ESSAYS IN CORPORATE FINANCE

A Dissertation

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ABSTRACT

The first essay, "Local Institutional Investors and the Maturity Structure of Corporate Debt", examines the relation between the geographic proximity of a firm's institutional shareholders and its debt maturity choices. Local institutional investors may pressure firms to employ short-term debt as a means of disciplining managers to reduce equity agency costs, and to reduce debt agency costs associated with debtholder-stockholder conflicts caused by monitoring of local institutional investors. Thus, we hypothesize that firms with local institutional investors choose shorter debt maturity structures. Using dynamic GMM estimators to account for endogeneity and dynamic relations between debt maturity structure and institutional proximity, we find that firms with local institutional investors have shorter maturity debt. Similar results obtain for the maturity of new debt issues. To help establish causality, we use Sarbanes-Oxley Act as a quasi-natural experiment, conduct a nearest neighbor matching analysis that holds location constant, and employ a sample of firms' headquarter relocations as quasi-exogenous shocks to the locality of institutional investors. The results demonstrate the importance of local institutional investors in affecting firms' debt maturity policy choices.

In the second essay, "The Effect of Algorithmic Trading on Firm Value", we study the overall impact of algorithmic trading on firm value. Extant literature has found mixed evidence on the impact of algorithmic trading on market quality, and it is still under intense public debate and controversy that whether algorithmic trading is beneficial or not. Using an algorithmic trading proxy based on electronic message traffic, we find a positive relation between algorithmic trading and firm value. The relation is stronger for firms with lower stock liquidity, higher idiosyncratic volatility, higher analyst coverage, and greater information asymmetry, which suggest that the value increases occur through market quality channels. The results are robust to various model specifications, reverse causality test using NYSE automated quote dissemination as an exogenous shock, and endogeneity concerns. The results imply net benefits of algorithmic trading to firms.

To my wife, Qin, and my daughter, Elena.

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1. INTRODUCTION

This dissertation consists of two essays in corporate finance, as presented in Sections 2 and 3, which are parts of larger research projects of Johnson and Zhang (2014), and Johnson, Wang, and Zhang (2014), respectively.

In the first essay, “Local Institutional Investors and the Maturity Structure of Corporate Debt”, we study the relation between the geographic proximity of a firm’s institutional shareholders and its debt maturity choices. This research is motivated by three lines of finance literature regarding agency conflicts and shareholder activism. It has been shown that institutional shareholders play important roles in mitigating agency conflicts between managers and shareholders. Independent institutional investors with large ownerships have the incentive and ability to monitor managers of their investee firms. Moreover, due to their information advantage stemming from geographic proximity, local institutions are more effective in monitoring managers. In addition, literature shows that short maturity debt can reduce agency conflicts between shareholders and managers and conflicts between shareholders and debtholders.

Combining the three lines of literature, we hypothesize that firms monitored by local institutional investors use shorter maturity debt to reduce agency problems. Local institutional investors may pressure firms to employ short-term debt as a means of disciplining managers and thereby reducing equity agency costs stemming from manager-shareholder conflicts. Monitoring by local institutional investors likely increases the intensity of debtholder-shareholder conflicts. Shorter debt maturity should reduce these conflicts and the associated debt agency costs. The two mechanisms both lead to the hypothesis that firms with local institutional investors use shorter maturity debt.

The empirical results from analyzing existing debt maturity and maturity of new debt issues are consistent with the hypothesis. Dynamic system GMM estimation is used to account for endogeneity and dynamic relations between debt maturity structure and institutional proximity; with the new debt issue sample, a natural experiment, a nearest neighbor matching analysis, and a sample of firms' headquarter relocations as quasi-exogenous shocks to the locality of institutional investors are employed to establish causality. Furthermore, the effect of local institutional investors on maturity of new debt issues is stronger for firms with CEO-Chair duality, suggesting that firms monitored by local institutions use shorter maturity debt to reduce equity agency cost. Regulation Fair Disclosure (Reg FD) is used as another natural experiment to rule out an alternative explanation that local institutions choose to invest in firms with shorter maturity debt. Overall results of the first essay demonstrate the importance of local institutional investors in affecting firms' debt maturity policy choices.

The second essay, "The Effect of Algorithmic Trading on Firm Value", examines whether algorithmic trading has an overall beneficial impact on firm value. Algorithmic trading is a major recent innovation in the way financial assets trade, and has become more common and predominant in major financial markets, representing an estimated 78% of all U.S. equity trading volume in 2012. Given the significant role of algorithmic trading in the stock market, investors, academics, and policymakers need a deeper understanding of its benefits and costs. Extant literature examines impact of algorithmic trading on financial market quality, but provides mixed results on the question of whether algorithmic trading is a beneficial financial innovation, leaving it the subject of intense public debate and controversy. So far very litter is known about how algorithmic trading affects firm value.

We contribute the first evidence of the effect of algorithmic trading on firm value. By examining the effect of algorithmic trading on firm value, our study also provides evidence useful for evaluating the net overall cost or benefit of algorithmic trading. If algorithmic trading has net benefit to financial market, it should have a positive effect on firm value, and vice versa. Using an algorithmic trading proxy based on electronic message traffic, we find a positive relation between algorithmic trading and firm value; firms whose stocks are more heavily traded by algorithmic traders have greater value as measured by Tobin's q. We use the NYSE automated quote dissemination as an exogenous shock to algorithmic trading to establish a causality from algorithmic trading to firm value. The positive effect is stronger for firms with lower stock liquidity, higher idiosyncratic volatility, higher analyst coverage, and greater information asymmetry, which suggest that algorithmic trading increases firm value by positively impacting financial market. The results imply net benefits of algorithmic trading to firms.

The rest of the dissertation is organized as follows. Section 2 contains the first essay, "Local institutional investors and the maturity structure of corporate debt". Section 3 contains the second essay, "The effect of algorithmic trading on firm value". Section 4 summarizes the dissertation.

2. LOCAL INSTITUTIONAL INVESTORS AND THE MATURITY STRUCTURE OF CORPORATE DEBT

We examine the relation between the geographic proximity of a firm's institutional investors and the maturity structure of its debt. Monitoring by local institutional investors likely increases the intensity of debtholder-stockholder conflicts. Shorter debt maturity should reduce these conflicts and the associated debt agency costs. Local institutional investors may also pressure firms to employ short-term debt as a means of disciplining managers and thereby reducing equity agency costs stemming from manager-stockholder conflicts. Thus, we hypothesize that firms with local institutional investors choose shorter debt maturity structures. Using dynamic system GMM estimators to account for endogeneity and dynamic relations between debt maturity structure and institutional proximity, we find that firms with local institutional investors have shorter maturity debt. Similar results obtain for the maturity of new debt issues. To help establish causality, we use Sarbanes-Oxley Act (SOX) as a quasi-natural experiment, conduct a nearest neighbor matching analysis that holds location constant, and employ a sample of firms' headquarter relocations as quasi-exogenous shocks to the locality of institutional investors. The results demonstrate the importance of local institutional investors in affecting firms' debt maturity policy choices.

2.1 Introduction

This research draws upon three lines of literature. The first line examines the role that institutional investors play in mitigating agency conflicts between shareholders and managers. Independent institutions with a long-term investment serve a monitoring role (Bushee (1998); Chen, Harford, and Li (2007)) and influence corporate behavior (e.g., Brickley, Lease, and Smith Jr. (1988); Hartzell and Starks (2003)). The second line examines the importance of the investors' geographic proximity to firms. Institutional and individual investors exhibit a preference for local firms, appear to trade local securities at an informational advantage, and earn significant abnormal returns on local investments consistent with an information advantage stemming from proximity (Coval and Moskowitz (1999) (2001); Baik, Kang, and Kim (2010); Ivkovic and Weisbenner (2005)). The information advantages of local institutional investors appear to increase their effectiveness in monitoring management-firms with local institutional investors are less likely to engage in empire building, to lead the quiet life, and to engage in corporate misbehavior such as earnings management and option backdating (Chhaochharia, Kumar, and Niessen-Ruenzi (2012)). The third line of literature focuses on how short debt maturity reduces the agency costs of managerial discretion (Rajan and Winton (1995); Stulz (2000)), reduces debt agency costs associated with asset substitution (Leland and Toft (1996)), and reduces managerial incentives to increase risk by exposing firms to liquidity risk (Barnea, Haugen, and Senbet (1980)).

Drawing together the three lines of literature, we hypothesize that firms with local institutional investors choose shorter debt maturity structures. A risk-averse, self-interested manager with relatively undiversified holdings of equity and human capital in a firm may reject risky, positive-NPV projects and pursue relatively safe financial policies that do not maximize shareholder wealth. More effective monitoring of firms by local institutional (equity) investors should encourage managers to make the risky investment and financing decisions that maximize shareholder wealth, but such risk choices can exacerbate debtholder-stockholder conflicts. If stockholders would bear the resulting debt agency costs, they have an incentive to reduce them. One solution is for the firm to choose a shorter debt maturity structure. The greater monitoring and control by debtholders with shorter maturity should reduce debt agency costs and could be the value-maximizing choice for shareholders.

The monitoring and discipline associated with shorter maturity debt also reduces equity agency costs if it reduces excess perquisite consumption by managers and/or improves managerial effort levels. For example, managers of firms with proportionately more debt maturing in the near term face greater liquidity risk, which may then translate into termination or other costs for the manager. A manager reduces the likelihood of bearing those costs by minimizing excess perk consumption and maximizing effort. If local institutional investors' information advantages increase their awareness of the need to reduce such equity agency costs at some firms, they could pressure the firms to borrow short term to employ the debt as a disciplining device that complements their own efforts. This creates a second reason to predict a positive relation between short debt maturity and local institutional investors.[1] It is worth emphasizing that the motivation of local institutional investors to reduce debt agency costs and the motivation for them to reduce equity agency costs are not mutually exclusive.

We examine the relation between firms' existing debt maturity structures and measures of the geographic proximity of its institutional investors. We first calculate the geographic distance between each firm's headquarters and its five independent institutional investors with the largest ownership fractions. Bushee (1998) and Chen et al. (2007) find that only *independent* institutions that have long-term investment horizons actively monitor firms, so we limit our analysis to independent institutions. Institutions with low ownership are unlikely to actively monitor management because information and monitoring costs may outweigh benefits from monitoring, so we focus on the five independent institutions with the largest ownership fractions in a firm.

We define three proximity measures to capture the geographic proximity of a firm's institutional investors: a dummy variable equal to one if a firm has one or more of its top five independent institutions located within 100 miles of the firm's headquarters; the number of a firm's top five independent institutions that are located within 100 miles; and a pure distance measure as the shortest distance between a firm's top five independent institutions and the firm's headquarters. Following Johnson (2003) and several other

[1] Our hypothesized positive effect of local institutional investors on short debt maturity is consistent with a complimentary relation between monitoring by institutional investors and monitoring effect of short term debt. Alternatively, these two monitoring effects may be purely substitutional. Although whether the relation is complimentary or substitutional is an empirical question, the complimentary relation is expected to occur in firms for which equity agency problems are relatively severe and intense monitoring is optimal, which is confirmed by our empirical results.

studies, we measure the debt maturity structure of each firm each year by the proportion of its total debt maturing within the next three years. We employ a dynamic panel model to take into account the dynamic relation between debt maturity structure and institutional ownership, and use two-step dynamic Generalized Method of Moments (GMM) estimation to alleviate endogeneity concerns due to unobserved heterogeneity and simultaneity.[2]

We find a significantly positive relation between the proportion of a firm's debt that matures within three years and the presence of a local independent institutional investor. The effect is large economically: all else equal, the proportion of debt that matures within three years is 20.4 percentage points higher for a firm with a local independent institutional investor compared to one without, which represents approximately 60% of the mean short maturity proportion. The results are qualitatively similar for the measures based on the number of top five independent institutional investors that are local and on the distance between a firm's headquarters and its geographically closest independent institutional investor. The results support the hypothesis that firms with local institutional investors use shorter maturity debt.

The tests differentiate between the proximity of institutional investors and the presence of institutional investors. In specifications that omit the proximity measures, we

[2] The capital structure literature has recognized the dynamic nature of leverage, i.e., current leverage depends on past values of leverage, and has applied dynamic GMM model to study the determinants of capital structure and capital structure adjustments (Antoniou, Guney, and Paudyal (2008); Gaud, Jani, Hoesli, and Bender (2005); de Miguel and Pindado (2001); Drobetz and Wanzenride (2006); Lemmon, Roberts, and Zender (2008)). Antoniou, Guney, and Paudyal (2006) apply the dynamic panel GMM estimator to examine the determinants of debt maturity structure. Wintoki, Linck, and Netter (2012) apply the dynamic GMM estimator to account for the dynamic relation between firm performance and corporate governance.

find that the proportion of debt that matures within three years is positively related to the total ownership proportion of a firm's top five independent institutional investors, and alternatively, the total ownership proportion of all of a firm's independent institutional investors. When including the proximity measures in the regressions, coefficients on the institutional ownership measures are sometimes significant and sometimes insignificant. In contrast, when controlling for institutional ownership measures, the proximity measures are consistently statistically significant across regressions. We interpret these results to mean that independent institutional investors have a reliable effect on debt maturity only when they are local.

The proportion of a firm's debt that matures in the near term could reflect debt maturity decisions that were made years before the point at which we measure that proportion. For example, a large 20-year maturity debt issue made ten years ago could still be in the denominator of the proportion of total debt maturing within three years, and push that ratio down even if the firm more recently chose shorter debt maturities. To focus on *incremental* debt maturity decisions, we also examine the maturity of new debt issues by the sample firms. We compute the issue size-weighted average maturity, and alternately the equal-weighted average maturity, of new debt issues within the fiscal year for each firm, and regress the average maturity on lagged values of the institutional proximity measures and the control variables. Consistent with the results based on proportions of debt maturing in the near term, the results show that firms with local institutional investors choose shorter maturities for their new debt issues.

The new debt issuance sample enables us to use exogenous events to identify the causal effect of monitoring by local institutional investors on maturity of new debt issues. We first use the implementation of the Sarbanes-Oxley Act of 2002 (SOX) as a quasi-natural experiment. SOX was enacted in July 2002 to increase the independence and oversight role of boards of directors. Prior studies have shown that overall corporate governance is improved and board monitoring is stronger in the post-SOX period. The enhanced monitoring by boards of director should reduce the need of monitoring by local institutional investors. If the effect of institutional proximity on debt maturity is attributable to effective monitoring by local institutional investors, we expect the effect to be weaker in the post-SOX period when monitoring by local institutional investors is less important. As expected, we find a diminished effect of institutional proximity on maturity of new debt issues in the post-SOX period, implying a causal effect of local institutional monitoring on debt maturity. Further analyses that use firms' headquarter relocations as quasi-exogenous shocks to institutional proximity provide additional support of a causal effect.

It is possible that purely area-specific effects drive the relation between debt maturity and local institutional investors. For example, institutional investors may locate in areas that also have large numbers of commercial banks. Given that bank loans tend to have relatively shorter maturity, if firms are more likely to borrow from local banks, the relation we find between short debt maturity and local institutional investors could be driven by the joint location of institutional investors and commercial banks, i.e., could be driven purely by an area-specific effect. We thus employ a nearest neighbor matching analysis to compare firms headquartered in an area that have local institutional investors with firms headquartered in the same exact area and yet do not have local institutional investors (along with several other matching criteria). Our main results hold in this matched sample.

As we note above, there is a potential debt agency cost motivation for local institutional investors to prefer shorter debt maturity and a potential equity cost motivation. Although the motives are not mutually exclusive, we conduct an additional test to shed light on the relative importance of the two. CEOs who are also chairman of the board of directors have more power than CEOs who are not chairman. The duality may weaken internal monitoring of CEOs, and exacerbate potential conflicts of interest between shareholders and managers (i.e., equity agency costs). Risk-averse CEOs with undiversified holdings of equity and human capital in a firm and with significant power might reject risky projects even though they are profitable, and/or might adopt safe financial policies (e.g., sub-optimally low leverage). Short-term lenders are unlikely to reduce these risk-related problems, and indeed may worsen them, because they benefit from low risk. In contrast, powerful CEOs might also consume excess perks and/or exert low effort, both of which harm stockholders and debtholders, and thus, create debt and equity agency costs. Monitoring and discipline by short-term lenders would be expected to reduce these perk and effort-related problems, and potentially generate spillover benefits for a firm's stockholders. We find that the effect of institutional proximity on the maturity of new debt issues obtains only for firms with dual CEO-Chair, and thus the potential for more severe equity agency problems. The result suggests that the potential reduction of equity agency costs (at least in part) drives the relation between debt maturity and local institutional investors.

An alternative explanation of our finding is that local institutional investors do not influence firms' debt maturity structure decisions, but rather that they simply choose to invest in local firms with shorter debt maturities. If local institutional investors' information advantages make them more aware of manager-stockholder conflicts in firms, they might seek out local firms with shorter debt maturities because managers at these firms would be better disciplined by the short-term debt. The negative relation we find between maturity of new debt issuances and lagged top institution proximity (as well as lagged top institution ownership) does not support the self-selection explanation, unless local institutions have superior information about local firms such that they know in advance or can predict the maturity structure of future debt issuances of the firms.

Nonetheless, to assess the plausibility of an information-based explanation for our findings, we conduct a test using the implementation of Regulation Fair Disclosure (Reg FD) in 2000 as a natural experiment. Gintschel and Markov (2004) find that Reg FD has been effective in reducing the informativeness of analyst information output, and Bernile, Kumar, and Sulaeman (2011) show that Reg FD eliminated the information advantage of local institutional investors, both of which would suggest weakening or disappearing of our finding after the implementation of Reg FD under an information-based explanation. We find that the impact of local monitoring institutions on maturity of new debt issues is not significantly weaker in the post Reg FD period. We infer similar conclusions when using inclusion in the S&P 500 as a proxy for the likelihood that local investors have an information advantage (Ivkovic and Weisbenner (2005)). Thus, it is unlikely that our results reflect solely an informational advantage of local institutions in choosing firms that benefit from short debt maturity.

Our paper contributes to the growing literature examining the effect of local investors on corporate governance and policies. Gaspar and Massa (2007) find that local investors improve corporate governance. Becker et al. (2011) find that firms are more likely to pay dividends and pay higher dividends if higher proportion of local population is senior, suggesting that investor base affects corporate policy decisions. Ayers et al. (2011) show that local monitoring institutions reduce financial reporting discretion. Chhaochharia et al. (2012) show that local institutional investors are effective monitors: they are more likely to submit shareholder proposals, reduce excess CEO compensation, and increase CEO turnover. Our paper contributes to this literature by providing evidence that local monitoring institutions influence firms' debt maturity, which is a key dimension of their financing choices.

Our paper also contributes to the large literature on corporate debt maturity structure. Firms' debt maturity choices have been linked to firm characteristics such as firm size, profitability, growth opportunities, leverage, firm level volatility, firm quality, asset maturity, etc. (e.g., Barclay and Smith (1995); Guedes and Opler (1996); Stohs and Mauer (1996); Johnson (2003)). Recent literature has investigated the role of short-term debt as a tool to discipline or monitor self-interested managers and reduce the agency problem between managers and shareholders, and shown that debt maturity structure is related to the severity of the agency problem, such as managerial ownership, managerial entrenchment, and board strength (e.g., Datta et al. (2005); Benmelech (2006); Harford, Li, and Zhao (2008)). Our paper shows that local institutional investors also affect debt maturity structure. To the best of our knowledge, the only other paper on a similar subject is Marchica (2011), who finds that short debt maturity is positively related to institutional ownership. Our paper differs from Marchica (2011) in that we focus on effect of geographic proximity, rather than ownership, of institutions; moreover, we find that in some specifications debt maturity is related to the proximity of institutional investors but not to their ownership proportions.

2.2. Data and Methodology

2.2.1. Sample

We obtain institutional stockholdings data from the quarterly Thomson Reuters Institutional (13f) Holdings database. The sample period is from 1988 to 2008, limited by our access to data on institutional locations. Following Chen et al. (2007), we define independent institutions as those that are independent from corporate management as defined by Brickley et al. (1998) and have a long-term investment classified as dedicated or quasi-indexer institutions based on Bushee (2001). For each firm, at the end of each quarter we identify all independent institutions that hold common shares of that firm, and calculate their ownership fraction. Institutions with higher ownership should have stronger incentive to monitor managers compared to institutions with low ownership who may find the costs for them to obtain information and monitor may outweigh their benefits from monitoring; thus, we focus on the top five independent institutions in terms of the size of shareholding, which we call monitoring institutions. For each of the monitoring institutions, we calculate the distance between the institution and the firm using the latitude and longitude coordinates of their headquarter locations. We obtain the zip codes of institutional locations from *Nelson Directory of Investment Managers*, and the zip codes of firms' headquarters from Compustat and Compact Disclosure, and then obtain the corresponding latitude and longitude coordinates from the *US Census Bureau's Gazetteer Place and Zip Code Database*.

We obtain the debt maturity and other firm-level data from the Compustat database, and merge this dataset with the Institutional Holdings data by matching each fiscal year end in Compustat data with the most recent quarter in the Institutional Holdings data for each firm.

2.2.2. Variables

2.2.2.1. Measure of Geographic Proximity

Our measures of institutional geographic proximity are based on the distance between institutions to firms. Following prior research (e.g., Coval and Moskowitz (1999); Ayers et al. (2011); Chhaochharia et al. (2012)), we calculate the distance between institution i and firm j, $dist_{ij}$, using the following formula:

$$dist_{ij} = (2\pi r/360)\times\arccos[\sin(lat_i)\sin(lat_j) + \cos(lat_i)\cos(lat_j)\cos(lon_i - lon_j)]$$

where *lat* and *lon* are latitude and longitude in radians, respectively, and r is the radius of the Earth in miles (r = 3,963 miles). For each firm, we calculate the distance to the firm for the top five independent institutions. We then define a dummy variable, *local*, which is set to one for firms with at least one of the top five independent institutions located within 100 miles. Our second measure of institutional proximity is *local_inst*, which is the number of top five independent institutions located within 100 miles. The last institutional proximity measure is *min_dist*, the shortest distance between the top five independent institutions and the investee firm. As a robustness check, we also measure the institutional proximity by the average distance from the top five independent institutions to the firm.

2.2.2.2. Debt Maturity Measures and Control Variables

Following Johnson (2003) and others, we measure the maturity structure of corporate debt by the proportion of total debt maturing in three years or less, *st3*. In a later section, we also study the maturity of new debt issues instead of the proportion of existing debt that matures in the short term.

Following prior literature on the determinants of debt maturity structure (e.g., Johnson (2003); Brockman et al. (2010)), we include a set of other control variables in the analysis.[3] Leverage, *leverage*, is the ratio of total debt to the book value of total assets. Firm size, *lsize*, is the market value of firm, computed as total assets minus book value of equity plus market value of equity, measured in logs, and *lsize2* is the square of *lsize*. Asset maturity, *asset_mat*, is the book value-weighted average of the maturities of property plant and equipment and current assets.[4] Market-to-book, *mb*, as a proxy for growth opportunities, is the ratio of market value of the firm's assets to the book value of total

[3] See Johnson (2003) and Brockman et al. (2010) for motivations to include these variables.
[4] Asset maturity is computed as (gross property, plant, and equipment (Item #7)/total assets (Item #6)) ∗ (gross property, plant, and equipment (Item #7) /depreciation expense (Item #14)) + (current assets (Item #4)/total assets (Item #6)) ∗(current assets (Item #4)/cost of goods sold (Item #41)).

assets. Abnormal earnings, *abnearn*, is defined as the year-over-year change in the operating earnings per share divided by the previous year's share price. Volatility, *volatility*, is defined as the standard deviation of first differences in EBITDA over the four years preceding the sample year, scaled by average assets over that period. Term spread, *term*, is the difference between the yield on ten-year government bonds and the yield on six-month government bonds at the fiscal year end.[5] Several dummy variables are included. The regulated firm dummy, *reg_dum*, equals to one for firms with SIC code between 4,900 and 4,939 and zero otherwise. The rated firm dummy, *rated*, equals to one for firms with rated debt and zero otherwise. Z-score dummy, *zscore_dum*, equals one if Altman's Z-score is greater than 1.81, and zero otherwise.[6] To separate the effect of proximity of institutions from that of their ownerships, we control for the total ownership of the top five independent institutions, *top5_io*.

2.2.3 Summary Statistics

Table 2.1 shows the summary statistics of the main variables. The average firm in our sample has 34.3% of its total debt maturing in 3 years or less; 19.1% of its shares are owned by independent institutions, with top five of the independent institutions holding 12.7% of shares. About one quarter of firms have at least one of the top five independent institutions located within 100 miles. The mean (median) of the shortest distance from the top five independent institutions to the firm is about 569 (356) miles.

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[5] The interest rates of government bonds are obtained from FRED at the Federal Reserve Bank of St. Louis.
[6] Altman's Z-score is computed as 3.3 ∗ Item #178/Item #6 + 1.2 ∗ (Item #4−Item #5)/Item #6 + Item #12 /Item# 6 + 0.6 ∗ Item #199 ∗ Item #25 / (Item #9+Item #34) + 1.4 ∗ Item #36/Item #6.

Table 2.1. Summary Statistics for Section 2

This table reports summary statistics of main variables of our sample. *st3* is the proportion of total debt maturing in three years or less. *io* is total ownership of all independent institutions. *top5_io* is the total ownership of monitoring institutions. *local* is a dummy variable that is set to one for firms with at least one of the top five independent institutional investors being located within 100 miles, and zero otherwise. *local_inst* is the number of monitoring institutional investors that are located within 100 miles from the investee firm. *min_dist* is the shortest distance between monitoring institutional investors and the investee firm. *leverage* is leverage ratio, the ratio of total debt to the book value of total assets. *lsize*, is firm size measured as the market value of firm (in million dollars) in logs. *asset_mat* is Asset maturity, computed as the book value-weighted average of the maturities of property plant and equipment and current assets. *mb*, is market-to-book, the ratio of market value of firm to the book value of total assets. *abnearn*, is abnormal earnings defined as the year-over-year change in the operating earnings per share divided by the previous year's share price. *volatility*, is defined as the standard deviation of first differences in EBITDA over the four years preceding the sample year, scaled by average assets over that period. Term spread, *term*, is the difference between the yield on 10-year government bonds and the yield on 6-month government bonds at the fiscal year end. *reg_dum*, is a dummy variable that equals to one for firms with SIC code between 4,900 and 4,939 and zero otherwise. The rated firm dummy, *rated*, is a dummy variable that equals to one for firms with rated debt and zero otherwise. Z-score dummy, *zscore_dum*, is a dummy variable that equals one if Altman's Z-score is greater than 1.81, and zero otherwise.

Variable	Mean	Std Dev	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl
st3	0.343	0.334	0.000	0.054	0.230	0.565	1.000
io	0.191	0.157	0.006	0.062	0.157	0.287	0.495
top5_io	0.127	0.102	0.005	0.048	0.105	0.185	0.315
local	0.254	0.435	0	0	0	1	1
local_inst	0.330	0.636	0	0	0	1	2
min_dist	569	609	7	95	356	845	2089
leverage	0.269	0.204	0.007	0.103	0.245	0.388	0.651
lsize	5.844	2.006	2.833	4.327	5.681	7.218	9.462
asset_mat	9.755	10.153	0.939	3.087	6.302	12.435	31.582
mb	1.904	1.576	0.816	1.091	1.398	2.059	4.678
abnearn	-0.011	0.276	-0.360	-0.034	0.006	0.029	0.250
volatility	0.084	0.067	0.017	0.040	0.065	0.107	0.217
term	1.472	1.271	-0.390	0.540	1.210	2.470	3.930
reg_dum	0.040	0.196	0	0	0	0	0
rated	0.281	0.449	0	0	0	1	1
zscore_dum	0.820	0.384	0	1	1	1	1

2.2.4. Methodology

In this section we discuss our model specification and the appropriateness of alternative estimation methods, including OLS, instrumental variables, difference-GMM, and the recently developed system-GMM estimation, and explain why we choose the system dynamic panel GMM method to analyzing existing debt maturity structure.

2.2.4.1. Model

We employ a panel data framework to examine the relation between existing debt maturity and the geographic proximity of institutional investors to control for unobserved firm heterogeneity. Specifically, we estimate the following dynamic panel model to examine the relation between *st3* and the institutional proximity measures,

$$st3_{it} = \beta_0 + \beta_1\, local_{it} \text{ (alternately, } local\_inst_{it} \text{ or } min\_dist_{it}) + \beta_2\, top5\_io_{it} + \beta_3\, st3_{i(t-1)} + \sum \beta_k\, x_{k,it} + u_i + v_t + \varepsilon_{it} \quad (2.1)$$

where x_k is the set of control variables defined above, including *leverage*, *lsize*, *lsize2*, *asset_mat*, *mb*, *abnearn*, *volatility*, *term*, *reg_dum*, *rated*, *and zscore_dum*, u_i represents time-invariant unobservable firm-specific effects (e.g., reputation, and capital intensity), and v_t represents time-specific effects (e.g., demand shocks, interest rates, etc.) that are common to all firms and can be time-varying. The lagged value of debt maturity, $st3_{i(t-1)}$, is included to account for the dynamic nature of the relation between debt maturity and institutional ownership as discussed below.[7]

[7] Wintoki et al. (2012) use a similar dynamic panel model to examine the relation between firm performance and corporate governance.

2.2.4.2. Methods of Estimation

The appropriate method to estimate Equation (2.1) must control for the endogeneity due to unobserved heterogeneity and simultaneity. OLS estimates of Equation (2.1) would be biased because u_i is unobservable and correlated with other independent variables (Hsiao (1985)), and may be inconsistent because lagged dependent variables can be correlated with the time-invariant firm specific effects (heterogeneity). Although first differencing would eliminate u_i, the OLS estimates would still be inefficient because $\Delta\varepsilon_{it}$ and $\Delta st3_{i(t-1)}$ are correlated through the correlation between $\varepsilon_{i(t-1)}$ and $st3_{i(t-1)}$.[8] The instrumental variables (IV) approach would not solve the problem either. $\Delta st3_{i(t-2)}$ and $st3_{i(t-2)}$ can be used as instruments for $\Delta st3_{i(t-1)}$, because $\Delta st3_{i(t-2)}$ and $st3_{i(t-2)}$ are correlated with $\Delta st3_{i(t-1)}$ but not with $\Delta\varepsilon_{it}$. However, the IV estimates are unlikely to be efficient, because the IV approach does not use all the moment conditions and does not account for the different structure of the error term.

Another source of endogeneity in Equation (2.1) is simultaneity. Existing literature shows that leverage and debt maturity are endogenously chosen and often estimates a system of equations where leverage and debt maturity are jointly determined (e.g., Barclay, Marx, and Smith (1997); Johnson (2003); Datta et al. (2005)). It is likely that other explanatory variables for debt maturity are also jointly determined with leverage and debt maturity, however, and shocks that affect leverage and debt maturity could also affect other explanatory variables such as firm size and abnormal earnings. Marchica (2011) uses

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[8] In addition, OLS estimation assumes that all independent variables are strictly exogenous, which may not be true in debt maturity decisions.

a system of equations where institutional investor ownership, leverage and debt maturity are jointly determined. Brockman et al. (2010) endogenize debt maturity, leverage, executive compensation related variables (delta and vega), R&D, and capital expenditure and estimate a system of six equations. Even though additional explanatory variables could be endogenized, but as more variables are endogenized, it is increasingly difficult if not impossible to find valid instruments.

Arellano and Bond (1991) suggest using of a dynamic panel GMM estimator to overcome these problems.[9] The dynamic panel GMM estimator can handle fixed effects, control for endogeneity, and eliminate dynamic panel bias. It accounts for unobservable heterogeneity by including firm fixed effects, and accommodate dynamic panel model by allowing current values of independent variables to be affected by past values of the dependent variable, an advantage over traditional fixed-effect estimators. Due to orthogonality conditions between past values of variables and the error term, lagged variables can be used as valid instruments to account for simultaneity, and utilizing such 'internal" instruments, dynamic panel GMM method provides consistent estimators (Arellano and Bond (1991)). Specifically, dynamic panel GMM estimation uses past values of endogenous variables as instruments, which eliminates the need for external instruments, an important advantage over the traditional instrumental variable estimates. Because of this aspect, dynamic panel GMM can accommodate multiple endogenous variables, and can treat all explanatory variables as endogenous, as we do in our

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[9] Several sets of authors worked to develop the dynamic panel GMM estimator: Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond(1998).

estimation. Therefore, the dynamic panel GMM estimator can accounts for endogeneity due to unobservable heterogeneity and simultaneity, as well as dynamic relations between dependent and independent variables.

We adopt system dynamic panel GMM model. Although the difference-GMM, GMM specification estimated in first-differences using instruments in levels, is superior to other methods, recent studies show problems with the difference-GMM estimator. First-differencing can result in information loss across firms, which can cause substantial loss of efficiency in dynamic GMM estimators (Arellano and Bover (1995)). Arellano and Bover (1995) propose the system-GMM specification, which is estimated in both levels and first difference using instruments in first differences for level equations and instruments in levels for first-difference equations. Blundell and Bond (1998) show that the efficiency of the system-GMM estimator is significantly higher than that of the difference-GMM estimator, especially for short sample period and persistent data.

To account for serial correlation and heteroscedasticity of error terms, we employ two-step approach to estimate the system dynamic panel GMM model. Using residuals from first-step estimation to construct asymptotically optimal weighting matrices, the two-step estimators are more efficient than one-step estimators if error terms are expected to be correlated over time or heteroskedastic across firms.

To ensure that the dynamic system GMM estimators are consistent, we perform several tests of validity of the orthogonality assumptions and the strength of the instruments. The key exogeneity assumption is that the historical values of dependent and independent variables are exogenous with respect to the current innovations of the dependent variable. For our GMM estimators, by construction, the first differencing transformation induces first-order serial correlation (AR(1)) in the differenced residuals, but no second-order correlation (AR(2)), a critical condition for the consistency of the GMM estimators. So the first test we conduct is a test of second-order serial correlation, AR(2) test, under the null hypothesis of no second-order correlation. The second test, Hansen test of over-identification, tests the validity of instrument. It yields a J-statistics that is distributed as chi-square under the null hypothesis of valid instruments. The third test is a Diff-in-Hansen test of exogeneity, which yields a J-statistics that is distributed as chi-square under the null hypothesis that instruments used for the equations in levels are exogenous. We examine all of these tests for our dynamic GMM estimators.

One caveat for the dynamic system GMM estimation is that in cases of numerous endogenous variables and absence of an optimal way to choose the instrument set, we may have the "many instruments" problem and could overfit the endogenous variables. Bearing this possibility in mind, we use the "collapse" option in *xtabond2* command when performing the dynamic system GMM estimation in Stata.[10]

[10] See Roodman (2009, 2009b) for more details on the use *xtabond2* command and the "too many instruments" problem.

Table 2.2. Relation between Current Institutional and Firm Characteristics and Past Debt Maturity Structure

This table reports the estimation results of ordinary least square (OLS) regressions of institutional ownerships (*io* and *top5_io*), institutional proximity measures (*local*, *local_inst*, and *min_dist*), firm leverage (*leverage*), and firm size (*lsize*) on past values of debt maturity structure (*lag_st3*) and other firm characteristics. The institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one).T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	io	top5_io	local	local_inst	min_dist	leverage	lsize
lag_st3	0.004	0.003	-0.012	-0.017	0.023	-0.010	-0.014
	(3.34)	(3.08)	(-2.52)	(-2.59)	(1.84)	(-5.93)	(-1.85)
lag_leverage	-0.014	-0.002	-0.019	-0.024	0.118	0.843	-0.078
	(-6.15)	(-1.24)	(-1.95)	(-1.75)	(4.72)	(219.42)	(-5.53)
lag_lsize	0.010	0.005	0.004	0.007	-0.051	0.000	0.977
	(29.63)	(21.16)	(3.69)	(4.46)	(-14.63)	(0.75)	(579.51)
lag_mb	0.000	-0.000	0.003	0.003	-0.003	-0.001	-0.024
	(0.24)	(-2.09)	(2.92)	(2.16)	(-0.97)	(-2.03)	(-10.67)
lag_roa	0.023	0.015	-0.023	-0.029	0.025	-0.023	0.115
	(11.23)	(9.90)	(-2.36)	(-2.20)	(0.91)	(-5.17)	(5.63)
lag_rated	-0.003	-0.002	-0.009	-0.011	0.040	0.010	0.032
	(-2.39)	(-2.81)	(-2.00)	(-1.60)	(3.64)	(7.30)	(5.57)
lag_zscore_dum	0.009	0.006	0.005	0.005	-0.041	-0.013	-0.014
	(7.94)	(7.04)	(1.03)	(0.70)	(-3.30)	(-8.01)	(-2.20)
lag_sp500	-0.023	-0.016	0.005	0.001	0.072	-0.012	0.042
	(-14.30)	(-13.02)	(0.67)	(0.05)	(4.56)	(-8.09)	(6.67)
lag_io	0.823						
	(217.81)						
lag_top5_io		0.783					
		(153.21)					
lag_local			0.643				
			(123.49)				
lag_local_dist				0.682			
				(113.32)			
lag_min_dist					0.581		
					(83.21)		
Obs.	58,178	57,748	57,958	57,958	57,958	58,178	58,178
adj. R^2	0.741	0.642	0.415	0.466	0.390	0.727	0.955

2.3. Main Results

2.3.1. Dynamic Relation between Debt Maturity and Institutional Ownership/Proximity

In this section we assess the dynamic relation between debt maturity and institutional ownership and geographic proximity to validate the use of the dynamic panel model shown in Equation (2.1). To show that the institutional ownership and geographic proximity are related to past debt maturity, we regress measures of institutional ownership and proximity on the lagged debt maturity and other firm-specific variables that are related to institutional ownership, including lagged dependent variables. As shown in Table 2.2, coefficients on lagged *st3* are significant in all regressions in which the dependent variables are the total ownership of all independent institutions (*io*), the total ownership of the monitoring institutions, or top five independent institutions, (*top5_io*), and the three measures of institutional geographic proximity (*local, local_inst, and min_dist*). Thus, institutional ownership and geographic proximity are significantly positively related to past debt maturity.[11]

Besides institutional ownership and geographic proximity, Table 2.2 shows that *leverage* and *lsize* are significantly negatively related to the lagged *st3*. This indicates that it is not only institutional ownership and the geographic proximity measures that can be considered endogenous, but other control variables are likely to be endogenous as well.

[11] Similar results are obtained when changes in, instead of levels of, institutional ownerships and geographic proximity are regressed on the lagged debt maturity and other firm-specific variables.

Table 2.3. Pooled OLS Regressions: Static vs. Dynamic

This table reports estimation results of pooled OLS regressions. The dependent variable is *st3*. In each panel, models (1) and (2) are the same except for that lagged *st3* (*lag_st3*) is included as an additional explanatory variable in model (2). The institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	Panel A		Panel B		Panel C	
	(1)	(2)	(1)	(2)	(1)	(2)
lag_st3		0.551		0.551		0.552
		(101.34)		(101.32)		(101.40)
local	-0.013	-0.004				
	(-2.83)	(-1.68)				
local_inst			-0.011	-0.004		
			(-3.54)	(-2.31)		
min_dist					0.004	0.001
					(2.08)	(1.00)
top5_io	0.088	0.041	0.090	0.042	0.089	0.041
	(4.03)	(3.18)	(4.11)	(3.23)	(4.06)	(3.18)
leverage	-0.295	-0.155	-0.295	-0.155	-0.296	-0.155
	(-21.69)	(-18.12)	(-21.70)	(-18.13)	(-21.72)	(-18.12)
lsize	-0.059	-0.030	-0.059	-0.030	-0.058	-0.030
	(-8.65)	(-8.08)	(-8.61)	(-8.05)	(-8.42)	(-7.92)
lsize2	0.003	0.001	0.003	0.001	0.003	0.001
	(5.38)	(5.43)	(5.34)	(5.40)	(5.20)	(5.32)
asset_mat	-0.001	-0.000	-0.001	-0.000	-0.001	-0.000
	(-3.31)	(-2.60)	(-3.33)	(-2.62)	(-3.26)	(-2.56)
mb	0.007	0.003	0.007	0.003	0.007	0.003
	(3.43)	(2.39)	(3.45)	(2.40)	(3.38)	(2.37)
term	0.008	0.004	0.007	0.004	0.008	0.004
	(6.21)	(4.48)	(6.17)	(4.46)	(6.22)	(4.48)
abnearn	-0.026	-0.024	-0.026	-0.024	-0.026	-0.024
	(-5.50)	(-5.28)	(-5.49)	(-5.28)	(-5.52)	(-5.29)
volatility	0.341	0.145	0.340	0.145	0.340	0.144
	(8.42)	(5.29)	(8.41)	(5.29)	(8.39)	(5.27)
reg_dum	-0.053	-0.028	-0.054	-0.028	-0.053	-0.028
	(-5.30)	(-5.65)	(-5.32)	(-5.66)	(-5.24)	(-5.60)
rated	-0.097	-0.047	-0.097	-0.047	-0.097	-0.047
	(-16.78)	(-14.27)	(-16.79)	(-14.28)	(-16.76)	(-14.26)
zscore_dum	-0.049	-0.033	-0.050	-0.033	-0.049	-0.033
	(-8.89)	(-9.21)	(-8.90)	(-9.22)	(-8.84)	(-9.18)
Obs.	50,604	50,604	50,604	50,604	50,604	50,604
adj. R^2	0.152	0.400	0.152	0.400	0.152	0.400

We further demonstrate the dynamic relation by comparing the estimation results of static and dynamic models, and showing how including past debt maturity in debt maturity regressions affects the estimation results. As shown in Table 2.3, we regress *st3* on *local* (Panel A), *local_inst* (Panel B), and *min_dist* (Panel C). In each panel, model 1 is static while model 2 is dynamic with lagged *st3* being included as the additional regressor. It is evident that by including lagged *st3* as the additional explanatory variable, the magnitude and significance level of the coefficients on the ownership and geographic proximity measures are significantly reduced in the dynamic models, and R-squares of the dynamic models are significantly higher than those of the static models. For example, as shown in Panel B, the coefficients on *local_inst* and *top5_io* in the dynamic model are less than half of those in the static model, and their *t*-statistics are also much lower in the dynamic model, while R-square increases from 0.152 to 0.400 when moving from the static model to the dynamic model. The results clearly indicate the importance of past debt maturity in assessing the relation between debt maturity and institutional geographic proximity. Past debt maturity explains a significant proportion of the variation of current debt maturity. The reduction in magnitude of the coefficients on institutional ownership and geographic proximity when moving from the static model to the dynamic model again suggests that current institutional ownership and geographic proximity are correlated with past debt maturity.

Although we show that including past debt maturity improves OLS estimation, it is very likely that unobservable heterogeneities are not fully captured by past debt maturity, and endogeneity due to simultaneity is not controlled for in OLS estimation. The dynamic relation between debt maturity and institutional ownership and proximity demonstrated in this section validate the use of the dynamic panel model. By including both past debt maturity and fixed effects and endogenizing all independent variables, dynamic system GMM estimators account for the dynamic relation, unobservable heterogeneity, and simultaneity. Therefore, in next section, we use the dynamic system GMM model to estimate the relation between debt maturity and institutional geographic proximity.

2.3.2. Dynamic Panel System GMM Estimation

In this section we discuss the results from two-step dynamic panel system GMM estimation. All estimations control for firm, industry and year fixed effects. Table 2.4 shows that the coefficients on all of three measures of institutional proximity are statistically significant. The positive coefficient on *local* implies that, compared to firms without local monitoring institutions, firms with at least one local monitoring institution have shorter debt maturity. The effect is large economically. Compared with firms without local monitoring institutions, firms with at least one local monitoring institution have an additional 20.4 percentage points of their debt maturing in the short term, which is 59.5% (0.204/0.343=59.5%) relative to the mean of *st3*. The significantly positive coefficient on *local_inst* implies that firms with more local monitoring institutions have shorter debt maturity. Again here, the effect is large economically: adding one more local monitoring institutional investor increases the proportion of short-term debt by 13.4%, or equivalently, by 39.1% (0.134/0.343=39.1%) relative to the mean of *st3*. The coefficient on *min_dist* is significantly negative, indicating that the proportion of debt that is short term decreases as the distance between firms and the monitoring institutions increases, or

Table 2.4. System GMM Estimates of Dynamic Panel Model: Institutional Proximity

This table reports the results of dynamic panel two-step system GMM estimation of relation between debt maturity structure and geographic proximity top five independent institutional investors. The dependent variable is *st3*. Independent variables of interest are *local*, *local_inst*, and *min_dist*. *min_dist* is standardized (mean is set to zero and standard deviation is one). Firm, industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics are in parentheses. *p*-values of *AR(2)* test, Hansen test, and Diff-in-Hansen test are reported.

	(1)	(2)	(3)
local	0.204		
	(2.83)		
local_inst		0.134	
		(2.62)	
min_dist			-0.084
			(-2.86)
top5_io	0.111	0.101	0.074
	(0.67)	(0.62)	(0.43)
leverage	-0.019	-0.013	0.069
	(-0.17)	(-0.12)	(0.59)
lsize	-0.137	-0.133	-0.154
	(-3.55)	(-3.46)	(-3.79)
lsize2	0.010	0.009	0.011
	(3.41)	(3.35)	(3.71)
asset_mat	0.002	0.002	0.002
	(1.22)	(1.22)	(1.00)
mb	-0.006	-0.005	-0.015
	(-0.23)	(-0.22)	(-0.66)
term	0.054	0.033	0.038
	(2.19)	(1.38)	(1.53)
abnearn	-0.258	-0.260	-0.271
	(-4.21)	(-4.24)	(-4.44)
volatility	-0.432	-0.321	-0.049
	(-0.67)	(-0.53)	(-0.08)
reg_dum	-1.583	-1.418	-1.523
	(-2.45)	(-2.33)	(-2.44)
rated	-0.088	-0.082	-0.093
	(-2.29)	(-2.15)	(-2.37)
zscore_dum	-0.061	-0.053	-0.046
	(-0.92)	(-0.82)	(-0.69)
lag_st3	0.515	0.538	0.526
	(5.70)	(5.77)	(5.61)
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
AR(2) test (*p*-value)	0.992	0.913	0.924
Hansen test of over-identification (*p*-value)	0.398	0.360	0.546
Diff-in-Hansen test of exogeneity (*p*-value)	0.179	0.147	0.396

equivalently, firms with monitoring institutional investors closer to their headquarters have higher proportions of short-term debt.

We note here that the coefficients on *top5_io* are not statistically significant. Untabulated results indicate that when institutional proximity measures are excluded from the estimation, the coefficients on *top5_io* are statistically significant. Thus, in these regressions, it is the geographic proximity of institutional investors that matters, not the ownership levels of those investors.

For all estimations reported in Table 2.4, *p*-values of the second-order serial correlation (AR(2)) test are all large such that we cannot reject the null hypothesis of no second-order serial correlation. The Hansen test and the Diff-in-Hansen test also produce insignificant *p*-values and as such, we cannot reject the null hypotheses that our instruments are valid and the instruments for the level equations are exogenous.

In summary, using dynamic panel system GMM estimators to account for unobservable heterogeneity, simultaneity, and the dynamic nature between debt maturity and institutional ownerships, we find statistically and economically significant evidence that local independent institutional investors are associated with shorter debt maturity. The results support the hypothesis that firms choose shorter debt maturity if they have local institutional investors who monitor the firm.

2.3.3. Maturity of New Debt Issues

In this section we provide additional evidence to support the finding in the previous section by examining the impact of institutional geographic proximity on the maturity of new corporate debt issues. Whereas a measure of the proportion of total debt maturing in the short-term could be affected substantially by debt maturity decisions made many years prior, this analysis of new debt issues has the advantage of focusing on incremental debt maturity decisions made at a particular point in time.

2.3.3.1. Baseline Results

We obtain debt issuance data from the Securities Data Company (SDC), and include all public bond issues, private (non-Rule 144A) issues, Rule-144A issues, and syndicated loans in the sample. To consolidate the issue-level observations into firm-year format, we treat multiple issues within a fiscal year as a single issue and compute an issue size-weighted average maturity (*sw_maturity*, in log) and an equal-weight average maturity (*ew_maturity*, in log) for firms with multiple issues. After merging the new issue data with the institutional ownership and geographic proximity data, there are 9,503 firm-fiscal year observations.

Following Brockman et al. (2010), we run pooled OLS regressions for our new issue sample. Considering that multiple debt issues can be issued anytime within a fiscal year, we lag independent variables by one year. Year and industry fixed effects are controlled. Table 2.5 presents the results. The dependent variables are *sw_maturity* and *ew_maturity* in Panel A and Panel B, respectively, and the results are similar for the two maturity measures. Although their coefficients are only marginally significant, both (lagged) *local* and *local_inst* are negatively related to the maturity of new debt issues, which suggests that firms with (more) local monitoring institutional investors issue shorter maturity debt. The significantly positive coefficients on (the lagged) *min_dist* suggest (inversely) that the

Table 2.5. Maturity of New Debt Issues

This table reports results of OLS regressions of maturity of new debt issues on institutional geographic proximity. The dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) in Panel A and the equal-weighted average maturity (*ew_maturity*, in *log*) in Panel B, respectively. Independent variables of interest are lagged *local*, *local_inst*, and *min_dist*. *min_dist* is standardized (mean is set to zero and standard deviation is one). All control variables are also lagged one year (denoted by prefix l_). Industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_local	-0.081			-0.088		
	(-1.61)			(-1.62)		
l_local_inst		-0.078			-0.079	
		(-1.77)			(-1.85)	
l_min_dist			0.045			0.045
			(1.72)			(1.82)
l_top5_io	-0.655	-0.645	-0.652	-0.706	-0.700	-0.712
	(-2.93)	(-2.87)	(-2.89)	(-2.96)	(-3.11)	(-3.17)
l_leverage	0.612	0.607	0.562	0.552	0.612	0.605
	(4.61)	(4.57)	(4.26)	(3.86)	(4.52)	(4.47)
l_lsize	0.351	0.357	0.330	0.308	0.292	0.280
	(3.07)	(2.53)	(2.86)	(2.50)	(2.11)	(2.42)
l_lsize2	-0.022	-0.022	-0.021	-0.017	-0.016	-0.015
	(-2.94)	(-2.30)	(-2.77)	(-2.11)	(-1.72)	(-2.09)
l_asset_mat	0.007	0.010	0.007	0.008	0.010	0.009
	(2.35)	(2.96)	(2.43)	(2.61)	(3.18)	(2.92)
l_mb	-0.012	-0.029	-0.013	-0.040	-0.040	-0.034
	(-0.50)	(-0.98)	(-0.50)	(-1.48)	(-1.30)	(-1.46)
l_term	-0.050	0.070	-0.050	-0.005	0.060	-0.071
	(-1.31)	(0.77)	(-1.32)	(-0.07)	(0.66)	(-1.83)
l_abnearn	0.184	0.221	0.188	0.177	0.203	0.237
	(2.52)	(2.01)	(2.49)	(2.12)	(1.78)	(2.93)
l_volatility	-0.123	-0.024	-0.148	-0.542	-0.297	-0.036
	(-0.20)	(-0.03)	(-0.24)	(-0.82)	(-0.37)	(-0.06)
l_reg_dum	-0.406	-0.360	-0.382	-0.395	-0.361	-0.346
	(-2.04)	(-1.76)	(-1.92)	(-2.08)	(-1.71)	(-1.73)
l_rated	0.049	0.032	0.059	0.048	0.028	0.060
	(0.72)	(0.42)	(0.83)	(0.71)	(0.37)	(0.86)
l_zscore_dum	-0.066	-0.087	-0.076	-0.015	-0.030	-0.024
	(-0.96)	(-1.02)	(-1.11)	(-0.20)	(-0.35)	(-0.35)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,387	7,387	7,387	7,388	7,388	7,388
adj. R^2	0.229	0.229	0.230	0.227	0.227	0.228

closer are the monitoring institutional investors located to the firm, the shorter is the maturity of the firm's new debt issues. The results are consistent with the findings in the previous section for existing debt maturity structure and support the hypothesis that local institutional investors prefer shorter debt maturity.

2.3.3.2. Sarbanes-Oxley Act as a Quasi-natural Experiment

When analyzing existing debt maturity structure in the earlier section, we employ system dynamic GMM estimators to mitigate endogeneity concerns. In this section, the new debt issuance sample enables us to use an exogenous event to identify the causal effect of monitoring by local institutional investors on the maturity of new debt issues. We use the implementation of the Sarbanes-Oxley Act of 2002 (SOX) as a quasi-natural experiment. SOX was enacted in July 2002 as a reaction to a number of high-profile corporate scandals and aimed to increase the independence and oversight role of boards of directors. Prior studies have shown that overall corporate governance is improved and board monitoring is stronger in the post-SOX period (e.g., Linck, Netter, and Yang (2008) (2009)). The improved monitoring by boards of director should reduce the need for monitoring by local institutional investors. If the finding of shorter debt maturity in firms with local institutional investors reflects more effective monitoring by local institutional investors, we expect to observe a diminished effect of institutional proximity on maturity of new debt issues in the post-SOX period.

To test this conjecture, we define a dummy variable, *post_sox*, which is set to one for post-SOX period (after 2002) and zero otherwise, and include in the new debt issue regressions an additional term that interacts one of the institutional proximity measures with the dummy variable *post_sox*. The regression results are shown in Table 2.6. The coefficients on the institutional proximity measures are highly significant and keep the same signs as those in Table 2.5, while the coefficients on interaction terms are significant and have signs opposite to those of the corresponding proximity measure.[12] The results indicate that the effect of institutional proximity on maturity of new debt issues is much stronger before implementation of SOX, consistent with the notion that effective monitoring by local institutional investors lead to shorter debt maturity in firms with local institutional investors.

The diminished effect of institutional proximity on debt maturity in the post-SOX period may explain the relatively marginal significance of the institutional proximity measures shown in Table 2.5. Comparing results in Table 2.5 and Table 2.6, we note that both the statistical and economic significance of the institutional proximity effect on debt maturity are greater in the pre-SOX subsample period (before 2003) than in the full sample period. For example, as suggested by the coefficients on *local* and *local_inst* in Panel A of Table 2.6, in the pre-SOX period, the maturity of new debt issued by firms with local institutional investors is 12% shorter than firms with no local institutional investors, and one more local institutional investor implies an 8% reduction in maturity of new debt issues.[13]

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[12]Results of F-tests indicate that the sum of the coefficients on each institutional proximity measure and its corresponding interaction term is not significantly different from zero, suggesting that the effect of institutional proximity on maturity of new debt issues diminishes in the post-SOX period. Subsample regressions also confirm the result.

[13] The maturity of new debt issues is log transformed. The coefficient on *local* of -0.129 indicates a reduction in log of maturity of 0.129, which is translated into a 12% decrease in maturity. Similarly, the coefficient on *local_inst* of -0.084 is translated into an 8% reduction in maturity.

Table 2.6. Maturity of New Debt Issues: SOX in 2002 as a Natural Experiment

This table reports results of OLS regressions that use Sarbanes-Oxley Act (SOX) of 2002 as a natural experiment to identify the causal effect of local institution monitoring on maturity of new debt issues. The dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) in Panel A and the equal-weighted average maturity (*ew_maturity*, in *log*) in Panel B, respectively. The institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). *post_sox* is a dummy variable that equals to one for all years after 2002 and zero otherwise. All independent variables are lagged one year (denoted by prefix l_). Industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_local	-0.129			-0.119		
	(-2.15)			(-1.95)		
l_local×post_sox	0.156			0.143		
	(2.56)			(2.34)		
l_local_inst		-0.084			-0.086	
		(-1.93)			(-2.02)	
l_local_inst×post_sox		0.114			0.122	
		(2.57)			(2.80)	
l_min_dist			0.056			0.048
			(2.27)			(1.93)
l_min_dist×post_sox			-0.086			-0.081
			(-2.99)			(-2.75)
post_sox	-0.353	-0.350	-0.527	-0.404	-0.406	-0.650
	(-3.34)	(-3.31)	(-3.85)	(-3.74)	(-3.76)	(-4.72)
l_top5_io	-0.326	-0.324	-0.398	-0.383	-0.378	-0.452
	(-2.01)	(-1.99)	(-2.41)	(-2.34)	(-2.30)	(-2.72)
l_leverage	0.461	0.457	0.487	0.451	0.449	0.479
	(4.85)	(4.82)	(4.86)	(4.56)	(4.55)	(4.54)
l_lsize	0.247	0.246	0.264	0.172	0.171	0.192
	(2.91)	(2.90)	(3.04)	(1.93)	(1.93)	(2.12)
l_lsize2	-0.014	-0.014	-0.015	-0.008	-0.008	-0.010
	(-2.73)	(-2.72)	(-2.87)	(-1.50)	(-1.50)	(-1.70)
l_asset_mat	0.005	0.005	0.006	0.005	0.005	0.006
	(2.12)	(2.15)	(2.37)	(2.25)	(2.27)	(2.50)
l_mb	-0.032	-0.032	-0.037	-0.037	-0.037	-0.043
	(-1.70)	(-1.70)	(-2.00)	(-1.89)	(-1.90)	(-2.22)
l_term	-0.030	-0.029	-0.040	-0.046	-0.045	-0.055
	(-1.06)	(-1.02)	(-1.41)	(-1.58)	(-1.55)	(-1.94)
l_abnearn	0.099	0.100	0.134	0.106	0.108	0.140
	(2.16)	(2.18)	(2.70)	(2.29)	(2.33)	(2.80)
l_volatility	-0.080	-0.070	0.125	-0.214	-0.200	0.023
	(-0.16)	(-0.14)	(0.26)	(-0.43)	(-0.40)	(0.05)

Table 2.6 Continued

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_reg_dum	-0.180	-0.181	-0.169	-0.154	-0.155	-0.142
	(-1.26)	(-1.26)	(-1.15)	(-1.11)	(-1.11)	(-1.01)
l_rated	0.028	0.027	0.022	0.030	0.030	0.031
	(0.63)	(0.61)	(0.47)	(0.69)	(0.68)	(0.66)
l_zscore_dum	-0.088	-0.089	-0.066	-0.068	-0.068	-0.047
	(-1.91)	(-1.92)	(-1.36)	(-1.43)	(-1.43)	(-0.94)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,387	7,387	7,387	7,388	7,388	7,388
adj. R^2	0.175	0.175	0.175	0.174	0.175	0.175

2.3.3.3. Headquarter Relocations

In this section we exploit change in institutional investor proximity after firms' headquarter relocations to further examine the causal effect of local institutional monitoring on maturity of new debt issues. Although firms may change headquarter locations due to a variety of reasons, it is reasonable to argue that firms' headquarter relocations represent quasi-exogenous shocks to their institutional investor proximity.

To construct the headquarter relocation sample for firms in the new debt issuance sample, we track their headquarter changes and define headquarter relocations in three alternative ways: as moving out of state; moving more than 100 miles; or moving more than 200 miles. We then require firms to have debt issues within the period of two years before and two years after the relocations. The period of two years is selected to allow sufficient time for monitoring institutions to impact firms' debt maturity policies, while minimizing confounding effects of other factors on debt maturity. The resulting sample has only 24 (25) relocations if relocation is defined as moving out of state or moving more than 200 miles (moving more than 100 miles).[14]

We first perform a univariate analysis. We focus on firms that have (do not have) local institutional investors before relocation and do not have (have) local institutional investors after relocation, and compute within-firm differences of the maturity of new debt issues across the changes. As show in Panel A of Table 2.7, firms with local institutional investors (*local* =1) issue shorter maturity debt than firms without local institutional investors (*local*=0), and the average difference in debt maturity is about 28% for firms moving out of state,[15] longer than 3 years, although it is only statistically significant at the .10 level under a one-tailed test, most likely due to the small sample size.

We then conduct a multivariate regression analysis. We regress changes in the average maturity of new debt issues before and after headquarter relocations on changes in institutional proximity measures and control variables over the same time period. The results are in Panel B of Table 2.7. When relocation is defined as moving out of state, changes in institutional proximity measures are significantly related to changes in maturity of new debt issues, and the negative (positive) coefficients on changes in *loca*l and *local_inst* (*min_dist*) suggest that firms with more or closer local institutional investors following headquarter relocation issue shorter maturity debt. The results under alternative definitions of relocation are similar, although the significance levels are reduced.

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[14] To be clear, there are over 170 headquarter relocations among the firms in our sample, but the overwhelming majority are not sufficiently near in time to new debt issues to permit a tight test.

[15] Note that the maturities are in logs. So a difference of 0.34 in *sw_maturity* is translated into 28% difference in raw values of maturity. When raw values of maturity are used in this test, the difference in debt maturity is 3.3 years.

Table 2.7. Maturity of New Debt Issues: Headquarter Relocations as Quasi-exogenous Shocks

This table reports analysis of maturity of new debt issues surrounding firms' headquarter relocations. A headquarter relocation is defined as moving out of state, moving more than 100 miles, or moving more than 200 miles. Maturity of new debt issues is measured by the issue size-weighted average maturity (*sw_maturity*, in *log*, abbreviated as *sw_mat* in Panel A) or the equal-weighted average maturity (*ew_maturity*, in *log*, abbreviated as *ew_mat* in Panel A). Panel A performs univariate analyses, focusing on firms that have (do not have) local institutional investors before relocation and do not have (have) local institutional investors after relocation, and comparing maturity of new debt issues of firms without (local=0) and with (local=1) local institutional investors. Panel B reports results of OLS regressions of change in maturity of new debt issues on changes in institutional proximity measures and control variables surrounding firms' headquarter relocations. Only the coefficients on institutional proximity measures are reported. *t*-statistics are reported in parentheses (standard errors are adjusted for heteroskedasticity).

Panel A: Univariate Analysis

	Moving out of state		Moving >100 miles		Moving >200 miles	
	sw_mat	ew_mat	sw_mat	ew_mat	sw_mat	ew_mat
local=0	1.89	1.88	1.88	1.87	1.92	1.91
local=1	1.55	1.57	1.56	1.60	1.55	1.60
Difference	0.34	0.31	0.32	0.27	0.37	0.31
p-value of t test (Ha: diff>0)	0.11	0.14	0.17	0.21	0.17	0.22
Obs.	20	20	16	16	14	14

Panel B: OLS Regression

	sw_maturity			ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
I. Moving out of state (Obs: 24)						
ch_local	-0.730			-0.743		
	(-2.07)			(-2.14)		
ch_local_inst		-0.643			-0.645	
		(-2.03)			(-2.04)	
ch_min_dist			0.672			0.750
			(2.40)			(2.74)

Table 2.7 Continued

	sw_maturity			ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
II. Moving more than 100 miles (Obs.: 25)						
ch_local	-0.623			-0.637		
	(-1.80)			(-1.79)		
ch_local_inst		-0.513			-0.521	
		(-1.58)			(-1.56)	
ch_min_dist			0.069			0.156
			(0.16)			(0.36)
III. Moving more than 200 miles (Obs.: 24)						
ch_local	-0.609			-0.621		
	(-1.89)			(-1.95)		
ch_local_inst		-0.505			-0.511	
		(-1.69)			(-1.73)	
ch_min_dist			-0.267			-0.188
			(-0.43)			(-0.30)
Change in controls	Yes	Yes	Yes	Yes	Yes	Yes

Although the small sample size limits the inference of our analyses, the results in this section using headquarter relocations as exogenous shocks to institutional proximity further support the causal effect of local institutional monitoring on debt maturity.

2.3.3.4. Nearest-neighbor Matching Estimator

Thus far we have used pooled OLS regressions to estimate the relation between institutional proximity and maturity of new debt issues. When the dummy variable *local* is the measure of institutional proximity, we compare the maturity of new debt issues between two groups, firms with and without local institutional investors. Ideally, we want firms in the two groups to be as similar as possible except for existence of local institutional investors. In particular, we want firms to be in the same locations but have some firms with local institutional investors and some firm without. Controlling more tightly for location allows us to avoid concerns about pure local-specific effects. For example, suppose that institutional investors cluster in areas where there are also large numbers of commercial banks. Further suppose that, all else equal, firms are more likely to borrow from local banks. Given that bank loans typically have shorter maturity than other private debt and public debt, firms headquartered in areas with high concentrations of institutional investors and commercial banks would exhibit a correlation between local investors and debt maturity driven solely by the joint location of both institutional investors and commercial banks.

To address this and similar concerns, we perform a nearest-neighbor matching estimation. Each year for each firm with local institutional investors, we find a matching firm without local institutional investors but from the same state and same industry by matching on the ownership of monitoring institutions, firm size, leverage, asset maturity, abnormal earnings, and rated firm dummy.[16] Any "commercial bank effects" or other purely area-specific effects should be netted out because each matched pair of firms is in the same area, but differs on whether they have local institutional investors. We estimate the average treatment effect using the Abadie-Imbens bias-corrected matching estimator (Abadie and Imbens (2011)). Given the earlier results documenting the importance of SOX, we estimate results separate for the pre and post-SOX periods.

[16] We choose the matching variables based on the pooled OLS regression results in Table 5. Variables that are significantly related to debt maturity are the matching variables.

Table 2.8. Nearest-neighbor Matching Estimation

This table presents nearest-neighbor matching analysis. Each year for each firm with local institutional investors, we find a matching firm without local institutional investors from the same state and same industry by matching on the ownership of monitoring institutions, firm size, leverage, asset maturity, abnormal earnings, and rated firm dummy. In each section, the first row reports the Abadie-Imbens bias-corrected average treatment effect (ATE) of local institutional investors on maturity of new debt issues using nearest neighbor matching estimation, the second row reports z-statistics (in parentheses) of ATE estimates, and the third row reports the z-statistics of Wilcoxon signed ranks test of maturity of new debt issues of matched firms with and without local institutional investors. Maturity of new debt issues is measured by the issue size-weighted average maturity (*sw_maturity*, in *log*) or the equal-weighted average maturity (*ew_maturity*, in *log*).

		sw_maturity	ew_maturity
I. Before 2003	ATE	-0.066	-0.059
(<=2002)	z-statistics of ATE	(-2.09)	(-1.87)
	z-statistics of Wilcoxon test	(-3.93)	(-3.18)
II. After 2003	ATE	-0.013	-0.018
(>=2003)	z-statistics of ATE	(-0.45)	(-0.59)
	z-statistics of Wilcoxon test	(-0.67)	(-0.99)

As shown in Table 2.8, the average treatment effect is significantly negative before implementation of SOX in 2002, but insignificant after SOX, suggesting that compared with similar firms without local institutional investors, firms with local institutional investors issue shorter maturity debt, and that the effect diminishes after SOX. These results are consistent with the findings from pooled OLS regressions.

In addition, we perform Wilcoxon signed ranks tests of equality of maturities of new debt issues of the matched pairs of firms with and without local institutional investors, and the z-statistics of the tests are shown Table 2.8. Consistent with the average treatment effect estimation, firms with local institutional investors issue significantly shorter maturity debt than the matched firms without local institutional investors, but the difference diminishes in the post-SOX period.

Overall results of the nearest neighbor matching analyses suggest that firms with local institutional investors issue shorter maturity debt and the result is not driven solely by pure local-specific effects.

2.3.3.5. Equity Agency Costs or Debt Agency Costs

As we note in the introduction, short debt maturity can potentially reduce debt agency costs that stockholders may otherwise have to bear and equity agency costs. Because the two effects are not mutually exclusive and both predict that local institutional investors would prefer shorter debt maturity, it is difficult to conceive of tests to sort out whether one or both effects drive the results. With that caveat, we examine a case where equity agency costs should be relatively greater. Specifically, we use CEO-Chair duality as a proxy for the magnitude of potential equity agency problems. CEOs who are also chairman of the board of directors have more power than those who are not chairman. This concentration of power puts CEOs in a position with less internal monitoring, so it can *potentially* exacerbate conflicts of interest between shareholders and managers, resulting in more severe equity agency problems and increasing the need for external monitoring by institutional shareholders. Risk-averse CEOs with undiversified holdings of equity and human capital in a firm and with significant power might reject projects that are more profitable but riskier, or might adopt financial policies (e.g., sub-optimally low leverage). Short-term lenders are unlikely to resolve these problems, and indeed may worsen them. In contrast, powerful CEOs may also consume excess perks and/or exert low effort, both

Table 2.9. Equity Agency Costs vs. Debt Agency Costs

This table reports results of pooled OLS regressions of maturity of new debt issues on institutional proximity including interaction terms between institutional proximity measures and CEO-Chair duality. The dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) in Panel A and the equal-weighted average maturity (*ew_maturity*, in *log*) in Panel B, respectively. *duality* is the dummy variable for CEO-Chair duality. Institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). All control variables are also lagged one year (denoted by prefix l_). Industry and year fixed effects are included, but their coefficients are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_local	0.060			0.040		
	(0.71)			(0.47)		
l_local×duality	-0.183			-0.184		
	(-1.85)			(-1.85)		
l_local_inst		0.062			0.047	
		(0.65)			(0.45)	
l_local_inst×duality		-0.144			-0.147	
		(-1.83)			(-1.84)	
l_min_dist			-0.048			-0.059
			(-1.14)			(-1.27)
l_min_dist×duality			0.097			0.101
			(1.77)			(1.75)
l_duality	0.011	0.006	-0.013	0.003	0.000	-0.022
	(0.20)	(0.11)	(-0.25)	(0.06)	(0.01)	(-0.41)
l_top5_io	-0.613	-0.621	-0.616	-0.765	-0.767	-0.770
	(-2.02)	(-2.05)	(-2.04)	(-2.52)	(-2.52)	(-2.52)
l_leverage	0.543	0.535	0.520	0.500	0.489	0.478
	(2.73)	(2.69)	(2.63)	(2.47)	(2.41)	(2.38)
l_lsize	-0.172	-0.178	-0.158	-0.325	-0.335	-0.314
	(-0.76)	(-0.79)	(-0.70)	(-1.42)	(-1.46)	(-1.36)
l_lsize2	0.008	0.008	0.007	0.018	0.019	0.018
	(0.58)	(0.60)	(0.50)	(1.39)	(1.42)	(1.31)
l_asset_mat	0.004	0.005	0.005	0.006	0.006	0.006
	(1.31)	(1.35)	(1.35)	(1.61)	(1.64)	(1.67)
l_mb	-0.005	-0.004	-0.002	-0.012	-0.012	-0.009
	(-0.17)	(-0.16)	(-0.07)	(-0.45)	(-0.45)	(-0.34)
l_term	-0.074	-0.074	-0.072	-0.103	-0.102	-0.098
	(-1.59)	(-1.58)	(-1.53)	(-2.14)	(-2.12)	(-2.01)
l_abnearn	0.137	0.138	0.123	0.177	0.182	0.162
	(1.22)	(1.24)	(1.08)	(1.51)	(1.57)	(1.37)
l_volatility	-0.419	-0.424	-0.423	-0.759	-0.770	-0.746
	(-0.49)	(-0.49)	(-0.49)	(-0.85)	(-0.86)	(-0.84)
l_reg_dum	-0.139	-0.151	-0.134	-0.123	-0.136	-0.123
	(-0.75)	(-0.82)	(-0.70)	(-0.69)	(-0.77)	(-0.67)

Table 2.9 Continued

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_rated	0.203	0.205	0.213	0.202	0.204	0.214
	(2.96)	(2.97)	(3.07)	(2.94)	(2.95)	(3.07)
l_zscore_dum	-0.154	-0.156	-0.159	-0.143	-0.146	-0.148
	(-1.73)	(-1.75)	(-1.78)	(-1.53)	(-1.57)	(-1.58)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,973	1,973	1,973	1,973	1,973	1,973
adj. R^2	0.161	0.161	0.160	0.161	0.161	0.159

of which harm stockholders and debtholders. Monitoring and discipline by short-term lenders would be expected to reduce these problems, and potentially generate spillover benefits for a firm's stockholders.

We define a dummy variable, *duality*, which is set to one for firms whose CEOs are also chairman and zero otherwise. We interact *duality* with the institutional geographic proximity measures and include the interaction terms in the regressions for the maturity of new debt issues. The results are shown in Table 2.9. The coefficients on the interaction terms between *duality* and *local* or *local_inst* are significantly negative and the coefficient on the interaction term between *duality* and *min_dist* is significantly positive. Strikingly, the coefficients on the stand-alone geographic proximity measures are not significantly different from zero. Thus, the impact of institutional proximity on the maturity of new debt issues obtains only for firms with dual CEO-Chair, and thus the potential for more severe equity agency problems. The result suggests that the potential reduction of equity agency costs (at least in part) drives the relation between debt maturity and local institutional investors.[17]

In summary, the positive effect of local institutional investors on short maturity debt found for existing debt maturity structure holds for new debt issues, and the causal effect of local institutional monitoring on maturity of new debt issues is identified using SOX as a natural experiment and headquarter relocations as exogenous shock to institutional proximity. The nearest neighbor matching analyses suggest that the effect is not driven solely by the joint location of both institutional investors and commercial banks. The motivation to reduce equity agency costs at least partially drives the effect.

2.4. Local Monitoring or Superior Information

An alternative explanation for our finding is that local institutional investors do not influence firms' debt maturity structures, but rather simply choose to invest in local firms with shorter debt maturities. Knowing that short-term debt enhances lender monitoring and can provide more effective discipline of managers, local institutional investors may simply seek out those firms that they know (based on their information advantage) would benefit from such monitoring and discipline. To assess the plausibility of an information-based explanation for our finding, we conduct additional tests in this section.

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[17] Our empirical results suggest that monitoring by local institutional investors and monitoring effect of short maturity debt are complimentary, at least for firms with more severe equity agency problems.

2.4.1. Regulation Fair Disclosure as a Quasi-natural Experiment

We first use the implementation of Regulation Fair Disclosure (Reg FD) in 2000 as a natural experiment to explore an information-based explanation for our finding. Gintschel and Markov (2004) find that Reg FD has been effective in reducing the informativeness of analyst information output. Bernile, Kumar, and Sulaeman (2011) show that Reg FD eliminated the information advantage of local institutional investors. Therefore, if our finding reflects solely a superior information advantage of local investors that permits them to invest in firms that benefit from shorter debt maturity, we would expect the effect of institutional geographic proximity on debt maturity to weaken or even disappear in the post-Reg FD period.

We apply a difference-in-difference estimation method to our new debt issue sample to examine this information hypothesis. Since Reg FD was implemented in October 2000, we define a post-Reg FD dummy, *post_reg*, which equals to one for years after 2000 (and before 2003)[18] and zero for years before 2000. We interact the dummy variable with each of the three institutional proximity measures, and include the interaction terms, as well as the post-Reg FD dummy variable, as additional explanatory variables in the specifications for maturity of new debt issues as shown in Table 2.5. An information advantage explanation for our finding would predict significantly positive coefficients on the interaction terms *local×post_reg* and *local_inst×post_reg* and a significantly negative coefficient on the interaction term *min_dist×post_reg*.

[18] The sample period for this test is ended in 2002 because our earlier results show that the effect of institutional proximity on debt maturity diminishes in the post-SOX period (after 2002).

Table 2.10. Active Monitoring or Information Advantage? Evidence from Reg FD

This table reports results of OLS regressions that use difference-in-difference method to test the information advantage based explanation. The dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) in Panel A and the equal-weighted average maturity (*ew_maturity*, in *log*) in Panel B, respectively. The institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). *post_reg* is a dummy variable that equals to one for all years after 2000 (and before 2003) and zero for all years before 2000. All independent variables are lagged one year (denoted by prefix l_). Industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_local	-0.115			-0.107		
	(-1.93)			(-1.75)		
l_local×post_reg	0.158			0.131		
	(1.31)			(1.10)		
l_local_inst		-0.073			-0.076	
		(-1.78)			(-1.79)	
l_local_inst×post_reg		0.091			0.066	
		(1.07)			(0.85)	
l_min_dist			0.057			0.051
			(1.97)			(1.76)
l_min_dist×post_reg			-0.011			-0.004
			(-0.20)			(-0.07)
post_reg	-0.588	-0.593	-0.544	-0.491	-0.502	-0.454
	(-3.65)	(-3.81)	(-3.47)	(-3.13)	(-3.59)	(-2.97)
l_top5_io	-0.695	-0.615	-0.698	-0.769	-0.684	-0.710
	(-2.81)	(-2.54)	(-2.82)	(-3.12)	(-2.85)	(-2.97)
l_leverage	0.542	0.548	0.522	0.549	0.546	0.535
	(3.86)	(3.97)	(3.48)	(3.83)	(3.84)	(3.45)
l_lsize	0.385	0.391	0.380	0.305	0.313	0.307
	(3.09)	(3.18)	(3.02)	(2.47)	(2.54)	(2.40)
l_lsize2	-0.024	-0.024	-0.024	-0.017	-0.017	-0.017
	(-2.94)	(-2.97)	(-2.92)	(-2.13)	(-2.15)	(-2.12)
l_asset_mat	0.008	0.007	0.011	0.009	0.008	0.012
	(2.62)	(2.44)	(3.21)	(2.80)	(2.63)	(3.41)
l_mb	-0.028	-0.027	-0.033	-0.038	-0.039	-0.045
	(-1.10)	(-1.08)	(-1.34)	(-1.42)	(-1.45)	(-1.75)
l_term	0.004	0.012	0.157	-0.014	-0.006	0.161
	(0.06)	(0.16)	(6.06)	(-0.19)	(-0.08)	(6.42)
l_abnearn	0.184	0.165	0.205	0.194	0.176	0.217
	(2.26)	(2.03)	(2.43)	(2.33)	(2.11)	(2.61)
l_volatility	-0.220	-0.325	-0.361	-0.414	-0.528	-0.562
	(-0.33)	(-0.49)	(-0.56)	(-0.63)	(-0.80)	(-0.86)
l_reg_dum	-0.386	-0.427	-0.403	-0.347	-0.397	-0.364
	(-1.96)	(-2.19)	(-2.22)	(-1.84)	(-2.10)	(-2.09)

Table 2.10 Continued

	Panel A: sw_maturity			Panel B: ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_rated	0.054	0.048	0.018	0.052	0.047	0.026
	(0.71)	(0.68)	(0.22)	(0.69)	(0.69)	(0.34)
l_zscore_dum	-0.064	-0.065	-0.025	-0.016	-0.016	0.021
	(-0.86)	(-0.88)	(-0.34)	(-0.22)	(-0.22)	(0.28)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,354	4,354	4,354	4,355	4,355	4,355
adj. R^2	0.227	0.225	0.225	0.225	0.225	0.225

The estimation results are shown in Table 2.10. In all specifications, the coefficients on the interaction terms are not significantly different from zero. The result suggests that local monitoring institutions have a significant impact on maturity of new debt issues even after the implementation of Reg FD, and the impact has not significantly weakened in the post-Reg FD period, which is not consistent with the information advantage explanation. Therefore, it is unlikely that our findings are simply driven by the informational advantage of local institutions in choosing firms that benefit from short debt maturity.

2.4.2. Information Asymmetry Hypothesis

Our second test for an information-based explanation is to examine whether the effect of institutional geographic proximity on debt maturity is stronger for firms with greater information asymmetry, such as non-S&P 500 firms. Previous studies show that investors exploit their superior information more effectively among firms with greater information asymmetry, and local institutional investors are more likely to exploit their local information advantage for firms with greater information asymmetry (e.g., Schultz (2010)). Ivkovic and Weisbenner (2005) use S&P 500 status as the proxy for information asymmetry and find that excess returns to investing locally are even larger among non-S&P 500 stocks, for which information asymmetries between local and nonlocal investors may be largest. If our finding merely reflects local information advantage of institutional investors, we would expect that the effect of institutional geographic proximity on debt maturity is stronger for firms not in the S&P 500 index, i.e., firms with greater information asymmetry.

We interact the institutional proximity measures with the S&P 500 dummy, *sp500*, which is set to one for S&P 500 firms and zero otherwise, and repeat the analyses of debt maturity structure (*st3*) and maturity of new debt issues by including the interaction terms as additional explanatory variables. The results are shown in Table 2.11. Panel A reports the dynamic system GMM estimators for debt maturity structure (*st3*), and Panel B reports the pooled OLS estimators for maturity of new debt issues. In all specifications, the coefficients on the interaction terms are insignificant, suggesting that the effect of institutional geographic proximity on debt maturity is not stronger for firms with greater information asymmetry. The results do not support an information advantage based explanation for our findings.

Table 2.11. Active Monitoring or Information Advantage? Testing Information Asymmetry Hypothesis

This table reports results of testing the information asymmetry hypothesis. Panel A shows the results of dynamic panel system GMM estimation of relation between debt maturity structure (*st3*) and institutional geographic proximity, and Panel B shows the results of pooled OLS regressions of maturity of new debt issues on lagged institutional geographic proximity. Institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). Interaction terms between the (lagged) institutional proximity measures and sp500 dummy are included as additional explanatory variables. In Panel A, the dependent variable is *st3*. Firm, industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics are in parentheses. In Panel B, the dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) or the equal-weighted average maturity (*ew_maturity*, in *log*). All control variables are also lagged one year (denoted by prefix l_). Industry and year fixed effects are included, but their coefficients are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm.

Table 2.11, Panel A. System GMM Estimates of Dynamic Panel Model

	(1)	(2)	(3)
local	0.194		
	(2.75)		
local×sp500	-0.182		
	(-1.33)		
local_inst		0.129	
		(2.48)	
local_inst×sp500		-0.081	
		(-0.92)	
min_dist			-0.083
			(-2.71)
min_dist×sp500			-0.018
			(-0.24)
sp500	0.120	0.067	0.128
	(0.80)	(0.44)	(0.67)
top5_io	0.113	0.126	0.085
	(0.70)	(0.79)	(0.48)
leverage	0.008	0.013	0.077
	(0.07)	(0.11)	(0.65)
lsize	-0.118	-0.120	-0.131
	(-2.62)	(-2.73)	(-2.17)
lsize2	0.008	0.008	0.008
	(1.91)	(1.99)	(1.35)
asset_mat	0.002	0.002	0.001
	(0.98)	(0.93)	(0.46)
mb	-0.012	-0.009	-0.011
	(-0.50)	(-0.39)	(-0.47)
term	0.057	0.038	0.034
	(2.36)	(1.59)	(1.36)
abnearn	-0.258	-0.265	-0.280
	(-4.31)	(-4.41)	(-4.29)

Table 2.11 Continued

	(1)	(2)	(3)
volatility	-0.207	-0.156	-0.100
	(-0.33)	(-0.26)	(-0.16)
reg_dum	-1.704	-1.531	-1.859
	(-2.42)	(-2.32)	(-2.69)
rated	-0.087	-0.087	-0.089
	(-2.26)	(-2.25)	(-2.10)
zscore_dum	-0.072	-0.057	-0.044
	(-1.06)	(-0.88)	(-0.64)
lag_st3	0.518	0.531	0.519
	(5.76)	(5.74)	(5.62)
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
AR(2) test (*p*-value)	0.948	0.903	0.944
Hansen test of over-identification (*p*-value)	0.421	0.327	0.585
Diff-in-Hansen test of exogeneity (*p*-value)	0.240	0.137	0.486

Table 2.11, Panel B. Pooled OLS Estimates of Maturity of New Debt Issues

	sw_maturity			ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_local	-0.144			-0.138		
	(-2.09)			(-1.98)		
l_local×sp500	0.097			0.097		
	(0.76)			(0.78)		
l_local_inst		-0.072			-0.069	
		(-1.75)			(-1.69)	
l_local_inst×sp500		0.019			0.073	
		(0.17)			(0.95)	
l_min_dist			0.066			0.062
			(2.20)			(2.08)
l_min_dist×sp500			-0.053			-0.057
			(-1.07)			(-1.17)
l_sp500	0.265	0.286	0.277	0.256	0.244	0.262
	(2.82)	(2.94)	(2.57)	(2.87)	(1.97)	(2.45)
l_top5_io	-0.869	-0.790	-0.809	-0.935	-0.805	-0.848
	(-3.52)	(-3.24)	(-3.83)	(-3.81)	(-3.81)	(-4.06)
l_leverage	0.640	0.623	0.649	0.630	0.690	0.651
	(3.90)	(3.84)	(4.93)	(3.77)	(4.92)	(4.79)
l_lsize	0.386	0.430	0.425	0.328	0.299	0.343
	(2.70)	(2.96)	(3.69)	(2.32)	(2.55)	(2.97)
l_lsize2	-0.027	-0.030	-0.029	-0.022	-0.019	-0.022
	(-2.91)	(-3.07)	(-3.81)	(-2.40)	(-2.51)	(-2.90)

Table 2.11 Continued

	sw_maturity			ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
l_asset_mat	0.013	0.012	0.009	0.014	0.011	0.010
	(3.67)	(3.44)	(2.79)	(3.87)	(3.30)	(3.09)
l_mb	-0.017	-0.014	-0.018	-0.031	-0.029	-0.030
	(-0.54)	(-0.46)	(-0.78)	(-0.99)	(-1.24)	(-1.29)
l_term	0.058	0.087	-0.063	0.059	-0.073	-0.072
	(0.64)	(0.93)	(-1.65)	(0.65)	(-1.86)	(-1.85)
l_abnearn	0.264	0.242	0.223	0.239	0.224	0.222
	(2.33)	(2.08)	(2.79)	(2.03)	(2.88)	(2.75)
l_volatility	-0.042	-0.141	0.010	-0.189	-0.039	-0.092
	(-0.05)	(-0.16)	(0.02)	(-0.22)	(-0.06)	(-0.15)
l_reg_dum	-0.309	-0.395	-0.383	-0.298	-0.336	-0.332
	(-1.51)	(-1.93)	(-1.91)	(-1.40)	(-1.68)	(-1.70)
l_rated	0.019	0.013	0.028	0.028	0.054	0.043
	(0.24)	(0.17)	(0.40)	(0.36)	(0.79)	(0.63)
l_zscore_dum	-0.083	-0.090	-0.070	-0.028	-0.025	-0.021
	(-1.03)	(-1.09)	(-1.06)	(-0.34)	(-0.37)	(-0.32)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,354	4,354	4,354	4,355	4,355	4,355
adj. R^2	0.235	0.235	0.233	0.233	0.237	0.236

2.5. Robustness Checks

In this section we perform several robustness checks to assess whether our main finding is robust to alternative measures of institutional proximity, alternative definition of monitoring institutions, clustering of local institutions and banks, and inclusion of additional control variables.

2.5.1. Alternative Measure of Institutional Proximity

The first robustness check is about the institutional proximity measures. One of our primary measures is the shortest distance between the monitoring institutions and the investee firm. An alternative measure would be the *average* distance between monitoring institutions (i.e., the top five independent institutions) and the investee firm, *top5_dist*. Sections I of Table 2.12 report the results of dynamic panel system GMM estimation of the relation between *st3* and *top5_dist* (Panel A) and pooled OLS regressions of maturity of new debt issues (Panel B). The average distance, *top5_dist*, is significantly negatively related to *st3* and significantly positively related to maturity of new debt issues, suggesting that firms with closer monitoring institutions have a higher proportion of short-term debt and issue shorter maturity debt. The results are qualitatively the same as our main finding.

2.5.2. Alternative Definition of Monitoring Institutions

Our next robustness check is regarding how to define monitoring institutions. In our main analysis, we classify independent institutions as those that are (1) independent from corporate management (i.e., they have no business relationships with the firm) as defined by Brickley et al. (1988) and (2) classified as dedicated or quasi-indexer institutions by Bushee (2001). We then define monitoring institutions as the top five independent institutions in terms of the size of their shareholdings. Alternatively, we define monitoring institutions as those that are top five institutions in terms of the size of their shareholdings and also meet the criteria (1) and (2) as stated above.[19] We then constructed the ownership and proximity measures of monitoring institutions under the alternative definition, and repeat our main analyses. Sections II of Table 2.12 report the dynamic panel system GMM

[19] According to the alternative definition, the monitoring institutions are among the top five of all institutional investors based on the size of their shareholdings, but the number of monitoring institutions may be less than 5. The monitoring institutions based on the original definition in the paper are the top five among all independent institutions based on the size of their shareholdings, but may not be the top five among all institutions.

Table 2.12. Robustness Checks: Alternative Measure of Institutional Proximity and Alternative Definition of Monitoring Institutions

This table reports results of robustness checks by using alternative measure of institutional proximity and alternative definition of monitoring institutions. Panel A reports dynamic panel system GMM estimation of the relation between debt maturity structure (*st3*) and institutional proximity, and Panel B reports pooled OLS estimates of relation between maturity of new debt issues and institutional proximity with sample period ending in 2002. In Session I of each panel, the average distance between monitoring institutions and the investee firm, *top5_dist*, is the alternative measure of institutional proximity. In Session II of each panel, the institutional proximity measures, *local*, *local_inst*, and *min_dist*, are constructed under an alternative definition of monitoring institutions. We first identify the largest five institutional investors in terms of the size of shareholdings, and then define monitoring institutions as those that are among the top five institutions, are independent from corporate management as defined by Brickley et al. (1998), and have a long-term investment as classified as dedicated or quasi-indexer institutions by Bushee (2001). The distance measures, *min_dist* and *top5_dist*, are standardized (mean is set to zero and standard deviation is one). In Panel A, the dependent variable is *st3*. In Panel B, the dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) or the equal-weighted average maturity (*ew_maturity*, in *log*), and independent variables are lagged one year (denoted by prefix l_). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. Only the estimation results for institutional proximity measures are reported, and control variables are included in estimations but not reported.

Table 2.12, Panel A. System GMM Estimates of Dynamic Panel Model

	I. Average distance as proximity measure	II. Alternative definition of monitoring institutions		
	(1)	(1)	(2)	(3)
top5_dist	-0.057			
	(-2.06)			
local		0.146		
		(1.96)		
local_inst			0.112	
			(1.83)	
min_dist				-0.055
				(-2.09)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
AR(2) test (*p*-value)	0.764	0.685	0.766	0.642
Hansen test (*p*-value)	0.463	0.112	0.125	0.145
Diff-in-Hansen test (*p*-value)	0.248	0.496	0.432	0.284

Table 2.12 Continued

Table 2.12, Panel B. Pooled OLS Estimates of Maturity of New Debt Issues

	I. Average distance as proximity measure		II. Alternative definition of monitoring institutions					
	sw_mat	ew_mat	sw_maturity			ew_maturity		
			(1)	(2)	(3)	(1)	(2)	(3)
l_top5_dist	0.049	0.046						
	(1.84)	(1.73)						
l_local			-0.140			-0.128		
			(-2.09)			(-1.93)		
l_local_inst				-0.141			-0.135	
				(-2.24)			(-2.17)	
l_min_dist					0.063			0.058
					(2.10)			(1.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,354	4,355	4,140	4,140	4,140	4,141	4,141	4,141
adj. R^2	0.185	0.182	0.253	0.252	0.252	0.249	0.247	0.247

estimation of the relation between debt maturity structure (*st3*) and the institutional proximity measures (Panel A), and the results of pooled OLS estimation of the relation between maturity of new debt issues and the institutional proximity measures (Panel B). The results are all qualitatively similar to our main results, and our finding is robust to the alternative definition of monitoring institutions.

2.5.3. Importance of California and New York

We next examine whether the results are driven by firms and investors located in California and New York because these states have high concentrations of both. We exclude firms located in the states of California and New York, and perform system dynamic GMM estimation of existing debt maturity structure and pooled OLS regressions of maturity of new debt issues. The results shown in Table 2.13 (Sections I) indicate that our main findings are not driven by firms and investors in California and New York.

2.5.4. Inclusion of Additional Control Variables

In the last robustness check, we add to our main specification additional control variables that may be related to debt maturity structure. Datta et al. (2005) and Brockman et al. (2010) show that executive incentives related variables such as CEO ownership, Delta and Vega can affect debt maturity. We collect CEO compensation and ownership information from Standard and Poor's ExecuComp database, compute Delta, Vega and CEO ownership, and repeat our main analyses with Delta, Vega and CEO ownership included as additional control variables. The results are shown in Table 2.13. Panel A, Section II reports the two-step dynamic system GMM estimation of the relation between debt maturity and institutional proximity, and Panel B, Section II reports the pooled OLS estimation of the relation between maturity of new debt issues and institutional proximity. The coefficients on all of the three measures of institutional proximity are statistically significant with the same signs as those shown in Table 2.4 and Table 2.5. Therefore, our results are robust to inclusion of additional executive incentive related control variables.

Table 2.13. Additional Robustness Checks: Excluding Firms Located in California and New York and Controlling for Variables Related to Executive Incentives

This table reports results of robustness checks by (I) excluding firms located in states of California (CA) and New York (NY) and (II) controlling for additional variables related to executive incentives, including Delta, Vega, and CEO ownership. Panel A reports dynamic panel system GMM estimation of the relation between debt maturity structure (*st3*) and institutional proximity, and Panel B reports pooled OLS estimates of relation between maturity of new debt issues and institutional proximity. The institutional distance measure, *min_dist*, is standardized (mean is set to zero and standard deviation is one). *delta* is the change in the value of CEO's stock and option portfolio due to a 1% increase in stock price (in *logs*). *vega* is the change in value of CEO's option portfolio due to 1% change in volatility of stock return. *own* is the fraction of the firm's shares held by its CEO. In Panel A, the dependent variable is *st3*. Firm, industry and year fixed effects are included, but their coefficients are not reported. The industry classifications are defined based on 2-digit SIC code. T-statistics are in parentheses. *p*-values of *AR(2)* test, Hansen test, and Diff-in-Hansen test are reported. In Panel B, the dependent variables are the issue size-weighted average maturity (*sw_maturity*, in *log*) or the equal-weighted average maturity (*ew_maturity*, in *log*). Independent variables are lagged one year (denoted by prefix l_). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. Only the estimation results for institutional proximity measures and incentive related variables are reported, and other control variables are included in estimations but not reported.

Table 2.13, Panel A. System GMM Estimates of Dynamic Panel Model

	I. Excluding CA and NY firms			II. Controlling for incentive related variables		
	(1)	(2)	(3)	(1)	(2)	(3)
local	0.164			0.183		
	(2.09)			(2.54)		
local_inst		0.130			0.108	
		(2.25)			(2.66)	
min_dist			-0.074			-0.064
			(-2.17)			(-2.31)
delta				-0.021	-0.015	-0.004
				(-1.82)	(-1.70)	(-1.67)
vega				0.000	0.016	0.012
				(0.74)	(0.99)	(0.75)
own				0.010	0.008	0.001
				(1.77)	(1.75)	(1.72)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
AR(2) test (p-value)	0.953	0.962	0.702	0.136	0.147	0.189
Hansen test (p-value)	0.675	0.711	0.867	0.671	0.739	0.169
Diff-in-Hansen test (p-value)	0.590	0.585	0.771	0.540	0.573	0.138

Table 2.13 Continued

Table 2.13, Panel B. Pooled OLS Estimates of Maturity of New Debt Issues

	sw_maturity			ew_maturity		
	(1)	(2)	(3)	(1)	(2)	(3)
I. Excluding CA and NY firms						
l_local	-0.155			-0.147		
	(-2.24)			(-2.10)		
l_local_inst		-0.105			-0.107	
		(-2.17)			(-2.28)	
l_min_dist			0.067			0.060
			(2.25)			(2.00)
II. Controlling for incentive related variables						
l_local	-0.110			-0.097		
	(-1.87)			(-1.75)		
l_local_inst		-0.082			-0.087	
		(-1.86)			(-1.99)	
l_min_dist			0.046			0.054
			(1.82)			(1.74)
l_delta	0.076	0.076	0.123	0.062	0.078	0.132
	(2.58)	(2.59)	(4.81)	(2.40)	(2.62)	(3.92)
l_vega	-0.040	-0.040	-0.071	-0.020	-0.041	-0.109
	(-1.64)	(-1.66)	(-3.70)	(-1.00)	(-1.67)	(-3.66)
l_own	-0.012	-0.012	-0.018	-0.013	-0.014	-0.022
	(-2.15)	(-2.11)	(-3.20)	(-2.41)	(-2.31)	(-3.32)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes

2.6. Conclusion

We examine the relation between the geographic proximity of institutional investors and the maturity structure of corporate debt. Tying together evidence on the external monitoring role by institutional investors, the benefits of investors' geographic proximity, and the potential monitoring and disciplinary benefits of short-term debt, we hypothesize that firms monitored by local institutional investors will have shorter debt maturity.

Using dynamic panel system GMM estimators to account for unobservable heterogeneity, simultaneity, and the dynamic relation between debt maturity and institutional ownerships, we find support for the hypothesis. Analysis based on the maturity of new debt issues using SOX as a quasi-natural experiment also supports the hypothesis, as well as results based on firm headquarter relocations which can be viewed quasi-exogenous shocks to local institutional investor status, and results based on a matching analysis that holds location constant. We cannot rule out the possibility that local institutional investors seeks to minimize both debt agency costs and equity agency costs, but we find evidence suggesting that the effect of local institutional investors on debt maturity is strongest among firms expected to suffer from greater equity agency costs. The test using implementation of Reg FD as a natural experiment indicates that the relation between institutional proximity and debt maturity is not consistent with a pure information advantage based explanation. Overall results suggest that local institutional investors play an active monitoring role and effectively monitor management by exerting influence on corporate debt maturity policies.

3. THE EFFECT OF ALGORITHMIC TRADIGN ON FIRM VALUE

Motivated by recent evidence that algorithmic trading impacts market quality, we examine the effect of algorithmic trading on firm value. Using an algorithmic trading proxy based on electronic message traffic, we find a positive relation between algorithmic trading and firm value. The relation is stronger for firms with lower stock liquidity, higher idiosyncratic volatility, higher analyst coverage, and greater information asymmetry, which suggest that the value increases occur through market quality channels. The results are robust to various model specifications, and reverse causality and endogeneity concerns. The results imply net benefits of algorithmic trading to firms.

3.1 Introduction

As commonly used, algorithmic trading refers to the use of computer algorithms to make trading decisions, submit orders, and manage orders after submission. Beginning in the U.S. equity market in the late 1990s, the use of algorithmic trading has become more common and predominant in major financial markets, representing an estimated 78% of all U.S. equity trading volume in 2012.[20] Given the significant role of algorithmic trading in the stock market, investors, academics, and policymakers need a deeper understanding of its benefits and costs. Some extant studies conclude that algorithmic trading benefits

[20] See http://neverlosstrading.com/Algorithmic%20Trading.html. We note that in 2009, the figure was 73% (see “Times Topics: High-Frequency Trading”, The New York Times, December 20, 2012), so there is an increase even from recent years.

capital markets by increasing trading volume and liquidity, reducing trading costs, and contributing to price discovery, while others conclude it increases volatility and harms capital markets. Moreover, algorithmic trading, especially the subset of it known as high frequency trading, has been criticized for contributing to the 2010 Flash Crash[21] (e.g., Kirilenko, Kyle, Samadi, and Tuzun (2011)). Collectively, the literature provides mixed results on the question of whether algorithmic trading is a beneficial financial innovation, leaving it the subject of intense public debate and controversy.

We contribute evidence to the debate by examining the impact of algorithmic trading on firm value. If algorithmic trading benefits the market quality of a firm's stock by increasing liquidity and improving price efficiency, it should reduce information asymmetry and cost of capital, leading to higher firm value. Improved price efficiency could also increase the effectiveness of managerial compensation contracts that are based on stock prices and improve managerial investment decisions. In contrast, if algorithmic trading increases idiosyncratic volatility or reduces liquidity, it may increase equity risk and cost of capital, resulting in lower firm value. Existing literature suggests that algorithmic trading may have different effects on different aspects of market quality, such as liquidity, volatility, and price efficiency or informativeness, and its short-term and long-term impacts may also differ.[22] These potentially contradicting complexities make it

[21] On May 6, 2010, the Dow Jones Industrial Average plunged about 1000 points, the second largest intraday point swing ever to that date. This brief period of extreme intraday volatility is commonly referred to as the "Flash Crash".

[22] See for example, Boehmer, Fong, and Wu (2012), Hendershott and Riordan (2013), Brogaard, Hendershott, and Riordan (2013), Brogaard (2011), and Zhang (2010).

difficult to assess the overall impact of algorithmic trading on market quality, and the costs and benefits of algorithmic trading. By examining the effect of algorithmic trading on firm value, we hope to augment extant studies on the effects of algorithmic trading, and provide evidence useful for evaluating the net overall costs and benefits of algorithmic trading.

To examine the relation between algorithmic trading intensity and firm value, we follow Hendershott, Jones, and Menkveld (2011), and Boehmer, Fong, and Wu (2012) to construct an algorithmic trading proxy based on message traffic using the Trades and Quotes (TAQ) database. We find that algorithmic trading activity is significantly positively related to firm value after controlling for other variables that affect firm value. The relation is robust to the inclusion of year, industry, and firm-fixed effects, different model specifications, the use of two-stage least squares approach to address endogeneity concerns, and the use of an alternative proxy for algorithmic trading activity.

To help establish a causal effect of algorithmic trading on firm value, we use the change to automated quote dissemination by the New York Stock Exchange (NYSE) in 2003 as an exogenous shock to algorithmic trading intensity. Automated quotation provides quicker feedback to algorithms and results in more electronic message traffic. We use the change in electronic message traffic from before to after the automated quote dissemination as an instrument for the change in algorithmic trading intensity. Stocks with a larger increase in algorithmic trading intensity following the change to automated quote dissemination exhibit a larger increase in firm value, consistent with a causal effect of algorithmic trading on firm value.

Having documented a positive effect of algorithmic trading on firm value, we then attempt to identify the channels through which the value effects occur. If algorithmic trading enhances firm value by increasing liquidity or reducing idiosyncratic volatility, we would expect that the algorithmic trading effect is stronger for firms whose stocks are less liquid or have more volatile returns. Consistent with this conjecture, we find that the effect of algorithmic trading on firm value is stronger for firms with less liquid stocks; additionally, the effect is stronger for firms with higher idiosyncratic volatility. If algorithmic trading increases firm value through efficiently contributing to price discovery and improving stock price informativeness, we would expect that the effect of algorithmic trading on firm value is stronger for firms with more publicly available information such as firms followed by more analysts, and stronger for firms with greater information asymmetry. Consistent with this expectation, we find that the effect of algorithmic trading on firm value is stronger for firms with higher analyst coverage and for firms with greater information asymmetry as measured by PIN (probability of informed trade). In sum, our results suggest that algorithmic trading increases firm value by improving stock liquidity, reducing idiosyncratic volatility, contributing to price discovery, and reducing information asymmetry. Combined with the evidence of beneficial effects of algorithmic trading on market quality, our results suggest significant benefits of algorithmic trading.

Our study is not designed to rule out the existence of any harmful effects of algorithmic trading, so we cannot and do not conclude that it has no harmful effects. It is conceivable that algorithmic trading leads to negative effects such as flash crashes that manifest themselves periodically while still providing net benefits to firm value for stocks with greater algorithmic trading. On the narrow firm value dimension, however, we can conclude that algorithmic trading is associated with increased firm value, especially for firms with illiquid and volatile stocks, and firms with greater information asymmetries.

Our study contributes to the limited, but fast growing, literature on algorithmic trading and high frequency trading in a unique way by directly testing the relation between algorithmic trading activity and firm value. Prior studies on algorithmic trading and high frequency trading focus on their impacts on measures of market quality. Our results on firm value, to our knowledge the first such evidence, are critical in assessing the net social benefits of algorithmic trading.

Our study also contributes to the strand of literature at the intersection of market microstructure and corporate finance, especially on the relation between financial markets and firm fundamentals. Financial markets not only reflect firm fundamentals, but they can also *affect* firm fundamentals. Baker, Stein, and Wurgler (2003), Luo (2005), and Chen, Goldstein, and Jiang (2007) provide evidence that market prices affect firms' investments via managerial learning and/or the firm's access to new capital. Roll, Schwartz, and Subrahmanyam (2009) study the effect of options trading on firm value and show that corporate investment in firms with greater options trading is more sensitive to stock prices. Fang, Noe, and Tice (2009) find that stock market liquidity positively impacts firm value through increasing the information content of market prices and of performance-sensitive managerial compensation. Our study contributes to this line of literature by showing that algorithmic trading affects firm value through improving market quality, including liquidity, volatility, and price discovery.

The rest of the chapter proceeds as follows. Section 3.2 reviews the literature and develops our hypotheses. Section 3.3 describes the sample, data sources and variable measurements. Section 3.4 presents the main empirical results, and Section 3.5 concludes.

3.2. Literature and Hypotheses

Given the rapid increase in algorithmic trading activity in recent years, a central question that interests financial market participants, policymakers, and academics is whether algorithmic trading should be encouraged or discouraged. The algorithmic trading literature has focused on the impact of algorithmic trading on market quality and provides mixed evidence. On one hand, several studies suggest that algorithmic trading or high frequency trading creates excess volatility and may be detrimental to financial markets. For example, Kirilenko, Kyle, Samadi, and Tuzun (2011) study how high frequency trading is related to the May 6, 2010 Flash Crash and conclude that although high frequency trading did not cause the crash, it worsened the crash by exacerbating market volatility. Zhang (2010) finds that high frequency trading is positively correlated with stock price volatility, and negatively related to the market's ability to incorporate information about firm fundamentals into asset prices. Boehmer, Fong, and Wu (2012) conduct an international study using message counts as a proxy for algorithmic trading, and show that algorithmic trading increases volatility.

On the other hand, many studies suggest a beneficial role of algorithmic trading in financial markets. Using NYSE electronic message traffic as a proxy for algorithmic trading activity, Hendershott, Jones, and Menkveld (2011) find that algorithmic trading improves liquidity and enhances price informativeness. Boehmer, Fong, and Wu (2012) provide international evidence showing similar results. Using a sample of algorithmic trading on the Deutsche Bourse, Hendershott and Riordan (2013) show that algorithmic traders consume liquidity when it is cheap and provide liquidity when it is expensive, which reduces liquidity risk. Groth (2011) finds that algorithmic trading does not create excess volatility, and does not reduce liquidity during periods of high volatility. Brogaard (2011) finds that high frequency trading reduces intraday volatility in the short-term. Brogaard, Hendershott, and Riordan (2013) find that overall high frequency trading enhances price efficiency. Similar evidence has also been found for algorithmic trading in other financial markets. Chaboud, Chiquoine, Hjalmarsson, and Vega (2013) provide evidence that algorithmic trading in exchange markets contributes to a more efficient price discovery process, and has a positive impact on market liquidity without creating excess volatility.

All else equal, greater liquidity, lower idiosyncratic volatility, and higher price informativeness should increase firm value. Thus, if algorithmic trading plays a beneficial role in financial markets by improving liquidity, reducing idiosyncratic volatility, and/or enhancing price informativeness, it should positively affect firm value. Both theoretical and empirical studies have shown that liquidity should be priced by the market. Amihud and Mendelson (1986) model effects of bid-ask speared on asset returns and predict that expected return is positively related to illiquidity. O'Hara (2003) argues that asset pricing models should incorporate transaction costs of liquidity. Acharya and Pedersen (2005) derive a liquidity-based capital asset pricing model, and show that an increase in liquidity results in higher contemporaneous returns and lower expected future returns. Thus, greater liquidity leads to higher current stock prices and greater firm value. Another line of literature relates liquidity to firm performance. Liquid markets permits non-blockholders to intervene and become blockholders, which then improves monitoring and corporate governance (Maug (1998)). Liquidity can also have a disciplinary effect on management by facilitating informed selling or "dumping" ("Wall Street Walk") (e.g., Edmans (2009); Admati and Pfleiderer (2009)). Subrahmanyam and Titman (2001) and Khanna and Sonti (2004) show that liquidity can positively affect firm performance by stimulating the entry of informed investors who make price more informative to stakeholders. Fang, Noe, and Tice (2009) show that stock market liquidity positively impacts firm value through increasing the information content of market prices and of performance-sensitive managerial compensation contracts.

Moreover, Merton (1987) predicts that idiosyncratic risk is positively related to the expected stock returns when market is information-segmented and investors are under-diversified. Fu (2009) empirically confirms the positive relation between idiosyncratic volatility and expected return. Lower idiosyncratic volatility would lead to lower risk and lower expected return or cost of capital, resulting in higher contemporaneous stock prices and firm value. In addition, more informative stock prices should help managers make better investment decisions and reduce the cost of capital by reducing information asymmetry (Diamond and Verrecchia (1991)) and by enabling firms to design more efficient managerial compensation contracts (Holmstrom and Tirole (1993)).

Thus, given that greater liquidity, lower idiosyncratic volatility, and higher price informativeness all lead to greater firm value, if algorithmic trading improves liquidity, reduces idiosyncratic volatility, and enhances price information efficiency, it should positively affect firm value. This leads to our main hypothesis:

H1: All else equal, firms whose stocks are more heavily traded using computer algorithms have higher value.

We next generate several hypotheses about the channels through which algorithmic trading might affect firm value. Hendershott and Riordan (2013) find that algorithmic trading supplies more liquidity when spreads are wide, suggesting a stronger positive effect of algorithmic trading on liquidity for less liquid stocks. As discussed above, both theoretical and empirical studies show that higher liquidity leads to higher firm value. Therefore, if algorithmic trading enhances firm value through increasing liquidity, its effect on firm value is expected to be stronger for firms with less liquid stocks. This leads to the following hypothesis:

H2a: All else equal, the effect of algorithmic trading on firm value is stronger when stock liquidity is lower.

Similarly, since lower idiosyncratic volatility is related to higher firm value, if algorithmic trading enhances firm value through reducing idiosyncratic volatility, its effect on firm value should be stronger for firms with higher idiosyncratic stock return volatility. This leads to the following hypothesis:

H2b: All else equal, the effect of algorithmic trading on firm value is stronger when idiosyncratic volatility is higher.

If algorithmic trading enhances firm value through contributing to price discovery, its effect should be stronger when algorithmic trading is more informative. Because algorithmic trading relies on computer algorithms to make trade decisions without human intervention, it does not rely on additional information that is not publicly available to contribute to price discovery. Instead, the advantage of algorithmic trading over human trading is the ability of computer algorithms to simultaneously process volumes of *public* information received electronically and make trading decisions at high speeds that ordinary human traders cannot match. In other words, algorithmic trading contributes to price discovery by efficiently incorporating already existing information into stock prices, not by producing new information. Thus, algorithmic trading should contribute relatively more to price efficiency if there is more public information available. If algorithmic trading increases firm value by improving price efficiency, the effect of algorithmic trading on firm value should be stronger for firms with more public information. We use the extent of analyst coverage as a measure of public information, which then leads to the next hypothesis:

H2c: All else equal, the effect of algorithmic trading on firm value is stronger for firms with higher analyst coverage.

Finally, if algorithmic trading enhances firm value by increasing price informativeness and reducing information asymmetry, its effect should be stronger for firms with greater information asymmetry. This leads to our last hypothesis:

H2d: All else equal, the effect of algorithmic trading on firm value is stronger for firms with greater information asymmetry.

3.3. Data

3.3.1. Sample Selection

We start with a sample of all stocks covered in the TAQ database from 2002 to 2006. We limit our attention to the post-decimalization period because decimalization in 2001 was a major structural change to the stock trading system, and we end our sample period in 2006 to avoid potential abnormal trading activities during the financial crisis of 2007-2008. TAQ contains intraday transaction (quotes and trades) data for all securities listed on NYSE, American Stock Exchange (AMEX), Nasdaq, and SmallCap issues. We obtain firm financial data from the Compustat database, stock return and total trading volume data from the Center for Research in Security Prices (CRSP), and analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S) database. We include only common stocks (those with a share code of 10 or 11 in the CRSP database). We also require each firm-fiscal year observation to have a non-missing value of Tobin's q, the measure of firm value, which we define below. Our final sample has 22,577 firm-fiscal year observations with 5,834 unique firms.

3.3.2. Variable Construction

3.3.2.1. Algorithmic Trading

Following Hendershott, Jones, and Menkveld (2011) and Boehmer, Fong, and Wu (2012), we construct a proxy measure for algorithmic trading based on electronic message traffic. Hendershott et al. (2011) have access to order-level messages and their algorithmic trading proxy is the number of messages normalized by dollar volume. Specifically, they define the algorithmic trading proxy as the negative of dollar volume divided by the number of messages, including order submissions, order cancellations and trades. They also use the number of messages normalized by number of trades or the raw message as proxies and find the same results. Boehmer et al. (2012) construct a similar proxy. Because they do not have access to order-level messages, and only observe each exchange's best quotes and trades, they define a message as either a trade or an update in the best bids and offers (BBO) and measure algorithmic trading as the negative of dollar volume associated with each message.[23]

The TAQ database that we use in this study contains transaction-level messages, but no order-level messages. Thus, we follow Boehmer et al. (2012) to define a message as either a trade or a change in BBO, and construct our algorithmic trading proxy measure as the normalized number of messages. To avoid a mechanical correlation between our algorithmic trading proxy and Tobin's q, we use number of trades instead of dollar volume to normalize the number of messages. Specifically, for firm *i*'s stock, its BBO is determined following Hasbrouck (2010),[24] and the number of trades and number of changes in BBO are aggregated over firm *i*'s fiscal year. Our algorithmic trading proxy, *Algo Trade*, is defined as the negative of number of trades divided by the number of

[23] Boehmer et al. (2012) point out that they can qualitatively replicate Hendershott et al. (2011) results using the U.S. portion of their sample and their algorithmic trading proxy constructed from the TAQ data.

[24] Following Hasbrouck (2010), we use all quotes available at a given time to determine the BBO, and do not drop quotes. If there are multiple quotes occurring in the same second, BBO is determined based on the order of quote records, and there can be updates in BBO in the same second.

messages that includes changes in BBO and trades. Greater *Algo Trade* indicates more messages per trade and higher algorithmic trading intensity.

Moreover, the TAQ database allows us to observe all quotes, not just BBO. Therefore, as a robustness check for *Algo Trade*, we construct an alternative algorithmic trading proxy, *Algo Trade_q*, by considering updates of all quotes, rather than only the best quotes, as messages. We define *Algo Trade_q*, as the negative of number of trades divided by the number of messages that includes updates in quotes and trades.[25] These two measures have a correlation of 0.55, which suggests that they have a strong common component, yet have some independent variation.

3.3.2.2. Other Variables

We use Tobin's q to measure firm value. Following Roll, Schwartz, and Subrahmanyam (2009), *Tobin's q* is computed as the ratio of the market value of assets to the book value of assets of the firm, where the market value of assets is calculated as the sum of the market value of common stock, the liquidation value of preferred shares, and the book value of long-term debt.

We include a wide range of control variables in our analysis. We control for stock return, lagged stock return, and turnover to capture factors from the stock market that may affect firm value. Stock return and lagged stock return are the accumulated daily return over a firm's current and prior fiscal years, respectively. Turnover is the total trading

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[25] There are some stocks that are thinly traded but have relatively large numbers of quote updates, and therefore, have high values of *Algo Trade* or *AlgoTrade_q*. Excluding those stocks by adding a minimum trade filter (e.g., 1,000 or 3,000 trades per year) for stocks to enter the sample does not change the results qualitatively.

volume over a firm's fiscal year divided by the number of shares outstanding at the beginning of the fiscal year. In alternative specifications, turnover is replaced by total trading volume or dollar volume.

Following Roll, Schwartz, and Subrahmanyam (2009) and Fang, Noe, and Tice (2009), we also control for several firm characteristics that are related to firm valuation. Return on assets (*ROA*) is net income divided by the book value of assets. *Capex* is capital expenditures divided by book value of assets. *Size* is measured as the natural logarithm of total book assets. *Leverage* is total debt divided by book value of assets. *Analyst* is the natural logarithm of one plus the number of analysts following a firm during the fiscal year. *Dividend* is an indicator variable for whether the firm pays a dividend during the fiscal year. *SP500* is an indicator variable for whether the firm is included in the S&P 500 during the fiscal year. Industries are defined based on the Fama and French 48 industry classifications. As mentioned above, we also control for *Return* and $Return_{t-1}$, which are stock returns over the fiscal years t and $t-1$, respectively.

3.3.3. Summary Statistics

Table 3.1 presents summary statistics for *Tobin's q*, *Algo Trade*, and the control variables. In our sample, the mean value of *Tobin's q* is 1.518, with a standard deviation of 1.492 and median of 1.077. For the average stock over our sample period, the average annual turnover is 1.686, with annual trading volume of 131.4 million shares and dollar volume of $3.459 billion. The mean value of *Algo Trade* is -0.441, which means that for the average stock, there are 0.441 trades per electronic message, or equivalently, 2.12 messages per trade.

Table 3.1. Summary Statistics for Section 3

The table reports summary statistics for the sample of stock-fiscal year observations. Tobin's q is the market value of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by the book value of assets. *Algo Trade* is the proxy for algorithmic trading, defined over firm *i*'s fiscal year as the negative of number of trades divided by the number of message that includes the number of changes in best bid-offer (BBO) and the number of trades. Turnover is the trading volume of firm *i*'s stock over the fiscal year divided by the number of shares outstanding at the beginning of the fiscal year. Volume is the trading volume of firm *i*'s stock over the fiscal year (multiplied by 10^{-8}). Dollar Volume is the dollar trading volume of firm *i*'s stock over the fiscal year (multiplied by 10^{-9}). ROA is return on assets measured as net income divided by book value of assets. Capex is capital expenditures divided by book value of assets. Firm size is measured by Log(Total Assets). Leverage is measured as total debt divided by book value of assets. Analyst is analyst coverage measured by the natural logarithm of one plus the number of analysts following firm *i* during fiscal year *t*. Stock Return is stock return over the fiscal year. Dividend is a dummy variable for whether the firm pays a dividend during the fiscal year. SP500 is a dummy variable for whether the firm is included in the S&P 500 during the fiscal year. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample.

Variable	Mean	Std. Dev.	5^{th} Pctl	25^{th} Pctl	Median	75^{th} Pctl	95^{th} Pctl
(1) Tobin's q	1.518	1.492	0.206	0.612	1.077	1.851	4.459
(2) Algo Trade	-0.441	0.236	-0.839	-0.596	-0.464	-0.273	-0.029
(3) Turnover	1.686	1.862	0.128	0.452	1.086	2.178	5.437
(4) Volume	1.314	3.056	0.005	0.044	0.279	1.066	6.145
(5) Dollar Volume	3.459	9.381	0.003	0.031	0.289	2.006	18.223
(6) ROA	0.036	0.219	-0.379	0.018	0.077	0.143	0.255
(7) Capex	0.041	0.051	0.001	0.010	0.025	0.052	0.143
(8) Firm Size	5.968	2.095	2.595	4.473	5.947	7.326	9.665
(9) Leverage	0.197	0.205	0	0.018	0.147	0.302	0.601
(10) Analyst	1.465	1.103	0	0	1.609	2.398	3.178
(11) Stock Return	0.205	0.664	-0.611	-0.150	0.104	0.388	1.374
(12) Dividend	0.367	0.482	0	0	0	1	1
(13) SP500	0.107	0.309	0	0	0	0	1

3.4. Results

3.4.1. Baseline Results

This section examines the effect of algorithmic trading on firm value measured by Tobin' q. The baseline specification is:

$$Tobin's\ q = a + b\times Algo\ Trade + c\times Turnover \text{ (alternately, } Volume \text{ or } Dollar\ Volume\text{)}$$
$$+ d\times ROA + e\times Capex + f\times Size + g\times Leverage + h\times Analyst + j\times Return$$
$$+ k\times Return_{t-1} + l\times Dividend + m\times SP500 + \text{error term} \qquad (3.1)$$

where *Algo Trade* is the proxy for algorithmic trading intensity, *Turnover*, *Volume* (total trading volume), or *Dollar Volume* (total dollar volume) are controlled in separate specifications, respectively, and the control variables are as defined in the previous section.

We start the analysis by estimating Equation (3.1) as a panel regression with firm fixed effects. Although Equation (3.1) controls for a series of variables related to stock market and firm characteristics, it is possible that some unobservable firm characteristics may affect algorithmic trading activity and also correlate with firm value, and such omitted variables can bias estimation results of a simple ordinary least square regression. We use firm fixed effects to control for the unobservable firm characteristics that are constant over time. We also control for year and industry fixed effects to capture factors such as macroeconomic conditions and industry specific factors that may affect all firms. All standard errors are adjusted for clustering at the firm level.

The panel regression results are shown in Table 3.2. Models in Panel A controls for firm fixed effects only. For the three specifications that control for turnover, total trading

Table 3.2. Firm Fixed Effects Panel Regressions

The table reports estimates of panel regressions controlling for firm fixed effects. The dependent variable is Tobin's *q*. The independent variables include algorithmic trading proxy (Algo Trade), Turnover (model (1)), Volume (model (2)), Dollar Volume (model (3)), ROA, Capex, Firm Size, Leverage, Analyst, Stock Return, Lagged Stock Return (Lagged Return), Dividend, SP500, year dummies (Panel B), industry dummies (Panel B), and firm dummies. The industry classifications are defined by Fama and French (1997). Coefficients on year, industry, and firm dummies are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample. See Table 3.1 for variable definitions.

	Panel A			Panel B		
	(1)	(2)	(3)	(1)	(2)	(3)
Algo Trade	0.287	0.253	0.200	0.281	0.248	0.196
	(6.17)	(5.46)	(4.30)	(5.98)	(5.33)	(4.18)
Turnover	0.073			0.062		
	(9.25)			(7.97)		
Volume		0.060			0.050	
		(7.37)			(6.44)	
Dollar Volume			0.028			0.024
			(12.27)			(10.59)
ROA	-0.388	-0.373	-0.369	-0.288	-0.272	-0.272
	(-2.51)	(-2.40)	(-2.38)	(-1.92)	(-1.81)	(-1.81)
Capex	1.667	1.766	1.627	1.567	1.651	1.555
	(5.88)	(6.19)	(5.71)	(5.57)	(5.84)	(5.51)
Firm Size	-0.415	-0.403	-0.437	-0.579	-0.573	-0.594
	(-12.35)	(-11.94)	(-12.91)	(-16.01)	(-15.75)	(-16.36)
Leverage	-0.124	-0.125	-0.078	0.003	0.005	0.041
	(-1.07)	(-1.07)	(-0.67)	(0.03)	(0.05)	(0.37)
Analyst	0.362	0.389	0.395	0.372	0.395	0.401
	(13.45)	(14.30)	(14.58)	(14.26)	(15.07)	(15.31)
Stock Return	0.618	0.640	0.639	0.625	0.643	0.640
	(37.88)	(38.91)	(38.93)	(36.41)	(37.22)	(37.12)
Lagged Return	0.255	0.275	0.269	0.255	0.271	0.264
	(23.26)	(25.10)	(24.81)	(22.38)	(23.81)	(23.52)
Dividend	0.246	0.246	0.229	0.154	0.153	0.141
	(6.99)	(7.03)	(6.51)	(4.42)	(4.37)	(4.03)
SP500	0.214	0.105	-0.010	0.187	0.095	-0.003
	(2.88)	(1.45)	(-0.14)	(2.51)	(1.29)	(-0.04)
Year Dummy	No	No	No	Yes	Yes	Yes
Industry Dummy	No	No	No	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,123	20,123	20,123	20,123	20,123	20,123
Adjusted R^2	0.353	0.348	0.356	0.377	0.373	0.379

volume, and total dollar trading volume, respectively, the coefficients on *Algo Trade* are all positive and significant at the 1% level, implying that firms whose stocks have higher algorithmic trading activities have greater firm value. The effect of algorithmic trading on firm value is also economically significant. For example, based on the standard deviation of *Algo Trade* and the sample mean of Tobin's q, the coefficient on *Algo Trade* in model (1) implies that a one standard deviation increase in *Algo Trade* results in an increase in Tobin's q by 0.068, which is about 4.5% of its sample mean. The significantly positive effect of *Algo Trade* on Tobins' q remains largely unchanged when year and industry fixed effects are included, as shown in Panel B.

Most of the control variables are significantly related to Tobin's q. As expected, the coefficients on turnover (in model (1)), volume (in model (2)), or dollar volume (in model (3)) are significantly positive, and stock return and lagged stock return are positively related to firm value. Firm size has a significantly negative coefficient, implying that on average smaller firms have higher Tobin's q, which is consistent with the findings in Fang, Noe, and Tice (2009).[26] Capital expenditure is positively related to firm value, indicating that firms with more future growth opportunities are more highly valued. Leverage has an insignificant effect, and contrary to expectation, return on asset has a significantly negative effect. Analyst coverage has a significantly positive coefficient suggesting that analyst coverage may create attention and lead to higher firm valuation.

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[26] In this paper and in Fang, Noe, and Tice (2009), firm size is measured by book value of assets, which is negatively related to Tobin's q. Roll, Schwartz, and Subrahmanyam (2009) measure firm size by market capitalization, which is positively related to Tobin's q, and find a positive relation between Tobin's q and firm size.

Both the dividend dummy and the SP500 dummy have significantly positive coefficients. Dividend-paying firms may have higher valuation than non-dividend paying firms because they are less financially constrained (Fazzari, Hubbard, and Petersen (1988)) and have lower agency costs of free cash flow or overinvestment (Rozeff (1982); Easterbrook (1984); Jensen (1986)). S&P 500 firms may have higher value than non-S&P 500 firms because they have greater liquidity.

In summary, the results in this section indicate that algorithmic trading activity has a significantly positive impact on firm valuation after controlling for other variables related to firm value, as well as firm, industry and year fixed effects. The results are consistent with hypothesis H1.

3.4.2. Reverse Causality and Endogeneity

In this section we perform several analyses to address concerns about reverse causality and endogeneity.

3.4.2.1. Reverse Causality

The results shown in the previous sections reveal a strong positive relation between algorithmic trading activity and firm value. We next attempt to establish whether the effect is causal from algorithmic trading to firm value. It is possible that the causality runs in the opposite direction. The positive relation between algorithmic trading and firm value may occur if higher firm value attracts more algorithmic trading activity.

We address the reverse causality question using an exogenous shock to algorithmic trading activity, which is the NYSE automated quote dissemination in early 2003.

Autoquote was an important innovation for algorithmic traders. Specialists used to manually disseminate the inside quote, whereas with autoquote a new automated quote is generated immediately whenever there is a change to the NYSE limit order book. An automated quote update could provide more immediate feedback about the potential terms of trade and more critical new information to algorithms. Thus, this exogenous shock in market structure increases the amount of algorithmic trading and results in more electronic message traffic.[27,28] Hendershott, Jones, and Menkveld (2011) show that autoquote is positively correlated with their electronic message based algorithmic trading measure, and they use autoquote as an instrument for algorithimic trading.

We use the change in the normalized electronic message, *Algo Trade*, from before to after the NYSE autoquote dissemination as an instrument for algorithmic trading. We can establish a causal effect of algorithmic trading on firm value by showing that stocks with a larger increase in algorithmic trading activity following the autoquote dissemination have a larger increase in firm value. Since the automated quote was introduced between January and May of 2003, the change in algorithmic trading activity before and after this exogenous shock is measured as the difference in *Algo Trade* between 2002 and 2004.[29] Changes in Tobin's q and the control variables are calculated over the same time period. Taking the change over two years also allows Tobin's q to respond to

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[27] See Hendershott, Jones, and Menkveld (2011) for more discussion about the NYSE automated quote dissemination.
[28] The mean values of *Algo Trade* are -0.470 and -0.402 in 2002 and 2004, respectively, corresponding to 2.12 and 2.49 messages per trade in 2002 and 2004, respectively.
[29] For this test we only include firms with fiscal year ending month being May or later to make sure that *Algo Trade* in year 2004 is measured starting from June 2003, which is after the NYSE had completed automated quote for all stocks.

changes in algorithmic trading activity. Our approach is the same as that in Fang, Noe, and Tice (2009), who use decimalization in 2001, another change in market structure, as the exogenous shock to liquidity to establish causality from liquidity to firm value. Similarly, they take changes around the decimalization as from 2000 to 2002.

To test the causality from algorithmic trading to firm value, the change in *Tobin's q* is regressed on the change in *Algo Trade* and the changes in the control variables. The specification is:

$$\Delta Tobin's\ q = a + b\times\Delta Algo\ Trade + c\times\Delta Turnover \text{ (alternately, } \Delta Volume \text{ or } \Delta Dollar\ Volume) + d\times\Delta ROA + e\times\Delta Capex + f\times\Delta Size + g\times\Delta Leverage + h\times\Delta Analyst + j\times\Delta Return + k\times\Delta Return_{t-1} + l\times\Delta Dividend + m\times\Delta SP500 + \text{error term} \quad (3.2)$$

where Δ represents the change from 2002 to 2004. Equation (3.2) is estimated using ordinary least squares (OLS) procedures with industry fixed effects. As shown in Table 3.3, the coefficient on *ΔAlgo Trade* is positive and significant, indicating that an increase in algorithmic trading activity following the automated quote dissemination results in an increase in firm value. We conclude that the results are consistent with algorithmic trading activity having a causal effect on firm value.

3.4.2.2. Two-stage Least Squares Regressions

In the earlier section, we establish our baseline results using panel regressions and include firm fixed effects to control for omitted unobservables that are constant over time. If the omitted variables vary over time, firm fixed effects would not be sufficient to control for endogeneity. Thus, in this section, we use a two-stage least squares (2SLS) regression

Table 3.3. Reverse Causality Test: NYSE Stocks

The table reports estimates of regressions using changes in variables from 2002 to 2004. The dependent variable is ΔTobin's q. The independent variables include ΔAlgo Trade, ΔTurnover (model (1)), ΔVolume (model (2)), ΔDollar Volume (model (3)), ΔROA, ΔCapex, ΔFirm Size, ΔLeverage, ΔAnalyst, ΔStock Return, ΔLagged Return, ΔDividend, ΔSP500, and industry dummies. Δ represents change from 2002 to 2004. The industry classifications are defined by Fama and French (1997). Coefficients on industry dummies are not reported. T-statistics in parentheses are based on standard errors adjusted for heteroskedasticity. Only common stocks (those with a share code of 10 or 11 in the CRSP database) listed on NYSE are included in the sample. See Table 3.1 for variable definitions.

	(1)	(2)	(3)
ΔAlgo Trade	0.233	0.235	0.219
	(2.20)	(2.32)	(2.24)
ΔTurnover	0.001		
	(0.02)		
ΔVolume		0.004	
		(0.29)	
ΔDollar Volume			0.010
			(1.90)
ΔROA	1.682	1.675	1.577
	(3.19)	(3.25)	(3.10)
ΔCapex	1.533	1.530	1.497
	(3.31)	(3.28)	(3.22)
ΔFirm Size	-0.294	-0.297	-0.329
	(-4.96)	(-5.12)	(-5.51)
ΔLeverage	0.131	0.133	0.173
	(0.85)	(0.86)	(1.10)
ΔAnalyst	0.126	0.126	0.127
	(4.22)	(4.19)	(4.23)
ΔStock Return	0.261	0.262	0.265
	(6.16)	(5.85)	(6.07)
ΔLagged Return	0.139	0.139	0.132
	(6.84)	(6.73)	(6.84)
ΔDividend	0.139	0.139	0.132
	(2.59)	(2.59)	(2.49)
ΔSP500	-0.114	-0.113	-0.136
	(-0.63)	(-0.63)	(-0.74)
Industry Dummy	Yes	Yes	Yes
Observations	1,197	1,197	1,197
Adjusted R^2	0.332	0.332	0.339

Table 3.4. Two-stage Least Squares (2SLS) Regressions with Firm Fixed Effects

The table reports the second stage regression results of 2SLS regressions with firm fixed effects. In the first-stage regressions, Algo Trade is regressed on its first lag, an instrumental variable, IV_Algo Trade, and other control variables that are included in the baseline specification (Equation (3.1)). In the second-stage regressions, Tobin's q is regressed on the predicted value of Algo Trade, Pred_Algo Trade, and all control variables. Models (1), (2) and (3) control for Turnover, Volume, and Dollar Volume, respectively. Year, industry, and firm dummies are included but their coefficients are not reported. For firm *i*, IV_Algo Trade is the average value of Algo Trade of two firms in the same industry as firm *i* with the closest stock return volatility. If firm *i* is the most (lest) volatile firm in its industry, the second most (lest) volatile firm in its industry is selected to compute IV_Algo Trade. The industry classifications are defined by Fama and French (1997). See Table I for definitions of other variables. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. *p*-values of Hansen' J-tests are reported. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample.

	(1)	(2)	(3)
Pred_Algo Trade	1.688	2.073	1.969
	(6.21)	(6.78)	(6.62)
Turnover	0.086		
	(8.43)		
Volume		0.077	
		(7.91)	
Dollar Volume			0.024
			(10.31)
ROA	-0.216	-0.194	-0.201
	(-1.37)	(-1.22)	(-1.27)
Capex	1.838	1.932	1.864
	(5.53)	(5.72)	(5.54)
Firm Size	-0.715	-0.708	-0.713
	(-16.47)	(-16.05)	(-16.11)
Leverage	0.034	0.045	0.075
	(0.26)	(0.34)	(0.57)
Analyst	0.365	0.408	0.415
	(12.91)	(13.70)	(13.96)
Stock Return	0.628	0.658	0.655
	(35.28)	(36.02)	(35.70)
Lagged Return	0.263	0.287	0.281
	(20.18)	(22.09)	(21.86)
Dividend	0.138	0.142	0.130
	(3.80)	(3.81)	(3.50)
SP500	0.187	0.079	0.013
	(2.61)	(1.17)	(0.20)
Year Dummy	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes
Observations	15,292	15,292	15,292
Adjusted R^2	0.329	0.286	0.297
p-value of Hansen' J-Test	0.254	0.126	0.184

approach to attempt to further address endogeneity concerns. In this approach the unobservables do not have to be constant over time. We use the lag of *Algo Trade* and the average *Algo Trade* of two industry comparable firms with the closest stock return volatilities as the instruments. These instrumental variables are believed to be exogenous, i.e., they are correlated with current algorithmic trading activity but should not affect current firm value. In the first-stage regressions, *Algo Trade* is regressed on the instruments as well as all control variables in the baseline specifications. The second-stage regressions are the same as the baseline specifications shown in Table 3.2 except for *Algo Trade* being replaced by the predicted value from the first-stage regressions. Regressions in both stages control for year, industry and firm fixed effects.

In the first-stage regressions (results not tabulated), the coefficients on all instruments are significantly positive, indicating that the instruments are correlated with *Algo Trade*. Hansen's J-test statistics shown in Table 3.4 are insignificant with large *p*-values, suggesting that the instruments are uncorrelated with the errors of the second-stage equation. Therefore, the instruments are significantly correlated with *Algo Trade,* but they are uncorrelated with Tobin's q, which implies that they are valid. In the second-stage regressions as shown in Table 3.4, consistent with the results from the baseline specifications, coefficients on the predicted values of *Algo Trade* are positive and significant at 1% level, confirming a significantly positive effect of algorithmic trading on firm value.

In summary, the results of a positive impact of algorithmic trading activity on firm value shown in the baseline specifications are robust to concerns about reverse causality and the use of the two-stage least squares approach. The results are consistent with algorithmic trading activity having a causal effect on firm value.

3.4.3. Liquidity, Idiosyncratic Volatility, and Information

In this section, we present additional tests to explore channels through which algorithmic trading affects firm value. Our hypotheses are that algorithmic trading enhances firm value through improving capital market quality, such as increasing liquidity, reducing idiosyncratic volatility, contributing to price discovery and reducing information asymmetry. We do not directly test whether algorithmic trading affects market quality as that is established in prior studies. Instead, we test hypotheses that are implied by the channels, as developed in the Section 3.2.

3.4.3.1. Liquidity Channel

If algorithmic trading enhances firm value through increasing liquidity, its effect on firm value is expected to be stronger for firms with less liquid stocks, as stated in the hypothesis H2a. We employ two approaches to test this hypothesis. First, we include an interaction term in the firm fixed effects panel regression. The model specification is similar to Equation (3.1), with an additional term interacting *Algo Trade* with lagged Amihud illiquidity, *Algo Trade**$Amihud_{t-1}$, included at the right-hand side.[30] Year and industry fixed effects are controlled. The results are shown in Panel A of Table 3.5. The coefficient on *Algo Trade* remains significantly positive as before, and the coefficient on

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[30] Stock liquidity is measured by Amihud illiquidity (Amihud, 2002), *Amihud*, defined as the annual average of daily ratio of the absolute stock return to its dollar volume over the fiscal year (multiplied by 10^3).

Table 3.5. Test Liquidity and Volatility Hypotheses Using Firm Fixed Effects Regression

The table reports results of firm fixed effects panel regressions. The dependent variable is Tobin's *q*. The independent variables are the same as in Equitation (3.1), with an additional interaction term between Algo Trade and lagged Amihud illiquidity (Algo Trade*Amihud$_{t-1}$, Panel A) or lagged idiosyncratic volatility (Algo Trade*IVOL$_{t-1}$, Panel B) included. Models (1), (2) and (3) control for Turnover, Volume, and Dollar Volume, respectively. Amihud illiquidity is the annual average of daily ratio of the absolute stock return to its dollar volume (multiplied by 10^3). Idiosyncratic volatility is defined as the standard deviation of the residuals from fitting the four-factor model (Fama-French (1993) three factors plus the momentum factor) to daily returns over the fiscal year. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks are included in the sample. See Table 3.1 for variable definitions.

	Panel A: Liquidity			Panel B: Volatility		
	(1)	(2)	(3)	(1)	(2)	(3)
Algo Trade	0.303	0.265	0.208	0.086	0.070	0.032
	(6.10)	(5.38)	(4.19)	(1.36)	(1.13)	(0.51)
Algo Trade*Amihud$_{t-1}$	0.249	0.271	0.284			
	(3.23)	(3.37)	(3.42)			
Algo Trade*IVOL$_{t-1}$				5.103	4.576	4.127
				(4.03)	(3.69)	(3.36)
Turnover	0.064			0.067		
	(8.04)			(8.49)		
Volume		0.050			0.053	
		(6.48)			(6.77)	
Dollar Volume			0.024			0.025
			(10.59)			(10.71)
ROA	-0.280	-0.262	-0.260	-0.302	-0.283	-0.281
	(-1.84)	(-1.71)	(-1.71)	(-1.99)	(-1.86)	(-1.85)
Capex	1.636	1.736	1.633	1.523	1.615	1.522
	(5.65)	(5.96)	(5.62)	(5.43)	(5.72)	(5.40)
Firm Size	-0.588	-0.581	-0.603	-0.587	-0.580	-0.601
	(-15.91)	(-15.63)	(-16.24)	(-16.09)	(-15.81)	(-16.39)
Leverage	-0.018	-0.014	0.023	-0.001	0.002	0.038
	(-0.16)	(-0.12)	(0.21)	(-0.01)	(0.02)	(0.34)
Analyst	0.377	0.400	0.406	0.364	0.390	0.396
	(14.14)	(14.94)	(15.18)	(13.91)	(14.78)	(15.07)
Return	0.637	0.657	0.653	0.632	0.651	0.646
	(36.37)	(37.11)	(36.98)	(36.89)	(37.75)	(37.57)
Lagged Return	0.254	0.271	0.263	0.257	0.274	0.267
	(22.08)	(23.53)	(23.21)	(22.56)	(24.06)	(23.76)
Dividend	0.144	0.143	0.130	0.152	0.150	0.138
	(4.06)	(4.03)	(3.67)	(4.32)	(4.27)	(3.94)
SP500	0.191	0.097	-0.001	0.192	0.094	-0.003
	(2.55)	(1.32)	(-0.01)	(2.55)	(1.27)	(-0.03)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,464	19,464	19,464	19,975	19,975	19,975
Adjusted R^2	0.380	0.376	0.382	0.378	0.374	0.380

the interaction term is also positive and significant, suggesting that the positive effect of algorithmic trading on firm value is stronger for firms with less liquid stocks, consistent with the hypothesis H2a.

Secondly, we apply a block diagonal regression approach to test the hypothesis H2a. Specifically, we sort stocks into quintile groups each year based on lagged Amihud illiquidity, and define new algorithmic trading activity measures, *Algo Trade_n*, for each illiquidity group. In general, *Algo Trade_n* equals to *Algo Trade* for stocks in lagged illiquidity quintile *n* and zero otherwise, where *n*=1, 2, 3, 4, 5. For example, *Algo Trade_1* equals to *Algo Trade* for stocks in lagged illiquidity quintile 1 (lowest Amihud illiquidity quintile) and zero otherwise, and *Algo Trade_5* equals to *Algo Trade* for stocks in lagged illiquidity quintile 5 (highest Amihud illiquidity quintile) and zero otherwise. This approach allows the effect of algorithmic trading to vary across firms with different levels of liquidity in a nonlinear way. We estimate the following firm fixed effects panel regression:

$$\begin{aligned} \textit{Tobin's q} = {} & \mathrm{a} + \textstyle\sum_n \mathrm{b}_n \times \textit{Algo Trade\_n} + \mathrm{c}\times \textit{Turnover} \text{ (alternately, } \textit{Volume} \text{ or } \textit{Dollar} \\ & \textit{Volume}) + \mathrm{d}\times \textit{ROA} + \mathrm{e}\times \textit{Capex} + \mathrm{f}\times \textit{Size} + \mathrm{g}\times \textit{Leverage} + \mathrm{h}\times \textit{Analyst} \\ & + \mathrm{j}\times \textit{Return} \;\; \mathrm{k}\times \textit{Return}_{t-1} + \mathrm{l}\times \textit{Dividend} + \mathrm{m}\times \textit{SP500} + \text{error term} \end{aligned} \tag{3.3}$$

where *n* =1, 2, 3, 4, 5. With this specification, b_n captures the effect of *Algo Trade* on *Tobin's q* for firms in the *n*th illiquidity quintile. Testing the differences among b_n allows us to examine the (il)liquidity dependence of the algorithmic trading effect on firm value. Compared to the first approach that includes *Algo Trade* interacting with lagged Amihud illiquidity, the advantage of the specification in Equation (3.3) is that it allows for the effect of algorithmic trading on firm value to vary in a nonlinear way based on (il)liquidity.

Table 3.6 Panel A reports the estimation results of Equation (3.3) with year, industry, and firm fixed effects. Models (1), (2), and (3) control for turnover, volume, and dollar volume, respectively. For brevity, only estimates of b_n, the coefficients on *Algo Trade_n*, are reported. In general the effect of *Algo Trade* on *Tobin's q* is positive and significant, and increases with lagged illiquidity. When turnover is controlled, the coefficients on *Algo Trade_n*, b_n, are significant across all illiquidity quintiles, and increase when moving from low quintiles to high quintiles, with b_5 being significantly greater than b_1. The difference between b_5 and b_1 is also economically significant. A one standard deviation increase in *Algo Trade* for firms in the lowest illiquidity quintile (quintile 1) results in an increase in *Tobin's q* by 0.034 (0.143×0.238), while a one standard deviation increase in *Algo Trade* for firms in the highest illiquidity quintile (quintile 5) leads to an increase in *Tobin's q* by 0.070 (0.41×0.170), which is twice as large as that for firms in the lowest quintile.[31] The results are similar when volume or dollar volume is controlled, although b_1 and b_2 are not significant in model (3) when dollar volume is controlled. So, the effect of algorithmic trading on firm value is stronger for firms with less liquid stocks, consistent with the results from the first approach and supporting the hypothesis H2a.

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[31] The standard deviation of *Algo Trade* for firms in the lowest (highest) lagged illiquidity quintile is 0.238 (0.170).

The overall results of testing liquidity channel indicate that the effect of algorithmic trading on firm value is stronger when stocks are less liquid (or more illiquid), consistent with the notion that algorithmic trading enhances firm value through increasing liquidity.

Table 3.6. Firm Fixed Effects Regressions with Effect of Algo Trade on Tobin's q Varying Across Lagged Amihud Illiquidity or Lagged IVOL Quintiles

The table reports the estimates of coefficients on Algo Trade of firm fixed effects panel regressions with effect of Algo Trade on Tobin's q varying across quintile groups based on the lagged Amihud illiquidity (Panel A) or the lagged idiosyncratic volatility (IVOL) (Panel B). The model specification is shown in Equation (3.3). Amihud illiquidity is the annual average of daily ratio of the absolute stock return to its dollar volume. Idiosyncratic volatility is defined as the standard deviation of the residuals from fitting the four-factor model (Fama-French (1993) three factors plus the momentum factor) to daily returns over the fiscal year. All control variables are included but only coefficients on Algo Trade are reported. Models (1), (2), and (3) control for Turnover, Volume, and Dollar Volume, respectively. The industry classifications are defined by Fama and French (1997). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample. See Table 3.1 for variable definitions.

	Panel A: Lagged Amihud Illiquidity			Panel B: Lagged IVOL		
Quintile (n)	(1)	(2)	(3)	(1)	(2)	(3)
1 (Lowest)	0.143	0.116	0.072	0.195	0.191	0.169
	(2.43)	(1.99)	(1.25)	(3.65)	(3.60)	(3.21)
2	0.165	0.120	0.042	0.144	0.131	0.091
	(2.98)	(2.16)	(0.76)	(2.82)	(2.57)	(1.81)
3	0.220	0.178	0.102	0.164	0.136	0.089
	(4.08)	(3.32)	(1.91)	(3.11)	(2.61)	(1.72)
4	0.298	0.269	0.212	0.280	0.243	0.183
	(4.77)	(4.31)	(3.38)	(5.31)	(4.65)	(3.49)
5 (Highest)	0.410	0.383	0.358	0.422	0.369	0.300
	(6.07)	(5.73)	(5.29)	(6.59)	(5.78)	(4.68)
Control for	Turnover	Volume	Dollar volume	Turnover	Volume	Dollar volume
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,123	20,123	20,123	20,123	20,123	20,123
Adjusted R^2	0.378	0.374	0.381	0.378	0.374	0.380

3.4.3.2. Volatility Channel

If algorithmic trading enhances firm value through reducing idiosyncratic stock return volatility, its effect on firm value is expected to be stronger for firms with higher idiosyncratic stock return volatility, which is hypothesis H2b. We use idiosyncratic volatility (*IVOL*) to measure stock return volatility,[32] with *IVOL* defined as the standard deviation of the residuals from fitting the four-factor model (Fama-French (1993) three factors plus the momentum factor) to daily returns over the fiscal year.[33] To test the hypothesis H2b, we take the same approaches as in the previous section. First, we include an interaction term between *Algo Trade* and lagged *IVOL*, $IVOL_{t-1}$, in the firm fixed effects panel regressions. The results are shown in Panel B of Table 3.5. Although *Algo Trade* itself becomes insignificant, the interaction term is positive and significant at 1% level, suggesting that the effect of algorithmic trading on firm value is stronger when idiosyncratic volatility is higher, consistent with the hypothesis H2b.

We then apply a block-diagonal regression approach to test the hypothesis H2b and to allow for a nonlinear stock return volatility dependence of the effect of algorithmic trading on firm value. Stocks are sorted into quintile groups each year based on $IVOL_{t-1}$,

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[32] The results are qualitatively the same when we use volatility of raw daily returns over the fiscal year instead of idiosyncratic volatility.

[33] Our measure of IVOL is computed similarly to Ang et al. (2006). Fu (2009) shows that the negative relation between IVOL and expected return found by Ang et al. (2006) is driven mainly by return reversals of a subset of small stocks with high IVOL, and that the true relation should be positive. To ensure that our measure of IVOL is positively related to future returns, we perform a test using our sample. We form decile portfolios each year based on lagged IVOL, and compute return of each portfolio. Then we compute the time series average of portfolio returns. We find a positive relation between lagged IVOL and return. The portfolio return increases when moving from the lowest IVOL portfolio to the highest IVOL portfolio, with the return of the highest IVOL portfolio more than double that of the lowest IVOL portfolio.

and we define *Algo Trade_n* for each $IVOL_{t-1}$ quintile. We then estimate firm fixed effects panel regressions using the specification of the Equation (3.3) with year and industry fixed effects controlled. As shown in Panel B of Table 3.6, the coefficients on *Algo Trade_n* are positive and significant across all quintiles in all three specifications, and generally increase when moving from low to high $IVOL_{t-1}$ quintiles, consistent with hypothesis H2b. Moreover, the effect of algorithmic trading on firm value is nonlinearly dependent on idiosyncratic stock return volatility. Moving up from the lowest $IVOL_{t-1}$ quintile, the coefficient on *Algo Trade_n* decreases slightly initially and then increases, and it is significantly greater for the highest $IVOL_{t-1}$ quintile than for the lowest $IVOL_{t-1}$ quintile. For example, in model (1) with turnover controlled, the coefficient on *Algo Trade_n* drops from 0.195 at the quintile 1 (the lowest quintile) to 0.144 at the quintile 2, followed by gradual increasing to 0.422 at the quintile 5 (the highest quintile), with the largest increase occurring from the quintiles 4 to 5.

The overall results of testing the volatility channel indicate that the effect of algorithmic trading on firm value is stronger for firms with more volatile idiosyncratic stock returns. The results are consistent with algorithmic trading enhancing firm value through a reduction of idiosyncratic stock return volatility.

Table 3.7. Test Price Discovery and Information Asymmetry Hypotheses Using Firm Fixed Effects Regression

The table reports results of testing price discovery and information asymmetry hypotheses using firm fixed effects panel regressions. The dependent variable is Tobin's *q*. The independent variables are the same as in equitation (1), with an additional interaction term between Algo Trade and Analyst (analyst coverage) (Panel A) or PIN (information asymmetry) (Panel B) included. Models (1), (2) and (3) control for Turnover, Volume, and Dollar Volume, respectively. Coefficients on year, industry, and firm fixed effects are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks are included in the sample. See Table 3.1 for variable definitions.

	Panel A: Analyst Coverage			Panel B: Information Asymmetry		
	(1)	(2)	(3)	(1)	(2)	(3)
Algo Trade	0.151	0.072	0.061	-0.008	-0.155	-0.225
	(2.23)	(1.07)	(0.89)	(-0.08)	(-1.63)	(-2.37)
Algo Trade*Analyst	0.128	0.177	0.134			
	(3.00)	(4.12)	(3.18)			
Algo Trade*PIN				1.099	1.573	1.675
				(3.13)	(4.64)	(4.99)
Turnover	0.062			0.056		
	(7.91)			(6.45)		
Volume		0.052			0.044	
		(6.72)			(5.38)	
Dollar Volume			0.024			0.024
			(10.53)			(10.13)
ROA	-0.287	-0.272	-0.271	-0.270	-0.257	-0.257
	(-1.92)	(-1.81)	(-1.81)	(-1.77)	(-1.68)	(-1.68)
Capex	1.568	1.647	1.555	1.556	1.622	1.523
	(5.57)	(5.83)	(5.51)	(5.38)	(5.60)	(5.27)
Firm Size	-0.578	-0.572	-0.593	-0.595	-0.593	-0.618
	(-15.97)	(-15.74)	(-16.31)	(-16.06)	(-15.94)	(-16.63)
Leverage	0.010	0.015	0.049	0.236	0.237	0.285
	(0.09)	(0.14)	(0.43)	(2.35)	(2.35)	(2.81)
Analyst	0.432	0.477	0.462	0.368	0.384	0.387
	(14.73)	(15.97)	(15.66)	(13.87)	(14.42)	(14.58)
Stock Return	0.623	0.640	0.637	0.623	0.637	0.632
	(36.23)	(37.05)	(36.95)	(35.83)	(36.41)	(36.35)
Lagged Return	0.255	0.272	0.265	0.252	0.264	0.256
	(22.45)	(23.89)	(23.59)	(21.63)	(22.55)	(22.21)
Dividend	0.152	0.150	0.139	0.162	0.159	0.145
	(4.37)	(4.32)	(3.99)	(4.54)	(4.45)	(4.07)
SP500	0.190	0.097	0.001	0.202	0.118	0.017
	(2.57)	(1.34)	(0.01)	(2.50)	(1.48)	(0.21)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,123	20,123	20,123	19,460	19,460	19,460
Adjusted R^2	0.377	0.374	0.380	0.378	0.376	0.383

3.4.3.3. Price Discovery Channel

If algorithmic trading enhances firm value by contributing to price discovery due to the superior ability of computer algorithms to efficiently incorporate information into stock prices, the effect of algorithmic trading on firm value is expected to be stronger for firms with more publicly available information, such as firms with higher analyst coverage, as stated in the hypothesis H2c. To test this hypothesis, we follow the same approaches applied above for testing H2a (illiquidity) and H2b (IVOL). First, we include an interaction term between *Algo Trade* and analyst coverage, *Algo Trade*Analyst*, in the firm fixed effects panel regression. As shown in Panel A of Table 3.7, the interaction term has significantly positive coefficients, and *Algo Trade* itself has positive coefficients that are significant in model (1) and insignificant in models (2) and (3). The results imply that the positive effect of algorithmic trading on firm value is stronger for firms with higher analyst coverage, consistent with the hypothesis H2c.[34]

We then explore the potential nonlinear relation between the effect of algorithmic trading on firm value and analyst coverage. We sort stocks into quintile groups each year based on analyst coverage, define *Algo Trade_n* for each analyst coverage quintile, and estimate firm fixed effects panel regressions using the specification in Equation (3.3) with year and industry fixed effects.

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[34] Analyst coverage is positively related to institutional ownership, and *Algo Trade* may be a better proxy for algorithmic trading for stocks with higher institutional ownership. To mitigate the concern that the stronger effect of *Algo Trade* on firm value for stocks with higher analyst coverage merely reflects a better proxy of *Algo Trade* for algorithmic trading for stocks with higher institutional ownership, we additionally control for institutional ownership, and the results are unaffected qualitatively, with the coefficients on analyst coverage (*Analyst*) and the interaction term (*Algo Trade*Analyst*) being significantly positive.

Table 3.8. Firm Fixed Effects Regressions with Effect of Algo Trade on Tobin's q Varying Across Analyst Coverage or Information Asymmetry Quintiles

The table reports the estimates of coefficients on Algo Trade of firm fixed effects panel regressions with effect of Algo Trade on Tobin's q varying across quintile groups based on analyst coverage (Panel A) or information asymmetry measured by PIN (Panel B). The model specification is shown in Equation (3.3). All control variables are included but only coefficients on Algo Trade are reported. Models (1), (2) and (3) control for Turnover, Volume and Dollar Volume, respectively. The industry classifications are defined by Fama and French (1997). T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample. See Table 3.1 for variable definitions.

	Panel A: Analyst coverage			Panel B: Information Asymmetry		
Quintile (n)	(1)	(2)	(3)	(1)	(2)	(3)
1 (Lowest)	0.149	0.096	0.071	-0.088	-0.177	-0.225
	(2.10)	(1.36)	(0.99)	(-1.25)	(-2.58)	(-3.24)
2	0.441	0.404	0.353	0.042	-0.034	-0.098
	(6.56)	(6.00)	(5.22)	(0.67)	(-0.56)	(-1.60)
3	0.332	0.315	0.240	0.249	0.211	0.158
	(5.41)	(5.14)	(3.92)	(4.45)	(3.85)	(2.88)
4	0.340	0.330	0.241	0.367	0.361	0.324
	(5.24)	(5.07)	(3.73)	(6.04)	(5.95)	(5.31)
5 (Highest)	0.388	0.410	0.319	0.374	0.399	0.384
	(4.92)	(5.17)	(4.12)	(5.22)	(5.59)	(5.38)
Control for	Turnover	Volume	Dollar volume	Turnover	Volume	Dollar volume
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,123	20,123	20,123	19,443	19,443	19,443
Adjusted R^2	0.378	0.375	0.380	0.380	0.379	0.385

The results are in Table 3.8, Panel A. The coefficient estimates show that the primary difference in the firm value-algorithmic trading relation is between firms in the bottom analyst quintile and firms in the upper four analyst quintiles. Indeed, unreported tests show that the coefficients for the bottom analyst quintile are significantly smaller than coefficients for the upper four quintiles, and the coefficients *among* the upper four quintiles generally do not differ significantly from each other. Thus, the effect of *Algo*

Trade on firm value is stronger when analyst coverage is higher, consistent with the hypothesis H2c. The results are consistent with algorithmic trading contributing to price discovery and thus increasing firm value.

3.4.3.4. Information Asymmetry Channel

Our hypothesis H2d is that if algorithmic trading enhances firm value through efficiently incorporating information into stock prices and reducing information asymmetry, its effect on firm value is expected to be stronger for firms with greater information asymmetry. To test H2d, we use PIN (probability of informed trade) to measure information asymmetry,[35] and again apply the two approaches, the firm fixed effects panel regression including an interaction term, and the block diagonal regression approach. As shown in the Panel B of Table 3.7, the coefficient on the interaction term between *Algo Trade* and PIN is negative and significant at 1% level, while the coefficient on *Algo Trade* is insignificant or significantly negative (in model (3)), suggesting that the effect of algorithmic trading on firm value is stronger for firms with greater PIN, i.e., greater information asymmetry, consistent with the hypothesis H2d. The results from the block diagonal regressions shown in Panel B of Table 3.8 reveal more details about the information asymmetry dependence of the effect of algorithmic trading on firm value. Moving from the lowest to the highest PIN quintiles, the coefficient on *Algo Trade_n* increases monotonically. For the bottom two PIN quintiles, algorithmic trading has an

[35] PIN data is downloaded from Stephen Brown's website (http://www.rhsmith.umd.edu/faculty/sbrown/pinsdata.html). We thank Stephen Brown for making this data available. The PINs are computed using an extended EKO (Easley, Kiefer, and O'Hara (1997)) model and are more robust than the basic EKO PINs according to Brown and Hillegeist (2007).

insignificant or even negative effect on firm value (two of the three coefficients for the bottom quintile are significantly negative). For the top three PIN quintiles, the effect of algorithmic trading on firm value is significantly positive, consistent with the hypothesis H2d that effect of algorithmic trading is stronger for firms with greater information asymmetry. The results are consistent with algorithmic trading efficiently reducing information asymmetry and thereby enhancing firm value.

In summary, the results in this section are consistent with hypotheses that algorithmic trading increases firm value through increasing stock liquidity, reducing stock return volatility, contributing to price discovery, and reducing information asymmetry.

3.4.4. Additional Robustness Checks

The results in previous sections show that the finding of a positive effect of algorithmic trading on firm value is robust to the inclusion of year, and industry fixed effects, the control for reverse causality, and the use of 2SLS regression approach. This section performs additional robustness checks.

One issue is the non-normality and skewness of the distributions of several dependent and independent variables. Summary statistics reported in Table 3.1 show that *Tobin's q*, *Turnover*, *Volume*, and *Dollar Volume* are right skewed. To address this concern, we use a rank regression approach. All variables in Equation (3.1), except for the dummy variables, are ranked from low to high in the 0 to 100 scale, and the ranks, instead of the original value, of the variables are used in regression analysis. The model specification is the same as Equation (3.1).

Table 3.9. Robustness Check: Firm Fixed Effect Panel Rank Regressions

The table reports results of firm fixed effects panel rank regressions. All variables (except for the dummy variables) in Equation (3.1) are ranked from low to high in the 0 to 100 scale, and the ranks of the variables are used in regressions. The independent variables include Algo Trade, Turnover (model (1)), Volume (model (2)), Dollar Volume (model (3)), ROA, Capex, Firm Size, Leverage, Analyst, Stock Return, Lagged Stock Return (Lagged Return), Dividend, SP500, year dummies, industry dummies, and firm dummies. The industry classifications are defined by Fama and French (1997). Coefficients on year, industry, and firm dummies are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks (those with a share code of 10 or 11 in the CRSP database) are included in the sample. See Table 3.1 for variable definitions.

	(1)	(2)	(3)
Algo Trade	0.058	0.075	0.071
	(7.90)	(10.45)	(10.45)
Turnover	0.145		
	(15.87)		
Volume		0.292	
		(17.36)	
Dollar Volume			0.457
			(28.10)
ROA	0.134	0.134	0.107
	(14.49)	(14.67)	(12.37)
Capex	0.053	0.053	0.036
	(6.97)	(7.09)	(5.01)
Firm Size	-0.619	-0.682	-0.858
	(-19.22)	(-21.10)	(-26.66)
Leverage	-0.003	0.001	0.015
	(-0.35)	(0.13)	(1.89)
Analyst	0.139	0.132	0.087
	(13.08)	(12.40)	(8.56)
Stock Return	0.225	0.226	0.206
	(63.20)	(63.51)	(59.76)
Lagged Return	0.102	0.100	0.076
	(32.07)	(31.32)	(23.83)
Dividend	0.034	0.034	0.025
	(4.23)	(4.33)	(3.30)
SP500	0.023	0.015	0.021
	(1.99)	(1.34)	(1.83)
Year Dummy	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes
Observations	18,625	18,625	18,625
Adjusted R^2	0.484	0.489	0.526

Table 3.9 reports the estimation results of firm fixed effects panel rank regressions with year and industry dummies also controlled. In the three models that control for *Turnover*, *Volume*, and *Dollar Volume*, respectively, the coefficient on *Algo Trade* is positive and significant at 1% level. The results are consistent with algorithmic trading having a positive impact on firm value. Thus, the main result is robust to the use of rank regressions.

The second robustness check is using alternative proxy for algorithmic trading. In the analysis thus far, we follow Boehmer et al. (2012) to define an electronic message as either a trade or a change in BBO, and construct the proxy *Algo Trade* as the negative of number of trade normalized message. However, algorithmic traders may submit orders both inside and outside the quotes. So, alternatively, we consider updates of all quotes, not just the best quotes, as messages, and define a message as either a trade or a change in quotes. We then define the alternative proxy for algorithmic trading, *Algo Trade_q*, as the negative of number of trades divided by the number of messages that include the number of updates in quotes and the number of trades. Table 3.10 reports results of the firm fixed effects panel regression using *Algo Trade_q* to measure algorithmic trading activity. The coefficient on *Algo Trade_q* is positive and significant in all model specifications. Therefore, our results are robust to the use of an alternative proxy for algorithmic trading.

Our measures of algorithmic trading and stock returns are constructed over fiscal years and the firm characteristics variables are measured at the end of fiscal years. Asynchronous fiscal years undermine the usefulness of year fixed effects for controlling for macroeconomic conditions. To mitigate this concern, we perform a robustness check

Table 3.10. Robustness Check: Firm Fixed Effect Panel Regressions Using Alternative Proxy for Algorithmic Trading

The table reports estimates of firm fixed effect panel regressions using an alternative measure of message traffic to construct proxy for algorithmic trading. The dependent variable is Tobin's *q*. The main independent variable is *Algo Trade_q*, a proxy for algorithmic trading defined over firm *i*'s fiscal year as the negative of number of trades divided by the number of message that includes the number of changes in quote and the number of trades. Other independent variables are the same as in equitation (1). Models (1), (2) and (3) control for Turnover, Volume, and Dollar Volume, respectively. Coefficients on year, industry, and firm dummies are not reported. T-statistics in parentheses are adjusted for both heteroskedasticity and within correlation clustered by firm. The sample period is from 2002 through 2006. Only common stocks are included in the sample. See Table 3.1 for definitions of other variables.

	Panel A			Panel B		
	(1)	(2)	(3)	(1)	(2)	(3)
Algo Trade_q	1.318	1.325	1.333	0.918	0.893	0.939
	(13.98)	(14.08)	(14.29)	(8.05)	(7.88)	(8.34)
Turnover	0.070			0.063		
	(8.99)			(8.07)		
Volume		0.060			0.053	
		(7.35)			(6.62)	
Dollar Volume			0.029			0.026
			(12.71)			(11.32)
ROA	-0.367	-0.352	-0.346	-0.318	-0.301	-0.301
	(-2.43)	(-2.32)	(-2.29)	(-2.13)	(-2.01)	(-2.02)
Capex	1.806	1.898	1.752	1.634	1.713	1.606
	(6.37)	(6.68)	(6.19)	(5.78)	(6.03)	(5.68)
Firm Size	-0.505	-0.495	-0.531	-0.576	-0.570	-0.592
	(-14.71)	(-14.37)	(-15.40)	(-15.84)	(-15.62)	(-16.26)
Leverage	-0.099	-0.098	-0.046	-0.027	-0.023	0.017
	(-0.87)	(-0.85)	(-0.40)	(-0.25)	(-0.21)	(0.15)
Analyst	0.364	0.390	0.397	0.366	0.390	0.396
	(14.00)	(14.90)	(15.27)	(14.16)	(15.03)	(15.35)
Stock Return	0.598	0.618	0.617	0.622	0.641	0.637
	(36.60)	(37.69)	(37.75)	(36.31)	(37.21)	(37.12)
Lagged Return	0.235	0.254	0.247	0.250	0.267	0.258
	(21.85)	(23.63)	(23.29)	(22.02)	(23.50)	(23.14)
Dividend	0.196	0.197	0.178	0.160	0.158	0.146
	(5.74)	(5.76)	(5.20)	(4.61)	(4.56)	(4.21)
SP500	0.229	0.121	-0.000	0.209	0.112	0.006
	(3.04)	(1.65)	(-0.00)	(2.78)	(1.52)	(0.07)
Year Dummy	No	No	No	Yes	Yes	Yes
Industry Dummy	No	No	No	Yes	Yes	Yes
Firm Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,123	20,123	20,123	20,123	20,123	20,123
Adjusted R^2	0.370	0.366	0.375	0.379	0.376	0.383

by analyzing firm-fiscal year observations with fiscal year ends of December only. The results are qualitatively similar to those reported.

3.5. Conclusion

While algorithmic trading is criticized for creating excess volatility and destabilizing stock market, some evidence suggests that algorithmic trading positively impacts market quality by increasing liquidity, reducing idiosyncratic volatility, and contributing to price discovery. We contribute evidence to the debate by examining the effect of algorithmic trading activity on firm value.

Using an algorithmic trading proxy based on electronic message traffic, we find a significantly positive effect of algorithmic trading on firm value. The result is robust to controlling for other variables related to firm value, the use of various specifications, inclusion of year, industry and firm fixed effects, reverse causality, the use of 2SLS regression approach to address endogeneity, and the use of alternative proxy for algorithmic trading. The positive effect of algorithmic trading is stronger for firms with lower stock liquidity, higher idiosyncratic volatility, higher analyst coverage, and greater information asymmetry, consistent with hypotheses that algorithmic trading increases firm value through increasing liquidity, reducing volatility, contributing to price discovery and reducing information asymmetry. The overall results in this study suggest that algorithmic trading generates net benefits for firm value.

4. SUMMARY

This dissertation includes two essays in corporate finance, with the first essay studying the impact of local institutional shareholders on corporate debt maturity policies, and the second essay focusing on the effect of algorithmic trading on firm value.

The first essay examines the relation between the geographic proximity of a firm's institutional investors (shareholders) and the maturity structure of its debt. Monitoring by local institutional investors likely increases the intensity of debtholder-stockholder conflicts. Shorter debt maturity should reduce these conflicts and the associated debt agency costs. Local institutional investors may also pressure firms to employ short-term debt as a means of disciplining managers and thereby reducing equity agency costs stemming from manager-stockholder conflicts. Thus, we hypothesize that firms with local institutional investors choose shorter debt maturity structures.

Using dynamic system GMM estimators to account for endogeneity and dynamic relations between debt maturity structure and institutional proximity, we find that firms with local institutional investors have shorter maturity debt. Similar results obtain for the maturity of new debt issues. To help establish causality, we use Sarbanes-Oxley Act (SOX) as a quasi-natural experiment, conduct a nearest neighbor matching analysis that holds location constant, and employ a sample of firms' headquarter relocations as quasi-exogenous shocks to the locality of institutional investors. The results demonstrate the importance of local institutional investors in affecting firms' debt maturity policy choices.

Motivated by recent evidence that algorithmic trading impacts market quality, the second essay examines the effect of algorithmic trading on firm value. Given the significant role of algorithmic trading in the stock market, investors, academics, and policymakers need a deeper understanding of its benefits and costs. Prior literature that studies the impact of algorithmic trading on market quality provides mixed results on the question of whether algorithmic trading is a beneficial financial innovation, leaving it the subject of intense public debate and controversy. We contribute evidence that should be useful to the debate by examining the impact of algorithmic trading on firm value.

Using an algorithmic trading proxy based on electronic message traffic, we find a positive relation between algorithmic trading and firm value. The result is robust to controlling for other variables related to firm value, the use of various specifications, inclusion of year, industry and firm fixed effects, reverse causality, the use of 2SLS regression approach to address endogeneity, and the use of alternative proxy for algorithmic trading. The positive effect of algorithmic trading is stronger for firms with lower stock liquidity, higher idiosyncratic volatility, higher analyst coverage, and greater information asymmetry, consistent with hypotheses that algorithmic trading increases firm value through increasing liquidity, reducing volatility, contributing to price discovery and reducing information asymmetry. The overall results in this study suggest that algorithmic trading generates net benefits for firm value.

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