash risk. We run a similar regression as in Equation 2.5.

$$DUVOL_{i,t} = a_0 + a_1 PHI_{i,t-1} + Controls + \varepsilon_{it} \tag{2.6}$$

We control for firm fixed effects and year fixed effects in all specifications, and cluster standard errors at the firm level. As reported in Column 3 and Column 4 of Table 2.2, the results are very similar to the ones with *NCSKEW* and are again stronger after controlling for *Weak PHI Dummy*.[14]

Overall, we find very consistent results that crash risk is reduced when the CEO and independent directors are better aligned in their political orientations. In contrast, having prior (social) connections with the board may be mainly associated with less monitoring of the manager and cannot prevent bad outcomes from happening. In line with this prediction, we find that connections between the CEO and the directors do not help reduce crash risks.

2.3.2 Firm valuation

If lower crash risk can be priced, then we would expect board friendliness to be associated with higher firm value. In this section, we empirically examine whether this is the case.[15]

[14] It is interesting to see if the effect of *PHI* is stronger for the firms which are more involved in political activities. In this case, whether a firm has a registered Corporate Political Action Committee (*Corporate PAC*)could serve as dummy variable measuring the political involvement of the firm. In the section A.2 we report the results for including the interaction of *PHI* and *Corporate PAC* in our baseline regression. The results show that the effect of *PHI* is not stronger for more politically involved firms.

[15] Lee, Lee and Nagarajan (2014) argue that political alignment impedes board independence and hurt firm value. In subsection 2.3.4, we examine the effect of political alignment under different corporate governance mechanisms.

Specifically, we run the following regression:

$$Q_{i,t} = a_0 + a_1 PHI_{i,t-1} + Controls + \varepsilon_{it} \tag{2.7}$$

The results are reported in Table 2.3. We control for firm fixed effects and year fixed effects in all specifications, and cluster standard errors at the firm level. Column 1 shows the result without any other control variable, and Column 2 shows the results with control variables, including textitBoard Size, 1-year lagged ROA and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*. The coefficients for *PHI* in both columns are significantly negative. The magnitude of the coefficient of *PHI* is also comparable to which in Lee, Lee and Nagarajan (2014) (-0.18 vs -0.22) .[16] The signs of control variables are consistent with expectations. For example, Board size has a negative effect on firm value, which is consistent with the results presented in Yermack (1996). Lagged *ROA* and *Investment* are positively correlated with *Q* and the coefficients are statistically significant at 1% level. $log(Assets)$ and *Market Leverage* are negatively correlated with *Q* at the 1% level of statistical significance. It is worth noting that the CEO-Director Connection Strength has a negative effect on *Q*, although only marginally significant, consistent with the common view that stronger social connection impedes the effectiveness of board monitoring and hurts firm value.

The above results appear to suggest that the alignment in political orientation between CEO and independent directors decreases firm value. However, in Column 3, when we additionally control for the case that *PHI* equals to one because of the 0 political contributions (*Weak PHI Dummy*), the coefficient of *PHI* in the regression of *Q* becomes positive and statistically significant. By construction of *PHI*, it takes a value of 1 when both CEO and independent directors make 0 political contribution (because Rep^{CEO} and Rep^{ID} both take the value of 0). In this case, the CEO and independent directors may NOT have exactly the same political orientation, although

[16]In untabulated analysis, we also control for the Rep^{CEO} to capture the marginal effect of political alignment, following Lee, Lee and Nagarajan (2014). The coefficient of *PHI* is still significantly negative. The coefficient for Rep^{CEO} is negative but not statistically significant.

the value of *PHI* appears so. For firms with *Weak PHI Dummy* taking a value of 1, around 90% of the CEOs and independent directors have never made any political contribution. Therefore the Republican index based on political contribution becomes less accurate for these individuals, and it is not surprising that the coefficient of *Weak PHI Dummy* is negative and statistically significant, making the net effect of *PHI* to be almost zero.

When controlling for *Weak PHI Dummy*, the positive coefficient of *PHI* suggests that the political alignment between CEO and independent directors is associated with higher firm value for firms whose CEO and directors actively make political contributions. The effect of political alignment on firm value under this specification is economically significant. The point estimate of 0.21 indicates that for a one standard deviation (0.13) increase in *PHI*, *Q* would increase by 0.0273, corresponding to 1.7% of the sample average (1.618).

2.3.3 Causality tests

The composition of the board is never an exogenous decision to the firm. It is possible that certain (unobserved) firm characteristics or shareholder preferences may drive both the political alignment and the crash risk of the firm. In this case, we would obtain a correlation between the *PHI* and the crash risk even when PHI does not affect the crash risk. To mitigate the endogeneity problem, we construct an instrumental variable for the change in firm *PHI* using the change in local political homogeneity (*Local PHI*) and perform a two-stage least squares estimation to verify our results.

Since independent directors are likely to be selected from the local business community (Knyazeva, Knyazeva and Masulis (2013)), we expect the political leaning of the local population to affect the expression of political leaning of independent directors .[17] We measure *Local PHI* as:

[17] It is possible that big companies can recruit nation wide so the local political environment has little affect on the firm level political similarity. In order to address this concern, we further run the IV test on a subsample which only includes the firms with total assets in the top quartile. The results of this robustness test still hold. They are reported in section A.3. Since we drop the *Weak*

$$Local\ PHI_{s,t} = |Local\ Rep_{s,t} - Local\ Dem_{s,t}| \tag{2.8}$$

where $Local\ Rep_{s,t}$ ($Local\ Dem_{s,t}$) represents the percentage of voting shares received by all Republican (Democratic) candidates in the most recent federal election cycle to year t in state s.[18] Therefore, *Local PHI* measures the absolute difference between the votes received by the two major parties in a federal election cycle. A higher *Local PHI* indicates that one party dominates with majority votes, which we usually observe in the so-called "Safe States" where one party has a base of support from which they can draw a sufficient share of the electorate. On the contrary, a lower *Local PHI* indicates that the votes obtained by Republican or Democratic candidates are very close in a federal election cycle. This pattern can be often observed in the battleground states or so-called "Swing States" where the elections are competitive.

In the first stage, we regress the change of *PHI* on the change of *Local PHI*, allowing the effect to differ between "Safe States" and "Swing States".

$$\begin{aligned} \Delta PHI_{i,t} &= a_0 + a_1 \Delta Local\ PHI_{s,t} \times Safe\ State\ Dummy_{s,t-1} + \\ &\quad a_2 \Delta Local\ PHI_{s,t} \times Swing\ State\ Dummy_{s,t-1} + a_3 PHI_{i,t-1} + Controls + \varepsilon_{it} \end{aligned} \tag{2.9}$$

where safe states are defined as states in which *Local PHI* is above the median and swing states are defined as states with a *Local PHI* below the median. The *Safe State Dummy* (*Swing State Dummy*) takes a value of 1 if the firm headquarter locates in a safe(swing) state, and 0 otherwise. To adjust for the misreporting in the historical states of incorporation and location in *Compustat* database, we use the parsed 10-K data from Bill McDonald's website[19] to identify the firm headquarter. We include lagged *PHI* to control for the mechanical reversal of *PHI* since it

PHI Dummy observations from the baseline regression, the remaining firms are in general bigger. Therefore, we can see that keeping the top quartile firms in terms of size only reduce the sample size to about half in our baseline IV test.

[18] Since some candidates may be from parties other than Republican and Democratic, the sum of $Local\ Rep_{i,t}$ and $Local\ Dem_{i,t}$ does not necessarily equal to one.

[19] `https://sraf.nd.edu/data/augmented-10-x-header-data/`.

is bounded between $[0,1]$ and include the same set of control variables as in the baseline regressions in the previous subsection. In addition, unlike in the baseline regression, we are not able to control for *Weak PHI Dummy*. Therefore, we drop all the observations with *Weak PHI Dummy* = 1 in the [-1, 1] year window, leaving us a much smaller sample comparing to the baseline regression.

In Column 1 of Table 2.4, we present the result for the first stage regression. We find that the impact of Δ*Local PHI* on Δ*PHI* indeed depends on the political environment of the state: Δ*Local PHI* affects the firm's Δ*PHI* positively in safe states, but negatively in swing states. This result is consistent with findings in political science studies. More specifically, a decrease in *Local PHI* in those safe states implies a less safe position for the dominating party and higher uncertainty in the forthcoming election. In this situation, voters have a higher tendency to participate as the prior belief that their votes are pivotal is increased (Lindbeck and Weibull (1987), Duffy and Tavits (2008)), leading to less predictable electoral outcomes and greater discrepancy in political ideology among people. Therefore, a decrease in Δ*Local PHI* predicts a decrease in the firm's Δ*PHI* in safe states. For swing states, however, unexpected electoral outcomes are more likely to occur when *Local PHI* increases (i.e., one party gains a more dominating position). Thus, an increase in Δ*Local PHI* leads to higher voter participation and a decrease in firm's Δ*PHI* in swing states.

The coefficients are both statistically significant for the safe states and swing states, and the F-statistic for the instrument variables is about 18.392. This suggests that we do not have a weak instrument problem. The coefficient of $PHI_{i,t-1}$ is negative and statistically significant, suggesting that there is a strong reversal mechanism for *PHI*. Moreover, while it is possible that election outcomes affect the local economy, as different parties have different preference over inflation and unemployment (see Garfinkel and Review (1994)), it is less likely that the change in local political homophily, Δ*Local PHI*, directly correlates with the change in crash risk and have an opposite effect in safe and swing states. Therefore, our instrument variable satisfies the exclusion conditions.

We present the results of the second stage regression in Column 2-4 of Table 2.4. In Column 2 and 3, we report the results for the crash risks measures. We are able to obtain very consistent results that board friendliness lowers the risk of crashes in stock price. In Column 4, we show that the effect of *PHI* on Q is not significant under the IV 2SLS regression. Thus, it is possible that omitted variables may drive firms' decision to hire CEO and independent directors with similar political orientation and a higher valuation. However, in contrast to Lee, Lee and Nagarajan (2014), our results reject the prediction that director friendliness hurts firm value. We also conduct the overidentifying restrictions test since we are using three instrument variables for one endogenous variable. Under the null hypothesis of the validity of the instruments, this J-test has a $\chi^2(2)$ distribution. For all of our models, we pass the hypothesis that all instruments are exogenous at the level of 10%.

2.3.4 Board Friendliness and Corporate Governance

A natural question that appears is how the effect of political alignment on crash risk and firm value interacts with corporate governance mechanisms. The answer to this question is not obvious from an *ex ante* point of view. On the one hand, independent directors receive heavier pressure from shareholders under stronger governance and may have a higher incentive to acquire information from the CEO. It thus predicts that better political alignment would be more effective in reducing the firm's crash risk when the firm adopts strong corporate governance structures. On the other hand, stronger corporate governance structures may deter the CEO's willingness to share information with the board. As hypothesized in Adams and Ferreira (2007), the CEO faces a trade-off when s/he decides whether to disclose information to the board or not. If the CEO shares information with the board, s/he is able to gain better advice. However, sharing private information imposes costs to the CEO as a more informed board would monitor the CEO more intensively. So, when the corporate governance structure is weaker (the independent directors are poorer monitors or the CEO is more entrenched), the CEO would be less worried about the discipline from the independent directors when s/he disclose more information.

In addition, when the CEO and directors face lighter shareholder pressure, they may be encouraged to build a culture that facilitates long-term strategic planning. Thus, it is also possible that the benefit of a friendly board is stronger when the corporate governance structure is weak. Therefore, we examine the relationship between corporate governance and the effect of board friendliness empirically in this section.

We first split the firms into two subsamples based on whether a staggered board is adopted or not. The staggered board is commonly viewed as a weak corporate governance structure. It also has a controversial implication on firm value. For example, Faleye (2007) and Bebchuk and Cohen (2005) find that classified boards are associated with more management entrenchment and less director effectiveness. Cremers, Litov and Sepe (2017), however, argue that staggered boards enhance the incentive of directors to build a stable relationship with executives. By examining how information sharing works with and without a staggered board, we contribute to the understanding of a specific channel for the staggered board to affect firm value.

We repeat the tests for the two subsamples. In all regressions, we use the same control variables as in the previous sections. To minimize the effect of noise in the measure of *PHI*, we also include *Weak PHI Dummy* for all specifications..[20] The results are presented in Panel A of Table 2.5. The effect of *PHI* on both measures of crash risk is not significant for the firms that adopt a staggered board. For firms without a staggered board, the coefficient of *PHI* is negative and statistically significant. The magnitude of the effect is also doubled to the magnitude we obtained from the whole sample. This finding supports the conjecture that the friendly board benefits the firm more under stronger governance structures when the board is not classified. We find no evidence that political alignment can reduce crash risk when the board is staggered.

Similarly, there is almost no effect of *PHI* on *Q* for the firms with a staggered board. However, for the firms without a staggered board, the effect of *PHI* on *Q* is

[20] All the results hold if we do not include the *Weak PHI Dummy*

positive and significant. The point estimation of 0.499 is doubled in the magnitude of the coefficient we obtained in the previous section for the whole sample.

Next, we examine the effect of a friendly board when the firm adopts both a staggered board and a poison pill. Faleye (2007) find that management is entrenched the most when combining staggered board and poison pill since blending the two provisions ensures that a firm can only be the consent of its directors. In Panel B of Table 2.5, we present the results of subsample regressions. Consistent with the previous findings, the coefficient of *PHI* is not significant in the subsample of firms with both a staggered board and a poison pill. The effect of *PHI* remains for the firms not simultaneously adopting a staggered board and a poison pill. These results show that the friendly board has no effect on firm value and crash risk if the directors and executives are shielded from potential discipline, and can benefit the firm when the managers are disciplined.

Finally, we partition the sample into halves based on the percentage of institutional ownership. The institutional investors have been argued to be one of the most important party who undertake monitoring over executives and also directors. Following similar logic, we test if the effect of *PHI* on crash risks is stronger for firms with higher institutional ownership. As shown in Panel C of Table 2.5, the negative association between *PHI* and crash risks only presents for firms with higher than average institutional ownership. We do not find any significant effect of *PHI* for the firms with lower than average institutional ownership. We find similar results for firm value. These findings are consistent with the results that the friendly board can only benefit the firm when the governance structure is strong.

An important takeaway of our results is that board friendliness in itself does not imply weak governance. On the contrary, when combines with strong shareholder protections and less management entrenchment, the friendly board can facilitate information sharing and reduces crash risk. This distinction sets board friendliness apart from board independence measures.

2.4 Evidence on Insider Tradings

Open market tradings made by the CEO and the independent directors are believed to be informative. Ravina and Sapienza (2010) find that both executives and independent directors earn positive substantial abnormal returns when they purchase their company stock. Moreover, executives on average earn more than independent directors when they make open market purchases, indicating that there is a gap between the information held by the CEO and the independent directors. In this section, we examine the returns of insider tradings by the CEO and the independent directors to further test if political alignment ease information sharing between the CEO and the independent directors.

Using data from the TFN Insider Filing, we empirically test if a higher political alignment between the CEO and the independent directors is associated with a smaller gap between the trading returns of open market purchases made by CEO and independent directors.[21] Specifically, we run the following regression:

$$\begin{aligned} R_{purchase} = a_0 + a_1 Trade\ Size + a_2 ID + a_3 PHI_{t-1} + \\ a_4 Trade\ Size \times ID + a_5 Trade\ Size \times PHI_{t-1} + a_6 PHI_{t-1} \times ID + \\ a_7 Trade\ Size \times ID \times PHI_{t-1} + a_8 PHI_{t-1} + a_9 Weak\ PHI\ Dummy_{t-1} + Controls + \varepsilon_{it} \end{aligned} \tag{2.10}$$

where $R_{purchase}$ denotes the replicating returns of the open market purchases made by the CEO and independent directors. *Trade Size* is the transaction size as a fraction of total market capitalization multiply by 100 to make it a number in percentage. *ID* is a dummy variable indicating whether the purchase is made by independent directors. It takes a value of 1 if the purchase is made by the independent directors, and 0 otherwise. The control variables are *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*. In all regressions, we cluster standard errors at the firm level. In addition,

[21]We focus only on open market purchases, since sales may be driven by diversification motives or liquidity needs and are thereby less informative.

we include firm and year fixed effects to control for any unobserved variation of insider trading gains across firms and time respectively.

We control for the size of the transaction for two reasons. First, it is possible that the size of the transaction is correlated with the incentive to trade better (Ravina and Sapienza (2010)). If the CEO or the independent director tend to make larger open market purchases, then we would observe higher returns for the group. Second, as documented in Fidrmuc, Goergen and Renneboog (2006), bigger transactions made by insiders indicate a higher likelihood that the insider is trading based on private information and generate larger price impact. Therefore, we include the interaction of *Trade Size* and *ID* in all regressions in order to investigate the marginal effect of transaction size to the difference in return earned by the CEOs and the independent directors.

In Table 2.6, we report the results for the market-adjusted returns of an individual's long position for 0, 30, 60, 90, 180 trading days. We find evidence supporting Ravina and Sapienza (2010). The positive constant indicates that insiders profit from open market purchases. On average, mimicking the CEO's long position yields a 7.5% market-adjusted return in 60 days. If we look at 180 trading days horizon, the gain increases to 16.3%. Since SEC requires insiders to surrender any profit made on transactions that are offset within six months, it is more interesting to look at the 180 trading day horizon. Yet for all holding horizons, the constants are statistically significant at the 1% level, suggesting that the insiders, in general, have more information comparing to the market. Moreover, we find that the coefficients of *ID* are negative and statistically significant in all holding horizons except overnight. This suggests that on average independent directors earn less abnormal returns comparing to CEOs, which is consistent with our expectation that the quantity of information acquired by independent directors is less than the private information acquired by the CEOs. The results are obtained after controlling for *Trade Size*. Therefore the higher abnormal return earned by CEOs is not fully explained by the transaction size difference between CEO and independent directors.

To investigate our hypothesis that political alignment between CEO and independent directors reduce the information gap between them, we include both *PHI* and the triple interaction of *Trade Size*, *ID*, and *PHI* in our regressions. The coefficients of *PHI* are not statistically significant, indicating that having a friendly board does not widen the information gap between insiders and the market. The triple interaction of *PHI* with *Trade Size* and *ID* has a positive coefficient for the 60, 90, and 180 trading days horizon and is statistically significant. The point estimate of 0.008 offsets about 31% of the point estimate of −0.026 for *ID*. The results confirm that political alignment between the CEO and the independent directors does increase the quantity of information acquired by independent directors. The effect of *PHI* is stronger when the size of insider tradings is larger. This is consistent with the conjecture that a friendly board is more desired when directors have a stronger incentive to acquire information from the CEO.

For similar concerns as in previous sections, we control the *Weak PHI Dummy* to reduce the impact of noise from cases when neither the CEO or the independent director made political contributions. The interaction of *Weak PHI Dummy* with *Trade Size* and *ID* is also included in all regressions. We do not find the *Weak PHI Dummy* to have any significant effect on the abnormal returns earned by insider tradings.

2.5 Conclusion

The increasing importance of board oversight has required greater board engagement and better communications with managers. Yet, the literature does not provide much guidance on how directors can better acquire firm-specific information, given that many board members are "independent" and have full-time jobs in other corporations.

In this chapter, we examine "friendliness" in terms of political similarity and study whether board friendliness reduces crash risk. Our hypothesis is that similarity in the political orientation of the CEO and board helps facilitate information sharing and reduces crash risk. When managers and boards have similar political orientation, they will cooperate more and jointly formulate policies that are in conformity with their common political priors. This suggests more information sharing, including information on bad outcomes in a timely manner, reducing the costs on the CEO for sharing information, and also leads to lower crash risks. We measure friendliness by the Political Homophily Index (*PHI*), which captures the similarity of political orientations of managers and directors. We find that firms' crash risk decreases in political homophily. The results are robust when we instrument the change in *PHI* by the change in local political homogeneity. Our results suggest that better alignment in political orientations facilitates information sharing, including information on bad outcomes in a timely manner. The effect is more pronounced when firms have stronger corporate governance mechanisms and directors have a stronger incentive to acquire information.

Table 2.1. Summary Statitics

This table reports the summary statistics for the key variables used in the empirical analysis. Individual political contribution records are obtained from the *Federal Election Commission* (FEC). Information on firm executives is from *Compustat*'s *Execucomp* database. The data of directors are obtained from *BoardEx* and RiskMetrics (through ISS Governance Services, and the database is maintained by IRRC before 2005). Financial variables and returns of the firms are based on the data from *Compustat* and *CRSP* databases. Panel A reports the summary statistics for the individual contribution made by CEO and independent directors, and the political leaning index. Panel B reports the summary statistics for the financial variables of the firms. Panel C reports the summary of the corporate governance devices and other governance related variables for the firm.

Panel A: Summary statistics for the individual political contributions and political leaning index

Variable	Mean	Std dev	Percentile					N
			10th	25th	50th	75th	90th	
Individual Contributions $								
- made by CEOs, all	2077.49	12294.42	250	454	1000	2000	5000	59288
- made by CEOs, to Republicans	2073.58	3772.30	500	1000	1000	2100	2500	27841
- made by CEOs, to Democrats	2131.13	3870.14	500	1000	1000	2300	2500	17623
- made by Independent Directors, all	2349.16	13939.40	250	500	1000	2100	5000	49982
- made by Independent Directors, to Republicans	2116.78	3835.85	500	650	1000	2000	2900	23471
- made by Independent Directors, to Democrats	2239.96	4099.01	500	1000	1000	2100	2400	15606
CEO Republican Index	0.12	0.46	-0.64	-0.19	0.00	0.07	0.99	19475
Independent Directors Republican Index	0.02	0.08	-0.06	0.00	0.00	0.03	0.12	19882
Firm PHI	0.81	0.13	0.39	0.72	0.86	1.00	1.00	19218

Panel B: Summary statistics for the financial variables

Q	1.618	1.288	0.662	0.872	1.245	1.910	2.952	19122
ROA	0.138	0.097	0.042	0.088	0.132	0.185	0.247	18799
Investment	0.221	0.146	0.077	0.118	0.185	0.287	0.415	18876
R&D	0.029	0.054	0.000	0.000	0.000	0.036	0.097	18917
log(Assets)	7.690	1.551	5.826	6.577	7.529	8.679	9.844	18955
Market Leverage	0.162	0.150	0.000	0.033	0.129	0.249	0.376	18955
Negative Coefficient of Skewness	0.001	0.104	-0.129	-0.066	-0.000	0.068	0.132	18955
Down to Up Volatility	0.000	0.142	-0.181	-0.095	0.000	0.095	0.183	18759

Panel C: Governance Characteristic

Board Size	10.511	3.202	7.000	8.000	10.000	12.000	14.000	18955
CEO-Directors Connection Strength	0.042	0.152	0.000	0.000	0.000	0.000	1.000	14631
Poison Pill Dummy	0.489	0.500	0.000	0.000	0.000	1.000	1.000	11841
Staggered Board Dummy	0.573	0.495	0.000	0.000	1.000	1.000	1.000	11841
Institutional Ownership (%)	0.755	0.191	0.492	0.634	0.776	0.889	0.976	11982

Weak PHI Dummy

Table 2.2. Friendly Board and Crash Risk

The table reports the results of friendly board and crash risk. The dependent variable is crash risk, measured by the negative coefficient of skewness (*NCSKEW*) and to down-to-up volatility (*DUVOL*), both capturing the negative skewness of the stock returns. The main explanatory variable is the Political Homophily Index (PHI), which measures the friendliness between the independent directors and CEO. In Column 1 and 3, we control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*. In Column 2 and 4, we further include the *Weak PHI Dummy* to control for the cases when both the CEO and independent directors made no contribution. We include firm fixed effects and year fixed effects in all the regressions. The standard errors are clustered at the firm level in all columns. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	NCSKEW		Duvol	
	(1)	(2)	(3)	(4)
PHI	-0.0146**	-0.0238**	-0.0176*	-0.0298**
	(-2.01)	(-2.24)	(-1.80)	(-2.15)
Weak PHI Dummy		0.00579		0.00698
		(1.39)		(1.29)
Board Size	-0.00105**	-0.000960*	-0.00129*	-0.00127*
	(-2.02)	(-1.77)	(-1.77)	(-1.74)
ROA	0.00274	0.00817	0.00871	0.00826
	(0.14)	(0.39)	(0.33)	(0.31)
Capx	0.00939	0.0112	0.00892	0.00893
	(0.81)	(0.86)	(0.56)	(0.56)
R&D	-0.0292	-0.0378	-0.0128	-0.0140
	(-0.56)	(-0.72)	(-0.18)	(-0.19)
log(Assets)	-0.00204	-0.00395	-0.00294	-0.00293
	(-0.54)	(-0.89)	(-0.57)	(-0.57)
Market Leverage	-0.0207	-0.0265	-0.0166	-0.0173
	(-1.30)	(-1.51)	(-0.77)	(-0.80)
CEO-Directors Connection Strength	0.00491	0.00542	0.00482	0.00471
	(1.52)	(1.63)	(1.08)	(1.06)
N	10986	10986	11796	11796
Adj R-square	0.001	0.019	-0.000	-0.000
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 2.3. Friendly Board and Firm Valuation

The table reports the results of friendly board and firm valuation. The dependent variable is firm valuation measured by Q. The main explanatory variable is the Political Homophily Index (PHI), which measures the friendliness between the independent directors and CEO. In Column 2 and 3, we control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*. In Column 3, we further include the *Weak PHI Dummy* to control for the cases when both the CEO and independent directors made no contribution. We include firm fixed effects and year fixed effects in all the regressions. The standard errors are clustered at the firm level in all columns. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

		Q	
	(1)	(2)	(3)
PHI	-0.182***	-0.178***	0.211**
	(-2.67)	(-2.89)	(2.17)
Weak PHI Dummy			-0.223***
			(-4.86)
Board Size		-0.0141***	-0.0146***
		(-4.06)	(-4.20)
ROA		1.159***	1.171***
		(3.59)	(3.68)
Capx		0.752***	0.751***
		(5.25)	(5.27)
R&D		0.675	0.710
		(0.71)	(0.76)
log(Assets)		-0.368***	-0.369***
		(-6.54)	(-6.56)
Market Leverage		-2.496***	-2.475***
		(-11.90)	(-12.02)
CEO-Directors Connection Strength		-0.0274	-0.0240
		(-1.36)	(-1.21)
Number of Observations	11944	11944	11944
Adj R-square	0.481	0.702	0.704
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Table 2.4. Instrument Variable Regression

The table reports the 2SLS regression results using the change in local political homophily index (Local PHI) and state political status as the instruments. In this sample, we only include the observations with non-zero weak PHI dummy, i.e. either CEO or independent directors have recent contribution record. The Local PHI is constructed as $Local\ PHI = abs(Rep\_local - Dem\_local)$ where Rep_local is the fraction of the voting share received by the Republican candidate in the most recent election year, and Dem_local is the voting share received by the Democratic candidates in the most recent federal election year. The Safe State Dummy takes a value of 1 if $Local\ PHI$ is above the median, and 0 otherwise. The Swing State Dummy takes a value of 1 if Local PHI is below the median, and 0 otherwise. In Column 1, the first-stage regression result is reported. In Columns 2, 3, and 4, the second-stage regression results for the change in negative coefficient skewness, change in down-to-up volatility, and the change in Q are reported respectively. The control variables in all columns are Board Size, one year lagged ROA, one year lagged investment, Market Leverage, R&D, log(Assets), and CEO-Directors Connection Strength. The standard errors are clustered within firm level. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	First-Stage	Second-Stage		
	ΔPHI	ΔNCSKEW	ΔDUVOL	ΔQ
	(1)	(2)	(3)	(4)
ΔLocal PHI × Safe State Dummy	0.0589*			
	(1.77)			
ΔLocal PHI × Swing State Dummy	-0.104**			
	(-2.52)			
Lagged PHI	-0.625***			
	(-17.57)			
ΔPHI (2SLS IV)		-0.107**	-0.128**	-0.0286
		(-2.25)	(-1.98)	(-0.22)
F-statistic	18.392			
J-statistic ($p - value$)		0.86	0.79	0.82
Number of Observations	2415	2415	2415	2415
Adj R-square	0.278	-0.111	-0.113	0.156
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Table 2.5. The Effect of Board Friendliness and Corporate Governance

This table presents the effect of board friendliness for subsamples. The dependent variable is crash risk, measured by the negative coefficient of skewness (*NCSKEW*) and to down-to-up volatility (*DUVOL*), and Q. The main explanatory variable is the Political Homophily Index (PHI), which measures the friendliness between the independent directors and CEO. The subsamples are divided based on (i) if the firm has a staggered board (Panel A), (ii) if the firm adopts both a staggered board and poison pill (Panel B), and (iii) if the fraction of shares owned by institutional investors is below median (Panel C). We control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, *CEO-Director Connection Strength*, and the *Weak PHI Dummy*. We include firm fixed effects and year fixed effects, and cluster standard errors at the firm level. t-statistics are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Subsamples based on if board is staggered

	NCSKEW		DUVOL		Q	
	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
PHI	-0.0138	-0.0367**	-0.0129	-0.0456**	0.00806	0.499***
	(-1.05)	(-2.22)	(-0.70)	(-2.06)	(0.06)	(3.40)
Weak PHI Dummy	0.00167	0.0130**	0.000492	0.0161*	-0.123*	-0.352***
	(0.32)	(2.06)	(0.07)	(1.91)	(-1.91)	(-4.95)
Number of Observations	6602	4897	6602	4897	6681	4954
Adj R-square	0.007	0.009	-0.007	0.008	0.677	0.746

Panel B: Subsamples based on if firm adopts both staggered board and poison pill

	(Yes)	(No)	(Yes)	(No)	(Yes)	(No)
PHI	-0.0117	-0.0329**	-0.0158	-0.0397**	0.149	0.216*
	(-0.68)	(-2.48)	(-0.65)	(-2.22)	(0.84)	(1.87)
Weak PHI Dummy	-0.00478	0.0114**	-0.00381	0.0132**	-0.169*	-0.246***
	(-0.67)	(2.32)	(-0.38)	(1.98)	(-1.81)	(-4.90)
Number of Observations	3810	7809	3810	7809	3859	7912
Adj R-square	0.009	0.001	0.013	-0.000	0.669	0.737

Panel C: Subsamples based on the fraction of institutional ownership

	(Low)	(High)	(Low)	(High)	(Low)	(High)
PHI	-0.0214	-0.0321**	-0.0234	-0.0424**	-0.0392	0.540***
	(-1.40)	(-2.13)	(-1.12)	(-2.07)	(-0.29)	(3.81)
Weak PHI Dummy	0.00487	0.00803	0.00598	0.00790	-0.0950**	-0.366***
	(0.84)	(1.34)	(0.74)	(0.96)	(-2.09)	(-4.63)
Number of Observations	5641	5737	5633	5744	5696	5789
Adj R-square	0.011	-0.005	-0.001	-0.003	0.730	0.700

Table 2.6. Political Alignment and Insider Tradings

This table reports the effect of board friendliness on insider purchasing returns. The dependent variable is the market-adjusted return of an individual's long position for 0, 30, 60, 90, and 180 trading days, respectively. The variable Independent Director is a dummy equal to 1 if the individual is an independent director, but not an executive officer. Trade Size is the transaction size measured by the fraction of market capitalization multiplied by 100. PHI is the firm level political homophily index between the CEO and independent directors. Weak PHI dummy takes a value of 1 if CEO and independent directors make no political contribution. The control variables in all columns are Board Size, one year lagged ROA, one year lagged investment, Market Leverage, R&D, log(Assets), and CEO-Directors Connection Strength. The standard errors are clustered within the same individual. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	Ret(t)	Ret(t+30)	Ret(t+60)	Ret(t+90)	Ret(t+180)
	(1)	(2)	(3)	(4)	(5)
Constant	0.004***	0.051***	0.075***	0.094***	0.163***
	(4.23)	(6.18)	(6.81)	(6.72)	(7.31)
Trade Size	0.001*	0.003	0.013	0.022*	0.011***
	(1.83)	(1.15)	(1.48)	(1.82)	(3.42)
Independent Director	-0.001	-0.006*	-0.013**	-0.017***	-0.024***
	(-0.87)	(-1.83)	(-2.25)	(-2.81)	(-3.21)
Independent Director × PHI	0.000	0.002	0.000	0.008	0.006
	(0.25)	(0.93)	(0.79)	(1.12)	(0.96)
Independent Director × Trade Size	-0.002	0.001	-0.003	-0.007*	0.008
	(-1.13)	(0.55)	(-0.79)	(-1.84)	(1.03)
Trade Size × PHI	-0.002	-0.002	-0.003	-0.007*	-0.003*
	(-1.11)	(-0.75)	(-1.33)	(-1.82)	(-1.78)
Trade Size × Independent Director	0.000	0.003	0.003*	0.005**	0.011**
× PHI	(0.52)	(0.48)	(1.79)	(1.98)	(2.32)
PHI	0.000	0.000	0.003	0.005	0.009
	(0.15)	(0.08)	(0.74)	(0.98)	(1.13)
Weak PHI Dummy	0.000	0.000	0.002	-0.003	-0.005
	(0.05)	(0.37)	(0.88)	(-0.47)	(-0.82)
Number of Observations	101,696	101,696	101,696	101,696	101,696
Controls	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Adj R-square	0.13	0.16	0.16	0.21	0.27

Chapter 3

Relative Performance Evaluation and Strategic Competition

3.1 Introduction

Relative performance evaluation (RPE) is an evaluation of an individual's performance that is based on peer performance. It is widely regarded in the literature on optimal contracts as an efficient tool to incentivize CEO effort. This efficacy arises because comparisons between competing agents can serve as a device to filter out common shocks and thus extract information about effort (Holmström, 1979, 1982). While the use of RPE reduces the executives' exposure to risk, it provides incentives for them to take actions that influence peer performance. In other words, RPE places a negative weight on the industry's performance, so a CEO receives higher compensation if peers in the industry perform worse (Aggarwal and Samwick, 1999). In this chapter, we consider these incentives for strategic interactions induced by RPE in executive compensation contracts. Specifically, we aim to examine how and to what extent the use of RPE affects industry competition.

However, two challenges arise in studying the effects of RPE on CEO incentives for strategic interactions. First, it is hard to measure the actual use of RPE. Proxy disclosures, under the SEC's 2006 executive compensation disclosure rules, provide useful information on specific contractual terms of RPE in public U.S. firms, but using such information to construct a measure of the use of RPE is complicated. For example, some firms tie RPE to a discretionary part of compensation and do not disclose it (Gong, Li and Shin, 2011; De Angelis and Grinstein, 2014). In other words, mandatory disclosures of RPE convey information about the explicit use of RPE, while leaving out the implicit use. Second, just as finding instruments for peer effects is challenging, it is also difficult to find a source of exogenous variation in the use of RPE, that is, a shock to the use of RPE that is exogenous to the industry-level competition.

To address these challenges, we examine the effects of using RPE in CEO compensation contracts by estimating a dynamic game of competition in an oligopoly market where CEOs, under given contracts, make entry-exit decisions to maximize their utility. We use observed market entry-exit decisions and CEO compensation contracts to infer the use of RPE and its impact on strategic interactions. This approach is appealing for two reasons. First, it helps us identify competitive effects by modeling the strategic interactions explicitly and imposing this structure on the data. Second, the theoretical framework allows us to conduct counterfactual experiments and thus to quantify the effects of RPE on CEO incentives for strategic interactions.

We develop and estimate a parsimonious dynamic game of competition with heterogeneous firms in an oligopoly market where CEOs, under given contracts, make entry-exit decisions to maximize their expected discounted inter-temporal utilities, taking as given their expectations about competitor actions. The model is based on a dynamic discrete choice structural framework (Aguirregabiria and Mira, 2010), in which firms make simultaneous moves but in which a CEO's market entry-exit decisions are dynamic or forward looking.[1] These decisions affect other firms' profits through their effect on equilibrium variable profits. Because RPE makes CEO

[1]The dynamic discrete choice structural framework developed by Aguirregabiria and Mira (2010) is widely used in dynamic game literature. Since the entry-exit decision is the simplest strategy that players can make in competition across multiple markets, several papers are using a similar framework to answer various questions. For example, in Gallant, Hong and Khwaja (2017) the authors look at the entry-exit decision in generic drug industry to study the spillover effect of competition. Aguirregabiria and Ho (2012) study the contribution of demand, costs, and strategic factors to the adoption of hub-and-spoke networks in the US airline industry.

compensation less sensitive to market conditions, managers, under RPE contracts, make entry-exit decisions while facing a tradeoff between the reduction in compensation based on market conditions, and the gain from being compared to competing agents. Therefore, the effects of RPE on CEO incentives for strategic competition depend not only on market conditions, but also on the firm's comparative advantage relative to its peers.

In this setting, we find that the use of RPE has an asymmetric effect on entry-exit decisions depending on market conditions: it decreases (increases) the probability of being active under bad (good) market conditions. Specifically, under bad market conditions, managers under RPE contracts benefit from being punished less for their bad performance and therefore are reluctant to operate in the market. In contrast, managers under RPE contracts lose out on the opportunity to free-ride on good market conditions. Instead, they benefit more from being compared to similarly well-performing peers and therefore are motivated to operate in the market. The use of RPE provides higher incentives to airlines with lower fixed operating costs to operate in the market; that is, RPE tends to increase more (decrease less) the probability of being active under good (bad) market conditions.

We estimate the model using data from the Airline Origin and Destination Survey (DB1B) of the U.S. Bureau of Transportation Statistics (BTS). The DB1B survey is a sample of 10% of all airline tickets from the large certified carriers in the United States. We use the information on quantities, prices, and route entry and exit decisions for every airline company operating in the routes between the 50 largest U.S. metropolitan statistical areas (MSAs). The dataset is ideal for two reasons. First, by treating a route as a market, we are able to observe the entry-exit decisions for all players in the airline industry. Observations of the entry-exit decisions at the market level are crucial for us to infer information about strategic interactions. Second, by focusing within a single industry, we can conduct the analysis without considering possible industry misclassifications (see, for example, Jayaraman, Milbourn and Seo, 2015).

Aggarwal and Samwick (1999) contains the first theoretical examination of strategic interactions induced by RPE. They show that the use of RPE depends on whether competition is Bertrand or Cournot. They also find an empirical correlation between the use of RPE and industry structure, as measured by the usual Herfindahl index. More recently, Antón et al. (2016) touch upon the incentives for strategic competition induced by the use of RPE. However, they are interested in whether common ownership helps explain variation in the use of RPE, and they tackle the question using reduced-form empirical methods. We examine a different but related question, namely, how the use of RPE influences industry competition. In addition, we take a different approach by estimating a dynamic discrete choice structural model. This strategy allows us to provide a quantitative assessment of the direct link between the use of RPE and subsequent competition outcomes.

3.2 Model

In this section, we present a parsimonious dynamic game of competition with heterogeneous airlines in an oligopoly market where CEOs, under given contracts, make entry-exit decisions to maximize their expected discounted inter-temporal utilities. We start with a description of the industry market structure and then move to the specification of CEO compensation. Finally, we discuss the optimization problem and its solution.

3.2.1 Competition

The industry is characterized by N airlines and M markets. A market is defined as a non-directional city-pair, that is, if an airline operates flights from A to B, then it should operate flights from B to A.

At each time t, airline i earns profits π_{imt}, which depend on three state variables and one choice variable. The three state variables can be divided into two groups. The first group comprises market size, as well as common knowledge among all airlines including incumbency status of airlines at time t. The second group consists of private information an airline receives before making decisions. Based on the set of state variables, CEOs decide whether to operate in the market m at time $t+1$.

The airline's incumbency status is denoted by a binary variable $x_{imt} \in \{0, 1\}$, which is equal to one if it operates in market m at time t, and zero otherwise. If airline i operates in the market m at time t, i.e., $x_{imt} = 1$, we refer to it as an incumbent airline. It competes with other incumbent airlines and earns equilibrium revenues y_{mt} that are determined by market conditions and the number of incumbents in market m at time t. Specifically, the revenues that the incumbent airline i earns are expressed as:

$$y_{mt}(s_{mt}, \boldsymbol{x}_{mt}) = \gamma_s s_{mt} + \gamma_n \ln(n_{mt}), \quad \text{where} \quad n_{mt}(\boldsymbol{x}_{mt}) = \sum_{j=1}^{N} x_{jmt}. \tag{3.1}$$

In (3.1), s_{mt}, referred to as "market size," represents exogenous market conditions of market m at time t that evolve according to a Markov process. The vector $\boldsymbol{x}_{mt} = \{x_{imt} : i = 1, 2, \cdots, N\}$ contains information on the number of incumbent airlines, which we denote as n_{mt}. The revenue function consists of two components that reflect the impact of demand and competition respectively. The impact of demand is captured by γ_s. The larger is γ_s, the more sensitive is variable profit to the market size, s_{mt}. The impact of competition is captured by γ_n. A large γ_n leads to more intense strategic interaction.[2] Note that in the model, the intensity of competition is characterized by the number of airlines present in the market. This feature of the model allows us to avoid imposing price or quantity competition structure, which may or may not be a reasonable assumption .[3]

The revenue y_{mt} captures the normalized revenue with market characteristic s_m earned by an incumbent airline. The incumbent airline i also pays fixed operat-

[2]The impact of competition γ_n is an average effect of competition on the number of player in the market. So we simply assume that the marginal effect by increasing one player in different market is the same

[3]Generally speaking, this model captures a reduced form of competition. Rather than explicitly model the choice of price or quantity of each player, we assume a static competition structure, that is we take equilibrium price and quantity decision as given once the firm has taken entry-exit decision. The only variable we need is the total market demand (market size) and the sensitivity of profit to market demand. Thus, we do not need our market structure to be strictly Cournot competition or Bertrand competition.

ing costs f_{im} that are airline- and market-specific. These costs thus capture time invariant airline heterogeneity across markets.

On the other hand, if airline i stays out of the market m at time t, i.e., $x_{imt} = 0$, we refer to it as a potential entrant. It gets zero profits. If airline i does not operate in market m, it can put its capital elsewhere. The profits of airline i are equal to the value of the best outside option. However, as the outside option is airline and market specific, it cannot be identified separately from the average fixed cost f_{im}. Therefore we normalize it to zero following, for example, Aguirregabiria and Mira (2007). Hereafter, the fixed cost f_{im} should be interpreted as including the opportunity costs.

Profits depend also on private information ϵ_{imt} that is revealed to airline i before it makes its decision. The private information is choice-specific and is an independent and identically distributed extreme value type I random variable, with zero mean and unit dispersion. This assumption is standard in dynamic discrete choice frameworks.[4]

Finally, airline i can decide whether to remain in the market at time $t + 1$. The decision whether to enter or exit the market m next period is denoted by a_{imt}, which is equal to one if the airline enters the market, and zero otherwise. By definition, $x_{im,t+1} = a_{imt}$, but it is convenient to use different letters to distinguish state and choice variables. Once airline i decides to enter, it has to pay entry costs e_m that are market-specific and homogeneous across airlines and time. The entry costs, e_m, are paid only when the airline is not active in market m at period t and when it decides to operate in the market next period, i.e., if $x_{imt} = 0$ and $a_{imt} = 1$. The new entrant is not active until the next period. The exiting airline is operative during time t and incurs no exit costs.[5]

The time line of events is as follows. At time t, airlines are characterized by their

[4]Permitting serial correlation in the privately observed shock would give rise to models of learning in which players form beliefs about other players' states based on past actions. To model these beliefs consistently, the state space would need to be amplified to include the set of all possible past actions. As such serial correlation is likely to render the method computationally infeasible. See, for example Pesendorfer and Schmidt-Dengler (2008), for a detailed discussion.

[5]It has been commonly discussed that barriers to exit are high in the airline industry. This is because airplanes are very specific assets and have little scrap value. However, we refer to exit a non-directional city pair rather than the entire business.

own incumbency status in market m. After the realization of the demand shock s_{mt}, which is common knowledge among all airlines, and the private shock ϵ_{imt}, which is choice-specific and is only observed by each airline, airlines earn revenues and pay operating costs depending on their incumbency status. CEOs then decide simultaneously whether to operate in the market at time $t+1$, taking as given their expectations about peer actions, to maximize their expected discounted inter-temporal utilities.

The profits of an airline i that decides to stay out of market m at time $t + 1$, $\pi_{imt}(a_{imt} = 0)$, is

$$\pi_{imt}(a_{imt} = 0) = x_{imt}\,(y_{mt} - f_{im}) + \epsilon_{imt}(a_{imt} = 0); \tag{3.2}$$

while the profits of an airline i that decides to operate in market m at time $t + 1$, $\pi_{imt}(a_{imt} = 1)$, is

$$\pi_{imt}(a_{imt} = 1) = x_{imt}\,(y_{mt} - f_{im}) - (1 - x_{imt})e_m + \epsilon_{imt}(a_{imt} = 1). \tag{3.3}$$

The interaction term between x_{imt} and $(y_{mt} - f_{im})$ captures the notion that only the incumbent airlines earn profits. Similarly, the interaction term between $(1 - x_{imt})$ and e_{imt} indicates that only new entrants pay entry costs.

The entry and exit decisions are dynamic, that is, they depend on expectations about future competition. Upon entry, however, the competition is static. As discussed in Aguirregabiria and Ho (2012), capacity constraints and inter-temporal price discrimination may generate dynamics in the pricing strategies of airlines. However, this type of pricing dynamics is short-run and at the level of individual flights. Therefore, we expect that these factors should play a very minor role in the dynamics of competition and therefore the effect of RPE on the competition.

3.2.2 Manager's Compensation and Utility

The CEO of airline i is subject to an exogenous representative compensation contract. In other words, we do not derive the form of an optimal contract but instead approximate contracts observed, i.e., the representative contract is inferred from data and may or may not be optimal.

The contract consists of two parts: a profit share and RPE, suggesting that the CEO is rewarded not only on absolute performance but also on the basis of peer performance. Formally, the contract is written as

$$u_{it} = \lambda_o \pi_{it} - \lambda_p \pi_{-it}, \tag{3.4}$$

where π_{it} represents performance of airline i at time t, which is the aggregated profits over markets, i.e., $\pi_{it} = \sum_{m=1}^{M} \pi_{imt}$. π_{-it} represents peer performance of airline i at time t, which is the average profits of all airlines other than i, i.e.,

$$\pi_{-it} = \frac{1}{N-1} \sum_{j \neq i} \pi_{jt}.$$

λ_o and λ_p are parameters representing the contract loadings on airline's own and peer performance respectively. The contract indicates that the CEO utility of airline i increases with that airline's own performance but decreases with peer performance.

After signing the contract, the CEO chooses a set of market entry-exit decisions $\boldsymbol{a}_{it} = \{a_{imt} : m = 1, 2, \cdots, M\}$ to maximize the present value of his future utility, taking into account the implications of his current choices on future profits and on the future reactions of competitors. We assume that CEOs' strategies depend only on payoff-relevant state variables, that is, we assume a Markov perfect equilibrium. An airline's payoff-relevant information at time t is $\{\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}\}$. Let $\boldsymbol{\sigma} = \{\sigma_i(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}) : i = 1, 2, \cdots, N\}$ be a vector of strategy functions, one for each airline. A Markov Perfect Equilibrium (MPE) in this game is a vector of strategy functions $\boldsymbol{\sigma}$ such that each airline's strategy maximizes the utility of the airline's manager for each possible state $(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it})$, taking as given other airlines' strategies. The Bellman equation for the problem is given by

$$U_{it}(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{\epsilon}_{it}) = \max_{\boldsymbol{a}_{it}} \left\{ u_{it} + \frac{1}{1+r} \mathbb{E}[U_{i,t+1}(\boldsymbol{x}_{t+1}, \boldsymbol{s}_{t+1}, \boldsymbol{\epsilon}_{i,t+1}) | \boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{a}_{it}] \right\}. \tag{3.5}$$

It is extremely challenging to solve and estimate the dynamic game of competition described above. This intractability arises because the equilibrium of this dynamic game of competition, an MPE, is based on information covering the space of all state variables $(\boldsymbol{x}_t, \boldsymbol{s}_t)$. For example, the dimension of the space $\boldsymbol{x}_t$, is 2^{NM}, as it contains all possible combinations of binary entry-exit decisions for all airlines in all markets. Given the number of markets and airlines in our empirical analysis, solving a dynamic game with this state space is not feasible.

To deal with this computational complexity, we therefore reduce the dimension of state space by assuming that an airline's entry-exit decisions are decentralized to local managers. That is, every airline has M local managers, one for each market. The local managers and the CEO have perfectly aligned interests. Each local manager (i, m) chooses $a_{imt} \in (0, 1)$ to maximize the present value of his future utility. Thus, the optimization problem in (3.4) and (3.5) can be decomposed and represented as:

$$U_{imt}(\boldsymbol{x}_{mt}, s_{mt}, \epsilon_{imt}) = \max_{a_{imt}} \left\{ u_{imt} + \frac{1}{1+r} \mathbb{E}[U_{im,t+1}(\boldsymbol{x}_{m,t+1}, s_{m,t+1}, \epsilon_{im,t+1}) | \boldsymbol{x}_{mt}, s_{mt}, a_{imt}] \right\}, \tag{3.6}$$

in which the one-period utility of the local manager (i, m) is

$$u_{imt} = \lambda_o \pi_{imt} - \lambda_p x_{imt} \pi_{-imt}. \tag{3.7}$$

In (3.7), peer performance of airline i in market m at time t, π_{-imt}, is written as

$$\pi_{-imt} = \frac{1}{n_{mt} - 1} \sum_{j \neq i} \pi_{jmt}.$$

Note that at the market level, RPE enters the utility of a local manager under two conditions. First, only local managers of incumbent airlines ($x_{imt} = 1$) get evaluated relative to their peers. Second, the market should have at least one incumbent airline other than i, i.e., $n_{mt} > 1$. Thus, the state space of the optimization problem of a local manager is reduced to $M \times 2^N$.

3.2.3 Effects of Relative Performance Evaluation

In this subsection, we discuss the two effects generated by the use of RPE. On the one hand, a common view in the theoretical literature on optimal contracts is that RPE can be used as a more efficient tool to incentivize CEO effort. This incentive effect arises because comparisons between competing agents can serve as a device to filter out common shocks and thus extract information about effort. On the other hand, the use of RPE also provides incentives for CEOs to take actions that influence peer performance. We term this second effect the competition effect. Because RPE places a negative weight on peer performance, CEOs receive higher compensation if peers perform worse.

We demonstrate these two effects by opening up an incumbent local manager's utility function, as only the manager of an incumbent airline get evaluated relative to his peers.

$$u_{imt} = \lambda_o(y_{mt} - f_{im} + \epsilon(a_{imt})) - \lambda_p \frac{1}{n_{mt} - 1} \sum_{j \neq i} (y_{mt} - f_{jm} + \epsilon(a_{jmt})).$$

Recall that incumbent airlines earn the same revenues $y_{mt}(s_{mt}, \boldsymbol{x}_{mt})$ in market m at time t but are heterogeneous in their fixed operating costs f_{im}. We rewrite the utility function as

$$u_{imt} = (\lambda_o - \lambda_p)y_{mt} - (\lambda_o - \lambda_p)f_{im} + \lambda_p(f_{-im} - f_{im}).$$

The first component reflects the incentive effect discussed in the theoretical literature. The presence of RPE ($\lambda_p > 0$) reduces the weight on revenues y_{mt} that are outside of the manager's control, making CEO compensation less sensitive to exogenous market conditions. The last component demonstrates the competition effect. The use of RPE adds extra rewards to the local manager if he maintains lower fixed operating costs (and thus higher profit margins) than the peer average. In other words, RPE provides higher incentives to the manager who maintains lower fixed operating costs to operate in the market.

3.2.4 Policy Functions

In this section, we numerically examine policy functions implied by the model, in order to explore the insights of the model. The policy function is a rule that provides the best choice in the next period for any given combination of state variables in the current period. Figure 3.2 Panel A plots equilibrium conditional probabilities across airlines as a function of the total market size s, evaluated at the steady-state distribution. The value of model parameters is taken from the set of estimation results specified in Table 3.5. Overall, the probability of being active $p(a = 1)$ rises with the market size s. Intuitively, a strong market incentivizes managers to operate in markets and earn profits. The response to market size differs across heterogeneous airlines. Airlines with lower fixed operating costs, such as Delta (DL) and Northwest (NW), behave more aggressively by being active in response to market conditions as compared to the ones with higher fixed operating costs such as Continental (CO) and American (AA). In Panel B of Figure 3.2, we show the response of market participation using separate data across markets. Overall, the policy functions show a similar pattern with those in Panel A. The only difference is that the market participation incentive is decreasing in the oversized market, shown as the downward sloping of the curves on the right end. This is because, in an overly crowed segment market, the marginal benefit of being active is not able to offset the marginal cost of increasing competition. This could be possible in the market like the route between Chicago and New York, in which the market saturation is high.

We proceed by conducting a comparative statics exercise to further explore the economic mechanism through which the use of relative performance evaluation affects airlines' entry-exit decisions. Specifically, we use the following two-step procedure. We first solve and simulate the model 21 times corresponding to 21 values of λ_p in the range of $[0, 0.5 \times 10^{-3}]$, while keeping the rest of parameters the same as specified in Table 3.5. We then calculate the average of the equilibrium probabilities over the simulated data that matches the real sample based on the steady state.

Figure 3.3 depicts the relation between the contract loading on peer performance λ_p and the airline's tendency to operate in a market under bad and good market conditions, respectively. Evidently, the use of RPE has an asymmetric effect on entry-exit decisions depending on market conditions, s_{mt}. RPE decreases (increases) the probability of being active under good (bad) market conditions. This asymmetric effect occurs because RPE makes CEO compensation less sensitive to market conditions. Managers, under RPE contracts, make entry-exit decisions while facing a tradeoff between the reduction in compensation based on market conditions, and the gain from being compared to competing agents. Specifically, under bad market conditions, managers under RPE contracts benefit from being punished less for any bad performance and therefore are reluctant to operate in the market. In contrast, managers under RPE contracts lose out on the opportunity to free-ride on good market conditions. Instead, they benefit more from being compared to similarly well-performed peers and therefore are motivated to operate in the market.

The trade-off discussed above, and therefore the effect of RPE on entry-exit decisions, naturally vary across heterogeneous airlines, depending on the airline's comparative advantage (i.e., fixed operating costs). Figure 3.4 depicts the asymmetric effect of RPE for each airline under different market conditions. For airlines with lower fixed operating costs, RPE tends to increase more (decrease less) the probability of being active under good (bad) market conditions. That is, RPE provides higher incentives to airlines with lower fixed operating costs to operate in the market. This incentive effect happens because RPE rewards managers that maintain lower fixed operating costs (and thus higher profit margins) than the peer average.

3.3 Data

Our analysis relies on several sources: the Origin and Destination Survey (DB1B) for airline entry and exit, ExecuComp for managerial compensation, and CRSP for stock returns.

3.3.1 Airline Entry and Exit

We construct the airline entry and exit data following Ciliberto and Tamer (2009) by using the DB1B survey provided by the Bureau of Transportation Statistics. The DB1B survey consists of a sample of 10% of all airline tickets from reporting carriers and classifies information at the coupon, market and tickets level separately. The ticket data set contains the summary characteristics of each itinerary, including reporting carrier, origin/destination, prorated airfare, etc. The market data set contains the directional market characteristics of the air tickets. The coupon data set contains the characteristics of each leg of the air tickets, such as operating carrier, origin/destination airport, number of passengers, fare class, etc.

We start with a sample of data from the first quarter of 1993 to the last quarter of 2015. Following Ciliberto and Tamer (2009), we take three steps to link all information in DB1B. In the first step, we merge the DB1B coupon data set with operating carrier information from the T-100 Domestic Segment Dataset and drop the unmatched coupons. The T-100 Domestic Market (U.S. Carriers) data reports all flights that occur in the United States in a given month of the year. In the second step, we merge this reduced DB1B coupon data set with the DB1B ticket data set by ticket identification numbers. Finally, we merge the cleaned ticket-coupon data set with the DB1B market data set to get the information on origin and destination airport.

In this process, we drop observations with following characteristics: (i) tickets with more than six coupons; (ii) tickets whose fare credibility is questioned by the Department of Transportation (variable dollarcred with value of 0); (iii) tickets that are neither one-way nor round-trip travel; (iv) tickets including travel on more than one airline on a directional trip (know as interline tickets); (v) tickets with a fare less than 20 dollars; (vi) tickets involving U.S. non-reporting carriers flying within North America (small airlines serving big airlines) and foreign carrier flying between two U.S. points; (vii) tickets that are part of international travel; (viii) tickets involving noncontiguous domestic travel (Hawaii, Alaska, and territories); (ix) tickets in the top and bottom five percentiles of the year-quarter fare distribution.

Markets We define a market as a trip between a pair of metropolitan statistical areas (MSAs), irrespective of intermediate stops and of the direction of the flight.[6] The sample includes markets between the top 50 MSAs ranked by the average population during the sample period from the U.S. Census Bureau. Table 3.1 presents the list of the 50 MSAs and their population. The markets considered are sizable: From 1993 to 2015, the top 50 MSAs cover on average 63.8% of the U.S. population; the markets between these 50 MSAs serve more than 66.61% of all passengers and generate more than 66.77% of all revenues over all reported market segments in DB1B.

For each MSA, we cluster all the primary airports classified by the Federal Aviation Administration, excluding the general aviation airports.[7] By doing so, we implicitly assume perfect substitution in demand and supply between two routes with the same MSAs but different airports and cities. There exists $M = (50 \times 49)/2 = 1,225$ possible markets. Table 3.2 presents the top 20 markets ranked by the average annual number of passengers served.

Airlines A ticket may involve more than one airline because of code shares.[8] We therefore use the reporting carrier at the ticket level in DB1B to identify the airline.[9] By doing so, we assume that the reporting carrier pays the cost of operating the flight and receives the revenue for providing this service.

We restrict our attention to the top airlines ranked by the annual number of passengers served for two reasons. First, we need comparable peers. Second, the state space grows exponentially with the number of airlines studied, which is clearly prohibitive with many airlines. For any N airlines, there are 2^N possible combinations of choice sets. To this end, we aggregate the regional affiliates to their holding

[6]Our definition is in line with the previous literature: Ciliberto and Tamer (2009) considers airport-pairs and Aguirregabiria and Ho (2012) considers city-pairs.

[7]General aviation airports are civilian airports that do not serve scheduled passenger service. These airports usually serve private aircraft and small aircraft charter operations.

[8]Approximately one third of tickets in our sample involve more than one airline.

[9]The reporting carrier is an airline that submits the ticket information to the Office of Airline Information. According to the directives of the Bureau of Transportation Statistics (Number 224 of the Accounting and Reporting Directives), the first operating carrier is responsible for submitting the applicable survey data as reporting carrier.

parent airlines and drop the regional carriers whose core business is not in cooperation with the major carriers. The process leaves us with 7 airline carriers in the refined sample. Table 3.3 presents our list of 7 airlines together with the annual number of passengers and the number of operating markets. Southwest is the airline that flies more passengers (about 2.5 million passengers in the 10% sample); while American, United, and Delta follow in the ranking. These 7 carriers in total served 80.49% passengers and generated 82.14% revenues in the markets between top 50 MSAs during 1993-2008.

Mergers, Acquisitions and Code-Share Agreements The U.S. airline industry has experienced substantial consolidation over the past few decades. A.4 lists the recent airline mergers and code-share agreements in the US airline industry.

Merges and acquisitions (M&A) can be considered as extreme cases of entry-exit decisions. Yet we do not explicitly model the M&A decisions in our dynamic model for two reasons. Theoretically, M&A decisions are sufficiently rare that the expectation of future mergers do not influence equilibrium play. Empirically, M&A in the U.S. airline industry are heavily regulated. Many policy makers feared that the commercial airline industry could become overly concentrated in the wake of the Airline Deregulation Act of 1978 and the closure of the Civil Aeronautics Board in 1985. Therefore, mergers between airlines on the verge of collapse were approved to maintain competition, while mergers between fiscally healthy airlines were generally prevented.

Nevertheless, the mergers and acquisitions have important implications for the estimation of our dynamic game because they change the number of global players defined in our dynamic game. To this end, instead of modeling the mergers and acquisitions explicitly, we take into account the industry revolution by estimating our dynamic game for the sample period 1993-2008. In this period, the global players are Southwest, American, Delta, United, US Airways, Northwest and Continental.

A code-share agreement allows an airline to sell seats on a partner's plane as if they were its own. This would potentially affect our estimation depending on whether the code-shared routes are complementary or overlapping. On the one hand, routes are complementary when together they allow travel between two cities that is not possible on either airline. A code-share agreement effectively enables the two airlines to enter a market jointly. The use of the reporting carrier has taken care of these cases.

On the other hand, routes are overlapping when both airlines offered competing service in the same market prior to the code-share alliance. In this market, an alliance could facilitate price collusion, which violates the model assumption of the negative relation between the number of incumbents and profits. Nevertheless, the concern of price collusion is alleviated in two ways. From a practical perspective, code-share agreements are subject to careful review by the U.S. Department of Transportation, which ensures the agreements are not anti-competitive or adverse to the public interest. From an academic perspective, Gayle (2007) uses a structural framework to examine the competitive effects of the code-share alliances among Continental, Delta, and Northwest in 2002, finding few significant departure between collusive and pre-alliance prices.[10]

3.3.2 Executive Compensation

For the airlines we consider, we collect managerial compensation information from ExecuComp and stock returns from CRSP. Note that ExecuComp covers only S&P 1500 firms starting from 1994. To supplement, we hand collect compensation information from SEC filings on EDGAR when missing.

Our final sample for estimation of the dynamic game consists of two annual-frequency panels from 1993 to 2008: a panel of managerial compensation and stock returns for 7 airlines and a panel of entry-exit data for 8,575 local managers (i.e., 7 airlines times 1,225 markets).

[10]Strategic alliances formed by code-sharing may have an impact on deterring potential competitors from entering a relevant market. This entry deterrent effect is captured by the market-specific entry costs.

3.3.3 Descriptive statistics

Figure 3.1 presents the distribution of the 1,225 markets examined across the number of incumbent airlines over our sample period. 12 markets have never been served by any of the airlines over the years. Approximately 75% of the markets have more than three airlines operating, and one-third of the markets on average have six incumbent airlines providing service. The average number of airlines operating per market is 4.69, guaranteeing the existence of the comparable peers.[11]

The data contain interesting information regarding market dynamics. On the one hand, the frequency of entry and exit per market is high. Among the 1,225 markets over the sample period, 81.39% (83.59%) of the markets have experienced at least one entry (exit). This significant turnover provides us with enough variation to identify the parameters of fixed and entry costs. On the other hand, the frequency of entry and exit per market-year is low. Panel A of Table 3.4 presents the distribution of market-year observations by the number of entrants and exits, respectively. Similar to Aguirregabiria and Ho (2012), the average numbers of entrants and exits per market-year are 0.13 and 0.18 respectively. These low frequencies suggest a high barrier to entry.

There exists considerable heterogeneity across airlines. Panel B of Table 3.4 presents statistics describing the differences among airline operations. The first part presents the number of "monopoly" markets across airlines over sample period. Delta and US Airways are the largest monopoly carriers, serving 32% and 29% of the monopoly markets, or on average 12 and 16 monopoly markets per year respectively. Southwest, at 14%, is a distant second.

The second part shows the average conditional probabilities of staying in markets across airlines. The conditional probabilities are calculated using the following two-step procedure. In the first step, we aggregate observations by state $(\boldsymbol{x}, s)$ de-

[11] Aguirregabiria and Ho (2012) reports the average number of airlines with non-stop flights per market is only 1.4. We have a much larger number for two reasons. First, we define a market as the trip between a pair of metropolitan statistical areas (MSAs), irrespective of intermediate stops and of the direction of the flight. Second, we consider and therefore aggregate quarterly data into yearly data.

fined in the model for each player and calculate the sample frequency of airline entry-exit decisions for each state-player pair. In the second step, we lump and average the sample frequencies of states when $x_i = 1$ for each airline i. This measure allows us to capture heterogeneous airline characteristics while controlling for market size, the level of competition, and the heterogeneity of peers which are important determinants of firm survival. Delta, with 87%, has the highest probability of staying in a market once it has entered; while Continental, with 68%, has the lowest probability of staying.

3.4 Estimation

This section describes our approach to estimating the parameters of our model. Because it would be too computationally burdensome to estimate all parameters simultaneously, we use a two-step strategy. We first estimate the process describing the dynamics of market size by formulating the process as a discrete Markov chain and estimating the transition probabilities. We then estimate the rest of parameters using the dynamic game of competition. For all estimations, the real risk-free interest rate, r, is set to 0.97% (i.e., an annual discount factor of 0.99) to match the average difference between three-month T-bill rate and the growth rate of the Consumer Price Index over our sample period.

3.4.1 Market Size

Recall that we assume that the size s_{mt} of market m evolves exogenously according to a Markov process. Our approach deviates from, for example, Aguirregabiria and Ho (2012), who model variable profits as the outcome of equilibrium price competition and estimate the resulting demand system using a nested logit model. We opt for our simpler approach because it provides us with the tractability to focus on the effects of compensation contracts on the dynamics of the competition. In this subsection, we discretize the continuous-valued market size using the approximation method proposed by Rouwenhorst (1995), where we choose this method because of the results in Kopecky and Suen (2010) and Galindev and Lkhagvasuren (2010) that this method is more accurate than other alternatives when persistence is high.

Estimating the market size presents a challenging task because of heterogeneity in local economies, airport network structures, and consumer preferences. However, the number of passengers served provides a useful measure of market size if we assume that realized demand is an equilibrium outcome of competition. In our own data, we face a further problem with this measure because we occasionally observe no passengers in a market. For these cases, our assumption of an equilibrium outcome implies that we conclude that there is no demand in the market. We overcome this problem by replacing zeros with imputed values from the following regression:

$$\begin{aligned}\ln(\text{Passenger}_{mt}) = \beta_0 + \beta_1 \ln(\text{Population}_{mt}) + \beta_2 \ln(\text{Income Per Capita}_{mt}) \\ + \beta_3 \text{Income Growth}_{mt} + \beta_{4m} + \beta_{5t} + \epsilon_{mt},\end{aligned} \tag{3.8}$$

where Passenger_{mt} stands for the number of passengers carried in market m at time t. We include three demographic variables: Population_{mt} is the sum of the metropolitan populations, $\text{Income Per Capita}_{mt}$ is the average of the metropolitan personal income per capita, and $\text{Income Growth}_{mt}$ is the average rates of income growth, which we use to measure the strength of the local economy. In addition, we include market fixed effects, β_{4m}, that capture between-market differences such as geographic location, which are constant over time. We also include year fixed effects, β_{5t}, to account for year-specific differences that are common for all markets, for example, the impact of September 11, 2001.

We obtain the data on personal income per capita for metropolitan areas from the Regional Economic Accounts of the Bureau of Economic Analysis (BEA). Unfortunately, the BEA provides estimates of GDP for metropolitan areas starting only in 2001. We therefore use the income growth to capture the strength of the economies.

We proceed to discretize market size and estimate its transition probability. As standard, we assume that market size follows an AR(1) process with drift in logs:

$$\ln(s_{m,t+1}) = \mu + \rho \ln(s_{mt}) + \sigma\omega_{m,t+1}, \tag{3.9}$$

where μ and ρ are the drift and the autoregressive coefficient respectively, and ω is a standard normal i.i.d. innovation. We obtain values of the drift, persistence and volatility of the market size by directly estimating the AR(1) regression. We then use the method in Rouwenhorst (1995) to discretize this AR(1) process and obtain the transition matrix of the discretized variable with 5 points of support. As shown in Kopecky and Suen (2010) the Rouwenhorst method is able to produce highly accurate approximations even when $N = 5$.

3.4.2 Estimation of the Dynamic Game

The estimation of the dynamic game is based on a representation of Markov perfect equilibria as fixed points of a best response mapping in the space of players' choice probabilities. We interpret these choice probabilities as players' beliefs about the behavior of their opponents. Given these beliefs, each player's problem can be interpreted as a game against nature with a unique optimal decision rule – the players's best response – in probability space.[12] The best response mapping is always a unique function of structural parameters and players' beliefs about the behavior of other players.

To estimate our dynamic game, we assume that the data have been generated by only one Markov perfect equilibrium. Thus even if the model has multiple equilibria, we do not need to specify an equilibrium selection mechanism because the equilibrium that has been selected will be identified from the conditional choice probabilities in the data.[13]

[12] In this paper we consider only pure-strategy equilibria because, according to Harsanyi (1973), they are observationally equivalent to mixed-strategy equilibria. Harsanyi's "purification theorem" established that a mixed-strategy equilibrium in a game of complete information can be interpreted as a pure-strategy equilibrium of a game of incomplete information. That is, the probability distribution of players' actions is the same under the two equilibria.

[13] See Aguirregabiria and Mira (2007) for a detailed discussion.

Estimator Since the model implies a probability distribution over the possible outcomes, a natural starting point is to construct a nested maximum-likelihood algorithm that, in each iteration, solves the fixed-point problem given the current estimate of the parameter values. However, such maximum likelihood estimators are limited to serve our application because of the following identification problem. Recall the parametric specification of the utility function (3.7), where the sets of contract- and profit-related parameters enter in a multiplicative form. As maximum likelihood estimation would only utilize market-level entry-exit data, the estimators would not contain enough information to disentangle and therefore separately identify these parameters.

To overcome this identification problem, we use the two-step of moments estimator in the spirit of Rust (1994). In the first step, the computation of a fixed point problem delivers the equilibrium choice probabilities for a given set of parameter values. In the second step, the parameters of interest are inferred by fitting a set of moments that match the equilibrium choice probabilities and value function in the model with their data analogs.[14] This approach overcomes the aforementioned identification problem by allowing for the incorporation of airline-level compensation data that facilitates the identification of contract-related parameters in the model.

Specifically, let $\boldsymbol{\theta}$ denote the vector of parameters to be estimated. The procedure follows two steps:

Step 1: solve a fixed point problem to obtain the conditional choice probabilities $\boldsymbol{p}$:

$$\boldsymbol{p}(\boldsymbol{\theta}) = \boldsymbol{\Psi}(\boldsymbol{p}(\boldsymbol{\theta})),$$

where $\boldsymbol{\Psi}$ denotes the policy interaction operator;

[14]Pesendorfer and Schmidt-Dengler (2008) show that structural estimators for dynamic models proposed by Rust (1994), Hotz and Miller (1993), and Aguirregabiria and Mira (2002) are asymptotic least squares estimators defined by a set of equilibrium conditions. The estimators differ in the weights they assign to individual equilibrium conditions.

Step 2: solve a least square problem to obtain the estimates of parameters:

$$\boldsymbol{\theta} = \arg\min_{\boldsymbol{\theta}} \boldsymbol{g}(\boldsymbol{\theta})'\boldsymbol{W}\boldsymbol{g}(\boldsymbol{\theta}),$$

where $\boldsymbol{W}$ denotes the weight matrix, and $\boldsymbol{g}(\boldsymbol{\theta})$ is the vector of moment differences between the data and the model equilibrium. The moment estimators are selected to make the actual and model moments as close to each other as possible.

Identification We need to estimate 12 parameters $\boldsymbol{\theta} = (\gamma_s, \gamma_n, f_i, e, \lambda_e, \lambda_p)'$ by matching moments predicted by the model to their analogs in the data. The moments we use consist of two sets: (1) OLS regression coefficients from the airline-level compensation data, and (2) state-specific entry probabilities from the market-level entry-exit data. The moments are selected to identify our structural parameter vector $\boldsymbol{\theta}$.

The contract-related parameters, i.e., the loading on CEO compensation for the firm's own and peer performance are identified using the airline-level compensation data. Specifically, we use as moments the coefficients from the following regression:

$$u_{it} = \hat{\lambda}_1 + \hat{\lambda}_o \pi_{it} + \hat{\lambda}_p \pi_{-it} + \epsilon_{it}, \tag{3.10}$$

where π_{it} and π_{-it} denote separately the profits (Compustat item NI) of airline i and its peers $-i$ at time t, where peer performance is measured as the value-weighted average profits of all airlines other than airline i. We let u_{it} denote CEO compensation (ExecuComp item TDC1), adjusting for the other compensation (ExecuComp item OTHCOMP), of airline i at time t. We use this adjustment because focusing on total CEO compensation (ExecuComp item TDC1), an approach used in previous studies, can underestimate the extent to which total executive pay is correlated with performance. Other compensation received by the CEO (ExecuComp item OTHCOMP), such as severance payments and signing bonuses, is largely unrelated to the performance of the firm during the executive's tenure.

In the airline industry, the leading roles are long-tenured, CEOs can switch CEOs switch companies within the industry. For example, there are two cases in which the same person served as CEO for different airlines during the sample period.[15] To this end, we include CEO times airline fixed-effects to control for CEO-airline matches. The procedure gives $\hat{\lambda}_o = 1.356 \times 10^{-3}$, and $\hat{\lambda}_p = -0.196 \times 10^{-3}$.

Note that the coefficients $\hat{\lambda}_o$ and $\hat{\lambda}_p$ do not correspond directly to the contract-related parameters in the model because the airline-level compensation data omits information at the market level. Thus, the regression is not able to capture a given airline's heterogeneity, such as the operating status, across markets. Nevertheless, the regression coefficients are useful moments with which to identify contract-related parameters. Importantly, as we hold these contract-related moments fixed across markets for a given airline and then solve for profit-related parameters, heterogeneity across markets is therefore attributed to profit-related parameters, such as entry costs and fixed operating costs. This approach reinforces our model assumption that local managers are subject to the same contract as the CEO.

The profit-related parameters are then identified using the market-level entry-exit data. Recall that the game has a Markov structure, that is, if $\{\boldsymbol{x}_k, s_k\} = \{\boldsymbol{x}_l, s_l\}$, then airline i's decisions at periods k and l are the same. In order to calculate the probability distribution of the Markov structure, we aggregate observations by state for each player and calculate the sample frequency of airline entry-exit decisions for each state-player pair. Specifically, let $p(a_i|\boldsymbol{x}, s)$ denote the probability that airline i selects entry-exit action a in state $\{\boldsymbol{x}, s\}$ for any given market. The sample frequency is calculated as

$$\hat{p}(a_i|\boldsymbol{x}, s) = \frac{\sum_t \mathbb{1}(a_{it} = 1, \boldsymbol{x} = \boldsymbol{x}_t, s = s_t)}{\sum_t \mathbb{1}(\boldsymbol{x} = \boldsymbol{x}_t, s = s_t)}.$$

As a result, the total number of $N \times M \times 2^N$ sample frequencies are obtained as moments that are used to match the equilibrium choice probabilities $\boldsymbol{p}$ from the model. The number $N \times M \times 2^N$ comes from multiplying the number of players N

[15] Stephen M. Wolf served as CEO of United from December 1987 to July 1994 and later as CEO of US Airways from January 1996 to November 1998. Richard H. Anderson served as CEO of Northwest from April 2001 to October 2004 and later on CEO of Delta from September 2007 to May 2016.

and the number of states $M \times 2^N$. The number of states is all possible combinations of market size M and the choices of the players 2^N.

We use variation in the choice probability across players and states to identify separately the profit-related parameters for each CEO contract. The revenue-related parameters γ_s and γ_n are identified through variation in choice probabilities in response to the market size and the number of incumbents. The vector of airline-specific fixed operating costs f, capturing market $\times$ airline fixed effects, is identified through variation in the probability of being active among incumbents. The entry cost e is identified from the differences in the probability of being active between incumbents and potential entrants.

We construct the weight matrix to match the two sets of moments described above. The weight matrix for the compensation regression coefficients is an identity matrix. The weight matrix for the state-specific entry probabilities is a diagonal matrix with elements equal to the frequency that the data visited per state. This choice implies that we assign the most weight to the state-specific entry probabilities that are observed most frequently. We then combine the two weight matrices by constructing a block diagonal matrix. Note that the compensation moments are small in magnitude compared to the state-specific entry probabilities. As such, a simple combination of the two weight matrices implicitly undermines the importance of the compensation moments. To compensate, we therefore multiply the identity weight matrix of the compensation regression coefficients by 10^4.

3.5 Results

3.5.1 Results Using Pooled Data Across Markets

We start by presenting our estimation results of the dynamic game using data pooled across markets. We observe 1,225 markets over 16 years which gives 18,375 (= $1,225 \times 15$) observed state-action profiles. By pooling data across markets, we implicitly assume that the observed state-action profiles are generated from an identical data generating process in all markets and, more importantly, a single and identical equilibrium of the game is played across all markets.[16] Therefore, we need to deal with unobserved market heterogeneity in order to apply the pooled data assumption. To this end, we obtain the persistence and volatility of average market size using data that have undergone a within-transformation and calculate the drift as the average of cross section's mean. The procedure gives $\mu = 8.191$, $\rho = 0.892$, and $\sigma = 0.090$. Accordingly, a representative market of the median size has 3,608 passengers.

Columns (1) and (2) of Table 3.5 present our estimation results. All of parameter estimates are significantly different from zero, including the estimate of the loading on peer firm performance for CEO compensation. This evidence provides a strong support to the existence of peer performance evaluation.

The first panel of Table 3.5 contains the point estimates and standard errors for the profit-related parameters.Our estimate of $\gamma_s = 0.04$ indicates that variable profits per airline increase significantly with market size, in dollar terms by \$40 per passenger. Given that on average each market has four operating airlines, the estimated γ_s implies a variable profit of \$160 per airfare. The estimated value also implies a variable profit of \$144.05 thousand for a monopolist in a market of median size. Competition intensity, measured by the logarithm of the number of incumbents, also has a significant effect on variable profits. The estimated value of γ_n suggests a \$1.90 thousand or 1.32% reduction in variable profits per airline when we go from a monopoly to a duopoly in a market of median size.

The average estimated fixed cost is \$97.46 thousand, ranging from \$88.41 thousand for Delta to \$104.64 thousand for Continental. It represents 68% of variable profit for a monopolist in a market of median size. These ratios are consistent with the statistics provided by the Air Transport Association of America, who reports

[16]Otsu, Pesendorfer and Takahashi (2016) propose several statistical tests to examine whether data from distinct markets can be pooled for finite state Markov games. The paper summarizes a few reasons for a violation of the data pooling assumption: (i) multiple equilibria are played across markets; (ii) the game form describing players' behavior and interactions differs across markets; and (iii) the specified model is not sufficiently rich as it does not control for all observable or unobservable market-level heterogeneity adequately.

that the average fixed operating costs amount to 71.2% of total operating expenses and 67.2% of revenue in 1993-1998. These results are also comparable to those reported in Aguirregabiria and Ho (2012), who find 75% using the variable profits attributable only to nonstop flights as the denominator. This high value of the ratio between fixed costs and variable profits implies substantial economies of scale in the airline industry. In addition, the rank of the estimated fixed costs among airlines is in line with Ciliberto and Tamer (2009), who show that fixed operating costs are low for Delta and high for United.

The average estimated entry cost is \$8,869.82 thousand, a figure that represents 91 times the average estimated fixed cost, and 62 times variable profit for a monopolist in a market of median size. This implied entry cost is much higher than the one estimated by Aguirregabiria and Ho (2012). The reason lies our pooling of data across markets. Recall that the absence of observed market entry can be attributed to two reasons. Either the market size is small and therefore has not enough demand or the airlines face substantial entry costs. The procedure of our market discretization naturally results in an inflation of small markets, leading to the overshooting of the implied entry costs. The model's tendency to overshoot the entry cost suggests the need to consider market heterogeneity.

The second panel of Table 3.5 presents the point estimates and standard errors of the contract-related parameters. The compensation loading on peer performance is 2.09×10^{-4}, suggesting a \$209 compensation reduction corresponding to a million dollar increase in the peer group.

Using the estimated model, we simulate data and obtain statistics that describe market structure. Table 3.6 compares simulated and actual values of the statistics. To obtain simulated data comparable to our real sample, we generate 1,225 markets over 15 periods. We start by finding the steady-state distribution of the state using the equilibrium choice probabilities and the transition probabilities for market size. The initial state values for each market $(s_{mt}, \boldsymbol{x}_{mt})$ are subsequently randomly drawn from the steady-state distribution of these variables. The entry-exit decision a_{imt} is calculated for a given state from the equilibrium choice probabilities. As the last step, we average these simulated values of a_{imt} over the simulations and over the sample.

Overall, the estimated model performs reasonably well. However, there are some biases in the predictions. First, the model over-predicts the proportion of markets with one incumbent by 13.0%, and under-predicts the proportion of markets with six incumbents by 15.2%. Second, the model under-predicts the amount of market turnover. As discussed above, this result is the consequence of pooling data across markets and therefore omitting market heterogeneity. The procedure of our market discretization naturally results in an inflation of extremely small markets and deflation of extremely large markets, which allows more markets with one incumbent and less markets with six incumbents. Also, the moderation of the market size reduces the probability that airlines drop out of the markets.

3.5.2 Results Using Separate Data Across Markets

The results above mask the substantial heterogeneity across markets. Specifically, different markets, defined as non-directional pairs of MSAs, differ in market size, entry costs, and airline-specific operating costs. More importantly, different markets might differ in the equilibrium played. To address this issue, we divide markets into 120 groups with similar size and estimate the dynamic game for each market subgroup. We use subgroups because of data limitations. Although it would be ideal to capture market heterogeneity by estimating the dynamic game by markets, in any individual market, we only observe a sequence of state-action profiles over 15 periods. This limitation means we have 105 (15×7) observations to identify 12 parameters, which weakens statistical power. Each of the 120 market subgroups pools data across 10 markets on average. The data aggregation is affirmed by the homogeneity test proposed by Otsu, Pesendorfer and Takahashi (2016), which is used to assess whether data from distinct markets can be pooled. Details regarding the homogeneity test are in A.5.

We make two modifications to the estimation procedure described previously.

The first modification concerns the profit-related moments. Because the sample size becomes much smaller, the relative frequencies of entry and exit calculated from the data are discrete in nature. To improve matching quality, we discretize the conditional choice probabilities from the model based on the frequency of observed states. The discretized conditional choice probabilities are then used in the econometric objective function, whose goal is to minimize the distance between the model and data moments.

The second modification relates to compensation-related moments. Note that the observed compensation moments are at the aggregate level over markets, corresponding to average contract loadings. When conducting estimation at the market level, the model generated compensation moments vary depending on the market size and observed entry-exit decisions. Therefore, we adjust the compensation-moment weights used in estimation for each market based on the distribution of market size that captures the market heterogeneity. We assign the most weights if the market size is closest to the sample median.

We aggregate the parameter estimates across market groups by calculating weighted averages. The weights are the same as those used for the compensation moments. This procedure gives $\mu = 7.716$, suggesting a representative market of median size has 2,244 passengers.

Columns (3) and (4) of Table 3.5 present the estimation results using data from separate markets. Similar to the pooled results, almost all of parameter estimates (except γ_n) are significantly different from zero. Yet, the estimated entry cost is more economically plausible. At \$2,424.33 thousand, it exceeds the average estimated fixed cost by a factor of 19. This piece of evidence confirms the importance of taking into account market heterogeneity. We also find a higher compensation loading on peer performance. However, this difference is accompanied by an almost identical increase in the compensation loading on the airline's own performance.

3.6 Conclusion

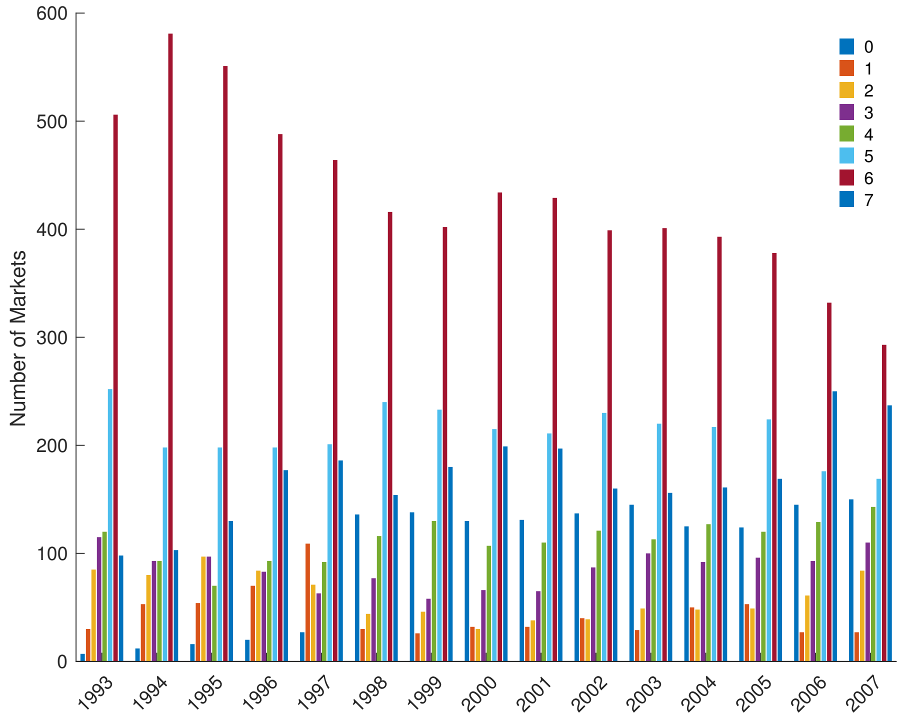
In this chapter, we investigate how and to what extent the use of RPE affects industry competition. Towards this end, we develop a dynamic game of competition with heterogeneous firms in an oligopoly market with the presence of RPE contracts. Using this framework, we obtain two main findings. First, the use of RPE has an asymmetric effect on entry-exit decisions depending on market conditions: it decreases the probability of being active in bad market conditions but increases the probability of being active in good market conditions. Second, this effect is stronger for firms with lower fixed operating costs.

The model also provides insights into the economic rationale behind these findings. Because RPE makes CEO compensation less sensitive to market conditions, managers, under RPE contracts, make entry-exit decisions while facing a tradeoff between the lower sensitivity to market conditions, and the gain from being compared to competing agents. Therefore, the effects of RPE on CEO incentives for strategic competition depend not only on market conditions but also on the firm's comparative advantage relative to its peers.

We estimate the model using data from the U.S. airline industry with information on entry and exit decisions for seven major airlines in the markets between the 50 largest MSAs. The estimated model is able to match key features of the market structure and dynamics. The estimation results confirm the existence of peer performance evaluation.

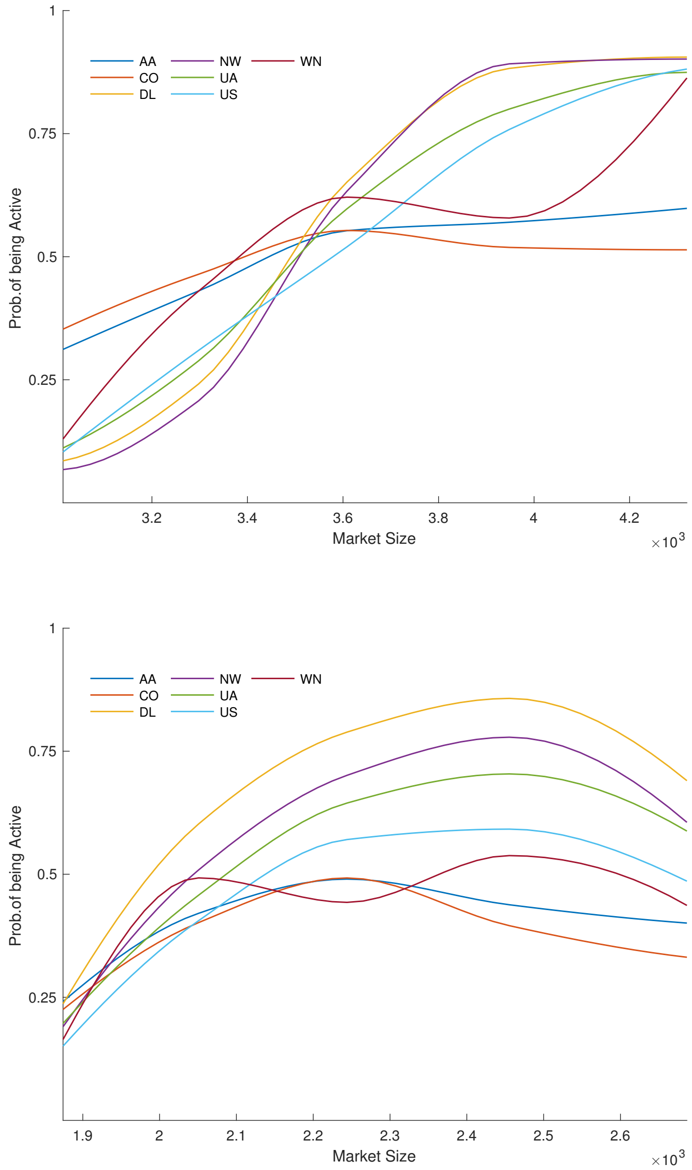
One direction for future research is based on our assumption of modeling observed instead of optimal contracts. We do not characterize an optimal contract, so the contract loadings on firms' own and peer performance are exogenous and fixed. While the rationale for this choice is based on the natural assumption of an incomplete contracting environment, we cannot ascertain whether the unintended effects on industry competition induced by the use of RPE is optimal. Finding an answer to this question is an interesting topic for future research.

Figure 3.1. Market Structure and Dynamics



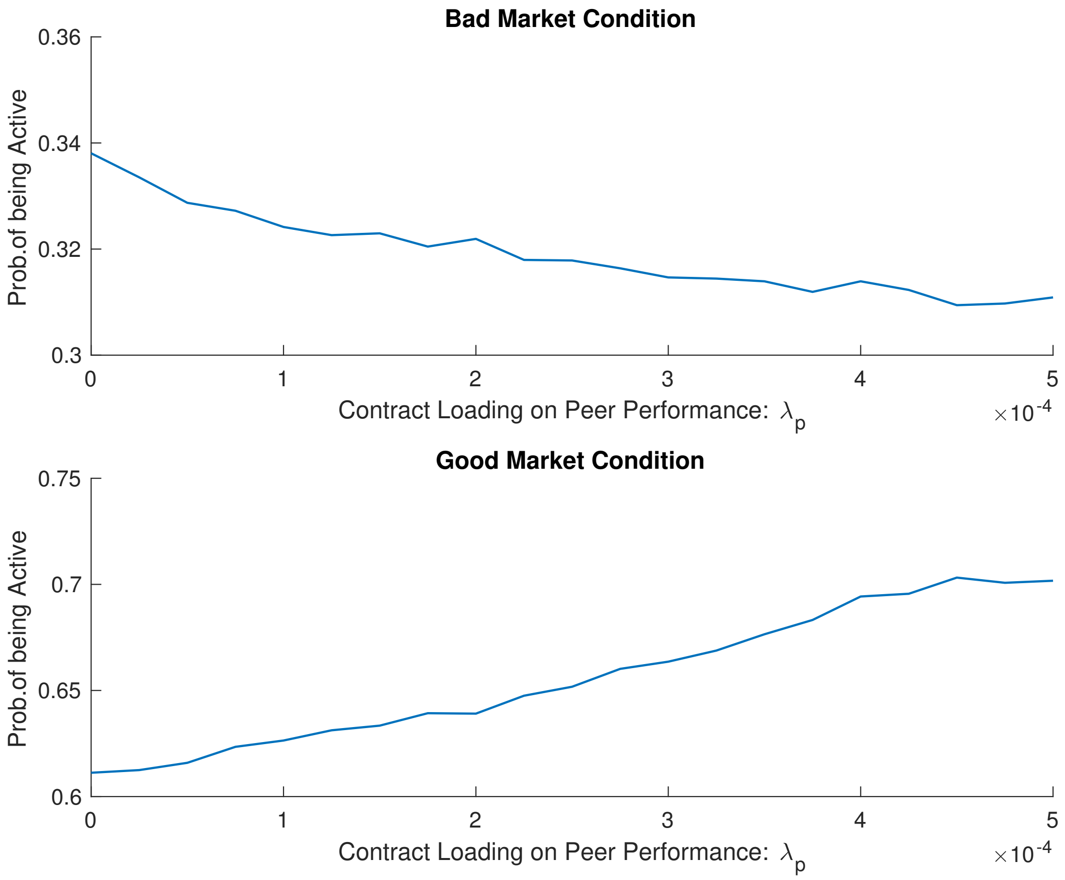
This figure presents the distribution of the 1,225 markets examined across the number of incumbent airlines between 1993 and 2007.

Figure 3.2. Policy Functions



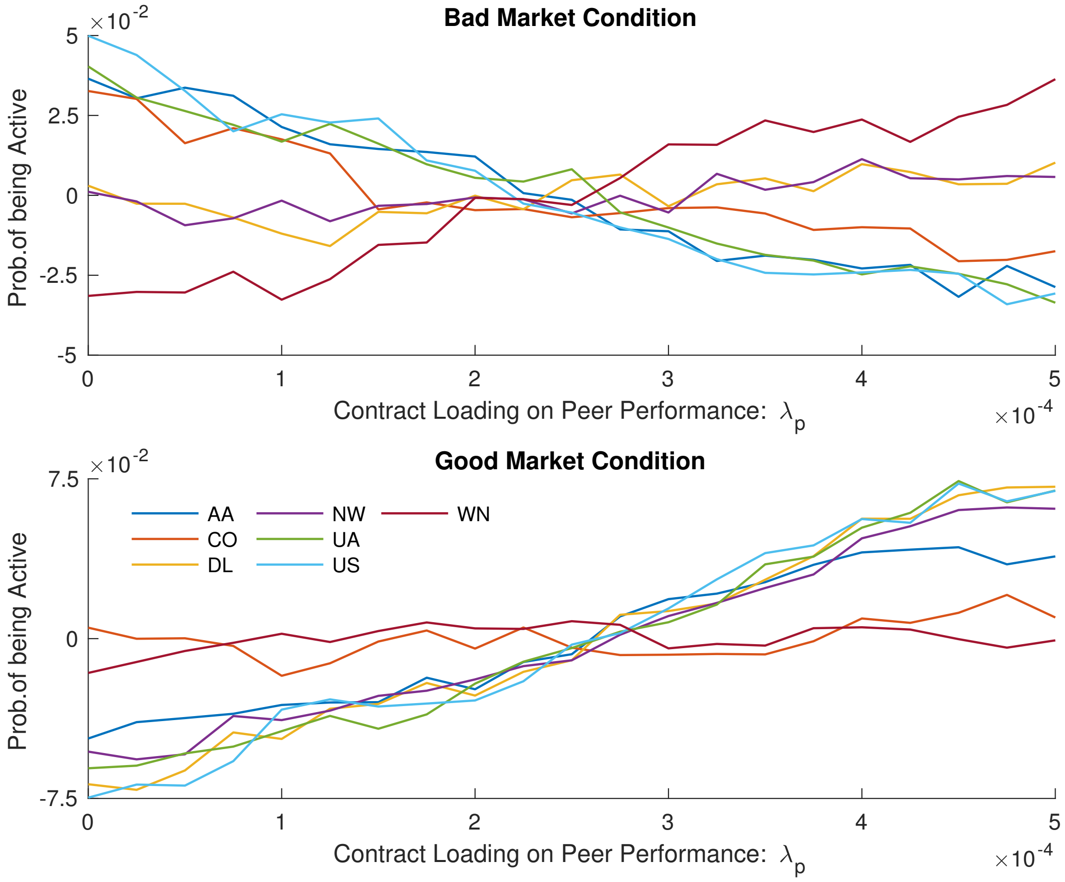
This figure depicts the equilibrium conditional probabilities across airlines as a function of market size, s, evaluated at the steady-state distribution. Model parameter values are taken from the set of estimation results specified in Table 3.5. Panel A uses the estimates from pooled data across markets, and Panel B uses the estimates from separate data across markets. The airlines considered are American(AA), Continental(CO), Delta(DL), Northwest(NW), United(UA), US Airways(US) and Southwest(WN).

Figure 3.3. Relative Performance Evaluation and Market Conditions



This figure depicts the relation between the contract loading on peer performance λ_p and the airline's tendency to operate in a market under bad and good market conditions respectively.

Figure 3.4. Relative Performance Evaluation and Airline Heterogeneity



This figure depicts the relation between the contract loading on peer performance λ_p and the airline's tendency to operate in a market across airlines. The first panel depicts the probabilities of airlines operating in a market under bad market conditions, and the second panel depicts the probabilities of airlines operating in a market under good market conditions.

Table 3.1. MSA and Population

The table presents the list of top 50 metropolitan statistical areas (MSAs) ranked by the average annual population between 1993 and 2008 from the US Census Bureau.

CBSA	MSA, State	Population
35620	New York-Newark-Jersey City, NY-NJ-PA	18,306,651
31080	Los Angeles-Long Beach-Anaheim, CA	11,751,734
16980	Chicago-Naperville-Elgin, IL-IN-WI	9,004,264
14460	Boston-Cambridge-Newton, MA-NH	6,175,536
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	5,680,094
19100	Dallas-Fort Worth-Arlington, TX	5,195,236
33100	Miami-Fort Lauderdale-West Palm Beach, FL	4,975,916
47900	Washington-Arlington-Alexandria, DC-VA-MD-WV	4,842,885
26420	Houston-The Woodlands-Sugar Land, TX	4,789,770
19820	Detroit-Warren-Dearborn, MI	4,456,654
12060	Atlanta-Sandy Springs-Roswell, GA	4,263,447
41860	San Francisco-Oakland-Hayward, CA	4,057,384
40140	Riverside-San Bernardino-Ontario, CA	3,409,758
38060	Phoenix-Mesa-Scottsdale, AZ	3,317,283
42660	Seattle-Tacoma-Bellevue, WA	3,029,570
33460	Minneapolis-St. Paul-Bloomington, MN-WI	2,957,210
41740	San Diego-Carlsbad, CA	2,825,013

Table 1. *(Continued)* MSA and Population

CBSA	MSA, State	Population
41180	St. Louis, MO-IL	2,668,021
12580	Baltimore-Columbia-Towson, MD	2,557,779
45300	Tampa-St. Petersburg-Clearwater, FL	2,413,157
38300	Pittsburgh, PA	2,380,470
39300	Providence-Warwick, RI-MA	2,164,859
19740	Denver-Aurora-Lakewood, CO	2,130,799
17460	Cleveland-Elyria, OH	2,125,131
17140	Cincinnati, OH-KY-IN	2,014,202
38900	Portland-Vancouver-Hillsboro, OR-WA	1,926,834
40900	Sacramento–Roseville–Arden-Arcade, CA	1,840,168
28140	Kansas City, MO-KS	1,832,935
41700	San Antonio-New Braunfels, TX	1,694,097
41940	San Jose-Sunnyvale-Santa Clara, CA	1,681,379
36740	Orlando-Kissimmee-Sanford, FL	1,677,544
25540	Hartford-West Hartford-East Hartford, CT	1,612,177
47260	Virginia Beach-Norfolk-Newport News, VA-NC	1,595,074
18140	Columbus, OH	1,587,790
26900	Indianapolis-Carmel-Anderson, IN	1,565,532
33340	Milwaukee-Waukesha-West Allis, WI	1,499,327
16740	Charlotte-Concord-Gastonia, NC-SC	1,420,926

Table 1. *(Continued)* MSA and Population

CBSA	MSA, State	Population
29820	Las Vegas-Henderson-Paradise, NV	1,382,835
34980	Nashville-Davidson–Murfreesboro–Franklin, TN	1,289,531
35380	New Orleans-Metairie, LA	1,268,270
12420	Austin-Round Rock, TX	1,264,960
14860	Bridgeport-Stamford-Norwalk, CT	1,228,752
32820	Memphis, TN-MS-AR	1,173,752
35300	New Haven-Milford, CT	1,165,669
15380	Buffalo-Cheektowaga-Niagara Falls, NY	1,156,330
27260	Jacksonville, FL	1,128,611
31140	Louisville/Jefferson County, KY-IN	1,109,337
49340	Worcester, MA-CT	1,096,765
36420	Oklahoma City, OK	1,065,238
40060	Richmond, VA	1,060,857

Table 3.2. Market and Number of Passengers in DB1B

The table presents the top 20 markets ranked by the average annual number of passengers served. The sample is based on DB1B and covers the period from 1993 to 2008.

	MSA Pair		Passengers
1	Los Angeles-Long Beach-Anaheim, CA	San Francisco-Oakland-Hayward, CA	209,215
2	Chicago-Naperville-Elgin, IL-IN-WI	New York-Newark-Jersey City, NY-NJ-PA	196,532
3	Boston-Cambridge-Newton, MA-NH	New York-Newark-Jersey City, NY-NJ-PA	153,296
4	New York-Newark-Jersey City, NY-NJ-PA	Orlando-Kissimmee-Sanford, FL	152,015
5	Atlanta-Sandy Springs-Roswell, GA	New York-Newark-Jersey City, NY-NJ-PA	143,795
6	Los Angeles-Long Beach-Anaheim, CA	New York-Newark-Jersey City, NY-NJ-PA	142,341
7	New York-Newark-Jersey City, NY-NJ-PA	Washington-Arlington-Alexandria, DC-VA-MD-WV	125,781
8	Miami-Fort Lauderdale-West Palm Beach, FL	New York-Newark-Jersey City, NY-NJ-PA	113,117
9	New York-Newark-Jersey City, NY-NJ-PA	San Francisco-Oakland-Hayward, CA	95,598
10	Dallas-Fort Worth-Arlington, TX	Houston-The Woodlands-Sugar Land, TX	92,642
11	San Diego-Carlsbad, CA	San Francisco-Oakland-Hayward, CA	85,216

Table 2. *(Continued)* Market and Number of Passengers in DB1B

	MSA Pair		Passengers
12	Chicago-Naperville-Elgin, IL-IN-WI	Los Angeles-Long Beach-Anaheim, CA	84,643
13	Boston-Cambridge-Newton, MA-NH	Washington-Arlington-Alexandria, DC-VA-MD-WV	80,666
14	New York-Newark-Jersey City, NY-NJ-PA	Tampa-St. Petersburg-Clearwater, FL	77,839
15	Las Vegas-Henderson-Paradise, NV	Los Angeles-Long Beach-Anaheim, CA	76,098
16	Chicago-Naperville-Elgin, IL-IN-WI	Minneapolis-St. Paul-Bloomington, MN-WI	74,020
17	Chicago-Naperville-Elgin, IL-IN-WI	Washington-Arlington-Alexandria, DC-VA-MD-WV	72,702
18	Atlanta-Sandy Springs-Roswell, GA	Chicago-Naperville-Elgin, IL-IN-WI	71,288
19	Dallas-Fort Worth-Arlington, TX	New York-Newark-Jersey City, NY-NJ-PA	70,436
20	Las Vegas-Henderson-Paradise, NV	San Francisco-Oakland-Hayward, CA	68,181

Table 3.3. Airline by the Numbers of Passengers and Markets

The table presents the list of 7 airlines together with the annual number of passengers and the number of operating markets served. The sample is based on DB1B and covers the period from 1993 to 2008.

Code	Airline	Passenger No.	Market No.
WN	Southwest	2,445,857	637
AA	American	2,107,029	1,064
UA	United	1,971,053	1,059
DL	Delta	1,843,527	1,119
US	US Airways	1,472,839	1,116
CO	Continental	1,282,698	1,139
NW	Northwest	1,236,952	998

Table 3.4. Market Structure and Dynamics

The table presents summary statistics of market structure and dynamics. The sample is based on DB1B and covers the period from 1993 to 2008. Panel A presents the distribution of market-year observations by the number of entrants and exits, respectively. Panel B presents statistics describing the differences of airline operations.

Panel A: Distribution of markets by number of entrants and exits

	0	1	2	>=3
Entrants	87.69%	11.27%	1.00%	0.04%
Exits	84.46%	13.66%	1.75%	0.14%

Panel B: Heterogeneity across airlines

	AA	CO	DL	NW	UA	US	WN
Monopoly markets							
Market No.	3	2	12	3	3	16	5
Market %	7%	5%	32%	8%	5%	29%	14%
Probability of staying in the industry							
	75%	68%	87%	80%	70%	75%	79%

Table 3.5. Structural Parameter Estimates

The table reports the parameter estimates with their corresponding standard errors in parentheses. The estimation is done with the two-step moments estimator in the spirit of Rust (1994). In the first step, a fixed point problem computes the equilibrium choice probabilities for a given set of parameter values. In the second step, the parameters of interest are inferred by fitting a set of moments that characterize the equilibrium choice probabilities and value functions in the model to the data. The data sample is constructed based on the DB1B survey and ExecuComp and covers 7 airlines over 1,225 markets from 1993 to 2008. γ_s and γ_n capture the impacts of demand and competition respectively. f stands for the fixed operating costs that are airline-specific. e stands for the entry costs. λ_o and λ_p are parameters representing the contract loadings on airline's own and peer performance respectively. We consider two versions of the model estimation: *Pooled* corresponds to the results using pooled data across markets and *Separated* corresponds to the results using separated data across markets.

	Pooled		Separated	
	Estimates	Std. Errors	Estimates	Std. Errors
Profit (in thousands)				
Variable Profits				
γ_s	0.04	(0.00)	0.05	(0.00)
γ_n	2.74	(0.24)	24.95	(16.27)
Fixed Costs				
f(AA)	97.73	(2.52)	130.61	(21.16)
f(CO)	104.64	(2.54)	145.43	(21.22)
f(DL)	88.41	(2.51)	101.28	(20.98)
f(NW)	95.76	(2.52)	115.42	(21.13)
f(UA)	92.84	(2.52)	117.00	(21.23)
f(US)	103.23	(2.53)	141.34	(21.39)
f(WN)	99.64	(2.50)	151.77	(21.29)
Entry Costs				
e	8,869.82	(0.20)	2,424.33	(12.08)
Compensation ($\times 10^3$)				
λ_o	1.96	(0.00)	3.09	(0.03)
λ_p	0.21	(0.02)	0.30	(0.09)

Table 3.6. Data and Model Predicted Statistics of Market Structure

This table compares simulated and actual statistics that describe market structure. We consider two versions of the model estimation: *Pooled* corresponds to the results using pooled data across markets and *Separated* corresponds to the results using separated data across markets.

	Data	Model	
		Pooled	Separated
Distribution of markets by number of incumbents			
0	7.9%	12.6%	13.8%
1	3.6%	16.6%	8.9%
2	5.0%	9.4%	6.5%
3	7.1%	7.7%	10.7%
4	9.3%	8.9%	16.0%
5	17.5%	13.3%	21.8%
6	35.5%	20.4%	17.9%
7	14.1%	11.1%	4.3%
Distribution of markets by number of new entrants			
0	87.69%	97.48%	97.79%
1	11.27%	2.25%	2.13%
2	1.00%	0.26%	0.08%
>= 3	0.04%	0.02%	0.01%
Distribution of markets by number of new exits			
0	84.46%	92.29%	62.92%
1	13.66%	6.90%	25.58%
2	1.75%	0.77%	8.85%
>= 3	0.14%	0.04%	2.65%

Chapter 4

Conclusion

In this thesis, I examine two important aspects of corporate governance and their effect on firm performance. In my first study, I empirically test if friendly boards benefit the firm. Using data on individual political donations, we construct measures of individual political orientation and political similarity between CEO and independent directors. Consistent with our hypothesis, we find that the political similarity between CEO and independent directors significantly correlates with lower crash risk in firm's stock price. In addition, the insider trading by independent directors is more informative if the political similarity between CEO and independent directors is high. The effect of political similarity is more pronounced when the corporate governance mechanisms are stronger, suggesting that the effect is mostly driven by the need of independent directors to acquire information from CEO. Overall, the results show strong support to the argument that friendly boards facilitate information sharing between CEO and independent directors thus benefit the firm.

In the second study, we develop and empirically estimate a dynamic game of competition with heterogenous firms in an oligopoly market to examine the effect of Relative Performance Evaluation (RPE) on firm performance. The model suggests that the use of RPE has asymmetric effect on firm strategy depending on market conditions: the use of RPE encourages firm to take more competition in good market condition, but discourages firm to take competition when the market condition is bad. Furthermore, using data in U.S. airline industry, we estimate the model to match the key features of the market structure and dynamics. The estimation results help explain why the evidence of RPE in practice is largely mixed.

In future studies, optimal board structure would be highly valuable to be examined. We do find friendly boards benefit the firm in certain aspect. However, it is still remain an open question that what would be the optimal structure of independent directors for different firms. Furthermore, although endogenous optimal contracting would unnecessarily complicates the model, it would be rewarding to examine in broader picture. The model developed in the second study of this thesis may be still useful when considering endogenous optimal contract.

Appendix

A.1 Robust Measures of PHI

The different measures of individual political orientation may affect the baseline results of crash risks significantly. In this section, we report various robust measures of individual political orientation following as which in Lee, Lee and Nagarajan (2014). Basically, the robust measures of individual political orientation adopt the alternative assumption that the political orientation of individual does not vary (or change gradually) over time. We define the following variables:

- R_i: Total dollar amount of political contribution made to Republican candidates by individual i over all election cycles from 1989 to 2010;
- D_i: Total dollar amount of political contribution made to Democratic candidates by individual i over all election cycles from 1989 to 2010;
- R_i^t: Total dollar amount of political contribution made to Republican candidates by individual i since 1989 to the end of year t;
- D_i^t: Total dollar amount of political contribution made to Democratic candidates by individual i since 1989 to the end of year t;

Using these variables we construct the following individual Republican indices:

- $Rep_i = \frac{R_i - D_i}{R_i + D_i}$, the time invariant individual political orientation measure;
- $Rep(strong)_i = \begin{cases} Rep_i, & \text{if } |R_i - D_i| \geq \$2000 \\ 0, & \text{otherwise} \end{cases}$, it is possible that individuals who always donate evenly to both parties are making opportunistic investment rather than revealing their true political orientation. $Rep(strong)_i$ minimize the noise from opportunistic donators;

- $Rep_i^t = \frac{R_i^t - D_i^t}{R_i^t + D_i^t}$, which measures individual political orientation using her total contribution from 1989 to year t. This measure assumes that the individual political orientation may change over time, but only change gradually;

Using above three measures of individual political orientation to replace Rep_{it}^{CEO} and Rep_{it}^{ID} in equation 2.2, we achieve three alternative *PHI* measures, namely *PHI(individual)*, *PHI(strong)*, and *PHI(prior)*. In addition, we drop all individuals with less than $2000 in total political contributions in measure *PHI(individual)* as the robustness measure namely *PHI(robust)* which only consider frequent donors.

Table A.1. Negative Coefficient of Skewness and Robustness Measure of PHI

The table reports the results of robustness measure of PHI and crash risk. The dependent variable is crash risk, measured by the negative coefficient of skewness ($NCSKEW$). The main explanatory variable is the four robustness measure of Political Homophily Index (PHI). In all columns, we control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength (Connection)*. In Column 2, 4, 6, and 8, we further include the $weakPHIdummy$ to control for the cases when both the CEO and independent directors made no contribution. We include firm fixed effects and year fixed effects in all the regressions. The standard errors are clustered at the firm level in all columns. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	Negative Coefficient of Skewness(NCSkew)							
	PHI(individual)		PHI(strong)		PHI(prior)		PHI(robust)	
PHI	-0.0139*	-0.00428**	-0.0148	-0.00791*	-0.0118*	-0.00598**	-0.0146**	-0.0271***
	(-1.89)	(-2.14)	(-1.68)	(-1.75)	(-1.75)	(-2.17)	(-2.03)	(-2.65)
Weak PHI Dummy		-0.0113*		-0.0134		-0.0119		0.00690*
		(-1.92)		(-1.19)		(-1.15)		(1.73)
Board Size	-0.00114**	-0.00123**	-0.00113**	-0.00123**	-0.00114**	-0.00124**	-0.00104**	-0.00102**
	(-2.21)	(-2.36)	(-2.19)	(-2.36)	(-2.21)	(-2.38)	(-2.02)	(-1.98)
ROA	0.00410	0.00474	0.00395	0.00421	0.00448	0.00591	0.00362	0.00340
	(0.22)	(0.25)	(0.21)	(0.22)	(0.24)	(0.31)	(0.18)	(0.17)
Capx	0.00991	0.0103	0.00996	0.0103	0.00974	0.00983	0.00936	0.00937
	(0.88)	(0.92)	(0.89)	(0.92)	(0.87)	(0.88)	(0.81)	(0.81)
R&D	-0.0302	-0.0303	-0.0294	-0.0289	-0.0297	-0.0301	-0.0272	-0.0279
	(-0.59)	(-0.59)	(-0.58)	(-0.57)	(-0.58)	(-0.59)	(-0.53)	(-0.54)
log(Assets)	-0.00199	-0.00238	-0.00199	-0.00239	-0.00191	-0.00227	-0.00183	-0.00180
	(-0.54)	(-0.65)	(-0.54)	(-0.65)	(-0.52)	(-0.62)	(-0.48)	(-0.47)
Market Leverage	-0.0237	-0.0232	-0.0236	-0.0239	-0.0236	-0.0230	-0.0208	-0.0215
	(-1.54)	(-1.51)	(-1.53)	(-1.55)	(-1.53)	(-1.50)	(-1.31)	(-1.35)
Connection	0.00387	0.00390	0.00386	0.00389	0.00384	0.00383	0.00498	0.00486
	(1.22)	(1.23)	(1.22)	(1.22)	(1.21)	(1.20)	(1.54)	(1.51)

Table A.2. Down-to-Up Volatility and Robustness Measure of PHI

The table reports the results of robustness measure of PHI and crash risk. The dependent variable is crash risk, measured by the Down-to-Up Volatility (*Duvol*). The main explanatory variable is the four robustness measure of Political Homophily Index (PHI). In all columns, we control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength (Connection)*. In Column 2, 4, 6, and 8, we further include the *weakPHIdummy* to control for the cases when both the CEO and independent directors made no contribution. We include firm fixed effects and year fixed effects in all the regressions. The standard errors are clustered at the firm level in all columns. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	Down-to-Up Volatility(Duvol)							
	PHI_individual		PHI_strong		PHI_prior		PHI_robust	
PHI	-0.0169*	-0.00703*	-0.0163	-0.0142*	-0.0133**	-0.0111*	-0.0178*	-0.0329**
	(-1.70)	(-1.83)	(-1.54)	(-1.89)	(-2.35)	(-1.92)	(-1.82)	(-2.35)
Weak PHI Dummy		-0.0150		-0.0182*		-0.0163		0.00824
		(-0.83)		(-1.79)		(-1.16)		(1.50)
Board Size	-0.00139*	-0.00151**	-0.00138*	-0.00151**	-0.00140*	-0.00152**	-0.00130*	-0.00127*
	(-1.92)	(-2.06)	(-1.90)	(-2.08)	(-1.92)	(-2.09)	(-1.78)	(-1.75)
ROA	0.0126	0.0137	0.0125	0.0131	0.0131	0.0151	0.0102	0.0101
	(0.49)	(0.53)	(0.49)	(0.51)	(0.51)	(0.58)	(0.38)	(0.38)
Capx	0.0100	0.0105	0.0101	0.0105	0.00985	0.00995	0.00899	0.00900
	(0.66)	(0.68)	(0.66)	(0.68)	(0.64)	(0.65)	(0.57)	(0.57)
R&D	-0.0149	-0.0148	-0.0139	-0.0136	-0.0143	-0.0147	-0.00957	-0.0102
	(-0.21)	(-0.21)	(-0.20)	(-0.19)	(-0.20)	(-0.21)	(-0.13)	(-0.14)
log(Assets)	-0.00341	-0.00392	-0.00337	-0.00394	-0.00329	-0.00376	-0.00283	-0.00280
	(-0.69)	(-0.80)	(-0.69)	(-0.80)	(-0.67)	(-0.77)	(-0.55)	(-0.55)
Market Leverage	-0.0183	-0.0177	-0.0183	-0.0185	-0.0183	-0.0175	-0.0164	-0.0171
	(-0.87)	(-0.85)	(-0.87)	(-0.88)	(-0.87)	(-0.83)	(-0.76)	(-0.80)
Connection	0.00347	0.00351	0.00345	0.00350	0.00344	0.00340	0.00499	0.00484
	(0.79)	(0.80)	(0.79)	(0.80)	(0.78)	(0.78)	(1.12)	(1.09)

A.2 Robustness Test for Political Involvement

The table reports the results of the robustness test for political involvement of the firms in our baseline regression. We measure the political involvement of the firm using whether it has an established corporate political action committee (*Corporate PAC*). The *Corporate PAC* is a dummy variable takes value of 1 (0) if the firm has (not) a registered Corporate PAC, which indicating the political involvement of the firm is high (low). In all regressions, we control for *Board Size, 1-year lagged ROA* and *Investment, R&D, log(Assets), Market Leverage*, and *CEO-Director Connection Strength*. In Column 2 and 4, we further include the *weakPHIdummy* to control for the cases when both the CEO and independent directors made no contribution. We include firm fixed effects and year fixed effects in all the regressions. The standard errors are clustered at the firm level in all columns. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	NCSKEW		Duvol	
	(1)	(2)	(3)	(4)
PHI	-0.0146**	-0.0235**	-0.0176*	-0.0299**
	(-2.01)	(-2.24)	(-1.80)	(-2.14)
PHI × *Corporate PAC*		-0.0013		-0.0009
		(-0.59)		(-0.46)
Weak PHI Dummy		0.00571		0.00689
		(1.34)		(1.27)
N	10986	10986	11796	11796
Adj R-square	0.001	0.019	-0.000	-0.000
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

A.3 IV Regression for Big Firms

The table reports the 2SLS regression results for big firms. In this sample, we only include the firms with size in the top quartile in our sample. In Column 1, the first-stage regression result is reported. In Columns 2, 3, and 4, the second-stage regression results for the change in negative coefficient skewness, change in down-to-up volatility, and the change in Q are reported respectively. The control variables in all columns are Board Size, one year lagged ROA, one year lagged investment, Market Leverage, R&D, log(Assets), and CEO-Directors Connection Strength. The standard errors are clustered within firm level. The t-statistics for each estimated coefficient are reported in parentheses. $*$, $**$, and $***$ denote the statistical significance at the 10%, 5%, and 1% level, respectively.

	First-Stage	Second-Stage		
	ΔPHI	ΔNCSKEW	ΔDUVOL	ΔQ
	(1)	(2)	(3)	(4)
ΔLocal PHI × Safe State Dummy	0.0712*			
	(1.82)			
ΔLocal PHI × Swing State Dummy	-0.121**			
	(-2.37)			
Lagged PHI	-0.519***			
	(-13.41)			
ΔPHI (2SLS IV)		-0.088**	-0.115**	-0.0159
		(-2.30)	(-2.02)	(-0.81)
F-statistic	16.911			
J-statistic ($p-value$)		0.77	0.75	0.77
Number of Observations	1137	1137	1137	1137
Adj R-square	0.255	-0.091	-0.101	0.124
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

A.4 US Airline Industry Evolution

Table A.3. US Airline Mergers, Acquisitions and Code-Share Agreements

Panel A: Mergers and Acquisitions	
1993	Southwest (WN) acquires Morris Air
1997	ValuJet merges with AirWays Corp., and becomes AirTran (FL)
1999	American (AA) acquires Reno Airways (QX)
2001	American (AA) acquires Trans World Airlines
2005	US Airways (US) merges with America West (HP)
2008	Delta (DL) merges with Northwest (NW)
2010	United (UA) merges with Continental (CO)
2011	Southwest (WN) merges with AirTran (FL)
2013	American (AA) merges with US Airways (US)
Panel B: Code-Share Agreements	
1998	American (AA) and Alaska (AS)
1998	Northwest (NW) and Continental (CO)
1999	Continental (CO) and Alaska (AS)
1999	Northwest (NW) and Alaska (AS)
2003	United (UA) and US Airways (US)
2003	Northwest (NW), Continental (CO) and Delta (DL)
2005	Delta (DL) and Alaska (AS)

Source: Mountford (2003); Ito and Lee (2007); Mills (2010)

A.5 Test of Pooling Data Across Markets

In this section, we give a brief outline of the homogeneity test for assessing whether data from distinct markets can be pooled. The test draws from Otsu, Pesendorfer and Takahashi (2016) and is adapted to our setting.

The test directly compares the set of conditional choice probabilities estimated from the pooled sample with those estimated from individual markets. It builds on the idea that under the null hypothesis, the observed state-action profiles are generated from an identical data generating process and the same equilibrium was played in all markets. This null hypothesis is then a maintained assumption for estimation based on pooled data.

Specifically, the test statistic is defined as

$$\mathcal{T} = \sum_{j=1}^{M} \sum_{d \in D} W_j(d) \left[\hat{p}_j(d) - \hat{p}(d) \right]^2 ,$$

where for each state-action profile, $d = (a|x, s)$, $\hat{p}_j(d)$ and $\hat{p}(d)$ denote the conditional choice probabilities for a market j and pooled markets respectively. $W_j(d)$ is a weight or standardization for obtaining a standard limiting distribution. The test statistic converges to a Chi-squared distribution as the length of time periods increases to infinity.

The critical values of the test statistic are obtained using bootstrapping. We consider 1,000 bootstrap iterations. For each iteration, b, we first simulate the game of the same size as the original and then compute the bootstrap counterpart of the test statistic $\mathcal{T}_b$. The data generating process used in the simulation is characterized by the state transition probabilities from the pooled sample.

Note that Otsu, Pesendorfer and Takahashi (2016) propose three statistical tests comparing the pairs of statistics estimated from the pooled (across markets) sample with those estimated from each market separately. The statistics concern (1) the set of conditional choice or state transition probabilities, (2) the steady-state distribution, and (3) the conditional state distribution given the initial observed state.

In particular, the steady-state distribution test assumes that there exists a unique steady-state distribution associated with a transition matrix of states. This test is limited to serve our application for two reasons. First, some of the markets in our data are new and growing and have not reached the steady state yet. Second, some of the markets have absorbing states and therefore have no unique steady-state distribution. The third test relaxes the restriction needed for the steady-state distribution test but loses statistical power for a small number of markets, that is, less than 40.

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