THREE ESSAYS ON STOCK MARKET LIQUIDITY AND EARNINGS SEASONS

A Dissertation

presented to

the Faculty of the Graduate School

University of Missouri - Columbia

In Partial Fulfillment
of the Requirements for the Degree

Doctor of Philosophy

by

ANDREI L. NIKIFOROV

Dr. Paul Brockman, Dissertation Supervisor

JULY 2009

The undersigned, appointed by the Dean of the Graduate School,
have examined the dissertation entitled

THREE ESSAYS ON STOCK MARKET LIQUIDITY AND EARNINGS SEASONS

Presented by Andrei Nikiforov

A candidate for the degree of Doctor of Philosophy

And hereby certify that in their opinion it is worthy of acceptance.

Professor Paul Brockman

Professor Stephen P. Ferris

Professor John S. Howe

Professor Douglas J. Miller

I wish to dedicate my dissertation to Natalia for all her support and unconditional love throughout my doctoral program, and to my parents for all their love, encouragement and sacrifices during these years of forced distance.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to all the committee members of my dissertation for all their invaluable help and support throughout my research.

I am extremely grateful to Professor Paul Brockman, the chair of my dissertation, not only for all his help, suggestions and corrections that significantly improved my dissertation, but also for his great mentorship throughout my doctoral program.

I also wish to thank Dr. Stephen P. Ferris and Dr. John Howe for all their support, encouragement, and extremely helpful suggestions. I thank Dr. Douglas J. Miller for his support and availability as a committee member and for his useful suggestions about econometric methods and techniques that greatly improved my dissertation.

TABLE OF CONTENTS

LIST OF FIGURES

Figure **Page**

LIST OF TABLES

THREE ESSAYS ON STOCK MARKET LIQUIDITY AND EARNINGS SEASONS

Andrei Nikiforov

Dr. Paul Brockman, Dissertation Supervisor

Abstract

In these essays, I identify the effects of earnings seasons (i.e., the clustering of earnings releases), on stock market liquidity and asset pricing. In the first essay, I document strong seasonal regularities associated with aggregate earnings announcements. Applying the large body of literature linking earnings announcements to liquidity effects, I argue that these earnings seasons create market-wide liquidity shocks and I show that both liquidity betas and liquidity risk change during earnings seasons

In the second essay, I test the impact of earnings seasons on commonality in liquidity as measured by both spreads and depths. I find that commonality significantly decreases during the four weeks of each calendar quarter when most companies release their earnings. These findings contribute to the literature by identifying and examining the clustering effect of firm-specific information on commonality in liquidity.

In the third essay, I extend the study of the liquidity effects of earnings seasons to a sample of 20 countries. I find that the international data corroborate both hypotheses. I also find that the aggregate quality of accounting information, and the duration and frequency of interim reporting periods are important determinants of the liquidity effects (both liquidity betas and commonality in liquidity) during earnings seasons.

CHAPTER 1

Introduction

1.1. Dissertation Overview

This dissertation empirically examines the effects of earnings seasons, clustering of earnings announcements around pre-specified dates, on stock market liquidity in the US and abroad. The first essay traces the effects of this clustering on stock prices through the changes in stocks' liquidity betas. This essay uses roughly 40 years of data to establish the pricing effects of liquidity shocks and is therefore limited to the US market.

The second essay examines how the commonality in liquidity, systematic co-variation of stock's liquidity and market liquidity, changes during earnings seasons. This essay is also limited to the US data.

Finally, the third essay extends the first two studies to 20 foreign countries testing the hypotheses about the effects of earnings seasons on a much larger scale. In addition, the international data allows me to test additional hypotheses about the determinants of the liquidity effects during earnings seasons.

1.2. Essay 1: Does the seasonality of aggregate earnings announcements affect asset prices?

In the first essay I argue that during earnings seasons, when public US companies report their quarterly and annual earnings, investors experience heightened uncertainty about the prospects of their portfolios. Since the information flow is highly concentrated in a very short interval, this creates a potential for marketwide liquidity shocks. These shocks result in time-varying liquidity risk which in turn leads to the changes in the liquidity risk premium that investors require to hold the stocks. I estimate that the *additional* liquidity risk premium lies in the range between 0.5% and 2.4% a year.

Even though none of the academic papers looked into the effects of earnings seasons on liquidity, numerous studies document that stock liquidity changes dramatically during the individual announcements. The main reason is the increase in the asymmetric information between informed and uninformed investors. When a company announces its quarterly earnings, the opportunity for informed trading in that stock is arguably at its highest and we know from prior studies that uninformed traders demand a premium for the risk of trading with informed traders. In addition, the uninformed traders change their trading behavior around the announcements thus affecting trading volume, returns, spreads, and depths.

Given that the earnings announcements by thousands of firms are densely packed into the so-called earnings seasons (40 to 45 day window after the end of each calendar quarter), I hypothesize that all the small individual liquidity impacts will add up to market-wide liquidity shocks.

The essay consists of two main parts. In part one I establish the significance of earnings seasons for the financial markets. I find that during earnings seasons the returns, turnover, and volatility are all affected exhibiting regular patters around these time periods.

In part two, I investigate the asset pricing implications of liquidity changes during earnings seasons. Specifically, I study the changes in liquidity betas and changes in conditional liquidity risk. I find that the liquidity betas, which measure the sensitivity of stock market returns to market wide liquidity, increase during the seasons. Then I test whether the stocks that stocks with higher conditional (on earnings seasons) liquidity betas demand extra premium. I find that even controlling for conventional determinants of stock returns (HML, SMB, and momentum), the additional risk premium is positive and significant. The results are robust to the use of different test assets and different stock exchanges.

1.3. Essay 2: The impact of earnings seasons on commonality in liquidity

In the second essay I look at how the clustering of firm-specific information during the earning seasons affects the commonality in liquidity. I argue that it does so for the following two reasons.

First, the flood of new information and heavy trading to rebalance portfolios in response to that information are the two most significant characteristics of earnings seasons. Both new information and trading volume have been shown to affect commonality in liquidity (Corwin and Lipson (2008)). Second, the information environment changes dramatically as the market goes through earnings seasons. The asymmetric information rises (reaches its peak) at the beginning of the seasons and then quickly decreases towards the end and it is well known that asymmetric information adversely impacts liquidity in any market.

This essay builds on my first essay and other previous findings to specifically investigate the effect of the earnings season on changes in *the commonality* in liquidity during earnings seasons. I use intra-day measures of liquidity such as spreads and depths and look at the issue at a much more detailed level than I did in the first essay.

Since firm specific information affects each firm in a unique way, investors react differently to each announcement. I argue that since all these individual announcements are concentrated within a relatively short time period, the co-variation between a stock's liquidity and the market liquidity should decrease during the peaks of earnings seasons.

I find that commonality significantly decreases during the peak weeks of earnings seasons when most firms issue their reports consistent with the idea that firm-specific information reduces common effects. I also find that intra-industry commonality in liquidity is largely unaffected consistent with the view that large amount of firm-specific information (negative effect on commonality) mitigates the increases in the intra-industry information transfers (positive effect on commonality). Another interesting finding is that the commonality decrease is especially pronounced for the largest firms. This is consistent with the fact that the media and the analysts concentrate almost exclusively on large firms during an earnings seasons. Finally, average spreads significantly widen during the first four weeks and average depths significantly decrease during this period producing market-wide liquidity shocks. The situation is reverse in the last two weeks (i.e. liquidity substantially improves to pre-season levels or even better)

1.4. Essay 3: Earnings seasons, liquidity, and asset prices: international evidence

In this essay I test the hypotheses proposed in the first two essays in the international setting. Specifically, I study the impact of the institutional characteristics of the interim reporting periods on the commonality in liquidity in 20 countries. The frequency and the duration (deadlines) of the interim reporting periods are set and enforced by each country's regulatory body such as SEC in the US and FSA in the UK. As a result, the reporting frequencies and the lengths of earnings seasons vary around the world. For example, SEC in the US requires that all public companies report their numbers within the first 30 to 45 days after the end of fiscal quarter and UK's FSA requires that British companies release their earnings results every half-year within 90 to 120 days.

The extension of the study to the international settings allows me not only to test my hypothesis about the impact of earnings seasons on liquidity for a much larger sample, but also to investigate the relative effect of the frequency and duration of reporting on liquidity. In addition, I explore the effect of countries' average quality of information disclosure and the strength of their insiders trading laws on liquidity.

I find that the sensitivity of stock returns to the market-wide liquidity shocks associated with earnings seasons increases for the international data which is consistent with my hypotheses. Unfortunately, due to the lack of long time series, I cannot test whether this increased sensitivity translates into higher liquidity risk premium. The second set of results, concerning the commonality in liquidity, is also consistent with my hypotheses. I find that commonality in liquidity decreases during the peaks of earnings seasons for the majority of the countries (with only one exception).

Looking into the determinants of the changes in commonality during the seasons, I also find several factors that actually mitigate the impact of these periods on commonality. For example, poor quality of accounting information (high opacity) and longer duration periods reduce the negative effect of earnings seasons on commonality. Surprisingly, the higher frequencies and weaker protection/law enforcement actually increase the negative impact of earnings seasons. The latter findings might be artifacts of the high negative correlations between frequency and duration and high positive correlation between law and opacity variables. Another explanation is that low frequency of reporting might actually encourage the companies to release important information between earnings seasons thus slightly, thus reducing their importance. At the same time, the countries with high frequency of reporting release all of the information within the seasons thus increasing their importance. This offers another possible explanation for these puzzling results.

Chapter 2

Does the seasonality of aggregate earnings announcements affect asset prices?

2.1 Introduction

In this paper I argue that during earnings seasons, when all public US companies report their quarterly and annual earnings, investors experience heightened uncertainty about the prospects of their portfolios. Since the information flow is highly concentrated in a very short interval, this creates a potential for marketwide liquidity shocks. These shocks result in time-varying liquidity risk which in turn leads to the changes in the liquidity risk premium that investors require to hold the stocks. I estimate that the *additional* liquidity risk premium lies in the range between 0.5% and 2.4% a year.

Earnings season is arguably one of the most important time periods on Wall Street. During these periods very important economic information floods the markets keeping busy thousands of analysts, professional and amateur traders, and business press. In spite of its significance for the Wall Street (and for practitioners in general), this unique time of the year has received scant (if any) attention from academia. This is surprising since as soon as we even slightly deviate from the world of perfect and complete information, the importance of information arrival (how, when, and how fast) on asset prices becomes significant (see O'Hara (2003) for a general discussion).

Even though the clustering effect of earnings seasons has been ignored, there is a vast stream of literature in finance and accounting that studies the impact of individual firm's earnings announcements on financial markets. Numerous studies have shown that just around the announcement the bid-ask spreads widen and depths on the limit books substantially decrease. In addition, trading volumes wildly oscillate sharply decreasing just before the announcement and surging right after (e.g. Chae (2005). Most authors conclude that the observed patterns are best explained by the changing information environment around these events. There are, however, several ways in which the information environment can affect asset prices.

When a company announces its quarterly earnings, the opportunity for informed trading (whether by insiders or by "better information processors") in that stock is arguably at its highest. Even though none of the previous studies looks at how the *changing* information environment impacts asset prices, there are many studies that argue the proportion of informed to uninformed ("noise" or "liquidity") traders matters enough to affect the required returns. For example, Easley et al. (2002) develop a multi-asset rational expectations equilibrium model in which stocks have differing levels of public and private information. They show that in equilibrium, uninformed traders require compensation to hold stocks with greater private information, resulting in cross-sectional differences in returns. Admati (1985) generalizes Grossman and Stiglitz (1980) analysis of partially revealing rational expectations equilibrium to multiple assets and show how individuals face differing risk-return trade-offs when differential information is not fully revealed in equilibrium. Wang (1993) provides an intertemporal asset-pricing model in which traders can invest in a riskless asset and a risky asset. In his model, the presence of traders with superior information induces an adverse selection problem, as uninformed traders demand a premium for the risk of trading with informed traders.

Information environment can also affect liquidity whose effect on asset pricing is thoroughly documented. The sharp changes in information environment, and more specifically in adverse selection, directly affect stock's liquidity and if the changes in liquidity across stocks are correlated, asset prices change. Kim and Verrecchia (1991) and Frazzini and Lamont (2006) show that the sensitivity of prices to volumes increases substantially around earnings announcements and demonstrate that market makers insure themselves against higher possibilities of informed trading by widening spreads and reducing the number of shares they are willing to buy or sell at any quoted price level (Koski and MIchaely (2000)). Given that the earnings announcements by thousands of firms are densely packed into the so-called earnings seasons (40 to 45 day window after the end of each calendar quarter), it is natural to hypothesize that all the small individual liquidity impacts will add up to market wide liquidity shocks.

Combining this observation with the burgeoning literature on the commonality in liquidity (Chordia et al. (2000)) which led several authors to conclude that the liquidity risk is priced in the cross-section of stock returns (e.g. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005)), we can further hypothesize that this commonality could, in part, be caused by the liquidity impacts of earnings seasons. In addition, since earnings seasons come and go turning into relatively "calm" seasons, we can speculate that the liquidity risk (and not just the liquidity level) also changes across these time periods.

My hypothesis is closely related to the model proposed by Gallmeyer et al. (2005) who show how sudden changes in heterogeneous investors' information sets lead to high and low preference-uncertainty periods. During these periods investors' uncertainty about each other's preferences is at its highest. Watanabe and Watanabe (2008) add transaction costs to Gallmeyer et al. (2005) model and demonstrate how these periods (identified by a surge in trading volume) lead to fluctuating liquidity risk. Gallmeyer et al. (2005) hypothesize that the possible sources of preference risk could include endowment shocks (Constantinides and Duffie (1996)), stochastic risk aversion (Campbell et al. (1993) and Gordon and St-Amour (2000)) the size of the pool of investors (Smith (1993)), funding and capital adequacy constraints, and uncertain subjective discount rates. Any (if not all) of the above reasons could play role during an earnings season. This realization together with the fact that earnings seasons are accompanied by higher trading volume, volatility, and absolute returns makes them perfect candidate for the high-preference-uncertainty periods.

I argue in this paper that earnings seasons can be viewed as the periods with high preference risk (when investors do not know how other investors will respond to future events) and so I can easily adopt the framework employed in Gallmeyer et al. (2005) and Watanabe and Watanabe (2008) to study how liquidity risk changes during earnings seasons.

The paper consists of two main parts and proceeds as follows. Part one establishes the significance of earnings seasons for the financial markets. In the first two sections of this part I provide basic institutional features that define earnings seasons and then briefly review the literature that documents the impact of individual earnings announcements on financial markets. The second section of this part sheds light on the aggregate effect of earnings seasons in general through its effects on aggregate returns, volatility, and trading volume, the variables that might affect the market-wide liquidity.

In part two, I investigate the asset pricing implications of liquidity changes during earnings seasons. Specifically, I study the changes in liquidity betas and changes in conditional liquidity risk. Section 2.1 discusses my methodology and describes the sample. Section 2.2 deals with changes in liquidity betas during earnings seasons. In section 2.3 I estimate the liquidity risk premium incurred during earnings seasons. Section 2.4 of this part provides a series of robustness checks and estimates the economic significance of the premium. The last part of the paper contains discussion and recommendations for future research.

2.2. Earnings Seasons

2.2.1 Seasonality in Earnings Announcements

General background on regulation. According to the Securities Exchange Act of 1934 (the Act) every public company (with the float of at least $74M) should report its quarterly and annual results within a certain time period following the end of fiscal quarters and companies' fiscal years. Specifically, the Act states that all public companies should file quarterly reports within 45 days after the end of fiscal quarter (40 days for companies with market value of $700M or more)[1] and annual reports within 90 days following the end of the *company's* fiscal year (75 days for firms with market value of $700M or more). In 2002 SEC published a new rule in order to accelerate the filing of

[1] See the Federal Regulation Code Title 17 parts 230 through 250 for terms and definitions.

these documents reducing the number of days to 35 for quarterly reports and to 60 for annual reports.[2]

Distribution of Earnings Announcement. In this section I describe the source of data for earnings reports and document the strong seasonality with which companies report the earnings information in the US.

I use the COMPUSTAT Industrial Quarterly database which reports the date when the earnings report was made available to the public for the first time (through the publication in the Wall Street Journal or newswire services.) Even though the database coverage starts in December 1970, the coverage is incomplete in the early years of the sample. The coverage of earnings announcement rises from 50% in 1974 to 95% in 2005 (for 2007 the coverage is still incomplete as of December 2008).

Figure 2.1 illustrates the coverage of the reporting firms from 1971 to 2006. The figure visually confirms that the coverage was relatively sparse in the 70s and 80s gradually increasing in the 90s and reaching the peak in 2001. The coverage dropped somewhat in 2003-2006 probably because of the merger wave and the bursting of the internet bubble.

I expect that the legally specified reporting intervals would result in strong seasonality of earnings releases. All public firms should report within 45 days after the end of fiscal quarter so that we should not see firms reporting outside the interval (which is 45 days BEFORE the next fiscal quarter). However, even though the seasonality is very strong, it is not perfect. The main reason is that only about two-thirds of companies

---

[2] RELEASE NOS. 33-8128; 34-46464; FR-63; (http://www.sec.gov/rules/final/33-8128.htm)

have their fiscal year ends in December with the rest filing their annual reports throughout the year. And since the reporting interval for annual reports is 75 to 90 days, there is usually not a single day in a year without a company reporting. Table 2.1 shows the distribution of announcements and fiscal year-ends by calendar month[3]. Most firms (around 60%) have December fiscal year-ends, while others have March (6%), June (8.9%), and September (7%) year ends. For the non-quarter-ends months the percentage of firms reporting is fairly small typically between 1 and 3 percent. This fact explains the absence of "no-reporting" days (every day some firms announces its earnings).

Next, I investigate the actual seasonality in the earnings announcements in a typical year in order to select the most representative time periods as my "earnings seasons". Figure 2.2 shows the average number of weekly reports for a period from 1971 to 2006. The seasonal pattern is striking. We can clearly identify the four earnings season's three of which are of exactly the same "form".

We can also see that the pattern for January and February are somewhat different from the rest of the year. This corresponds to the fact that for most firms December is the end of fiscal year and so they have 75 to 90 days (instead of usual 30 to 45) to report their earnings. As a result, the pick of earnings in January is lower than that of any other quarter but the duration is longer.

The lowest number of earnings announcements corresponds to the last week and the first week of each quarter. The highest peaks correspond to the third and fourth weeks of each quarter with slight decline during weeks 5 and 6 of the quarter and then peaking

[3] The proportions of firms having fiscal year ends other than December stay fairly constant from 1971 to 2006.

again in week 7- the last week of the 45 day period. As we can see, substantial number of firms “procrastinates” until the last day of the allowed period.

The number of firms reporting during the fourth week of a quarter (the highest peak) is on average 7 times (5 to 11 for different quarters) greater than the number of firms reporting during the first week and the last week (the lowest). The average number of firms reporting during the whole earnings seasons (the first six weeks of each quarter) to the number of firms reporting outside the season is above 3 (3.2). This leads me to conclude that there is a very strong seasonality in the discharge of economically significant information in the US economy. The next section reviews the literature on the effect of individual earnings announcements and then investigates the impact of the well pronounced seasonality in earnings announcements on aggregate returns, trading volume, and stock market volatility.

The impact of the individual earnings announcements. Earnings release is arguably the most important informational event in the financial life of a corporation. Numerous studies look into the effects of these releases and find that they influence price, volatility, volume, liquidity, adverse selection, trading patterns etc. (See e.g. Lee (1992) and Lee et al. (1993)) In this study I am mostly concerned with the effects of earnings announcement on market liquidity.

The most important characteristic of this short period (typically, the papers look at just 3 days surrounding the release) is the increase in information risk (and in particular, information asymmetry) between different types of investors and, also, between investors and market makers. The literature usually distinguishes three types of players involved in the trading (following Kyle (1985)): the informed investor (might be either a trader with insider information or with a better information processing skills), the uniformed investor (also called liquidity or noise trader), and the market maker (specialist in most studies). Each party is aware of the presence of the other two and so when they interact trying to optimize their behavior around earnings releases, the unique empirical patterns affecting many variables emerges.

The most pronounced feature of any (scheduled) earnings release is the distinct pattern of change in the trading volume. The amount of shares traded sharply falls below long-term average and then dramatically surges immediately following the announcement (See e.g. Chae (2005) for an overview). The usual explanation (George et al, (1994) is that the uninformed traders know about their disadvantage just before the earnings release (the state of high information asymmetry) and wait until after the event, when the uncertainty is partially resolved, to continue their trading. However, the information asymmetry continues to stay higher than the average for several days because the informed traders actively trade utilizing their advanced knowledge (or the information processing skills). Market makers are aware of the active presence of the informed investors and facing adverse selection try to manage the risk by widening bid-ask spreads and decreasing depths (Lee et al. (1993), Krinsky and Lee (1996), and Kavajecz (1999) among others). As a result, we observed a unique combination of high volume and low liquidity during an individual announcement.

All of the above studies explore the effect of earnings announcements on individual firm's liquidity ignoring the clustering of earnings releases during earnings seasons. Intra-industry information transfers provide further indication that during "earnings seasons" the overall markets could experience abnormally low levels of liquidity. Foster (1981) initiates the stream of literature in this direction showing that a single earnings announcement affects not only the reporting firm but also the other companies in the same industry. For example, Kovacs (2005) finds that a firm's stock price is positively related to industry peers' earnings surprises regardless of whether the firm has already announced its own quarterly earnings. This suggests that earnings announcement contain substantial industry-relevant information that is not fully captured by a firm's own earnings. Sun (2006) investigates the timing of an announcement within earnings seasons and finds evidence consistent with information transfer. Specifically he reports that late-reported good news announcements are accompanied by significant pre-announcement price increase.

In addition, firms provide much more than just past quarter's earnings. Brandt et al. (2006) note that firms' press releases elaborate on the earnings report as well as provide forward looking information. For example, firms provide expanded information about components of earnings such as sales and operating margin as well as future sales forecasts. In other words, market participants become aware of significant pieces of new information in addition to earnings at the earnings announcement date.

Even though important information that could affect firms' valuation is released throughout the year (retail industry's same-store sales, consumer sentiment index, and the like), the importance of earnings releases cannot be underestimated. Chiang and Mensah (2006) investigate the inferential value of earnings releases by comparing them with other sources of information. They find that excess returns measured around earnings announcement dates are more highly correlated with changes in future firm performance than similar measures in the non-disclosure periods. They conclude that earnings reports provide a more definitive basis for the capital markets to perform a reality check on previous assumptions derived from the alternative sources.

The cumulative evidence presented in this section points out to a significant effect that earnings seasons could potentially have on the overall market. The next session addresses the aggregate effect of earnings releases through its effect on returns, trading volume, and market volatility.

2.2.2 The aggregate effects of Seasonality in earnings announcements

This section documents the effect that the seasonality in aggregate earnings releases has on significant economic variables such as aggregate returns, trading volume, and marketwide volatility.

Returns. The fact that the returns during the first two weeks of each earnings season (recall that the earnings season is defined as the 45 days after the end of each calendar quarter or, equivalently, the first 45 days of each new quarter) has long been established. Penman (1987) was the first to connect this pattern in returns and the distribution of earnings released within an earnings season. He argues that the aggregate returns tend to be positive because typically only firms with very good news tend to release their earnings figures in the first two weeks. He identifies this seasonality in index returns over a period of 20 years (up to 1982). No other study has updated the results but it seems that the results could be driven by the January effect since he does not control for it.

I investigate this issue with a much longer time-series spanning from 1962 to 2006. I test for seasonality in returns over three different periods all related to earnings seasons. The first period is the first two weeks of each earnings seasons, the second is the first month of earnings seasons (these are January, April, July, and October), and the third period is the full 45-day window after each calendar quarter when all firms have to report their quarterly numbers. The returns are from CRSP index file and both value- and equal weighted returns are used.

The results, presented in Table 2.2 Panel A, show that the seasonality is present in the equal- but not the value-weighted return series. This may be due to the fact that the returns of smaller firms are much more sensitive to the earnings news. Unlike big firms which are usually followed by analysts and business press, small firms are more likely to have most of their relevant information released during earnings seasons with no news in between.

The direction of the returns is not intuitively clear. The typical logic runs as follows (see Amihud (2002) for the original argument.) On the one hand, if earnings seasons are characterized by higher non-diversifiable information (or preference) risk, the stocks that are most sensitive to it should provide investors with higher expected returns. On the other hand, to provide the higher expected return, the stock's price should first decline and that is exactly what might happen during earnings seasons. In other words, to get higher expected earnings on stocks affected during earnings seasons, the investors might get lower realized returns during earnings seasons. The factor that complicates this logic is the fact that the timing of earnings seasons is perfectly predictable and only the information content of the earnings release matters.

The findings, at first, seem to contradict the above analysis. As we can see for all three period lengths, the realized returns during earnings seasons are higher than the returns during regular seasons (significantly higher for equal-weighted confirming my conjecture about the effect on small firms).

However, I argue that it is the January effect that drives the returns above average. Keim (1983) and Reinganum (1983) show that much of the abnormal return to small firms (measured relative to the CAPM) occurs during the first two weeks in January. Roll (1983) hypothesizes that the higher volatility of small-capitalization stocks causes more of them to experience substantial short-term capital losses that investors might want to realize for income tax purposes before the end of the year. This selling pressure might reduce prices of small-cap stocks in December, leading to a rebound in early January as investors repurchase these stocks to reestablish their investment positions.

To control for this effect, I exclude the first two weeks of January from my analysis. This significantly changes the results, presented in Table 2.2 Panel B. The returns turn from slightly positive to become slightly negative (significantly negative at 5% for equal-weighted market returns).

After controlling for the January effect (the anomaly that doesn't seem to go away since it was first discovered), the overall results corroborate my hypothesis about the direction of the returns.

In addition to lower realized returns, I also expect the trading volume to be lower in the beginning of earnings seasons (higher information uncertainty) and higher thereafter as the information uncertainty is resolved. The next section explores this dimension of earnings seasons.

Trading volume. Even though the volume is one of the most important characteristic of a stock market, the comprehensive theory of volume is still not in sight. In rational expectations (homogeneous agents) framework information does not cause agents to trade (the famous "no-trade" theorems- e.g. Milgrom and Stokey (1982)). Instead, prices just change without any trades. This is completely opposite to what we observe in the real stock markets: volume surges as new information comes in. Gallmeyer et al. (2005) working with heterogeneous agents hypothesize that the new information causes changes in investors' preferences and so volume surges in response to the need to adjust the portfolios to the new market conditions. Since earnings seasons are characterized by the release of new and important information in a very short period of time, I hypothesize that this period of time will be accompanied by the changes in trading volume. I cannot predict the direction (up or down) since the earnings are characterized by sharp drop in volume just before the announcement and a surge just after. But I can speculate though that as the earnings season starts, the volume will fall since the possibilities for the informed trading rapidly increase and the liquidity/noise traders drop out of the market. However, as we progress through the earnings season and the uncertainty is resolved, the trading volume should increase above average.

One of the difficulties in measuring trading volume is the choice of the appropriate metric. Lo and Wang (2000) analyze most of the measures used to compute volume and grouped them into five most commonly used sets. Then they perform somewhat of a "horse race" and conclude that the best measure of trading volume is the share turnover (the number of shares traded as a percent of total shares outstanding). However, since the share turnover is very sensitive to the transaction costs (lower costs associated with higher turnover) and the transaction costs dropped precipitously during the last 10-20 years, the time series needs to be scaled.

I follow a conventional approach and define the share turnover as a ratio of the average number of shares traded during a week to the average number of shares outstanding during that week. To eliminate possible serial correlation and to account for the decreasing transaction costs during the study period, I scale the obtained turnover time-series by a 24-week average. The same approach was applied in Eckbo and NorlI (2002) and in Watanabe and Watanabe (2008). A typical pattern of trading volume fluctuations over a year is presented in Figure 2.3. I average weekly trading volumes over 45 years (1962-2006) and imposed them on the graph showing the average number of firms reporting during a particular week of the year. As we can see the trading volume exhibit a famous pattern that has been detected in several studies (see e.g. Statman et al. (2006)) with high values at the beginning and the end of the year and very low values in the middle (August). The second observation is that there is a clear quarterly pattern with turnover high in the middle of a typical earnings season and low at the very beginning and the end. My interest is to test statistically whether the series exhibit quarterly seasonality.

After running simple OLS with dummies for different weeks of the year (testing with dummies for four different period lengths: first two weeks, middle two weeks -the peak of the season, one months, and full 45 day season), I find that in fact the first 2 weeks of a new quarter (the beginning of the earnings season) is characterized by a significant decrease in trading volume (see Table 2.3), if I control for January effect in my analysis. Testing the next two weeks (the peak of earnings seasons) I in fact find that the volume is significantly higher (see Table 2.3).

The last two rows show that the regressions that use one month and the full season (45 days) produce insignificant coefficients. However, I do expect that given that volume changes dramatically from well below the average in the beginning to well above the average during the peak of the season. I also observe that January effect plays a significant role in driving the average yearly volume up and it is therefore very important to control for this effect. Next I will investigate whether earnings seasons affect the aggregate volatility.

Volatility. It is well known that the volatility of stock returns varies over time. This variation can induce changes in the investment opportunity set by either changing the expectation of future market returns, or by changing the risk-return trade-off. The main reason for the variation in volatility is economic uncertainty (see e.g. Schwert (1989)). Veronesi (1999) presents a theoretical model that formalizes the link between economic uncertainty and stock market volatility. He shows that investors are more sensitive to news during periods of high uncertainty, which in turn increases asset price volatility. Since earnings seasons are characterized by a highly concentrated disgorgement of new information about companies' fundamentals (and therefore making it possible for investors to infer the state of a broader economy), I hypothesize that these periods (earnings seasons) will be accompanied by heightened aggregate stock market volatility.

To test my conjecture I need to choose a measure of volatility. The difficulty of using volatility as a variable is that this economic factor is not observable. Instead, I have to infer it from the returns data which requires making certain assumptions. Using realized squared returns (a measure popular in the last century) gives a "quick and dirty" estimate of volatility but it is very unreliable (and sometimes is simply incorrect) because it assumes normality and white noise process (which is completely at odds with my goal to detect seasonality). GARCH/ARCH and stochastic volatility frameworks are more flexible on the one hand, but require a lot more assumptions on the other (Tsay, 2005).

The most attractive measure of volatility that is becoming the measure of choice for academics in the last decade is the CBOE Volatility Index (VIX). Ang et al*.* (2006) investigate the performance of different volatility measures and found the VIX to be the most appealing. The VIX provides a minute-by minute snapshot of expected stock market volatility over the next 30 calendar days. This volatility is calculated in real-time from stock index option prices and is continuously disseminated throughout the trading day (CBOE website: http://www.cboe.com/micro/vix/vixwhite.pdf) The VIX estimates expected volatility from the prices of stock index options in a wide range of strike prices, not just at-the-money strikes. Also, the VIX is independent of any model. Instead, it uses a newly developed formula to derive expected volatility by averaging the weighted prices of out-of-the money puts and calls.

After calculating weekly VIX and computing the innovations in volatility (by finding the first difference),[4] I ran simple regression models to check for seasonality in the innovations. I find that the only week (of each quarter) where innovations in VIX are

[4] VIX is very persistent with correlation of more than 90%. See Ang, Hodrick, Xing, and Zhang (2006)

significantly (p-value is 0.037) higher is the last week of the quarter (or equivalently, this is the week just before the earnings season). By the definition of VIX, it means that during the last week of the calendar quarter, the expected volatility over the next 30 days (the larger part the earnings season) is significantly higher than the expected volatility during any other time of the year.

Summary. As we can see from the above analyses, the aggregate effect of earnings seasons on the financial markets is significant. In particular, the realized returns seem to be smaller (especially for smaller stocks) if I control for the January effect. The trading volume (share turnover) is significantly lower during the first two weeks of the seasons and significantly higher during the rest of the season. Also, the volatility (VIX) is at its highest precisely the week before the start of earnings seasons suggesting that traders/investors expect the next month (the peak of earnings seasons) to be especially unpredictable. Having established the economic significance of earnings seasons, in the next part, I investigate the aggregate liquidity effects of earnings seasons. The first section of part two explores whether the stocks' liquidity betas are significantly higher during earnings seasons and the second section explores the whether the liquidity risk changes during these periods.

2.3. Changes in Liquidity Betas and Liquidity Risk

2.3.1 Overview and Hypotheses Development

Several studies document the existence of aggregate fluctuations in liquidity and its effect on asset prices. Chordia et al. (2000) introduced the term "commonality in liquidity”. They argue that liquidity, trading costs, and other individual microstructure phenomena have common underlying determinants and that some portion of individual transaction costs co-vary through time. They suggest several sources of commonality in liquidity: variation in dealers’ inventory levels, variation in market-wide volatility, and program (or portfolio) trading that produces changes in inventory pressure across broad market sectors. They also pose a question whether the variations in asymmetric information could have some systematic market-wide component and therefore be another important source of commonality in liquidity. Huberman and Halka (2001) document the presence of a systematic time-varying component in liquidity by finding the seasonal regularities in the bid-ask spread of the NYSE-traded stocks.

As soon as the commonality in liquidity was well established, several studies looked at how the systematic component of liquidity affects the asset prices. In one of the first such studies, Chordia et al. (2001) investigate the relationship b/w trading activity (their chosen proxy for liquidity) and expected stock returns. To their surprise, they find that there is a strong *negative* correlation robust to different model specifications. Pastor and Stambaugh (2003) show that it’s not the volatility in individual stock’s liquidity per se that is important to investors but rather the sensitivity of this liquidity variation to the aggregate market liquidity fluctuations. They find that stocks’ “liquidity betas”, the unconditional sensitivities to innovations in aggregate liquidity, play a significant role in asset pricing. The inclusion of the Fama-French factors as well as the momentum into the model does not eliminate the liquidity effect. Later, Longstaff (2005) and Acharya and Pedersen (2005) develop theoretical models showing how the innovations in aggregate liquidity become priced if the trading costs are included in the models.

Even though many papers find that the fluctuations in aggregate liquidity have systematic components and should be priced, only a few explanations of such variations were proposed. They range from the compensation for the transaction costs to random market wide shocks to liquidity (such as a country crisis) to somewhat more exotic. For example, one of the explanations is offered by DeGennaro et al. (2006) who try to explain the seasonal variation in bid-ask spreads by the so-called Seasonal Affective Disorder (SAD). They argue that the number of daylight hours a day strongly influences the risk-aversion of traders and market makers.

One of the main puzzles that emerges from the fact that liquidity is priced is a simple observations that investors can easily avoid (or significantly reduce) their transaction costs by trading less (Constantinides, 1986). If investors could practically avoid this cost, why should it be priced? Several hypotheses were put forward to explain the phenomenon. All of them are based on the assumption that the liquidity cost proxies are highly correlated with other sources of risk that could be priced and, therefore, the observed liquidity risk premium is in fact a premium for that unobservable source of risk.

One of the first models was developed by Huang (2003) who assumes that agents face surprise liquidity shocks and invest in liquid and illiquid riskless assets. The random holding horizon from liquidity shocks makes the return of the illiquid security risky. He finds that Illiquidity can have large effects on asset returns when agents face liquidity shocks and borrowing constraints.

Easley et al. (2002) and O'Hara (2003) focus on differences in information sets across investors, each of whom knows the structure of returns, and find that information-based trading has a large and significantly positive effect on asset returns (their estimated information variable (PIN) and firm size are the predominant factors explaining returns.) According to them, the uninformed traders understand that they will lose to better informed agents but since they still have portfolio choices to make, they choose assets in which the information risk, the risk of losing to better informed traders, is lower.

Gallmeyer et al. (2005) address the problem by assuming that investors are asymmetrically informed about each other preferences and that trading is an important source of revealing that information. This preference uncertainty could expose investors to the resale price risk because they are uncertain about future asset demands of their trading counterparties. Trading however helps fully or partially reveal the preferences so that the level of preference risk is endogenously determined. They also assume the stochastic nature of changes in future preferences and hypothesized the existence of high and low preference risk environments concluding that the preference risk is priced in equilibrium. Watanabe and Watanabe (2008) extend the model to study the effect of the time-varying liquidity risk on the cross-section of stock returns. They also introduce the liquidity costs (the costs of selling) into Gallmeyer et al. (2005) model and hypothesize that liquidity betas are positive and larger during the periods when investors face a higher level of preference uncertainty and that the liquidity risk premium also rises during the times of high preference uncertainty.

What is common to these models trying to explain the liquidity risk premium is the existence of two time periods with different levels of risk. Huang (2003) needs periods with liquidity shocks and Gallmeyer et al. (2005) postulate the periods with high and low preference uncertainty. Even though Easley et al. (2002) assume constant PIN for each firm, they speculate (their footnote 8) on whether there is a common (systematic) time-varying component in private information across stocks.

In this paper I argue that earnings seasons are ideal candidates for these periods of high level of risk (be it high illiquidity, high preference uncertainty, or high probability of informed trading). The recognition and documentation of this fact is the main contribution of this study.

Following Gallmeyer et al. (2005) framework with the illiquidity costs (as in Watanabe and Watanabe (2008)), I first examine the effect of preference uncertainty during earnings seasons on liquidity betas. I argue that during earnings seasons the liquidity betas will be larger in magnitude (more negative) than during the regular seasons. The logic of the argument is as following. Even though earnings seasons are well known in advance, the content of the information flow is stochastic which leads to a stochastic change in investors' expectations and illiquidity. When there is an unanticipated increase in the next period's illiquidity cost, it will also raise subsequent periods' costs due to persistence in illiquidity, which is widely documented in the empirical literature (see also Amihud (2002) for the original argument.) The rise in future illiquidity costs will in turn decrease the next period's price, because it is the sum of discounted future payoffs after cost ,leading to a larger return decrease under higher preference uncertainty. This results in a lower current price that marginal investors require in order to compensate themselves for future resale price risk. This argument is also proven formally in Acharya and Pedersen (2005). Based on the above analysis I expect that the liquidity beta of an asset will be negative in part because a rise in market illiquidity reduces asset values. This beta affects required returns negatively because investors are willing to accept a lower return on an asset with a high return in times of market illiquidity. Consequently, the more negative the exposure of the asset to marker illiquidity, the greater the required return (see a summary of the argument in Amihud et al. (2005).

Therefore, my first testable hypothesis is that the return sensitivity to illiquidity shocks is negative and larger in magnitude, or equivalently, liquidity betas are more negative when investors face a higher level of preference uncertainty.

Next, the changing level of preference uncertainty during earnings seasons will also affect liquidity risk premium. Liquidity risk is priced because illiquidity shocks make investors' consumption volatile and risk-averse investors dislike volatile consumptions; the more volatile their consumptions become, the more risk premium they will require. I propose that preference uncertainty during earnings seasons makes their consumptions more sensitive to the illiquidity shocks and hence more volatile, because the sensitivity is proportional to trading volume. Intuitively, as investors accommodate larger sell trades from their counterparties under higher preference uncertainty, they will have to pay more illiquidity costs when they close out their positions in the future. This leads to my second hypothesis that the liquidity risk premium rises during earnings seasons. In the next section I describe the data used in testing of the first hypothesis, the construction of the liquidity measure and provide some evidence regarding the variability of liquidity betas. The second hypothesis (liquidity risk premia estimation) is dealt with in Part 3 of the paper.

2.3.2 Data and Methodology

I begin my empirical analysis by examining the changes in liquidity betas across the two seasons (earnings vs. "calm"). I use two extreme size deciles of size-sorted portfolios given by the value-weighted size-sorted portfolios of stocks listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ all obtained from CRSP database for the period from 1962 to 2006). To account for the "double-counting" of volumes for the NASDAQ stocks I divided their reported volumes by half (the procedure widely used in the finance literature (see Atkins and Dyl (1997) and Anderson and Dyl (2003) among others). Another potential drawback of including the NASDAQ stock is that the time-series for the majority of stock starts only in the late 70s-early 80s and thus the sample size substantially increases after that period. I address both problems in the robustness section of the paper where I run the tests on a smaller sample that excludes NASDAQ firms.

Most studies on the asset pricing implications of liquidity use monthly returns. However, as I indicated in the previous section earnings seasons' information flow peak at the end of week four and remains elevated from week 2 to week 7. To preserve the monthly time period in this study and to capture the effect of earnings seasons I shift all months by two weeks forward. For example, the redefined January starts on January 16th and ends on February 14th and I did so for the whole time series. To get monthly stock and factor returns I use compounded daily returns from the CRSP daily stock file calculated over the redefined months.

Since earnings seasons can be perfectly identified, I test my first hypothesis using simple OLS regression with dummy variables for earnings seasons. Specifically, the dummy ES is defined as one if the (shifted) months are January, April, July, or October and zero otherwise.

I fit the following OLS model to the excess returns of the smallest and largest size-decile portfolios:

$$r_t = \alpha_t + \beta^{INIL}{}_t INIL_t + \beta^{ES} ES_t + \beta^{INIL*ES}{}_t ES_t INIL_t + ES_t \varepsilon_t \tag{1}$$

, where INILt is the "Innovation in Illiquidity" factor (described below and called simply the "liquidity factor" thereafter), r_t is the series of excess returns on the smallest or the largest decile portfolios, and β^{INIL} is the liquidity beta. If $\beta^{INIL*ES}$ is positive and significantly different from zero, then the betas during the earnings and the "calm" seasons have different slopes (I expect more negative betas during earnings seasons (ES)) which would be consistent with my first hypothesis. The product of variables ES_t and $INIL_t$ equals INIL during the earnings season and zero otherwise. In other words it is a Liquidity factor conditional on earnings seasons. I am going to denote it $INILES_t$ in my further analysis and instead of writing a somewhat cumbersome $\beta^{INIL*ES}$ I am going to use β^{INILES}.

Equation (1) does not control for factors commonly used in asset pricing tests. I argue that this is sufficient for the unconditional state identification. For example, if I include the market return, the estimated liquidity betas would be those conditional on it (see a similar argument in Watanabe and Watanabe (2008). Also, we know that unexpected liquidity shocks and the market return are correlated (e.g.,Amihud (2002)), and I consider the level of the market return (and possibly other variables) to be an important characteristic of earnings seasons. I use full specification models in the asset pricing section of this paper.

2.3.3 Liquidity measure

Researchers have used several methods to create monthly liquidity factor for asset pricing tests. Hasbrouck (2006) conducts a "horse race" among different measures of liquidity and concludes that ‘‘among the proxies considered here, the illiquidity measure [proposed by Amihud (2002)] appears to be the best." The same price-impact proxy was used in Acharya and Pedersen 2005) as a measure of illiquidity costs. Following them I compute ILLIQ as:

$$ILLIQ_{j,t} = \frac{1}{D_{j,t}} \sum_{d=1}^{D_{j,t}} \frac{|r_{j,d,t}|}{vol_{j,d,t}} \qquad (2)$$

, where D is the number of trading days in stock j in a month t and r and vol are daily return and trading volume correspondingly. The intuition behind this illiquidity measure is as follows. A stock is illiquid—that is, has a high value of $ILLIQ_{j,t}$—if the stock's price moves a lot in response to little volume.

Following many other studies I use only ordinary common shares (SHRCD equals 10 or 11 in CRSP database) on NYSE , AMEX, and NASDAQ with Dj,t >= 15 and the beginning-of-the-month price between $5 and $1,000. The aggregate price impact ($AILLIQ_t$) is simply the cross sectional average of individual ILLIQ over month t from August 1962 to December 2006.

Since the illiquidity series is very persistent, I follow Acharya and Pedersen (2005) and use an AR(2) model to extract innovations. Specifically I fit the following model:

$$(AILLIQ_t \times P_{t-1}^M) = \alpha + \beta_1(AILLIQ_{t-1} \times P_{t-1}^M) + \beta_2(AILLIQ_{t-2} \times P_{t-1}^M) + \varepsilon_t, \quad (3)$$

, where P_{t-1}^M is the ratio of market cap of the stocks used to calculate $AILLIQ_t$ at the end of the previous month to the total market value of the used stocks in August 1962. This ratio is used to control for the decreasing time trend in AILLIQ and makes the time series more or less stationary. Following Acharya and Pederson (2005) I use the estimated residuals, ε_t as my liquidity factor (Innovation in illiquidity), INILt, which starts in October 1962.

2.3.4 Variation in liquidity betas

The results of the OLS regression with dummy variables are presented in Table 2.4. Consistent with my first hypothesis I find significant and negative relationship between hypothesized liquidity shocks during earnings seasons and contemporaneous returns (that is returns are higher for more liquid stocks), as indicated by significant and negative liquidity betas (both β^{INIL} and β^{INILES} are negative and significant at 3% level) for the smallest and the largest decile portfolios. The likelihood ratio test rejects the null hypothesis that the two betas (β^{INIL} and β^{INILES}) are the same at 1% level. Therefore we can conclude that the sensitivity of returns during earnings seasons to liquidity shocks is substantially higher (or more negative) than during regular (or “calm”) seasons. This finding stresses the importance of earnings seasons for market-wide liquidity since it is consistent to other findings in Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pederson (2005) and others who also find that the contemporaneous returns decline with higher illiquidity.

A notable additional finding from Table 2.4 is the cross-sectional difference in liquidity-beta spreads. The spread of the estimated parameters between the two states is 0.00031 (= -0.00407 – (-0.00376)) for the smallest decile and 0.00155 (= -0.00259 – (-0.00104)) for the largest. The most striking fact is that the largest stocks experience greater sensitivity to the fluctuations in market illiquidity during earnings seasons. In fact, since I measure the additional sensitivity, it is only natural to expect that the bigger and most followed stocks will be most affected by the unexpected liquidity shock during the season when both analysts and investors are closely watching the stocks. Despite the fact that the incremental sensitivity is larger for the largest decile, the absolute values of the liquidity betas are more than 2 times bigger for the smallest stocks (a very similar pattern was observed in Chordia et al (2000)). This is in complete agreement with both Amihud (2002) and Acharya and Pedersen (2005) who previously find that small illiquid stocks have higher liquidity betas (more negative) than large liquid stocks on average.

However my result adds to theirs by documenting new evidence that such cross-sectional asymmetry in liquidity betas exhibits state-dependent time variation. The last two columns report the results of the test when all portfolios are used to check if the results are not driven by the extreme stocks. I find that all the coefficient preserve their significance, signs, and magnitudes.

Having established the variation of liquidity betas across seasons, next I explore whether the liquidity risk premium exhibits similar variation.

2.4. Time variation in liquidity risk premium

2.4.1 Methodology

To utilize the basic pricing relation E[mt+1(1 + ri,t+1)] = 1 where the Stochastic Discount Factor (SDF) is a function of constant coefficients (Cochrane, 2005) with my hypothesis' assumption that the SDF is state-dependent, I model it as a function of scaled factors (Watanabe and Watanabe (2008)). I define the conditional liquidity factor as:

$$INILES_t = ES_t * INIL_t \qquad (4)$$

, where ES_t is an indicator variable that takes a value of 1 during earnings seasons (shifted) months and 0 otherwise.

To understand how the role of $INILES_t$ factor in the asset pricing equation consider a simple return-generating process:

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{INIL} INIL_t + \beta_i^{INILES} INILES_t + \varepsilon_{i,t} \qquad (5)$$

, which can be re-written as:

$$r_{i,t} = \alpha_i + \beta_i^{MKT} MKT_t + (\beta_i^{INIL} + \beta_i^{INILES} ES_t) INIL_t + \varepsilon_{i,t} \qquad (6)$$

The term $\beta_i^{INILES} I_t$ captures the time variation in liquidity beta and makes the beta effectively β_i^{INIL} during the regular ("calm") seasons and $\beta_i^{INILES} + \beta_i^{INIL}$ during earnings seasons months. I call β_i^{INILES} the conditional liquidity beta.

I follow the standard Fama and MacBeth (1973) two-pass procedure to estimate the factor premia in equation (5) with additional factors added (these are B/M, Size, and Momentum). I use the entire sample in the first-pass beta estimation since the rolling beta approach is redundant because the liquidity beta is effectively time varying as in (5).

2.4.2 Characteristics of Liquidity Portfolios

To test my second hypothesis which states that the conditional liquidity beta is significant and positive, that is the liquidity risk premium varies across seasons, I form 25 test portfolios by sorting NYSE, AMEX, and NASDAQ stocks on the book-to-market ratio (B/M) and the price-impact proxy (ILLIQ) using NYSE breakpoints. The practice of forming portfolios of assets is very common and is used to get a sufficient variation in the variables of interest (see Fama and French (1993,1996) who use Size and Book-to-Market). Following this tradition I try to produce sufficient dispersion in liquidity betas while at the same time to represent as diverse cross sections as possible. Thus I replace the sorting by size with that by ILLIQ[5]. The portfolios are formed at the end of each year from 1964 through 2006, and the value-weighted monthly portfolio returns[6] are calculated for the subsequent years from January 1965 through December 2006. As usual, stocks are admitted to portfolios if they have the end-of-the-year prices between $5 and $1000 and more than 100 daily-return observations during the year to avoid the "penny stocks" and stocks with infrequent trading.

---

[5] In the robustness section below I run the tests with the returns on the conventional B/M by Size portfolios with essentially the same results.

[6] Note, that as in the previous part of the paper I use compounded daily returns to calculate the monthly returns for shifted months.

To get some idea about the test assets used in this section, I first look at the characteristics of the ILLIQ-sorted decile portfolios in Panel A of Table 2.5 where Rank 1 corresponds to the lowest ILLIQ (most liquid) and rank 10 the highest (most illiquid). To compute the portfolio characteristics presented in Table 2.5, I first compute pre-ranking ILLIQ for each stock at the end of each year. The annual ILLIQ is then used for portfolio formation. All the returns and characteristics in the table are time-series averages of post-ranking monthly portfolio returns and characteristics. These monthly portfolio returns and characteristics are calculated each month as value-weighted cross-sectional averages of member stocks' returns and characteristics except for size (which is a simple cross-sectional average) and the number of stocks. These procedures are similar to the ones used in Watanabe and Watanabe (2008) and size and B/M characteristics are computed after Fama and French (1993)

Consistent with the results reported in previous studies on illiquidity premium (Amihud (2002), Acharya and Pederson (2005) among others), the average raw return generally increases with ILLIQ. Other characteristics exhibit expected near-monotonic relations with the ILLIQ ranking. Thus, more illiquid stocks tend to have more volatile ILLIQ, lower price, smaller market cap (Size) and greater B/M. These results suggest that it is important to control for the size and value factors as well as the illiquidity-level characteristic in my asset pricing test. Note that the most illiquid portfolio contains 8 times as many stocks as other portfolios indicating that NASDAQ stocks are generally less liquid than NYSE stocks.

Panel B of Table 2.**5** reports selected summary statistics for the 25 portfolios formed at the intersection of B/M and ILLIQ quintiles (rank 1 has the lowest value of each characteristic). In Panel B(i), I observe that the average raw returns generally increase with both B/M and ILLIQ. Moreover, the illiquidity effect is stronger for value stocks (in the bottom rows) and the B/M effect is strong except for the most liquid stocks (the left-most column). Panel B (ii) confirms that I get dispersion in post-ranking illiquidity levels as measured by ILLIQ. The dispersion is slightly wider for value than growth stocks. Achieved variation shown in this table justifies my portfolio approach and I am ready to look into the main results of this section.

2.4.3 Main Results

Using the 25 portfolios sorted on B/M and ILLIQ, I estimate factor premia each month by a cross-sectional regression in equation (5) with the additional factors. Table 2.6 reports the time-series means of the risk premia and their p-values.

Column 1 shows the simplest model including only MKT, INIL, and INILES (the conditional liquidity factor). As we can see, the INIL premium is negative and significant with INILES positive but not significant. A significant positive constant and a negative significant MKT premium, however, suggest omitted factors and that the model is grossly misspecified. Column 2 introduces INILES, which corresponds to the model in equation (5). While the INIL premium remains significant, INILES carries an insignificant premium. However, since both the constant and the MKT premium are still significant (MKT with the “wrong” sign), there are still significant factors missing. Column 3 adds the size (SMB) factor. The factor enters insignificantly with a very small coefficient but actually adds significance to the INILES factor leaving the significance of the intercept and the MKT essentially unchanged. The next column (4) adds B/M factor (HML) to the model used for column 3. At this point the intercept's coefficient drops (but still remains significant at the conventional levels) and the MKT factors become insignificant. INILES however survives the inclusion of this factor at better than 1% level of significance. When, finally I include the last commonly used factor (column 5), the momentum, (UMD), the contribution of the INILES remains very high end highly significant.

The overall conclusion is that earnings seasons introduce undiversifiable liquidity risk to investors and they require additional risk premium for holding securities that are most sensitive to the liquidity shocks during these periods. The next section provides a battery of robustness checks.

2.4.4 Robustness Checks

Sample without NASDAQ. Many studies, including very well cited such as Acharya and Pederson (2005) or Pastor and Stambaugh (2003), avoid using NASDAQ firms arguing that this market's structure may affect the accuracy of reported volumes. Researchers that do use NASDAQ firms overcome that problem by using a "rule of thumb" when they simply half the reported NASDAQ volume (see Atkins and Dyl (1997) for the discussions on the validity of the rule). I argue that the inclusion of NASDAQ firms and the positive and significant results that I obtained with this sample show that my findings are applicable to the whole universe of stocks. However, to alleviate possible concerns that the results could be driven by the peculiar characteristics of the NASDAQ marketplace, I re-run my asset pricing tests on the restricted sample that includes only NYSE and AMEX securities.

Table 2.7 shows the time series means of the risk premia and their p-values computed using exactly the same procedure as above but on the restricted sample with all NASDAQ firms dropped. As we can see the magnitude of the coefficients decreases but the significance and all the signs are the same. The results indicate that the findings are not driven just by the inclusion of the smaller NASDAQ stocks and that the liquidity effects of earnings seasons are “felt” across the whole universe of stocks (though a little bit stronger for smaller stocks which is completely natural since the latter are much less liquid).

Alternative assets. Since I sort the stocks into 25 portfolios by B/M and illiquidity, the results become “biased” towards my hypothesis of changing liquidity risk premium. To see if the results still stand if I use the traditional sorting, I run the asset pricing tests on 25 portfolios sorted by B/M and Size (I follow Fama and French (1993, 1996) in constructing the portfolios).

Table 2.8 shows the average monthly risk premia for two samples. The full sample includes the stocks from all three exchanges NYSE, AMEX, and NASDAQ, while the restricted sample contains only stocks from NYSE and AMEX. As we can see the results are supportive of my hypothesis. However, the model with the full sample appears to be better specified since both the constant and the MKT factor are not significant at the 10% level. Even though the conditional liquidity factor (INILES) is significant “only” at the 6% level in both samples, the results are still much stronger than the ones obtained for the similar assets in other studies on liquidity. For example, Acharya and Pederson (2005) concludes that "With B/M-by-size portfolios (their Table 7B), the model performs poorly." …producing the premia with the "wrong" sign. Similarly Watanabe and Watanabe (2008) obtained results significant only at 8% level with the same test assets.

Also, as in the previous subsection, the values of the premia even though smaller than for the original sorting are still of the same magnitude (again the INILES values are several times higher for the full sample). To summarize, the robustness checks conducted in this section supports the important role that earnings seasons play in affecting the changes in liquidity risk premiums. The next section estimates the economic effect of this variability.

2.4.5 Economic significance

It is always interesting to estimate the economic impact of the changes in the conditional liquidity risk due to earnings seasons. In this section I follow Acharaya and Pederson (2005) approach by computing the annual return premium required to hold the same portfolio in two different time periods ("calm" seasons vs. earnings seasons). This is computed as the product of the additional risk premium and the difference in liquidity risk (betas) across the two states. Specifically, the effect of the earnings season on the smallest decile is

$-\lambda\ (\beta^{INILES} - \beta^{INIL})$ x 12 months x 100%= -1.297x (-0.00407-(-0.00376)) x12x100%=0.48% per year.

The effect of earnings seasons on the largest decile is

-1.297 x (-0.00259-(-0.00104)) x 12 x 100%=2.41% per year.

To summarize the additional risk premium required by the portfolio return's sensitivity to earnings seasons varies between 0.5% and 2.5% per year. The estimates appear reasonable. If we compare them with the ones obtained by Acharya and Pederson (2005), between 0.25 and 2% per year), it is reasonable to argue that most of that premium comes from the sensitivity of returns to the illiquidity shocks produces by earnings seasons.

2.5. Discussion and conclusion

Just in the last 10 years scholarly journals have published several hundred papers where one of the keywords was "earnings announcement". [7]Clearly, this is one of the most dynamic and important areas in accounting and financial research. The importance of earnings announcements for the firm's value has long been recognized and several well know anomalies associated with the announcement periods, including the Post-earnings-announcement-drift and the announcements premium, have been documented. Despite the flood of research on this important topic, none of the studies look at what the impact of the *aggregate* earnings announcement on the overall market is. This is especially surprising since all earnings announcements (for every public corporation in the US) are concentrated within a relatively short window of 40 to 45 days after the end of each calendar quarter. The basic intuition tells us that if the individual earnings are so

[7] I used ABI Inform database to search for the keyword "earnings announcement" after 01/01/1998 and found 240 scholarly articles.

important, then their aggregate concentrated impact might be important too. The intuition could be (and often is) wrong and that is why the thorough study of this phenomenon is necessary.

This paper is one of the first to investigate the impact of aggregate earnings impact on asset prices. I hypothesize that earnings seasons have a distinct impact on the markets and therefore might affect the returns on different assets (I study portfolios of stocks).

First, I review the literature to establish some stylized facts related to the individual earnings announcements. Most researchers agree that just before the earnings release the trading volume dramatically declines but surges right after the announcement is made. The bid-ask spread widens and the depth for each price level declines precipitously. The common explanation for the observed patterns is the variation in information environment: as the earnings announcement date approaches the possibilities for informed trading increases driving uninformed traders out of the markets and forcing the market makers to protect themselves against such trading by widening spreads and reducing depths.

Second, I investigate the aggregate impact of earnings seasons on three economically-important variables that could affect overall market liquidity. Specifically, I establish that controlling for January effect, the equal-weighted CRSP index returns are significantly lower during the seasons. The fact that the value-weighted index returns are not significantly different from the returns during the "calm" seasons indicates that this time period impacts mostly small firms and which in turn is consistent with the special informational role of earnings seasons. [8]

The aggregate trading volume during earnings seasons exhibits the same pattern as the trading volume of individual firms during their quarterly announcements. Specifically, the volume significantly decreases during the first couple of weeks of the earnings season, then surges closer to the middle of the earnings season, and then drops to the normal level. This is consistent with the view that noise (liquidity) traders exit the market at the beginning of the season due to the heightened probability of trading with an informed trader, only to start trading actively after the information release when the uncertainty is mostly resolved.

Finally, the third variable that I deal with in the first part of the paper is volatility. I determine that the aggregate volatility, as measured by the CBOE VIX index, drops sharply exactly during the week that precedes the start of earnings seasons. Since the VIX measures the expected volatility over the next 30 days, this drop in VIX values confirms that traders are very much aware of the special information status of earnings seasons, their heightened uncertainty.

After I establish the economic significance of earnings seasons for unconditional returns, trading volumes, and volatility, I move on to examine the effect of these time periods on asset prices controlling for known factors. A straightforward way to investigate this connection is to directly examine the liquidity effects of earnings seasons. If I can establish that during earnings seasons markets experience liquidity shocks, then

[8] For larger firms, the quarterly and annual reports are not as important since they frequently release information in between and usually have good business press and analyst coverage.

using the burgeoning literature on the commonality of liquidity I can study the asset pricing connection within an established framework (Acharya and Pederson (2005), and Pastor and Stambaugh (2003)).

During the first step, therefore, I select a liquidity measure (Amihud's illiquidity) and test whether earnings seasons are characterized by different (from the regular seasons) liquidity betas. I indeed find that liquidity betas are significantly lower (more negative) during earnings seasons. At first glance, this is surprising since because it means that the more liquid stocks provide higher return. However, this finding is in total agreement with others who also find *negative* and significant liquidity betas (Acharya and Pederson (2005), Amihud (2002), and Amihud et al (2005)).

The last part of the paper investigates whether there is an additional liquidity risk premium that is required because of the sensitivity of stock's return to the liquidity shocks during earnings seasons. I construct a conditional liquidity factor and employ the most commonly used asset pricing testing procedure, the Fama-Macbeth regressions, to test whether this conditional factor is priced. By adding the commonly used factors one by one, I explore their effect on the magnitude and the significance of the conditional liquidity risk premium. I find that after including HML (book-to-market), UMD (momentum), INIL (unconditional liquidity factor), SMB and MKT (CRSP value-weighted index), the INILES (conditional liquidity factor) is still significantly priced.

To summarize, this paper is the first to demonstrate the importance and economic significance of earnings seasons and suggests that these time periods of highly concentrated informational releases can hold large potential in revealing important knowledge about financial markets and investors' behavior.

Since this is the first study of asset pricing implications of earnings seasons, the directions of further research are numerous. Among them are questions on whether this identified liquidity premium is due to the real or information frictions (Stoll, 2000). Also interesting is the question of how this premia varies across different earnings seasons since we know that earnings seasons themselves are not "created all equal".

Several recent papers (e.g. Ng, 2006)), argue that liquidity effects are related to the magnitude and direction of earnings surprises and not to the announcements per se. Perhaps, to even better capture the liquidity effects I should differentiate earnings seasons by the ratio of bad to good surprises. This direction is also consistent with the general trends in the accounting literature that moves towards greater differentiation of the effects related to earnings seasons to explain the well-known anomalies.

Another direction would be to extend the study to the international markets. Since earnings seasons are not uniquely US phenomenon, the international data provides an excellent opportunity to test the hypotheses proposed in this study. In addition, since earnings seasons differ across countries in frequency and duration, it might be possible to find the determinants of liquidity effects during earnings seasons.

Still other directions call for investigation of the effects in other than equity markets such as derivatives (options and credit-default swaps), where the information's impacts on the prices is amplified. No matter what the direction of future studies is going to be, the recognition of the importance of earnings seasons on asset prices will definitely improve our understanding of how the financial markets work.

Table 2.1
The distribution of fiscal year-ends for firms in the COMPUSTAT Quarterly Database (1971-2006)

The table shows the average distribution of Fiscal-Year-Ends (FYE) by months. Within 75 to 90 days after the firm's year-end it has to file the annual report. The highlighted months (in bold) are the months in which earnings seasons begin. The majority of the FYE falls on December. The table does not show the distribution of quarterly earnings (they are shown in the Figure 2.2 above).

Month (FYE)	Number of firms	Percent of firms	Cumulative number	Cumulative percent
January	47250	3.52	47250	3.52
February	24002	1.79	71252	5.3
March	81881	6.09	153133	11.4
April	30651	2.28	183784	13.68
May	30106	2.24	213890	15.92
June	119772	8.91	333662	24.83
July	30336	2.26	363998	27.09
August	31418	2.34	395416	29.43
September	94989	7.07	490405	36.49
October	45570	3.39	535975	39.89
November	25798	1.92	561773	41.81
December	782019	58.19	1343792	100

Table 2.2
Seasonality in returns

The table shows the results of simple OLS regression with dummy variables for earnings seasons. The depended variable is excess returns on CRSP Equal- or Value-weighted CRSP indices and the independent variable is one of the three proxies. I use three different proxies for earnings seasons: the first two weeks after the end of each quarter, the one full month, and the first 45 days after the end of each calendar quarter. Panel A presents the results for the full sample (1962-2006) and panel B with the first two weeks of January removed. The star (*) denotes the values significant at 5% or better.

	First two weeks		One month		45 days	
	coefficient	p-val	coefficient	p-va	coefficient	p-val
A. Full Sample						
Equal-Weighted Returns	0.00095*	0.00	0.00039*	0.01	0.00049*	0.00
Value-Weighted Returns	0.00032	0.16	0.00012	0.50	0.00028	0.08
B. Without 2 first weeks of the year						
Equal-Weighted Returns	-0.00021	0.32	-0.00058*	0.00	-0.00044*	0.00
Value-Weighted Returns	0.00017	0.52	-0.00008	0.66	0.00008	0.63

Table 2.3
Seasonality in Aggregate Trading Volume

The table shows the seasonality in aggregate trading volume as measured by the Share Turnover. First I calculate the share turnover for each firm for each week. Then I calculate the aggregate share turnover for each week by simple-averaging the individual share turnovers. Finally, I average the aggregate weekly share turnovers over 45 year period (1962-2006). To get the estimates in each row I run simple OLS with respective dummies for earnings seasons. The dependent variable is the aggregate scaled average weekly share turnover and the independent variable is one of the four dummies: first two weeks, middle two weeks, one full months, and full 45 day season. The star (*) denotes the values significant at 5% or better.

	A. Full Sample		B. Without the January Effect	
	coefficient	p-value	coefficient	p-value
Dummy for:				
The first two weeks	-0.0158	0.32	-0.0391*	**0.03**
The middle two weeks	0.0321*	**0.04**	0.0269*	**0.05**
One month	0.0295	0.22	0.0069	0.76
45 day season	0.0210	0.24	0.0070	0.78

Table 2.4
Liquidity betas

The Table shows the results of testing whether the liquidity betas are different (lower) during earnings seasons.

$$r_t = \alpha_t + \beta^{INIL}{}_t\mathrm{INIL}_t + \beta^{ES}ES_t + \beta^{INILES}{}_t ES_t INIL_t + ES_t\varepsilon_t \ ,$$

where the dependent variable is the excess return on the size-sorted decile portfolios (NYSE breakpoints). INIL is the unconditional liquidity factor- the innovations in market-wide liquidity constructed after Amihud (2002) and Acharya and Pederson (2005). ES is the dummy for earnings season months (shifted by two weeks) (January, April, July, and October). INILES is the conditional liquidity factor. It equals INIL during earnings seasons and zero otherwise. The star (*) denotes the values significant at 5% or better.

	Smallest Decile		Largest Decile		All	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
intercept	0.01243*	0.00	0.00504*	0.02	0.00137	0.15
INIL	-0.00376*	0.00	-0.00104*	0.09	-0.00291*	0.00
ES	0.00113	0.85	0.00417	0.28	0.00121	0.46
INILES	-0.00407*	0.02	-0.00259*	0.03	-0.00321*	0.00

Table 2.5

The characteristics of test assets (portfolios)

This table shows the characteristics of test portfolios. Panel A shows the characteristics of 10 ILLIQ-sorted portfolios with average characteristics. I compute pre-ranking ILLIQ for each stock at the end of each year which is then used for portfolio formation. All the returns and characteristics in the table are time-series averages of post-ranking monthly portfolio returns and characteristics. These excess monthly portfolio returns and characteristics are calculated each month as value-weighted cross-sectional averages of member stocks' returns and characteristics except for size (which is a simple cross-sectional average) and the number of stocks. The Size and B/M characteristics are computed after Fama and French (1993). All months in the study are shifted by two weeks forward.

Panel B shows the characteristics of 25 test portfolios sorted on B/M and ILLIQ (with rank 1 being the lowest in each category. Panel B(i) shows returns for each portfolio, and Panel B(ii) shows ILLIQ values.

Panel A. ILLIQ-sorted portfolio characteristics

Decile	Mean Ret	N	ILLIQ	Size	σ (returns)	σ (ILLIQ)	Price	B/M
1	0.0087	145.6	0.0031	39407.8	0.015	0.003	76.76	0.598
2	0.0097	148.4	0.0141	4541.7	0.017	0.017	45.20	0.754
3	0.0108	157.9	0.0261	2464.5	0.018	0.027	37.82	0.741
4	0.0106	171.9	0.0448	1536.8	0.019	0.055	35.74	0.744
5	0.0105	186.0	0.0727	1058.7	0.019	0.091	32.87	0.744
6	0.0118	208.9	0.1139	760.2	0.023	0.157	30.89	0.761
7	0.0116	233.0	0.1782	543.0	0.025	0.250	26.50	0.815
8	0.0118	263.2	0.2846	415.6	0.026	0.422	25.06	0.884
9	0.0123	353.6	0.4997	286.0	0.029	0.702	21.51	0.924
10	0.0117	1107.1	2.1231	171.5	0.034	2.340	14.48	1.053

Panel B.

			ILLIQ					
(i)	Returns		1	2	3	4	5	5-1
		1	0.008	0.009	0.008	0.008	0.009	0.001
		2	0.009	0.010	0.010	0.011	0.010	0.001
B/M		3	0.009	0.011	0.012	0.011	0.012	0.002
		4	0.010	0.013	0.012	0.013	0.013	0.003
		5	0.012	0.013	0.014	0.016	0.014	0.002
		5-1	0.003	0.004	0.006	0.008	0.005	

			ILLIQ					
(ii)	ILLIQ		1	2	3	4	5	5-1
		1	0.00495	0.03564	0.10302	0.2662	1.7518	1.74685
		2	0.00495	0.03861	0.102	0.2585	1.7499	1.74495
B/M		3	0.00714	0.03774	0.0969	0.2486	1.8981	1.89096
		4	0.00918	0.03774	0.0969	0.2519	1.9247	1.91552
		5	0.0121	0.0418	0.1056	0.253	2.5542	2.5421
		5-1	0.00715	0.00616	0.00258	-0.0132	0.8024	

Table 2.6
Estimated Risk Premia for the full sample

The table shows estimated monthly percentage premia for different models. The predictor variable is the returns on 25 test asset sorted on B/M and ILLIQ. MKT is the excess returns on CRSP value-weighted index, INIL is the liquidity factor (innovations in Amihud (2002) illiquidity measure). INILES is the conditional liquidity factor equal INIL during the earnings season months and zero otherwise. UMD is the momentum factor. HML and SMB are B/M and size factors obtained from K. French's website and the monthly returns are recalculated for my shifted (by two weeks forward) months. The estimation period covers 42 years (504 months of data) of data from 01/01/1965 to 12/31/2006. The star (*) denotes the values significant at 5% or better.

	1		2		3		4		5	
	Premia	p-val.	Premia	p-val.	Premia	p-val.	Premia	p-val.	Premia	p-val.
Const.	0.019*	0.00	0.013*	0.00	0.025*	0.00	0.009*	0.02	0.008*	0.03
MKT	-0.013*	0.00	-0.015*	0.01	-0.02*	0.00	-0.004	0.37	-0.004	0.41
INIL	-1.707*	0.01	-0.912*	0.02	2.092*	0.04	1.3279	0.17	1.3204	0.15
INIL ES			0.0229	0.34	1.387*	0.00	1.300*	0.00	1.297*	0.00
SMB					0.0001	0.96	0.0011	0.44	0.0011	0.43
HML							0.005*	0.00	0.005*	0.00
UMD									-0.002	0.69

Table 2.7
Estimated Risk Premia for the restricted sample (only NYSE and AMEX stocks)

The table shows estimated monthly risk premia for different models. The predictor variable is the returns on 25 test asset sorted on B/M and ILLIQ. MKT is the excess returns on CRSP value-weighted index, INIL is the liquidity factor (innovations in Amihud (2002) illiquidity measure). INILES is the conditional liquidity factor equal INIL during the earnings season months and zero otherwise. UMD is the momentum factor. HML and SMB are B/M and size factors obtained from K. French's website and the monthly returns are recalculated for my shifted (by two weeks forward) months. The estimation period covers 42 years (504 months of data) of data from 01/01/1965 to 12/31/2006. The star (*) denotes the values significant at 5% or better.

	1		2		3		4		5	
	Premia	p-val.	Premia	p-val.	Premia	p-val.	Premia	p-val	Premia	p-val.
Const.	0.017*	0.00	0.017*	0.00	0.02*	0.00	0.01*	0.01	0.009*	0.04
MKT	-0.012*	0.00	-0.013*	0.00	-0.02*	0.00	-0.005	0.29	-0.003	0.46
INIL	-0.101*	0.02	-0.097*	0.02	-0.024	0.75	0.187*	0.03	0.1650	0.07
INILES			0.143*	0.01	0.168*	0.00	0.151*	0.01	0.143*	0.02
SMB					0.0010	0.52	0.0022	0.14	0.0023	0.13
HML							0.006*	0.00	0.006*	0.00
UMD									0.0015	0.80

Table 2.8
Estimated Risk Premia for the alternative assets (B/M by Size)

The table shows estimated monthly risk premia for two samples. The full sample includes stocks from NYSE, AMEX, and NASDAQ. The restricted sample includes only NYSE and AMEX stocks. The predictor variable is the returns on 25 test asset sorted on B/M and SIZE. MKT is the excess returns on CRSP value-weighted index, INIL is the liquidity factor (innovations in Amihud (2002) illiquidity measure). INILES is the conditional liquidity factor equal INIL during the earnings season months and zero otherwise. UMD is the momentum factor. HML and SMB are B/M and size factors obtained from K. French's website and the monthly returns are recalculated for my shifted (by two weeks forward) months. The estimation period covers 42 years (504 months of data) of data from 01/01/1965 to 12/31/2006. One star (*) denotes the values significant at 5% or better and two stars (**) denote the values significant at 10% or better.

	Full sample		Restricted sample	
	coefficient	p-value	coefficient	p-value
Const.	0.0067	0.11	0.0164*	0.00
MKT	-0.0017	0.70	-0.0107**	0.05
INIL	0.3214	0.74	0.0682	0.37
INILES	0.8948**	0.06	0.1147**	0.06
SMB	0.0026**	0.08	0.0037*	0.01
HML	0.0044*	0.00	0.0040*	0.01
UMD	-0.0005	0.93	0.0089	0.14

Fig. 2.1
The number of firms reporting each week covered by COMPUSTAT Quarterly database (1971-2006).

The fraction of firms covered by the database increases from less than 50% in the 1970s to almost 100% in 2000s.

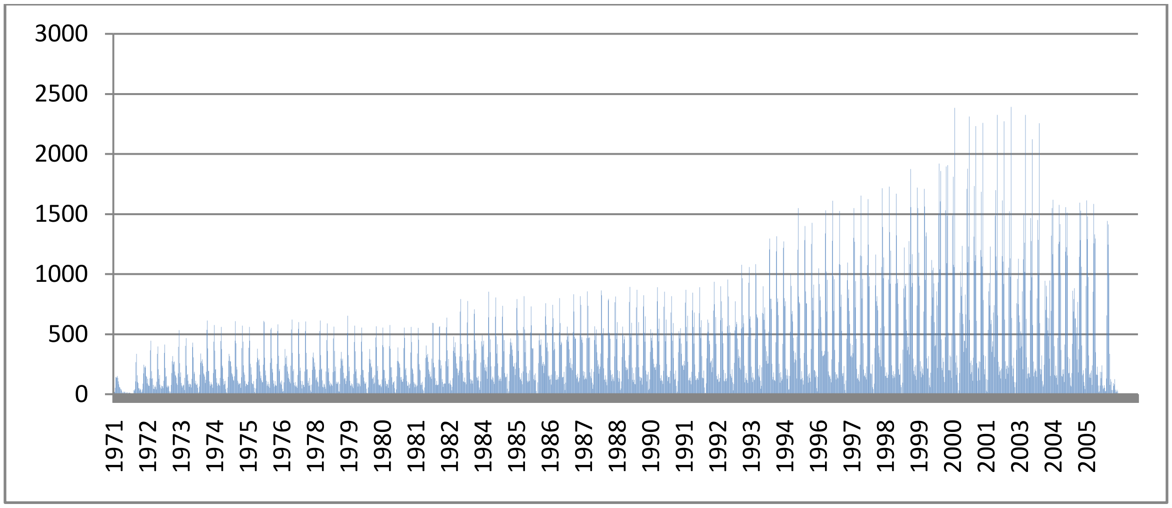


Fig. 2.2

The average number of firms reporting each week for the period from 1971 to 2006.

This pattern stays relatively constant for every year in the period covered.

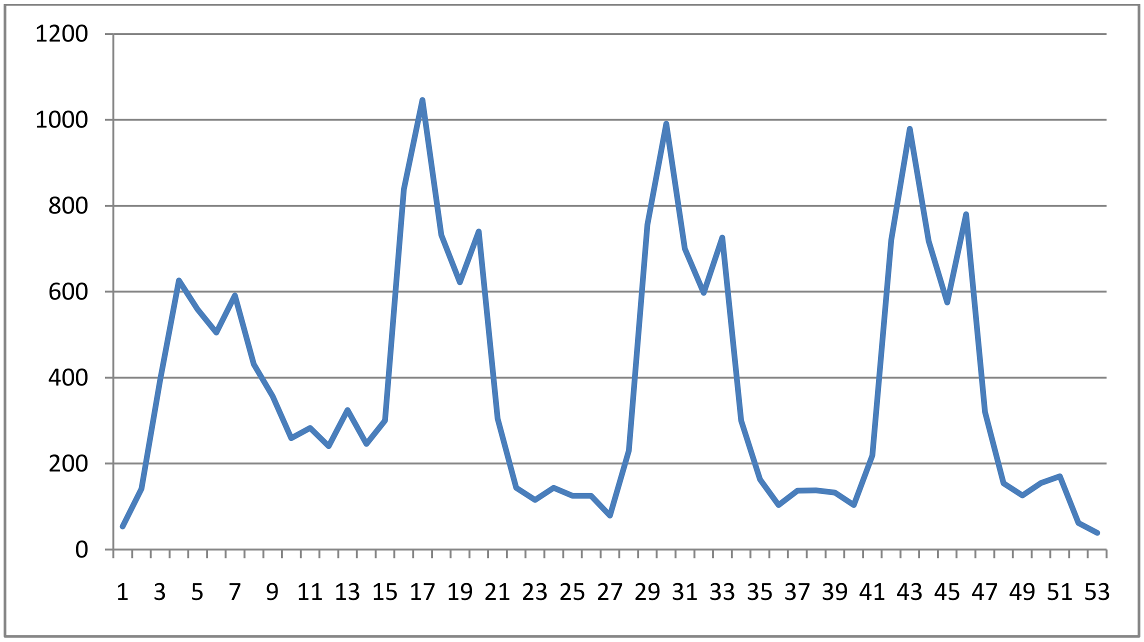
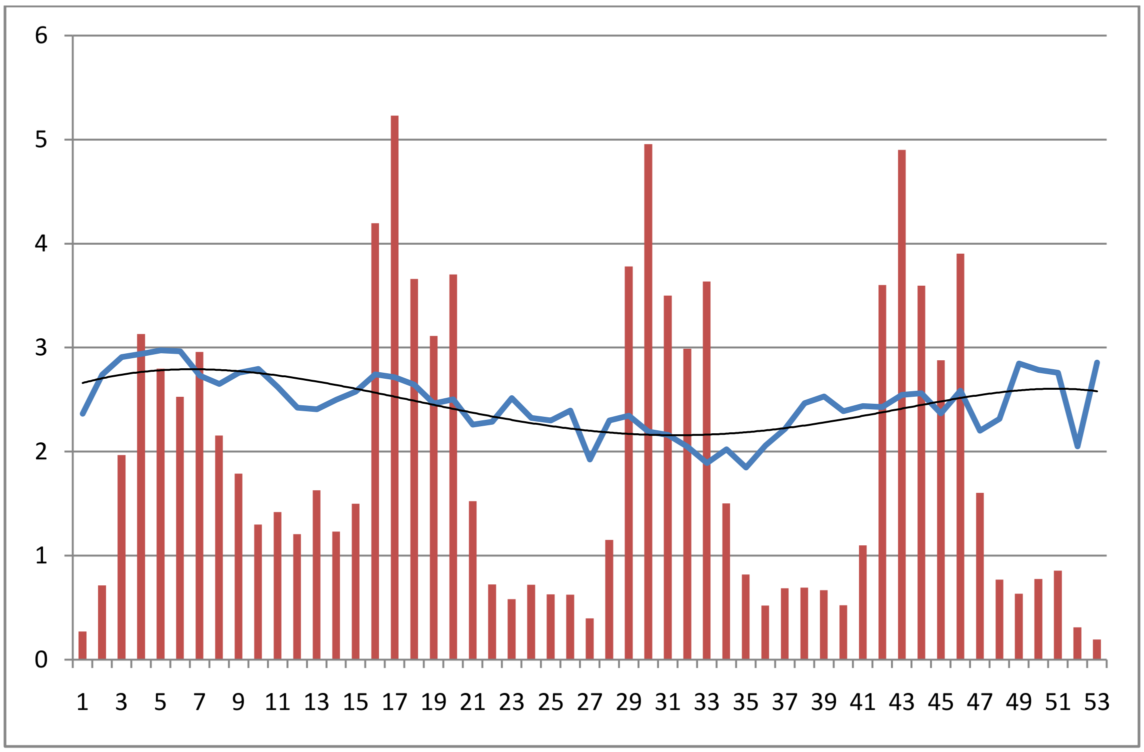


Fig. 2.3

The average (over 1962-2006) aggregate weekly share turnover in percent (a thick line) imposed over the average number of firms that report during that week (bar).

First I calculate the share turnover for each firm for each week. Then I calculate the aggregate share turnover for each week by simple-averaging the individual share turnovers and multiply the resulting time series by the 24-week average (a scale factor to remove the overall increasing trend). Finally, I average the aggregate weekly share turnovers over 45 year period (1962-2006). To aid the visual comparison I divided the number of firms reporting by 200 and added a polynomial (5th degree) trend line for the turnover series.



Chapter 3

The Impact of Earnings Seasons on Commonality in Liquidity

3.1 Introduction

Understanding the co-movements in asset characteristics is central to asset pricing. Until recently, liquidity, one such characteristic, was thought to be exclusively firm-specific. However, in the last decade several studies have established that liquidity also has a systematic component. Chordia et al (2000) coined the term “commonality in liquidity” to designate this phenomenon. Other early studies also confirm the existence of commonality in liquidity (Huberman and Halka (2001) and Hasbrouck and Seppi (2001) in the US.

Specifically, these papers find that even after controlling for well known individual liquidity determinants (such as volatility, volume, price, etc.), the correlated movements in liquidity remain significant. This result spurred a vast stream of literature trying to confirm these findings and, later to understand the issue better by looking at different settings, assets, and markets.

In particular, researchers have broadened the studies of commonality to include other US and foreign exchanges (Brockman et al (2008)), different measures of liquidity ((Bekaert et al. (2007), Karajczyk and Sadka (2007)), and different asset classes such as options (Cao and Wei (2008)).

Despite the increase in the number of publications dealing with commonality in liquidity, the investigation of this phenomenon is still in its infancy. Very few studies concentrate on the factors that actually drive commonality. Among them are Coughenour and Saad (2004) who find that common market-makers is one of the factors that influence commonality in liquidity. Corwin and Lipson (2008) use the principal component analysis and find that commonality is driven in part by the correlated trading decisions of professional traders, especially the ones executed through program trades. Finally, Brockman et al (2008) find that the commonality strongly responds to changes in the domestic and global macroeconomic environment.

In this paper I look at how the clustering of firm-specific information affects the commonality in liquidity. In particular, I investigate whether earnings seasons, relatively short periods after the end of each fiscal quarter, influence the commonality in liquidity. The reasons that I would expect this influence are straightforward.

First, the flood of new information and heavy trading to rebalance portfolios in response to this information are the two most significant characteristics of earnings seasons. And these were shown to affect the commonality (Corwin and Lipson (2008)). Second, the information environment changes dramatically as the market goes through earnings seasons and it is well known that asymmetric information adversely impacts liquidity in any market (Akerlof (1970)). The asymmetric information rises (reaches its peak) at the beginning of the season and then drops dramatically towards the end (Kim and Verrecchia(1995). Accordingly, my first essay shows that earnings seasons have a significant economic impact on asset prices because they cause market-wide liquidity shocks. This study builds on the previous findings but specifically investigates the effect of the earnings season on changes in *the commonality* in liquidity during earnings seasons.

I hypothesize that due to the flood of firm specific information during the peak of earnings seasons, commonality in liquidity decreases. In other words, commonality in liquidity is lower during earnings seasons than during any other time of the year because firm-specific information affects each company differently. This effect is the opposite of the effect produced by *macroeconomic* information which tends to increase the commonality because it affects similar firms in a similar way (Brockman et al, (2008)). I control for the intra-industry information transfer which was shown to be very strong during earnings seasons (Sun (2006)), and for the size effect to check the possibility that the phenomenon is mainly driven by the smallest firms.

In addition, I also look at the behavior of simple average marketwide liquidity measures around earnings seasons to see if it is affected by the changing information environment. My hypothesis is that liquidity worsens during the beginning of earnings seasons when the asymmetry in information is at its highest but substantially improves at the end due to the reduction in information asymmetry.

My empirical results show that (1) commonality significantly decreases during the peak weeks of earnings seasons when most firms issue their reports, consistent with the idea that firm-specific information reduces common effects; (2) intra-industry commonality in liquidity is largely unaffected, consistent with the view that a large amount of firm-specific information (negative effect on commonality) mitigates the increases in the intra-industry information transfers (positive effect on commonality); (3)

the commonality decrease is especially pronounced for the largest firms which is consistent with the fact that the media and analysts concentrate almost exclusively on large firms during earnings seasons; and, (4) average spreads significantly widen during the first four weeks and average depths significantly decrease during this period producing market-wide liquidity shocks. The situation is reverse in the last two weeks (i.e. liquidity substantially improves to pre-season levels or even better).

The paper is organized as follows. The next section gives a brief background on earnings seasons, reviews relevant literature, and develops testable hypotheses. Section 3.3 describes the data and methodology. Section 3.4 discusses the results and section 3.5 offers my conclusions and recommendations for further research.

3.2 Hypotheses Development

3.2.1 Institutional Background on earnings Seasons

According to the Securities Exchange Act of 1934 (the Act) every public company (with a float of at least $74M) should report their quarterly and annual results within a certain time period following the end of fiscal quarters and companies' fiscal years. Specifically, the Act states that all public companies should file quarterly reports within 45 days after the end of fiscal quarter (40 days for companies with market value of $700M or more)[9] and annual reports within 90 days following the end of the *company's* fiscal year (75 days for firms with market value of $700M or more). In 2002 SEC

[9] See the Federal Regulation Code Title 17 parts 230 through 250 for terms and definitions.

published a new rule in order to accelerate the filing of these documents reducing the number of days to 35 for quarterly reports and to 60 for annual reports.[10]

My first essay (Chapter 2) documents the striking pattern in earnings releases during an average year (Figure 3.1). I show that vast majority of earnings reports concentrate in just 4 months. These are January, April, July, and October. Three out of four seasons have identical shapes with the first seasons (January-February) although slightly different but still preserving the general patter. Thus the largest number of reports (the highest peak) within each season corresponds to the third and fourth weeks of each quarter with a slight decline during weeks 5 and 6 of the quarter and then a slight increase again in week 6 or 7 – whichever is the last week of the 45 day period. The lowest number of earnings announcements corresponds to the first two weeks of each quarter. In my first essay I establish that such clustering and unique shape of earnings seasons affect aggregate liquidity, volatility, turnover, and returns.

3.2.2 Potential Effect of Earnings Seasons on Commonality in Liquidity

Liquidity is affected by the information asymmetry (Akerlof, 1970) and financial markets experience sharp changes in information asymmetry as they go through earnings seasons (Kim and Verrecchia (1995)). Indeed, numerous studies look into the effects of *individual* releases on economically important variables and find that they (releases) influence not only liquidity but also price, volatility, volume, adverse selection, trading

[10] RELEASE NOS. 33-8128; 34-46464; FR-63; (http://www.sec.gov/rules/final/33-8128.htm)

patterns etc. (see, e.g. Lee (1992) and Lee et al. (1993)). During this period information asymmetry increases between different types of investors and, also, between investors and the market makers. The literature usually distinguishes three types of players involved in such trading (following Kyle (1985)): informed investors (who might be either a trader with insider information or with better information processing skills), uniformed investors (also called liquidity or noise traders), and a market maker (a specialist in most studies). Each party is aware of the presence of the other two and so when they interact trying to optimize their behavior around earnings releases, the unique empirical patterns affecting many variables emerges.

Usually, when the timing of the information release is unknown, the trading volume will increase in information asymmetry. The reason for this relation is that an informed investor will start trading in addition to uninformed investors who will continue trading as usual. However, when the timing of information releases is known in advance to all players as is the case during earnings seasons, the pattern of trading changes dramatically. The uninformed traders will postpone their trading until after the announcement to minimize adverse selection cost (George et al (1994)). They are partially replaced by the traders with private information who try to realize their advantage. As long as the average proportion of liquidity traders to informed traders is greater than one, we will observe a decline in volume just prior to the announcements and a surge thereafter. This pattern was documented in Chae (2005) for individual securities and in my first essay for the aggregate volume.

Market makers are aware of the active presence of informed investors and, facing adverse selection, try to manage the risk by widening bid-ask spreads and decreasing depths (Lee et al. (1993), Krinsky and Lee (1996), and Kavajecz (1999) among others). However, all of the above mentioned studies deal with individual securities. I argue that because of the concentration of earnings reports during earnings seasons (see Figure 3.1) this pattern, the widening of the bid-ask spread and decreasing depths, should also be observed in the aggregate. Therefore, my first hypothesis about the effect of firm-specific information clustering during earnings seasons on the aggregate liquidity is:

> H1: In the first four weeks of each earnings season, which corresponds to the weeks with the highest uncertainty about the upcoming earnings, we will observe increased *average* bid-ask spreads and decreased *average* depths.

The last two weeks of each quarter experience the declining number of firms reporting. Since the vast majority of firms have already released their earnings, the information asymmetry also declines and it would be natural to expect improvement in the aggregate measures of liquidity. However, a large portion of firms is still about to report and this contributes to an elevated level of information asymmetry. It is therefore an empirical question which factor dominates and whether the market-wide liquidity measures improve during the last two weeks of the seasons. I look into this question as a part of my first hypothesis.

The above hypothesis deals with the aggregate liquidity levels. To address the commonality in liquidity during earnings seasons, I develop my second hypothesis. Based on the analysis of numerous empirical studies investigating individual securities (or a cross-section of individual securities) reviewed above, I argue that the commonality in liquidity is at its lowest during the weeks with the largest number of firms reporting.

The main reason for the commonality decreasing during the peak of earnings seasons is the high inflow of firm-specific information. Brockman et al (2008) show that the commonality in liquidity is driven in part by the macroeconomic announcements such as GDP growth and unemployment reports. This suggests two points. First, commonality responds to information flow, and second, commonality is strengthened by the information *common* to all firms. I hypothesize that since earnings seasons are characterized by flood of information, the commonality will also be strongly affected. But since all the information is firm-specific, its effect on commonality will be *negative* since each firm will be impacted differently according to the specific to that firm information.

Second, Acharya and Pederson (2005) show that adding transaction costs to the expected returns generates three liquidity-related covariances in equilibrium (between firm's returns and market liquidity, between firm's liquidity and market liquidity, and between firm's liquidity and market return), that carry positive risk premium. Since I expect the transaction costs to change during earnings seasons (my Hypothesis one), I also expect that this change will affect the three covariances (at least to some degree). My first essay looks into the same intervals within earnings seasons and finds that that the covariance between the stocks' returns and the market wide liquidity intensifies during earnings seasons which leads to asset pricing implications. In this paper I look into the commonality, which is the covariance between stocks' liquidity and the market liquidity. Based on the above two reasons, my second hypothesis is as following:

H2: During the peak of earnings seasons (weeks 3 through 6) which corresponds to the period with the largest number of firms reporting, commonality in liquidity is substantially lower than the average commonality over the year.

Even though I expect that the flood of firm specific information will decrease the commonality in liquidity during earnings seasons, there is one effect that acts in the opposite direction and can actually increase the commonality during this period. The literature on intra-industry information transfers provides some indication that during earnings seasons the companies in the same industry could experience abnormally high level of co-movements in different stock characteristics (and this might include liquidity). For example, Kovacs (2005) finds that a firm's stock price is positively related to industry peers' earnings surprises regardless of whether the firm has already announced its own quarterly earnings. This suggests that earnings announcements contain substantial industry-relevant information that is not fully captured by a firm's own earnings. Sun (2006) investigates the timing of an announcement within earnings seasons and finds evidence consistent with information transfer. Specifically he reports that late-reported good news announcements are accompanied by significant pre-announcement price increases. I test this conjecture as a part of my second hypothesis.

Also, it would be interesting to examine the effect of the firm size on the commonality in liquidity during earnings seasons. The results in Chordia et al (2000) were puzzling in that large firms experience higher commonality than their smaller counterparts which the authors attribute to institutional herding. In earnings seasons framework I would expect to find the opposite effect. During earnings seasons, when thousands of firms report within a relatively short time periods it is only natural for the analysts, the business media, and the investors to concentrate only on the largest firms thereby reducing the commonality for this size group. Therefore, my third hypothesis is as following:

> H3: During the peak of earnings seasons (weeks 3 through 6) which corresponds to the period with the largest number of firms reporting, commonality in liquidity for the largest firms is substantially lower than the commonality for the smallest firms.

The next session describes the data and methodology.

3.3 Data and Methodology

3.3.1 Sample Development

In order to empirically test the proposed hypotheses I use several different databases. The intraday data come from the New York Stock Exchange Trades and Automated Quotes (TAQ) database which includes data for NYSE for the period January 1993 through December 2002. The CRSP daily/monthly stock return database is also used to obtain stock returns, number of shares outstanding, returns, and volumes.

Following other studies on commonality I focus on NYSE-listed stocks because NASDAQ uses a different trading mechanism (also see Chordia et al (2001)). Since the trading characteristics of ordinary equities might differ from those of other assets, I retain only ordinary common stocks (CRSP share codes 10 or 11), that is, I remove certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., and Americus Trust components.

Since the raw data stored on the TAQ database is not ready to be processed immediately, it must be cleaned first. As in Chordia et al (2000, 2002), I use only BBO (best bid or offer)-eligible primary market (NYSE) quotes. I discard the trades that are out of sequence, that are recorded before the opening or after the closing time, or that have special settlement conditions. Negative bid-ask spreads and transaction prices are also eliminated from the data set. To avoid after hours liquidity effects (see, e.g., Barclay and Hendershott (2004)), the opening trade is ignored.

Following Karajczuk and Sadka (2008), quotes with implausibly large spreads are discarded. Only quotes that satisfy the following filter conditions are retained: the bid-ask spread is positive and below $5, and the bid-ask spread divided by the midpoint of the quoted bid and ask (henceforth, the quoted spread) is less than 25% if the midpoint is less than or equal to $20. These conditions ensure the use of reasonable quotes in my analysis. Finally, I exclude stocks whose prices are below $2 and above $1,000.

In addition, since some stocks are rarely traded and would not provide reliable observations, I require that a stock be continually listed throughout the year on NYSE, trading at least once on at least 10 trading days that year. Following Chordia et al (2000) I also exclude stocks with splits and/or stock dividends during the year.

For every transaction, I compute five different measures: the quoted and effective bid-ask spreads, the proportional quoted and effective spreads, and quoted depth in number of shares (as in Chordia et al (2000)).

After preparing the intraday data sets for each of the ten years (1993 through 2002), I average each liquidity measure over all daily trades for each stock for each year. This helps smooth out intraday observations and thus promotes greater synchronicity in addition to reducing my data to more manageable levels. Thus, for each stock that I end up with for 1993-2002, the working sample consists of at most 254 observations for each year, one for each trading day during the year. Finally, the sets are merged by matching the firms on TAQ with CRSP by their CUSIPs (this approach induces the highest matching rate, as discussed in Hvidkjaer (2006)). Table 3.1 presents the resulting sample. It shows that the final data set includes 1017 NYSE-listed stocks for the period 1993–2002. During the construction of the final sample, the number of firms in the sample changes from year to year from 1235 stocks in 1993 to 1502 stocks in 1999 and to 1325 stocks in 2002. That the final sample contains significantly lower number of shares (1017) reflects the constraints imposed on the stocks to be included in my sample. Specifically, I require that the stock be continually listed on NYSE from 1993 to 2002 and meet all other requirements imposed above for individual years.

3.3.2 Methodology

Since most studies indicate that the time series of liquidity levels are not normally distributed (Chordia et al (2000)), I use a simple non-parametric test, Wilcoxon Rank Sum, to test my first hypothesis. The Wilcoxon Rank Sum tests the null that the two samples are from the same distribution against the alternative that they have different medians (since the sample distribution is not normal, tests about the medians are preferred to tests about the means). Specifically, I form two samples. The first sample consists of all stock-days that fall into the first four weeks of all earnings seasons for 1993 – 2002. The second sample includes all other stock-days. I expect to find significantly higher spreads and significantly lower depth in the first month of each quarter due to the heightened information asymmetry. Additionally, I also test the last two weeks of each quarter, to see if the uncertainty is resolved and the liquidity levels "recover" to the pre-season values or better.

To test the second hypothesis, which states that the commonality in liquidity will be at its lowest during the peak weeks with the largest number of firms reporting, I employ the same methodology as was used in Chordia et al (2000). Specifically, I fit the following regression model.

$$\Delta Liquidity_{F,t} = \alpha + \beta_{EN} Liquidity_{E,t} \times EN + \beta_1 \, \Delta Liquidity_{E,t} + \beta_2 \, \Delta Liquidity_{E,t+1} + \beta_3 \, \Delta Liquidity_{E,t-1} + \delta_1 Return_{E,t} + \delta_2 Return_{E,t+1} + \delta_3 Return_{E,t-1} + \delta_4 Volatility_{F,t} + \varepsilon_{F,t} \tag{1}$$

,where $Liquidity_{F,t}$ stands for the five liquidity measures defined earlier. I run this model for *each* of my five measures. EN is the dummy that equals one during the weeks 3 through 6 of every earnings season with the largest number of firms reporting (or other time periods within earnings seasons depending on model specification). Each liquidity measure is the average of intra-day liquidity measures for firm *F* on day *t*. $Volatility_{F,t}$ is the return volatility for firm *F* on trading day *t* and is measured as the average squared return. $Liquidity_{E,t}$ is an equal-weighted average of each corresponding liquidity measure for all firms trading on NYSE. $Return_{E,t}$ is the equal-weighted average of the daily return for all firms trading on the same stock market. All dependent and independent variables are expressed in terms of proportional changes (denoted as Δ) in the variable across successive trading days. All averages exclude the dependent-variable firm; that is, $Liquidity_{E,t}$ and $Return_{E,t}$ are calculated using all firms on the exchange except firm F.

Following Chordia et al (2000) my primary variables of interest are the contemporaneous coefficient on $\Delta Liquidity_{E,t}$ (i.e.,β_1) and the coefficients on the dummy variable β_{EN}. A negative and significant β_{EN} (the dummy for earnings seasons) along with positive and significant β_1 (the rest of the year) would mean that the commonality in liquidity for firm F's decreases during the peak of the earnings season.

To test the intra-industry effects I follow the general idea outlined in Chordia et al (2000) and add two more variables to the model specification (1). The first is the industry variable: $Liquidity_{IND,t}$ (with coefficient β_{IND}) which is equal to the industry-wide liquidity for each measure (excluding firm i). I assign each firm to one of the 10 industry using the definition of the industry groups (based on the first four digits of SIC codes) provided by Kenneth French on his website. In addition to this variable, I also add a dummy variable for the peaks of earnings seasons: $IND - EN * Liquidity_{IND,t}$ which is equal to that firm's industry average measure during the peak of earnings seasons and zero otherwise (the coefficient for this variable is β_{IND-EN}).

To test my third hypothesis, I divide my sample into quintiles and use the two extreme size groups. That is I run model specification (1) for the largest and the smallest stocks separately. Assuming that the main research activities of the analysts and the business media are focused on the largest firms, I expect the coefficients to be more negative (and more significant) for the largest quintile.

The next section presents the main results.

3.4 Results

3.4.1 Univariate results

In this section I present the descriptive statistics for my sample and test my first hypothesis about the changes in the levels of market-wide liquidity measures.

Table 3.2 Panel A shows the average liquidity measures for the final sample (1993-2002). Panel B presents the same characteristics but for each year in the sample. As we can see the liquidity of NYSE is steadily improving with all average spread measures decreasing from year to year. There is however a curious pattern in how liquidity improves. We can see that during 1999 and 2000 three out of five measures (PQSPR, PESPR, and DEP) actually increased slightly only to sharply improve in 2001 and 2002. This is curious because 1999-2000 are characterized by the peak of the internet bubble and the spike in illiquidity is probably an artifact of that period. The averages for 1993 are also close to the values reported in Chordia et al (2000) for 1992.

Even though the medians and means are relatively close for spreads, the means are greater than the medians for all measures and the distributions are therefore positively skewed. This is consistent with the results shown in Chordia et al (2000). As a result, I cannot use the standard parametric procedures and instead use the Wilcoxon Scores (Rank Sums) which tests the null hypothesis that the medians of the two samples are the same.

Table 3.3 presents the results for three different time periods**. Panel A** shows the results for the test that the median liquidity measures in the first four weeks of earnings seasons are the same as during the rest of the year. The test soundly rejects this null since all five measures are significantly worse during the first four weeks of earnings seasons. Consistent with my first hypothesis all spreads measures are significantly (at 5% level) higher during this period of highest uncertainty and the depth measure is significantly (at 11% level) lower than during the rest of year.

Panel B looks into the peak (weeks 3 through 6) of earnings seasons when the number of firms issuing their numbers to the public is at its highest (see Figure 3.1). As we can see all measures preserve the signs displayed in Panel A but they do not differ significantly from the rest of the year. That is even during the peak seasons the liquidity is still worse than during the regular time periods. The fact that none of the measures is now significantly different from zero is consistent with overall improving liquidity towards the end of the seasons as the uncertainty is partially resolved and the information asymmetry declines.

To shed some light on the behavior of the liquidity measures at the very end of earnings seasons, Panel C looks at the last two weeks of this period. As we can see all four spread measures reversed their signs. This is an indication that during the last 2 weeks of earnings seasons liquidity substantially improves. Indeed, judging by the signs, it seems that the liquidity levels during these 2 week intervals are even better than during the rest of the year (though none of the measures is statistically significant). Also, the quoted depth (DEP) remains abnormally low (though also not statistically significant). This finding is consistent with almost complete resolution of uncertainty. Liquidity traders have returned to their trading as usual but the informed traders have not yet left the market. As a result the liquidity has improved to its pre-season levels or better.

The results of this section are consistent with my hypothesis that the overall levels of liquidity change as the market goes through earnings seasons. Specifically, during the first four weeks of earnings seasons, which is characterized by the highest uncertainty, the market-wide spreads are substantially higher and quoted depth is significantly lower. As the market progresses towards the end of the seasons, the liquidity levels recover to their pre-season levels or even better. In orders words, I find that the behavior of the aggregate measures of liquidity mirror the pattern found for individual stocks.

3.4.2 Multivariate results

This section presents the main results of the paper. Here I test my second hypothesis about the effect of earnings seasons on commonality in liquidity. I also control for the intra-industry effects and for the size of the firms.

*Main results***.** Table 3.4 presents the results of running model 1 with three different specifications for the dummy variables. Panel A shows the results with the seasonal dummy for the peak of earnings seasons (weeks 3 through 6). We can immediately see that the coefficients for the dummies are negative (both means and medians) for all 5 variables and the coefficients for the market are all positive. The only insignificant at 15% dummy beta (for QSPR) corresponds to the positive but also insignificant at 15% level market beta. All other coefficients are significant at 1%, 5%, and 15%. These results are consistent with the story that the influx of large amount of firm-specific information reducing the commonality in stocks' liquidity measures (especially for the proportional quoted spreads and the depth)

To further deepen our insight into the commonality effects of earnings seasons and to compare the results of this section to the results from the univariate analysis section, I also investigate how the commonality changes during the full season (all 6-7 weeks) and the last two weeks of earnings seasons. Panel B presents the results of testing a model (1) specification with the dummy corresponding to the full season. It is obvious that the results don't change much. All signs but one are preserved and the coefficients for PQSPR became stronger while the coefficients for PESPR and ESPR became weaker statistically. This result might suggest that unlike the liquidity levels, the commonality in liquidity does not change dramatically during the seasons. Also, since the only difference between the simple spreads and the proportional spreads is a price in the denominator, the prices movements across the seasons may contribute to the observed patterns.

Since earnings seasons are the time intervals where the intra-industry information transfer is especially likely (see Sun (2006) for discussion), it would be sensible to test whether my results are affected by the this phenomenon. I expect that the intra-industry transfer will actually increase the commonality within the industry because when a company releases its earning and the investors respond, the stocks of other companies in the same industry are often affected to same degree.

*Industry effects***.** Table 3.5 shows the result of a variant of model specification (1) where two additional variables are added.

$$\Delta Liquidity_{F,t} = \alpha + \beta_{EN} EN \times Liquidity_{E,t} + \beta_1 \, \Delta Liquidity_{E,t} +$$

$$\beta_{IND} \, \Delta Liquidity_{IND,t} + \beta_{IND-EN} \, IND - EN \times \Delta Liquidity_{E,t} +$$

$\beta_2\ \Delta Liquidity_{E,t+1} + \beta_3\ \Delta Liquidity_{E,t-1} + \delta_1 Return_{E,t} + \ \delta_2 Return_{E,t+1} +$

$\delta_3 Return_{E,t-1} + \delta_4 Volatility_{F,t} + \varepsilon_{F,t}$ (2)

First I add the industry-wide liquidity measure $\Delta Liquidity_{IND,t}$ and second, I add the dummy for this variable corresponding to the peak of earnings seasons (weeks 3 through 6), $IND - EN \times \Delta Liquidity_{E,t}$ which is equal the industry-wide liquidity measure during the peaks of earnings seasons and zero otherwise. I calculate the equally-weighted industry average liquidity measure with company i's values removed (see Chordia et al (2000)). I utilize 10 broad industry groups based on the first four digits of SIC using the definition supplied by Kenneth French's data library. Panel A of table 3.5 presents these industry definitions and the proportions of each industry group within my sample.

Panel B shows the coefficients for four model variables: two seasonal dummies (market dummy and industry dummy), the market, and the industry. Looking first at the industry dummy, we observe that three out of five measures are negative although only one is significantly so (DEP). The proportional quoted spread (PQSPR) is significantly positive and the simple quoted spread (QSPR) is positive but not significantly so. All coefficients for the industry-wide measures are positive and all but one (PQSPR) are significant at 1%, 5% and 10% levels.

If we compare these results to the market seasonal dummies and their corresponding market betas, we observe that all measures but one have negative signs (for the market dummies) and these are significant at 1%, 5% or 15% levels. The market betas are all positive and significant at 5% level except for QSPR which is significant at 15% level.

Insignificant (if any) reduction in commonality *within* industries contrasts with sharp decrease in commonality *between* companies in different industries. To illustrate, commonality between Microsoft and the software industry is relatively unchanged during earnings seasons while the commonality between Microsoft and any other industry drops dramatically.

The results are consistent with my hypothesis that the intra-industry information transfer which intensifies during earnings seasons prevents the reduction in commonality for firms in the same industry. As a result, we can now see that the decrease in commonality is accounted for almost entirely by the decrease in the commonality *between* the industry groups during this period.

Next, I separate my sample into size quintiles and test my third and final hypothesis that the largest firms experience the steepest drop in commonality.

Size effects. In this, final, section I test my third hypothesis that the larger firms will experience sharper decrease in commonality compared to the smaller ones. Before running regressions, I want however investigate the effect of firm size on the levels of liquidity during earnings seasons.

Panel A of Table 3.6 shows the cross-sectional time-series means for all five measures separated into size-based quintiles. The smallest firms exhibit uniformly higher illiquidity (higher spreads) than do the largest ones. The liquidity improves consistently as we move from the smallest to the largest firms. The quoted depth also consistently increases with the firm size. These observations are consistent with the bulk of the literature devoted to relation between the size and liquidity.

Panel B compares the medians of the liquidity measures during the first four weeks of earnings seasons (the interval that was shown in the previous section to have the lowest liquidity) to that of medians for the rest of the year. As we can see from the table the results are somewhat mixed. Both spread measures become insignificant (more so for the smallest firms) and the proportional spreads become much stronger for the smallest ones and a little weaker for the largest firms with the depth variable virtually unchanged for the smallest firms and turning positive (but not significant) for the largest quintile. Since the proportional spreads are formed by dividing the simple spreads by prices, the increased significance of PQSPR and PESPR for the smallest firm suggests that the prices for this category of firms drops during the first four weeks of earnings seasons. However, the price drop cannot explain the increasing illiquidity for the whole sample since the simple spreads (QSPR and ESPR) also become significantly larger during this time period. This suggests that the effect for the simple spreads is concentrated mostly within the middle quintiles.

Finally, **Panel C** presents the results of running the regression model specification (1) for the largest and smallest quintiles separately. The first set of coefficients in Panel C is for the smallest decile and the dummy corresponds to the peak of earnings seasons (weeks 3 through 6). As we can see none of the coefficients for the dummy variable is significant in the smallest quintile regression and only three out of five variables have the expected (negative) signs. Three out of five market betas are significant at 1% level. This suggests that the commonality does not change for the smallest quintile.

In contrast, three out of five measures of liquidity are significant at 1% or 10% levels and all the variables have the expected (negative) sign. Also, all but one market betas have the expected positive sign with three out of five coefficients significant at 1% level. These results suggest that the commonality reduces significantly for the largest quintile. This is also consistent with my third hypothesis that the largest firms will experience the largest decline in commonality due to the heightened research activity by media and analysts who tend to concentrate on the largest firms during earnings seasons.

3.5 Discussion and Conclusion

The discovery of commonality in liquidity took the world of academic finance as a surprise, since until a decade ago most studies treated liquidity (bid-ask spreads, depths, etc.) as a firm-specific characteristic. The fact that a firm's liquidity co-moves with the market-wide liquidity has opened up a whole new and exciting area in finance. It has resulted in an ever increasing number of papers investigating different aspects of commonality.

One of the most important aspects of this phenomenon is the drivers behind it. Despite the obvious importance of this question, relatively few papers concentrate on this important issue. Among the few are the study by Corwin and Lipson (2008) who show that program trading by institutions is an important factor that drives commonality, a paper by Coughenour and Saad (2004) who find that common market-makers is one of the factors that influence the commonality in liquidity an Brockman et al (2008) who show that commonality in liquidity is affected by the public releases of macroeconomic announcements.

In this paper, I argue that the release of firm-specific information drives commonality. In particular, I argue that the *clustering* of company's financial reports releases, a phenomenon known as earnings seasons to the practitioners, in effect reduces commonality in liquidity as investors, analysts and business media follow companies a little more closer than they do during other time periods of the year. Also, during the "regular seasons" the information that dominates the news tends to be macroeconomic in nature and affect many firms at once thus potentially strengthening the commonality. Quite contrary, during earnings seasons the proportion of firm-specific information to the macro-economic information explodes thus potentially reducing the commonality during these periods.

I start by showing that average market-wide liquidity, as measured by 5 most-commonly used bid-ask based liquidity measures, substantially decreases during earnings seasons. Because of high uncertainty about the numbers to be released the spreads go up and the depths go down substantially during the first 30 days of each quarter. Consistent with the information story, the market-wide liquidity measures substantially improve in the last two weeks of the seasons when the vast majority of firms have already reported.

Next, I show that the flood of firm specific information during earnings seasons causes considerable reduction in commonality despite the fact that two important pieces of economic information are released during the same periods. I also control for the intra-industry information transfer which is especially strong during earnings seasons and which can potentially increase the commonality. By introducing the industry dummies I was able to illuminate the fact that the commonality in liquidity stays the same *within* the industry groups but decreases very sharply *between* industries. This indicates that even though the clustering of firm-specific information tends to break down the commonality in liquidity, it is not enough to affect the intra-industry commonality which remains as strong as during other times of the year.

Finally, I investigate the impact of firm size on the commonality in liquidity. I break down my sample into quintiles and then use the two most extreme quintiles to run my main regression model. I find that for the small firms, commonality is essentially unaffected during earnings seasons. In contrast, the commonality reduction for the largest quintile is very strong. This result is consistent with the information-driven commonality and corroborates my third hypothesis: the active research by analysts, media journalists, and investors, which tends to concentrate in the largest firms, substantially reduces the common components in firm's liquidity.

In summary, this paper contributes to the literature by shedding light on a significant driver of commonality in liquidity in the US market.

Table 3.1
Sample development

Shows the number of firms during each year and the corresponding number of observations (at most 254 for any firm) as well as the total number of firms/ observations.

Year	Number of Firms	Number of Observations
1993	1235	304,875
1994	1377	336,049
1995	1378	337,614
1996	1406	347,554
1997	1388	344,785
1998	1438	353,724
1999	1502	369,165
2000	1418	343,090
2001	1346	320,948
2002	1325	324,525
1993 – 2002	1017	3,377,894

Table 3.2
Time-series average liquidity measures for the final sample (1993-2002) and for each year separately.

QSPR is quoted spread, PQSPR- proportional quoted spread, ESPR- effective spread, PESPR- proportional effective Spread, DEP- quoted number of shares (the sum of bid and ask). N is the number of observations used.

Panel A. Sample statistics for the final sample 1993-2002

	Mean	Median	Std. Dev	N
QSPR	0.1576	0.1500	0.2146	3,377,894
PQSPR	0.0094	0.0063	0.0097	3,377,894
ESPR	0.1076	0.1042	0.1698	3,377,894
PESPR	0.0066	0.0042	0.0075	3,377,894
DEP	4,948	2,564	8,415	3,377,894

Panel B. Sample statistics for each year in the sample 1993 through 2002

Year	QSPR	PQSPR	ESPR	PESPR	DEP	N
1993	0.2154	0.0126	0.1370	0.0084	6,723	304,875
1994	0.2036	0.0122	0.1332	0.0084	6,715	336,049
1995	0.1907	0.0113	0.1282	0.0079	7,625	337,614
1996	0.1880	0.0104	0.1280	0.0074	7,183	347,554
1997	0.1649	0.0086	0.1167	0.0063	5,617	344,785
1998	0.1615	0.0084	0.1103	0.0058	3,543	353,724
1999	0.1563	0.0096	0.1050	0.0066	3,905	369,165
2000	0.1435	0.0105	0.0988	0.0073	4,749	343,090
2001	0.0905	0.0060	0.0680	0.0044	1,984	320,948
2002	0.0597	0.0041	0.0490	0.0033	1,432	324,525

Table 3.3

The impact of earnings seasons on the average (market-wide) liquidity measures.

Wilcoxon signed-rank test is used to test the difference in medians for all panels. Panel A shows the market-wide liquidity levels during the first four weeks of earnings seasons. Panel B shows the market-wide liquidity levels during the peak (weeks 3 through 6) of earnings seasons. Panel C shows the market-wide liquidity levels during the last two weeks of earnings seasons. QSPR is quoted spread, PQSPR- proportional quoted spread, ESPR- effective spread, PESPR- proportional effective Spread, DEP- quoted number of shares (the sum of bid and ask). The estimation period covers 10 years of data from 01/01/1993 to 12/31/2002. One star (*) denotes the values significant at 5% or better and two stars (**) denote the values significant at 15% or better. N is the sample size.

Panel A. The first four weeks of earnings seasons

First Four Weeks						N	
	QSPR	PQSPR	ESPR	PESPR	DEP	4 weeks	ELSE
Z-score	2.41*	2.2515*	1.8479*	2.0639*	-1.23**	844	1676
p-value	0.008	0.0122	0.0323	0.0195	0.1094		

Panel B. The Peak of earnings seasons (weeks 3 through 6)

THE PEAK						N	
	QSPR	PQSPR	ESPR	PESPR	DEP	PEAK	ELSE
Z-score	1.172**	0.4316	0.3753	0.5237	-0.8678	870	1650
p-value	0.1206	0.333	0.3537	0.3002	0.1927		

Panel C. The last two weeks of earnings seasons

LAST TWO WEEKS						N	
	QSPR	PQSPR	ESPR	PESPR	DEP	Last weeks	ELSE
Z-score	-0.8837	-0.6186	-1.16**	-0.6315	-0.4279	428	2092
p-value	0.1884	0.2681	0.1231	0.2638	0.3344		

Table 3.4

The changes in commonality in liquidity during the earnings seasons

The mean betas are for the coefficients β_{EN} (Dummies) and β_1 (Market) from Equation 1. EN betas are the average regression coefficients on β_{EN} from the equation (1) where EN takes on three different intervals in the three specifications. In Panel A EN corresponds to the peak of earnings seasons (weeks 3 through 6). In Panel B, EN stands for the full season and in Panel C for the last two seeks of earnings seasons. Market Betas are the average regression coefficient on contemporary equal-weighted market-wide liquidity. The p-values are for the one-sided t-test null that the average coefficient is not zero (negative for dummies and positive for the market). All variables are proportionally differenced. QSPR is quoted spread, PQSPR- proportional quoted spread, ESPR- effective spread, PESPR- proportional effective Spread, and DEP- quoted number of shares (the sum of bid and ask). The estimation period covers 10 years of data from 01/01/1993 to 12/31/2002. One star (*) denotes the values significant at 5% or better and two stars (**) denote the values significant at 10% or better. N is the number of stocks.

Panel A

PEAK		Dummies			Market	
Variable	N	median	mean	p-val	mean	p-val
QSPR	1017	-0.001	-0.002	0.46	0.0054	0.28
PQSPR	1017	-0.065	-0.06*	0.02	0.758*	0.00
ESPR	1017	-0.002	-0.027	0.13	0.0120	0.17
PESPR	1017	-0.054	-0.09*	0.01	0.706*	0.00
DEP	1016	-0.103	-0.14*	0.00	0.830*	0.00

Panel B

FULL SEASON		Dummies			Market	
Variable	N	median	mean	p-val	mean	p-val
QSPR	1017	-0.001	-0.002	0.46	0.0021	0.42
PQSPR	1017	-0.063	-0.08*	0.00	0.776*	0.00
ESPR	1017	-0.001	-0.001	0.42	-0.016	0.15
PESPR	1017	-0.061	-0.06**	0.07	0.690*	0.00
DEP	1017	-0.145	-0.15*	0.00	0.871*	0.00

Panel C

LAST TWO WEEKS		Dummies			Market	
Variable	N	median	mean	p-val	mean	p-val
QSPR	1017	-0.002	0.021**	0.09	-0.001	0.35
PQSPR	1017	-0.147	-0.116*	0.00	0.752*	0.00
ESPR	1017	-0.003	-0.029	0.11	-0.012	0.18
PESPR	1017	-0.141	-0.122*	0.00	0.695*	0.00
DEP	1017	-0.168	-0.183*	0.00	0.806*	0.00

Table 3.5
Industry definitions and industry effects on the commonality in liquidity during earnings seasons.

The mean betas are for the coefficients β_{EN}, $\beta_{IND-EN,}$ β_{IND} and β_1 (equation 2). EN betas are the average regression coefficients on β_{EN} from the equation (1) where EN corresponds to the peaks of each earnings seasons (calendar weeks 3 through 6). Market Betas (β_1) are the average regression coefficient on contemporary equal-weighted market-wide liquidity. β_{ENxIND} is the dummy for the industry-wide liquidity during the peak of earnings seasons, and the β_{IND} is the beta for industry-wide liquidity measures. The p-values are for the one-sided t-test null that the average coefficient is not zero. All variables are proportionally differenced. QSPR is quoted spread, PQSPR- proportional quoted spread, ESPR- effective spread, PESPR- proportional effective Spread, DEP- quoted number of shares (the sum of bid and ask), TOTDEP – quoted depth in thousands of dollars (the sum of bid and ask). The estimation period covers 10 years of data from 01/01/1993 to 12/31/2002. One star (*) denotes the values significant at 5% or better and two stars (**) denote the values significant at 10% or better.

Panel A. Industry groups definitions and frequencies

Industry Group	Num. of Obs.	Percent
1. Consumer Non-Durables	597,606	31.32
2. Consumer Durables	76,721	4.02
3. Manufacturing	430,014	22.53
4. Energy	118,044	6.19
5. Business Equipment	152,609	8.00
6. Telecom	27,888	1.46
7. Retail	214,298	11.23
8. Health Care	84,587	4.43
9. Utilities	203,948	10.69
10. Other	2,520	0.13

Panel B. Regressions with the industry dummies

		INDUSTRY	DUMMY		INDUSTRY	
Variable	N	median	mean	p-value	mean	p-value
QSPR	1017	0.0025	0.0033	0.47	0.152*	0.00
PQSPR	1017	0.0161	0.0503*	0.01	0.0010	0.47
ESPR	1017	-0.0003	-0.0060	0.39	0.142*	0.00
PESPR	1017	-0.0034	-0.0032	0.45	0.037**	0.10
DEP	1017	-0.0704	-0.101*	0.02	0.126*	0.00

		MARKET	DUMMY		MARKET	
Variable	N	median	mean	p-value	mean	p-value
QSPR	1017	-0.0017	0.0005	0.49	0.0199	0.15
PQSPR	1017	-0.0865	-0.115*	0.00	0.672*	0.00
ESPR	1017	-0.0016	-0.026*	0.01	0.019*	0.02
PESPR	1017	-0.0358	-0.0384	0.14	0.641*	0.00
DEP	1017	-0.1363	-0.121*	0.02	0.688*	0.00

Table 3.6
The effect of firm sizes on the changes in commonality in liquidity during the earnings seasons

Panel A presents the cross-sectional statistics for time-series means for each liquidity measure. Panel B shows the effect of firm size on the levels of liquidity during the first four weeks of earnings seasons. Panel C gives the mean betas for the coefficients β_{EN} (Dummies) and β_1 (Market) from Equation 1. EN betas are the average regression coefficients on β_{EN} from the equation (1) where EN corresponds to the peak of earnings seasons (weeks 3 through 6). Market Betas are the average regression coefficient on contemporary equal-weighted market-wide liquidity. The p-values are for the one-sided t-test null that the average coefficient is not zero (negative for dummies and positive for the market). All variables in Panel C are proportionally differenced. QSPR is quoted spread, PQSPR- proportional quoted spread, ESPR- effective spread, PESPR- proportional effective Spread, and DEP- quoted number of shares (the sum of bid and ask). The estimation period covers 10 years of data from 01/01/1993 to 12/31/2002. One star (*) denotes the values significant at 5% or better and two stars (**) denote the values significant at 10% or better. N is the number of stocks.

Panel A. The average values of liquidity variables by quintiles.

	QSPR	PQSPR	ESPR	PESPR	DEP
smallest	0.1752	0.0179	0.1226	0.0128	3195
2	0.1688	0.0089	0.1161	0.0062	3445
3	0.1591	0.0060	0.1070	0.0041	3947
4	0.1432	0.0044	0.0944	0.0030	5895
biggest	0.1322	0.0030	0.0880	0.0020	8023

Panel B. Wilcoxon signed-rank test for extreme quintiles.

		QSPR	PQSPR	ESPR	PESPR	DEP
(Smallest)	Z score	0.7972	2.4303	1.3444	2.6309	-1.2396
	p-value	0.2127	0.0075	0.0894	0.0043	0.1076
(Largest)	Z score	1.2192	2.0892	1.0648	1.8371	0.4151
	p-value	0.1114	0.0183	0.1435	0.0331	0.339

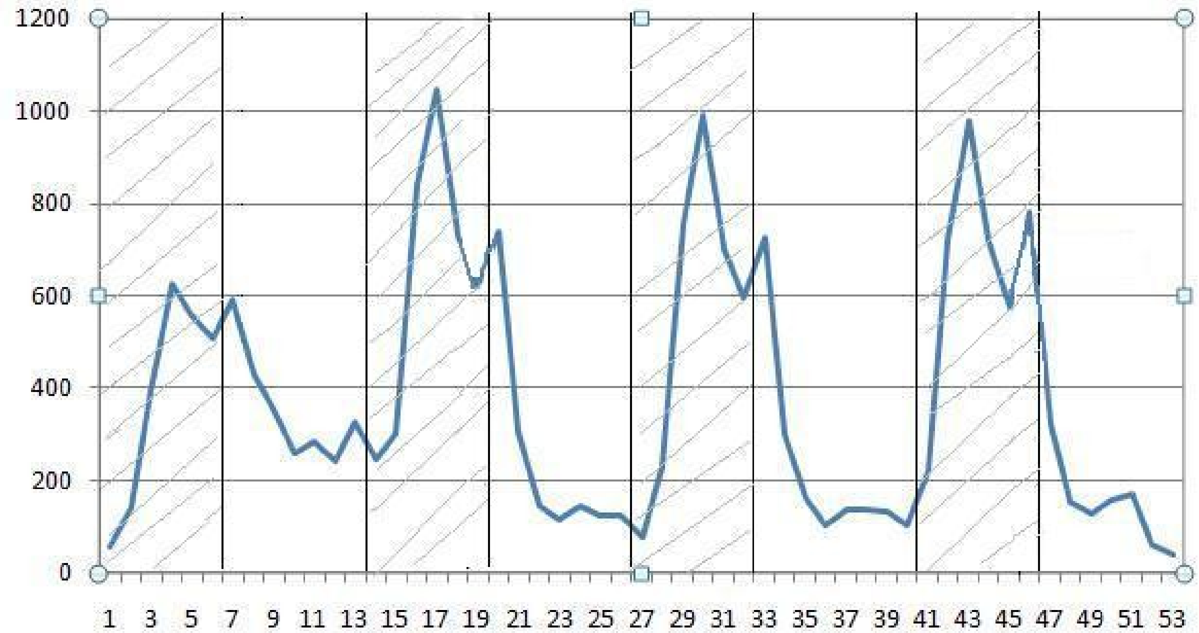
Panel C. Regression results for smallest and the largest quintiles during the peak of earnings seasons

			Dummies			Market	
(smallest)	Variable	N	median	mean	p-val	mean	p-value
	QSPR	345	-0.0003	0.0162	0.40	-0.0323	0.23
	PQSPR	345	-0.0009	0.0553	0.27	0.6481*	0.00
	ESPR	318	-0.0007	-0.0768	0.14	0.0008	0.44
	PESPR	317	0.0303	-0.0702	0.24	0.6535*	0.00
	DEP	343	-0.0528	-0.1646	0.13	0.6706*	0.00
(largest)	QSPR	272	-0.0009	-0.0129	0.23	-0.0054	0.17
	PQSPR	272	-0.0887	-0.104*	0.00	0.525*	0.00
	ESPR	272	-0.0015	-0.008**	0.07	0.0073	0.17
	PESPR	272	-0.0656	-0.088*	0.00	0.464*	0.00
	DEP	272	-0.1183	-0.0550	0.19	0.966*	0.00

Fig. 3.1

The average number of firms reporting each week for the period from 1971 to 2006

Shaded area corresponds to the calendar earnings seasons. This striking pattern stays relatively constant for every year in the period covered.



Chapter 4

Earnings seasons, liquidity, and asset prices: international evidence

4.1 Introduction

It has long being thought that liquidity is a firm-specific characteristic and as such this phenomenon was almost exclusively confined to the market microstructure literature. However, in the last 10 to 15 years several researchers realized that the implications of liquidity are much more important and go to the heart of important questions in financial economics. The first of several papers to establish that individual firms' liquidity has a common component were Chordia et al (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001). They show that liquidity can be decomposed into firm-specific and systematic components. This conclusion led to the explosion of the literature on the asset pricing implications of the systematic component. Pastor and Stambaugh (2003), Acharya and Pederson (2005) and a few other papers demonstrate that the liquidity factor in fact requires an additional risk premium in equilibrium even when controlling for all other firm characteristics.

Even though the facts that liquidity co-varies and is priced have been established, the reasons behind the phenomenon of "systematic liquidity" are still poorly understood. In the last few years, the number of papers investigating this issue turned into a vast stream expanding the research into different settings, assets, markets, and countries. Specifically, researchers have broadened the studies of commonality to include other US and foreign exchanges (Brockman and Chung (2008)), different measures of liquidity ((Bekaert et al.

(2007), Karajczyk and Sadka (2007)), and different asset classes such as options (Cao and Wei (2008)).

Due to the relative novelty of the subject, the first wave of publications dealing with commonality in liquidity necessarily focuses on the descriptive issues. Very few early studies actually concentrate on the factors that actually drive the commonality. Among those who do are Coughenour and Saad (2004) who find that common market-makers is one of the factors that influence the commonality in liquidity. Corwin and Lipson (2008) using the principal component analysis find that commonality is driven in part by the correlated trading decisions of professional traders, especially the ones executed through program trades. And Brockman et al (2008) find that the commonality strongly responds to changes in the domestic and global macroeconomic environment.

In my first two essays (chapters 2 and 3) investigate the effect of clustering of firm-specific information (earnings seasons) on both the commonality in liquidity and the clustering's asset pricing implications. Specifically, in my first essay, I argue that the high concentration of firm-specific information during earnings seasons, pre-determined short time periods following each calendar quarter, leads to high preference uncertainty among investors and creates (according to the model by Gellmeyer et al (2005)) market-wide liquidity shocks. I find that earnings seasons, in fact, impact returns, volatility, volume, and liquidity betas.

My second essay investigates whether earnings seasons influence the commonality in liquidity. I expect that the commonality will be influenced for the following reasons. First, the flood of new information and heavy trading to rebalance portfolios in response to that information are the two most significant characteristics of earnings seasons. And these were shown to affect the commonality (Corwin and Lipson (2008)). Second, the information environment changes dramatically as the market goes through earnings seasons and it is well known that asymmetric information adversely impacts liquidity in any market (Akerlof (1970)). The asymmetric information rises (reaches its peak) at the beginning of the seasons and then drops dramatically towards the end (Kim and Verrecchia(1995). Accordingly, the first essay shows earnings seasons have significant economic impact on asset prices because they cause market-wide liquidity shocks.

This study builds on the previous findings but specifically investigates the effect of the earnings season on changes in *the commonality* in liquidity during earnings seasons. I hypothesize that due to the flood of firm specific information during the peak of earnings seasons, the commonality in liquidity decreases. In other words, the commonality in liquidity is lower during earnings seasons than during any other time of the year because firm-specific information affects each company differently. This effect is the opposite of the effect produced by *macroeconomic* information which tends to increase the commonality because it affects similar firms in a similar way (Brockman et al, (2008)). I control for the intra-industry information transfer which was shown to be very strong during earnings seasons (Sun (2006)), and for the size effect to check the possibility that the phenomenon is mainly driven by the smallest firms. In addition, I also look at the behavior of simple average marketwide liquidity measures around earnings seasons to see if it is affected by the changing information environment. My hypothesis is that the liquidity worsens during the beginning of earnings seasons when the asymmetry in information is at its highest but substantially improves at the end due to the reduction in information asymmetry.

I find that commonality significantly decreases during the peak weeks of earnings seasons when most firms issue their reports consistent with the idea that firm-specific information reduces common effects. The effect is especially pronounced for the largest firms, a finding consistent with the fact that the media and the analysts concentrate almost exclusively on large firms during earnings seasons. And, finally, I establish that the average spreads significantly widen during the first four weeks and average depths significantly decrease during this period producing market-wide liquidity shocks. The situation is reversed in the last two weeks (i.e. liquidity substantially improves to pre-season levels or even better)

In this paper, I extend the first two essays to the international setting. Specifically, I study the impact of the institutional characteristics of the interim reporting periods on the commonality in liquidity in 20 countries. The frequency and the duration (deadlines) of the interim reporting periods are set and enforced by each country's regulatory body such as SEC in the US and FSA in the UK. As a result, the reporting frequencies and the lengths of earnings seasons vary around the world. For example, SEC in the US requires that all public companies report their numbers within the first 30 to 45 days after the end of fiscal quarter and UK's FSA requires that British companies release their earnings results every half-year within 90 to 120 days.

The extension of the study to the international settings allows me not only to test my hypothesis about the impact of earnings seasons on liquidity for a much larger sample, but also to investigate the relative effect of the frequency and duration of reporting on liquidity. In addition, I explore the effect of countries' average quality of information disclosure and the strength of their insiders trading laws on liquidity.

My empirical results show that liquidity betas in fact increase in magnitude during earnings seasons for the international sample. I also find that the commonality sharply drops during these time periods, both finding consistent with my hypotheses proposed in the first two essays. In addition, the results favor my hypotheses about the cross-country determinants that mitigate or amplify the liquidity effects during the periods of interim reporting. Specifically, I find that poor quality of accounting information (high opacity) and longer duration reduce the negative liquidity effects of earnings seasons. The impact of the frequency of reporting (per year) and insider law enforcement remains inconclusive.

The paper proceeds as follows. In Section 1 I review the existing literature and formulate two sets of testable hypotheses. In section 2 I describe my data, variables used in the study and methodology. Sections 3 shows the main finding and robustness checks and, finally, section 4 concludes with discussions and recommendations for future research.

4.2 Overview and Hypotheses Development

4.2.1 Overview

Anecdotal accounts suggest that earnings seasons are very important time periods for investment public. During these periods significant amount of economic information inundates the markets keeping busy thousands of analysts, institutional and retail investors, and business media. In spite of its significance for practitioners, this unique phenomenon has received almost no attention from academic research.

The importance earnings seasons, which cause the firm-specific information to cluster around a few relatively short periods, stems from its impact on the information environment (Kim and Verrecchia (1995)). Akerlof (1970) show that information asymmetry adversely impacts market liquidity. In fact, numerous studies look into the effects of *individual* releases and find that they influence not only liquidity but also price, volatility, volume, adverse selection, trading patterns etc. (see e.g. Lee (1992) and Lee et al. (1993)). During this period the information asymmetry increases between different types of investors and, also, between investors and the market makers.

Market makers are aware of the active presence of the informed investors and, facing adverse selection, try to manage the risk by widening bid-ask spreads and decreasing depths (Lee et al. (1993), Krinsky and Lee (1996), and Kavajecz (1999) among others). However, all of the above mentioned studies deal with individual securities. I argue that because of the concentration of earnings reports during earnings seasons (see the first two essays)) this pattern, the widening of the bid-ask spread and decreasing depths, should also be observed in the aggregate. This phenomenon is not limited to any single country but should be observed whenever a country's laws require interim reporting.

As I mentioned above each country's accounting and auditing requirements are set and enforced by that country's regulatory body such as SEC in the US, Securities Regulatory Commission in China, or FSA in the United Kingdom. Each regulator typically sets the frequency and the duration of the interim reporting periods. Thus the regulatory agencies set the general framework while the firms still have some flexibility in choosing the exact date of reporting as long as it is before the law-imposed deadline.

Both the frequency and the duration of the interim reporting periods differ widely across the world. Table 4.1 shows the distribution of both characteristics along with other variables for the counties used in this study. This variability allows us to test additional, unique for the international data, hypotheses.

4.2.2 Hypotheses development

My first set of hypotheses is simply an extension of the tests performed in my first two essays. One concerns with the liquidity betas and the other tests the commonality for a broader sample.

> H1: The return sensitivity to liquidity shocks associated with earnings seasons is positive and larger in magnitude.

> H2: Commonality in liquidity is affected by earnings seasons. It decreases considerably during the peak weeks of the seasons.

The extension of these hypotheses to the international setting acts as an out of sample test for my US-data based hypotheses tested in the first two essays. That is if the hypotheses are supported in the international setting, the importance of earnings seasons will only grow. If however the data rejects the hypotheses, the significance of earnings seasons as an institutional feature of a country's regulatory environment will be diminished. Even in the latter case, however, the rejection of the hypotheses might simply be an artifact of the quality of the international data (see the data description section for more details)

In addition to the out- of- sample test, the foreign country data also give me an opportunity to investigate additional issues. Specifically, I argue that the reporting frequency and the lengths of earnings seasons in addition to the countries' legal and disclosure environment could also impact liquidity, commonality in liquidity, and therefore asset prices, around earnings announcements.

First, all of the effects that I find in my first two essays are caused by the changing information environment during earnings seasons. Therefore if the disclosure frequency, the lengths of earnings seasons, the quality of disclosed information, and the enforcement of insider trading laws all affect the information environment, then they could also affect the liquidity impact of earnings seasons. As is the case with the US market, there are no studies that would deal with the aggregate earnings announcements outside the US. However, there are a few papers that deal with the effect of reporting frequency and the investor protection on the informational environment of *individual* stocks. For example, Welker (1995) Healy et al. (1999) Leuz and Verrecchia (2000) all find that expanded disclosure (voluntary or required) improves stock liquidity by reducing information asymmetry. Butler et al (2008) examine whether financial reporting frequency affects the speed with which accounting information is reflected in security prices. They find that firms that voluntarily increased reporting frequency from semiannual to quarterly experienced increased timeliness, the speed with which accounting information is impounded into price, even controlling for self-selection.

In another stream of literature, DeFond et al (2007) draw on the investor protection literature to explain cross-country differences in the information content of annual earnings announcements. Using data from over 50,000 annual earnings announcements in 26 countries, they find that annual earnings announcements are *more* informative in countries with higher quality earnings and/or better enforced insider trading laws, and that annual earnings announcements are *less* informative in countries with more frequent interim financial reporting. They also find that, on average, that earnings announcements are more informative in countries with strong investor protection institutions. Based on the above reasoning, my second set of hypotheses is:

> H3: Higher reporting frequencies are associated with smaller liquidity effects during earnings seasons. That is the liquidity betas will be lower and the commonality in liquidity will not be as low.

> H4: Countries with higher quality of earnings reports will experience larger liquidity effects during earnings seasons and vice versa high opacity will dissipate the liquidity effect. That is the liquidity betas will be higher and the commonality will be even lower.

> H5: Countries with more diligent enforcement of insider trading laws will experience higher liquidity effects during earnings seasons. That is the liquidity betas will be higher and the commonality will be even lower.

Finally, my last hypothesis deals with the duration of the interim reporting periods. The hypothesis is a simple logical consequence of the argument behind the importance of earnings seasons. Since the main reason why earnings seasons matter is because they lead to the clustering of releases of firm-specific information, “tighter” clustering will cause larger liquidity effects and vice versa. Thus, the international setting allows me to test this hypothesis indirectly. Specifically,

> H6: Longer duration reporting periods lead to lower liquidity effects, that is both the liquidity betas and the commonality in liquidity will not be as extreme.

The next section describes the data used in the study and the methodology.

4.3 Data and Methodology

4.3.1 Sample construction

To obtain the international daily pricing and volume data I use Matlab DataFeed utility to extract the daily price and trading volume data from Yahoo! Finance service which in turn aggregates the quote and daily volume information from its partners: either directly from the international exchanges or through Telekurs, one of the largest providers of financial information in Europe. The data covers 27 exchanges from 21 countries for the period of 3 to 6 years. The data items include adjusted daily pricing information and adjusted daily trading volumes. The composition of my initial sample is presented in Table 4.1.

In order to eliminate the influence of no-trading firms, I follow Karolyi et al (2008) and use the following screens. I exclude non-trading days, which I define as days on which 90% or more of the stocks listed on a given exchange have a return equal to zero. I also exclude a stock if the number of zero-return days is more than or equal to 80% in a given month. I calculate the daily returns from the pricing data and set them to missing if the value of the return for either the previous or the current day is below 0.01.

The information about the frequency and the duration of the interim reporting periods is obtained from several overlapping sources. My main source is CIFAR, the Center for International Financial Analysis and Research, which publishes the International Accounting and Auditing Trends handbook and in which it provides the information needed for my research. Since the latest edition was published in 1995 and it therefore doesn't reflect the changes made in each country for the last decade, I update this information by going to each country's regulatory agency and checking their websites for the updates. The updated information on the distribution of frequencies and durations of interim reporting periods along with the number of stocks for each country, the opacity of accounting information score, and law enforcement and protection index are listed in Table 4.1.

4.3.2 Methodology

Since the intraday price information outside the US is not readily available, I use the daily price impact measure of Amihud (2002) as the proxy for liquidity. It is calculated as the absolute daily stock return divided by the daily dollar volume. The intuition behind the Amihud's measure is very simple, if the stock's price changes a lot (high absolute return) in response to higher dollar volume, then the stock is relatively illiquid. If the stock's price doesn't move (zero return) in response to higher volume, the stock is extremely liquid. There are several reasons why I use this measure. First, Amihud (2002) shows that this measure is strongly positively related to microstructure estimates of illiquidity such as the bid-ask spread, price impact, and fixed trading costs. Second, Hasbrouck (2006) runs a “horse race” among different measures of price impact and reports that the Amihud illiquidity measure is highly correlated with a price impact coefficient calculated using intra-day price and volume data for the U.S. Third, Lesmond (2005) demonstrate that this liquidity proxy has a high correlation with bid-ask spreads in 23 emerging markets which implies its usefulness in the international settings when the intra-day data is not available. Finally, the calculation of this measure does not require extensive computing powers and all that is needed is a daily return and a daily volume multiplied by price.

This proxy has been widely used in recent years. For example, Acharya and Pederson (2005) employ this measure to test pricing implications of “systematic” liquidity. Spiegel and Wang (2005) utilize the measure to investigate the link between firm’s idiosyncratic volatility and firm’s liquidity. While Kamara et al (2007) use it to investigate the link between firm’s liquidity and institutional ownership. Finally, Karolyi et al (2008) used the daily Amihud’s measures to investigate the commonality in liquidity for international stocks. Since the last study is very close to subject of this essay, I closely follow their methodology in constructing the liquidity proxy and running the commonality regressions.

Specifically, following Karolyi et al (2008) I construct the Amihud’s measure for each stock -day as follows:

$$\mathrm{LIQ}_{\mathrm{i,d}} = -log\left(1 + \frac{|R_{i,d}|}{P_{i,d}VOL_{i,d}}\right), \tag{1}$$

where $R_{i,d}$ is the return in local currency, $P_{i,d}$ is the price in local currency, and $VOL_{i,d}$ is the trading volume of stock i on day d. It is multiplied by -1 to turn the

Amuhud's Illiquidity (ILLIQ) into liquidity (LIQ) measure. To construct a weekly or monthly time series of LIQ for each stock, I average the daily LIQ over the appropriate periods (week or month).

To test the univariate component of my hypotheses (about the liquidity levels) I also construct market-wide measure for each market for each day by finding a simple average of all the stocks traded on that day in each country. Specifically,

$$\mathrm{MLIQ}_{\mathrm{m,d}} = \sum_{i=0}^{n} \mathrm{LIQ}_{\mathrm{i,d}}, \tag{2}$$

where MLIQ is the average LIQ of all stocks on day d in market m and LIQ is defined above (equation 1). To construct the aggregate LIQ series for intervals, I use either weekly or monthly LIQ depending on the specification.

To test the components of my hypotheses about the changing sensitivity of the liquidity betas I follow the methodology outlined in Watanabe and Watanabe (2008). First, since the LIQ measure is very persistent, I extract the AR(2) residuals and use them in my regression analysis. They represent changes in LIQ and are serially uncorrelated (Acharya and Pederson, 2005). I use the following model to extract the AR(2) residuals for each stock and for the market aggregate (by dropping the I subscript and using MLIQ instead of LIQ):

$$LIQ_{i,d} = \alpha_i + \beta_{1,i} LIQ_{i,d-1} + \beta_2 LIQ_{i,d-2} + INLIQ_{i,d}, \tag{3}$$

where $\mathrm{INIL_d}$ is the AR(2) residual which represents the innovations in either firm-specific (i) or market-wide liquidity (MLIQ is defined above (equation 2)). Again, depending on the specification the weekly and monthly (instead of the daily) time series of INLIQ are constructed similarly

Since earnings seasons can be perfectly identified, I test my first hypothesis using simple OLS regression with dummy variables for earnings seasons. Specifically, the dummy ES is defined as one during the peaks of earnings seasons and is different for each country. The peaks are defined as the periods of earnings seasons when the majority of firms disclose their numbers. Judging by the US data, the peaks occur a week after the mid-period. Since the duration of the reporting periods differs across countries, I assign different peaks to different durations. In particular for 30-day periods, the peak is the last two weeks, for 45-day periods, the peak is the last 30 days, for 60-day periods the peak is the middle 30 days, for 90-day periods the peak is the middle 30 days, and for 120-day period the peak is the middle 60 days. Then, for each country I fit the following OLS model to the excess returns of each stock:

$$r_{i,t} = \alpha_t + \beta^{INLIQ}{}_t INLIQ_t + \beta^{INLIQ*ES}{}_t ES_t INLIQ_t + \varepsilon_t \ , \qquad (4)$$

where $INLIQ_t$ is the "Innovation in Liquidity" market-wide factor (defined by equation 3 with MLIQ instead of LIQ), $r_{i,t}$ is the series of excess returns on each stock in time period t (daily, weekly, or monthly depending on the specification), β^{INLIQ} is the liquidity beta and $\beta^{INLIQ*ES}$ is the conditional (on earnings seasons) liquidity beta. If $\beta^{INLIQ*ES}$ is positive and significantly different from zero, then the betas during earnings seasons have higher slopes which would be consistent with my first hypothesis. The product of variables ES_t and $INLIQ_t$ equals $INLIQ_t$ during the earnings season and zero otherwise. In other words it is a Liquidity factor conditional on earnings seasons. I am are going to denote it $INLIQES_t$ in my further analysis and instead of writing a somewhat cumbersome $\beta^{INIL*ES}$ we are going to use β^{INILES}.

Equation (4) does not control for factors commonly used in asset pricing tests. Following Watanabe and Watanabe (2008) I argue that this is sufficient for the unconditional state identification. For example, if I included the market return, the estimated liquidity betas would be those conditional on it. Also, It is well known that unexpected liquidity shocks and the market returns are correlated (e.g.,Amihud (2002)), and I consider the level of the market return (and possibly other variables) to be an important characteristic of earnings seasons.

To obtain the measure of commonality I follow the approach outlined in Karolyi et al (2008). Instead of relying on the sum of the average beta coefficients, as was done in Chordia et al (2000), Karolyi et al (2008) use the R-squared from the regressions. Specifically, I use the following model to construct the measures of commonality in liquidity for each stock all based on daily observations within a specified time period (weekly, monthly other time periods depending on the model specification):

$$\mathrm{INLIQ}_{\mathrm{i,d}} = \alpha_i + \sum_{j=-1}^{1} \beta_{\mathrm{i,j}} \mathrm{INLIQ}_{\mathrm{d+j}} + \varepsilon_{\mathrm{i,d}} \ , \qquad (5)$$

where $\mathrm{INLIQ}_{\mathrm{i,d}}$ is the daily innovation in liquidity for stock i, $\mathrm{INLIQ}_{\mathrm{d}}$ is the aggregate innovation in liquidity (either monthly or weekly). The condition liquidity beta is defined above (see equation 4) I also include the lagged and lead aggregate return for each market and the standard deviation. I require a minimum of 4 observations for the weekly series and 10 observations for the monthly series for each stock i. If my hypothesis is correct then the average R^2 series will be lower during the interim reporting periods which would indicate the commonality in liquidity declines during earnings seasons.

For the second set of hypotheses that deal with the cross-country differences in information quality and law enforcement, I construct two variables. To capture the information quality of earnings reports I use the aggregate earnings measurement score from Leuz et al (2003) which is widely used in the accounting and finance literature. They develop four different country-level measures of earnings management that capture various dimensions along which insiders can exercise their discretion to manage reported earnings. The four measures capture outcomes of insiders' earnings management activities and avoid the problem that stated accounting rules can be (and often are) circumvented by insiders and hence do not reflect firms' actual reporting practices. Then they combine these measures into the aggregate earnings management score which I use in this study. However, the measure is a score where the country with the lowest quality of information is assigned the highest score. Therefore, I refer to this variable as opacity (OP) and expect the coefficient for this factor to work in the direction opposite to the one predicted by my hypothesis.

To capture the strength of the insider trading laws I use the data collected in Bhattacharya and Daouk (2002). I construct an indicator variable based on the country's insider law enforcement incidents. That is if the country has at least one case of prosecution of insider trading, I assign the value of this indicator to 1. Otherwise the value of the variable is zero. Since most countries (18 out of 20) in my sample do enforce their insider laws (that is there was at least one prosecution during the length of my sample period) I do not get much variability. To improve this variable I combine it with the minority shareholder rights protection index that varies from zero to 5 and constructed after the anti-director index from LLSV (1998). Thus I multiplied the insider trading law score by the anti-director score. Since both measures work separately in the same direction and are highly correlated, I do not lose information by combining them while gaining needed variability.

To test my second set of hypotheses I, first, construct two samples and run several non parametric tests for the differences in means for different variables depending on my hypothesis. Second, I ran a simple OLS regression, where my dependent variables are (1) liquidity betas during earnings seasons and (2) the R^2 commonality measures. Since the second variable is limited to [0, 1] interval, I do the logistic regressions (following Morck et al (2000). The next section outlines my results.

4.4 Results

4.4.1 Sample characteristics

Table 4.1 reports the general characteristics of my sample. Yahoo! Finance provides financial information, daily adjusted prices and volumes for companies from 27 exchanges which covers 21 country. After filtering procedures described above only 16 stocks remained from Indonesia. To strike a balance between the number of stocks that would be enough to represent a country and the breadth of coverage, I decided to have at least 30 stocks for a country. Thus, after the elimination of Indonesia the number of stocks for each country varies from the low of 36 for Spain to the high of 1382 for the United Kingdom. The sample starts in different months for different countries. Yahoo! Finance tries to provide at least 5 years of data for free and charges a fee for anything beyond that (if the data is available). So, my earliest observations are for Brazil which starts in January of 2000 with the starting date for other countries varying between 2002

(Spain, India) to 2004 for Mexico. For the vast majority of countries the sample starts in January of 2003. Since the last observation in my sample is January of 2008 that leaves me with full 5 years of data for most countries.

Table 4.1 also shows the countries' interim reporting characteristics along with country general legal and accounting characteristics. The frequency of reporting varies from 2 to 4 with Sweden having 3 and other countries split almost evenly between 2 (eleven countries) and 4 (eight countries). The duration of these interim reporting periods exhibits wider variations. For example, Mexico and Taiwan give their companies only 30 days to provide investors with quarterly information while France, Italy, New Zealand, Spain, and UK are very "generous" and allow up to 120 days after the end of fiscal "half-year". Three other duration periods are 45, 60, and 90 days. We would expect that the countries with higher frequencies of reporting also exhibit shorter durations. However, this (in general) is not true as can be seen from the Table.

Two other variables shown in Table 4.1 are the inverse of the aggregate quality of accounting information (opacity) and the investor protection/law enforcement index. The opacity (OP) ranges from the low of 4.8 for Australia to a high of 26.8 for South. Seuz et al (2003) constructed this score to evaluate the firms' opportunities to manage their earnings in each country. Their higher score means *lower* quality of information and vice versa. Thus Australia has the highest quality (no attempts by management to manage the earnings) and South Korea has the worst quality of accounting information (managers have plenty of opportunities to engage in managing the earnings of their firms). This score is relevant to this study since the higher the quality of the reports, the stronger the investors' reaction to that information during earnings seasons. Five countries don't have the index values assigned to them.

The investor protection/law enforcement index (LAW for short) is the product of the law enforcement dummies (Bhattacharya and Daouk, 2002) and the Anti-director index (LLSV, 1998). The index ranges from zero (low investor protection and no insider's law enforcement) to 5 (the highest investor protection, strong insider law enforcement).

Table 4.2 presents the cross-sectional correlations between the main variables of interest. It would seem that the two variables (OP and LAW) would have high correlation, however, the table shows that this is not necessarily so. For example, South Korea, the country with the lowest OP has quite respectable LAW (3 out of 5). At the same time Sweden, the country with one of the highest OP, has very low LAW score (2 out of 5). Three countries in my sample have values for LAW equal to zero. As a result LAW's correlation with OP is only around 40%.

Frequency of reporting and the duration of earnings seasons have the highest (even though it is negative) correlation between any two variables. We would expect this correlation to be high since in general if a country's firms have fewer periods to report their earnings , they usually have more time to do so within each period. Even though the correlation is high (-0.7), it is not perfect. For example, South Korea requires only two interim reports from its firms but it limits the length of these periods to 45 days while countries such as Australia, Brazilia, Canada, and China demand four interim reports but give their companies 60 days to disperse the quarterly earnings. The R-squared variable has its highest correlation with OP, LAW, and Returns.

Table 4.3 present summary statistics for the sample. In addition to the number of firms for each country it also shows the number of observations per country, countries' monthly market returns (both equal- and value- weighted) and equal- and value-weighted market-wide liquidity. The last column shows the measure of commonality in liquidity, R-squared.

As we can see the number of observations is generally correlated to the number of firms even though the correlation is not perfect. The total number of observations before the data processing step was over 15 million. The filters (closely following Karolyi et al (2008)) reduced that number to a little over 8 million. Thus I eliminated almost half of the original sample because of data errors, zero day returns, or missing volume.

Market returns for each country are calculated as the cross-sectional averages of the individual time-series monthly returns. Both equal- and value-weighted returns are presented to show the different effect of small firms in different markets. For example, the monthly returns for the small UK firms were much higher than for the large companies which can be inferred from the fact that equal-weighted returns are much higher than the value-weighted returns. On the other hand, Indian large companies have much higher returns their smaller counterparts. Anecdotal evidence suggest that it's the largest companies that attracted the widest base of foreign (mainly US institutional) money. For example, during this time period one of the largest companies in India Reliance Industries increased in value by more than 600% making one of the company's founders the richest person on the planet. We can see this trend in general from the table.

The market-wide liquidity measure, which is a time-series average of the cross-sectional averages for each country, is much noisier. Lower liquidity (more negative) is not necessarily a characteristic of the developed markets in this sample. For example, Brazil and Taiwan enjoyed better liquidity than Germany and France. One explanations could be that even after filtering there are still enough near zero-return days with non-zero volumes (i.e. possible data errors) in the sample to affect the market-wide liquidity , or that in fact the largest firms in Brazil and Taiwan were somewhat more liquid if measures are calculated in local currencies (not in dollars).

The last column of Table 4.3 shows my measure of commonality in liquidity- the R-squared for regressions of individual liquidity measures on (lead, lagged, and contemporaneous) measures of market-wide liquidity and market-wide returns. To save space, only equal-weighted results are shown for R-squared but value-weighted measures are very similar. As we can see there is some variation in commonality across countries with the UK having the lowest commonality and Taiwan and China having the highest. This is consistent with findings in Karolyi et al (2008) and Morck et al (2000).

In the next section I present the results of testing my first set of hypotheses- the effect of earnings seasons on the liquidity betas.

4.4.2 Time-varying liquidity betas

Table 4.4 presents the result of a series of simple OLS regression models with dummy variables. The table lists five specifications that correspond to testing the effect of four variables on the commonality during earnings seasons plus the simplest model that tests whether the liquidity betas (slopes) are different during the seasons.

Since I am interested in a broad characterization of liquidity, I am mainly using the equal-weighted measures because value-weighted measures reflect primarily the effect of largest-cap stocks. Since the largest stocks are also the most liquid with almost no variability in liquidity across time, the value-weighted measures are not representative of the whole market (see Pastor and Stambaugh, 2003 for an extended argument in using the equal-weighted measures for market-wide liquidity). However, I present the regressions with both equal- and value-weighted measures in all tables.

The first specification in the table only includes the market-wide liquidity (INLIQ) and the conditional liquidity factor (INLIQES) which equals one times INLIQ during earnings seasons and zero otherwise. Both coefficients are positive and highly significant. This means that during earnings seasons the sensitivity of stock returns to marketwide liquidity fluctuations is much higher. Thus my first hypothesis, about the special effect of earnings seasons on the liquidity betas, is also supported with the use of the international data. Therefore, these effects are not the US phenomenon.

The next four specifications add an additional variable. They are intended to test the cross-country determinants that influence the strength of liquidity effects (changes in liquidity betas) during earnings seasons. The second model specification adds the opacity variable (OP). We can see that its effect on the liquidity beta is negative. Taking into account that high OP corresponds to the lower quality of accounting information, this negative sign is consistent with my hypothesis. Specifically, I predict that higher quality information (lower OP) will intensify the effects of earnings seasons (contribute to higher liquidity betas) since when investors trust the information they react with more force. The opposite effect is also true: when investors don't trust the accounting numbers, the liquidity effects are on average lower. Thus, the results of the second specifications are consistent with my hypothesis that lower quality information mitigates the increase in liquidity betas during the seasons. However, the effect of OP does not negate the liquidity shock during the seasons completely. That is even in the countries with low quality of information; the liquidity betas are still higher during earnings seasons.

The next two specifications test the effect of frequency and duration of earnings seasons on the liquidity betas. My hypotheses predict that higher frequency and/or longer duration will decrease the sensitivity of returns to the liquidity shocks during the seasons (that is I expect the negative sings for both coefficients). My hypothesis about the frequency of the reports appears to have support in the data. The coefficient is negative and significant at 5% level but its magnitude is not enough to completely negate the increase in liquidity betas due to the mere fact of earnings seasons (0.30 vs. -0.05). Thus even for countries with very high frequency of interim reporting, the stock returns are still much more sensitive to the market-wide liquidity shocks during the seasons.

The model specification that tests the duration of the interim reporting periods on the liquidity betas contradicts my hypothesis. Since the sign of the coefficient is positive it appears that the longer duration actually increases the liquidity betas during the seasons. However, the coefficient is not significant at 5% level.

The last model specification deals with the effect of the countries' legal environment. Specifically, my hypothesis predicts that countries with higher LAW index (strong investor protection combined with strong enforcement of insider trading laws) will experience higher liquidity betas during the seasons. However, the coefficient in this regression is negative even though statistically not significant.

In summary, the international evidence supports my general hypothesis about the importance of earnings seasons for security returns. Specifically, the liquidity betas, the sensitivity of stock returns to market-wide liquidity shocks increases during the periods when firms report their interim accounting numbers. The second set of hypothesis about the cross-country determinants of the increased sensitivity received mixed support. It seems that the low quality of accounting information (high opacity) somewhat reduces the increased sensitivity without completely negating it. The effect of the interim reporting frequency is also consistent with my hypothesis. Namely, higher frequency somewhat negates the effect of earnings seasons but it is still far from completely eliminating it.

The sign of the effect for the other two variables, duration and LAW, is the opposite to what my hypotheses predict. However, both coefficients are not significant at the conventional confidence level (5%)

Having established the effect of earnings seasons on liquidity betas, I next move to investigate how earnings seasons affect the commonality in liquidity.

4.4.3 Commonality in liquidity

In my second essay I show that commonality in liquidity responds strongly when the US markets go through earnings seasons. I document that during the peaks of the seasons (weeks 2 through 6 after the end of every fiscal quarter) the commonality drops. This finding is consistent with my hypothesis on the influence of information environment co-movements in liquidity. However, since my hypothesis is not exchange or country specific, the international data provides a great opportunity to test it for a mix of 20 countries.

Table 4.5 presents the results of testing my hypothesis for every country in my sample. Since the intraday pricing data is rarely available for a broad international sample, I cannot use the methodology outlined in Chordia et al (2000). Instead I follow Karolyi et al (2008) who also tested the commonality in liquidity as well as in returns and in commonality for a sample of 40 countries. In particular, I use daily Amihud measures instead of the average bid-ask spread as a measure of liquidity. Instead of the average beta coefficients (used in Chordia et al (2000) paper) I, following Karolyi et al (2008) and Morck et al (2000) use the coefficients of determinations (R^2 from regressions of firm-specific liquidity on (lead, lag, and contemporaneous) market liquidity and returns.

To test whether the commonality during earnings seasons is different from the regular seasons, I run the average bi-weekly R-squared coefficients (altered by the logistic transformation into an "unlimited" variable) on earnings seasons dummy for each country. The simple interpretation of this model is that during a "calm" or regular season the dummy equals zero and the intercept shows the average (transformed) value of R-squared. Whereas a significant (positive or negative) coefficient on the seasons dummy indicates that the R-squared changes significantly during the seasons.

Table 4.5 lists the results for all 20 countries in my sample. As we can see, consistent with my hypothesis all but three countries experience decline in commonality during the peaks of earnings seasons. However, only 6 have statistically significant negative coefficients (at 5% level) for the equal-weighted liquidity measures and 7out of 20 for the value-weighted measures. One country, Singapore, has a positive and significant coefficient which would be indicative, contrary to my hypothesis, of the increase in commonality during earnings seasons. On the other hand, given that I run 20 regressions, I can expect that one of them will come out with the opposite sign by pure chance (at 5% level).

In Table 4.6 I combined all countries into a single large sample on which I then test my hypotheses about the effect of earnings seasons and the cross-country determinants of the liquidity effects: opacity, duration, frequency, and legal environment. Concentrating on the equal-weighted measures of liquidity (see the discussion in the previous section) we can see that the whole sample regression on the seasons dummy corroborates my hypothesis. The commonality in liquidity substantially declines during earnings seasons.

Model specifications 2 through 5 test the cross-country determinants of liquidity effects during earnings seasons. Here all the variables (OP, FREQ, DUR, and LAW) are conditional on earnings seasons. That is they are all equal their values during earnings seasons and zero otherwise. The interpretation of these model specifications is simple. If the coefficients for these variables are significant (positive or negative), then they affect the average commonality *during* earnings seasons.

Regarding the quality of accounting information, my hypothesis predicts that the OP variable should have a negative coefficient negating the effect of earnings seasons on commonality. This is precisely what we observe: the OP coefficient is negative and significant at 5% level. My hypothesis also predicts that higher frequency of interim reporting will negate the effect of earnings seasons since investors don't get as much information during each period when they it (information) is evenly distributed across a calendar year. The data however is not consistent with this conjecture. The coefficient on FREQ is negative and significant at 1% level. This means that countries with high frequency of reporting experience sharper drops in commonality during those seasons. One of the reasons for why this might be the case is the with higher frequency investors decide to trade on information *only* during earnings seasons and thus concentrating their informed trading exclusively during these periods. In the low frequency countries, investors will have to trade during regular periods in additional to trading during the seasons.

Since longer duration of earnings seasons reduces their "informational intensity" I expect that this variable mitigates the negative effect of earnings seasons. Since the coefficient on the DUR variable is in fact positive (and significant at 1% level), the finding is consistent with my hypothesis. The last variable I test, LAW, also has positive and significant coefficient. This contradicts my hypothesis which suggests that the stronger the investor protection and insider law enforcement the higher the liquidity effect. The intuition behind the reasoning is simple- if the insider trading law is not enforced and minority shareholders are not protected, then managers (or any other insider) can trade prior to releasing the earnings information to the public. Investors will anticipate this and will not act on the information when it is actually released. The international data however does not support this conjecture.

The last model specification includes all four country variables along with the seasons dummy. In this specification two coefficients (the dummy and DUR) change their signs but also become statistically insignificant. The other three coefficients (OP, FREQ, and LAW) preserve their signs and significance.

4.4.4 Alternative specification for earnings seasons

My first two essays show that the "composition" of an earnings season is highly non-homogeneous in terms of the influence on important economic variables. The beginning of the seasons is characterized by very low number of firms reporting accompanied by the decrease in volume. As the earnings season progresses, the number of firms reporting surges along with the trading volume. Both are sharply decreasing toward the end of the seasons. As a result, the finding in my first two essays are highly sensitive to where I use the full calendar earnings seasons or limit the length of the period to the few most "intense" week. The results are strong and significant (statistically and economically) only when I use the so-called "peaks" of earnings seasons and not the full calendar seasons. In order to investigate this sensitivity to earnings seasons dummy specification for my international sample I re-ran my main results with the dummy that represents the full calendar seasons. The results are presented in Tables 4.7 and 4.8.

Table 4.7 presents the regressions testing the time variation in liquidity betas. Focusing on the equal-weighted liquidity measures (left panel) we can see that in general the coefficient on seasons dummy changes sign. The simplest model, with marketwide liquidity and the seasons dummy, still corroborates my hypothesis. However, when I add other variables (OP, FREQ, and LAW), the full seasons specification does not support it. Specifically, all the coefficients on the variables have reversed their signs along with the coefficients on the seasons dummy. The coefficients that are statistically significant point in the direction that is opposite the one predicted by my hypotheses. The value-weighted specification (the right pane) is similar to the equal-weighted specification except that for the value-weighted liquidity measures the full seasons dummy coefficient turns negative (against my hypothesis).

Table 4.8 presents the re-run tests of commonality with the full calendar season specification. We can see that the basic commonality results are not very sensitive to the changes in specification. All signs are preserved even though the statistical significance drops (sometimes) dramatically. For the commonality tests, both equal- and value-weighted results are pretty similar.

In summary, the international data seem to corroborate with my hypotheses about the strong effect of the peaks of earnings seasons on the commonality in liquidity. In a country-by-country regressions the coefficients on the peaks of the seasons dummy for the vast majority of the countries has the expected negative signs and a third of the coefficients are significantly so. In a combined sample, the support for my hypothesis is even stronger with the peaks of the seasons dummy having negative and significant coefficients in both equal- and value-weighted model specifications. The effects of the opacity of accounting information and duration of the interim reporting periods are in line with what I expect according to my hypotheses. However, the frequency, and the LAW variables have the unexpected direction and are very statistically significant. In addition, the tests of the time-varying liquidity betas are very sensitive to how I define the dummy for earnings seasons. As with the US market, all results hold only if the dummy is confined to the peaks of earnings seasons. When the dummy corresponds to the calendar earnings seasons, most coefficients reverse their sings or lose significance. The commonality results, however, are robust to such changes in dummy definition.

4.5 Discussion and Conclusion

The discovery of the co-movement in liquidity (systematic liquidity) has opened a floodgate of research into this issue. The first papers deal with descriptive issues eventually moving towards theoretical constructs. But before the comprehensive theory of co-movements in liquidity is developed, we need to identify the key determinants of this phenomenon. This paper is a step forward in this direction as it establishes the importance of the information flow into the markets for liquidity. Specifically, using the international data it confirms that the *concentration* of information flow from the firms to the investors cases severe liquidity shocks. I investigate two aspects of this process.

First I look into the changing sensitivity of stock returns to the market-wide liquidity shocks caused by earnings seasons. The fact that this sensitivity changes was documented for the US market in my first essay and it was important to test whether this is a local characteristic stemming from the institutional characteristics of the US markets. This paper documents the changing sensitivity during earnings seasons for the sample of 20 different countries that vary in many important aspects such as financial development, investor protection, quality of accounting information, frequency, and duration of the interim reporting periods. This variability also allows me to test additional hypotheses about the determinants that affect this changing sensitivity (liquidity betas) during these periods. In particular I find that high quality of accounting information and low frequencies of interim reporting all contribute to higher liquidity betas. The findings about the duration of the seasons and the strength of the investor protection/law enforcement are not conclusive.

Next, I look at yet another measure of co-movement in liquidity, the commonality. Adapting the methodology to the international data I, following Karolyi et al (2008) and Morck et al (2000) use the R-squared of the regressions of individual liquidity on the market-wide liquidity. I find that for 85% of the countries in my sample, the average commonality drops sharply during earnings seasons. When using the combined sample to test the hypothesis, I find that the results are even stronger.

Looking into the determinants of this drop in commonality during the seasons, I find several factors that mitigate the impact of these periods on commonality. For example, poor quality of accounting information (high opacity) and longer duration periods reduce the negative effect of earnings seasons on commonality. Surprisingly, the higher frequencies and weaker protection/law enforcement actually increase the negative impact of the seasons. The latter findings might be the artifacts of the high negative correlations between frequency and duration and high positive correlation between law and opacity variables.

There are three obvious directions for further research. First, the sample size and the breadth of coverage could easily be extended. For example, Thomson Financial Datastream covers more than 10 years of daily pricing and volume data for more than 40 countries. The increase of the sample size will lend more weight to the findings outlined in this paper.

Second, the cross-country variables used in this study (opacity, investor protection/law enforcement, and frequency and duration of earnings seasons) undergo constant changes especially in the emerging economies. For example, China moved from half-year 120-day earnings seasons towards quarterly 60-days interim periods in just the last 7 years. The quality of accounting information has also been steadily improving. The same is true for many other countries. This changes offer both challenges and opportunities for research. The main challenge is that it is very hard to collect all that data on the changes. But the main opportunity is that these changes offer natural experiments (before and after) to test my hypotheses.

The third direction is the employment of more sophisticated econometric techniques. The simple OLS regression models that I use to test my conjectures make unrealistic assumptions about the potential missing variables and error distribution function. Testing model specifications and correcting (if wrong) them by adding plausible instruments with estimation via 2SLS or a more general method of moments would be an improvement.

Table 4.1
Characteristics of earnings seasons for countries used in the study.

The data is obtained from 27 exchanges via Yahoo! Finance using Matlab Datafeed utility. Reporting frequency and the Duration of earnings seasons are from CIFAR and the countries' regulators. The quality of accounting information is the Aggregate Earnings Management score from Leuz et al (2003) where higher score corresponds to lower quality of information (high opacity) in the earnings reports. Investor protection and law enforcement index is a product of the anti-director index (LLSV, 1998) and Law enforcement dummy (Bhattacharya and Daouk, 2002).

Country	# of Stocks	Reporting Frequency	Duration of earnings seasons	The opacity of accounting information	Investor protection and law enforcement	From
Australia	849	4	60	4.8	4	2003:03
Brazil	117	4	60	n/a	4	2000:01
Canada	878	4	60	5.3	4	2003:02
China	1125	4	60	n/a	0	2003:01
France	680	2	120	13.5	2	2003:01
Germany	701	2	90	21.5	1	2003:01
Hong Kong	582	2	90	19.5	5	2003:01
India	364	2	60	19.1	2	2002:08
Israel	137	4	45	n/a	3	2002:08
Italy	242	2	120	24.8	0	2003:01
Mexico	79	4	30	n/a	0	2004:04
Netherlands	110	2	60	16.5	2	2003:01
New Zealand	121	2	120	n/a	0	2003:01
Norway	161	4	45	5.8	3	2003:01
Singapore	353	2	90	21.6	4	2003:01
South Korea	462	2	45	26.8	3	2002:04
Spain	36	2	120	18.6	2	2002:01
Sweden	346	3	60	6.8	2	2003:04
Taiwan	600	4	30	22.5	3	2003:01
UK	1382	2	120	7.0	4	2003:01

Table 4.2
Correlations between variables

The table presents cross-sectional correlations between the variables in the study where OP is the opacity index (the higher the worse), FREQ is the frequency of earnings seasons in a year, DUR is the duration of the seasons in days, and LAW is the index that combines the country's insider law enforcement dummy with the LLSF (1998) andi-director index. The star (*) denotes the values significant at 5% or better for the null hypothesis of zero correlation. The sample covers 20 countries from 2003 to 2008.

	FREQ	DUR	LAW	OP	Return	R2
FREQ	1					
DUR	-0.7230	1				
	0.00					
LAW	0.0179	0.0010	1			
	0.94	1.00				
OP	0.5934	-0.1751	0.4040	1		
	0.02	0.52	0.12			
Return	0.2544	-0.3123	-0.0436	-0.0394	1	
	0.27	0.17	0.86	0.88		
R2	0.0302	0.0284	0.1181	0.3130	0.1973	1
	0.90	0.90	0.62	0.24	0.39	

Table 4.3
Summary Statistics.

The table reports market returns and liquidity for 20 countries as well as the number of firms and total observations for each country. Stock market returns are in percent per month in local currency. Monthly liquidity for individual stocks is calculated as the average of daily Amihud measures, defined as the ratio of absolute returns to the local currency trading volume. Individual stock liquidity measures are then averaged for each month for each county to get the Market-wide liquidity. These series are then averaged across time. Both equal and value-weighted measures are reported. R-squared is time-series average of the bi-weekly averages for each country in percent per month. It is calculated at the coefficient of determination of bi-weekly regressions of daily values of Amihud measures for individual stocks on the (lead, lag, and contemporaneous) aggregate daily values of Amihud measures and Market returns.

		Number of	Market Returns		Market Liquidity		R-
country	N	Observations	Equal	Value	Equal	Value	squared
Australia	849	577,124	1.87	1.07	-1.222	-0.091	8.80
Brazil	117	115,365	1.99	2.00	-0.106	-0.044	8.78
Canada	878	852,687	1.17	1.27	-0.641	-0.089	8.71
China	1125	1,332,872	0.98	2.34	-0.904	-0.833	11.31
France	680	671,236	1.09	0.65	-1.852	-0.038	8.82
Germany	701	623,559	0.30	0.94	-3.993	-1.298	9.11
Hong Kong	582	542,057	1.38	1.66	-0.171	-0.020	9.03
India	364	230,529	2.74	3.81	-1.005	-1.000	8.86
Israel	137	112,635	2.13	1.89	-0.242	-0.097	9.06
Italy	242	197,270	1.14	1.26	-0.158	-0.031	8.42
Mexico	79	30,661	2.22	2.29	-0.884	-0.093	9.58
Netherlands	110	79,423	1.69	1.05	-0.672	-0.030	9.12
New Zealand	121	62,111	2.11	1.19	-2.364	-0.781	9.24
Norway	161	45,918	2.48	2.51	-1.181	-1.267	7.49
Singapore	353	186,321	2.51	2.93	-0.542	-0.120	8.69
South Korea	462	404,612	-0.20	1.09	-0.980	-0.870	9.25
Spain	36	32,703	1.54	0.99	-0.428	-0.022	8.85
Sweden	346	240,062	1.72	1.57	-0.114	-0.008	8.73
Taiwan	600	487,878	2.21	3.33	-0.003	-0.002	12.56
UK	1382	1,199,518	1.91	1.57	-1.190	-0.161	8.19
TOTAL	9,325	8,024,541					

Table 4.4

Changes in liquidity betas during the peaks of earnings seasons.

The Table shows the results of testing whether the liquidity betas are higher during earnings seasons.

$$r_{i,t} = \alpha_t + \beta^{INLIQ}{}_t INLIQ_t + \beta^{INLIQ*ES} \quad INLIQES_t + \varepsilon_t \quad ,$$

where the dependent variable is the excess return for each stock in the sample. 13-week US T-bills are used as the proxy for the risk-free rate. INLIQ is the unconditional liquidity factor- the innovations in market-wide liquidity constructed after Amihud (2002) and Acharya and Pederson (2005). ES is the dummy for peaks of earnings seasons individual for each country. INLIQES is the conditional liquidity factor. It equals INLIQ during earnings seasons and zero otherwise. OP is the quality of information index (the higher the worse), FREQ is the frequency of earnings seasons in a year, DUR is the duration of the seasons in days, and LAW is the index that combines the country's insider law enforcement dummy with the LLSF (1998) andi-director index. The star (*) denotes the values significant at 5% or better. The sample covers 20 countries from 2003 to 2008.

	Equal Weighted			Value-Weighted		
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.47	0.00	0.0010*	94.34	0.00
INLIQ	0.0174*	3.47	0.00	0.4571*	2.7	0.01
INLIQES	0.1300*	5.96	0.00	0.7909	1.18	0.24
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0011*	85.33	0.00	0.0011*	88.44	0.00
INLIQ	0.0445*	8.32	0.00	1.7826*	8.99	0.00
INLIQES	0.4315*	5.23	0.00	-3.4839	-1.86	0.06
OP*ES	-0.0200*	-3.88	0.00	0.1480	1.16	0.25
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.47	0.00	0.0010*	94.33	0.00
INLIQ	0.0173*	3.46	0.00	0.4499*	2.66	0.01
INLIQES	0.3089*	3.46	0.00	-4.0358*	-1.93	0.05
FREQ*ES	-0.0510*	-2.06	0.04	1.5671*	2.43	0.02
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.47	0.00	0.0010*	94.33	0.00
INLIQ	0.0173*	3.46	0.00	0.4497*	2.66	0.01
INLIQES	0.0581	1.18	0.24	4.1395*	2.73	0.01
DUR*ES	0.0012	1.63	0.10	-0.0429*	-2.46	0.01
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	90.62	0.00	0.0010v	93.34	0.00
INLIQ	0.0207*	4.08	0.00	0.6242*	3.56	0.00
INLIQES	0.1843*	3.09	0.00	1.2667	0.91	0.36
LAW*ES	-0.0182	-0.87	0.38	-0.2026	-0.38	0.70

Table 4.5

The effect of earnings seasons on commonality in liquidity by country

The table shows the effect of earnings seasons on the average commonality in liquidity as measured by R^2 from bi-weekly regressions of daily values of Amihud measures for individual stocks on the (lead, lag, and contemporaneous) aggregate daily values of Amihud measures and market returns. The R-squared are transformed via the logistic transformation. The regressions are run for each country separately. The ES dummy equals 1 during the country's earnings seasons and zero otherwise. The star (*) denotes the values significant at 5% or better. The sample covers 20 countries from 2003 to 2008.

	Equal-weighted			Value-weighted		
Country	ES	t-stat	Prob	ES	t-stat	Prob
Australia	-0.1548*	-1.85	0.03	-0.1829*	-2.18	0.01
Brazil	-0.1355*	-1.80	0.04	-0.1349*	-1.81	0.04
Canada	-0.2988*	-4.47	0.00	-0.2953*	-4.34	0.00
China	-0.1830*	-2.27	0.01	-0.2445*	-1.83	0.03
France	-0.0422	-0.63	0.26	-0.0455	-0.68	0.25
Germany	0.0528	0.59	0.28	0.0177	0.20	0.42
Hong Kong	0.0465	0.45	0.33	0.0397	0.38	0.35
India	-0.1240	-1.01	0.16	-0.1395	-1.22	0.11
Israel	-0.1790*	-2.08	0.02	-0.1717*	-1.98	0.02
Italy	-0.0741	-0.87	0.19	-0.1144	-1.30	0.10
Mexico	-0.1130	-0.91	0.18	-0.1392	-1.01	0.16
Netherlands	-0.1708*	-1.60	0.05	-0.1843*	-1.61	0.05
New Zealand	-0.1332	-1.39	0.08	-0.1692	-1.57	0.06
Norway	-0.1487	-1.37	0.09	-0.1993*	-2.00	0.02
Singapore	0.2258*	1.90	0.03	0.1980*	1.64	0.05
South Korea	-0.0981	-0.82	0.21	-0.1390	-1.15	0.12
Spain	-0.0407	-0.46	0.32	-0.0711	-0.84	0.20
Sweden	-0.1214	-1.24	0.11	-0.1250	-1.24	0.11
Taiwan	-0.1060	-0.82	0.21	-0.1042	-0.89	0.19
UK	0.0036	0.04	0.49	0.0112	0.12	0.45

N=9,560

Table 4.6

The effect of earnings seasons on the commonality in liquidity for the whole sample

The table shows the effect of earnings seasons on the average commonality in liquidity as measured by R^2 from bi-weekly regressions of daily values of Amihud measures for individual stocks on the (lead, lag, and contemporaneous) aggregate daily values of Amihud measures and market returns. The R-squared are transformed via the logistic transformation. The regressions are run for the whole sample – 20 countries (from 2003 to 2008). The ES dummy equals 1 during the *peak of the* country's earnings seasons and zero otherwise. OP is the quality of information index (the higher the worse), FREQ is the frequency of earnings seasons in a year, DUR is the duration of the seasons in days, and LAW is the index that combines the country's insider law enforcement dummy with the LLSF (1998) andi-director index. The last four variables are conditional on earnings seasons. That is their values are the products of earnings seasons dummies and the raw values for the four indices. The star (*) denotes the values significant at 5% or better.

Equal-weighted	Intercept	ES	OP*ES	FREQ*ES	DUR*ES	LAW*ES
1	0.8662*	-0.0843*				
	0.00	0.00				
2	0.8698*	-0.1237*	0.0072*			
	0.00	0.01	0.03			
3	0.8662*	0.1629*		-0.0837*		
	0.00	0.01		0.00		
4	0.8662*	-0.2799*			0.0025*	
	0.00	0.00			0.00	
5	0.8632*	-0.1734*				0.0344*
	0.00	0.00				0.01
6	0.8698*	0.3402	0.0413*	-0.3551*	-0.0006	0.0671*
	0.00	0.07	0.00	0.00	0.33	0.00

Value-weighted	Intercept	ES	OP*ES	FREQ*ES	DUR*ES	LAW*ES
1	0.8821*	-0.1036*				
	0.00	0.00				
2	0.8797*	-0.1451*	0.0073*			
	0.00	0.00	0.03			
3	0.8821*	0.1140*		-0.0737*		
	0.00	0.05		0.00		
4	0.8821*	-0.2838*			0.0023*	
	0.00	0.00			0.00	
5	0.8783*	-0.2010*				0.0377*
	0.00	0.00				0.01
6	0.8797*	0.2579	0.0385*	-0.3327*	-0.0004	0.0722*
	0.00	0.12	0.00	0.00	0.38	0.00

N= 9,560

Table 4.7
Changes in liquidity betas during full earnings seasons

The Table shows the results of testing whether the liquidity betas are higher during earnings seasons.

$$r_{i,t} = \alpha_t + \beta^{INLIQ}{}_t INLIQ_t + \beta^{INLIQ*ES} \quad INLIQES_t + \varepsilon_t \quad ,$$

where the dependent variable is the excess return for each stock in the sample. 13-week US T-bills are used as the proxy for the risk-free rate. INLIQ is the unconditional liquidity factor- the innovations in market-wide liquidity constructed after Amihud (2002) and Acharya and Pederson (2005). ES is the dummy for the *full* earnings seasons individual for each country. INLIQES is the conditional liquidity factor. It equals INLIQ during earnings seasons and zero otherwise. OP is the quality of information index (the higher the worse), FREQ is the frequency of earnings seasons in a year, DUR is the duration of the seasons in days, and LAW is the index that combines the country's insider law enforcement dummy with the LLSF (1998) andi-director index. The star (*) denotes the values significant at 5% or better. The sample covers 20 countries from 2003 to 2008.

	Equal Weighted			Value-Weighted		
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.17	0.00	0.0010*	94.51	0.00
MLIQ	0.0182*	3.55	0.00	0.6978*	4.01	0.00
INILES	0.0590*	3.63	0.00	-1.5002*	-2.93	0.00
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0011*	85.1	0.00	0.0011*	88.6	0.00
MLIQ	0.0471*	8.58	0.00	2.0380*	10.03	0.00
INILES	-0.0823	-1.81	0.07	-9.9116*	-7.88	0.00
OP*ES	0.0087*	2.88	0.01	0.5725*	6.21	0.00
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.17	0.00	0.0010*	94.5	0.00
MLIQ	0.0183*	3.56	0.01	0.6921*	3.98	0.00
INILES	-0.0642	-1.17	0.24	-8.4378*	-5.76	0.00
FREQ*ES	0.0376*	2.34	0.02	2.4300*	5.05	0.00
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	91.17	0.00	0.0010*	94.5	0.00
MLIQ	0.0182*	3.55	0.01	0.6934*	3.98	0.00
INILES	0.0840*	2.27	0.02	2.6012*	2.04	0.04
DUR*ES	-0.0004	-0.75	0.45	-0.0496*	-3.52	0.00
Variable	Estimate	t-value	Prob	Estimate	t-value	Prob
Intercept	0.0010*	90.34	0.00	0.0010*	93.49	0.00
MLIQ	0.0216*	4.15	0.00	0.8363*	4.67	0.00
INILES	-0.1220*	-2.77	0.01	-7.3370*	-7.07	0.00
LAW*ES	0.0719*	4.56	0.00	2.7064*	6.64	0.00

Table 4.8

The effect of the *full* earnings seasons on the commonality in liquidity for the whole sample

The table shows the effect of earnings seasons on the average commonality in liquidity as measured by R^2 from bi-weekly regressions of daily values of Amihud measures for individual stocks on the (lead, lag, and contemporaneous) aggregate daily values of Amihud measures and market returns. The R-squared are transformed via the logistic transformation. The regressions are run for the whole sample – 20 countries (from 2003 to 2008). The ES dummy equals 1 during the country's earnings seasons and zero otherwise. OP is the quality of information index (the higher the worse), FREQ is the frequency of earnings seasons in a year, DUR is the duration of the seasons in days, and LAW is the index that combines the country's insider law enforcement dummy with the LLSF (1998) andi-director index. The last four variables are conditional on earnings seasons. That is their values are the products of earnings seasons dummies and the raw values for the four indices. The star (*) denotes the values significant at 5% or better.

Equal-weighted	Intercept	ES	OP*ES	FREQ*ES	DUR*ES	LAW*ES
1	0.8228*	0.0378*				
	0.00	0.04				
2	0.8339*	-0.109*	0.0154*			
	0.00	0.00	0.00			
3	0.8228*	0.1160*		-0.0271*		
	0.00	0.01		0.03		
4	0.822*8	-0.0368			0.0009*	
	0.00	0.21			0.03	
5	0.8209*	-0.0290				0.0251*
	0.00	0.20				0.01
6	0.8339*	0.6396*	0.0529*	-0.3815*	-0.0023*	0.0289*
	0.00	0.00	0.00	0.00	0.01	0.02
Value-weighted						
	Intercept	ES	OP*ES	FREQ*ES	DUR*ES	LAW*ES
1	0.8383*	0.0291				
	0.00	0.09				
2	0.8488*	-0.126*	0.0153*			
	0.00	0.01	0.00			
3	0.8383*	0.0774		-0.0168		
	0.00	0.06		0.13		
4	0.8383*	-0.0285			0.0007	
	0.00	0.27			0.07	
5	0.8370*	-0.0332				0.0225*
	0.00	0.17				0.01
6	0.8488*	0.5868*	0.0505*	-0.3688*	-0.0023*	0.0364*
	0.00	0.00	0.00	0.00	0.00	0.01

N= 9,560

References

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk, Journal of Financial Economics 77, 375-410

Admati, A.R., 1985. A noisy rational expectations equilibrium for multi-asset securities markets, Econometrica 53, 629-657

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects, Journal of Financial Markets 5, 31-56

Amihud, Y., Mendelson, H., Pedersen, L.H., 2005. Liquidity and asset prices, Foundations and Trends in Finance 1, 1-96

Anderson, A.-M., Dyl, E.A., 2003. Market structure and trading volume, Working paper, unpublished.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns, The Journal of Finance 61, 259-299

Atkins, A., Dyl, E.A., 1997. Market structure and reported trading volume: NASDAQ versus the NYSE, Journal of Financial Research 52, 309-326

Barber, B., Odean, T., 2006. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors, Working paper, unpublished

Barclay, M., Hendershott, T., 2004. Liquidity externalities and adverse selection: evidence from trading after hours, Journal of Finance 59, 681-710

Beck, A.D.-K., Levine, R., 2000. A new database on the structure and development of the financial sector, World Bank Economic Review 14, 597–605

Bekaert, G., Harvey, C.R., Lundblad, C., 2007. Liquidity and expected returns: lessons from emerging markets, Review of Financial Studies 20, 1783-1831

Brandt, M.W., Kishore, R., Santa-Clara, P., Venkatachalam, M., 2006. Earnings announcements are full of surprises, Working paper, unpublished

Brockman, P., Chung, D.Y., Perignon, C., 2008. Commonality in liquidity: a global perspective, Journal of Finance and Quantitative Analysis, forthcoming

Butler, M., Kraft, A., Weiss, I.S., 2007. The effect of reporting frequency on the timeliness of earnings: The cases of voluntary and mandatory interim reports, Journal of Accounting and Economics 43, 181-217

Cao, M., Wei, J., 2008. Option market liquidity: commonality and other characteristics, Working paper, unpublished

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns, The Quarterly Journal of Economics 108, 905-940

Chae, J., 2005. Trading volume, information asymmetry, and timing information, Journal of Finance 60, 413-442

Chiang, C.C., Mensah, Y.M., 2006. The inferential value of quarterly earnings announcements relative to other sources of information, Working paper, unpublished

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity, Journal of Financial Economics 56, 3-28

Chordia, T., Subrahmanyam, A., Anshuman R., 2001. Trading activity and expected stock returns, Journal of Financial Economics 59, 3-32

Cochrane, J.H., 2005. Asset pricing, Princeton University Press, Princeton and Oxford.

Constantinides, G.M., 1986. Capital market equilibrium with transaction costs, The Journal of Political Economy 94, 842-863

Constantinides, G.M., Duffie, D., 1996. Asset pricing with heterogeneous consumers, The Journal of Political Economy 104, 219-242

Corwin, S., Lipson, M., 2008. Order characteristics and the sources of commonality in prices and liquidity, Working paper, unpublished

DeFond, M., Hung, M., Trezevant, R., 2007. Investor protection and the information content of annual earnings announcements: International evidence, Journal of Accounting and Economics 43, 37-67

DeGennaro, R.P., Kamstra, M.J., Kramer, L.A., 2006. Seasonal variation in bid-ask spreads, Working paper, unpublished

Djankov, S., LaPorta, R., Lopez-de-Silanes, F., Shleifer, A., 2008. The law and economics of self-dealing, Journal of Financial Economics 88, 430-465

Durnev, A., Kim, E.H., 2005. To steal or not to steal: firm attributes, legal environment, and valuation, Journal of Finance 60, 1461–1493

Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns? The Journal of Finance 57, 2185-2222

Eckbo, B.E., NorlI, Ø., 2002. Pervasive liquidity risk, Working paper, unpublished

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33, 3-57

Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies, The Journal of Finance 51, 55-85

Fama, E.F., MacBeth, J.D., 1973. Risk return and equilibrium: empirical tests, The Journal of Political Economy 81, 607-636

Foster, G., 1981. Intra-industry information transfers associated with earnings releases, Journal of Accounting and Economics 3, 201-233

Frazzini, A., Lamont, O., 2006. The earnings announcement premium and trading volume, Working paper, unpublished

Gallmeyer, M., Hollifield, B., Seppi, D.J., 2005. Demand discovery and asset pricing, Working paper, unpublished

George, T.J., Kaul, G., Nimalendran, M., 1994. Trading volume and transaction costs in specialist markets, The Journal of Finance 49, 1489-1506

Gordon, S., St-Amour, P., 2000. A Preference regime model of bull and bear markets, The American Economic Review 90, 1019-1034

Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets, The American Economic Review 70, 393-408

Hasbrouck, J., 2006. Trading costs and returns for us equities: estimating effective costs from daily data, Working paper, unpublished

Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows and liquidity, Journal of Financial Economics 59, 383-411

Healy, A.H., Palepu, K., 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure, Contemporary Accounting Research 16, 485–520

Huang, M., 2003. Liquidity shocks and equilibrium liquidity premia, Journal of Economic Theory 109, 104-129

Huberman, G., Halka, D., 2001. Systematic liquidity, Journal of Financial Research 24, 161-178

Hvidkjaer, S., 2006. Small trades and the cross-section of stock returns, Working paper, unpublished

Ince, O., Porter, R.B., 2006. Individual equity return data from thomson datastream: handle with care, Journal of Financial Research 29, 463-479

Kavajecz, K.A., 1999. A specialist's quoted depth and the limit order book, The Journal of Finance 54, 747-772

Keim, D.B., 1983. Size-related anomalies and stock return seasonality: further empirical evidence, Journal of Financial Economics 12, 13-33

Kim, O., Verrecchia, R.E., 1991. Trading volume and price reactions to public announcements, Journal of Accounting Research 29, 302-321

Korajczyk, R.A., Sadka, R., 2008. Pricing the commonality across alternative measures of liquidity, Journal of Financial Economics 87, 45-72

Karoliy, A.G., Lee, K.-H., van Dijk, M.A., 2008. Common patterns in commonality in returns, liquidity, and turnover around the world, Working paper, unpublished

Koski, J., MIchaely, R., 2000. Prices, liquidity, and the information content of trades, The review of financial studies 13, 659-697

Kovacs, T., 2005. Intra-industry information transfers: Evidence from earnings announcements, Working paper, unpublished

Krinsky, I., Lee, J., 1996. Earning announcements and the components of the bid-ask spread, The Journal of Finance 51, 1523-1536

Kyle, A.S., 1985. Continuous auctions and insider trading, Econometrica 53, 1315-1336

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance, Journal of Political Economy 106 1113–1155

Lee, C.M.C., 1992. Earnings news and small traders: an intraday analysis, Journal of Accounting and Economics. 15, 265-303

Lee, C.M.C., Mucklow, B., Ready, M.J., 1993. Spreads, depths, and the impact of earnings information: an intraday analysis, The Review of Financial Studies 6, 345-375

Lesmond, D.A., 2005. Liquidity of emerging markets, Journal of Financial Economics 77, 411-452

Leuz, K., Verrecchia, R.E., 2000. The economic consequences of increased disclosure, Journal of Accounting Research, 91–124

Lo, A.W., Wang, J., 2000. Trading volume: definitions, data analysis, and implications of portfolio theory, The Review of Financial Studies 13, 257-300

Longstaff, F.A., 2005. Asset pricing in markets with illiquid assets, Working paper, unpublished

Milgrom, P., Stokey, N., 1982. Information, trade and common knowledge, Journal of Economic Theory 26, 17-28

Ng, J., 2006. Earnings surprises and changes in liquidity, Working paper, unpublished

O'Hara, M., 2003. Presidential address: liquidity and price discovery, The Journal of Finance 58, 1335-1354

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns, Journal of Political Economy 111, 642-685

Pistor, M.R., Gelfer, S., 2000. Law and finance in transition economies, The Economics of Transition 8, 325–368

Penman, S.H., 1987. The distribution of earnings news over time and seasonality in aggregate stock returns, Journal of Financial Economics 18, 199-229

Reinganum, M.R., 1983. The anomalous stock market behavior of small firms in january: empirical tests for tax-loss selling effects, Journal of Financial Economics 12, 89-105

Roll, R., 1983. On computing mean returns and the small firm premium, Journal of Financial Economics 12, 371-387

Schwert, W.G., 1989. Why does stock market volatility change over time? The Journal of Finance 44, 1115-1155

Smith, R.T., 1993. Market risk and asset prices, Journal of Economic Dynamics and Control 17, 555-570

Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume, Review of Financial Studies 19, 1531-1537

Stoll, H.R., 2000. Friction: presidential address, Journal of Finance 55, 1479-1515

Sun, Q., 2006. The timing of earnings announcements and market response to earnings news, Working paper FMA 2006 meeting, unpublished

Tsay, R.S., 2005. Analysis of financial time series, Wiley, New York.

Veronesi, P., 1999. Stock market overreactions to bad news in good times: a rational expectations equilibrium model, The Review of Financial Studies 12, 975-1007

Wang, J., 1993. A model of intertemporal asset prices under asymmetric information, The Review of Economic Studies 60, 249-282

Watanabe, A., Watanabe, M., 2008. Time-varying liquidity risk and the cross section of stock returns, Review of Financial Studies forthcoming

Welker, M., 1995. Disclosure policy, information asymmetry, and liquidity in equity markets, Contemporary Accounting Research 11, 801–827

VITA

Andrei L. Nikiforov was born on October 2, 1975 in Perm region, Russian Federation. He received a B.S. and M.S. degree in Geophysics from the Perm State University in 1999.

While attending the University, Andrei worked part-time at the Mining Institute of the Russian Academy of Sciences. After graduation Andrei continued working at the Mining Institute on a full-time basis as a junior scientist. His responsibility was to develop and estimate large scale geodynamics models. In late 2001 Andrei moved to the United States to work at the Geodynamics Laboratory at the University of Missouri, Columbia. There he studied the Madrid Fault Zone that produced one of the largest earthquakes in the US more than 200 years ago.

In January of 2003 Andrei joined the MBA program at University of Missouri, Columbia full time. In the Fall 2005, just one semester before the completion of his MBA, Andrei joined the Ph.D. program in Finance at the University of Missouri. He graduated in July 2009. Andrei will join the Finance Department at Rutgers University, Camden N.J. as an Assistant Professor in Fall 2009.

Andrei is married to Natalia and has two children, Daniel and Sophia.