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Two Essays on Corporate and Institutional Investors' Usage of Options, Financial Constraints, and Firm Performance

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Abstract

This dissertation consists of two major parts. Essay I examines the relationship between the firm's derivative risk management and its financial constraint. Firms face a wedge between their internal and external financing for their investments. I test whether this wedge reduces the firm's financial constraint when it hedges using interest rate, foreign currency, and commodity derivatives. Using a difference-in-difference framework around the implementation of Financial Accounting Standard (FAS) 123R, this study shows a strong causal relationship between hedging intensity and the financial constraint. I find that net debt increases for the derivative hedging firms, on the other hand, cash holding and net equity issuance decreases. When managers of non-financial corporations believe that their firm will face a liquidity shortage in the future, they save more cash out of cash flow as a precautionary measure. Both cash flow-cash sensitivity and investment-cash flow sensitivity decrease. As a result of this decrease, undrawn bank lines of credit and total lines of credit increase. The analysis also shows that both the loan spread and the probability of covenant violation decrease after firms start derivative hedging. The main implication of the analysis is that the risk management influences the asymmetric information between lenders and borrowers: increase in risk management intensity, the less the asymmetry.

In Essay II , I propose a novel instrument %ΔEPCMPNIO, defined as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. %ΔEPCMPNIO predicts Earnings Announcements Abnormal Returns (EAR) and Standardized Unexpected Earnings (SUE) over the next quarter. This evidence suggests that institutional investors possess private information about individual securities. Moreover, this instrument shows a relation with many intuitive determinants, such as future stock returns and momentum. In all the cross-sectional return predictability regressions, %ΔEPCMPNIO dominates the

change in institutional investors' equities ownership (ΔEIO). In addition, this instrument subsumes all the option-based institutions' measures used in Lowry, Rossi, and Zhu (2019). Furthermore, I find strong evidence of a cross-sectional relationship between my measure and Generalized Probability of Informed Trading (GPIN). Additional tests reveal that the positive relation between %ΔEPCMPNIO and mean analyst forecast in the month prior to the fiscal quarter reflects that sophisticated investors have better knowledge about the factors related to forecast accuracy.

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Table of Contents

List of Tables

List of Figures

1 Essay I : Does effective financial derivative hedging reduce firms financial constraints?

1.1 Introduction

One of the important issues in corporate finance is the effect of cash flow volatility on the firm's capital structure decision. A higher variability of cash flow can restrict the firm's external finance and/or bank lines of credit. It can even revoke existing bank lines of credit or lead to technical defaults.[1] In addition, a growing literature suggests that a higher cash flow volatility negatively affects investment in advertising, capital expenditure, and R&D. Hence, due to various financial frictions, firms rely only on cash for immediate liquidity.[2] Disatnik, Duchin, and Schmidt (2013) suggest that cash flow derivative hedging has a first-order effect on the firm's liquidity choices, which in turn influences its value. Furthermore, in their model, cash flow hedging increases lines of credit and decreases the demand for precautionary cash holding. Therefore, due to the presence of various financial frictions, the firm should not determine liquidity choices in isolation.[3] Moreover as an ongoing entity, corporations simultaneous engagement of derivative hedging and liquidity, are optimal in an uncertain business environment (Tirole (2006)). On the practitioner side, Shimko (1997) states As risk managers, we spend much of our time examining the factors that cause cash flows to fluctuate. In a recent analysis, Giambona, Graham, Harvey, and Bod-

[1]Minton and Schrand (1999) show that a higher cash flow volatility is costly for firms external financing and overall investment. Sufi (2007) researched extensively that bank lines of credit, which acts as a precautionary measure for future liquidity depends on higher cash flows. Chava and Roberts (2008) provide evidence that firms having significantly lower cash flow proceed toward technical defaults, which is violations of financial covenants other than one requiring the payment of interest or principal.

[2]Acharya, Almeida, and Campello (2007) show that financially constrained firms that are in need of liquidity save more cash out of cash flow.

[3]"Besides liabilities and payouts, the potential for liquidity shortages also depends on income and its availability. ....Income availability also depends on income variability, which in turn can be decreased or increased by diversification choices and by corporate risk management." Tirole (2006), Chapter 5, Page 199

nar (2018), using survey data of the chief financial managers of firms around the globe, find that approximately ninety percent of managers pursue derivative hedging to increase expected cash flows. [4] A seminal study by Froot, Scharfstein, and Stein (1993) suggests that effective derivative hedging can help firms to lower down cash flow volatility, which in turn helps to reduce the under investment problem. Also, as concluded by Almeida, Campello, and Weisbach (2004) cash to cash flow sensitivity increases for financially constrained firms. The research on the interaction between firms derivative hedging and its financial constraints level is unavailable because of the lack of data.

The objective of this study is to show that effective derivative hedging can help relieve the firm's financial constraints.[5] This study identifies an exact mechanism through which hedging affects a firms financial constraint. Managers of non-financial corporations save more cash out of their cash-flow as a precautionary measure, when they believe that their firm may face a future liquidity shortage. This paper finds that when non-financial firms start hedging using derivatives, their cash holdings decrease, and their bank lines of credit and net debt ((total leverage cash)/assets) increase. The finding that an increase in net debt is due to a decrease in the loan spread, is consistent with that of Campello, Lin, Ma, and Zou (2011). Furthermore, I show that the probability of covenant violation decreases after the firm starts hedging. Hence, the firm builds an excellent reputation, which allow it to increase the debt component of its capital structure. In the seminal paper, Almeida et al. (2004), using a sample of manufacturing firms, conclude that the cash flow sensitivity of cash is positive for the financially constrained firms. A sample in this analysis shows a decreasing trend in cash to cash flow volatility and investment to cash flow sensitivity. On the other hand, when the firm stops derivative hedging, I find the opposite results. This paper is in the spirit of Erel, Jang, and Weisbach (2015). They find that acquisitions relieve the target firm's financial constraint by reducing its sensitivity of

[4]"Potential effect of cash flow volatility on our ability to execute our [Merck & Co.] strategic plan particularly, to make the investments in R&D that furnish the basis for future growth." - Lewent and Kearney (1990)

[5]Financially constrained firms may face higher wedge between its internal and external financing.

cash to cash flow as well as the sensitivity of investment to cash flow. Therefore, the research question raised in this study is, Does derivative hedging relieve firms financial constraint?

In his seminal study, Myers (1977) provides various theoretical solutions to resolve information asymmetry between creditors, borrowers, and investors. Further, in the pecking order theory, Myers and Majluf (1984) conclude that asymmetric information between the lenders and borrowers is a primary concern for the firm in pursuing the best investment opportunity. This early literature and other follow up empirical studies conclude that firms mainly rely on cash holdings rather than debt or equity issuance, when the managers information set tends to be different from that of the creditors and investors. Findings in this paper suggest that derivative hedging helps to reduce information asymmetry both ex-ante and ex-post between the managers and lenders. This paper suggests that net debt increases following the initiation of the risk management program. The channel through which a net debt increases ex-ante is the decrease in loan spread Campello et al. (2011) and reduction in the probability of violation of the existing technical covenants (Chava and Roberts (2008)). In addition, this study shows that the ex-post channel is the reduction in cash to cash flow volatility and investment to cash flow sensitivity for all firms and financially constrained firms sample, separately. On the other hand, I find that net equity issuance (measured following Leary and Roberts (2014)) decreases after the derivative hedging starts. Hence, this result suggests that derivative hedging does not help to reduce information asymmetry in the equity market.

The research question I address is crucial for finance scholars, policymakers, and practitioners alike. For empirical corporate finance academicians, this research may provide the base to investigate more real and financial issues related to financial constraint firm's hedging policy. Hedging can increase cash flow, which prevents firms from bypassing investments such as R&D, advertising, etc. In a cross-section analysis, Li (2011) concludes that an increase in R&D intensity generates abnormal return of 1.27% per month. Hence, asset-pricing scholars can extend this research in the view of derivative hedging. Moreover, Campello, Graham, and Harvey (2010) suggest that the increase in the levels of investment of financially constrained firms may improve the strength of future economic growth, which is one of the critical questions for policymakers. Risk managers can use this research to implement their hedging policy in the presence of various risk exposure to firm characteristics.

Corporate risk management data for all the U.S. firms is absent, which is the main reason that an empirical research on derivative hedging behavior of the financially constrained firms remains an open question. In derivative hedging literature, researchers considered either only big firms by asset size or only one industry to maintain a homogeneity of risk exposure and firm characteristics. Graham and Rogers (2002) find that hedging increases with firm size. Further, Géczy, Minton, and Schrand (2007) suggest that the economies of scale exist to start a risk management program because of the fixed cost associated with it. In addition, Bodnar, Hayt, and Marston (1998) conclude that big firms are better equipped to cover the derivative positions than small firms. Also, most of the proxies of financially constrained firms require the bottom three decile (or lower median) of the total sample of observations from an index such as the log of assets size, Kaplan and Zingales, Hadlock-Pierce index. Hence, the previous literature either fail to identify the financial constraint firms in their sample or have limited statistical power to explore the issue in their study (See Adam (2009)). In a seminal study of the real and financial implication of derivative hedging, Campello et al. (2011) analyze only a sample of 2718 firm-years in the 1996 to 2002 period. Similarly, in the present study, the sample period falls in the 1996 to 2016 period. On the other hand, Adam (2009), using a sample of the North American gold mining industry, shows that more financially constrained firms use collar strategies to hedge by selling calls and purchasing puts. Moreover, they find that the most financially constrained firms pursue hedging strategies to buy call options only. As a measure of financial constraint, Almeida et al. (2004) suggest small firms as one of the five proxies, which are more susceptible to capital market imperfection because typically they are young. Hence, to the best of my knowledge, this study is the first to investigate the effect of derivative hedging on the liquidity choices and investment of financial constraint firms.

While various hedging studies provide evidence that an optimal hedging increases firm value [e.g. Allayannis and Weston (2001), Pérez González and Yun (2013), and more], others (Guay and Kothari (2003), and Jin and Jorion (2006)) find a weak relationship between hedging and firm size for non-financial corporations. Recently, Campello et al. (2011) studied the effects of firms hedging policies on their financing and investment using the tax-based instrumental variable approach. They find that hedgers get favorable financing terms on debt issuance, which help them to avoid an under-investment problem. I provide direct evidence that hedging has a first-order impact on a firms financial constraint.

This study builds on prior research insights by focusing on the firms initiation of derivative usage to mitigate its financial constraints. Endogeneity is one of the biggest concerns cited in empirical corporate finance. The primary sources of endogeneity in this research are simultaneity and omitted variables. As derivative hedging implementation remains under a firms control, an endogeneity problem may also exist in this study. Also, Beatty, Petacchi, and Zhang (2012) find that hedging reduces agency cost of debt, which, in turn decreases interest rate charges. Hence, hedging and borrowing choices determine simultaneously. Moreover, to decrease simultaneity bias, I present all the results after the exclusion of the firm-year observation in the derivative hedging start year. This longitudinal setting follows Roberts and Whited (2013) suggestion to use fixed effect for partial removal of omitted variable bias. Hence, the omitted variable issue address with the help of firm, industry, and year fixed effects. This, in turn, helps to partially eliminate firm, industry, and year variation from the estimation.

Furthermore, to overcome an endogeneity issue, I use an event study approach that examines the firms two years before and three years after engagement in risk management using derivative instruments. As previous research suggests that firms' debt covenant requires to hedge using the interest rate derivatives. Hence, I exclude the first year of risk management establishment to avoid the simultaneity bias. In addition, I implement difference-in-differences analysis around the Financial Accounting Standard (FAS) 123R to show the consistency of results with that of the event study. Bakke, Mahmudi, Fernando, and Salas (2016) utilize the same regulation as a base to show causality between a decrease in executives option pay and an increase in hedging intensity in the oil and gas industry. They argue that the changes in compensation affect a managers risk-taking behavior. In short, when an incentive to smooth cash flow is high, managers engage in more derivative hedging. Similarly, the prediction in this study for financial constraints firms' is that when the hedging intensity increases, which results in a decrease in the cash holding, net equity issuance, cash to cash flow volatility, and investment to cash flow sensitivity. The question at hand requires the heterogeneous industry sample to distinguish a firm as a constrained or an unconstrained every year of the sample. On the other hand, the difference-in-differences methodology requires sample data on firms to have some homogeneity to interpret the causal effects of risk management for financial constraints firms.Hence, to match derivative users and non-users the primary requirement is either at the industry level or the level of risk exposure of the firm. The rationale is that the firms from the same industry may have similar risk exposure. Further, Leary and Roberts (2014) suggest that peer firms from the same industry possess identical capital structures. Therefore, when the debt level and/or investment of firms remain similar, this in turn suggests that their risk exposure also consists of some form of similarity.

Researchers have different prediction models of risk management for constrained firms. In their seminal study, Froot et al. (1993) predict that if a firm is financially constrained and faces non-linear risk exposure on its capital expenditure, then it should use option contracts for value maximization. On the other hand, Rampini and Viswanathan

(2010) model suggests that more collateral constrained firms should hedge less. Analysis in this paper finds an increasing trend of hedging by more constrained [6] firms in recent years using popular proxies of the financial constraint.

As data on risk management is not readily available, I parse the firms annual financial statements (10-K) for their derivative usage. To examine a decrease in a firms financial constraint, a study requires a sample of a firms' risk management data in order to perform event study, such as before and after hedging. This study follows an analysis of Erel et al. (2015) for a non-financial corporations sample of 7,980 firm-year observations of the data on financial variables available two years before and three years after the initiation of derivative hedging. Therefore, in this paper, I employ the event study approach to measure the firms liquidity choices and investment, in other words, to evaluate the extent to which the derivative usage led to improved access to capital.

I use most of the popular proxies of financial constraints in a particular firm before and after hedging to examine whether risk management can have a predictive effect on its growth. The vital measure utilized for the empirical analysis is the level of cash holdings at a firm if managers believe they may face more significant financial constraints in the future. Moreover, similar to Erel et al. (2015), I use the sensitivity of cash to cash flow and sensitivity of investment to cash flow as a dependent variable. Hence, I predict optimal risk management using various derivative instruments can decrease cash holding, the cash to cash flow, and the investment to cash flow sensitivity.

To perform a reliable test of hedging, one needs to identify correctly which firms hedge and which firms do not hedge. For those that do, the financial instrument to which firms hedge is vital to investigate the derivative risk management theories. The Statement of Financial Standards (SFAS) No. 105 [FASB 1990], effective from June 15, 1990, requires firms to report detailed information principally about financial instruments using an off-

[6] Financially constrained firms distinguish using proxies define in the finance literature such as the small firms, non-dividend payers, non-rated, collateral constrained, Kaplan-Zingales index, Whited-Wu index, Hadlock-Pierce index.

balance sheet detailing accounting gain or loss on risk management. Various earlier studies use survey data to examine the determinants of corporate hedging (Nance, Smith Jr, and Smithson (1993), Dolde (1995), Jalilvand (1999), Géczy et al. (2007)). In this study, researchers surveyed firms and asked respondents for their firms derivatives usage policy. With the increase in disclosure in financial statements such as 10-K, several authors perform text analysis on these reports for qualitative disclosures and define hedgers as firms whose reports included references to terms such as risk management or derivatives or hedging. Also, they reference various derivative instruments such as foreign currency derivatives or interest rate swaps (Mian (1996) and Géczy, Minton, and Schrand (1997)). I improved upon these data parsing techniques and consider if firms specifically mention the use of derivative for hedging purposes. This is important because a firm can hedge without derivatives such as foreign-denominated debt, which may act as a natural hedge of foreign revenue or purchase obligations. Hence, to the best of my knowledge, this is the first study which uses parsing techniques that considers hedging using derivative phrases for comprehensive research.

This essay contributes to the literature by documenting that small or financial constraint firms hedge using financial derivatives, which contradicts the widespread consensus that small firms do not use derivative instruments to hedge. [7] In addition, findings in this essay significantly contribute to corporate risk management literature by providing the positive causal effect of derivative hedging incentives on financial constraint firms.

The remainder of the paper proceeds as follows. Section 1.2 discusses the data sample and derivative parsing techniques. Section 1.3 summarizes all the main and control variables. Section 1.4 presents both event study and difference-in-differences methodology. Section 1.5 summarizes empirical results. Section 1.6 presents a detailed description and

[7]Previous research in corporate risk management only considers a sample of large firms in terms of asset size. Graham and Rogers (2002) state, “Hedging increases with firm size. This result is consistent with fixed costs limiting hedging by small firms, but not consistent with informational asymmetry leading to increased hedging". In addition, Campello et al. (2011) used parsed 10K statement sample from 1996 to 2002, and their analysis considered firms with a log of asset size 6.538. For the same period, firms with a lower end of median log of total assets is 4.387; that is, small firms also use financial derivatives for hedging purposes.

results of a quasi-natural experiment around FAS 123R regulation, and Section 1.7 concludes.

1.2 Data Sample and Derivative Parsing Techniques

1.2.1 Sample Selection

The main objective of this article is to take advantage of a firm's initiation of derivative hedging. In this research, I show that hedging affects the capital structure decision over time for a sample of the financial constraint firms. This study uses the non-financial and non-utility firms from the Compustat dataset on firm size, leverage, sales, investments, liquidity ratios, profitability, cash flows, cash flow volatility, and return on assets. As financial firms (SIC code 6,000 to 6,999) may have different motives and strategies about risk management because of their high debt levels. In the United States, utility firms (SIC code 4,900 to 4,949) are highly regulated, which in turn affects their derivative usage policy. To perform analysis consistent with prior literature, I exclude observations which have missing data on total assets. Also, in this article, Compustat datasets are used for the creation of a sample of financial constraint indexes such as Kaplan-Zingales, Hadlock-Pierce, and Whited-Wu index. Moreover, firms use private loans and lines of credit for future liquidity purposes to a great extent. For loans and bank lines of credit variables used in this study, I rely on Thomson Reuters DealScan data for the information about firms' borrowing decisions. Sufi (2007) provides detailed information on bank credit lines data for non-financial firms. Hence, the variables related to a loan are consistent with that of Sufi (2007).

1.2.2 Hedging Data Collection Process

In this analysis, the sample falls within the 1996 to 2016 time period. I collected the derivative usage data from all the 10-K, 10KSB, 10KSB40, 10-K405, and 10-KT SEC documents (hereafter filing) with the help of matching hedge strings such as we do use derivative for hedging, Company uses financial derivatives only to hedge, and the various similar phrase. The program first converts the whole document text into uppercase and removes all the HTML code. Also, the parsing algorithm maintains only one space between words by deleting all the additional spaces and tabs. These steps help to remove errors in the textual analysis process. Therefore, a program creates a derivative variable that is 1, if it finds a required phrase in a filing and 0 if the search term is not in the filing. When the document contains a derivative hedging phrase (such as when derivative=1), then a parsing algorithm searches for the usage of a specific derivative instrument to build a comprehensive firm-level risk management dataset. Hence, a program executes scrapping for the interest rate, currency, and commodity derivatives usage keywords. To check data consistency, I perform a manual reading on random samples of firm filings.

The filings download and the parsing algorithm builds using the R language software and extensively utilizes third-party libraries. While doing textual analysis, this program may be unable to recognize all the derivative user firms correctly. Therefore, the null hypothesis is that filing for a particular year does not use derivatives for hedging. This issue leads to a Type I error when the algorithm finds that the firm uses derivative hedging when it actually does not use it. That is the rejection of the null hypothesis. On the other hand, a Type II error generates when the algorithm finds that the firm does not use derivative hedging when it actually does use it. That is the acceptance of the null hypothesis.

For a Type I error, the algorithm searches for all the sentences in a document where the required string found related to the firms hedging. Hence, after this process the Type I error remains negligible. To resolve the Type II error, the text-analysis algorithm generates a file, which contains two lines before and after a search string position, similar to Sufi (2007). Then, another round of the textual analysis performed on a small sample of firms to resolve Type II errors by reading sentences around the required string.

After the creation of a derivative variable, further an algorithm search for a derivative instrument and store a complete sentence in a separate document. This step is useful to find the firms choice between linear and non-linear derivative contracts; that is when the firm uses Options, Swaps, Futures, or Forwards. Adam (2009), using the gold mining industry data, concludes that the most financially constrained firms use non-linear contracts, especially involve in selling calls. Hence, the selection of a derivative instrument is essential for firms with varying levels of risk exposure and a capital structure.

The notional value of a derivative usage is not consistent in the SEC EDGAR filings. To be consistent with the prior literature this study uses a binary variable of derivative hedging for all of its analysis. Further, the algorithm follows the S. Huang, Peyer, and Segal (2013) strategy to measure the increase in risk exposure and hedging intensity of a firm. The extent of market and non-market risk exposure created by counting the number of times derivative instruments mentioned in a filing. Therefore, to measure a hedging intensity and a risk exposure of a firm, I use log of (1+ number of times hedging instrument present in a filing) in all the analyses. This variable is different from a Campello et al. (2011) risk exposure variable creation, they used the "expos" and "market risk" keywords to measure interest rate or foreign exchange rate exposure to a firm. As this study considers inter-temporal increase in risk management activity, hence hedging intensity growth from the previous fiscal year to the current year provide more robustness for the results. Therefore, analysis suggests that the cash to cash flow volatility decreases when firms hedge using derivatives following increase in risk exposure of a firm.

1.3 Summary Statistics

To evaluate the effect of initiation of hedging on the firms financial constraints, I focus on its liquidity choices and insurance for future borrowing capacity, which are the bank lines of credit or revolving credit facility. Besides, the risk exposure of an individual and the combined derivative instrument examine the financial factors. Table 1.1 presents a summary statistics for the sample of total 7,980 firm-year observations from the 1,501 different firms use in this analysis. The average size (log of total assets) of firms in a sample is consistent with that of Campello et al. (2011), but in my sample the standard deviation is almost double that of previous studies. It is because in a recent period after 2011 small firms (bottom median sorted by total assets), around 23 percent of total non-financial firms also participate in derivative hedging. The statistics on all the financial variables present in Table 1.1 are consistent with previous research on non-financial firms. The sample size on the loans and lines of credit is less than other financial factors because DealScan data consists of selective observations on bank loans.

Around 40 percent of the firms use interest rate derivatives (IRD) for hedging in my sample, with the highest intensity of 1.45, amongst all three derivative instruments. The foreign exchange (FX) derivatives hedging with that of IRD is 1.68, especially for big and multinational firms. These firms manage fluctuation in their foreign sales with the help of a derivative instrument. More than 23 percent of the firms participate in FX hedging with or without the other strategies. All the results in Table 1.1 show consistency with that of previous seminal research (see Campello et al. (2011), Disatnik et al. (2013), Allayannis and Weston (2001), and others).

Table 1.2 presents the statistics of derivative hedgers and non-hedgers, individually and in combination with each other. The propensity to save the cash is higher among firms, who manage the risk than non-hedgers. These results are consistent with that of Campello et al. (2011) and Disatnik et al. (2013). Further, univariate results for an individual hedging instrument suggests that the IRD and the commodity hedgers save less cash than their non-hedger counterparts. On the other hand, the FX derivative users save more cash than their non-users counterparts. The cash flow and gross investment are higher for firms who manage their risk efficiently. The average investment of the commodity risk handling firms is 50 percent more than non-commodity hedgers. On average, in this studys sample, IRD and commodity hedgers also get better terms on their loans.

However, it is difficult to draw inferences from both the summary statistics table because endogeneity issue exists with derivative hedging within a firm. Secular trends, as well as the changing composition of firms in the sample, are likely to mask the incremental effect the hedging has on these variables. Hence, to evaluate the effect of hedging on firms financial policies, it is essential to hold firm composition constant over time and to control for other factors statistically.

1.4 Methodology

1.4.1 Event Study : Hedging Program Initiation

In this paper, the generalized version of the Erel et al. (2015) model, used extensively to show the effect of hedging initiation on various firms liquidity choices and their variants. In particular, I estimate the following specification:

$$\frac{Cash}{TotalAssets} = \alpha + \beta\, After\_Hedge + \gamma\, Controls + \epsilon \tag{1.1}$$

Where *After_Hedge* is a binary variable that takes a value of one after the hedging and a zero before risk management starts. The potential variation in this regression specification after adding the control variables are between firm, industry, and year. Hence, to remove this variation firm, industry, and year fixed effects included in equation 2.13, to estimate variables efficiently in a longitudinal setting. Also, to limit the effect of changing macroeconomic situations, I use nominal GDP (Gross Domestic Product) growth to price ratio, credit spread, and term spread. In all estimations, standard errors corrected for the clustering of observations at the firm level.

Moreover, firms do not start risk management operations in isolation. Beatty et al. (2012) argue that corporations pursue debt financing and risk management decisions simultaneously. Also, researchers argue that capital requirement is high as well as a bit more sophistication required to establish risk management strategies. Hence, simultaneity bias exist in the equation 2.13 specification, to address this issue, I exclude first year of hedging initiation in all regressions. Results are consistent even after excluding $year_t$ and keeping only $year_{t+1}$ & $year_{t+2}$ in all the specifications. The significance level increases in some regression specification where loan spread and probability of covenant violations are dependent variables. This results suggest that lenders prefer borrowers with the efficient risk management strategies in place.

In the empirical model of a Guay (1999) where impact of interest rate and foreign exchange rate hedging on firm's risk measured overtime. He showed that derivative usage can decrease firm's risk exposure. In addition, Donohoe (2015) use derivative initiation in a difference-in-differences setting to address omitted variable bias in the cross-sectional data with levels tests of derivative users and non-users. Following similar prior techniques in the hedging literature to address an endogeneity issue, I show that derivative program initiation can helps to decrease in financial constraints.

1.4.2 Difference-in-Differences Specification

Recently Bakke et al. (2016) used quasi-natural experiment created by the FAS 123R, to show a causal relation between the firm's risk management and chief executive officers (CEO) option pay. They conclude that when the corporations reduce a CEO's option pay, their propensity to hedge using derivative increases. I argue that increase in derivative hedging at the firm level help to relieve the firm's financial constraints. Therefore, I use a difference-in-differences (Diff-n-Diff) regression analysis around the FAS 123R compliance year i.e. fiscal year end 2005 (base year). To show the causality between firm's hedging intensity and their financial constraints. As firm's in a sample are heterogeneous in terms of industry, financial, and real measures. Hence, to reduce a bias caused by unobserved confounding factors, I use the nearest neighbor matching of the propensity scores with a replacement (see Becker and Ichino (2002)). In this matching technique all the treated units find at-least one match with the control group. The treated sample is the derivative users having increase in risk exposure from a previous fiscal year. The control sample is the non-derivative users even after increase in a risk exposure from a previous fiscal year. Both treated and control group of firms belongs to same two digit industry segment.

I estimate the following a Diff-n-Diff specification;

$$Dependent\ Variable_{i,t} = \alpha + \beta_1\, Hedge\_Deriv_i + \beta_2\, Post_t + \beta_3\, Hedge\_Deriv_i * Post_t + Controls_{i,t} + Firm\ FE_i + \epsilon_{i,t} \quad (1.2)$$

In equation 2.2.2, the main aim is to show the first order effect of derivative hedging on following dependent variables; cash-to-asset ratio, change in cash to asset minus cash ratio, change in investment to assets ratio, net debt to asset ratio, unused lines of credit. The value of treatment dummy $\mathrm{Hedge\_Deriv_i}$ is one when firms hedge using derivative only after increase in the overall risk exposure from a previous fiscal year, otherwise it's zero. The post event dummy $\mathrm{Post_t}$ is one for fiscal years 2005, 2006 and 2007, otherwise it's zero for fiscal years 2003 & 2004. The important estimate to provide a support for a financial constraints reduction hypothesis is the treatment dummy $\mathrm{Hedge\_Deriv_i}$ interacted with the post event dummy $\mathrm{Post_t}$.

1.5 Results

1.5.1 Effect of the derivative hedging initiation on cash to total assets

In Table 1.3 panel A, I attempt to show that the cash holding of all the firms in a sample decreases after they start a derivative hedging program. The seminal paper by Bates, Kahle, and Stulz (2009) suggests that the cash to asset ratio of non-financial U.S. firms increases from 10.5 in 1980 to 23.2 in 2006. The results are very striking in this study. I find that for the complete sample in all columns, cash to asset ratio significantly decreases by 0.7 to 1.2%, which is the coefficient on *After_Hedge* dummy variable (-0.007 to -0.012). In other words, the average value of a cash holding for the derivative users in Table 1.2, suggests that this decrease ranges on an average from 7.5 to 12.8 percent. This finding is consistent with and very close to that of Disatnik et al. (2013) and Erel et al. (2015). Also, Jensen (1986) predicts that firms with more significant agency problems save more cash in the absence of profitable investment opportunities. Without the control variables, the model in column 1 shows the adjusted R^2 of 0.039. With the inclusion of control variables such as total leverage (short and long term), tangibility, cash flow, and sales growth, column 4 shows the adjusted R^2 of 0.176. The result shows an almost five-fold increase in explanatory power. The most important control variables affecting cash holding of the firms are the total leverage and the tangibility. Both are negatively significant. The sign and significance level is consistent with previous literature in the same specification[8].

One of the agendas of this paper is to show that the cash holding of a financially constrained firms decrease after they start derivative hedging. Bates et al. (2009) argues that the cash to asset ratio increases dramatically for non-dividend payer firms in their sample period of 27 years, i.e. from 1980 to 2006. The empirical analysis time range of this study also coincides with that of the previous study. In the theoretical model, Jensen (1986) suggests that the firms' cash holdings increase when managers prefer not to distribute cash for dividends and also in the absence of good investment projects. Hence, this is also another reason to examine non-dividend payer firms and their average cash to asset ratio after derivative hedging. Findings in Table 1.3, panel B suggests that non-dividend payer firms save more cash out of cash flow than a complete sample of firms (Panel A),

[8] In Table IV. of Disatnik et al. (2013) infers that the cash flow hedging has an effect on firm's liquidity choices. Erel et al. (2015) in their cash-to-assets ratio as a dependent variable finds that total leverage is negatively significant.

when they start a hedging program. Besides, hedging literature argues that the cost of implementation of risk management strategies is high (see (Graham and Rogers (2002) and Bodnar et al. (1998))). Therefore, only big firms in terms of asset size can hedge effectively. In the seminal empirical study of corporate cash holdings, Opler, Pinkowitz, Stulz, and Williamson (1999) suggest that mostly financially unconstrained firms pay out more cash in the form of a dividend. Farre-Mensa and Ljungqvist (2016) shows that among the firms classified as constrained under the non-dividend payers, 86 percent are unrated. Furthermore, they show a higher correlation between non-dividend payer firms and that of the HP (Hadlock-Pierce) as well as WW (Whited-Wu) constraint indices. Hence, Table 1.3, panel B (column 5-8) presents the result for non-dividend payer firms. In this analysis, I exclude the first year of derivative implementation by all the firms, to address the endogeneity issue. The economical and statistical significance of the *After_Hedge* coefficient increases to a great extent for financially constrained firms. For these firms, the result suggests that the propensity to save cash out of cash flow decreases even if they do not pay a dividend. The non-dividend paying firms, over time after hedging initiation, save approximately 1.1 to 2.2 percent less cash out of cash flow.

1.5.2 Effect of the derivative hedging initiation on the lines of credit

This section examines how the other precautionary liquidity choices of a firm fare when the cash holding of corporations decreases at a statistically significant and economically important level. I show in Table 1.4, that after firms start risk management, their unused and total bank lines of credit increase (revolving credit facility) in the regression specification models (column 1-9). In a column 10, total bank lines of credit statistically insignificant with a positive sign on the coefficient with the inclusion of sales growth as a control variable in the model. The increase in available lines of credit varies between 4.3

and 5.2 percentage points. The result here suggests that derivative hedging helps firms to rely more on debt for their future investment, which in turn avails tax saving on interest expenses (See Graham and Rogers (2002)). Moreover, columns 6-9 suggests an increase in the total line of credit around 2.7 to 3 percent. These results are consistent with Disatnik et al. (2013), they find the positive significant line of credit for derivative users without firm and year fixed effects. In all the regression estimations I used similar fixed effects for removing the effect of between firm, industry, and year variations. The unused lines of credit for a sample of constrained firms before initiation of the hedging suggests that a coefficient on *After_Hedge* is positive in all specifications. However, these results are statistically and economically significant only for firms constrained by small firms and WW indices (see Table 1.7).

1.5.3 Effect of the derivative hedging initiation on net debt

The increase in bank lines of credit also gives rise to net debt over time after the implementation of hedging programs. The net debt is total firm debt minus cash, divided by total book assets. Bates et al. (2009) use a similar type of measure to show that for non-financial U.S. firms net debt shows a sharp decrease in their sample period. Results using the derivative hedging initiation show an opposite trend on net debt in this study. Moreover, Sufi (2007) provides extensive research on how bank lines of credit lead to an increase in total leverage. In Table 1.5, net debt shows significantly positive trends on *After_Hedge* in all the regression specifications. The coefficient on the before and after dummy suggests that the net debt increases by up to 1.3 percent, with the inclusion of control variables already used in finance and accounting literature. Hence, with the help of results in Tables 1.3, 1.4, and 1.5, I can infer that hedging helps to relieve agency problems in the capital market. The adjusted R^2 is 0.21 for the column 5 model specification, suggesting that addition of control variables improves regression fit. Results are consistent with the theoretical model of Mello and Parsons (2000); they hypothesized that the optimal hedge ratio depends on the firms financial constraints, which in turn helps the borrower to increase their debt capacity.

1.5.4 Effect of the derivative hedging initiation on net equity issuance

To explore more on the firms' liquidity choices after they start risk management, I examine the firms' equity issuance decisions in the view of derivative hedging. The striking results in Table 1.6, shows that after the initiation of a derivative hedging program firms' net equity issuance decreases on an average up to 2.6 percentage points. The theory behind these findings goes back to the seminal study on a firms corporate financing decision by Myers and Majluf (1984), well known as pecking order theory. Using their model, they suggest that, when the information asymmetry regarding a firms investment opportunity is higher, then corporations prefer debt financing instead of equity issuance. Results are consistent with the seminal study that firms rank debt higher over equity to finance their investment. In addition, empirical findings of Masulis and Korwar (1986), Asquith and Mullins Jr (1986), and Mikkelson and Partch (1986) conclude that following firms' equity issuance, stock prices show a sharp decline. The adjusted R^2 increases a bit when more control variables are added in the regression specification (Column 4). To the best of my knowledge, this is a first study, which shows a consistent negative effect of a firms' derivative hedging on equity issuance.

1.5.5 Effect of the derivative hedging initiation on cash to cash flow volatility and investment to cash flow sensitivity

Researchers and practitioners alike have argued unanimously that the main reason to hedge using the derivative is to decrease the cash flow volatility of a firm (See Bakke et al. (2016)). Furthermore, reduction in cash flow volatility increases the bank lines of credit observed by Sufi (2007) and others. Hence, this decrease helps to reduce information asymmetry between lenders and borrowers. In the financial constraint theory, Almeida et al. (2004) provide a theoretical framework in which the cash to cash flow sensitivity acts as a good measure of financial constraint. On the same line, Hankins (2011) finds that operational hedging sometimes substitutes financial hedging, which may also decrease cash flow volatility. In the specification similar to Erel et al. (2015), Table 1.7 (Column 1-4), suggests that cash to cash flow volatility decreases after initiation of a hedging program. The prediction is that, before the start of hedging at the firm level, cash flow volatility is higher. On the other hand, depending on the risk management effectiveness after hedging, cash flow volatility decreases. This behavior of the cash flow occurs because the firms manage uncertainty, in the same direction as that of the risk exposures on their debt and assets.

Moreover, to show that the cash flow volatility decreases after a derivative hedging initiation, following Almeida et al. (2004), I estimate an equation 2.13, with a dependent variable as the change in cash scaled by total assets including cash and the change in cash divided by total assets excluding cash. In order to calculate cash flow volatility after the hedging initiation, I interact cash flow divided by total assets with a dummy variable *(After_Hedge)* for after derivative hedge. The null hypothesis to test for the estimation of cash flow volatility using the Chow test is that summation of the coefficient on cash flow and a cash flow interacted with the *After_Hedge* dummy is zero and statistically significant. This Chow test estimation means that cash flow volatility after hedging does not change; in other words, derivative hedging has no effect on cash to cash flow volatility. The alternative hypothesis is that the coefficient on cash flow and cash flow interacted with *After_Hedge* dummy is not zero and statistically insignificant. The rejection of the null hypothesis means cash to cash flow volatility decreases following the risk management program at a firm level.

In Table 1.7, column 1, the coefficient on cash flow is positively significant, and the coefficient on cash flow interacted with *After_Hedge* is negatively significant. This opposite sign on the coefficient suggests that the cash flow variability changes after hedging. The summation of the cash flow and cash flow interacted with *After_Hedge* is not zero and is statistically insignificant. Therefore, I reject the null hypothesis because the result shows the opposite signs on the coefficient, and their addition is not statistically significant using the Chow test. Similarly, after the inclusion of leverage and sales growth in the same regression specification, results in column 2 suggest the rejection of the null hypothesis. The sign on cash flow coefficient before and after differ and the Chow test suggests that their sum of coefficient is statistically insignificant. The results are consistent with the prediction that the cash to cash flow volatility decreases after the initiation of derivative risk management.

Apart from cash to cash flow volatility, another widely debated measure of the firms financial constraint is the investment to cash flow sensitivity, and its usefulness argued by Fazzari, Hubbard, and Petersen (2000). The prediction in this view of derivative hedging is that a firms under investment problem may resolve after risk management starts. The one period theoretical model by Froot et al. (1993) and the multi-period model of Adam (2009) both suggest that derivative hedging can relive under investment problems up to a great extent. Campello et al. (2011) provide empirical evidence for an increase in a firms hedging intensity effect on its positive future investment growth only for big firms by asset size. In this study, the prediction is that hedging initiation decreases investment to cash flow sensitivity.

To estimate the degree of investment to cash flow volatility, a revised version of an equation 2.13 use with the dependent variable as a change in gross investment. The focus of estimation is on the cash flow and cash flow interacted with the *After_Hedge* dummy coefficient in columns 3 and 4 of Table 1.7. To simplify the interpretation and maintain consistency, I use the same procedure as that of cash to cash flow volatility, i.e. significance test of summation of coefficient on cash flow and interaction of cash flow with that of *After_Hedge*. The coefficient on cash flow is 0.168, significantly different from zero; this result suggests that firms are financially constrained before risk management starts. The coefficient on cash flow interacted with *After_Hedge* is significant at the 95 percent level, and value is -0.177. The negative sign on coefficient suggests that investment-cash flow sensitivity decreases after the use of derivative instruments starts at the firm level. The Chow test on the sum of both coefficients is insignificant; this result supports a research question that hedging relieves firms financial constraint by reducing investment to cash flow sensitivity. The estimates in column 4 using Chow test on cash flow and cash flow interacted with *After_Hedge* is also insignificant. Overall, results from Table 1.7 strongly suggest that hedging helps to decrease a firms financial constraint.

1.6 Quasi-natural experiment around FAS 123R regulation

The risk management literature points to two causes of endogeneity, firstly simultaneity between debt, investment, and hedging. Secondly, omitted variable bias because of unknown factors affect derivative hedging. Also, the single time-series difference panel specification in equation 2.13 can lead to a non-zero selection bias. This study resolves both endogeneity issues using the difference-in-differences methodology, which exploits the FAS 123R regulation enacted in the fiscal year 2005. Using the primary dependent variables in this analysis from Table 1.3 to 1.7, I show that cash holding decreases, net debt increases, cash to cash flow volatility as well as investment-cash flow sensitivity decreases. Also, consistent with results in Table 1.2 unused line of credit increases.

Table 1.8 shows an estimation of equation 2.2.2s specification with the response variable used in previous tables. The focus of this inquiry relies on a coefficient of *Hedge_Derv* * Post, which is a difference-in-differences coefficient. The increase in risk exposure with derivative instrument usage and non-usage is the first difference. Before and after implementation of FAS 123R rule is the second difference. This analysis also shows consistency with previous results, cash holding of firm decrease by 7 percent (same in Table 1.3, column1). In addition, the Chow test on the coefficients of cash flow and cash flow interacted with the post-2005 dummy suggests that cash to cash flow volatility decreases. Similarly, investment-cash flow sensitivity decreases after the hedging intensity increases in 2005. Results are also consistent with previous analysis on net debt, which increases about seven percentage points. The sign on the unused lines of credit is positive, consistent with Table 1.2 but insignificant. Moreover, gross investment increases for corporations when their hedging intensity increases after 2005.

To show consistent estimates for the financially constrained (non-dividend payer) firms' similar to that of Table 1.8, difference-in-differences methodology used. In Table 1.9 column 1, the cash holding to total assets decreases by 1.2 percentage points for non-dividend payer firms. Previous literature uses non-payout firms as a financially constrained sample (See Farre-Mensa and Ljungqvist (2016)). Further, the cash to cash flow volatility and the investment-cash flow sensitivity decreases suggests the Chow test for financially constrained firms. The net debt increases by 1.2 percent for non-dividend paying firms. The correlation between small and non-dividend payer corporations is 86 percent, who face higher levels of information asymmetry in capital markets. Hence, a rise in net debt suggests that an increase in hedging intensity helps to remove information asymmetry between borrowers and lenders. In addition, for financially constrained firms I find that gross investment increases after the rise of hedging intensity.

1.7 Probability of covenant violation and Loan Spread

The channel through which information asymmetry between the creditors and borrowers decreases is the reduction in the probability of covenant violation, which sends a clear signal about the credibility of the borrower (Watts and Zimmerman (1978) and Watts and Zimmerman (1986)). Recently, Demerjian and Owens (2016) suggest an aggregate probability of covenant violation measure to reduce an agency conflict. This increase in confidence gives better loan spreads on the new loan. Table 1.10 shows that aggregate probability decrease range is between -13.1 percent to -16.3 percent. This decrease is statistically significant.

The decrease in information asymmetry between lenders and borrowers observed in their covenant in the form of a loan spread. Campello et al. (2011) find that spread on loan decreases when hedging intensity increases; also, the number of covenant on future loan contracts is less. The results in Table 1.11 are consistent with previous literature. The loan spread decreases after the initiation of derivative risk management. A dependent variable here is the log of loan spread, the coefficient on *After_Hedge* is -0.127, negative and statistically significant in column 4, represents a 12.7 percent relative decrease in loan spread. This estimate is economically significant when average loan spread of derivative users in Table 1.2 is 146.09 basis points. Therefore, the in-sample results overall suggest that the hedging helps to get better contractual terms on loans, which in turn helps to reduce an under investment problem.

1.8 Placebo test matching on the industry one year before hedging starts

In this section robustness test shows consistency of all the previously estimated regressions using the matching sample of similar financial constraints firms from the same industry. A placebo test performs in Table 1.12 with the sample of corporations belongs to the small firms category with a mean log of total asset size 4.963, which is much lower than the average size of firms in this analysis (6.287). Estimation results also provide supporting evidence that the matched firms show enough homogeneity between analyzed firms to reduce changes in their financing behavior. The results in Table 1.12 show consistency for small firms matched on two-digit industry one year before they start hedging. The result of a matched sample suggests that cash holding to total assets decreases with a greater magnitude of -1.7 percent after they start hedging. The Chow test suggests that cash to cash flow sensitivity and investment cash flow volatility also reduce at a greater extent. Net debt increased by around 1.7 percent after the initiation of the hedging program for small firms. Also, results using the sample of only small a firm suggests that corporations get better contract terms on their loan, that is log of loan spread decreases by 9.7 percent relative to average loan spread. Overall, coefficients in Table 1.12 provide more robustness to the research question at hand for financially constrained corporations.

1.8.1 Small Firms

Prior studies including Opler, Pinkowitz, Stulz, and Williamson (2001) on corporate holdings of cash suggests that smaller firms tends to hold more cash as a percentage of total assets compare to larger firms. Also, small firms are more vulnerable to capital market imperfections because of the less analyst coverage and the institutional ownership, therefore they are unknown to the investors. Hence, small firms are more vulnerable to face higher borrowing cost (price constraint) and credit rationing (quantity constraint). In this paper, the firms belong to a bottom median of asset size considered as small firms, following the previous literature on financial constraints Almeida et al. (2004) and Hadlock and Pierce (2010). In addition, theoretically, Myers and Majluf (1984) argue that the firms with total asset size on lower-end show a higher degree of information asymmetry. Table 1.13 presents results consistent for supporting a research question that hedging helps to increase debt (2.01%) and decrease cash holding (1.4%). The widely used measure in a firm liquidity decision, cash to cash flow volatility, and investment-cash flow sensitivity both decrease, conclude using the Chow test. In other words, hedging at the firm level is one of the mechanisms to reduce information asymmetry in the capital market.

1.8.2 Kaplan and Zingales index

As prior research suggests that the small firms and financial constraints is not perfectly correlated. Another widely used measure of the financial constraints, suggested by Kaplan and Zingales (1997) (KZ index) makes it clear that all the firms face some form of the wedge between its internal and external cost of funds. To measure the level of a firm's financial constraints according to KZ index, I used method designed by Lamont, Polk, and Saaá-Requejo (2001)[9]. This index loads positively on leverage and Q & negatively on cash flow, leverage, and cash holding of a firm. To be consistent with previous literature, firms from the top median of KZ index ranking marked as the financially constrained, otherwise unconstrained, one year before the hedging program starts. The analysis in this section presents the effect of the risk management initiative on firms' financial constraints sorted by KZ index. The results are very much striking in Table 1.14. The firms cash holding (-0.5%), cash to cash flow volatility, and investment-cash flow sensitivity decrease significantly. Net debt (1%) and change in investment (3.4%) after hedging increases. Hence, financially constrained firms sorted using KZ index shows a decrease in a wedge between internal and external cost of funds after derivative hedging initiation.

1.8.3 Whited and Wu index

The synthetic specification of KZ index is widely criticized a presence of the Tobin's Q variable in its calculations. This Q shows great degree of measurement error (see Erickson and Whited (2000)). Instead of relying on the previous measures of financial friction in raising a new capital, Whited and Wu (2006) (famously WW index) construct a new specification to measure a firms financial constraint using the inter-temporal structural investment model. Hence, following the Hennessy and Whited (2007) estimation technique the WW index build and firms are grouped as a constrained (top median) or unconstrained

[9]Please refer an appendix A for the construction of KZ index.

(bottom median) a year before the derivative hedging initiation (see Appendix A) . The generalized method of moments estimation suggests that the firms falls in the financially constrained sample shows following characteristics; low analyst coverage, small, without bond rating, and under-invested. On the other hand, one of the most important reasons to pursue risk management is to reduce under investment. The findings in Table 1.15 suggest that firms fall in the top median of WW index saves less cash (-1.4%) out of cash flow, their net debt increases (2.2%), and bank lines of credit increase (20%). Also, the change in investment is economically positive, 3.6 percentage points, and statistically significant. Further, cash to cash flow volatility and investment-cash flow sensitivity decreases confirmed using the Chow test. Overall results in Table 1.15 find that the firms categorize as financially constrained shows significant decrease in information asymmetry between the lenders and the borrowers.

1.8.4 Hadlock and Pierce index

The essential factors to sort firms in a financial constraint sample are firm size and age, as suggested by Hadlock and Pierce (2010) (HP). They also provide an estimation of ordered logit on all the six variables included in WW index and suggests that three other variables such as sales growth, industry sales growth, dividend dummy has opposite signs and significance in their sample. In HP index, the age and size are negatively and size-square is positively loaded. Hence, I sort a complete sample and place firms in the upper median as financially constrained, otherwise unconstrained. When firms sorted by HP index, the estimation of equation 2.13 in this particular sample suggest consistency with prior regression analysis. Table 1.16 concludes that cash holding decreases (-1.1%), change in investment (+2.4%) and net debt (+2.2%) increases with high statistical significance.

1.8.5 Unrated Firms

Prior research in finance presents evidence that firms whose bond rating not present falls in financial constraint samples (See Whited and Wu (2006)). Firms without rating on their debt (non-rated) sample tested in the same specification as that of equation 2.13 and using previously analyzed variables in this paper. The results present in Table 1.17 suggest that even for unrated firms, cash to total asset ratio decreases by 1.5 percentage points. The cash to cash flow volatility and investment-cash flow sensitivity decrease significantly suggested by opposite sign-on cash flow and cash flow interacted with *After_Hedge* and summation of both the coefficients using the Chow test (in column 2-3). Net debt (2.3%) and change in investment (6.1%) increases at the economically and the statistically significant level.

1.8.6 Cash and Collateral Constrained Firms

Hahn and Lee (2009), in their model and empirical analysis on manufacturing firms, suggest that collateral constrained, highly leveraged firms show the higher wedge in investment financing. They also design two proxies for the firm's falls in the collateral constrained sample, one without total debt and another, including total debt. In addition, the third proxy, which consists of the total mortgage (variable) for its construction to test effect of total collateral constraint on various financial variables (see Appendix A). The Tables 1.18, 1.19, and 1.20 suggest that when firms sorted in collateral constraint sample starts hedging their investment increases. Besides, their cash to cash flow volatility and investment-cash flow sensitivity decreases. Overall, a piece of evidence from these three tables shows the results consistency with previous tables that hedging helps to relieve the firms financial constraint. These results have very high importance in a five and seven-factor asset pricing theory because of positive change in investment using risk management, which in turn can also have a positive effect on expected returns.

1.9 Effect of the derivative hedging stoppage

Previous research on corporate finance provides evidence that the Firm is an ongoing entity that changes its financing behavior overtime. Similarly, firms can change their risk management behavior during its life cycle. The analysis on a firms stoppage of derivative risk management may provide additional robustness for the effect of derivatives on a firms financing. Therefore, the sample firms who pursue a risk management initially and then stop for two years *(Stop_Hedge)* created to estimate firms financing and investment using following regression specification:

$$\frac{Cash}{TotalAssets} = \alpha + \beta\, Stop\_Hedge + \gamma\, Controls + \epsilon \tag{1.3}$$

The dependent variables used in equation 2.2.2 specification is the same as that of previous tables in this study, i.e., cash to total assets, net debt, gross investment. The sample size for bank lines of credit and loan spread is minimal; therefore, their analysis excluded in this section. The results of Table 1.21, especially on *(Stop_Hedge)* dummy (one after firms stop hedging and zero before stop), suggest that cash to total assets increases approximately around 2.2 percent significantly. When research and development control variables added in a regression specification (column 2) then cash holding increases by around 3.0 percentage points. On the other hand, net debt shows negative signs on *(Stop_Hedge)* coefficient (column 3) but is statistically insignificant. Column 4 shows negative significant results for net debt when firms stop using derivative hedging. These results suggest that firms save more cash to fund their investment when derivative hedging is not present in their risk management strategy. The last column suggests that gross investment decreases by around 19.9 percent points. This magnitude is enormous for the decrease in investment of firms additional, empirical tests required to provide causality for this result. Overall, a decrease in risk management using derivative hedging suggests that firms are going into financial constraints. Results in Table 1.21 show consistency with the research question that effective hedging reduces firms financial constraint.

1.10 Conclusion

In this paper, I argue that effective derivative hedging helps a firm to relieve financial constraints. To show that a firm may rely less on precautionary cash saving and more on external finance when loan spread is lower. The event study approach in the form of initiation of derivative hedging used in the longitudinal setting. To perform useful analysis the firms sorted into various financial constraint indexes one year before hedging and then examined their financial constraints levels. Results present in this study show the various channels through which wedge between external and internal financing decreases. Also, decrease in wedge can increases investment analyzes in great detail. This paper utilizes difference-in-differences methodology before and after the implementation of the FAS 123R rule to establish causality between firms' derivative risk management and liquid choices.

Findings in this paper contribute to the vast literature on risk management, financial constraint, and firms liquidity choices. This study using the sample from 1996 to 2016 period for the non-financial U.S. firms suggests that derivative hedging able to relieve the firms financial constraints. The endogeneity concern addressed using the difference-in-difference analysis and shows the causal effect of risk management on the firms financial constraints.

Using six different financially constrained indexes, a sub sample of firm-years observation creates before the firms start derivative hedging. Except for collateral constrained firms, all five indexes show that initiating risk management helps a firm reduce its cash holding and increase net debt. The collateral constrained firm shows the positive effect of hedging on change in investment. For all six collateral constrained indexes, cash to cash flow volatility and investment-cash flow sensitivity decreases. Overall, results in this paper conclude that derivative risk management reduces a firms financial constraint.

1.11 Appendix A. Variable Definition

Main firm level variables:	**Definition:**
Derivative (Yes=1)	Derivative is an indicator equal to 1 if a firm engage in hedging using derivative contract. The variable created by parsing firms financial statement (10-K) for their usage of derivative for hedging purpose. I read a text surrounding derivative keyword and code as one if combination of phrase suggests, we do use derivative for hedging purpose. Moreover, I crawl through financial statement to check usage of different derivative contracts such as Interest Rate (IR), Currency (FX), and Commodity derivative. I assign one for respective derivative contract if used by firm for risk hedging. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.
IR Hedging Dummy (Yes=1)	IR Hedging dummy set to 1 if firm manage interest rate risk using interest rate (IR) derivative contracts. I search for various derivative contracts use by firm such as IR swaps, IR forwards etc. in their financial statement for hedging purpose. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.

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FX Hedging Dummy (Yes=1)	FX Hedging dummy set to 1 if firm manage interest rate risk using foreign currency (FX) derivative contracts. I search for various derivative contracts use by firm such as FX options, FX forwards etc. in their financial statement for hedging purpose. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.
Comm. Hedging Dummy (Yes=1)	Comm. Hedging Dummy set to 1 if firm manage commodity price risk using commodity (Comm.) derivative contracts. I search for various derivative contracts use by firm such as Comm. options, Comm. forwards etc. in their financial statement for hedging purpose. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SICs 6000-6999). I use sample period 1996-2016.
GDP Growth	Annual percentage nominal growth of GDP in dollars.
Log of total assets/GDP	Log total assets divided by GDP is the logarithm of start of fiscal year total assets (COMPUSTAT item at) in year 2005 real dollars.
Cash/Assets	Cash is the ratio of cash and marketable securities (COMPUSTATs item che) to book assets (COMPUSTATs item at). The variable is winsorized at the 1st and 99th percentiles of its distributions. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.

Cash Flow Volatility	Cash Flow Volatility is a ratio of standard deviation of annual cash flows from operations (COMPUSTATs item oibdp) to the book assets (COMPUSTATs item at) of respective year over the four fiscal year. The variable is winsorized at the 1st and 99th percentiles of its distributions. I include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.
Investment Volatility	Investment Volatility is a ratio of standard deviation of annual cash flows from operations (COMPUSTATs item oibdp) to the book assets (COMPUSTATs item at) of respective year over the four fiscal year. The variable is winsorized at the 1st and 99th percentiles of its distributions. We include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SIC 6000-6999). I use sample period 1996-2016.
Leverage	Leverage is the ratio of long term total debt (COMPUSTATs item dltt) plus total debt in current liabilities (COMPUSTATs item dlc) to the total book assets (COMPUSTATs item at). The variable is winsorized at the 1st and 99th percentiles of its distributions. We include from our general COMPUSTAT sample firms with FIC ISO Country code of incorporation is USA, total assets larger than $1 million in every sample year and non-financial firms except (SICs 6000-6999). I use sample period 19962016.
M/B	M/B is the ration of market-to-book value of the firm. M is the market value, closing share price times common shares outstanding. B is the book value of common shareholders equity as of the end of fiscal year.

Net Debt	Leverage-cash/total assets
Net Equity Issuance	COMPUSTAT items [(dlttt+ dlct) - (dltt(t-1) + dlc(t-1))]/at(t-1)
Credit Spread	The difference between the yields of average BAA corporate bond and AAA corporate bond.
Nondividend payers	Nondividend payers is a binary variable represent one if firms do not pay dividend on a common stock otherwise zero (COMPUSTAT item dvc).
Dividend payers	Dividend payers is a binary variable represent one if firms pay dividend on a common stock otherwise zero (COMPUSTAT item dvc).
Unrated	Unrated firms is a binary variable represents one if do not have credit rating either from Moodys, Fitch, S&P, or Duff & Phelps otherwise zero, using data obtained from COMPUSTAT (COMPUSTAT item splticrm) .
Rated	Rated firms is a binary variable represents one if have a rating either from Moodys, Fitch, S&P, or Duff & Phelps otherwise zero, using data obtained from COMPUSTAT (variable splticrm) .
Tangibility	Tangibility is the net property, plant, and equipment(COMPUSTAT item ppent over total assets).

Continued on next page

KZ Index	KZ Index is computed as 1.001909 [(ib+dp)/lagged ppent] + 0.2826389 [(at + prcc_f*csho - ceq - txdb)/at] + 3.139193 [(dltt + dlc)/(dltt + dlc + seq)] 39.3678 [(dvc + dvp)/lagged ppent] 1.314759 [che/lagged ppent], where all variables in italics are Compustat data items. Following Lamont, Polk, and Saa-Requejo (2001), firms are sorted into median based on their index values in the previous year. Firms in the top median are coded as constrained and those in the bottom median are coded as unconstrained.
WW Index	WW Index is computed as 0.091 [(ib + dp)/at] 0.062 [indicator set to one if dvc + dvp is positive, and zero otherwise] + 0.021 [dltt/at] 0.044 [log(at)] + 0.102 [average industry sales growth, estimated separately for each three-digit SIC industry and each year, with sales growth defined as above] 0.035 [sales growth], where all variables in italics are COMPUSTAT data items. Following Hennessy and Whited (2007) and Whited and Wu (2006), firms are sorted into median based on their index values in the previous year. Firms in the top median are coded as constrained and those in the bottom median are coded as unconstrained.
HP Index	HP Index is computed as 0.737 Size + 0.043 Size^2 0.040 Age, where Size equals the log of inflation-adjusted COMPUSTAT item at (in 2005 dollars), and Age is the number of years the firm is listed with a non-missing stock price on COMPUSTAT. In calculating the index, I follow Hadlock and Pierce (2010) and cap Size at (the log of) $4.5 billion and Age at 37 years. Following a literature, firms are sorted into median based on their index values in the previous year. Firms in the top median are coded as constrained and those in the bottom median are coded as unconstrained.

1.12 Appendix B. Hedging Variables Information

To create corporation's derivative hedging usage data, I parsed 10-K filings and their amendments for keywords related to interest rate, foreign currency, and commodity derivatives. Every sentence where risk management keywords available analyzed carefully to find when firm mention their usage of derivative instruments for hedging purposes. In every sentence purpose of derivative engagement for risk management separately parse using R software libraries (i.e. hedging or speculation). If I find usage of derivative for the purpose of hedging only in the presence of risk exposure. Then, following Manconi, Massa, and Zhang (2017) search sentences for interest rate and foreign currency derivative exposure and its instruments. Also, for commodity derivatives traded contracts, I use table C of Almeida, Hankins, and Williams (2017). The keywords use in textual analysis of financial statement for risk management data presents in following table. In addition, similar to S. Huang et al. (2013) risk exposure calculation method, I use number of times hedging instrument present in a financial statement in the particular year. If firms mentioned that they use derivative for hedging purposes.

Main firms level variables:	**Definition:**
Interest rate derivative (IRD)	"INTEREST RATE SWAP, INTEREST RATE CAP, INTEREST RATE COLLAR, INTEREST RATE FLOOR, INTEREST RATE FORWARD, INTEREST RATE OPTION, AND INTEREST RATE FUTURES
Foreign Currency Derivative (FX)	CURRENCY RATE FUTURE, FOREIGN EXCHANGE SWAP, CURRENCY SWAP, FOREIGN EXCHANGE RATE SWAP, CURRENCY RATE SWAP, FOREIGN EXCHANGE CAP, CURRENCY CAP, CURRENCY FORWARD, CURRENCY RATE FORWARD, FOREIGN EXCHANGE OPTION, CURRENCY OPTION, FOREIGN EXCHANGE RATE CAP, CURRENCY RATE CAP, FOREIGN EXCHANGE COLLAR, CURRENCY COLLAR, FOREIGN EXCHANGE RATE COLLAR, CURRENCY RATE COLLAR, FOREIGN EXCHANGE FLOOR, CURRENCY FLOOR, FOREIGN EXCHANGE RATE FLOOR, AND CURRENCY RATE FLOOR FOREIGN EXCHANGE FORWARD, FORWARD FOREIGN EXCHANGE, FOREIGN EXCHANGE RATE FORWARD, FOREIGN EXCHANGE RATE OPTION, CURRENCY RATE OPTION, FOREIGN EXCHANGE FUTURE, CURRENCY FUTURE, FOREIGN EXCHANGE RATE FUTURE.
Commodity Derivative	COMMODITY FORWARDS, COMMODITY OPTIONS, AND COMMODITY FUTURES,SOYBEANS CONTRACTS, OILSEEDS CONTRACTS, WHEAT CONTRACTS, CORN CONTRACTS, RICE CONTRACTS, COTTON CONTRACTS, SUGAR BEETS CONTRACTS, CATTLE CONTRACTS, SWINE CONTRACTS, SHEEP AND WOOL CONTRACTS, CRUDE PETROLEUM AND NATURAL GAS CONTRACTS, LIQUID NATURAL GAS CONTRACTS, COAL CONTRACTS, ANTHRACITE COAL CONTRACTS, GOLD ORES CONTRACTS, SILVER ORES CONTRACTS, LEAD AND ZINC ORES CONTRACTS, PETROLEUM REFINERY PRODUCTS CONTRACTS, IRON AND STEEL MILLS CONTRACTS, and others.

Table 1.1: **Summary Statistics**
This table reports summary statistics of firm-year observations for the financial, derivative hedging, and macroeconomic variables used in an all the event study analysis. The sample of firms are all non-financial firms in the annual Compustat database between 1996 and 2016. For the variable definition and creation (see Appendix A). The entire continuous firm financial factor variables winsorized at the 1st and 99th percentile.

	N	Average	SD	Min.	Max.
Firm Financial Factors					
Size	7980	6.287	1.686	2.62	10.376
Cash/Assets	7978	0.149	0.175	0	0.993
Net Debt/ Assets	7955	-0.149	0.175	-0.776	0.002
Cash Flow (CF)	7873	0.616	0.456	0.027	2.244
Leverage	7955	0.239	0.21	0	0.941
Tangibility	7963	0.298	0.242	0.007	0.904
Sale growth	5614	-2.121	1.22	-9.7	0.52
Gross Investment	7873	0.616	0.456	0.027	2.244
Div. and Rep.	7297	0.04	0.115	0	4.427
Unused Line of Credit	1126	0.402	0.341	0.001	1
Loan Spread (all in Spread drawn)	1192	181.063	115.784	14.803	573.376
Total Line of Credit	1117	0.634	0.336	0.005	1
Altman z	7566	1.444	2.333	-11.497	5.364
Firm Derivative Hedging Information					
Derivative Hedging Dummy	7980	0.600	0.490	0	1
Derivative Hedging Intensity	4640	1.450	1.270	0	4.810
IRD Hedging Dummy	7980	0.400	0.490	0	1
IRD Hedging Intensity	3096	1.240	1.230	0	4.730
FX Hedging Dummy	7980	0.230	0.420	0	1
FX Hedging Intensity	1832	1.030	1.160	0	4.370
Commodity Hedging Dummy	7980	0.110	0.310	0	1
Commodity Hedging Intensity	839	0.480	0.870	0	4.780
IRD * FX Dummy	7980	0.080	0.270	0	1
IRD * FX Intensity	634	1.680	2.960	0	16.140
IRD * Commodity Dummy	7980	0.050	0.210	0	1
IRD * Commodity Intensity	386	0.880	1.860	0	8.970
FX * Commodity Dummy	7980	0.030	0.180	0	1
FX * Commodity Intensity	275	0.820	2.280	0	15.760
IRD * FX * Commodity Dummy	7980	0.020	0.140	0	1
IRD * FX * Commodity Intensity	168	1.680	5.290	0	30.510
Macroeconomic Variable					
GDP/Price	7909	4.572	0.219	4.125	4.958
Credit Spread	6738	1.065	0.339	0.69	1.978
Term Spread	6738	0.759	0.593	-0.387	1.815

Table 1.2: **Summary Statistics on the Financial Variables of the Hedgers and Non-Hedgers**
This table reports averages of all the financial variable of derivative hedgers and non-hedgers, including IRD, FX, and Commodity hedging. The sample of all non-financial firms in the annual Compustat database between 1996 and 2016 with non-missing data for all analysis variables (see Appendix A).

Financial Variables	Derivative Hedging		IRD Hedging		FX Hedging		Commodity Hedging	
	Non-User	User	Non-User	User	Non-User	User	Non-User	User
Size	7.197	7.392	7.126	7.546	7.293	7.386	7.296	7.399
Cash/Assets	0.098	0.094	0.101	0.089	0.094	0.103	0.099	0.072
Net Debt/ Assets	-0.097	-0.094	-0.1	-0.089	-0.094	-0.102	-0.099	-0.071
Cash Flow (CF)	0.09	0.094	0.091	0.094	0.093	0.089	0.094	0.083
Leverage	0.236	0.252	0.234	0.26	0.248	0.232	0.238	0.293
Tangibility	0.298	0.333	0.303	0.337	0.322	0.301	0.294	0.471
Sale growth	-2.062	-2.443	-2.124	-2.488	-2.235	-2.489	-2.277	-2.321
Gross Investment	0.611	0.684	0.625	0.691	0.664	0.609	0.613	0.914
Div. and Rep.	0.045	0.034	0.042	0.035	0.04	0.035	0.041	0.024
Unused Line of Credit	0.356	0.345	0.371	0.322	0.349	0.352	0.344	0.382
Loan Spread (all in spread drawn)	157.3	146.098	158.886	140.429	150.07	153.863	152.196	141.832
Total Line of Credit	0.612	0.57	0.617	0.55	0.593	0.565	0.586	0.603
Altman z	2.104	2.126	2.126	2.105	2.111	2.14	2.16	1.839

Table 1.3: **The effects of initiation of hedging using financial derivative on firms cash holdings**
This table reports coefficients estimated from regression of level of cash holding (dependent variable) before and after derivative hedging represented in equation (1). AFTER is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Total Sample				Panel B. Non-Dividend Payers and Excluding First Year of Hedging			
After_Hedge	-0.007*	-0.006*	-0.007**	-0.012***	-0.011**	-0.010*	-0.011**	-0.022***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)
Size	-0.018**	-0.022***	-0.020***	(0.014)	-0.020**	-0.022**	-0.022**	(0.012)
	(0.008)	(0.008)	(0.008)	(0.012)	(0.010)	(0.010)	(0.010)	(0.016)
Cash Flow		0.022***		0.004		0.019***		(0.021)
		(0.005)		(0.028)		(0.006)		(0.062)
ROA			0.021***				0.020***	
			(0.005)				(0.006)	
Leverage				-0.069***				-0.058*
				(0.022)				(0.030)
Tangibility				-0.527***				-0.548***
				(0.042)				(0.058)
Sale Growth				-0.003*				-0.002
				(0.001)				(0.003)
GDP/Price	8.450***	8.495***	8.654***	0.823***	0.091*	0.085*	0.090*	0.060
	(0.142)	(0.136)	(0.150)	(0.215)	(0.047)	(0.049)	(0.047)	(0.082)

Table 1.3 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Total Sample				Panel B. Non-Dividend Payers and Excluding First Year of Hedging			
Credit Spread	0.081***	0.082***	0.082***	-0.021	-0.051**	-0.041*	-0.052**	-0.018
	(0.012)	(0.011)	(0.011)	(0.029)	(0.025)	(0.025)	(0.025)	(0.034)
Term Spread	-0.862***	-0.868***	-0.890***	-0.018	0.032*	0.031*	0.030*	0.043
	(0.024)	(0.023)	(0.025)	(0.023)	(0.018)	(0.018)	(0.018)	(0.029)
Constant	-41.436***	-41.646***	-42.427***	-3.641***	-0.102	-0.085	-0.087	0.111
	(0.686)	(0.657)	(0.719)	(1.075)	(0.185)	(0.195)	(0.186)	(0.305)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6736	6262	6722	4409	3554	3243	3545	2251
adj. R2	0.039	0.05	0.044	0.176	0.028	0.029	0.032	0.154

Table 1.4: **The effects of initiation of hedging using financial derivative on firms unused and total line of credit**
This table reports coefficients estimated from regression of unused line of credit (Panel A) and total line of credit (Panel B) on before and after derivative hedging represented in equation (1). AFTER is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. Unused Line of Credit (Dependent Variable)					**Panel B. Total Line of Credit (Dependent Variable)**				
After_Hedge	0.048***	0.052**	0.046**	0.052**	0.043*	0.030**	0.028**	0.027*	0.028**	0.018
	(0.022)	(0.022)	(0.023)	(0.022)	(0.024)	(0.014)	(0.014)	(0.014)	(0.013)	(0.023)
Size	-0.087***	-0.084***	-0.089***	-0.084***	-0.152***	-0.112***	-0.100***	-0.112***	-0.104***	-0.121***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.036)	(0.028)	(0.029)	(0.028)	(0.030)	(0.033)
Cash Flow		-0.213		-0.11	0.13		-0.144		0.007	0.122
		(0.163)		(0.169)	(0.318)		(0.133)		(0.153)	(0.231)
ROA			-0.468**					-0.420***		
			(0.208)					(0.159)		
Leverage				0.197	0.330**				0.289***	0.263**
				(0.142)	(0.141)				(0.104)	(0.120)
Tangibility				0.444**	0.562***				0.534***	0.516***
				(0.184)	(0.197)				(0.144)	(0.169)
Sale growth					-0.002					-0.009
					(0.009)					(0.008)

Table 1.4 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. Unused Line of Credit (Dependent Variable)					**Panel B. Total Line of Credit (Dependent Variable)**				
Gdp/Price	-0.601	2.203***	-2.054***	2.031***	-0.319**	-5.812***	1.027***	-7.103***	0.876***	-0.309***
	(0.601)	(0.332)	(0.793)	(0.346)	(0.134)	(0.482)	(0.220)	(0.678)	(0.211)	(0.080)
Credit Spread	0.226***	0.167***	0.282***	0.166***	0.311**	0.271***	0.131***	0.320***	0.135***	0.152
	(0.012)	(0.017)	(0.028)	(0.019)	(0.133)	(0.009)	(0.012)	(0.022)	(0.013)	(0.096)
Term Spread	0.336***	-0.129***	0.616***	-0.109***	-0.008	1.064***	-0.081***	1.312***	-0.057***	0.006
	(0.072)	(0.025)	(0.130)	(0.026)	(0.080)	(0.061)	(0.009)	(0.113)	(0.011)	(0.052)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.318	-9.995***	10.253***	-9.373***	2.411***	28.681***	-3.852***	34.820***	-3.332***	2.528***
	(2.990)	(1.635)	(3.853)	(1.677)	(0.523)	(2.431)	(1.086)	(3.344)	(1.039)	(0.331)
Observations	934	892	932	888	643	926	884	924	880	637
adj. R2	0.365	0.33	0.378	0.348	0.436	0.446	0.406	0.461	0.441	0.502

Table 1.5: **The effects of initiation of hedging using financial derivative on firms net leverage**
This table reports coefficients estimated from regression net leverage on before and after start of derivative hedging program at the firm level represented in equation (1). After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Total Leverage less Cash / Assets (Nebt Debt / Assets)				
After_Hedge	0.006*	0.006*	0.006**	0.010**	0.013**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Size	0.019**	0.022***	0.021***	0.013	0.011
	(0.008)	(0.008)	(0.008)	(0.012)	(0.014)
Cash Flow		-0.021***		-0.002	-0.005
		(0.005)		(0.028)	(0.035)
ROA			-0.020***		
			(0.005)		
Leverage				0.082***	0.087***
				(0.020)	(0.024)
Tangibility				0.545***	0.577***
				(0.044)	(0.053)
Sale growth				0.003*	0.002
				(0.002)	(0.002)
Gdp/Price	-8.442***	-8.481***	-8.630***	-2.101***	-1.203***
	(0.097)	(0.103)	(0.105)	(0.214)	(0.203)
Credit Spread	-0.081***	-0.083***	-0.082***	-0.201***	-0.186***
	(0.010)	(0.011)	(0.010)	(0.029)	(0.039)
Term Spread	0.862***	0.866***	0.887***	-0.173***	-0.100***
	(0.017)	(0.018)	(0.019)	(0.023)	(0.025)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	41.391***	41.576***	42.307***	10.257***	5.773***
	(0.469)	(0.493)	(0.500)	(1.070)	(1.034)
Observations	6717	6246	6703	4409	2961
adj. R2	0.043	0.053	0.047	0.181	0.208

Table 1.6: **The effects of initiation of hedging using financial derivative on firms net equity issuance**
This table reports coefficients estimated from regression net equity issue on before and after start of derivative hedging program at the firm level represented in equation (1). After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)
Dependent Variable	Net Equity Issue	Net Equity Issue	Net Equity Issue	Net Equity Issue
After_Hedge	-0.022*	-0.021*	-0.023*	-0.026*
	(0.012)	(0.012)	(0.013)	(0.015)
Size	-0.009	-0.008	0.000	-0.003
	(0.022)	(0.024)	(0.026)	(0.026)
Cash Flow (CF)			-0.224**	-0.266**
			(0.092)	(0.118)
After_Hedge x CF				0.064
				(0.116)
ROA		-0.132		
		(0.088)		
Leverage		-0.015	-0.021	-0.015
		(0.077)	(0.074)	(0.074)
Tangibility		-0.394**	-0.385**	-0.400***
		(0.156)	(0.158)	(0.154)
Gdp/Price	-1.226***	-2.751***	-1.991***	-2.111***
	(0.443)	(0.909)	(0.542)	(0.516)
Credit Spread	0.071*	0.056	0.044	0.056
	(0.037)	(0.042)	(0.044)	(0.045)
Term Spread	0.228***	0.400***	0.278***	0.295***
	(0.069)	(0.116)	(0.079)	(0.077)
Firm Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Constant	6.001***	13.617***	9.859***	10.462***
	(2.141)	(4.470)	(2.647)	(2.511)
Observations	1274	1269	1164	1164
adj. R2	0.071	0.085	0.097	0.097

Table 1.7: **The effects of initiation of hedging using financial derivative on firms difference in cash to total assets**

This table reports coefficients estimated from regression difference in cash to total assets and change in investments on before and after start of derivative hedging program at the firm level represented in equation (1). After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)
Dependent Variable	(Cash/(Assets-Cash))		(Investment/Assets)	
After_Hedge	0.175*	0.134**	0.055***	0.049***
	(0.106)	(0.068)	(0.012)	(0.017)
Size	0.405	0.09	-0.035*	-0.017
	(0.255)	(0.057)	(0.019)	(0.028)
Cash Flow	1.275**	0.806	0.168**	0.127
	(0.571)	(0.724)	(0.077)	(0.137)
After_Hedge x Cash Flow	-1.287**	-1.908**	-0.177**	-0.179
	(0.575)	(0.772)	(0.075)	(0.120)
Leverage		-0.172		0.158*
		(0.128)		(0.083)
Tangibility	-0.774***	-0.403*	0.678***	0.566***
	(0.236)	(0.221)	(0.096)	(0.145)
Sale growth		-0.023*		-0.004
		(0.012)		(0.006)
Gdp/Price	19.182***	0.565*	-2.334***	-2.485***
	(3.767)	(0.316)	(0.371)	(0.777)
Credit Spread	0.953**	0.617***	0.189***	1.326***
	-0.388	-0.17	-0.032	-0.396
Term Spread	-1.250*	-0.021	0.297***	-0.234***
	(0.742)	(0.041)	(0.061)	(0.030)
Firm Fixed Effects	YES	YES	YES	YES
Industry Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Constant	-98.406***	-3.888**	11.264***	10.844***
	(17.632)	(1.618)	(1.779)	(3.472)
Observations	5348	2874	5272	2817
adj. R2	0.042	0.144	0.057	0.089

Table 1.8: **The effect of increase in risk exposure and derivative hedging before and after implementation of Financial Accounting Standard (FAS 123R) in fiscal year 2005**
This table reports coefficients estimated from equation 2 difference-in-difference regression model. For sub-sample of firms matched over same hedging risk exposure with or without derivative hedging firms (Hedge_Dervi). I exploit before and after FAS 123R (Post) regulation implementation on various firms liquidity choices and investments. Hedge_Dervi is a firm level hedging with positive risk exposure from previous year variable. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
Hedge_Derv	0.005	0.023	0.008	-0.005	-0.004
	(0.003)	(0.030)	(0.012)	(0.003)	(0.017)
Post	0.004	0.104	-0.032*	-0.004	-0.044*
	(0.004)	(0.135)	(0.018)	(0.004)	(0.026)
Hedge_Derv* Post	**-0.007***	-0.079*	-0.011	**0.007***	**0.031**
	(0.004)	(0.048)	(0.013)	**(0.004)**	**(0.021)**
Size	-0.022***	0.03	-0.029	0.020***	-0.100***
	(0.007)	(0.251)	(0.025)	(0.007)	(0.030)
Cash Flow	0.02	**2.437***	**0.096**	-0.02	-0.336**
	(0.022)	**(1.323)**	**(0.078)**	(0.022)	(0.153)
Cash Flow *Post		**-0.015**	**-0.013**		
		(0.773)	**(0.057)**		
Tangibility	-0.528***	-1.647**	0.760***	0.530***	0.359**
	(0.039)	(0.813)	(0.143)	(0.039)	(0.159)
Leverage	-0.139***	0.726**	0.027	0.145***	0.299***
	(0.016)	(0.362)	(0.090)	(0.016)	(0.094)
GDP/Price	0.011	14.272	2.581***	-0.037	-0.008
	(0.193)	(9.156)	(0.993)	(0.194)	(1.586)
Credit Spread	0.022	4.228	0.685**	-0.029	0.032
	(0.057)	(2.718)	(0.291)	(0.057)	(0.465)
Term Spread	0.005	1.548	0.223**	-0.008	-0.025
	(0.021)	(1.002)	(0.109)	(0.021)	(0.172)
Firm Fixed Effects	YES	YES	YES	YES	YES
Observations	8238	7899	7818	8238	1420
adj. R2	0.141	0.011	0.023	0.143	0.139

Table 1.9: **The effect of increase in risk exposure and derivative hedging before and after implementation of Financial Accounting Standard (FAS 123R) in fiscal year 2005 for non-dividend payers**
This table reports coefficients estimated from equation 2 difference-in-difference regression model for financially constrained firms (non-dividend payers). For sub-sample of financially constrained firms matched over risk exposure of either interest rate, foreign exchange, or commodity risk. The first difference is derivative (Hedge_Dervi=1) or non-derivative (Hedge_Dervi=0) hedging firms. The second difference is the before (Post=1) and after (Post=0) FAS 123R regulation implementation on various firms liquidity choices and investments. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
Hedge_Derv	0.007 (0.005)	0.035 (0.053)	0.01 (0.017)	-0.007 (0.005)	-0.005 (0.039)
Post	0.009 (0.006)	0.165 (0.190)	-0.051** (0.026)	-0.009 (0.006)	-0.099 (0.062)
Hedge_Derv* Post	**-0.012*** **(0.006)**	**-0.149*** **(0.087)**	-0.001 (0.017)	**0.012*** **(0.006)**	**0.062** **(0.046)**
Size	-0.027*** (0.009)	-0.037 (0.363)	-0.046 (0.034)	0.025*** (0.009)	-0.131*** (0.049)
Cash Flow	0.021 (0.026)	**3.127*** **(1.650)**	**0.171**** **(0.076)**	-0.023 (0.026)	-0.254 (0.252)
Cash Flow * Post		**0.279** **(1.032)**	**-0.056** **(0.069)**		
Tangibility	-0.601*** (0.060)	-2.286* (1.230)	0.925*** (0.189)	0.603*** (0.059)	0.353 (0.312)
Leverage	-0.152*** (0.022)	1.115** (0.534)	0.003 (0.093)	0.159*** (0.022)	0.443** (0.173)
GDP/Price	0.102 (0.315)	26.603 (17.023)	2.962** (1.423)	-0.133 (0.315)	-1.27 (3.115)
Credit Spread	0.051 (0.092)	7.752 (5.030)	0.773* (0.417)	-0.06 (0.093)	-0.321 (0.900)
Term Spread	0.018 (0.034)	2.851 (1.852)	0.251 (0.156)	-0.02 (0.034)	-0.167 (0.342)
Firm Fixed Effects	YES	YES	YES	YES	YES
Observations	4725	4459	4409	4725	595
adj. R2	0.152	0.015	0.032	0.153	0.258

Table 1.10: **The effects of initiation of hedging using financial derivative on loan spreads**
This table reports coefficients estimated from equation 2 difference-in-difference regression model. For sub-sample of firms matched over same hedging risk exposure with or without derivative hedging firms (Hedge_Dervi). I exploit before and after FAS 123R (Post) regulation implementation on various firms liquidity choices and investments. Hedge_Dervi is a firm level hedging with positive risk exposure from previous year variable. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)
Dependent Variable	Loan Spread	Loan Spread	Loan Spread	Loan Spread
After_Hedge	-0.082*	-0.112*	-0.091**	-0.124*
	(0.046)	(0.065)	(0.045)	(0.066)
Size	-0.112	-0.192*	-0.112	-0.161
	(0.105)	(0.108)	(0.100)	(0.108)
Cash Flow (CF)	-1.532***	-0.476		
	(0.578)	(0.851)		
ROA			-1.502***	-0.965
			(0.515)	(0.866)
Leverage		0.598		0.57
		(0.398)		(0.410)
Tangibility	0.024	-0.016	0.04	0.044
	(0.414)	(0.526)	(0.424)	(0.526)
Sale Growth		-0.023		-0.018
		(0.025)		(0.024)
GDP/Price	1.192***	1.601***	1.175***	1.630***
	(0.287)	(0.263)	(0.274)	(0.260)
Credit Spread	0.496***	0.509***	0.471***	0.498***
	(0.069)	(0.116)	(0.066)	(0.109)
Term Spread	0.061	0.096*	0.065*	0.101**
	(0.037)	(0.049)	(0.037)	(0.050)
Firm Fixed Effect	YES	YES	YES	YES
Constant	-0.086	-1.725	0.092	-1.977
	(1.358)	(1.221)	(1.284)	(1.230)
Observations	1133	825	1187	859
adj. R2	0.18	0.165	0.176	0.175

Table 1.11: **The effects of initiation of hedging using financial derivative on probability of covenant violation**

This table reports coefficients estimated from regression of probability of covenant violation before and after derivative hedging represented in equation (1). After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)
	Prob. of Cov. Violation_t	Prob. of Cov. Violation_t	Prob. of Cov. Violation_t+1	Prob. of Cov. Violation_t+1
After_Hedge	-0.061	-0.068	-0.163**	-0.131*
	(0.062)	(0.060)	(0.071)	(0.078)
Size	-0.065	-0.165	0.098	-0.087
	(0.194)	(0.162)	(0.165)	(0.139)
Cash Flow (CF)	-0.412		-0.722	
	(1.112)		(1.012)	
ROA		-2.524***		-2.492**
		(0.895)		(1.102)
Leverage	1.121***	1.214***	1.158	1.443*
	(0.421)	(0.336)	(0.904)	(0.783)
Tangibility	0.16	0.56	-0.17	0.749
	(0.419)	(0.414)	(0.663)	(0.641)
Sale Growth	-0.081**	-0.067*	-0.028	-0.048
	(0.040)	(0.036)	(0.029)	(0.036)
Z-Score	0.025	0.074	0.114	0.004
	(0.115)	(0.111)	(0.142)	(0.137)
GDP/Price	0.047	0.588	0.345	0.981
	(0.686)	(0.505)	(0.647)	(0.605)
Credit Spread	-0.076	-0.247	-0.128	-0.558*
	(0.189)	(0.216)	(0.185)	(0.299)
Term Spread	-0.213	-0.234	-0.171	-0.17
	(0.215)	(0.199)	(0.227)	(0.307)
Firm Fixed Effect	YES	YES	YES	YES
Ind. Fixed Effect	NO	NO	NO	NO
Year Fixed Effect	YES	YES	YES	YES
Constant	0.211	-1.358	-2.108	-3.36
	(2.545)	(2.034)	(2.255)	(2.345)
Observations	387	417	314	338
adj. R2	0.358	0.423	0.57	0.55

Table 1.12: **Placebo test on bottom median of small firms by asset size**
This table reports coefficients estimates of our basic regressions using the sample of industry, size, and bottom median of small firms. For each firm in a sample, I match a similar firm by two digit industry code that had the closest assets at the year of derivative hedging. This placebo test perform on data two years before and three years after derivative hedging starts. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program start by a firm. The data collected from annual Computstats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The heteroskedasticity consistent standard errors clustered at the firm level reported in parenthesis. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cash/ Asset	(Cash / Assets)	(Cash / Assets-Cash)	Net Debt /Assets	Net Equity Issue	(Investment/ Assets)	Loan Spread	Unused Line of Credit
After_Hedge	-0.017***	-0.010*	0.095***	0.017***	-0.005	0.032***	-0.097*	0.028
	(0.004)	(0.005)	(0.031)	(0.004)	(0.018)	(0.011)	(0.058)	(0.029)
Size	0.000	0.004	0.010	0.000	-0.012	-0.003	-0.162***	-0.135***
	(0.004)	(0.003)	(0.013)	(0.004)	(0.011)	(0.004)	(0.032)	(0.018)
Cash Flow (CF)	-0.077***	0.068***	1.256***	0.079***	-0.379***	0.098**	-0.913***	0.233
	(0.016)	(0.024)	(0.127)	(0.015)	(0.065)	(0.049)	(0.304)	(0.153)
After_Hedge x Cash Flow		0.093***	-1.249***			-0.126**		
		(0.033)	(0.152)			(0.058)		
Leverage	-0.140***	-0.015	-0.006	0.150***	-0.062	0.000	1.134***	0.603***
	(0.016)	(0.017)	(0.066)	(0.015)	(0.054)	(0.023)	(0.166)	(0.094)
Tangibility	-0.338***	-0.051***	0.02	0.332***	0.002	0.066***	-0.261**	0.113
	(0.021)	(0.013)	(0.057)	(0.020)	(0.046)	(0.019)	(0.129)	(0.071)
Sale Growth	0.002	0.008***	-0.026***	-0.003	0.025***	-0.007**	0.034	0.009
	(0.002)	(0.002)	(0.010)	(0.002)	(0.007)	(0.003)	(0.021)	(0.011)

Table 1.12 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cash/ Asset	(Cash / Assets)	(Cash / Assets-Cash)	Net Debt /Assets	Net Equity Issue	(Investment/ Assets)	Loan Spread	Unused Line of Credit
GDP/Price	0.061***	0.000	-0.062	-0.058***	-0.046	0.047*	0.547***	-0.276***
	(0.021)	(0.017)	(0.076)	(0.021)	(0.066)	(0.026)	(0.187)	(0.102)
Credit Spread	0.000	0.002	0.058	0.000	-0.031	0.001	0.303***	-0.068
	(0.006)	(0.008)	(0.041)	(0.006)	(0.025)	(0.014)	(0.100)	(0.050)
Term Spread	0.020***	0.015***	0.005	-0.019***	0.023	0.004	0.054	-0.012
	(0.003)	(0.004)	(0.023)	(0.003)	(0.017)	(0.008)	(0.048)	(0.023)
Constant	0.020	0.012	-0.008	-0.029	0.444	-0.268**	3.321***	2.543***
	(0.091)	(0.077)	(0.351)	(0.091)	(0.317)	(0.120)	(0.816)	(0.452)
Observations	2373	2276	2035	2373	533	1998	268	218
adj. R2	0.239	0.028	0.062	0.247	0.304	0.017	0.316	0.532

Table 1.13: **A sample of small firms before the initiation of hedging using financial derivative**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of small firms (bottom median of firm size) on before and after start of derivative hedging program at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.014*	0.07	0.039**	0.021***	0.325***
	(0.008)	(0.079)	(0.018)	(0.008)	(0.105)
Size	-0.005	0.212**	-0.01	0.008	-0.363***
	(0.018)	(0.085)	(0.034)	(0.018)	(0.064)
Cash Flow (CF)	-0.004	0.54	0.077	0.045	1.383**
	(0.032)	(0.753)	(0.130)	(0.032)	(0.542)
After_Hedge x CF		-1.621*	-0.116	-0.128***	-1.505**
		(0.963)	(0.097)	(0.030)	(0.685)
Leverage	-0.111***	-0.594**	0.176**	0.102***	0.076
	(0.026)	(0.248)	(0.090)	(0.026)	(0.245)
Tangibility	-0.592***	-1.103***	0.456**	0.577***	-0.553
	(0.067)	(0.376)	(0.208)	(0.066)	(0.707)
Sale growth	-0.004*	-0.032*	-0.004	0.004*	0.023*
	(0.002)	(0.017)	(0.006)	(0.002)	(0.014)
GDP/Price	3.197	5.084	0.9	-7.538**	-1.300***
	(3.179)	(3.343)	(1.458)	(2.993)	(0.316)
Credit Spread	0.119**	-2.192	-0.144	0.073	-1.635***
	(0.052)	(1.670)	(0.185)	(0.049)	(0.502)
Term Spread	0.221	-0.243	0.126**	-0.447*	1.100***
	(0.255)	(0.507)	(0.059)	(0.240)	(0.273)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	NO
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	-15.676	-23.617	-4.519	37.038**	9.794***
	(15.896)	(15.265)	(7.041)	(14.966)	(1.783)
Observations	2678	2068	2013	2678	302
adj. R2	0.187	0.116	0.105	0.206	0.65

Table 1.14: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by the Kaplan-Zingales index**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of financially constrained firms fall in the top median of KZ index two years before hedging initiate. Effect of start of derivative hedging program before and after on this financially constrained sample at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.005*	0.082	0.034**	0.010*	0.046
	(0.003)	(0.064)	(0.014)	(0.005)	(0.035)
Size	-0.011***	0.005	-0.011**	0.011***	-0.165***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.008)
Cash Flow (CF)	-0.067*	1.149	0.109	0.112***	0.061
	(0.037)	(0.745)	(0.092)	(0.041)	(0.200)
After_Hedge x CF		-0.912	-0.232**	-0.071	-0.153
		(0.698)	(0.096)	(0.044)	(0.292)
Leverage	-0.073***	0.041	0.05	0.098***	0.361***
	(0.016)	(0.075)	(0.037)	(0.016)	(0.087)
Tangibility	-0.311***	-0.064*	0.110***	0.248***	0.117*
	(0.025)	(0.036)	(0.031)	(0.017)	(0.065)
Sale growth	0.001	-0.016*	-0.009**	-0.003**	-0.002
	(0.001)	(0.008)	(0.004)	(0.001)	(0.009)
GDP/Price	0.070***	-0.066**	0.012	-0.025***	0.340***
	(0.020)	(0.028)	(0.021)	(0.009)	(0.047)
Credit Spread	0.004	0.146*	0.001	-0.144***	-0.578**
	(0.005)	(0.079)	(0.071)	(0.027)	(0.266)
Term Spread	0.012***	-0.045	-0.012	0.031***	0.554***
	(0.003)	(0.032)	(0.021)	(0.008)	(0.105)
Firm Fixed Effects	NO	NO	NO	NO	NO
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	NO	YES	YES	YES	YES
Constant	-0.106	-0.083	-0.345*	0.105	1.922***
	(0.090)	(0.202)	(0.199)	(0.091)	(0.408)
Observations	3006	2396	2341	3006	451
adj. R2	0.163	0.06	0.084	0.261	0.549

Table 1.15: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by the Whited-Wu index**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of financially constrained firms fall in the bottom median of WW index two years before hedging initiate. Effect of start of derivative hedging program before and after on this financially constrained sample at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.014*	0.071	0.036**	0.022***	0.200**
	(0.007)	(0.077)	(0.015)	(0.007)	(0.080)
Size	-0.012	0.141	-0.013**	0.016	-0.112
	(0.018)	(0.090)	(0.005)	(0.018)	(0.072)
Cash Flow (CF)	0.005	0.571	0.123	0.045	0.515
	(0.031)	(0.800)	(0.095)	(0.032)	(0.362)
After_Hedge x CF		-1.585*	-0.171*	-0.146***	-0.917*
		(0.874)	(0.095)	(0.029)	(0.485)
Leverage	-0.127***	-0.522**	0.031	0.114***	0.222
	(0.030)	(0.247)	(0.038)	(0.029)	(0.233)
Tangibility	-0.594***	-0.985**	0.075***	0.579***	0.495
	(0.064)	(0.449)	(0.027)	(0.062)	(0.401)
Sale growth	-0.001	-0.042**	-0.008*	0.002	0.027
	(0.002)	(0.018)	(0.004)	(0.002)	(0.017)
GDP/Price	3.542	4.505	0.033	-7.898***	-0.278
	(2.984)	(3.088)	(0.023)	(2.794)	(0.224)
Credit Spread	0.147***	-1.952	-0.049	0.047	-0.056
	(0.049)	(1.485)	(0.073)	(0.046)	(0.079)
Term Spread	0.251	-0.08	-0.124***	-0.477**	0.037
	(0.239)	(0.402)	(0.047)	(0.224)	(0.030)
Firm Fixed Effects	YES	YES	NO	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	NO
Year Fixed Effects	YES	YES	YES	YES	NO
Constant	0.283	-1.346	-0.559	-0.263	-11.975*
	(0.303)	(0.960)	(0.376)	(0.298)	(6.298)
Observations	2750	2140	2084	2750	317
adj. R2	0.193	0.106	0.043	0.216	0.194

Table 1.16: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by the Hadlock-Pierce index**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of financially constrained firms fall in the bottom median of HP index two years before hedging initiate. Effect of start of derivative hedging program before and after on this financially constrained sample at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.011**	0.044	0.024**	0.022***	0.038
	(0.005)	(0.093)	(0.012)	(0.006)	(0.047)
Size	-0.029**	0.086	-0.011**	0.030**	-0.155***
	(0.015)	(0.068)	(0.005)	(0.014)	(0.008)
Cash Flow (CF)		-1.564	-0.149	-0.164***	-0.589
		(1.347)	(0.093)	(0.038)	(0.451)
After_Hedge x CF	-0.015	-1.061	0.111	0.074**	0.039
	(0.044)	(0.880)	(0.104)	(0.034)	(0.225)
Leverage	-0.130***	-0.276	0.038	0.117***	0.393***
	(0.026)	(0.206)	(0.045)	(0.027)	(0.098)
Tangibility	-0.493***	-0.461	0.134***	0.485***	0.158**
	(0.065)	(0.345)	(0.038)	(0.064)	(0.074)
Sale growth	-0.003	-0.018	-0.010**	0.004*	0
	(0.002)	(0.014)	(0.004)	(0.002)	(0.010)
GDP/Price	-11.853***	-34.827**	0.018	-3.344**	0.240***
	(1.500)	(16.675)	(0.023)	(1.498)	(0.022)
Credit Spread	-0.059	-9.887**	-0.01	-0.248***	-0.043
	(0.047)	(4.820)	(0.072)	(0.044)	(0.042)
Term Spread	-0.961***	-3.594**	-0.133**	-0.274**	0.328***
	(0.124)	(1.725)	(0.057)	(0.124)	(0.030)
Firm Fixed Effects	YES	YES	NO	YES	NO
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	59.594***	183.891**	-	16.379**	-
	(7.531)	(88.116)		(7.519)	
Observations	2671	2061	2005	2671	395
adj. R2	0.217	0.169	0.129	0.249	0.448

Table 1.17: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by their debt rating (unrated firms)**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of unrated firms on before and after start of derivative hedging program at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.015**	0.077	0.061***	0.023***	0.035
	(0.007)	(0.072)	(0.018)	(0.005)	(0.075)
Size	-0.011	0.074	-0.007	0.003	-0.06
	(0.018)	(0.048)	(0.027)	(0.013)	(0.145)
Cash Flow (CF)	0.005	0.061	0.088	0.044	-0.206
	(0.031)	(0.403)	(0.133)	(0.029)	(0.585)
After_Hedge x CF		-1.149	-0.2	-0.145***	-0.308
		(0.789)	(0.128)	(0.026)	(0.599)
Leverage	-0.128***	-0.237*	0.186**	0.102***	0.866***
	(0.030)	(0.143)	(0.088)	(0.021)	(0.261)
Tangibility	-0.592***	-0.837***	0.663***	0.535***	1.025**
	(0.064)	(0.250)	(0.163)	(0.048)	(0.411)
Sale growth	-0.001	-0.022**	-0.002	0.003**	-0.005
	(0.002)	(0.009)	(0.004)	(0.002)	(0.014)
GDP/Price	3.554	5.763	-1.977***	0.291*	-2.994
	(2.987)	(5.165)	(0.602)	(0.166)	(9.472)
Credit Spread	0.147***	0.321	0.008	0.199***	-5.873
	(0.049)	(0.277)	(0.045)	(0.017)	(16.900)
Term Spread	0.252	-0.188	-0.057**	0.179***	-0.517
	(0.239)	(0.238)	(0.028)	(0.014)	(2.131)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	-17.436	-29.039	9.533***	-2.035**	21.578
	(14.942)	(25.773)	(3.021)	(0.826)	(65.337)
Observations	2750	3207	3148	3817	510
adj. R2	0.193	0.092	0.076	0.212	0.301

Table 1.18: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by their cash in hand**

This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of cash constrained (bottom median of cash to assets ratio) on before and after start of derivative hedging program at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	0.007**	0.013**	0.051*	-0.001	0.029
	(0.003)	(0.007)	(0.029)	(0.005)	(0.064)
Size	-0.012	0.023*	-0.014	0.012	-0.117
	(0.010)	(0.014)	(0.032)	(0.010)	(0.072)
Cash Flow (CF)	-0.001	0.066	0.101	0.028	-1.305*
	(0.029)	(0.052)	(0.299)	(0.039)	(0.716)
After_Hedge x CF		0.106	-0.29	-0.073	0.678
		(0.067)	(0.276)	(0.049)	(0.611)
Leverage	-0.038**	-0.008	0.200*	0.040**	0.482**
	(0.017)	(0.022)	(0.118)	(0.017)	(0.221)
Tangibility	-0.336***	-0.240**	0.384**	0.335***	0.729**
	(0.044)	(0.095)	(0.176)	(0.043)	(0.322)
Sale growth	0.000	-0.003*	-0.003	0.000	-0.008
	(0.001)	(0.002)	(0.005)	(0.001)	(0.014)
GDP/Price	0.947	-0.392	-0.251	-5.252***	-0.445
	(0.592)	(0.248)	(0.579)	(0.597)	(0.714)
Credit Spread	0.113***	0.052	0.054	0.081***	-0.138*
	(0.013)	(0.053)	(0.087)	(0.014)	(0.083)
Term Spread	0.039	0.045	0.042	-0.264***	0.268***
	(0.047)	(0.038)	(0.040)	(0.048)	(0.088)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	-4.495	1.723	1.076	25.691***	1.076
	(2.960)	(1.204)	(2.763)	(2.986)	(2.763)
Observations	3203	2593	2539	3203	523
adj. R2	0.176	0.112	0.089	0.182	0.454

Table 1.19: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by their collateral constrained (without debt or mortgage)**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of collateral constrained (bottom median of collateral constraint proxy without debt or mortgage) on before and after start of derivative hedging program at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
	Cash/Asset	(Cash/ Assets-Cash)	(Investment /Assets)	Net Debt /Assets	Unused Line of Credit
After_Hedge	-0.001	0.019	0.075**	0.007	0.076
	(0.004)	(0.014)	(0.032)	(0.006)	(0.065)
Size	0.000	0.054**	-0.020	0.001	-0.033
	(0.014)	(0.023)	(0.030)	(0.014)	(0.079)
Cash Flow (CF)	0.019	0.161	0.483	0.013	-0.137
	(0.034)	(0.118)	(0.370)	(0.043)	(0.534)
After_Hedge x CF		0.030	-0.506	-0.074	-1.018
		(0.133)	(0.322)	(0.060)	(0.663)
Leverage	-0.062***	-0.075*	0.220*	0.063***	0.789***
	(0.022)	(0.046)	(0.117)	(0.022)	(0.224)
Tangibility	-0.343***	-0.335***	0.432**	0.348***	0.703
	(0.052)	(0.118)	(0.193)	(0.052)	(0.434)
Sale growth	-0.001	-0.001	-0.005	0.001	-0.014
	(0.001)	(0.003)	(0.005)	(0.001)	(0.010)
GDP/Price	1.242***	1.762***	4.699**	-2.544***	0.197
	(0.221)	(0.347)	(1.902)	(0.223)	(0.791)
Credit Spread	0.072**	0.336***	0.684***	-0.301***	-0.204***
	(0.028)	(0.055)	(0.250)	(0.030)	(0.070)
Term Spread	0.050**	0.099**	0.226	-0.243***	0.204**
	(0.024)	(0.047)	(0.157)	(0.024)	(0.082)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	-5.993***	-2.512	-24.172**	12.728***	-0.707
	(1.111)	(1.767)	(9.707)	(1.124)	(3.484)
Observations	3162	2552	2495	3162	509
adj. R2	0.128	0.072	0.084	0.136	0.586

Table 1.20: **The effect of the initiation of financial derivatives hedging on the financial constraints firm's characterized by their collateral constrained (with debt or mortgage)**
This table reports coefficients estimated from regressions of equation from table 3-6. For subsample of collateral constrained (bottom median of collateral constraint proxy with debt and without mortgage) on before and after start of derivative hedging program at the firm level. After_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program starts by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm, year, and one digit industry fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Cash/Asset	(2) (Cash/ Assets-Cash)	(3) (Investment /Assets)	(4) Net Debt /Assets	(5) Unused Line of Credit
After_Hedge	0.002	-0.022	0.065**	0.005	0.080
	(0.004)	(0.037)	(0.027)	(0.005)	(0.067)
Size	0.001	0.072***	-0.028	0.000	-0.082
	(0.013)	(0.024)	(0.024)	(0.012)	(0.075)
Cash Flow (CF)	0.011	-0.470	0.465*	0.011	-0.007
	(0.026)	(0.549)	(0.257)	(0.032)	(0.590)
After_Hedge x CF		0.298	-0.480**	-0.087*	-0.652
		(0.304)	(0.236)	(0.050)	(0.648)
Leverage	-0.052***	-0.118**	0.195*	0.051***	0.644**
	(0.019)	(0.057)	(0.110)	(0.019)	(0.249)
Tangibility	-0.374***	-0.429***	0.320*	0.381***	0.850**
	(0.046)	(0.111)	(0.182)	(0.046)	(0.395)
Sale growth	-0.001	-0.001	-0.003	0.001	-0.021*
	(0.001)	(0.003)	(0.005)	(0.001)	(0.013)
GDP/Price	1.141***	-12.552***	0.315*	-2.386***	0.292
	(0.203)	(3.675)	(0.188)	(0.205)	(0.791)
Credit Spread	0.063**	-1.633***	0.070**	-0.287***	-0.12
	(0.026)	(0.509)	(0.032)	(0.027)	(0.081)
Term Spread	0.039*	-1.144***	-0.168***	-0.226***	0.144
	(0.022)	(0.335)	(0.013)	(0.022)	(0.088)
Firm Fixed Effects	YES	YES	YES	YES	YES
Ind. Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Constant	-5.494***	63.880***	-1.566*	11.939***	-1.027
	(1.013)	(18.819)	(0.923)	(1.028)	(3.479)
Observations	3279	2669	2612	3279	521
adj. R2	0.137	0.065	0.062	0.149	0.511

Table 1.21: **The effects of stoppage of hedging using financial derivative on firms financials**
This table reports coefficients estimated from regression of various financial two years before and after stoppage of derivative hedging represented in equation (2). Stop_Hedge is a dummy variable that equals zero (one) for the years before (after) a derivative hedging program stopped by a firm. The data collected from annual Compustats file over the 1996-2016 period. Hedging data parsed from firms annual financial statements (10-K). The definition of all the variables and their creation reported in Appendix A. All specifications are estimated using firm fixed effects. The symbols ***, ** , and * denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1) Cash/Asset	(2) Cash/Asset	(3) Net Debt /Assets	(4) Net Debt /Assets	(5) Gross Investment
Stop_Hedge	0.022* (0.012)	0.030* (0.016)	-0.021 (0.013)	-0.029* (0.017)	-0.199* (0.110)
Size	0.000 (0.038)	-0.009 (0.043)	0.000 (0.038)	0.009 (0.044)	0.374 (0.319)
Cash Flow (CF)	-0.085 (0.092)	-0.07 (0.106)	0.095 (0.094)	0.081 (0.109)	
Total Payout	0.142 (0.141)	0.060 (0.140)	-0.152 (0.145)	-0.064 (0.153)	
Tangibility	-0.768*** (0.198)	-0.568* (0.297)	0.788*** (0.202)	0.595* (0.302)	1.347 (3.747)
R and D		0.008 (0.007)		-0.008 (0.007)	
Firm Fixed Effect	YES	YES	YES	YES	YES
Constant	0.379 (0.228)	0.409 (0.248)	-0.381 (0.230)	-0.418 (0.252)	-1.895 (2.608)
Observations	189	129	183	123	212
adj. R2	0.144	0.059	0.147	0.057	0.035

2 Essay II : An Option and Equity Based Measure of Institutional Informed Trading

2.1 Introduction

The financial world considers institutional investors as some of the most highly sophisticated. But which financial instrument should institutions use to benefit from their private information? Do they exclusively trade using equities or options? [1] The answer depends on the availability of asset type and its liquidity, expertise of investors, quality of private information, availability of leverage, regulations, and trading costs.[2] [3] [4] [5] Hence, the derivatives market can be a preferred destination for the unconstrained informed traders, because options provide higher leverage and downside protection; however, underlying stocks suffer from margin restrictions (e.g., Black (1975)). In a similar vein, Chakravarty, Gulen, and Mayhew (2004) find that a relative share of price discovery takes place in both equities and options markets. They suggest that informed trading venues for investors depend on options and an underlying equity's volume, leverage, and liquidity.

Furthermore, Pan and Poteshman (2006) provide robust results for the predictability of short-term future stock returns through the options trading volume. They rationalize this

[1] Although technically I prefer the term "institutional investors"' in the context of this paper, I am using terms institutions', investment managers, fund managers, fund advisors, and investment advisors interchangeably.

[2] Skinner (1990) (p. 297) conclude that "[the] exchange-traded options, when combined with trading in the underlying stock, provide a more cost-effective tool for trading on private information than does trading in the stock alone."

[3] Aragon and Martin (2012) pointed out that the lightly regulated hedge fund industry attracts highly skilled and best informed investment managers.

[4] Some mutual fund managers face a wide variety of restrictions, including constraints from their investors not to hold equity options found on the SEC's Form N-SAR.(see e.g. Almazan, Brown, Carlson, and Chapman (2004)). Recently, Cici and Palacios (2015) found that portfolio managers' experience, gender characteristics, and education are the main determinants of their equity options ownership.

[5] Merton (1995) (p. 463) "[Financial] innovations involving derivatives can improve efficiency by expanding opportunities for risk sharing, by lowering transaction costs and by reducing asymmetric information and agency costs."

relation based on informed investors trading in the options market instead of market inefficiency. Recently, Lowry et al. (2019) suggested that informed fund managers from the same advising banks' merger and acquisition division leverage their private information through the options market ahead of merger announcements. However, the arrival of private information and informed trading in the equities and options market, by definition, is unobservable. Therefore, to measure the information content of investment managers' holdings, it requires researching both options and their underlying stocks.

The main goal of this paper is to propose a robust instrument that measures institutional investors' informed trading using both equities and options holding. This new instrument has more explanatory power than previously used institutions private informed trading measures. In addition, I provide sources of institutional managers' private information trading. This papers focus comes at a crucial time when investors equity and options trading activity has increased significantly. [6] Previous research in finance and accounting used the change in fund managers' equity holdings (ΔEIO) or the change in the number of stocks ownership by institutional investors, normalized by the number of all institutions in the market (ΔEBREADTH), as a measure of informed trading. Empirical findings from these proxies are inconclusive, showing a limited and mixed effect on the prediction of returns and earnings announcement abnormal returns by institutions. In addition, Bushee and Goodman (2007) also provide the limited presence of private information trading by investment advisors. Despite sparse evidence, most of the studies suggested that the presence of institutional investors helps price discovery in the equity markets. Hence, to resolve discrepancies from the previously used equity-based fund managers' informed trading measures predictability issues, researchers suggest range of alternative techniques. Similarly, Guo and Qiu (2016) proposed a new instrument to resolve discrepancies from the previously used equity-based fund managers informed trading measures. They find that the

[6] see "More Investors Play the Stock-Options Lottery," Jan 5, 2020, The Wall Street Journal, "Since the year 2000, while stock-market trading volume has more than doubled, stock-options volume has grown to more than six times what it was then, at around 4.4 billion options contracts in 2019, according to Options Clearing Corp."

percentage change in the number of a stock's institutional investors holdings (hereafter %ΔENIO or PC_NII) performs better than other proxies used in prior research. However, all the proxies of institutions informed trading consider only equity holdings and fail to include the institutions' total portfolio of individual security.

In contrast to previous equity-based studies, Lowry et al. (2019) and Anand, Hua, and Puckett (2020) use only institutions options based measures, the number of call option holdings minus the number of put option holdings (Net Options), to recognize informed trading and abnormal stock returns predictability around corporate events. Anand et al. (2020) only used equity option positions in their analysis; they state that they cannot match the parsed 13f option holdings dataset with standard Thomson-Reuters 13f underlying equity data. Moreover, to repeat, institutional investors hold both equities and respective options in their portfolios. I used Nearest Neighbor Matching Algorithm to match parsed 13f with standardized 13f underlying equity datasets. Hence, with the help of these matched datasets, I construct a new instrument of institutions' informed trading, the percentage change in the derivatives plus their underlying stock's institutional investors (hereafter %ΔEPCMPNIO). This article concludes that fund managers use both options and underlying equities to trade on their private information.

Understanding the role of this new instrument in finance, economics, and accounting literature is important for several reasons. First, researchers use institutional ownership in the corporate finance literature to measure the firms' information asymmetry in the financial market, Chemmanur, Hu, and Wei (2021) provide a comprehensive review of institutional investors' role in corporate finance. Second, researchers provide evidence of the relationship between the institutional ownership differential and equities price discovery in the stream of asset pricing literature (e.g., Zhang (2010)). In addition, recent empirical findings by Cao, Liang, Lo, and Petrasek (2018) and Boehmer and Kelley (2009) imply that higher institutional ownership leads to greater informational efficiency of security prices. Third, Aghion, Van Reenen, and Zingales (2013) find that the institutional holding of securities plays a significant role in innovation for growth and the wealth of a nation. Fourth, practitioners spend ample time formulating profit-taking trading strategies by herding high-flying institutional investors (see Sias (2004)). The new equity and options-based institutional instrument devised in this paper provides practitioners unique insight into equity and options trading strategies. Fifth, investors closely watch superior institutions ability to hold profit-making portfolios. For that reason, new findings in this paper will motivate investors to make informed decisions (see Keswani and Stolin (2008)). Sixth, after the 2008 financial crisis, the Securities and Exchange Commission (SEC) oversight committee reviews derivative instruments used by fund managers to monitor trading in equities and options throughout the U.S. markets more accurately and efficiently. Thus, equity and option-based institutions' private informed trading instruments can be helpful for regulators (see Cici and Palacios (2015)). For the preceding six reasons, a novel measure of institutional investors' informed trading (i.e., %ΔEPCMPNIO) allows researchers, practitioners, and regulators alike to investigate the robustness of existing and future corporate finance, asset pricing, and market microstructure research.

This paper provides a new institutional informed trading instrument %ΔEPCMPNIO drawing on two different sets of theoretical models of aggregate private informed trading by equities and options. The first set of models of rational trade introduced by Kim and Verrecchia (1991, 1997) provide motives for investors information gathering ahead of anticipated public announcement. Hence, institutional investors gather and trade on information related to expected earnings announcements in the next quarter. The second set of models by Hirshleifer, Subrahmanyam, and Titman (1994) is well suited to institutional advisors holding options and underlying equity to make profit-taking strategies on accurate information and herding for the same stocks in the short term. In addition, their model has important implication for differential timing of information arrival for the informed institutional investors to trade on the same stock with different instruments in the same trading round (same quarter). Contrary to this argument, institutional investors may herd because they follow the same signal, which affects asset prices contemporaneously and in the future.[7]Thus, I aggregate institutional holdings of both long option and underlying equity to investigate their information acquisition and firm performance over time.

All the empirical findings in this paper over the fourth quarter of 2004 to the fourth quarter of 2019 (spanning 61 quarters) suggest that %ΔEPCMPNIO performs better than previously used equity (ΔEIO, ΔEBREADTH, %ΔENIO) and options (Net Options) based measures. In total, there are 4.02 million options contracts and 69.3 million equities held by institutions. Drawing from the standard cross-sectional methodology of Fama and MacBeth (1973), I illustrate that %ΔEPCMPNIO subsumes return predictability of all the previously devised measures. Moreover, I examine how institutional investors trade around scheduled news events; I consider earnings announcements for a broad sample of stocks. The cross-sectional regression between the current quarter-end %ΔEPCMPNIO and the next quarter three days earnings announcement abnormal returns (EAR (-1,0,1)) is positive and statistically significant; the coefficient is around 8.2 with a t-statistic of 10.36 (without control variables). This result represents the amount of institutional investors private information about earnings that the market cannot deduce when the institutions trade at different venues but is reflected in the underlying equity prices at the earnings announcement.

The above results are more pronounced in recent years because of ten-fold increase in the asset management industry. Furthermore, figure 1 plots the increasing quarterly trend of large institutional investors who file 13F filings with the Securities and Exchange Commission (SEC) from 1982:Q1 to 2019:Q4. According to the U.S. congress enactment of Section 13(f) in 1975 of the Securities Exchange Act of 1934, if institutions hold over $100 million of publicly traded convertible bonds, long equities, and long options at the end of the year. Then, those institutions must report their holdings on Form 13F. The number of fund managers increased from 551 at the beginning of the sample period in 1982 to

[7]See Nofsinger and Sias (1999), Froot, Scharfstein, and Stein (1992), Froot et al. (1992), Wermers (1999)

5422 at the end of 2019. This growth is almost tenfold, which suggest that asset management firms are the dominant trader in publicly traded securities exploiting their massive economies of scale. As figure 1 shows, there is an overall increasing trend but during 2008 financial crisis reports decrease in institutions' from 2964 at the end of 2008:Q2 to 2799 at the end of 2010:Q3. This trend is consistent with Ben-David, Franzoni, and Moussawi (2012) findings that hedge funds' redemption and margin calls impede their performance. In some cases, the total value of their publicly traded asset holding decreased by less than $100 million. Undoubtedly, fund managers play a crucial role during economic downturns and booms at the economy-wide level.[8]

In addition, to estimate the effect of %ΔEPCMPNIO on the one quarter ahead earnings announcement abnormal returns, this article adds to the private information trading by fund managers by showing a relationship between equity and respective options holding and future Standardized Unexpected Earnings (SUE). The cross-sectional regression of each firm's holding and SUE is highly significant statistically and economically, with the coefficient on average from 1.3 to 2.4. This result suggests that institutions possess the expertise to evaluate next quarter's SUE and profit from their private information.

Having established the sign and predictability for the %ΔEPCMPNIO instrument and event study relation, I further establish the source of the private information richness of fund managers. I investigate whether institutional investors change their ownership based on month-to-month percentage changes in consensus estimates of analyst forecast. This channel of anticipated information acquisition by institutions is already presented by Walther (1997), A. G. Huang, Tan, and Wermers (2020), and others. However, earlier results on the relationship between institutions and analyst earnings forecast change are inconclusive. I find that the change in mean analyst forecast in the month prior to the fiscal quarter-end (chfeps) is increasing in percentage change in the equities plus respective net options ownership by institutions' (%ΔEPCMPNIO). More precisely, the concurrent

[8]See DeGeorge, Reiter, Synn, and Williams (2019)

month's chfeps positively associated with %ΔEPCMPNIO, with a coefficient on average varies from 0.54 to 0.84 and t-statistics from 10.09 to 9.4 respectively. This robust result suggests that the fund managers closely follow the change in analyst forecast for a firm and trade using both equities and options on that information.

Further, I use a different and more direct approach than previous studies, which involves first examining the relationship between lagged Generalized Probability of Information-Based Trading (GPIN) suggested by Duarte, Hu, and Young (2020) and various proxies of institutions' informed trading[9]. Specifically, the previous month's GPIN is positively associated with %ΔEPCMPNIO with a coefficient of 0.07 for the complete sample. This result is interesting because, despite intimations in the past theoretical and empirical research about the information content of institutional investors' equity and options holding there has been no direct work on understanding their probability of informed trading. Hence, this article provides evidence of institutional private information trading using the GPIN.

Finally, the contribution of this essay is to show that well-designed novel institutional investors' informed trading measure (%ΔEPCMPNIO) has better stock returns predictability than previously used instruments in the literature. In addition, I find that institutional investors, on average, possess private information, and they trade on their information using different financial instruments depending on their expertise and availability. Previous researchers only used institutions equity holding to investigate their private information acquisition and trading. On the contrary, %ΔEPCMPNIO is robust, persistent, strongly significant, economically intuitive, and consistent with trading theory. Hence, this measure is beneficial to various financial market stakeholders, including but not limited to academic researchers, practitioners, and regulators for their specific analysis. Thus, this essay contributes to the literature by documenting that informed trading by fund managers is widespread, but the choice of financial instrument for the same firm differs.

[9] I followed specification of Lai, Ng, and Zhang (2014), where they use lagged probability of information-based trading (PIN) as a dependent variable and different firm-level measures of information asymmetry as independent variables (See Table 3).

The remainder of the essay proceeds as follows. Section 2.2 discusses the superiority of %ΔEPCMPNIO measure over other institutional investors' equity and options trading measures. Section 2.3 summarizes the empirical frameworks used in this article. Section 2.4 presents data. Section 2.5 presents descriptive statistics of the data sample. Section 2.6 summarizes empirical results, and section 2.7 concludes.

2.2 Institutional Investors' Informed Trading Measures

2.2.1 Description and Merits of Institutional Investors' Information Proxies

Academic researchers and practitioners have long had the consensus that institutional investors' contribute to the price discovery of stock prices through their trading. However, there are interesting differences in the institutional investors informed trading measures and their predictability for the stock returns. First, the changes in the fraction of shares owned by institutions' (ΔEIO) measures used in the literature, display varied results in different time periods and empirical settings. One of the earliest and seminal research in institutional investors' herding and stock returns predictability, by Nofsinger and Sias (1999) from 1977 till 1996 sample period, suggests that ΔEIO exhibits positive correlation with stock returns over institutions' herding interval. Importantly, Sias, Starks, and Titman (2006) conclude that the quarterly changes in institutional ownership contemporaneously correlated with stock returns. [10] On the contrary, almost with the same overlapping sample period, Gompers and Metrick (2001) find that ΔEIO is a noisier measure because it reflects trades of a small fraction of institutions in any given stock. Bushee and

[10] Similarly, Ke and Petroni (2004) conclude that change in transient institutions' equity holding predict a break in a string of consecutive increases in quarterly earnings.

Goodman (2007) use the same measure extensively and suggest that informed trading by institutions is limited to transient investors. This contradictory and limited predictability of stock returns is due to the strong assumption behind the construction of ΔEIO, that institutional investors are better informed than individual investors. On the contrary, Kaniel, Liu, Saar, and Titman (2012) find aggregate individual informed investor trades predict future stock returns around an earnings announcement. Furthermore, in my sample, ΔEIO is inferior to all other measures of institutions' informed trading.

Second, using a sample of mutual funds Chen, Hong, and Stein (2002) find that ΔEBREADTH, defined as the ratio of the number of institutions' ownership of the stock to the total number of institutions in the sample for that quarter, is positively associated with future stock returns. They attribute this association to the mutual fund managers better stock picking skills which generate positive returns in the next quarter. Similarly, (Lehavy & Sloan, 2008) use ΔEBREADTH as a proxy for investor recognition and show the contemporaneous correlation with stock returns. They attribute this correlation due to a momentum effect Jegadeesh and Titman (1993) from the previous four quarters. In my sample, the predictive power of ΔEBREADTH diminished to a statistical insignificant level. With the inclusion of %ΔEPCMPNIO in a cross-sectional regression of next quarter's stock return predictability ΔEBREADTH shows a negative relation with next quarter returns.

The %ΔEPCMPNIO variable dominates over other institutions' proxy due to the inclusion of options ownership. As the number of 13F filing fund managers increased tenfold, so did the number of long options and long equity holding institutions'. At the end of 2004:Q4, only 320 institutions traded long equity options compared to 829 institutions' by the end of 2019:Q4, as shown in Figure 2. This increase in equity and option holding institutions provides early motivation to include options holdings in the new fund managers' private informed trading instrument. Evidence from previous literature is inconclusive concerning the private information trading of aggregate institutions holdings[11]. Furthermore, this new proxy consisting of long options and their underlying equity will be helpful in investigating issues related to the short-termism nature of institutions and its effect on underlying firms' characteristics.

Third, Guo and Qiu (2016) recently designed a proxy consisting of only equities held by the institutions, defined as the percentage change in the number of a stock's institutional investors (%ΔENIO). This proxy performs better to predict future returns and dominate over all the previously used equity based institutional informed trading measures (e.g., ΔEIO, ΔEBREADTH) in a Fama and MacBeth (1973) regression. However, all these informed trading proxies do not consider options ownership of institutions', which can help to exploit their informational advantage.

Fourth, investment advisors' portfolio of derivative and underlying equity holding provides an attractive setting in which to study the implementation of their informed trading strategies. The few empirical studies emphasize the effect of mutual fund equities and options holdings on their portfolio risk or trading cost (e.g. see Koski and Pontiff (1999) and Deli and Varma (2002)). In another study of US hedge funds, Aragon and Martin (2012) examined the effect of stocks and options holding separately on the predictability of future returns and return volatility. They conclude that the hedge funds portfolio of options and underlying equities points out the informed trading behavior, generating higher average returns with smaller standard deviations. There is, nonetheless, recent research by Lowry et al. (2019) and Anand et al. (2020) that contributes to the effect of investment advisors options holding on different corporate events. Although Lowry et al. (2019) control for the level of institutional investors' equity holding for the same quarter, this variable gives a biased estimation than that of the first differencing of institutional ownership in a cross-section regression. Therefore, a percentage change in option and underlying equity based instrument will better able to detect investment managers informed trading behavior. Fol-

[11] See Bushee and Goodman (2007), Lehavy and Sloan (2008)

lowing, Lowry et al. (2019) I created institutional fund managers' measure consisting of only their options holding %ΔOPTNIO, defined as the percentage change in the number of a call options minus number of put options holding of institutional investors.

Indeed, more recent research shows that institutional investors' equities trading can explain a variety of short and long term effects due to its role in influencing the stock market efficiency (e.g., Boehmer and Kelley (2009) and Cao et al. (2018)). The empirical results of these market efficiency papers support the sophistication of institutions' hypothesis (hereafter SIH) in an equity market. Similarly, researchers in asset pricing have been increasingly investigating institutional demand and asset returns over short and long run.[12] Also, many studies show that institutions' trading helps to disseminate accounting information of the financial assets in various markets. Therefore, a better instrument consisting of equity and options will allow researchers in the areas of economics, finance, and accounting to more accurately measure the institutional investors' informed trading.

In addition, to show an association between the fair market value of options holding with the earning announcements abnormal returns, I create an institutional investors' options and equities holdings measure following the popularized options to stock trading volume (O/S) measure by the Roll, Schwartz, and Subrahmanyam (2010). They show that O/S measure cross-sectionally depends on institutional stock holding. Hence, in all the cross-sectional regression analysis I control a measure %ΔO/SIO which is defined as; the percentage change in the number of a options divided by their underlying equities holding of institutional investors'.

2.2.2 Designing of Institutional Investors' Information Proxies

For each firm, I aggregate the individual options and their underlying equities that are held by all the institutional investors filing 13 statements with SEC. All the following six measures are calculated quarterly and aggregated at the firm level.

[12] see Edelen, Ince, and Kadlec (2016)

$$\%\Delta\text{EPCMPNIO}_{i,t} = \frac{(IO\_EQT_{i,t} + IO\_NETCALL_{i,t}) - (IO\_EQT_{i,t-1} + IO\_NETCALL_{i,t-1})}{(IO\_EQT_{i,t-1} + IO\_NETCALL_{i,t-1})} \tag{2.1}$$

$$\Delta\text{EIO}_{i,t} = IO\_EQT_{i,t} - IO\_EQT_{i,t-1} \tag{2.2}$$

$$\Delta\text{EBREADTH}_{i,t} = \frac{\text{IO\_}EQT_{i,t} - IO\_EQT_{i,t-1}}{(\text{Total Number of 13F Institutional Investors' at Time})_{t-1}} \tag{2.3}$$

$$\%\Delta\text{ENIO}_{i,t} = \frac{IO\_EQT_{i,t} - IO\_EQT_{i,t-1}}{IO\_EQT_{i,t-1}} \tag{2.4}$$

$$\%\Delta\text{OPTNIO}_{\text{i,t}} = \frac{\frac{IO\_CALL_{i,t} - IO\_PUT_{i,t}}{IO\_OPT_{i,t}} - \frac{IO\_CALL_{i,t-1} - IO\_PUT_{i,t-1}}{IO\_OPT_{i,t-1}}}{\frac{IO\_CALL_{i,t-1} - IO\_PUT_{i,t-1}}{IO\_OPT_{i,t-1}}} \tag{2.5}$$

$$\%\Delta\text{O/SIO}_{i,t} = \frac{\frac{IO\_OPT_{i,t}}{IO\_EQT_{i,t}} - \frac{IO\_OPT_{i,t-1}}{IO\_EQT_{i,t-1}}}{\frac{IO\_IO\_OPT_{i,t-1}}{IO\_EQT_{i,t-1}}} \tag{2.6}$$

Where $\%\Delta\text{EPCMPNIO}_{\text{i,t}}$ is the percentage change in the aggregate equity holding (IO_EQT) plus respective aggregate IO_NETCALL (Long Calls minus Long Puts) institutional investors' ownership of firm i in quarter t. $\text{IO\_EQT}_{\text{i,t}}$ and $\text{IO\_EQT}_{\text{i,t-1}}$ represent aggregate institutional investors' Equity ownership for firm i in quarter t and t-1, respectively. Similarly, $\text{IO\_NETCALL}_{\text{i,t}}$ and $\text{IO\_NETCALL}_{\text{i,t-1}}$ represent aggregate institutional investors' long calls minus long puts options ownership for a firm i in quarter t and t-1, respectively.

First, the widely used equity-based institutional informed trading proxy in finance and accounting literature is $\Delta\text{EIO}_{\text{i,t}}$ defined as the change in the aggregate Equity ownership (IO_EQT) by institutional investors' for firm i in quarter t. Second, $\Delta\text{EBREADTH}_{\text{i,t}}$ is the change in the aggregate Equity holding (IO_EQT) by institutional investors' for firm i in quarter t. Third, $\%\Delta\text{ENIO}_{\text{i,t}}$ is the percentage change in the institutional ownership of aggregate equity holding of firm i in quarter t.

Apart from equities plus options-based proxy of informed institutional trading, I also control for other options-based instruments. Firstly, $\%\Delta \mathrm{OPTNIO}_{\mathrm{i,t}}$ is the percentage change in the number of a Netcall (Long Calls minus Long Puts) breadth institutional investors'. $\mathrm{IO\_CALL}_{\mathrm{i,t}}$ and $\mathrm{IO\_CALL}_{\mathrm{i,t\text{-}1}}$ represent aggregate institutional investors' long calls holding of firm i in quarter t and t-1, respectively. $\mathrm{IO\_PUT}_{\mathrm{i,t}}$ and $\mathrm{IO\_PUT}_{\mathrm{i,t\text{-}1}}$ represent aggregate institutional investors' long puts ownership of firm i in quarter t and t-1, respectively. $\mathrm{IO\_OPT}_{\mathrm{i,t}}$ and $\mathrm{IO\_OPT}_{\mathrm{i,t\text{-}1}}$ represent all institutional investors' options holding of firm i in quarter t and t-1, respectively. Secondly, %ΔO/SIO is defined as the percentage change in the number of options divided by their underlying equities holdings of institutional investors. All the proxies designed in this section are used in every cross-sectional regression to show superior performance of $\%\Delta \mathrm{EPCMPNIO}_{\mathrm{i,t}}$ over others.

2.3 Empirical Framework

2.3.1 Univariate Portfolio Analysis

In the empirical asset pricing literature, portfolio sorting methodology investigates the cross-sectional relation between future stock returns and any set of variables. The portfolio analysis is a nonparametric technique used to show the concurrent or lead effect of a sort variable (independent variable) on the outcome variable (dependent variable).[13] Hence, I utilize univariate portfolio analyses as a first step to examine the cross-sectional relation between %ΔEPCMPNIO with other investment advisors' private informed trading instruments and various firm characteristics. The main advantage of single-sort portfolio analysis over cross-sectional regression analysis is that it shows nonlinear relations between variables. The drawback of this analysis is that the inclusion of other control variables in a portfolio is computationally tricky, and interpretation of the result is uncertain.

[13]Nonparametric technique does not enforce assumptions relating to nature of relation between variables under investigation.

2.3.2 Bivariate Conditional Portfolio Analysis

This paper shows that the %ΔEPCMPNIO instrument performs better than widely used institutions' informed trading proxy ΔEIO in predicting future stock returns. Therefore, I utilize bivariate conditional-sort portfolio analysis, which examines a direct relation between %ΔEPCMPNIO and Fama-French five factor-alpha (FF-5 Factor) (see Fama and French (2015)) after controlling ΔEIO. I implement a two-variable dependent sort by forming breakpoints for the %ΔEPCMPNIO variable within each group of the ΔEIO and vice versa. Among the bivariate variable dependent sorts, the only variable of interest is the relation between the second sort variable and the outcome variable (FF-5 Factor). Hence, for interpreting the statistical significance of cross-sectional results of the conditional sort, the main focus is given to the second sort variable. The result section will cover the construction and interpretation of the double sort methodology in great detail.

2.3.3 Cross-Sectional Regression Analysis

The portfolio sorting technique does not allow a large set of control variables to measure the clean effect of multiple factors in a single analysis. In addition to portfolio analysis, to get precise multivariable information, in this article I perform a Fama and MacBeth (1973) two-step cross-sectional regression analysis that controls for various institutional investors' equity and option-based informed trading proxies and stock characteristics. The first step is to run each stock return variable on the various factors to estimate factor loading. In the second step, regression estimates aggregate in the time dimension from the first step. The main advantage of this regression analysis is that it's a statistical analysis designed to examine the relationship between pairs of variables. The Fama and MacBeth (1973) regression mean "pooled time-series coefficient averages from many cross-sections."

$$\begin{aligned} Y_{\mathrm{i,t+1}} = \gamma_{0,\mathrm{t}} + \gamma_{1,\mathrm{t}}\ \%\Delta\mathrm{EPCMPNIO} + \gamma_{2,\mathrm{t}}\ \%\Delta\mathrm{O/SNIO} + \gamma_{3,\mathrm{t}}\ \%\Delta\mathrm{OPTNIO} + \gamma_{4,\mathrm{t}}\ \%\Delta\mathrm{ENIO} \\ + \gamma_{5,\mathrm{t}}\ \Delta\mathrm{EIO} + \gamma_{6,\mathrm{t}}\ \Delta\mathrm{EBREADTH} + \gamma_{7,\mathrm{t}}\ \mathrm{Y}_{\mathrm{i,t}} + \gamma_{9,\mathrm{t}}\ \mathrm{BETA}_{\mathrm{i,t}} + \gamma_{10,\mathrm{t}}\ \mathrm{SIZE}_{\mathrm{i,t}} \\ + \gamma_{11,\mathrm{t}}\ \mathrm{BM}_{\mathrm{i,t}} + \gamma_{12,\mathrm{t}}\ \mathrm{MOM}_{\mathrm{i,t}} + \gamma_{13,\mathrm{t}}\ \mathrm{BASPREAD}_{\mathrm{i,t}} + \gamma_{14,\mathrm{t}}\ \mathrm{IDIOVOL}_{\mathrm{i,t}} + \epsilon_{i,t+1} \end{aligned} \tag{2.7}$$

Equation 7 is a cross-sectional regression specification, estimated using standard Fama and MacBeth (1973) quarterly regressions from 2004Q4 to 2019Q4 to determine a better instrument of informed institutional trading. Following previous institutional private informed trading literature, I use various dependent variables: future [-1,+1] cumulative earnings announcement returns, expected standardized unexpected quarterly earnings, and future excess stock returns. These are standard dependent variables used in finance and accounting literature. In addition to the expected dependent variable, I use the contemporary exogenous variable relationship to show the effect and source of private information by newly designed proxy %ΔEPCMPNIO. As Bali, Engle, and Murray (2016) suggested in their influential book, I only winsorize independent variables excluding lagged security returns winsorized at the 1^{st} and 99^{th} percentiles.

2.4 Data

2.4.1 Data Sources and Sample Construction

To investigate the effect of percentage change in institutions options and underlying equity on various stock characteristics, this study combines several datasets related to institutional ownership and firm performance.

2.4.2 Institutional Equity Ownership Data

In the U.S., large institutional investment managers who hold more than $100 million in equity securities need to file their holdings to the Securities and Exchange Commission (SEC) every quarter. This mandatory disclosure is under the section 13f of the Securities Exchange Act of 1934 ("1934 Act"), which has been added as part of the Securities Act Amendments of 1975. The SEC amended this disclosure to analyze the effect of large fund managers holding on the national market system, liquidity, block trading, etcetera. These institutions' filings are compiled by Thomson Financial (also known as CDA/Spectrum S34) and aggregated at the management institution level. I begin with the entire universe of 13F institutional investors' including hedge funds, mutual funds, insurance companies, pension funds, bank trusts, independent advisors, and endowments.

I used two datasets for the equities holding as per Wharton Research Data Services (WRDS) and Ben-David, Franzoni, Moussawi, and Sedunov (2021) suggestion due to inconsistency in institutions filings. Firstly, I used quarterly (S34) Thomson Reuters' data from the fourth quarter of 2004 till the second quarter of 2013. After June 2013, the SEC changed 13F filings to an XML (Extensible Markup Language) format. Hence, I used the SEC Analytics Suite by WRDS datasets from the third quarter of 2013 till the fourth quarter of 2019. Further, following Lewellen and Lewellen (2022), I use the Center for Research in Security Prices (CRSP) stock split adjustment factor to adjust equity holdings that occur between the "filing" and "report" dates. In addition, Thomson Reuters uses multiple entities to report Blackrock and Capital Group holdings; I followed Ben-David et al. (2021) suggestions to aggregate these filings.

2.4.3 Parsing and Merging Institutional Equity-Options Ownership Data

All the proprietary databases such as Thomson Reuters Financial or SEC 13F Holdings Data by the WRDS provide only equity holdings of institutional managers'. Both data vendors exclude equity options, debentures, and warrants from their master 13F datasets. To include equity options in my analysis to show consistent private information trading by institutions'. I download all the 13F HR and their amendments/restatements filings from 1999 till 2019 by first downloading master files[14]. Then, I parsed all the master files us-

[14]For further details of SEC master files which include all the mandatory disclosure reports Web Links, Form Type (13F or 10K), Central Index Key (CIK), Date Filed and Company Name refer following website: https://www.sec.gov/Archives/edgar/full-index/.

ing a textual analysis algorithm to get a sample of only 13F HR or 13F HRA. These steps help me get a complete population of 13F filers directly from the primary source.

Further, I download all the institutional investors' mandatory reports with the help of SEC master files[15]. I parse options holding of institutional investors from quarterly 13F filings with the help of machine learning tools. To clean and analyze all fillings and their amendments from 1999 to 2019, I use Lonare, Patil, and Raut (2020) package in the R language. First, from 1999 till the second quarter of 2013, 13F filings are in a text format. To extract equity options data, I read each line using a text mining algorithm for the following strings or option identifiers in a filing, "CALL", "CAL", "C", "CALLS", "PUT", "PUTS", "P" with spaces and tab before and after each of them. After this first round of string matching, I used Nearest Neighbor Matching to classify false-positive cases in a sample of data. This two-step process provides a clean sample of the equity options dataset till June 2013.

Second, after June 2013, SEC started publishing filling in eXtensible Markup Language (XML) format. I parse a portfolio of the entire population of institutional investors using a specialized XML/JSON extraction algorithm. This step provides all the institutional holdings available on the SEC website. Even standard database Thomson Reuters Financial or SEC 13F Institutional Holdings Data by the WRDS lack all the SEC filings. Hence, using two different parsing algorithmic techniques, I collect an entire sample of 13F holdings from 1999 to 2019. The final clean data contains information for long option holding a "CALL" or a "PUT", name of the company, Committee on Uniform Securities Identification Procedures (CUSIP), number of shares, and the fair market value of the securities listed, as of the end of the calendar quarter.

Finally, after merging equity and options data, I visualize the proportion of institutional investors' options to underlying equity holdings. Figure 5 plots the number of call or put

[15]To access all the filings consistently for an anlysis, all the downloaded filings are named as CIK_FilingDate_QuarterEndDate. That is unique Central Index Key for each institution, FilingDate represents actual filing date with the SEC, QuarterEndDate represents the quarter for which filings reported.

contracts scaled by total equities holdings of institutional investors. In detail, I first aggregate all options (Calls/Puts) and scale them by respective aggregated equities holdings (Options/Equities Shares) of institutional investors, I then sum this ratio in each quarter across all equities. The solid line represents the calls to equity shares ratio; in most years, this ratio is higher than the put to equity shares ratio (dotted line), except for the following three short periods. First, from 2005:Q4 to 2006:Q2, just before housing market prices started to fall. Second, from 2010:Q4 to 2011:Q4, around the Quantitative Easing 2 (QE2) and at the time when S&P 500 return did not change. Third, recently after 2019:Q2, just before COVID-19 pandemic evolved and progressed worldwide. These increases in Put / Equity Shares of institutional investors around the central bank policy intervention, major stock indexes' abysmal performance, and pandemic related economic downturn provide initial evidence that institution's use options to trade on their private information. In addition, I plot aggregate institutional investor's quarterly dollar value investment in Call and Put options in figure 6. The total investment value of all institutions in call and put increased staggeringly after 2017:Q4. Especially, an increase in total long put values compared to long call values suggest portfolio hedging by institutions.

2.4.4 Merging Institutional Investors Holding Data with Market and Accounting Data

To investigate the effect of institutional investors' options and underlying equity holding around earnings announcements, I use the Center for Research in Security Prices (CRSP) dataset stock prices and returns. I include only common stocks in this analysis, as determined by the CRSP share codes 10 and 11, and I exclude other share codes related to Exchange Traded Funds (ETFs), closed-end funds, etc. This selection is consistent with previous finance and accounting event studies because common stock directly affects information dissipation around earnings announcements. I merge CRSP and accounting data

Compustat with institutions holding using six-digit CUSIP.

I obtain analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S). This data contains a detailed history of quarterly analysts' earnings forecasts. As I/B/E/S data does not include analyst forecasts for all U.S. firms, I allow a final sample to vary based on the dependent variable measure used in this study.

To show the direct effect of private information trading by institutional fund managers on bid-ask spread fluctuations, I use the Generalized Probability of Information-Based Trading model (GPIN), which is shared publicly by Duarte et al. (2020)[16]. The sample period of their study is only till 2012, so for the cross-sectional regression analysis of GPIN and %ΔEPCMPNIO, the sample period is from 2004Q4 till 2012Q4.

2.5 Descriptive Statistics

Table 2.1 gives summary statistics for %ΔEPCMPNIO by representative quarter, calendar year, and five-year interval. Panel A, B, and C show quarterly, annual, and quinquennial distribution of %ΔEPCMPNIO. As institutional investors' 13F holdings are at a quarterly frequency, Panel A provides the representative quarters summary statistics for the %ΔEPCMPNIO. The average number of observations declined throughout the sample period from 2005:Q1 to 2019:Q4, consistent with the decrease in public-company listings in the United States.[17] The average number of firm-quarter holding observations decrease from 2,710 at the start to 1,442 at the end of the sample period. In column 2; the cross-sectional average of %ΔEPCMPNIO shows variation at different points of time. This measure shows the dramatic variation during 2007, the mean value is highest in 2007:Q3 and lowest in 2007:Q4. This trend is self-explanatory at the start of the financial crisis when

[16] I am grateful of Duarte et al. (2020) for kindly sharing their GPIN dataset and providing comprehensive detail of their algorithm to create GPIN measure

[17] see "Reports of corporates demise have been greatly exaggerated," October 21, 2021, McKinsey & Company, "According to our analysis, the number of public companies listed in the United States dropped from about 5,500 in 2000 to about 4,000 in 2020."

margin calls and redemption increased many folds, a primary reason for equity selloffs (See Ben-David et al. (2012)). Throughout the quarterly sample, the cross-sectional median (Column 4) is smaller than the cross-sectional average (Column 3). This pattern suggests that the distribution of %ΔEPCMPNIO is positively skewed. The standard deviation shows stability after a financial crisis. The first (25^{th} percentile) and fourth quartile (75^{th} percentile) depict variation across the sample period.

Further, Table 2.1 Panel B shows the annual cross-sectional distribution of %ΔEPCMPNIO. Column 3 exhibits a small decline in the average values in a recent decade except in 2013 due to augmentation of a new XML filing dataset from SEC WRDS Analytics after 2013:Q3 (See data section of Lewellen and Lewellen (2022)). As figure 1 reveals, the number of institutional investors increased recently, but the number of publicly traded equity and option securities decreased; this, in turn, decreased the cross-sectional standard deviation of %ΔEPCMPNIO. This result suggests that equity and options holdings are concentrated among a few institutional investors. Moreover, figure 3 demonstrates the year-end percentage of zero, negative, and positive values of %ΔEPCMPNIO over an entire sample period. The solid line shows that, except during the 2008 financial crisis period for all the years, %ΔEPCMPNIO remained positive. The percentage of zeros decreased from 10.36% in 2005 to 4.6% in 2019; this trend suggests that institutional investors' portfolio turnover increased over time, consistent with institutional investors' short-termist behavior (see Della Croce, Stewart, and Yermo (2011)).

Table 2.1 Panel C exhibits five-yearly and complete sample distribution of %ΔEPCMPNIO excluding 2013:Q3. I exclude one quarter because, as discussed in the data section, Thomson Reuters dataset does not the contain complete population of 13F filings after 2013:Q3. This discrepancy is also observable in Panel B for the annual distribution of %ΔEPCMPNIO in 2013, after merging the complete SEC analytics dataset. The five-yearly cross-sectional mean of %ΔEPCMPNIO shows a decreasing trend. In addition, the 2015-2019 quinquennial sample has a lower standard deviation and first quartile value of %ΔEPCMPNIO. These results provide initial evidence that institutional investors' holdings of call options and their underlying equities declined in recent years.

Further, figure 4 provides the first look of the total number of the individual call, put, or both options holdings by institutional investors in each quarter. On average, fund managers held 708882 long equity options contracts in their portfolios. I observed that total individual firms' long calls or puts options holdings decreased during the financial crisis, but after 2010, options holdings almost tripled by the end of 2019. This decrease during the 2008 financial crisis is due to the decline in liquidity and high volatility of assets and hedge funds margin calls (see Brunnermeier and Pedersen (2009), Ben-David et al. (2012)). The total long call options holding of individual firms by institutions exceeded the total long put options holding in most of the sample period, except in 2005 and 2011.

As per SEC regulations, institutional investment managers must report every security's fair market value on form 13F. [18] Figure 6 presents the aggregate fair market value of the equity options at the end of the calendar quarter. This figure shows the stunning trend of higher long put than long call options holdings' total fair value nine quarters before the financial crisis. This preliminary trend suggests that institutions trade using options to profit from their private information. On the contrary, from 2017:Q3 to 2019:Q4, on average investment managers invested more in call options than put options. This shift toward the call option suggests a bullish view of institutions toward the stock market.

[18] Section 13(f) Securities act fund managers do not require to report dollar value, exercise price, or expiration date of these options positions on the 13F form.

2.6 Results

2.6.1 Univariate Portfolio Sorts

Portfolios Sorted on %ΔEPCMPNIO and Other Institutional Proxy for Each Decile

Panel A of Table 2.2 shows that stocks with higher percent change in NetCall and underlying equity ownership of institutions also have bigger changes in equity turnover in the same quarter. I form decile portfolios for each calendar quarter during my sample period, based on %ΔEPCMPNIO rebalance every quarter. Portfolio 1 (Decile 1) contains stocks with the lowest percentage change in institutional ownership of equity plus their respective NetCall options in the current quarter. Portfolio 10 (Decile 10) consists of stock with the highest change in institutional ownership of equity plus their respective NetCall options in the current quarter. Column 1 (%ΔEPCMPNIO) exhibits substantial monotonous variation in decile portfolios. The average value of %ΔEPCMPNIO changes from -17.34 percent for decile 1 to 44.63 percent for decile 10. The difference between the top and bottom-ranked portfolio of %ΔEPCMPNIO is positive, with a significant t-statistic of 61.97. Clearly, the overall pattern in the other two (%ΔO/SIO and %ΔOPTNIO) institutional investors' options based on private information proxies do not exhibit any relation with %ΔEPCMPNIO. However, a t-test on the mean differential between the top-minus-bottom decile portfolio for both %ΔO/SIO and %ΔOPTNIO, comes out to be significant.

One of the most popular institutional investors' information proxies ΔEIO increases monotonically from top to bottom decile (t-statistics 105.41). Similarly, recently devised measure of institutional informed trading %ΔENIO shows systematic relation with %ΔEPCMPNIO (t-statistics 48.26). On the contrary, another only equity-based proxy used in literature ΔEBREADTH shows no association with %ΔEPCMPNIO (t-statistics -0.101).

Portfolios Sorted on %ΔEPCMPNIO and Contemporaneous Stock Characteristics

In Panel B of Table 2.2, I examine the relation between contemporaneous stock characteristics and %ΔEPCMPNIO. To investigate this relation, I form the decile portfolio ranked on %ΔEPCMPNIO rebalanced every quarter. Column 1 shows that the contemporaneous mean values of raw return of stocks in the top decile (decile 1) with the lowest %ΔEPCMPNIO is -0.1 percent per quarter, which monotonically increases to 4 percent per quarter for stocks in bottom decile (decile 10). The raw return in each decile portfolio is equally-weighted and balanced each quarter. The difference between the top and bottom-ranked portfolios of raw returns is positive 4.1 percent, with a significant t-statistic of 21.09. This initial evidence suggests that institutional trading in both equity and options affects contemporaneous average raw returns of a stock. Column 2 presents the cumulative average returns that are adjusted using the characteristic-matched (size, book-to-market, and momentum) benchmark of Daniel, Grinblatt, Titman, and Wermers (1997) (hereafter DGTW) returns, at the same time t as that of portfolios rebalancing of %ΔEPCMPNIO. The DGTW returns utilize monthly stock returns data consisting of 10 portfolios sorted on book-to-market and 10 portfolios sorted on size in total 100 portfolios. To maintain consistency with quarterly %ΔEPCMPNIO, I aggregate monthly DGTW returns to quarterly cumulative returns. The average DGTW return of stocks in decile 1 with the lowest %ΔEPCMPNIO is -1.2 percent per quarter and this monotonically increases to 2.8 percent per quarter for stocks in declile 10. The difference in DGTW characteristic-matched benchmark returns between top-minus-bottom is 3.9 percent, with a highly significant t-statistic of 20.14.

In addition, for each %ΔEPCMPNIO decile, I calculate the average values of cumulative abnormal returns around earnings announcements EAR(-1,1) for firm-quarter observations in a particular decile, with results present in Panel B of Table 2.2. The simultaneous equal-weighted earnings announcement returns show a monotonous rise in

%ΔEPCMPNIO. The difference between the top and bottom deciles is a statistically significant 1.4 percent per quarter. These results suggest that %ΔEPCMPNIO rises monotonically with current quarter earnings announcement returns. Besides, I also analyze equal-weighted mean simultaneous unexpected quarterly earnings (SUE) for each %ΔEPCMPNIO decile. This portfolio sort does not show any cross-sectional relation. Another strand of research finds that if investors correctly identify an error in the current consensus mean analyst forecast, they can earn risk-adjusted excess returns (see (Hawkins, Chamberlin, & Daniel, 1984)). Following this research, I use similar portfolio sorting technique for the average of mean analyst forecast error (CHFEPS) for the current firm quarter. The average CHFEPS of stocks in decile 1 with the lowest %ΔEPCMPNIO is -5.8 percent every quarter, and this continuously increases to 5.1 percent every quarter for stocks in decile 10. The difference in CHFEPS's top-minus-bottom portfolio is 10.9 percent, with a highly significant t-statistic of 19.41. Detailed definitions of the EAR(-1,1) (CAR), SUE, and CHFEPS variables are in Appendix A.

As the study by Grinblatt, Titman, and Wermers (1995) found that 77 percent of mutual fund investors were momentum investors, their fund performance was strong. The past 11-month momentum (MOM column in Panel B of Table 2.2) cumulative return from month t-12 to month t-2 (See Jegadeesh and Titman (1993)). The MOM variable construction stops two months before the calendar quarter-end date to avoid the short-term return swing. The MOM exhibits a continuous increase in the decile portfolios sorted on %ΔEPCMPNIO. The top-minus-bottom decile portfolio is statistically significant with t-statistics of 31.82. This result suggests that contemporaneous %ΔEPCMPNIO is positively associated with the momentum factor. In addition, a monotonous pattern of average MOM indicates that institutions buy past winners and sell past losers.

Portfolios Sorted on %ΔEPCMPNIO and Subsequent Stock Characteristics

In Panel C of Table 2.2 presents the predictive ability of institutional measure %ΔEPCMPNIO for various stock characteristics, which have become the academic standard over the past thirty-year. Probably the most important and convincing results in this article are the future average values of cumulative abnormal returns around earnings announcements EAR(-1,1), which increase with the portfolio decile ranks of %ΔEPCMPNIO (column 3). This monotonous rise indicates the predictability of %ΔEPCMPNIO around scheduled firm-event such as earnings. The decile 10 portfolios of stocks with the highest value of %ΔEPCMPNIO generate 2.5 percent return per quarter, which is percent higher than decile 1 portfolio, with highly significant t-statistic of 36.73. Similarly, one quarter ahead mean values of unexpected quarterly earnings (SUE) produce a monotonic increasing pattern in %ΔEPCMPNIO decile (column 4). The average return difference (Decile10 - Decile1) is 0.8 percent per quarter, with a t-statistic of 6.2.

Moreover, Graph A of Figure 7 depicts a monotonic relation of future abnormal returns around earnings announcements and future raw stock returns of a decile portfolio against lagged %ΔEPCMPNIO. This analysis is consistent with the new tests of monotonic portfolio patterns designed by Patton and Timmermann (2010). First, I divide the entire sample into deciles by one-quarter lagged %ΔEPCMPNIO. I then calculate the average values of the three-days abnormal return around earnings announcement and quarterly raw returns for each decile portfolio. As hypothesized, I detect a strictly monotonic trend in the cumulative abnormal returns (CAR(-1,1)) as %ΔEPCMPNIO increases. Similarly, the average raw return on the higher %ΔEPCMPNIO exceeds that of the lower %ΔEPCMPNIO; furthermore, a t-test on the top-minus-bottom returns comes out to be highly significant (t-statistic=21.02). These results confirm the institutional investors' ability to predict the future returns and CAR(-1,1) by holding without any linearity assumption between variables.

Equally important, Graph B of Figure 7 presents future abnormal returns around earnings announcements and future raw stock returns on stocks sorted into deciles according to lagged ΔEIO. The relation between the cumulative abnormal returns (CAR(-1,1)) and lagged ΔEIO shows an upward trend but not strictly increasing. Further, the overall pattern in the average raw stock returns is reverse U-shaped and does not show any relation with ΔEIO. Therefore, both explanatory variables show no predictability with that of lagged ΔEIO. These finding from figures 7A and 7B collectively provide preliminary evidence for the positive relation between %ΔEPCMPNIO and the holding firm's performance measure. Hence, %ΔEPCMPNIO can be a superior instrument of institutional investors' informed trading than ΔEIO. Even though interesting, these non-parametric techniques require more refined multivariate tests, which I present in the next section.

Column 1 of Table 2.2A (Raw Returns) indicates a higher percentage change in NetCall and their underlying equity by all institutions shows positively significant future returns. The average portfolio raw returns in the following quarter exhibit a monotonic increasing pattern in the %ΔEPCMPNIO decile. The average quarterly return of the long-short portfolio Decile10 - Decile1, formed by long decile one and short decile ten, is 0.8 percent with a t-statistic of 4.22. The return of Decile10 - Decile1 is also economically significant.

Further, to adjust for variations in risk characteristics of stocks, I use three different models. First, I use DGTW benchmark-adjusted returns, which adjust for the size, book-to-market, and momentum effect. The mean values of future DGTW-adjusted returns do not show an increasing trend for portfolios sorted on %ΔEPCMPNIO. The average return difference (Decile10 - Decile1) decreases to 0.7 percent using DGTW-adjusted returns, but is statistically significant (t-statistics = 3.982). These results are consistent with Yan and Zhang (2009) findings that short-term institutional ownership predicts future stock returns. Second, I use the Fama and French (1993) three-factor model, consisting of market, size, and book-to-market factors (hereafter FF3). The one quarter-ahead average FF3-Alpha monotonous increase in %ΔEPCMPNIO decile portfolio. The difference in returns between deciles 1 and 10 is 1.6 percent per quarter (t-statistics = 2.68). Third, I investigate the recently published Fama and French (2015) five-factor model alpha, which includes investment, profitability, size, market, and book-to-market factors (hereafter FF5). The monotonous trend and differences in returns between deciles 1 and 10 (1.9 percent per quarter) are similar to that of FF3 alphas.

2.6.2 Fama and MacBeth Regression Analysis

The previous univariate portfolio analysis section, only considers relation between %ΔEPCMPNIO and other institutional or firm characteristics without incorporating different control variables. The Fama and MacBeth (1973) two-step regression analysis mitigates the issue of multiple control variables.

Cross-Sectional Regression Analysis of EAR(-1,1) and %ΔEPCMPNIO

In this section, I examine the effect of %ΔEPCMPNIO and other institutional private information proxies together in a regression framework that controls for the other firm characteristics. Following prior literature, I use three days of cumulative earnings announcement raw (unadjusted) returns EAR(-1,1) as dependent variables and %ΔEPCMPNIO as an independent variable (See Guo and Qiu (2016)). I run the following Fama and MacBeth (1973) cross-sectional regression every quarter and report t-statistics on the basis of the Newey and West (1987) two-lag standard errors to account for serially correlated residuals.

$$CAR_{\mathrm{i,t+1}} = \alpha_{\mathrm{t}} + \beta_{\mathrm{1,t}}\ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.8}$$

Where i denote the stock, t denotes the calendar quarter, and $\mathrm{CAR}_{\mathrm{i,t+1}}$ is the cumulative abnormal returns around three days announcement for firm i in quarter t+1. Regression specification in equation 8 is consistent with previous studies (See Ali, Durtschi, Lev, and Trombley (2004)). In this article, both institutional investors and earnings announcement returns are available at a quarterly frequency. Hence, it's a reasonable choice to use calendar quarter cross-sectional regression.[19].

The main independent variable of interest in all regressions is the percentage change in equity and netcall institutional ownership %ΔEPCMPNIO. In addition, I include two institutions' holdings of equity options measures and three institutions' holdings equity measures as control variables. Further, following previous asset pricing literature, I use standard individual firm characteristics that explain the cross-section of returns and might affect the announcement outcome. Following previous literature, the independent variables (except lag dependent variable) are winsorized at the 1 and 99 percentiles each quarter.

All models in Table 2.3 show that %ΔEPCMPNIO is positively associated with future cumulative abnormal returns around announcements with or without control variables, with highly significant t-statistics. All the results present in this section are the time-series averages of cross-sectional regressions by quarter and t-statistics adjusted using the Newey-West correction. In model 1, I regress CAR on %ΔEPCMPNIO, and the coefficient is positive and highly significant at the 1 percent level (0.082, t-statistic 10.36). In other words, stocks with an increase in netcall options and underlying equities tend to have higher earnings announcement abnormal returns. Model 2 shows the results of %ΔEPCMPNIO together with two other institutional investors' options-based information proxies. The Number of observations in this specification is almost half than the first one. This decrease in sample size is because the only subset of institutional investors uses options in the early sample period. The coefficient on %ΔEPCMPNIO remains positively significant in the presence of other options proxies, with a t-statistic of 11.12. Only %ΔO/SNIO shows partial significance with a positive coefficient. This finding suggests that aggregate institutional investors' change in netcall and underlying equity holdings together signal positive information about firms' earnings announcement abnormal returns.

[19] Although the standard asset pricing literature used lower frequency (monthly/weekly) cross-sectional regression. Some of the previous researchers use quarterly cross-sectional Fama and MacBeth (1973) regression (See Akbas (2016))

In model 3, I add the ΔEIO, %ΔENIO, and ΔEBREADTH variables to the model 1 regression to evaluate whether previously used institutions' equity-based private information instrument subsumes the effect of %ΔEPCMPNIO. The widely used proxy ΔEIO's coefficient is positive and marginally significant (t-statistic 2.06). Similarly, the recently devised proxy %ΔENIO is positively significant with other regression variable. However, ΔEBREADTH is negative and insignificant in specification 3. None of the previously used proxies of institutional investors' private information trading dominates %ΔEPCMPNIO in the cross-sectional regression. The coefficient of %ΔEPCMPNIO remains positive and highly significant (t-statistic 11.01). Therefore, results in this regression specification support a conjecture that, on average, institutional investors are sophisticated traders and use different trading instrument to exploit their private information.

After inclusion of both equities and/or options-based fund managers' informed trading proxies. The positive highly significant (at 1 percent level) coefficient on %ΔEPCMPNIO remains unchanged. The equity-based instrument %ΔENIO developed by Guo and Qiu (2016) shows that its explanatory power persists to a lesser extent than %ΔEPCMPNIO. Hence, the result in model 4 confirms that the positive relation between CAR and %ΔEPCMPNIO arises because of institutional investors' aggregate holdings of equity and netcall.

To show that the inclusion of various stock characteristics used in prior literature as a risk measure does not affect the relation between %ΔEPCMPNIO and CAR, following (Fama & French, 1992) and Daniel et al. (1997), I include portfolio BETA, market capitalization (SIZE), and boot-to-market (BM) in a regression. Similarly, Guo and Qiu (2016) note that institutional investors' closely follow three-to-twelve month momentum strategies. Hence I also use the past 12-months' cumulative stock return in models 5-7. In addition, I added monthly Idiosyncratic return volatility aggregate at the quarterly level (IDIOVOL), and average of daily bid-ask spread divided by the average of daily spread at monthly frequency suggested by Green, Hand, and Zhang (2017). Above all, Model 5 in Table 2.3 exhibits complete regression specification, including institutional investors' proxies and stock characteristics. The predictive power of %ΔEPCMPNIO stays almost the same as a simple cross-sectional regression. The coefficient on BETA is positive and highly significant. This result is consistent with the fact that institutions' follow smart beta trading strategies. Moreover, the sign and significance of BM match with a previous study by (Ali et al., 2004); they used same regression specification like Model 5.

The coefficient on the %ΔEPCMPNIO for large firms (market capitalization greater than the median in my sample), is highly significant and positive, with t-statistics is 10.24. But, in model 5, the coefficient on %ΔENIO is insignificant. This result suggests that institutional investors prefer options instruments over equities for their short-term profit-making and do not change equity holdings of large firms frequently. In model 7, for small firms (market capitalization smaller than the median in my sample) predictive power of %ΔEPCMPNIO decreases a little, and the coefficient on %ΔENIO is positively significant. I find these results to be intuitive, given that small firms sometimes do not have highly liquid Call/Put options. Therefore, institutions' mostly rely on small firms' equities to trade their private information. All the variables used in Table 2.3 describe in detail in Appendix A.

Cross-Sectional Regression Analysis of Standardized Unexpected Quarterly Earnings (SUE) and %ΔEPCMPNIO

In this section, I show that %ΔEPCMPNIO proxy can predict changes in firm fundamentals (changes in a firm's cash flow prospects), that is standardized unexpected quarterly earnings. To show this relation, I run the following cross-sectional regression every quarter:

$$SUE_{\mathrm{i,t+1}} = \alpha_{\mathrm{t}} + \beta_{\mathrm{1,t}}\ \ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.9}$$

Similar to the previous section, the first model shows simple univariate regression of the SUE (dependent variable) on the %ΔEPCMPNIO. This regression finds that the institutions' aggregate equity and netcall holding predicts unexpected quarterly earnings in the next quarter. The coefficient on %ΔEPCMPNIO is positive and highly significant, with the t-statistic of 6.11. Further, in Table 2.4 model 2-5 shows the predictive power of %ΔEPCMPNIO persists with the inclusion of other institutions' proxies and characteristics of firm fundamental. The positive and significant coefficient on all specifications (model 2-5) suggests that the %ΔEPCMPNIO proxy contains information about changes in firm fundamentals, especially unexpected earnings surprises. Surprisingly, sub-sample analysis of large and small firms in models 6 and 7, respectively, shows the predictive power of %ΔEPCMPNIO instrument diminished. Hence, the coefficient on %ΔEPCMPNIO is statistically indistinguishable from zero. These results provide evidence that institutional option and equity holdings predict firms' fundamentals correctly irrespective of their market capitalization.

Cross-Sectional Regression Analysis of Future Stock Returns and %ΔEPCMPNIO

Following Guo and Qiu (2016), I test a conjecture that institutional aggregate holdings of equities and options forecast future stock returns because of their private informed trading around an earnings announcement. To show the predictability of %ΔEPCMPNIO in a short-term up to one week and up to two months after a calendar quarter, I run following Fama and MacBeth (1973) cross-sectional regression:

$$Ret_{\mathrm{i,t+1}} = \alpha_{\mathrm{t}} + \beta_{\mathrm{1,t}}\ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.10}$$

Table 2.5 reports the cross-sectional regression of future excess returns ($\mathrm{Ret}_{\mathrm{i,t+1}}$) on %$\Delta$EPCMPNIO and other control variables. The analysis for weekly raw stock returns indicates a strong positive relation between %ΔEPCMPNIO and $\mathrm{Ret}_{\mathrm{i,t+1}}$, as univariate regression (model 1) produces an average slope on %ΔEPCMPNIO of 0.93 with a corresponding t-statistic of 2.26. In addition, in multivariate regression analysis, I find almost same results when controlling for other confounding institutional and fundamental factors.

After controlling for commonly referred stock return characteristics and popular institutional trading and herding instruments, the important regression outcome is model 4. The coefficient on %ΔEPCMPNIO is 6.7, and the t-statistic more than doubled to 4.67. These analyses suggest that %ΔEPCMPNIO has robust power to explain weekly stock returns in the cross-sectional regression with all control variables. The predictive power decreases for the univariate regression model.

On the contrary, the univariate regression between two months ahead raw stock returns and %ΔEPCMPNIO (model 5) shows stronger predictive power than a similar multivariate regression analysis (model 6-8) with all control variables. These results suggests that the predictive ability of %ΔEPCMPNIO is not subsumed by institutional or firm return characteristic control variables used in previous literature.

Further, following a suggestion from Kothari and Warner (2001) and Wermers (2011), I use the Daniel, Grinblatt, Titman, and Wermers (DGTW) stock characteristic-adjusted return to test the advantage of using %ΔEPCMPNIO over other institutional investors' proxies. In model 9, univariate regression, the coefficient on %ΔEPCMPNIO is 0.017 and is statistically significant at the 1 percent level. Model 10-12 indicates that the predictive power of %ΔEPCMPNIO decreases slowly with the addition of more control variables. These results suggest that the relation of %ΔEPCMPNIO and DGTW returns is explained by some linear combination of the added control variables. Overall, findings from Table 2.5 provide substantial evidence that %ΔEPCMPNIO proxy subsumes all the other institutional investors' private information trading instrument and have enough predictive power to explain the cross-section of expected raw and DGTW returns.

Cross-Sectional Regression Analysis of Contemporaneous Stock Returns and %ΔEPCMPNIO

Merton (1987)'s theoretical framework provides a single line of inquiry by institutional investors' trading and anomalous stock price behavior by keeping the firm's fundamental constant. To document empirical evidence for this theoretical model, Lehavy and Sloan (2008) use ΔEBREADTH as a proxy for investor recognition of security. And they find that the contemporaneous raw and size-adjusted returns are positively associated with ΔEBREADTH. Hence, I run the following cross-sectional regression to extend Lehavy and Sloan (2008) findings with the new institutional private information proxy from this article, which contains options and their underlying equities.

$$Ret_{\mathrm{i,t}} = \alpha_{\mathrm{t}} + \beta_{1,\mathrm{t}}\ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.11}$$

Table 2.6, models 1-12, shows the superior performance of %ΔEPCMPNIO over other proxies, especially ΔEBREADTH in the cross-section of contemporaneous raw/DGTW stock returns. For all models, %ΔEPCMPNIO loads with a positive coefficient having a t-statistic between 8.24 and 2.6. This high significance level suggests that the current calendar week and month represent considerable trading. This reasoning is consistent with Merton (1987) argument that firm value is directly proportional to investor recognition holding firms' fundamental constant, in other words, popularly known as the "investor recognition hypothesis". Findings in Table 2.6 are consistent with previous research that average coefficient on ΔEBREADTH is negative in all regressions (see Lehavy and Sloan (2008) and Guo and Qiu (2016)). In addition, the surprising negative loading on momentum (MOM) in models 4 & 8 needs further empirical analysis. Further, positive loading on the average bid-ask spread (BASPREAD) is opposite of Table 2.5. Overall, the results in Table 2.6 are consistent with a research question in this article that %ΔEPCMPNIO is a better proxy for institutional investors' private information trading.

Cross-Sectional Regression Analysis of Change in Mean Analyst Earning Forecast and %ΔEPCMPNIO

In financial markets, sophisticated investors have the advantage over unsophisticated investors in earning a return on their superior information. The primary purpose of institutional investors in a financial market is to earn maximum profit by collecting accurate information about firms' fundamentals before this information incorporated in security prices. A recent paper by Lowry et al. (2019) provides evidence that asset managers gather and trade on mergers and acquisitions of firms' information from their advisor bank. They find that this private information trading is mostly observed in equity options holdings of institutions. But, one question remains unanswered, what is the main source of all institutional investors' private information at the aggregate level? To answer this question, I use a regression specification suggested by Bonner, Walther, and Young (2001). I run the following cross-sectional regression where a change in mean analyst earnings (chfeps) is the dependent variable and %ΔEPCMPNIO is the main independent variable.

$$chfeps_{\mathrm{i,t}} = \alpha_{\mathrm{t}} + \beta_{1,\mathrm{t}}\ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.12}$$

Table 2.7, Model 1-6 shows the results of the mean of all the analysts current month's change in earnings forecasts. For all models, the coefficient on %ΔEPCMPNIO is positive and highly significant, with t-statistics between 7.7 and 10.09. These exceptional results indicate that institutional investors closely follow the current month's change in analyst forecast for their private information trading. This informational gathering reflects the aggregate institutional investors' change in options and underlying equities holding for each quarter. Further, regression in models 1-6 suggests that the current month's change in earnings forecast by analysts positively related to %ΔEPCMPNIO irrespective of firms' size.

Models 7-12 of Table 2.7 provide the baseline regression model results, which include the mean of the current calendar quarter change in analysts' earnings forecasts. This regression specification also shows positive significant relation between %ΔEPCMPNIO and the mean of the quarterly change in analysts forecast irrespective of firm size (t-statistics between 7.37 and 9.39). Therefore, overall findings in Table 2.7 confirm the widespread view that institutional investors trade using both options and their underlying equities based on current quarter/month's change earnings forecasts by the firm's analyst. And %ΔEPCMPNIO correctly identifies one of the institutions' private information sources. In the next section, I analyze if institutional investors' private information trading is observable in the Probability of Informed Trading (PIN) drawn from Trades and Quotes.

Cross-Sectional Regression Analysis of Generalized Probability of Informed Trading (GPIN) and %ΔEPCMPNIO

In this section, I use the recently published measure of the Generalized Probability of Informed Trading (GPIN) by (Duarte et al., 2020) to show that change in institutions' holding reflects in the average GPIN measure. To illustrate this relation, I run the following (Fama & MacBeth, 1973) cross-sectional regression:

$$GPIN_{\mathrm{i,t}} = \alpha_{\mathrm{t}} + \beta_{1,\mathrm{t}}\ \%\Delta\mathrm{EPCMPNIO} + \beta_{\mathrm{x,t}}\ \mathrm{Controls}_{\mathrm{i,t}} + \epsilon_{i,t+1} \tag{2.13}$$

For all regression specifications of Generalized Probability of Informed Trading in Table 2.8, there is a positive and significant relation between %ΔEPCMPNIO and GPIN. The positive coefficients on %ΔEPCMPNIO are consistent with the idea that institutions' private information trading of a given stock is observable in the order flow data. The rationale is that sophisticated institutional investor shifts their portfolio weights based on their private information (see Easley and O'hara (2004)). This information reflects in investors' trades and quotes value gathered from stock exchange order flow data. More importantly, the coefficient on %ΔEPCMPNIO remains positive and significant even after the inclusion of other firm characteristics. Surprisingly, loading on the stocks' idiosyncratic volatility (IDIOVOL) is positive and highly significant (models 3 and 6). This result can suggest that private information trading of a stock affects their idiosyncratic volatility but need further empirical investigation, which is not the focus of this article.

2.6.3 Double Portfolio Sorting: %ΔEPCMPNIO better measure than ΔEIO

This section examines the predictive power of %ΔEPCMPNIO controlling for ΔEIO. First, I create a quintile portfolio of %ΔEPCMPNIO with approximately the same level of ΔEIO. This bivariate portfolio sorting can provide evidence that the%ΔEPCMPNIO is a better measure of institutions' informed trading than ΔEIO.

To pursue dependent portfolio sort analysis, I first sort stocks equally into five portfolios by ΔEIO. Then, within each ΔEIO, I form a second set of quintile portfolios ranked on %ΔEPCMPNIO. Hence, I can investigate the expected return difference using five factor alphas due to the %ΔEPCMPNIO category controlling the effect of ΔEIO. I hold these portfolios for a quarter and then rebalance at the end of each quarter.

Table 2.9, Panel A, details quarterly returns (Fama and French (2015) five-factor alpha) of dependent sort portfolios. Generally, return increases across columns from Low to High, and the difference in high and low portfolios in Panel A shows positive returns. High and Average rows show a positive monotonous increase in returns across columns. The high minus low return difference across columns is 0.52 percent per quarter, with a t-statistic of 3.24. The return difference between the high and low aggregate %ΔEPCMPNIO quintiles is around 0.21 percent per quarter, with a t-statistic of 6.6. These results suggest that the return differential is entirely explained by %ΔEPCMPNIO after controlling ΔEIO.

Table 2.9, Panel B utilizes the same portfolio analysis technique as Panel A but include a sort on %ΔEPCMPNIO and subsequently on ΔEIO. This dependent sorting creates portfolios with disparate ΔEIO orders after controlling the private information holdings in %ΔEPCMPNIO. This process provides a non-parametric technique to inspect the stock returns predictive ability of ΔEIO. Panel B does not reveal increasing returns across columns; also, one of the high minus low returns is negative. The return difference between the high and low aggregate ΔEIO quintiles is insignificant, with a t-statistic of 1.53.

Thus, ΔEIO does not show predictive power for future stock returns after controlling for %ΔEPCMPNIO. Overall, Table 2.9 provides a piece of evidence using the non-parametric dependent sort technique that %ΔEPCMPNIO is a superior instrument of institutional investors' informed trading then ΔEIO.

2.7 Conclusion

Given the widespread importance of asset managers' varying levels of securities trading in the financial markets and their consequences on the economy, it is paramount to understand the effect of institutional investors' portfolio holdings (option and underlying equity) on respective firms' stock price behavior. This paper analyzes six institutional investors' private informed trading proxies: %ΔEPCMPNIO, %ΔOPTNIO, %ΔO/SIO, ΔEIO, ΔEBREADTH, %ΔENIO. I show that the %ΔEPCMPNIO performs better than all other proxies in cross-sectional regression and non-parametric portfolio analysis. In contrast, the other five institutional investor proxies are inferior to %ΔEPCMPNIO in predicting returns around earnings announcements and short-term raw returns.

I find that %ΔEPCMPNIO forecasts next quarter returns around earnings announcement and standardized unexpected earnings with or without controlling other risk-based stock characteristics. These findings are consistent with Kim and Verrecchia (1997)'s single model of rational trade, where sophisticated investors' demand for securities changes surrounding an anticipated event such as an earnings announcement. Hence, the percentage change in netcall and underlying equity ownership by institutions in a specific firm is consistent with informed trading. Finally, further test reveals that the calendar quarter-end %ΔEPCMPNIO measure contains information to consistently predict weekly and monthly stock returns.

A deeper empirical examination of the %ΔEPCMPNIO reveals that institutions' options and underlying equities quarterly demand depends on the contemporaneous change in a mean analyst earnings forecast. In addition, the %ΔEPCMPNIO novel measure information content is reflected in the Generalized PIN model (GPIN), which requires only order flow data to estimate. In sum, this paper's empirical results suggest that %ΔEPCMPNIO is a better measure of institutional investors' informed trading. In general, %ΔEPCMPNIO is a promising novel measure containing both equity and options holding of institutions', which can provide new avenues for further research.

2.8 Appendix C. Variable Definitions

%ΔEPCMPNIO : Percentage change in the number of a Call options minus number of Put options plus their underlying stock's holding of institutional managers'.

%ΔO/SIO : Percentage change in the number of a Options divided by their underlying equities holding of institutional investors'.

%ΔOPTNIO : Percentage change in the number of a Call options minus number of Put options holding of institutional investors'.

%ΔENIO : Percentage change in the number of a stock's institutional advisors'.

ΔEIO: Change in institutional advisors' equity holdings

ΔEBREADTH: Change in breadth of institutional advisors' equity holdings

CAR (EAR(-1,1)): Three-day cumulative abnormal size-adjusted return in the window (1,0,1) around the earnings announcement

SUE: Unexpected quarterly earnings standardized by end of quarter stock's market capitalization. Earnings measure is I/B/E/S actual earnings subtracted by median predicted earnings if present, otherwise earnings measure used from Compustat dataset.

MOM: Past eleven month's cumulative returns ending one month before calendar quarter end.

3-Factor Alpha: This variable calculated using Fama-French three factor model following Fama and French (1996)

5-Factor Alpha: This variable calculated using Fama-French three factor model following Fama and French (2015)

CHFEPS: Average analyst prediction one month before the fiscal period end date from I/B/E/S dataset subtracted by the same months' average forecast for previous fiscal period using yearly earnings predictions.

GPIN: Generalized Probability of Informed Trading model using only order flow alone suggested by Duarte et al. (2020).

BETA: Estimated market beta from weekly returns and equal weighted market returns for 3 years ending month t-1 with at least 52 weeks of returns

SIZE: Natural log of market capitalization at end of month t-1.

BM: Book value of equity (ceq) divided by end of fiscal year-end market capitalization.

BASPREAD : Monthly mean of daily bid-ask spread standardized by mean of daily spread

IDIOVOL:Standard deviation of residuals of weekly returns on weekly equal weighted market returns for 3 years prior to month end

Table 2.1: **Summary statistics for %ΔEPCMPNIO at various time intervals**
This table reports summary statistics of percentage change in a number of call options minus a number of put options (netcall) plus underlying stock holding of institutional investors'. The sample consists of options and equities holding of all the institutional advisors' 13F filings from 2004Q4 to 2019Q4. I compute equal-weighted cross-sectional statistics for every period and report statistics on different time intervals. Panel A provides detailed distribution of a sample of representative quarters. Panel B reports the annual distribution of %ΔEPCMPNIO over an entire period used in this article's analysis. Panel C presents five-year and full-time period statistics of %ΔEPCMPNIO. This institutional investor's informed trading measure is winsorized at both the 1^{st} and 99^{th} percentiles. The definition of all the variables and their creation reported in Appendix A.

Panel A. Representative quarters						
Period	**NOB**	**Mean**	**Median**	**Std dev**	**25^{th} Percentile**	**75^{th} Percentile**
2005Q1	2710	2.992	0.000	16.877	-4.396	6.250
2005Q2	2670	4.385	1.685	17.491	-2.932	7.895
2005Q3	2702	2.037	0.000	17.519	-5.202	5.946
...						
2007Q2	2598	4.026	1.274	14.865	-3.145	7.531
2007Q3	2576	7.344	4.783	17.947	0.000	11.111
2007Q4	2492	-2.998	-3.942	11.815	-9.302	0.858
...						
2010Q1	1935	1.061	0.000	11.571	-4.545	4.167
2010Q2	1869	-1.770	-2.985	14.237	-7.752	1.316
2010Q3	1866	4.260	3.158	9.989	-0.813	8.511
...						
2015Q2	1788	1.239	0.637	12.409	-3.208	5.447
2015Q3	1776	3.369	1.371	11.244	-2.251	6.323
2015Q4	1737	-0.735	-0.743	9.499	-5.682	3.954
...						
2019Q2	1494	-0.974	-1.601	9.717	-5.612	2.410
2019Q3	1466	0.011	0.257	12.941	-3.540	4.783
2019Q4	1442	2.507	3.467	12.983	-1.163	7.645
Panel B: 1-year quarterly averages						
2005	10763	3.103	0.654	17.077	-4.092	6.897
2006	10632	5.909	2.857	16.703	-1.824	9.772
2007	10069	3.495	1.282	15.412	-4.444	8.333
2008	8374	1.356	0.000	13.576	-5.682	6.226

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Panel B: 1-year quarterly averages						
Period	**NOB**	**Mean**	**Median**	**Std dev**	**25th Percentile**	**75th Percentile**
2009	7281	3.539	1.667	14.228	-3.226	7.522
2010	7560	2.153	0.769	12.357	-3.922	6.452
2011	7229	0.842	1.499	24.733	-4.294	7.759
2012	7060	4.129	1.587	18.381	-2.436	6.822
2013	7126	28.073	4.374	168.598	0.000	10.526
2014	7229	2.204	1.075	10.717	-2.941	5.917
2015	7014	1.832	1.042	10.872	-3.226	5.814
2016	6571	2.500	1.846	9.339	-2.353	6.548
2017	6420	1.895	0.886	11.502	-3.333	6.886
2018	6203	1.486	0.406	11.421	-3.564	4.938
2019	5894	0.950	0.805	11.407	-3.333	5.565
Panel C: 5-year quarterly averages and full sample excluding 2013:Q3						
2005-2009	47119	3.577	1.242	15.700	-3.846	7.843
2010-2014	34414	3.082	1.493	18.883	-2.985	7.143
2015-2019	32102	1.752	1.020	10.930	-3.175	5.952
Full Sample	113635	2.912	1.250	15.637	-3.361	7.059

Table 2.2: **Decile Portfolios of Stocks Sorted on %ΔEPCMPIO**
This table provides averages of various institutional managers' proxies and firm characteristics equally weighted decile portfolios formed on %ΔEPCMPNIO. Fund portfolios are rebalanced quarterly. The sample in analysis is based on NYSE, NASDAQ, and AMEX-listed common stocks of all firms from the Center for Research in Security Prices (CRSP) dataset. Panel A presents equally-weighted averages of various options and equities based institutional advisors' information proxies used in literature. Panel B reports contemporaneous stock characteristics portfolio formed on %ΔEPCMPNIO across total sample. One period ahead stock characteristics portfolio formed on %ΔEPCMPNIO are present in Panel C. The sample period of all the variables are from 2004Q4 to 2019Q4. Definition of variables and their creation reported in Appendix A. All the variables are winsorized at 1 percent and 99 percent each quarter.

	Panel A : Institutional Investor Measures Decile Sorting					
	Institutional Investors' Equity and Option Holding			**Institutional Investors' Only Equity Holding**		
Decile	**%ΔEPCMP-NIO**	**%ΔO/S-NIO**	**%ΔOPT-NIO**	**%ΔENIO**	**ΔEIO**	**ΔEBREADTH**
1	-17.339	92.726	-29.764	-17.045	-13.220	-0.065
2	-6.030	11.143	-53.845	-5.861	-8.431	-0.070
3	-2.855	10.213	-50.669	-2.725	-5.198	-0.123
4	-0.970	10.127	-53.801	-0.847	-2.053	-0.015
5	0.728	7.945	-44.944	0.735	1.901	-0.135
6	2.510	8.498	-48.239	2.474	6.423	0.013
7	4.349	9.201	-51.043	4.268	9.760	-0.085
8	7.072	10.137	-51.763	6.957	12.650	-0.056
9	11.402	12.145	-52.574	11.213	13.949	-0.068
10	44.629	12.062	-57.068	43.569	15.922	-0.069
10 -1 Diff.	61.968	-80.665	-27.304	60.614	29.142	-0.004
t-stat.	(49.780)	(-10.664)	(-3.346)	(48.256)	(105.415)	(-0.101)

	Panel B : Contemporaneous Stock Characteristics					
Decile	**Raw Returns**	**DGTW Returns**	**EAR(-1,1)**	**SUE**	**MOM**	**CHFEPS**
1	-0.001	-0.012	0.000	-0.016	0.068	-0.058
2	0.002	-0.007	0.001	-0.008	0.080	-0.028
3	0.006	-0.004	0.002	0.007	0.086	-0.016
4	0.007	-0.001	0.003	-0.002	0.103	-0.002
5	0.009	-0.002	0.004	-0.001	0.114	0.005
6	0.010	0.004	0.005	0.001	0.130	0.017
7	0.013	0.005	0.006	0.137	0.148	0.023
8	0.020	0.008	0.007	0.005	0.166	0.035

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Decile	**Raw Returns**	**DGTW Returns**	**EAR(-1,1)**	**SUE**	**MOM**	**CHFEPS**
9	0.024	0.013	0.010	-0.018	0.209	0.042
10	0.040	0.028	0.015	0.044	0.305	0.051
10 -1 Diff.	0.041	0.039	0.014	0.060	0.237	0.109
t-stat.	(21.019)	(20.137)	(15.147)	(1.383)	(31.816)	(19.409)

	Panel C : One Quarter Ahead Stock Characteristics					
Decile	**Raw Returns**	**DGTW Returns**	**EAR(-1,1)**	**SUE**	**3-Factor Alpha**	**5- Factor Alpha**
1	-0.005	-0.004	-0.011	-0.006	-0.001	-0.003
2	0.000	-0.001	-0.008	-0.003	0.000	-0.002
3	0.000	0.000	-0.003	-0.002	0.000	0.000
4	0.003	0.000	0.000	-0.001	0.002	0.001
5	0.000	-0.002	0.003	0.000	0.003	0.003
6	0.000	0.002	0.005	-0.001	0.004	0.003
7	0.005	0.003	0.009	-0.001	0.005	0.005
8	0.003	0.000	0.013	0.000	0.007	0.007
9	0.003	0.002	0.017	0.001	0.009	0.009
10	0.003	0.003	0.025	0.002	0.014	0.017
10 -1 Diff.	0.008	0.007	0.036	0.008	0.016	0.019
t-stat.	(4.223)	(3.982)	(36.727)	(6.202)	(2.679)	(3.075)

Table 2.3: **The Effect of Institutional Investors' Equities and Options Holding %ΔEPCMPNIO on Cross-Section of Expected Abnormal Returns Around Three-Day Earnings Announcement**
This table presents analysis of quarterly Fama and MacBeth (1973) regressions using three-day cumulative abnormal returns around earnings announcements, CAR, as the dependent variables. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variable						Firm Size	
CAR						Large	Small
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
%ΔEPCMPNIO	0.082***	0.125***	0.122***	0.159***	0.134***	0.125***	0.143***
	(10.362)	(11.124)	(11.013)	(12.051)	(11.455)	(10.237)	(8.592)
%ΔO/SNIO		0.001*		0.001	0.000	0.000	-0.001
		(1.932)		(0.920)	(0.615)	(0.474)	(-0.732)
%ΔCMPNIO		-0.003		-0.002	0.001	-0.017	0.102
		(-0.142)		(-0.106)	(0.045)	(-0.796)	(1.563)
%ΔENIO			0.001***	0.001***	0.001***	0.000	0.001***
			(5.745)	(5.560)	(5.629)	(1.043)	(3.471)
ΔEIO			0.667**	0.357	0.195	0.074	1.268
			(2.066)	(0.733)	(0.437)	(0.203)	(0.266)
ΔEBREADTH			-0.004	-0.000	0.002	0.003	-0.007
			(-1.023)	(-0.269)	(1.074)	(1.045)	(-0.664)
Lag_CAR					-0.084***	-0.088***	-0.089***
					(-10.595)	(-9.441)	(-6.822)
BETA					0.005***	0.005**	0.003
					(3.187)	(2.660)	(1.403)
SIZE					-0.000	-0.001	0.003*
					(-0.698)	(-1.437)	(1.678)
BM					0.002*	0.002	0.004
					(1.704)	(1.311)	(1.550)
MOM					0.044***	0.047***	0.040***
					(16.053)	(16.828)	(8.845)
BASPREAD					-0.210***	-0.174*	-0.348***
					(-3.311)	(-1.838)	(-3.319)
IDIOVOL					-0.013	-0.017	0.057
					(-0.308)	(-0.388)	(0.955)
Constant	0.003***	0.003**	0.000	0.002**	0.002	0.008*	-0.051**
	(2.990)	(2.360)	(0.013)	(2.404)	(0.466)	(1.932)	(-2.468)
R-squared	2.400%	3.300%	3.200%	4.000%	10.000%	11.100%	14.400%
N	107485	53491	107168	53216	52243	40839	11404

Table 2.4: **The Effect of Institutional Investors' Equities and Options Holding %ΔEPCMPNIO on Cross-Section of Future Standardized Unexpected Quarterly Earnings (SUE).**
This table presents analysis of quarterly Fama and MacBeth (1973) regressions using future standardized unexpected earnings as the dependent variables. I define SUE as the unexpected quarterly earnings (I/B/E/S actual earnings) standardized by quarter-end market capitalization of a stock. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variable						Firm Size	
SUE						Large	Small
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
%ΔEPCMPNIO	0.013***	0.021***	0.020***	0.024***	0.018***	-0.015	0.015
	(6.109)	(4.348)	(8.775)	(3.841)	(2.695)	(-0.544)	(1.657)
%ΔO/SNIO		-0.001		-0.002	-0.001	0.000	-0.000
		(-0.667)		(-0.846)	(-0.863)	(0.452)	(-0.267)
%ΔCMPNIO		0.003		-0.000	0.002	0.012	0.003
		(0.228)		(-0.028)	(0.123)	(1.100)	(0.078)
%ΔENIO			0.000*	0.001	0.000	-0.014	0.001
			(1.992)	(0.852)	(0.108)	(-0.840)	(0.582)
ΔEIO			-0.196	0.176	0.234	0.073	0.187
			(-0.655)	(0.909)	(1.235)	(0.632)	(0.103)
ΔEBREADTH			0.001	0.000	-0.006	0.004	-0.005
			(0.414)	(0.976)	(-1.115)	(0.787)	(-0.678)
Lag_SUE					0.179***	0.010	0.231***
					(2.726)	(0.089)	(3.191)
BETA					0.003**	0.003***	0.001
					(2.412)	(2.917)	(0.715)
SIZE					-0.001**	-0.000	0.002*
					(-2.076)	(-0.227)	(1.942)
BM					-0.004**	-0.004**	-0.006**
					(-2.587)	(-2.370)	(-2.209)
MOM					0.009***	0.007***	0.009***
					(3.781)	(5.889)	(2.808)
BASPREAD					-0.367***	-0.238***	-0.326***
					(-4.401)	(-3.099)	(-2.673)
IDIOVOL					0.028	-0.017	0.043
					(0.816)	(-0.518)	(0.696)
Constant	-0.001	-0.002**	-0.001	-0.000*	0.005	0.005	-0.023
	(-1.608)	(-2.016)	(-0.804)	(-1.726)	(1.083)	(1.392)	(-1.539)
Adj. R	0.400%	1.000%	0.700%	1.800%	15.800%	27.100%	26.500%
N	107481	53474	107164	53199	52220	40816	11404

Table 2.5: **%ΔEPCMPNIO as a Predictor of Future Stock Returns**

This table presents analysis of quarterly Fama-MacBeth regressions using future weekly and monthly raw/characteristic adjusted returns as the dependent variables. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variables	1- Week Ahead Raw Stock Returns				2-Months Ahead Raw Stock Returns				2-Months Ahead DGTW Stock Returns			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
%ΔEPCMPNIO	0.929**	1.263*	6.508***	6.705***	0.018***	0.066**	0.066**	0.072**	0.017***	0.049*	0.047*	0.043*
	(2.264)	(1.862)	(4.381)	(4.671)	(2.717)	(2.564)	(2.549)	(2.494)	(3.063)	(1.969)	(1.906)	(1.678)
%ΔO/SNIO		0.129**	0.119**	0.105**		0.001	0.001	0.001		0.001	0.000	0.000
		(2.418)	(2.328)	(2.256)		(1.291)	(1.053)	(1.076)		(0.777)	(0.477)	(0.295)
%ΔCMPNIO		-3.002*	-3.114*	-2.528*		-0.045	-0.043	-0.062*		-0.034	-0.026	-0.025
		(-1.796)	(-1.883)	(-1.816)		(-1.609)	(-1.531)	(-1.990)		(-1.365)	(-1.016)	(-0.934)
%ΔENIO			-0.530***	-0.558***			0.001	0.000			0.002	0.002
			(-2.755)	(-3.494)			(0.403)	(0.063)			(1.426)	(1.164)
ΔEIO			11.966	30.263			0.341	0.102			-0.223	-0.348
			(0.503)	(1.305)			(0.698)	(0.216)			(-0.526)	(-0.747)
ΔEBREADTH			-0.035	0.193			-0.002	0.002			-0.000	-0.000
			(-0.342)	(1.138)			(-0.758)	(0.370)			(-0.373)	(-0.303)
Lag Dep. Var.				-0.030***				0.004				-0.004
				(-3.219)				(0.499)				(-0.442)
BETA				-0.135				0.001				
				(-0.991)				(0.372)				
SIZE				-0.085***				-0.000				
				(-3.113)				(-0.404)				
BM				0.146				-0.008***				
				(1.271)				(-2.986)				
MOM				-0.094				-0.002				
				(-0.537)				(-0.371)				
BASPREAD				-7.088				-0.304				-0.195
				(-0.741)				(-1.646)				(-1.350)
IDIOVOL				3.124				0.110				0.136*
				(0.719)				(1.392)				(1.992)
Constant	0.162	0.019	-0.079	1.668***	0.001	0.002	-0.001	0.003	0.000	0.000	-0.001	-0.000
	(0.594)	(0.066)	(-0.364)	(3.503)	(0.204)	(0.330)	(-0.156)	(0.344)	(0.395)	(0.012)	(-1.315)	(-0.018)
R-squared	0.70%	1.20%	1.60%	11.10%	0.30%	0.90%	1.20%	6.90%	0.20%	0.60%	0.90%	2.60%
N	115186	56051	55771	53654	114205	55633	55353	53262	107693	53043	52774	52214

Table 2.6: **Relation of %ΔEPCMPNIO and Contemporaneous Weekly or Monthly Stock Returns**
This table presents analysis of quarterly Fama-MacBeth regressions using concurrent weekly and monthly raw/characteristic adjusted returns as the dependent variables. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variables	Concurrent Weekly Raw Stock Returns				Concurrent Monthly Raw Stock Returns				Concurrent Monthly DGTW Stock Returns			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
%ΔEPCMPNIO	1.001***	1.173**	6.479***	4.909***	0.079***	0.136***	0.137***	0.101***	0.079***	0.118***	0.118***	0.116***
	(3.555)	(2.573)	(3.469)	(3.027)	(7.366)	(3.395)	(3.499)	(2.784)	(8.239)	(2.846)	(2.943)	(3.390)
%ΔO/SNIO		0.131**	0.114*	0.098*		0.004***	0.003***	0.001		0.003***	0.002*	0.001
		(2.177)	(1.752)	(1.791)		(3.903)	(3.137)	(1.426)		(3.009)	(1.856)	(1.670)
%ΔCMPNIO		-0.964	-0.951	-0.089		-0.024	0.004	0.073**		-0.016	0.021	0.044
		(-0.668)	(-0.627)	(-0.062)		(-0.793)	(0.129)	(2.209)		(-0.477)	(0.567)	(1.388)
%ΔENIO			-0.537***	-0.361**			0.004*	0.007**			0.007**	0.008**
			(-2.818)	(-2.227)			(1.707)	(2.333)			(2.067)	(2.580)
ΔEIO			66.015**	75.432**			1.261*	1.776**			1.401**	1.536**
			(2.243)	(2.418)			(1.739)	(2.356)			(2.232)	(2.360)
ΔEBREADTH			-0.085	-0.485*			-0.006*	-0.003			-0.000	0.004**
			(-0.700)	(-1.977)			(-1.851)	(-0.528)			(-1.077)	(2.474)
Lag Dep. Var.				-0.032***				-0.039***				-0.036***
				(-2.811)				(-3.450)				(-2.885)
BETA				-0.352*				-0.005				
				(-1.856)				(-1.634)				
SIZE				-0.089*				-0.003***				
				(-1.759)				(-3.617)				
BM				0.025				0.002				
				(0.227)				(0.660)				
MOM				-0.003				-0.012**				
				(-0.016)				(-2.661)				
BASPREAD				23.513*				0.092				0.027
				(1.927)				(0.430)				(0.179)
IDIOVOL				1.777				0.060				0.018
				(0.290)				(0.787)				(0.302)
Constant	0.409	0.331	0.158	0.390	0.011*	0.009	0.002	0.039***	0.001	-0.000	0.000	0.001
	(1.519)	(1.120)	(0.551)	(0.564)	(1.820)	(1.342)	(0.426)	(3.355)	(1.063)	(-0.277)	(0.044)	(0.562)
R-squared	0.40%	0.90%	1.30%	10.20%	1.40%	2.10%	2.80%	10.80%	1.30%	1.80%	2.50%	5.20%
N	115186	56051	55771	53654	114935	55945	55665	53550	108272	53305	53036	52475

Table 2.7: **Relation of %ΔEPCMPNIO and Change in Mean Analyst Earning Forecasts**

This table presents analysis of quarterly Fama-MacBeth regressions using Change in Mean Analyst Earning Forecasts as the dependent variables. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variables	Current Month's Change in Analyst Earnings Forecasts						Mean of Current Quarter Change in Analyst Earnings Forecasts					
					Firm Size						Firm Size	
					Large	Small					Large	Small
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
%ΔEPCMPNIO	0.545***	0.817***	0.844***	0.631***	0.679***	0.616***	0.240***	0.358***	0.382***	0.304***	0.320***	0.285***
	(10.086)	(9.428)	(9.410)	(10.068)	(7.697)	(8.442)	(9.393)	(8.251)	(8.502)	(8.445)	(8.324)	(7.368)
%ΔO/SNIO		-0.005	-0.007	-0.004	-0.012	0.004		0.001	-0.002	-0.001	0.002	0.001
		(-0.688)	(-1.030)	(-0.770)	(-1.243)	(0.637)		(0.232)	(-0.729)	(-0.809)	(0.916)	(0.146)
%ΔCMPNIO		-0.098	-0.145	-0.209	-0.166	-0.131		0.002	-0.021	-0.005	-0.017	0.057
		(-0.501)	(-0.742)	(-0.952)	(-0.609)	(-0.259)		(0.025)	(-0.244)	(-0.054)	(-0.191)	(0.183)
%ΔENIO			-0.048	-0.021	-0.031	0.025			-0.036	-0.025	-0.028	-0.013
			(-1.076)	(-0.588)	(-0.783)	(0.327)			(-1.477)	(-1.240)	(-1.157)	(-0.316)
ΔEIO			-4.318*	-2.121	-1.829	-2.183			-1.559	-0.126	-0.243	3.103
			(-1.792)	(-1.138)	(-1.060)	(-0.191)			(-1.529)	(-0.138)	(-0.269)	(0.552)
ΔEBREADTH			-0.000	-0.004	0.012	-0.034			0.001	-0.001	0.007	-0.035
			(-0.060)	(-0.100)	(0.256)	(-0.447)			(0.488)	(-0.055)	(0.329)	(-1.108)
LAG_CHFEPS				0.503***	0.557***	0.375***				0.132***	0.138***	0.083*
				(6.811)	(6.499)	(3.974)				(4.130)	(3.750)	(1.953)
BETA				0.038***	0.044***	0.015				0.016**	0.021**	0.010
				(3.757)	(3.328)	(1.217)				(2.281)	(2.266)	(1.529)
SIZE				0.014**	0.018***	-0.001				0.003	0.004	-0.010
				(2.242)	(2.816)	(-0.049)				(0.770)	(1.290)	(-1.536)
BM				-0.002	0.008	-0.033				-0.008	0.003	-0.035**
				(-0.203)	(0.519)	(-1.394)				(-1.105)	(0.289)	(-2.223)
MOM				0.112***	0.129***	0.072***				0.076***	0.084***	0.052***
				(6.733)	(6.540)	(3.468)				(6.532)	(7.284)	(4.590)
BASPREAD				-2.024*	-1.633	-3.107**				-1.551***	-2.025***	-0.983*
				(-1.986)	(-1.496)	(-2.324)				(-3.080)	(-3.334)	(-1.886)
IDIOVOL				-0.277	-0.308	0.036				0.331*	0.459*	0.067
				(-0.663)	(-0.700)	(0.066)				(1.938)	(1.939)	(0.312)
Constant	0.006	0.011	0.012	-0.096	-0.121*	-0.020	0.002	0.002	0.008*	-0.057	-0.054	-0.006
	(0.491)	(0.763)	(1.472)	(-1.607)	(-1.951)	(-0.178)	(0.284)	(0.310)	(1.915)	(-1.517)	(-1.487)	(-0.081)
R-squared	1.70%	2.60%	3.00%	12.40%	14.30%	20.00%	1.40%	2.20%	2.60%	13.90%	15.70%	20.30%
N	93160	53090	52829	51836	40947	10889	94560	53699	53430	52385	41329	11056

Table 2.8: **Relation between Generalized Probability of Informed Trading (GPIN) and %ΔEPCMPNIO**
This table presents analysis of quarterly Fama-MacBeth regressions using Generalized Probability of Informed Trading (GPIN) calculated only from order flow as dependent variable. The main independent variable of interest is %ΔEPCMPNIO, as the percentage change in the equities plus respective net options (the number of call options holding minus the number of put options holding) ownership by institutions. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics reported in parentheses are based on 2-lag Newey and West standard errors.**

Dependent Variable	Previous One-Month PIN Measure			Previous Two-Month PIN Measure		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
%ΔEPCMPNIO	0.077**	0.084**	0.033*	0.076**	0.082**	0.030*
	(2.587)	(2.563)	(1.766)	(2.613)	(2.577)	(1.696)
%ΔO/SNIO		0.001	0.005		0.002	0.004
		(0.039)	(0.208)		(0.054)	(0.176)
%ΔCMPNIO		-0.012	-0.041		-0.016	-0.036
		(-0.045)	(-0.190)		(-0.055)	(-0.160)
%ΔENIO		0.069*	0.063**		0.071*	0.065**
		(1.984)	(2.184)		(2.017)	(2.229)
ΔEIO		0.307	-0.064		0.348	-0.042
		(0.659)	(-0.147)		(0.721)	(-0.096)
ΔEBREADTH		-0.067***	-0.022		-0.067***	-0.023
		(-3.698)	(-0.511)		(-3.691)	(-0.530)
BETA			0.013			0.012
			(1.345)			(1.267)
SIZE			0.011			0.011
			(1.637)			(1.549)
BM			0.010*			0.011*
			(1.839)			(2.036)
MOM			-0.011			-0.009
			(-0.856)			(-0.709)
IDIOVOL			3.198***			3.195***
			(5.542)			(5.480)
Constant	0.282***	0.126***	-0.053	0.283***	0.127***	-0.053
	(44.845)	(6.493)	(-0.852)	(46.455)	(6.480)	(-0.830)
R-squared	0.40%	1.60%	10.90%	0.40%	1.60%	10.90%
N	23942	18217	18117	23952	18219	18119

Table 2.9: **Double Sort Portfolio (Dependent Sorts) To Show Better Informed Trading Predictability by %ΔEPCMPNIO and ΔEIO**

In Panel A, I created quintile portfolios formed by first sorting stocks based on ΔEIO. Then, inside each ΔEIO quintile portfolio, stocks are sorted again into quintile portfolios based on %ΔEPCMPNIO so that Low (High) contains stock with the lowest (highest) %ΔEPCMPNIO. Similarly, Panel B use same dependent portfolios sorting technique but first sort on %ΔEPCMPNIO and then on ΔEIO. In Panel A and B, High - Low documents the average 5-factor return difference between High and Low portfolios of bivariate dependent sort. The sample period of all the variables are from 2004Q4 to 2019Q4. Detailed definition of all the variables reported in Appendix A. The first row gives the coefficients while the second row gives the t-statistics in parentheses. **All t-statistics are reported in parentheses.**

Panel A. Dependent Sort First on ΔEIO then on %ΔEPCMPNIO

		%ΔEPCMPNIO						
		Low	2	3	4	High	High-Low	t-statistics
ΔEIO	Low	0.300	0.246	0.364	0.522	0.390	0.089	(1.87)
	2	0.238	0.302	0.300	0.337	0.371	0.133	(3.73)
	3	0.348	0.330	0.259	0.452	0.419	0.072	(3.94)
	4	0.354	0.420	0.404	0.542	0.564	0.210	(1.05)
	High	0.471	0.584	0.728	0.758	0.991	0.519	(3.24)
	Average	0.342	0.377	0.423	0.546	0.550	0.207	**(6.60)**

Panel B. Dependent Sort First on %ΔEPCMPNIO then on ΔEIO

		ΔEIO						
		Low	2	3	4	High	High-Low	t-statistics
%ΔEPCMPNIO	Low	0.297	0.295	0.331	0.452	0.311	0.015	(3.16)
	2	0.340	0.282	0.229	0.159	0.301	-0.040	(-3.52)
	3	0.356	0.338	0.404	0.282	0.431	0.076	(4.82)
	4	0.411	0.384	0.449	0.455	0.556	0.145	(0.66)
	High	0.560	0.711	0.819	0.614	0.986	0.426	(3.91)
	Average	0.393	0.406	0.456	0.426	0.516	0.124	**(1.53)**

FIGURE 1

Number of Institutional Investors' Filed 13F in Each Quarter From 1982-2019

Figure : 1 plots quarterly time series of all Institutional Investors' who file 13F filing with the U.S. Securities and Exchange Commission (SEC) from 1982 to 2019. Quarter represents the period in which institutions' filed their portfolio with SEC. Till second quarter of 2013, I used all the filings from Thomson Reuters, and after 2013 quarter three, I used WRDS SEC Analytics Suite - 13F Holdings Data.

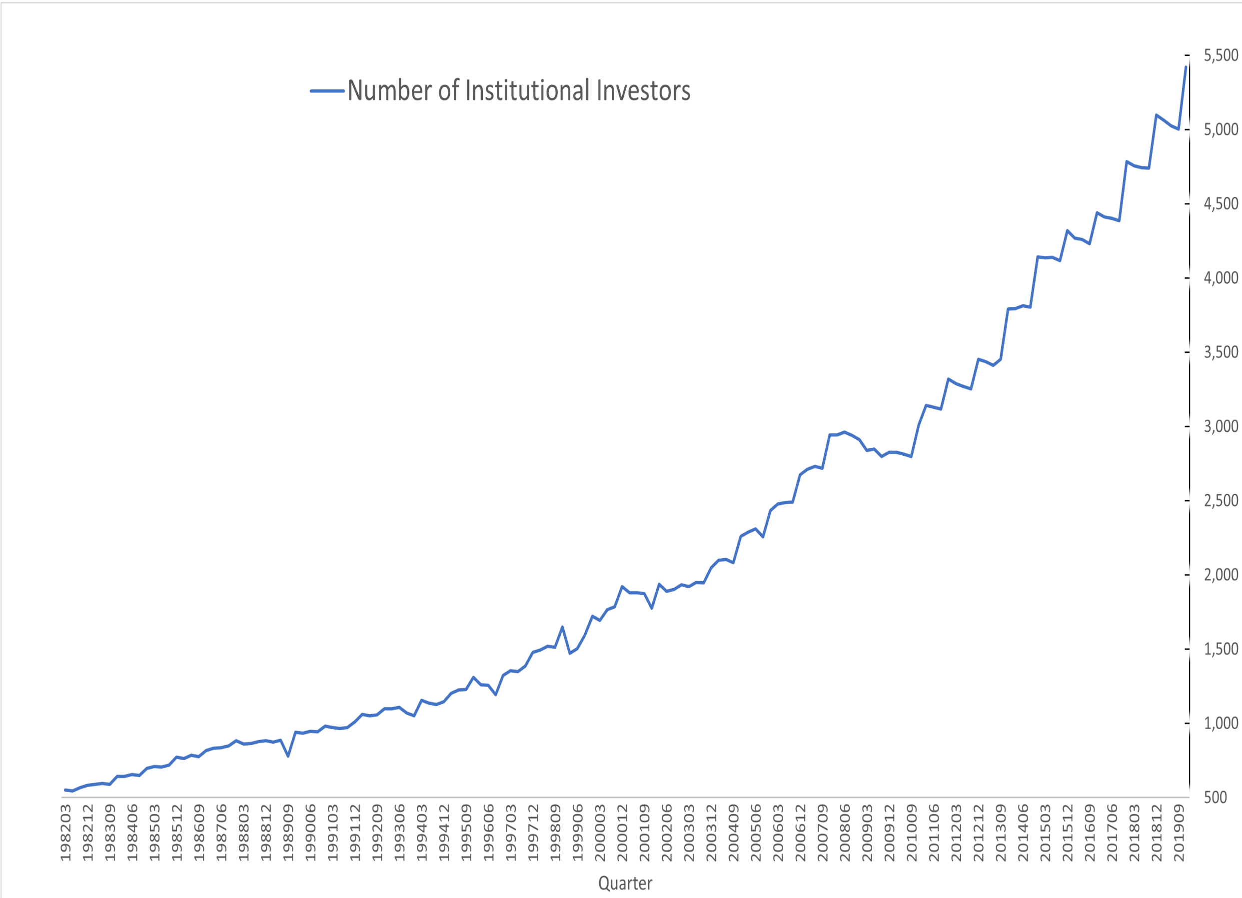


FIGURE 2
Number of Institutional Investors' Ownership of Equities and Options

Figure : 2 describes a bar plot of the number of institutional investors' holding of Equities and Options from 2004:Q4 to 2019:Q4 in each quarter. The light grey (slate color) bars presents number of institutions' holding equities in their portfolio, and the dark color (blue color) bar depicts number of institutions' holding equity options in each quarter. This plot shows that in-total number of institution holding option double during sample period.

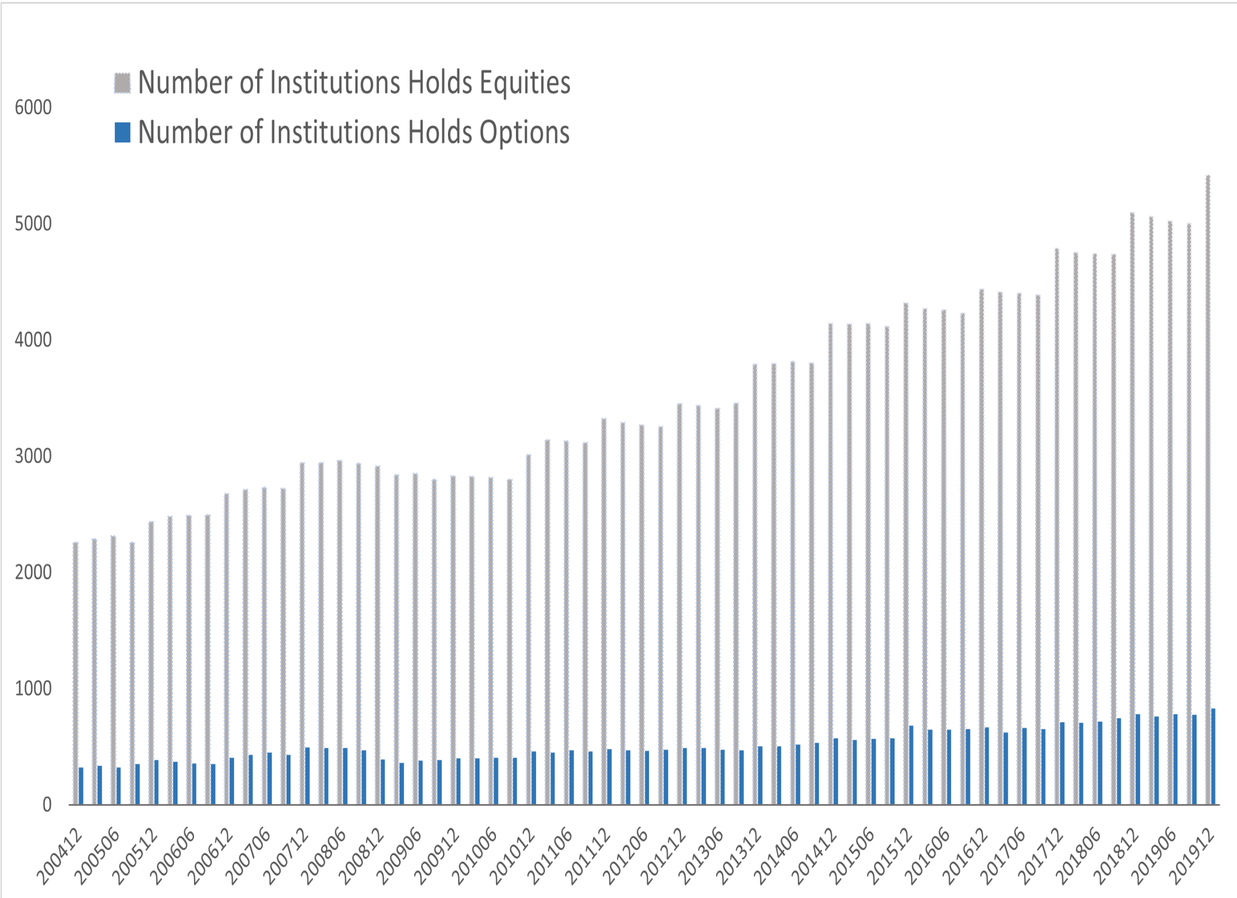


FIGURE 3

Fraction of Zero, Positive, and Negative Stocks Changes in %ΔEPCMPNIO

Figure : 3. The sample consists of 115425 observations from 2004:Q4 to 2019:Q4, as described in Table 1. The dotted line (Blue Color) depicts the percent of zero %ΔEPCMPNIO over the sample period. Dashed line (Orange Color) shows percent of negative %ΔEPCMPNIO variations throughout the timeline of a sample. Solid line (Green Color) represent percent of positive %ΔEPCMPNIO over the sample period.

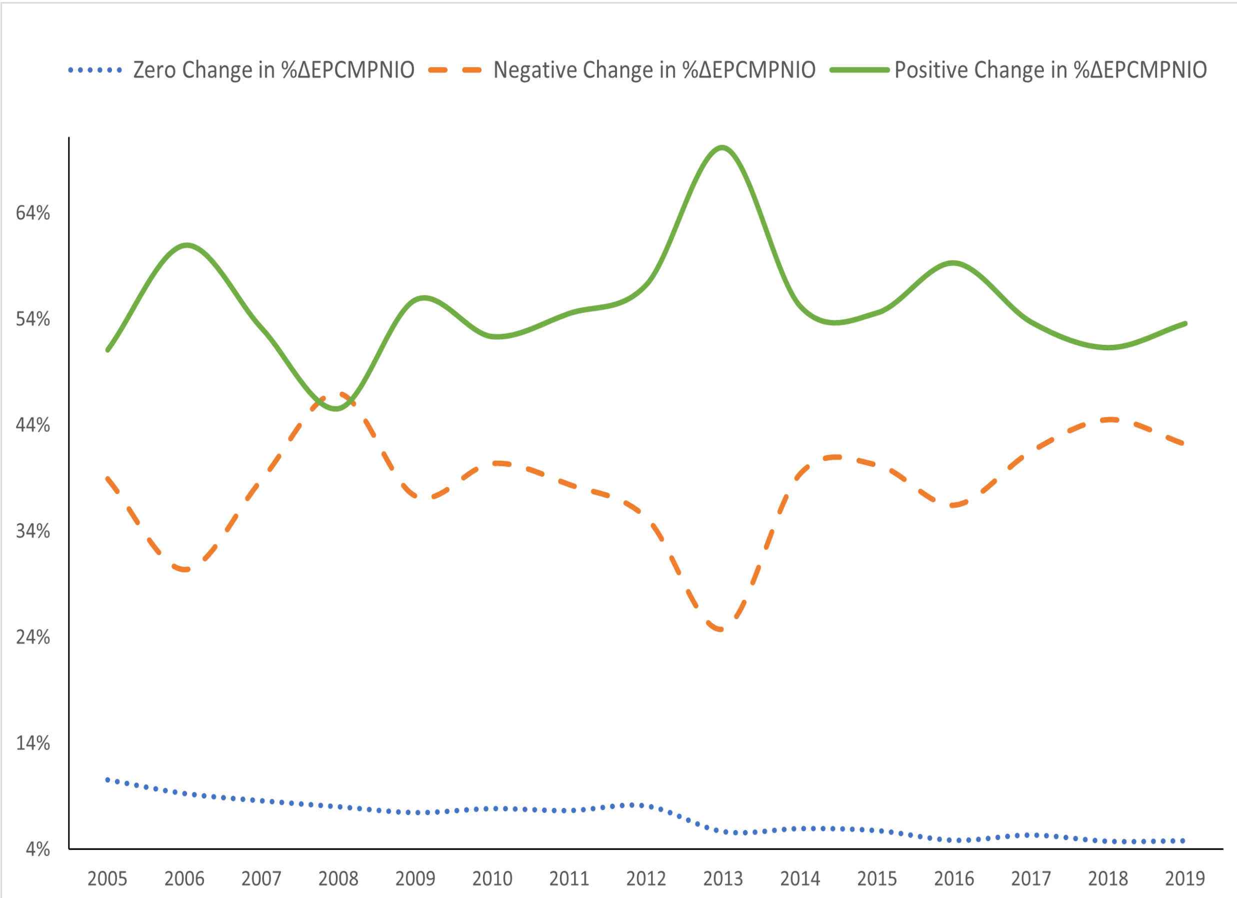


FIGURE 4

Average of Total Call, Put or Call/Put Options Holding Institutions'

Figure : 4 presents the mean of Total Call, Put and Call/Put Options Contracts of individual firms Held by Institutions' from 2004Q4 to 2019Q4. First I calculated number of only Call or Put equity option holding of individual firms in each quarter (CRSP PERMNO CALL/PUT in each Quarter for all the Central Index Key (CIK)'s or the Manager Number of institutions'). Similarly, I measure number of only Call or only Put for individual security. This figure shoes continuous increase in option holding over the sample period.

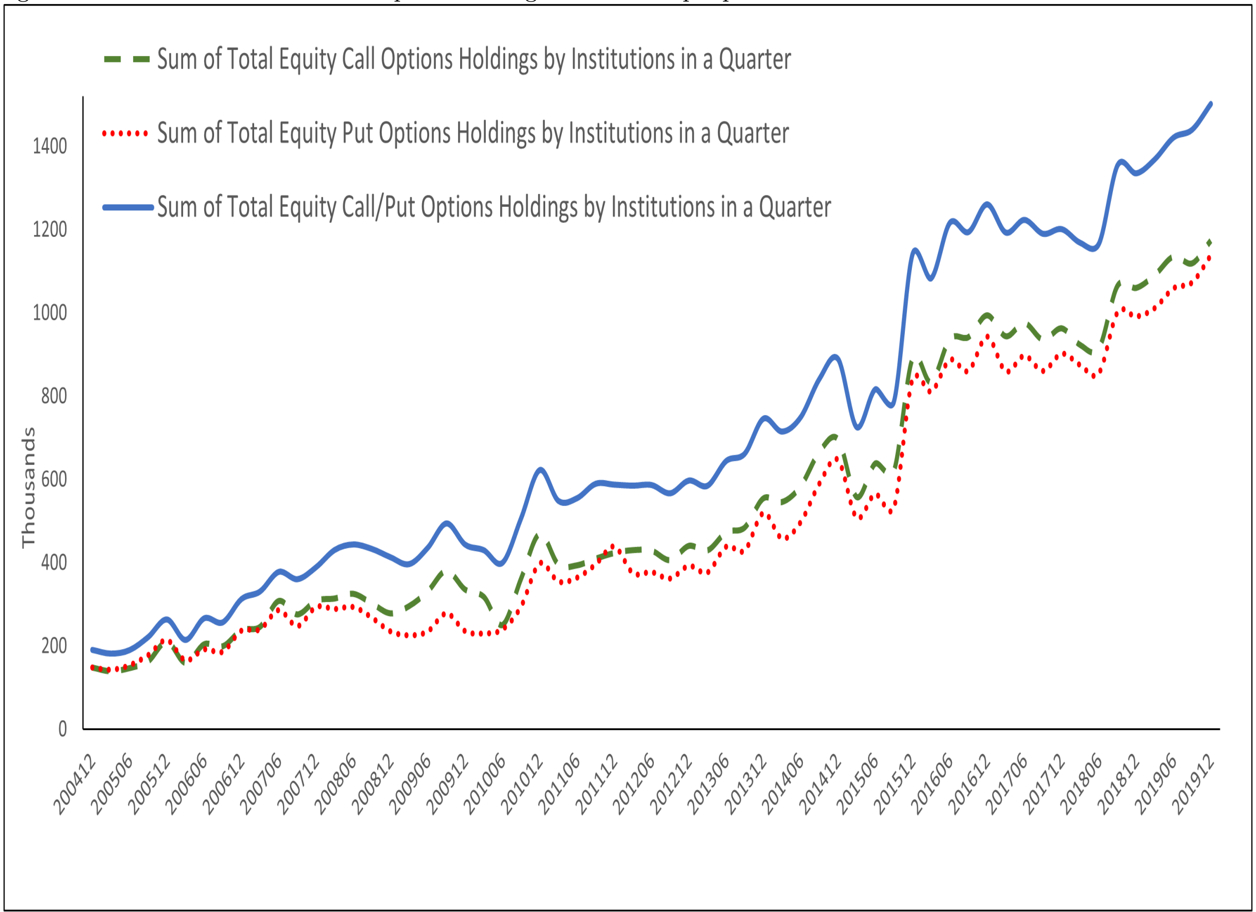


FIGURE 5
Sum of Ratio of Institutions' Total Call and Put Shares holding to Underlying Equity Ownership

Figure : 5 presents Sum of Ratio of Institutions' Total Call and Put Shares holding to Underlying Equity Ownership from 2004:Q4 to 2019:Q4. The solid line (Blue Color) represent Call/ Equity shares holding and dotted line (Orange Color) represents Put/Equity shares holding.

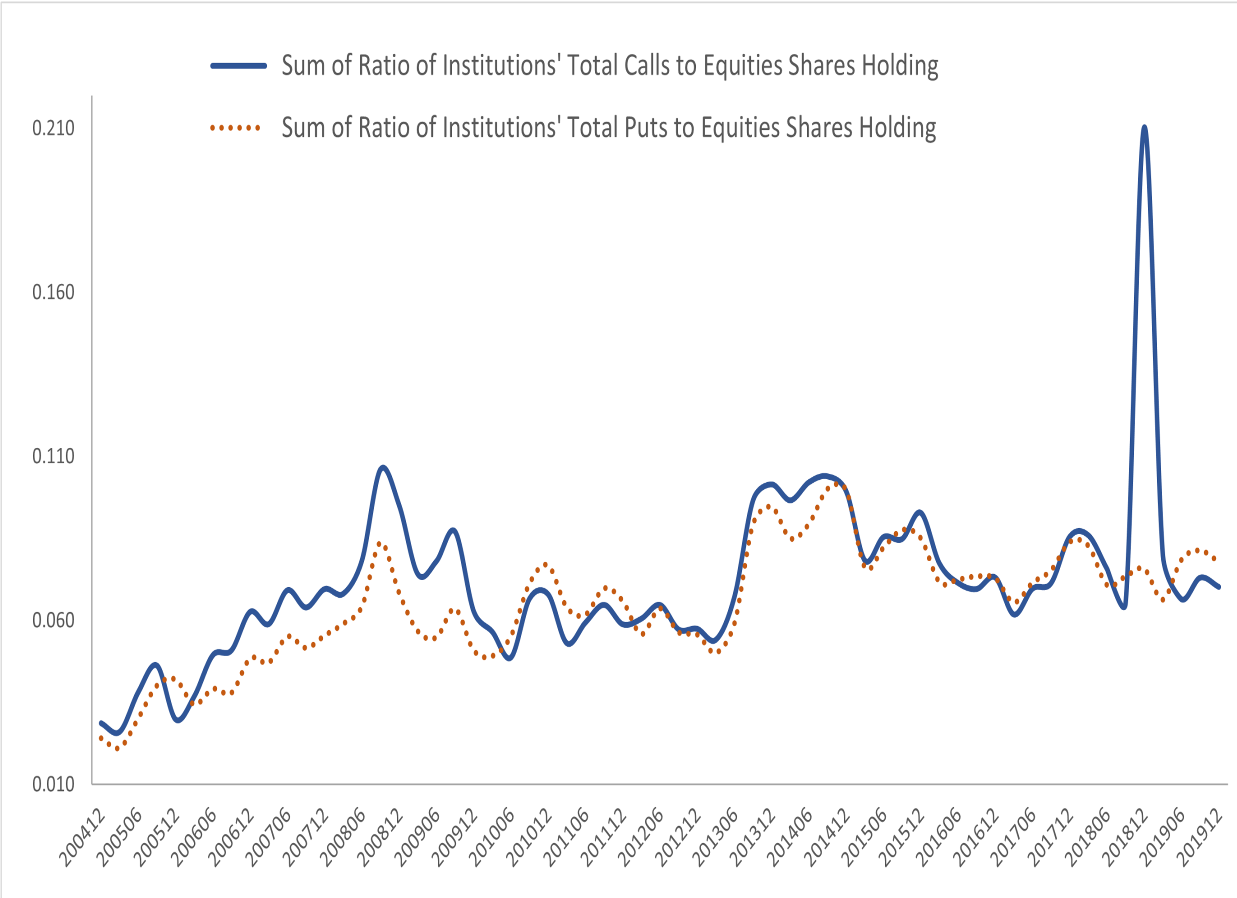


FIGURE 6
Amount of Money Invested in Call and Put Options (in Billions) (Fair Value Section from 13F filings) by All Institutional Investors' in Each Quarter

Figure : 6 presents the total fair value dollar amount invested in Call or Put options held by all the institutions' from 2004:Q4 to 2019:Q4. I first measure the fair value of each firm's Call or Put Equity Options positions in each quarter for all institutions. Then, I took a sum of total dollar value in each quarter. The solid bar (Blue Bar) represents total call values and light dashed bar (Light Gray Bar) represents total put values of all institutional investors.

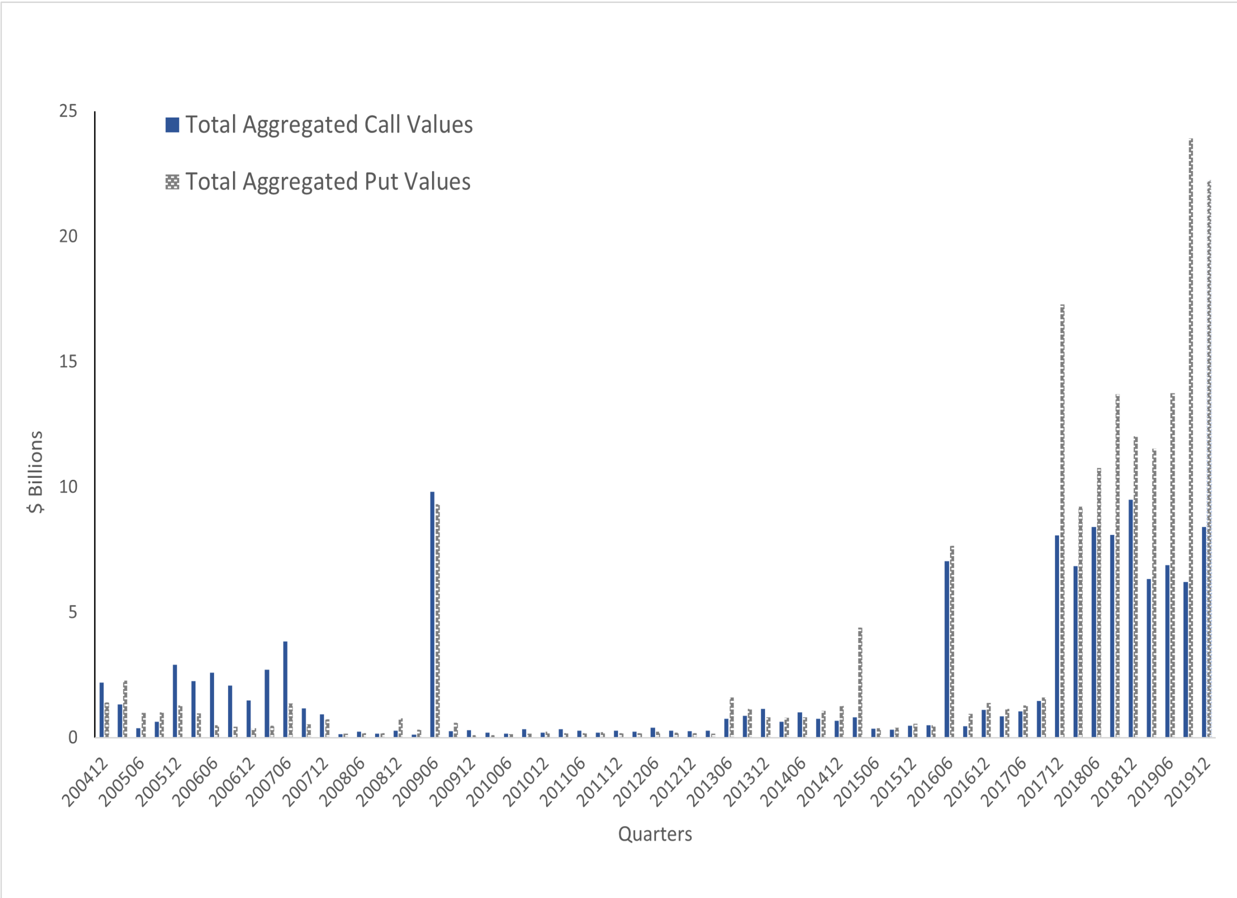
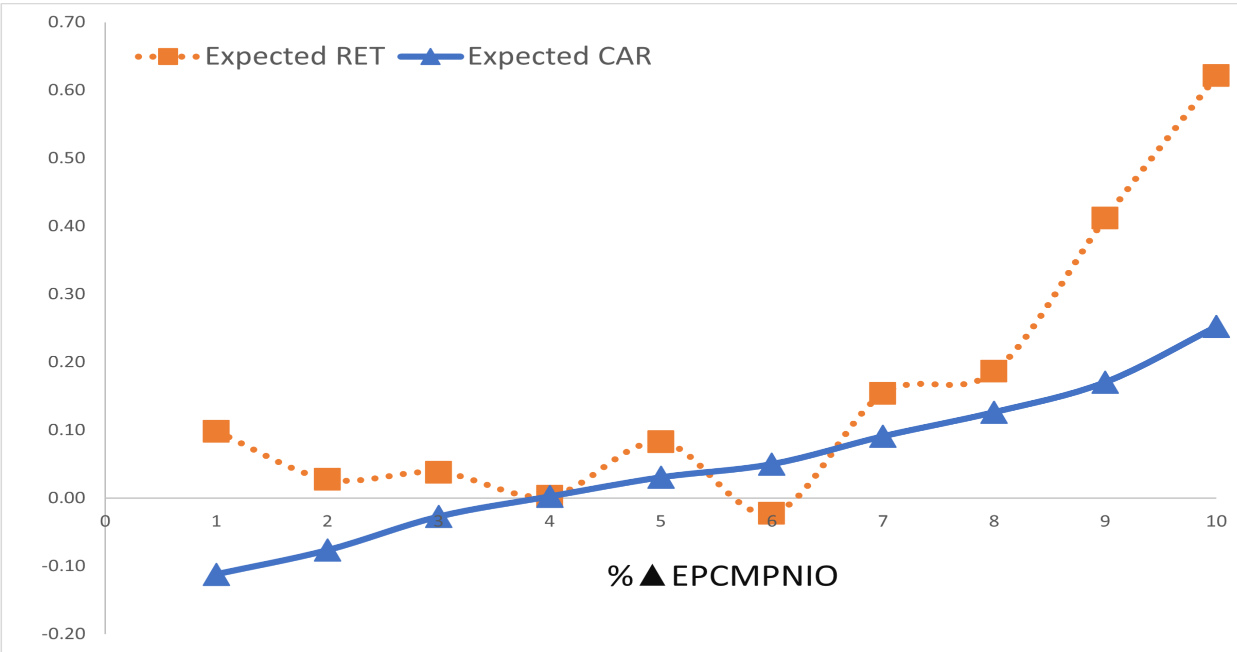


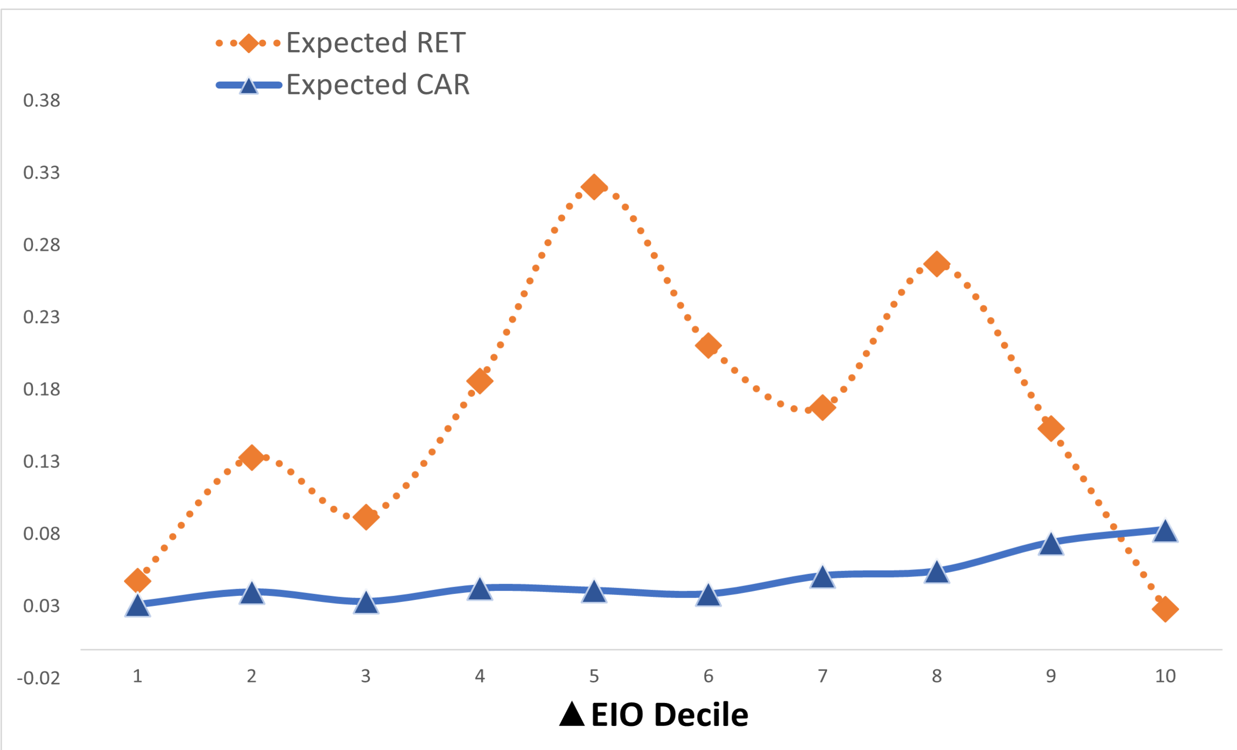
FIGURE 7
Plot of Future CAR and RET for %ΔEPCMPNIO and ΔEIO

Figure : 7 presents the mean values of expected (one-quarter ahead) three-days cumulative abnormal returns around earnings announcement and expected raw returns on decile portfolios of %ΔEPCMPNIO and ΔEIO. %ΔEPCMPNIO defined as percentage change in the number of a Call options minus number of Put options plus their underlying stocks holding of institutional investors. ΔEIO defined as Change in institutional advisors equity holdings.

Graph A.%ΔEPCMPNIO Decile



Graph B. ΔEIO Decile



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Awards and Grants

Outstanding Graduate Instructor Award at Syracuse University	2020
Graduate Teaching Assistantship	2016 to 2022
Summer Research Grants	2016 to 2021
MA Applied Economics Merit Scholarship	2013 to 2014
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Professional Experience

IMOB Research Institute, Belgium
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