AN ESSAY ON ASSET PRICING AND INDIVIDUAL TRADING BEHAVIOR

by

XUE HAN

(Under the Direction of Jeffry Netter and Annette Poulsen)

ABSTRACT

According to popular views in asset pricing, investors require higher returns for holding stocks they perceive to be more risky. However, many studies provide empirical evidence that returns are not always related to risks. These deviations are called anomalies. One of the well-documented anomalies is the new issue puzzle, where stocks of newly listed firms (IPO firms) underperform. The first two essays of my dissertation discuss why stocks of IPO firms perform poorly, and, despite their underperformances, the advantages related with going public.

In my first essay, I examine whether IPO firms underperform because they are less risky. Because risk is difficult to measure, previous studies use ex post realized returns as a proxy for risk, which has been shown to deviate from investors' perception of risk. I use a new measure of ex ante expected return, the market-implied cost of capital (ICC). With this measure, I find that investors actually expect to earn higher returns from investing in IPO firms than in similar established firms. However, investors are negatively surprised by the performances of newly listed firms. These results contradict previous arguments that IPO firms are less risky. My second essay investigates firms' advantages in going public. I find that, by going public, large IPO firms can exert competitive pressure on their competing firms. Consequently, their competing firms experience drops in their market value, declines in their operating performances, and their default probability increases significantly. Moreover, these competing firms' stock returns become more sensitive to macro-economic conditions and also exhibit positive risk-adjusted returns. These results suggest that investors perceive competing firms as having higher risk exposure than previously.

In my third essay, I study how stock liquidity affects individual investors' preferences of holding periods. I empirically document that individual investors' holding periods are negatively related to stock liquidity, both in the United States and Finland, suggesting investors minimize their transaction costs per period. This effect is stronger for financially sophisticated investors. It help shed new lights on individual investors' trading behavior.

INDEX WORDS: Going public, IPO firm, New issue puzzle, Competitive advantage, Liquidity, Transaction cost, Individual Investor, Holding period

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DEDICATION

I dedicate this dissertation to my beloved parents, and daughter.

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CHAPTER 1

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1. Introduction

Once a firm becomes publicly listed, its aftermarket stock prices should reflect the firm's intrinsic value appropriately. Consequently, risk-adjusted post-listing stock performances should be unpredictable. However, empirical studies find that newly listed firms underperform the market within three to five years after their offerings (e.g., Ritter, 1991, Loughran & Ritter, 1995), which has attracted great academic interest. Some studies (Eckbo & Norli, 2005, Eckbo, Masulis, & Norli, 2000) argue that IPO firms underperform because they are less risky. They argue that equity issuance via IPOs helps newly listed firms reduce leverage and increase liquidity, thus alleviating distress and liquidity risk.

One problem related to these arguments is that to measure risk, these studies use ex-post realized returns to proxy for ex-ante expected returns, assuming that ex-post realized returns provide a good estimate of ex-ante expected returns, reflecting the level of risk. However, ex-ante expected returns could deviate significantly from ex-post realized returns. Elton (1999) argues that information events may not cancel each other out in small samples where firms in the portfolio are affected similarly. Under such a scenario, ex-post realized returns can be poor proxy for ex-ante expected returns. In the case that ex-post realized returns are noisy proxy for expected returns for IPO firms, the explanation that IPO firms are low-risk firms is weak.

On one hand, newly listed firms as a portfolio are likely to be affected similarly by economic shocks and information surprises. On the other hand, newly listed firms are still relatively young and small. Their value is embedded mostly in their growth opportunities. Therefore, there are more uncertainties related to newly listed firms than to established firms, and stock returns of newly listed firms could be more volatile. According to Lundblad (2007), higher return volatility could impede the detection of the true risk-return relationship. Overall, it is unclear whether realized returns for new-issue firms could proxy for their ex-ante expected returns and capture the true risk-return relationships for IPO firms.

To shed more light on investors' expectations for newly listed firms, this study employs a new measure of market ex-ante expected returns: implied cost of equity capital (ICC). My study shows that newly listed firms exhibit higher return volatilities than their size matched firms, as well as than their size and book-to-market matched firms. Thus, ex-post realized returns provide noisy proxy for investors' ex-ante expected returns for the portfolio of IPO firms. The lower realized returns of IPO firms could not represent investors' true expectations for IPO firms. Consistently, I document that IPO firms have higher implied costs of capital (ICC) than their matched firms. These results imply that the underperformance of new issues occurs because these firms perform worse than investor expectations, and investors become negatively surprised. In other words, the new issue puzzle is likely to be attributable to the unexpected negative cash flow shocks.

Consistent with my speculation, I do find that IPO firms have negative unexpected profits, while their matched firms have insignificant unexpected profits. This suggests that realized cash flows for newly listed firms are lower than investors' expectations. Furthermore, this result is stronger for small and growth IPO firms. However, these negative cash flow surprises dor the IPO firms eventually disappear after three years subsequent to their offerings. There are two possible explanations for these temporary cash flow shocks. One could be that the limited trading periods for newly listed firms prevent investors from fully digesting the large amount of information included in the IPO firms' prospectus, and to make it worse, information regarding the historical performances of these new issue firms is also limited. An alternative could be that it is difficult for investors to accurately evaluate the growth opportunities embedded in IPO firms.

Investors expect to earn higher returns by investing in IPO firms but are surprised by IPO firms' under-expectation performances, which consequently generates the lower realized returns. As investors learn more about IPO firms moving forward, these underperformances disappear.

That IPO firms have higher market implied costs of equity (ICC) than their size or size and book-to-market matched firms implies that investors perceive IPO firms to be riskier than similar firms, which is inconsistent with the previous argument that IPO firms have reduced risk. The different conclusion that Eckbo, Masulis and Norli (2000) draw, that IPO firms have higher liquidity and lower liquidity risk, may come from their measure of liquidity. They show that IPO firms have higher turnover than matched firms, while turnover is argued to proxy for information uncertainty rather than liquidity. In comparison, I measure liquidity using other instruments, including the Amihud illiquidity ratio, Roll's measure, zero return frequency, effective tick size, and Pastor and Stambaugh's gamma measure. I discover no evidence that IPO firms have higher liquidity than their matched firms. These results contradict previous findings that explain IPO firms' lower realized returns as a hedge against liquidity risk. Overall, my results provide a new explanation for IPO underperformance.

The rest of the paper is organized as follows. Section II introduces related literature on the new issue puzzle. Section III develops hypotheses. Section IV describes the sample and data. I investigate the differences between implied cost of capital and ex-post realized returns for IPO and matched firms in section V. Section VI examines the unexpected performances for IPO and matched firms. Section VII provides robustness tests, and section VIII concludes the paper.

2. Previous Literature

2.1 New Issue Puzzle

Starting with Ritter's (1991) study, people began to realize that newly listed firms underperform the market within three to five years after they go public. Longhran and Ritter (1995, 1997) further document that the underperformance of newly listed firms not only exists in the stock market, but newly listed firms also exhibit lower profitability after they go public. While the stock market underperformances seem quite likely an asset pricing issue, the declining operating performances add some behavioral flavor to the problem. Various explanations have been proposed to solve this puzzle.

Among behavioral explanations, Jensen (1968) suggests that agency problem could be more severe in IPO firms that have more information asymmetry. Mikkelson, Partch, and Shah (1997) argue that divergence in ownership and control rights accompanied with going public decrease executive incentives, making the free cash flow problem more severe. Newly listed firms squander cash, which generates low post-issuance returns. Consistently, Jain and Kini (1994) document that after the offerings, operating performance and profitability of newly listed firms' decline, which suggests that these firms waste the money they raised after they get listed.

However, Brav, Geczy and Gompers (2000) find that underperformances of newly listed firms are concentrated in the smallest size quintile and the highest market-to-book quintile, i.e. small growth IPO firms underperform the most. This casts some doubt on previous behavioral explanations, since small growth firms have more growth opportunities, and they usually don't have much cash to waste. Brav, et al. (2000) argue that "there should be a common factor behind the new issue puzzle and the small growth anomaly". However, it is unclear whether the common factor is a risk factor or another behavior story. It could be either that IPO firms are just the type of firms we don't know how to price (behavior story), or that they are a certain type of firms that have lower risk and thus lower returns (risk story).

The stream of literature providing risk explanations for the new issue puzzle generally argues that IPO firms on average have lower risk, and the new issue puzzle is simply an artifact of missing risk factors. Eckbo, Masulis, and Norli (2000) argue that the new issue puzzle results from a reduced default risk for IPO firms after they go public. Specifically, when firms issue equity, they lower their leverage and become less likely to default. Consequently, investors require low returns for new issue firms. But the problem is that default risk is negatively related to stock returns cross sectionally. Firms with higher distress risk should have lower realized returns (i.e. distress anomaly as mentioned in Dichev, 1998), according to which new issues with reduced distress risk should have higher returns. Eckbo and Norli (2005) propose another risk explanation and claim that issuing equity creates additional liquidity, which makes the IPO firms' stock less risky. But it is unclear why the extra float and turnover created by the new issue fail to continue generating lower returns beyond the three- to five-year horizon after the firms go public. Besides, their measure of liquidity can arguably capture liquidity. Lyranders, Sun and Zhang (2008) argue that firms only raise capital when they have projects with low required rates of return. With an investment factor, Lyranders et al. (2008) show that newly listed firms resemble firms that have high investments. However, their story can hardly shed light on why the underperformances concentrate in small growth IPO firms but not in large and value firms. Overall, the existing literature is ambiguous regarding whether IPO firms have lower risk.

Some related studies also show that firms with higher discretionary accruals have stronger post-IPO underperformance (Rangan, 1998, Teoh, Welch & Wong, 1998). This finding suggests that investors are likely to be misled by accounting information and believe the firms are better than they actually are. Investors eventually realize this and adjust their expectations, and IPO underperformances eventually disappear. However, a recent study by Armstrong, Foster, and

Taylor (2008) finds that after controlling for common biases in the estimation of discretionary accruals, there is rare evidence that IPO firms engage in earnings management, and lower profitability for IPO firms following their issuances is partially due to their large amount of investment.

A sound explanation for the new issue puzzle has to answer the following questions altogether: why it exists, why it is stronger for small growth firms, and why it lasts only for three to five years and then disappears. However, in general, existing explanations can only answer part of these questions. Recent developments in the research of ICC measures provides us with a better measure of ex-ante expected returns and offers us a new opportunity to revisit the new issue puzzle. The current paper attempts to tackle the new issue puzzle and answer all the three questions at the same time, using ICC measures. I define the measure of ICC in the following sections and then develop my test hypotheses.

2.2 Implied Cost of Capital (ICC)

Previous studies involving realized returns usually assume that ex-post realized returns are a decent estimate of ex-ante expected returns. However ex-post realized returns could be a noisy proxy for expected returns (Pastor et al. 2008). Elton (1999) provides several examples to demonstrate that the relationship between risk and realized returns can be anomalously negative, and the deviation of realized returns from ex-ante expected returns could persist even over longer periods. He argues further that information shocks can affect firms in a portfolio in similar ways that even using portfolio returns could not alleviate this concern.

To address this concern, recent finance and accounting studies (Gebhardt, Lee, & Swamimathan, 2001, Hou, van Dijk & Zhang, 2012) developed an alternative measure of ex-ante expected returns: the implied cost of capital (ICC). ICC is defined as the internal rate of return that equals the present value of firms' expected cash flows in the future to their current stock prices in the stock market. In other words, ICC is the discount rate that the market uses to discount the firms' future cash flows. The computation of ICCs relies neither on noisy realized returns nor any specific asset pricing model (e.g., CAPM or Fama French multi factor models). In contrast with previous proxies, the ICC method derives expected returns from stock prices and cash flow forecasts. Pastor et al. (2008) show that under reasonable assumption about dividend growth and payout process, ICCs can be a better approximation for the firms' expected returns than ex-post realized returns.

ICCs have several advantages as measures of ex-ante expected returns. First, by construction, ICC is a forward-looking discount rate. Moreover, it doesn't require any specific asset pricing model. For every anomaly that has been documented, there is ongoing debate regarding whether it is a model problem or market inefficiency. Since the estimation of ICC involves no asset pricing models, using ICC measures to explain asset pricing puzzles is exempt from this critique of model problem.

According to the estimation method of future expected cash flows, ICCs can be categorized into two types. ICC measures predict firms' future cash flows with analyst earnings forecasts are called analyst-based ICCs (e.g., Gordon & Gordon, 1997, Claus & Thomas, 2001, Gebhardt et al. 2001, Easton, 2004, Ohlson & Juettner-Nauroth, 2005). Though this method doesn't depend on any earnings forecast model, it has several weaknesses. First, it is documented that small firms are underrepresented in analyst coverage samples. This makes the analyst-based ICC measures have limited coverage, and tend to cover more large firms than small. Second, even for firms with analyst coverage, I/B/E/S only began its coverage in 1982, which makes the study of earlier periods unlikely. Earnings forecasts beyond the second year or long-term earnings forecasts may not be available (which are required to calculate analyst-based ICCs). Lastly, analysts are reported to be over-optimistic, and thus their cash flow forecasts can exhibit upward biases.

To address these deficiencies, Hou, Van Dijk, and Zhang (2012) propose another method to estimate ICC. They derive earnings forecasts from cross-sectional earnings forecast models instead of using analyst forecasts, and call the new measure model-based ICCs. The estimation of model-based ICCs uses a large amount of cross-sectional data and has great statistical power. The coverage of model-based ICCs is much larger than that of analyst-based ICCs. Hou et al. (2012) demonstrate further that for firms with a poor information environment (small or young firms), model-based ICCs perform better than analyst-based ICCs. Relating to the current context, IPO firms tend to be relatively small and young firms with poor information environments; where analysts may have more information advantages. However, they are arguably superior to model forecasts (Brown et al. 1987). Therefore, I apply both analyst-based and model-based ICCs in the current study to measure ex-ante expected returns for IPO firms[1].

2.2.1 Analyst-Based ICC

The implied cost of capital measures used in Gerbhardt, Lee, and Swaminathan's (2001) study (GLS 2001 hereafter) are calculated based on a form of discounted cash flow model called the residual income model, or the GLS model, which is shown below:

$$P_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r_e)^i}$$

where the current stock prices equal to the present value of all future expected cash flows. According to "clean surplus" accounting, changes in book equity are equal to earnings less dividends (i.e. $B_t = B_{t-1} + NI_t - D_t$). The above equation is transformed into the following:

[1] The current study focuses on the GLS (Gerbhardt, Lee, & Swaminathan, 2001) model. There are several other models in the literature. However, according to Larocque and Lyle (2014), not all ICC measures work, while the GLS measure works.

$$P_t = B_t + \sum_{i=1}^{\infty} \frac{E_t(NI_{t+i} - r_e B_{t+i-1})}{(1+r_e)^i}$$

$$= B_t + \sum_{i=1}^{\infty} \frac{E_t((ROE_{t+i} - r_e) B_{t+i-1})}{(1+r_e)^i}$$

where B_t refers the book value at time t, NI_{t+i} refers to the net income for period t+i, and ROE_{t+i} represents the after-tax return on book equity for period t+i. To make it practical, the infinity form above is simplified into an estimation for a certain specific period plus the expected value beyond that time period as follows:

$$P_t = B_t + \frac{FROE_{t+1} - r_e}{(1+r_e)} B_t + \frac{FROE_{t+2} - r_e}{(1+r_e)^2} B_{t+1} + \frac{FROE_{t+3} - r_e}{(1+r_e)^3} B_{t+2} + TV$$

where TV is usually called "terminal value," and:

$$TV = \sum_{i=4}^{T-1} \frac{FROE_{t+i} - r_e}{(1+r_e)^i} B_{t+i-1} + \frac{FROE_{t+T} - r_e}{(1+r_e)^{T-1}} B_{t+T-1}$$

$FROE_{t+i}$ is the forecasted ROE for period t+1, and is calculated as $FEPS_{t+i}/B_{t+i-1}$. According to GLS (2001), earnings for the first three years are explicitly estimated using analyst forecasts from I/B/E/S. Earnings beyond the first three years are assumed to be mean reverting to the median industry ROE eventually by period t+T through linear interpolation[2]. B_{t+i} is estimated as $B_{t+i-1} + FEPS_{t+i} - FDPS_{t+i}$ according to the "clean surplus" principle, where $FDPS_{t+i}$ is the forecasted dividend per share and is estimated using the current dividends payout ratio (k=D/E=$FDPS_{t+i}/FEPS_{t+i}$). The terminal value is calculated as a perpetuity, where T=12.

Analyst-based ICCs have been employed in several empirical works. Chava and Purnanandam (2010) attempt to explain the distress anomaly with analyst-based ICCs. They

[2] Median industry ROE is calculated as the moving median of past ROEs from all firms in the same Fama French 48 industry. Loss firms are excluded on the basis that the population of profitable firms better represents the long-term industry equilibrium.

document a positive relationship between analyst-based ICCs and distressed risk, suggesting that investors expect to earn a high risk premium for investing in stocks with high default risk. But investors are negatively surprised by the lower-than-expected performances of distressed firms during the 1980s, translating into lower realized returns and the negative correlation between distress risk and realized stock returns. Campbell, Dhaliwal and Schwartz, Jr. (2012) find that increases in internal financing constraints increases ICCs, resulting in foregoing investment.

However, one disadvantage of using analyst-based ICCs is that there is limited analyst coverage for firms, and some works have already pointed out that analysts tend to cover larger and more visible firms. This inevitably brings survivorship bias to empirical works that use analyst-based ICCs measures.

2.2.2 Model-Based ICC

Hou, van Dijk and Zhang (2012) develop another approach to estimate the internal cost of capital. Instead of using analyst forecasts to predict future earnings, they develop a cross-sectional profitability model to estimate future earnings. The model is an extension and variation of the earnings forecast model used in Fama and French (2000; 2006), and Hou and van Dijk (2011) and is as follows:

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \varepsilon_{i,t+\tau}$$

where $E_{i,t+\tau}$ refers to the earnings of firm i in year t+ τ ($\tau = 1\ to\ 3$), $A_{i,t}$ is the total asset, $D_{i,t}$ is dividends payments, $DD_{i,t}$ is a dummy variable which equal to 1 for firms paying dividends and 0 otherwise, $NegE_{i,t}$ is another dummy variable which equal to 1 for firms with negative earnings in year t, and zero otherwise, $AC_{i,t}$ denotes accruals.

This model is estimated using pooled data from the previous 10 years. Forecasted earnings are calculated by multiplying the accounting variables for each firm with estimated coefficients from the regression. Once the forecasted earnings are calculated, ICCs are estimated similarly with the same procedure as used in the GLS model. The only difference is that expected earnings for the first three years now come from the estimation of the above earnings forecast model rather than from analyst earnings forecasts. Hou, van Dijk, and Zhang (2012) document that the model-based ICCs have more coverage for firms, lower levels of forecast bias, and higher levels of earnings response coefficient (ERC) than analyst-based ICCs during the sample period from 1982-2008. In unreported results, I find patterns and differences between model-based ICCs and analyst-based ICCs for IPO firms from year 1982 to year 2014 are similar to those documented in their study.

3. Hypotheses Development

Some studies try to explain the new issue puzzle by asserting that IPO firms have less risk (lower default risk or liquidity risk), but these studies are based on the assumption that ex-post realized returns is a good proxy for ex-ante expected returns and is positively related to the risk of underlying stocks. But Elton (1999) argues that ex-post realized returns are noisy proxies for ex-ante expected returns. Moreover, Lundblad (2007) argues that higher return volatility could impede the detection of true risk-return relationships.

H1: IPO firms have higher return volatility than similar firms

Since IPO firms are likely to be young and small, they are more likely to fail and have higher exit rates (Haltiwanger, Jarmin & Miranda, 2012). In addition, young firms are more vulnerable to economic shocks, which implies that IPO firms are likely to have higher volatility. If this is the case, then ex-post returns could not serve as a good proxy for ex-ante expected returns. Therefore, first I examine the idiosyncratic volatility of newly listed firms and existing listing firms after the offerings. The finding that IPO firms have higher return volatility justifies the use of ICCs as a proxy for ex-ante expected returns for IPO firms.

H2: IPO firms exhibit higher ICC than similar firms.

If, as suggested by previous risk explanation, IPO firms are less risky, then investors would require lower returns for holding IPO firms' stock, and I should observe a lower discount rate for their future cash flows (lower ICCs). Alternatively, if lower realized returns of IPO firms result from overvaluation, these stocks should have an abnormally low implied risk premium until the mispricing is corrected. This implies we should observe a lower ICC for new issuing firms after they go public[3]. If IPO firms raise money because they have projects with lower required rates of return as suggested by Lyandres, Sun, and Zhang (2008), I also expect to observe lower ICCs for IPO firms than for similar firms.

In contrast, behavioral stories arguing that IPO firms waste money have no clear prediction regarding whether IPO firms should have higher or lower ICCs. If IPO firms are just certain firms that investors have difficulty valuing as suggested by Brav et al. (2000), it is likely that the ex-post realized returns deviate from ex-ante expected returns. There is no prediction from their paper regarding the direction the deviation might take. However, Brav et al., (2000) find that the majority of IPO firms belong to the smallest size quintile and highest market-to-book quintile (small growth firms)[4], which have higher uncertainty and are more likely to fail intuitively. Therefore, I expect higher ICCs for IPO firms.

H3: IPO firms have negative unexpected profitability and negative analyst forecast error.

[3] Overvaluation implies that the current stock price is higher than its true value, which suggests that investors discount the future cash flows of these stocks with extremely low discount rates. Therefore, overvaluation implies lower ICC for newly listed firms.

[4] Brav et al. (2000) use 5x5 size and market-to-book portfolio.

The finding that IPO firms have higher ICCs suggests that investors expect to earn a higher risk premium for holding the stocks of IPO firms. However, realized ex-post returns of IPO firms are lower than the market (Loughran & Ritter, 1991, 1995; Ritter & Welch, 2001). This suggests that investors must be negatively surprised by the performances of IPO firms. In other words, there should be negative cash flow shocks for newly listed firms. To investigate this problem, I compare further the unexpected profitability for IPO firms with that of similar firms. I expect that IPO firms experience more negative earnings surprises than similar firms.

One of the explanation about the relative higher ICCs of IPO firms compared with similar firms could be investors perceive IPO firms to be more risky than similar firms. I explore further what kind of risk might be related to IPO firms. In the sense that there is less "soft" information in the market for the newly listed firms compared with firms that have been listed for a long time, there is probably higher information uncertainty for newly listed firms. Eckbo and Norli (2005) document that IPO firms have significantly higher turnover than similar firms, which also suggests that information uncertainty is likely to be higher for IPO firms.

4. Sample and Data Description

My initial sample includes all the firms that went public between 1982 and 2013, obtained from the SDC new issue database. Since the calculation of analyst-based ICC requires available analyst forecasts from I/B/E/S, which is commonly available for firms since 1982, thus, my sample starts in 1982. Following the previous literature on IPOs, I exclude LBOs, spin-offs, carve-outs, unit issues, reverse LBOs, foreign issues, and financial firms. IPOs have to be listed in major exchanges in the United States (NYSE/AMEX/NASDAQ). There are 4335 IPO event firms available at the intersection of CRSP and Compustat. Among these firms, 67% have analyst coverage on I/B/E/S.

I define matching firm using both size, and size and book-to-market together following Eckbo and Norli (2005). For a certain firm i, its matching firm has to be public listed on NYSE/AMEX/NASDAQ for at least four years before the year of the IPO event. A size-matched firm is the firm which is closest in market capitalization to the IPO firm, where the IPO firm's market capitalization is measured as the first available market capitalization on the CRSP monthly tapes after the offering date. Size and book-to-market matched firms refer to firms which have equity market values within 30% of the issuers' market capitalization, and have the closest book-to-market ratio to that of the IPO firms, where book-to-market ratios are measured at the end of the year prior to the issue year. Altogether, there are 4196 IPO event firms with size matches and 4158 IPO event firms that have size and book-to-market matched firms.

5. Empirical Results

In this section, I examine the post-issuance returns for newly listed firms after their offerings in order to provide recent evidence of IPO underperformance. Monthly IPO portfolios are constructed by including all firms that go public within the past 36 months. Table 1.1 reports the returns of IPO portfolio in calendar time. Panel A documents the results using equal-weighted returns, while panel B documents the results using value-weighted returns. Results in the first column show that IPO firms generally underperform the market, where the equal weighted CAPM alpha is a monthly significant -0.51%. The value weighted CAPM alpha is significantly at -0.55% per month. Once taking into account the size and value premium, momentum and investment factor, the underperformance become insignificant. These results are consistent with previous studies.

From column 2 to 4 in Table 1.1, I sort IPO firms into three portfolios according to their market capitalization. Results show that underperformance of new issues concentrates in the smallest size portfolio and highest market-to-book portfolio, consistent with previous evidence (e.g. Brav, Geczy, and Gompers 2000, Loughran and Ritter 1991, 1995, Ritter and Welch 2001). Alphas for equal weighted returns of the smallest size portfolio range from -0.46% to -0.97%, while alphas for value weighted returns range from -0.91% to -1.26%. Returns for different market-to-book portfolio are reported from column 6 to 8. Only IPO firms with the highest market-to-book ratio underperform the market. For firms with the highest market-to-book ratios, alphas for the equal weighted returns range from -0.56% (significant) to 0.23% (insignificant), while alphas for the value weighted returns range from -0.78% (significant) to -0.03% (insignificant). The underperformance goes away after controlling for size, market-to-book, momentum and investment [5]. To conclude, with the calendar time portfolio approach recommended by Fama and French (1993), IPO firms included in my sample still underperform the market, and the underperformance is strongest for small and growth IPO firms.

5.1 Analyst-based ICC

I calculate analyst-based ICCs for each IPO firm, its size matched firm and size and book-to-market matched firm for up to five years after its offering year. I compare their ICCs and report the results in Table 1.2. Panel A and B report the analyst –based ICCs for size-matched firms and size and book-to-market matched firms respectively. The results indicate that IPO firms have higher ICCs than their matched firms. The results start from one year after IPO events, since only

[5] One thing worth mentioning is that all IPO firm portfolios load negatively on the investment factor, suggesting that IPO firms are similar to high investment firms.

close to 15% of the IPO firms are covered by analysts during the year they go public (year 0). The percentage of IPO firms being covered by analysts increase to around 75% in the second and third year, and then stay around 60% for the following two years.

Panel A of Table 1.2 shows that analyst-based ICCs of IPO firms are always significantly higher than their size matches. Results are similar for size and book-to-market matches in Panel B, ICCs of newly listed firms are significantly higher than those of their matched firms even after taking into account of their growth opportunities. It is worth noting that moving from year 1 to 5, ICCs for matched firms are relative stable, while in contrast, ICCs of IPO firms decrease almost monotonically. This suggests that investors required rate of return decline through time, implying that investors perceive the risk of IPO firms may decrease eventually after they go public.

5.2 Model-based ICC

People might argue that analysts exhibit biases in the forecasts (i.e. over-optimistic), and the relative higher ICCs for IPO firms could come from analysts' over-optimism towards IPO firms. To mitigate this concern, I estimate the model-based ICCs for IPO firms and their matched firms following the procedure in Hou, van Dijk, and Zhang (2012).

Table 1.3 documents the estimated results for model-based ICCs. Panel A reports the estimated coefficients for the earnings forecast model included in Hou, van Dijk, and Zhang (2012). The model is estimated with pooled data from the previous 10 years. The cross-sectional earnings forecast model does capture a substantial part of the variation in future earnings. The average adjusted R-squares for the one-, two-, and three-year ahead earnings are 87%, 82%, and 79% respectively. The estimated coefficients are consistent with those reported in Hou, van Dijk, and Zhang (2012). Earnings are highly persistent. Specifically, the estimated coefficients for past earnings are 0.80, 0.72, and 0.71 for the one-, two-, and three-year-ahead earnings regressions, respectively. Earnings are also significantly positively correlated with asset and dividends payout, but negatively correlated with accruals. The negative earnings dummy is also significantly positively correlated with future earnings.

I calculate expected earnings for each firm for the next three years respectively using the estimated coefficients documented in panel A in each year. Assuming all firms' ROEs to be mean reverting and to reach industry median ROE by year 11 (the same as in analyst-based ICCs), I calculate for each firm every year the implied discount rate that equals the present value of its future expected cash flows to its current stock price. The estimated discount rates are the model-based ICCs. Panel B of Table 1.3 compares the model-based ICCs of IPO firms with those of their matched firms. Similar to previous results with analyst-based ICCs, Table 1.3 panel B shows that model-based ICCs for IPO firms are also always significantly higher than those for their size matched firms, as well as those for their size and book-to-market matched firms. These results confirm my second hypothesis that IPO firms have higher discount rates, which implies that investors expect to earn higher returns from investing in IPO firms.

6. Negative Cash Flow Shocks

Although empirical results in the previous session show that IPO firms have higher ICC than similar firms, alphas calculated from ex-post realized returns are small and negative for IPO firms. One possibility for the lower realized returns could be that newly listed firms are affected by some negative economic events, and experience unexpected negative cash flow shocks on average. To investigate this possibility, I examine the unexpected profitability for IPO firms and their matched firms. If the lower realized returns are attributable to the negative cash flow shocks for IPO firms, then I expect IPO firms to have negative unexpected profitability and negative analyst forecast errors during the years they underperform.

6.1 Unexpected profitability

To calculate profitability shocks, I need to compute the expected profitability first, which is estimated from the profitability forecasting model proposed by Fama and French (2000), and expanded by Vuolteenaho (2002), Hou and Robinson (2006). Unexpected profitability is the residual from the profitability model. Specifically, I estimate the following model with Fama-Macbeth regression:

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t$$

where E/A measures profitability, and is calculated as earnings scaled by the book value of total asset; V/A is the ratio of market value of asset to the book value of asset; DD is a dummy variable for non-dividend-paying firms; and D/B is the ratio of dividend payments to book equity. I add lagged profitability following Vuolteenaho (2002). Regression residual captures unexpected profitability for each firm-year observation.

Panel A of Table 1.4 reports the average estimated coefficients from the Fama-Macbeth regressions. Loadings on dividends payout and the dividend payer dummy are statistically significant, and have the expected signs, suggesting that dividends-paying firms have higher profitability than non-dividends-paying firms, consistent with the results reported in Hou and Robinson (2006) and Fama and French (2000). Lagged profitability is positively related with current profitability and highly significant. Inclusion of lagged profitability helps improve the regression R^2 to 48.6% as suggested in Vuolteenaho (2002)[6].

[6] The only difference from previous results is that the estimated coefficient on V/A reverses its sign. It might be attributable to the fact that my sample period has more observations (weight) around internet bubble period.

Panel B of Table 1.4 compares the unexpected profitability of IPO firms and those of their matched firms. Results in column 3 and 7 indicate that IPO firms always have negative unexpected profitability during the first three years after their offerings, ranging from -4.2% to -0.51%. However, these negative cash flow suprises for newly listed firms decrease in magnitude afterwards, and eventually these IPO firms begin to have slightly positive unexpected earnings in the fourth and fifth year after their offerings.

In contrast to the newly listed firms, matched firms always have positive earnings surprises. As shown in Table 1.4 column 4 and 8, the positive earnings surprises for the matched firms range from 0.88% to 1.28%. The differences between IPO firms and matched firms are always significant during the first three years after the offering. Later, these differences in unexpected profitability between IPO firms and matched firms disappear. This helps to shed some lights on why IPO underperformances eventually goes away around five years after their offerings.

6.2 Analyst forecast errors

Besides unexpected profitability, I also compare analyst forecast errora for IPO firms' earnings and matched firms' earnings to examine how they change during the first five years after the offerings. Analyst forecast errors are computed as the differences between actual EPS and forecasted EPS. Table 1.5 presents analyst forecasts errors for both the IPO firms and their matched firms for up to five years after the offering. First, on average all analyst forecast errors are negative, which implies that analysts are generally over-optimistic. Moreover, there is no significant difference between analyst forecast errors for IPO firms and those for matched firms. However, this result has to be interpreted with cautions. First, on average, analysts only cover around 60% to 75% of newly listed firms during the first 5 years after they go public. This means that results related with analyst forecast errors may not be representative of all IPO firms. Second, it is documented that analysts tend to cover relatively larger and visible firms, which perform well. This is also true for IPO firms. In unreported results, I show that IPO firms covered by analysts perform better than the rest IPO firms. Thus the insignificant differences between analyst forecast errors for IPO and matched firms might be the result of survivorship bias and could only be explained as that there is no significant differences in analyst forecast errors between good-performing IPO firms and their matched firms.

6.3 Cross Sectional Cash Flow Shocks

Since empirical results show that the IPO underperformances mainly concentrate in small growth IPO firms, I specifically examine the negative cash flow shocks for each IPO size and book-to-market portfolio. If my hypothesis that negative cash flow shocks attribute to IPO underperformance is true, I should observe the negative cash flow shocks are most significant in small and growth IPO firms. In unreported results, I find this is the case. Only small and growth IPO firms have negative unexpected profitability which significantly differ from those of their matches. These results confirm my third hypothesis.

7. Risk explanation

Results in previous sections indicate that investors expect higher risk premium for holding IPO stocks, and suggest that investors expect IPO firms to be more risky. This is inconsistent with the argument of Eckbo and Norli (2005), and Eckbo, Masulis, and Norli (2000) that IPO firms are less risky. In this section, I re-examine their risk stories by using other liquidity measures rather than turnover.

Following Eckbo and Norli's (2005) study, I compare the turnover of IPO firms and those of their matched firms for up to five years after the offerings. Results in Table 1.6 show that IPO firms have significantly higher turnovers than their matched firms after the offerings, consistent with those documented by Eckbo and Norli (2005). However, turnover is related to trading volume, which captures information uncertainty and dispersion of opinion. Thus, the result that IPO firms have higher turnovers than their matched firms does not necessarily mean that IPO firms have higher liquidity than their matched firms. Furthermore, it is not clear why the increased liquidity disappears after five years.

To further explore this problem, I examine whether the liquidity results persist when using other liquidity measures. I report in the Appendix A1 the comparison of liquidity between IPOs and their matched firms with alternative liquidity measures, including zero return frequency, Amihud illiquidity, effective spread, Pastor and Stambaugh's Gamma, Roll's (1986) measure, and effective tick size. Generally speaking, the evidence of enhanced liquidity is weak or unsupported. For example, results with zero return frequency and Amihud measure show that IPO firms have higher liquidity than their matched firms only during the first year after the offerings. This liquidity improvement goes away starting the second year after the offerings. Liquidity measured with other proxies doesn't differ significantly between IPO firms and their matched firms. Some other measures, such as spread, the Roll's measure and effective tick size even show the opposite result, i.e. IPO firms have significantly lower liquidity than their matched firms. Thus, the inference from turnover cannot be generalized to other liquidity measures, and the implication that IPO firms have higher liquidity is not conclusive.

Since turnover doesn't capture liquidity, it rather captures information uncertainty, a source of risk for which investors may require higher returns as compensation. I estimate the idiosyncratic return volatility for IPO firms and matched firms for up to five years after the offering. Specifically, idiosyncratic volatility is estimated per month as the standard deviation of daily excess returns (with Fama French 3 factor model), and then averaged annually. Table 1.7 reports the comparison of idiosyncratic volatility between IPO firms and their matched firms. We can see that IPO firms have significantly higher idiosyncratic volatility than their matched firms, consistent with that IPO firms have higher information uncertainty. The higher idiosyncratic volatility of IPO firms also justify the usage of ICCs as a proxy for investors' *ex-ante* expected returns.

8. Conclusion

Results in this paper show that the new issue anomaly only exists when we use noisy ex-post returns as proxy for ex-ante expected returns. Using both analyst-based ICCs and model-based ICCs, the current paper documents that IPO firms have higher ICCs than their size, and size and book-to-market matched firms. Furthermore, I provide some evidence that the underperformances of IPO firms' ex-post realized returns come from the negative earnings surprises that IPO firms have after the offerings. These results suggest that investors expect to earn a higher risk premium for holding stocks of IPO firms' but are negatively surprised by the performances of IPO firms. The present study also sheds new light on whether IPO firms are more risky than matched firms, and what kind risk they have. Specifically, I document that IPO firms have higher turnovers and idiosyncratic return volatility, implying that they are likely to have higher information uncertainty. A potential reason for the relatively higher information uncertainty may be that the IPO firms have only been public for a relatively short period of time and there is less "soft" information on them in the market compared with other stocks. Another reason might be that these newly listed firms have large growth potentials, which incorporate great information uncertainty.

References

Armstrong, Chris, George Foster, Daniel J. Taylor, 2008, Earnings management around initial public offerings: a re-examination, *working paper*.

Brav, Alon, Christopher Geczy, Paul A. Gompers, 2000, Is the abnormal return following equity issuances anomalous? Journal of Financial Economics 56(2): 209-249.

Campbell, John L., Dan S. Dhaliwal, and William C. Schwartz, Jr., 2012, Financing Constraints and the Cost of Capital: Evidence from the Funding of Corporate Pension Plans, Review of Financial Studies: 868-912.

Chava, Sudheer, Amiyatosh Purnanandam, 2010, Is default risk negatively related to stock returns?, Review of Financial Studies: 2523-2559.

Dichev, Ilia, 1998, Is the risk of bankruptcy a systematic risk? the Journal of Finance 53 (3): 1131-1147.

Eckbo B. Espen, Ronald W. Masulis, Øyvind Norli, 2000, Seasoned public offerings: resolution of the 'new issues puzzle', Journal of Financial Economics 56(2):251-291.

Eckbo, B. Espen, Øyvind Norli, 2005, Liquidity risk, leverage and long-run IPO returns, Journal of Corporate Finance 11(1-2): 1-35.

Elton, Edwin J., 1999, Presidential address: expected return, realized return, and asset pricing tests, The Journal of Finance, 54(4): 1199-1220.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of financial economics 33 (1): 3-56.

Fama, Eugene F., and Kenneth R. French, 2000, Forecasting profitability and earnings, Journal of Business 73: 161–175.

Gebhardt, William R., Charles M. C. Lee, Bhaskaran Swaminathan, 2001, Toward an Implied Cost of Capital, Journal of Accounting Research 39(1): 135-176.

Haltiwanger, J., R. Jarmin, and J. Miranda, 2010, "Who Creates Jobs? Small vs. Large vs. Young", *working paper*.

Hou, Kewei, David T. Robinson, 2006, Industry Concentration and Average Stock Returns, the Journal of Finance 61(4): 1927-1956.

Hou, Kewei, Mathijs A Van Dijk, Yinglei Zhang, 2012, The implied cost of capital: A new approach, Journal of Accounting and Economics 53 (3): 504-526.

Jain, Bharat A., Omesh Kini, 1994, The Post-Issue Operating Performance of IPO Firms, the Journal of Finance 49(5): 1699-1726.

Jain, Bharat A., Omesh Kini, 1995, Venture capitalist participation and the post-issue operating performance of IPO firms, Managerial and Decision Economics 16(6): 593-606.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, The American Economic Review 76 (2): 323-329.

Loughran, Tim, Jay R. Ritter, 1995, The New Issues Puzzle, the Journal of Finance 50(1): 23-51.

Loughran, Tim, Jay R. Ritter, 1997, The Operating Performance of Firms Conducting Seasoned Equity Offerings, the Journal of Finance 52(5): 1823-1850.

Lyandres, Evgeny, Le Sun, Lu Zhang, 2008, The New Issues Puzzle: Testing the Investment-Based Explanation, Review of Financial Studies 21(6): 2825-2855.

Mikkelson, Wayne H., M. Megan Partch, Kshitij Shah, 1997, Ownership and operating performance of companies that go public, Journal of Financial Economics 44(3): 281-307.

Pástor, Ľuboš, Lucian A. Taylor, Pietro Veronesi, 2009, Entrepreneurial Learning, the IPO Decision, and the Post-IPO Drop in Firm Profitability, Review of Financial Studies 22(8): 3005-3046.

Rangan, Srinivasan, 1998, Earnings management and the performance of seasoned equity offerings, Journal of Financial Economics 50(1): 101-122.

Ritter, Jay R., 1991, The Long-Run Performance of initial Public Offerings, the Journal of Finance 46(1): 3-27.

Ritter, Jay, Ivo Welch, 2001, A review of IPO activity, pricing, and allocations, The Journal of Finance 57 (4), 1795-1828.

Roll, Richard, 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, The Journal of Finance 39(4): 1127-1139.

Teoh, Siew Hong, Ivo Welch, and T.J. Wong, 1998, Earnings management and the long-run market performance of initial public offerings, The Journal of Finance 53 (6), 1935-1974.

Vuolteenaho, Tuomo, 2002, What Drives Firm-Level Stock Returns? The Journal of Finance 57(1): 233-264.

Table 1.1: Post-issuance performances of IPO calendar time portfolio

My IPO sample covers 4335 firms that went public between year 1982 and 2013. Calendar time portfolio is constructed each month, with all firms that go public within the past 36 months. This table reports the calendar time portfolio alpha for CAPM model, Fama French 3 factor and 5 factor models. IPO firms are further sorted into three portfolios according to their size and market-to-book ratios. Panel A reports the results for equal weighted returns, while Panel B reports the results for value weighted returns.

Panel A:	Equal Weighted Returns								
	all	Size1	Size2	Size3	1-3	MB1	MB2	MB3	3-1
α_CAPM	-0.508**	-0.967***	-0.389	-0.137	-0.679	0.239	-0.129	-0.560*	-0.881
	-1.91	-2.21	-1.33	-0.30	-1.18	0.54	-0.49	-1.73	-1.79
α_FF3	-0.260	-0.760**	-0.152	0.325	-0.966	0.286	0.010	-0.188	-0.555
	-1.50	-1.87	-0.65	0.85	-1.58	0.63	0.05	-0.71	-1.20
α_FF5	0.115	-0.464	0.204	0.690	-1.051	0.535	0.276	0.232	-0.333
	0.65	-1.07	0.81	1.81	-1.68	0.88	1.14	0.82	-0.67
Panel B:	Value Weighted Returns								
	all	Size1	Size2	Size3	1-3	MB1	MB2	MB3	3-1
α_CAPM	-0.545***	-1.260***	-0.635***	-0.266	-0.935	0.440	0.128	-0.782**	-1.171
	-2.03	-2.67	-2.33	-0.59	-1.65	0.94	0.41	-1.99	-2.20
α_FF3	-0.158	-1.101***	-0.191	0.132	-1.175	0.722	0.266	-0.304	-0.957
	-0.84	-2.45	-0.99	0.33	-1.66	1.64	0.94	-1.07	-1.79
α_FF5	-0.047	-0.908**	-0.111	0.350	-1.216	0.628	0.368	-0.029	-0.571
	-0.23	-1.88	-0.60	0.87	-1.68	1.4	1.24	-0.09	-1.04

Table 1.2: Comparison of Analyst-based ICC for IPO firms and matched firms

This table reports the analyst-based ICC for IPO firms and their matched firms for up to five years after the offerings. Analyst based ICCs are calculated following Gebhardt, Lee, Swamimathan (2001). Analyst forecasts of future earnings are obtained from I/B/E/S, current stock price is obtained from CRSP, dividends payout ratio is calculated as current payout ratio from Compustat. The P-value of the differences between the IPO firms and matched firms in analyst-based ICCs is also reported.

Panel A:	IPO and Size-Match Firms			
Year	N	IPO	Match	*P-Value*
1	2696	0.1162	0.0579	*0.0003*
2	2844	0.1245	0.0593	*0.0001*
3	2384	0.1004	0.0477	*0.0001*
4	2035	0.1000	0.0559	*0.0015*
5	1731	0.0972	0.0529	*0.0020*
Panel B:	IPO and Size & B/M Match Firms			
Year	N	IPO	Match	*P-Value*
1	2690	0.1145	0.0697	*0.0031*
2	2839	0.1233	0.0700	*0.0000*
3	2378	0.1000	0.0626	*0.0046*
4	2029	0.0997	0.0615	*0.0073*
5	1729	0.0971	0.0573	*0.0134*

Table 1.3: Comparison of model-based ICC for IPO firms and matched firms

This table reports the model-based ICC for IPO firms and their matched firms for up to five years after the offerings. Model-based ICCs are calculated following Hou, van Dijk, Zhang (2012). Profitability are estimated as the fitted part from the following pooled regression using data from the past 10 years: $E_{i,t+\tau} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \varepsilon_{i,t+\tau}$, where $E_{i,t+\tau}$ refers to the earnings of firm i in year t+ τ ($\tau = 1\ to\ 3$), $A_{i,t}$ is the total asset, $D_{i,t}$ is dividends payments, $DD_{i,t}$ is a dummy variable that equal to 1 for firms paying dividends and 0 otherwise, $NegE_{i,t}$ is another dummy variable that equal to 1 for firms with negative earnings in year t, and zero otherwise, $AC_{i,t}$ denotes accruals. Panel A reports the estimated coefficients for the above equation where $\tau = 1\ to\ 3$. Panel B documents the calculated model-ICC for IPO firms and their matched firms. The P-value of the differences between the IPO firms and matched firms are also reported.

Panel A: Estimated coefficients for profitability model

		intercept	A	D	DD	E	NegE	Accr	adj.R2
E_t+1	Coefficient	0.0539	0.0044	0.2836	0.9681	0.7979	3.2855	-0.0669	0.8732
	t-stat	*0.08*	*13.13*	*20.34*	*1.25*	*124.89*	*2.19*	*-22.07*	
E_t+2	Coefficient	1.1723	0.0078	0.4257	1.0897	0.7244	4.6982	-0.0917	0.8202
	t-stat	*0.65*	*18.21*	*21.81*	*1.27*	*83.77*	*2.41*	*-22.76*	
E_t+3	Coefficient	2.9067	0.0104	0.5014	0.0516	0.7130	6.6225	-0.1123	0.7883
	t-stat	*1.17*	*24.13*	*19.49*	*-0.73*	*80.55*	*3.32*	*-23.96*	

Panel B: Model ICCs for IPO and matched firms

IPO and size matched firms					IPO and size and B/M matched firms				
Year	N	Issuer	Match	*p-diff*	Year	N	Issuer	Match	*p-diff*
1	3021	0.1221	0.0995	*0.0395*	1	2998	0.1164	0.0968	*0.0437*
2	3823	0.1433	0.1022	*0.0233*	2	3797	0.1404	0.1134	*0.0702*
3	3503	0.1678	0.0955	*0.0004*	3	3499	0.1655	0.1026	*0.0003*
4	3047	0.1747	0.1031	*0.0001*	4	3039	0.1724	0.1030	*0.0006*
5	2675	0.1744	0.1022	*0.0000*	5	2663	0.1734	0.1084	*0.0008*

Table 1.4: Unexpected profitability of IPO firms and matched firms

This table reports the unexpected profitability of IPO firms and matched firms, which are measured as the residual from the following profitability model (as appeared in Hou and Robinson 2006): $\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t$, where E/A measures firm profitability, and is calculated as earnings scaled by the book value of total asset; V/A is the ratio of market value of asset to book value of asset; DD is a dummy variable for non-dividend-paying firms; and D/B is the ratio of dividend payments to book equity. The model is estimated using Fama Macbeth regression, and the residual from the regression is unexpected profitability. Panel A document the estimated coefficient for the above regression. Panel B compares the unexpected profitability of IPO firms and matched firms after the offering.

Panel A: Expected Profitability Regressions							
		α_0	lag(V/A)	lag(DD)	lag(DB)	lag (E/A)	_RSQ_
E/A	estimate	0.012	-0.004	-0.035	0.118	0.719	0.4863
	t-stat	2.10	-2.35	-5.42	1.87	62.24	

Panel B: Unexpected Profitability of IPO and matched firms								
	Size-Matched Firm				Size & B/M Matched Firms			
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
1	4206	-0.0419	0.0113	0.0000	4182	-0.0415	0.0141	0.0000
2	3687	-0.0281	0.0143	0.0003	3672	-0.0280	0.0255	0.0000
3	3207	-0.0052	0.0098	0.0118	3187	-0.0051	0.0158	0.0028
4	2804	0.0091	0.0120	0.4921	2791	0.0088	0.0168	0.2033
5	2425	0.0128	0.0124	0.9059	2412	0.0126	0.0208	0.1596

Table 1.5: Analyst Forecast Errors for IPO firms and matched firms

This table reports analyst forecast errors for IPO firms and their matched firms for up to five years after the offering. Analyst forecast errors are calculated as the differences between actual EPS and forecast EPS. Analyst forecast is obtained from I/B/E/S. P-values of the differences between the forecast errors of IPO firms and matched firms are also reported.

	Size-Matched Firm				Size & B/M Matched Firm			
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	2754	-0.0009	-0.0029	0.7851	2994	-0.0009	-0.0025	0.2411
1	2696	-0.0023	-0.0060	0.5049	2951	-0.0028	-0.0051	0.1957
2	2325	-0.0062	-0.0039	0.4698	2578	-0.0076	-0.0047	0.2436
3	1938	-0.0068	-0.0086	0.9123	2152	-0.0049	-0.0095	0.8247
4	1582	-0.0033	-0.0033	0.5653	1731	-0.0036	-0.0043	0.7175
5	1325	-0.0026	-0.0042	0.8309	1470	-0.0070	-0.0022	0.6673

Table 1.6: Turnover of IPO and matching firms after offerings

This table reports the turnover of IPO firms and their matched firms for up to five years after the offerings. Turnover is defined as trading volume scaled shares outstanding, and is calculated at annual frequency. Daily trading data is acquired from CRSP daily files. P-values of the differences between IPO firms and their matched firms are reported.

	Size Matched firm				Size- B/M matched firm			
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	4218	0.0356	0.0298	0.0013	3912	0.0369	0.0331	0.0270
1	4331	0.0374	0.0303	0.0000	4061	0.0387	0.0345	0.0026
2	3844	0.0393	0.0310	0.0000	3619	0.0410	0.0356	0.0008
3	3183	0.0396	0.0308	0.0000	2995	0.0403	0.0351	0.0004
4	2566	0.0393	0.0307	0.0000	2412	0.0394	0.0353	0.0001
5	2113	0.0375	0.0296	0.0000	1983	0.0375	0.0342	0.0002

Table 1.7: Idiosyncratic Volatility of IPO and matched firms

This table documents the idiosyncratic return volatility of IPO and matched firms for up to 5 years after the offerings. Idiosyncratic volatility is the standard deviation of daily excess returns (with Fama French 3 factor model) calculated per month, and then averaged annually. Daily return data come from CRSP daily stock file. Size and value factors are obtained from Kenneth French's library.

	Size Matched firm				Size- B/M matched firm			
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	4218	0.0356	0.0298	0.0013	3912	0.0369	0.0331	0.0270
1	4331	0.0374	0.0303	0.0000	4061	0.0387	0.0345	0.0026
2	3844	0.0393	0.0310	0.0000	3619	0.0410	0.0356	0.0008
3	3183	0.0396	0.0308	0.0000	2995	0.0403	0.0351	0.0004
4	2566	0.0393	0.0307	0.0000	2412	0.0394	0.0353	0.0001
5	2113	0.0375	0.0296	0.0000	1983	0.0375	0.0342	0.0002

Appendix

A1: Comparison of other liquidity measures between IPO and matched firms

This table reports the comparison of other liquidity measures between IPO and their matched firms, which include zero return frequency, Amihud illiquidity measure, spread, Pastor and Stambaugh's Gamma, Roll (1986) measure and effective tick size. Data used to calculate liquidity measure is acquired from CRSP daily stock files. P-values about the differences between IPO firms and matched firms are also reported

	Size-matched Firms				Size/book-to-market matched Firm			
Panel A: Zero-return frequency								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	4639	0.2332	0.2517	0.0034	4303	0.2399	0.2442	0.9787
1	4410	0.2234	0.2453	0.0002	4140	0.2286	0.2403	0.4618
2	3932	0.2226	0.2368	0.0159	3694	0.2272	0.2386	0.4291
3	3216	0.2223	0.2331	0.0939	3025	0.2269	0.2361	0.6862
4	2594	0.2167	0.2244	0.9366	2436	0.2188	0.2268	0.5674
5	2145	0.2110	0.2115	0.8441	2004	0.2109	0.2141	0.8747
Panel B: Amihud Illiquidity								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	719	0.9835	1.3966	0.2122	659	1.0438	2.0555	0.0339
1	4090	1.7888	2.3021	0.0330	3850	1.9735	3.1904	0.0201
2	3434	3.1039	3.1534	0.3765	3208	3.6466	3.9185	0.6585
3	2739	5.0684	4.4480	0.8928	2554	5.8651	3.4342	0.0088
4	2231	4.9281	5.3544	0.7705	2099	5.7404	4.3812	0.5261
5	1845	5.3072	8.0968	0.2972	1720	5.6421	5.9073	0.9293
Panel C: Spread								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	1605	0.0181	0.0179	0.5464	1525	0.0190	0.0206	0.2136
1	4098	0.0192	0.0182	0.1277	3860	0.0201	0.0208	0.8115
2	3466	0.0202	0.0184	0.0381	3266	0.0208	0.0203	0.1113
3	2780	0.0213	0.0190	0.0667	2627	0.0215	0.0216	0.5414
4	2255	0.0222	0.0198	0.0188	2140	0.0230	0.0225	0.3203
5	1867	0.0209	0.0192	0.1171	1757	0.0217	0.0223	0.9398
Panel D: Pastor and Stambaugh Gamma								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	1028	0.0015	0.0044	0.0043	928	0.0012	0.0042	0.0162
1	3000	0.0013	0.0025	0.2954	2674	0.0016	0.0033	0.0687
2	2205	0.0020	0.0026	0.9268	1897	0.0025	0.0037	0.8819
3	1655	0.0019	0.0030	0.8262	1418	0.0019	0.0035	0.4146
4	1303	0.0014	0.0013	0.7958	1140	0.0016	0.0035	0.3960
5	1067	0.0018	0.0023	0.7678	905	0.0023	0.0047	0.0380

A1: Comparison of other liquidity measures between IPO and matched firms (Cont.)

	Size-matched Firms				Size/book-to-market matched Firm			
Panel E: Roll (1986) measure								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	4461	2.9224	2.5887	0.0174	4150	3.0224	2.7580	0.1746
1	4353	3.0397	2.7150	0.0115	4089	3.1704	2.9643	0.3030
2	3861	3.3936	2.8111	0.0001	3637	3.5636	3.1127	0.0093
3	3158	3.3868	2.8068	0.0018	2976	3.4880	3.0650	0.0239
4	2550	3.4164	2.8530	0.0007	2392	3.4433	3.1035	0.0045
5	2099	3.2229	2.7420	0.0029	1965	3.2090	3.0212	0.0248
Panel F: Amivest measure								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	719	331.96	2311.68	0.2505	659	252.75	421.79	0.0773
1	4090	1143.56	6902.63	0.3020	3850	615.45	2290.80	0.2225
2	3434	1196.01	1852.85	0.1648	3208	710.72	914.88	0.7058
3	2739	3629.97	2128.25	0.8522	2554	3084.19	13239.66	0.3972
4	2231	1310.23	3187.49	0.3249	2099	727.77	1952.09	0.1760
5	1845	1965.58	16686.45	0.1636	1720	1086.73	3433.49	0.2012
Panel G: Effective tick size								
Year	N	Issuer	Match	*p-diff*	N	Issuer	Match	*p-diff*
0	4543	0.0399	0.0414	0.8783	4228	0.0416	0.0478	0.0416
1	4320	0.0451	0.0438	0.4258	4065	0.0473	0.0523	0.0666
2	3838	0.0558	0.0458	0.0002	3618	0.0591	0.0596	0.9314
3	3131	0.0606	0.0476	0.0042	2957	0.0626	0.0597	0.3557
4	2525	0.0621	0.0478	0.0000	2372	0.0632	0.0602	0.2076
5	2078	0.0627	0.0479	0.0009	1943	0.0612	0.0588	0.2486

CHAPTER 2

COMPETITIVE ADVANTAGES OF GOING PUBLIC:

EVIDENCE FROM INCUMBENT FIRMS

1. Introduction

Going public is one of the most important and complex decisions that a firm can make. Yet, the determinants of firms' IPO decisions are still not fully understood by the academia. Pagano, Panetta, and Zingales (1998) recommend assessing this problem not only from *ex ante* characteristics of the firms but also from *ex post* consequences of these decisions[1]. In practice, studies on firms' ex ante motivations to go public are constrained by the limited access to data from private firms. Extensive literature focuses on the *ex post* impacts of firms' listing decisions to investigate why firms go public.

While earlier studies offer insights of the going-public decision from the perspective of capital market[2], recent research increasingly emphasizes the product market competitive advantages associated with a firm's IPO as a determinant of the listing decisions. Going public sends positive signals to the public regarding issuing firms' own quality and their product quality (e.g., Stoughton, Wong, and Zechner, 2001, Hsu, Reed, and Rocholl, 2010); provides first-mover advantages (e.g., Spiegel and Tookes, 2009, and Maksimovic and Pichler, 2001); helps firms engage in more aggressive and riskier strategic activities such as R&D (e.g., Chod and Lyandres, 2011). Moreover, capital collected through IPOs can help facilitate firm's investment, mergers and acquisitions (e.g., Brau and Fawcett, 2006, and Celikyurt, Sevilir, and Shivdasani, 2010);and enable firms to acquire related patents (e.g. Berstain, 2012).

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[1] They suggest this because ex post effects can complement the evidence inferred from ex ante characteristics for two reasons. First, some motivation can only be assessed by looking at ex post data. Second, some effects may not be fully anticipated, and can only be uncovered by using ex post data

[2] These works include but not limited to: enhancing liquidity (e.g., Amihud and Mendelson, 1986,); reducing information asymmetry (e.g., Benveniste and Spindt, 1989); diversifying owner risk (e.g., Chemmanur and Fulghieri, 1999, and Mikkelson, Partch, and Shah, 1997); improving public monitoring (e.g., Holmstrom and Tirole, 1993) and helping early stage investors exit.

Does the public channel actually matter in product markets? Chemmanur, He and Nandy (2010), and Chemmanur and He (2011) provide direct empirical evidence that listing firms exhibit increase in their market shares after IPOs, while the market shares of industry incumbents (i.e. existing firms in the same industry) decrease. These studies pay solely attention to product market advantages for issuing firms associated with IPOs. However, since IPO firms are on average much smaller than incumbent firms, it is not quite clear whether these IPOs can actually impact industry incumbents. Some recent studies attempt to examine incumbents' stock price reaction to IPO events in order to infer the existence of IPO-related competitive effects on industry incumbents, but find mixed results (Akhigbe, Borde and Whyte, 2003, Hsu, Reed, and Rocholl, 2010, and McGilvery, Faff and Pathan, 2012).

If negative valuation effects exist for industry incumbents around IPO events, it implies that the market expects lower future cash flows and/or higher risk for industry incumbents. Yet, it is unknown whether the negative valuation effects result only from the cash flow effect, or alternatively, it also relates to the increase in risk. The current work investigates this unexplored risk effect of IPOs, i.e. whether IPOs increase industry incumbents' risk and thus cost of equity. I provide empirical evidence that large IPO events alter the cost of equity of industry incumbents[3]. Results in this paper indicate that observed short-term negative price reactions for industry incumbents around large IPO events reflect not only expectations of lower future cash flows, but also higher risk premia associated with intensified competitive pressure and higher default risk.

More specifically, I document first that incumbent firms exhibit positive abnormal returns during the post-listing period after controlling for existing factors[4], and their abnormal returns co-

[3] The reason why this paper focuses on large IPOs only will be discussed later in the literature review section.
[4]Abnormal returns do not conflict with market efficiency in the case that such positive abnormal returns reflects additional risk not captured by existing factors. In the current context, abnormal returns don't imply

vary positively with macroeconomic conditions. Compared with prior-IPO period, industry incumbents experience an increase in abnormal returns ranging from 0.2% -0.3% monthly (around 3% per year). Moreover, compared with pre-IPO periods, the co-variation of industry incumbent firms' returns with macroeconomic conditions ('beta's) also increases subsequent to large IPO events. This suggests that increase in returns likely to be associated with risk.

An essential question here is the channel through which IPOs increase the risk of industry incumbents and what kind of risk it is. The answer is that IPOs change the product market structure within the industry (Chemmanur et al., 2010 and Chemmanur et al., 2011), which has risk implications that are priced in stock returns (Hou and Robinson, 2006). In particular, IPO events intensify the competition within their industry[5] and impose competitive threats to their industry incumbents, increase their default risk and thus their cost of equity. Using the default probability measure of Campbell et al. (2008), I further document that industry incumbents face significantly higher probability of default after large listing events in their industries.

Furthermore, if enhanced competition risk accounts for higher abnormal return after IPO, incumbent firms operating in industries where IPOs are associated with more competitive advantages should have higher increases in risk and thus higher expected returns subsequently. I find consistent evidence using cross sectional tests. My results show that IPOs' effect on incumbent firms is stronger in competitive industries, i.e. industries with higher level of product substitutions, industries with larger firm number, and industries with smaller market size[6].

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the market is inefficient. If the market is inefficient, we should either observe that the negative reaction continues after the IPO date (underreaction) or subsequent positive returns that have similar magnitude as the negative returns around IPO dates (overreaction), but, instead, we observe positive returns subsequent to IPOs which are much larger in magnitude.

[5] Spiegel and Tookes (2014) construct a model where industry become more homogeneous in their product environment and customers are more likely to switch between firms after IPOs.

[6] According to Karuna (2007), competition is multi-dimensional instead of the single dimension captured by the Herfindahl Index. Specifically, controlling for industry concentration (Herfindahl index), high price

Moreover, such competitive effect is stronger for industry followers (incumbent firms with smaller market shares) than for industry leaders (incumbent firms with greater market shares). Overall, my results suggest that IPOs do impose negative impact on industry incumbents.

The present study adds new empirical evidence to the discussion of IPO related advantages. It shows that IPOs can increase the cost of equity for industry incumbent firms subsequently. Based on the average market capitalization of industry incumbents in my sample (3397 mil), 3% increases in returns can translate into more than 100 million increase in cost of equity each year. Knowledge with regard to this long-term stock market impact has implications for both investors and related firms. First, as listing firms only account for a small portion of the stock market[7], it is beneficial for investors to know the valuation effects of listing events on incumbent firms both in the short-term and long-term, so that they can adjust their allocation decisions more efficiently according to their investment horizons. Second, IPO firms and private firms that are considering public financing would like to know the market opinion regarding their decision to go public and, more critically, the real consequences of listing on themselves and their competitors. Last, existing incumbent firms would also benefit from understanding what competitive advantages accrue to issuing firms so that they can adjust their operation decisions to respond in an optimal manner.

The remainder of this paper proceeds as follows. Section II briefly introduces related studies and how the current studies fit to previous literature. Section III discusses methodology, and develops hypotheses. Section IV describes my sample and data resources. Section, V and VI

substitutability, large firm number, and larger market size all capture greater competition at different dimensions. I discuss this in more detail in the cross sectional analysis.

[7] Using a similar sample, Hsu, Reed, and Rocholl (2010) show that existing publicly traded firms (industry incumbents) comprise 97.5% of the total post-IPO market capitalization of industries in which IPO occurs. In contrast, IPO firms comprise the rest 2.5% of industry portfolio value.

document the empirical results. Section VII provides robustness tests, and the last section concludes.

2. Previous Literature

Existing literature develops several theories regarding the driver of IPO activities. Most fundamentally, IPOs involve extensive information disclosure and sales of firm shares to broader basis of investors, which increase liquidity and reduce information asymmetry. Thus, firms can raise capital at lower costs through IPOs[8] (Maksimovic and Pichler, 2001, Maksimovic and Pichler, 2006).

Once newly listed firms obtain capital, they can reduce leverage (Eckbo and Norli, 2005), enjoy greater investment flexibility (Lang, Ofek and Stulz, 1996, Zingales, 1998), and pursue new projects and growth opportunities (e.g., Chevalier, 1995, and Phillips, 1995). Further, collected capital can fuel innovations and acquisitions. Spiegel and Tookes (2008) construct a model where firms compete for market share and show that firms go public to finance their innovations. Similarly, Chod and Lyandres' (2011) argue that going public can help diversify the idiosyncratic risk for owners of the firm and show empirically that firms invest more in riskier projects, such as R&D after they go public. Consistent with the survey results of Brau and Fawcett (2006), Booth and Chua (1996), and Celikyurt, Sevilir, and Shivadasani (2010) show that going public facilitates acquisitions, and newly listed firms outpace existing incumbents in term of acquisition activities. Besides acquisition of firms, Bernstein (2012) further documents that going public increases issuing firms' acquisitions of external innovations.

[8] While some issuing firms using IPOs as a form of entry, other issuing firms already exist before going public. My following arguments hold true for both types of firms. This is to say, IPO doesn't have to serve as a form of entry to provide competitive advantages.

In addition to raising capital, IPOs can also serve as a positive signal for issuing firms' quality. Stoughton, Wong, and Zechner (2001) establish a model in which stock prices contain information about product quality. The model predicts that only good-quality firms go public. Chemmanur and Fulghieri (1994) show that highly ranked investment banks can play an important role in certifying firm value. IPOs underwritten by prestigious investment banks are associated with lower risk and better long-term operating performance (Carter and Manaster, 1990, Carter, Dark, and Singh, 1998). Going public indicates to the market that the firm has recently completed the certification process of investment banks.

However, are the fore-mentioned advantages able to actually generate real impacts in the product markets, i.e. change product market structure? Theoretical works of Maksimovic and Pichler (2001) and Spiegel and Tookes (2008) suggest that IPO firms' market share should increase in the years subsequent to IPOs. Chod and Lyandres (2011), Chemmanur, He, and Nandy (2010), and Chemmanur and He (2011) find consistent empirical evidence that newly listed firms experience increases in their market shares after IPOs[9].

Since industry incumbent firms and IPO firms share the same industry environment and compete with each other, the existence of competitive shift between them suggests that good news for the issuing firms should have negative implications for industry incumbents (Kim, Lacina, and Park, 2008). Intuitively, if going public helps issuing firms gain advantages (good news), IPO events should have negative information for industry incumbents. Three recent studies directly

[9] People may argue that there is lots of empirical evidence showing that IPO firms have declining profitability and efficiency after IPOs, which seems contradictory to evidence about increasing market share for issuing firms post listing. Clementi (2002) argue theoretically that IPOs can increase the operating scale of issuing firms, which contributes to declined profitability and productivity. Chemmanur, He and Nandy (2010) provide consistent empirical evidence documenting that while productivity and sales growth decline after firms going public, their sales, capital expenditure, total employment, etc., keep increasing over the years before and after public listing.

examine the short term valuation effects of IPO events on industry incumbents, in other words, how incumbent firms' stock prices react to IPO events within the same industry.[10] Akhigbe, Borde, and Whyte (2003) find insignificant short term valuation effect. In contrast, Hsu et al. (2011) and McGilvery et al. (2012) focus only on large listing events and find significantly negative valuation effect around the announcement and listing dates of large IPO events.

One possible explanation for the discrepancy in their results is differences between their samples. Akhigbe, et al. (2003) study the average effects of all IPOs. In contrast, Hsu et al. (2001) and McGilvery et al. (2012) only focus on large IPO events. Since new issuing firms on average are much smaller than existing incumbents, the competitive impacts they generate might be quite limited.[11] Thus, including small IPO events in the sample may contaminate the valuation effects of large IPO events and lead to insignificant valuation effects on average. The discrepancy of these results also indicates the cross sectional differences in IPOs' effect on their industry incumbents. To the extent that larger IPOs have greater competitive impacts, I focus solely on large IPO events for the current paper.

The presence of negative valuation effect suggests that an large IPO implies either decreased future expected cash flow or increased risk (discount rate), or both for industry incumbents. Hsu et al. (2010) document that compared with prior-IPO periods, incumbent firms' operating performance and profitability decline within 4 years subsequent to IPO events, consistent with declined future expected cash flows for industry incumbents after large IPO events. This raises the

[10] From a methodological perspective, some studies have examined the intra-industrial effect of certain corporate events. For example, Lang and Stulz (1992) study the effect of bankruptcy announcement on industry rivals and distinguish between competitive effects and contagion. Kim, Lacina, and Park study the effects of earnings announcements on industry rivals and document negative information transfer due to competitive shifts.

[11] It is also likely that negative signals embedded in small IPOs are smaller in magnitude, and easily offset by positive signals regarding growth perspective, lead to overall unobservable valuation effects.

question whether IPOs also convey information related to the risk and thus cost of equity for their industry incumbents.

The answer is likely to be a "yes". Hou and Robinson (2006) show empirically that product market structure has risk implications that is priced but not captured by market risk premium, size, value and momentum factors. Since an IPO can change product market structure, it also changes risk within its industry. Hou and Robinson (2006) further argue that firms in competitive industries confront higher default risk and invest more in innovation activities (higher innovation risk) than firms in concentrated industry. Investors care about these risks and require higher returns as compensation, generating higher risk premium for firms in competitive industries. As newly listed firms gain market shares from industry incumbents, they impose credible threats to industry incumbents. Therefore, incumbents firms have greater distress risk. Moreover, confronting intensified competition, industry incumbents are likely to change their operating strategies as responses, in particular, increase their R&D investment, which in turn increase their innovation risk. These enhanced risk predict increased abnormal return for industry incumbents during the post-issuance era. Using a calendar time portfolio (as recommended by Fama (1998), and Mitchell and Stafford (2001)), I find consistent evidence.

3. Hypotheses Development

I start my analysis by examining the short term price reaction of incumbent firms' stock price to the announcements of large listing events since large IPOs are more influential. I follow the approach applied in Hsu et al.'s (2011) study. Since I apply different filtering criteria and cover a different sample period[12], it is important to confirm that IPO-related valuation effect exists for my sample before I can further evaluate the long-term impact of IPO events on stock returns. If large

[12] IPO firms in my samples are only 50% - 75% in term of market capitalization, sales, and/or assets compared with IPO firms in Hsu et al. (2011).

IPO events included in my sample provide issuing firms with competitive advantages, successful completion of these IPOs should be viewed as bad news for industry incumbents and generate negative valuation effect on incumbent firms' stock prices. [13]

Hypothesis 1 (H1): Incumbent firms' stocks experience negative return around large IPO events in the same industry.

Moreover, if large listing events shift competitive advantages towards issuing firms, operating performances of industry incumbents' should decline in the long run.

Hypothesis 2 (H2): Incumbent firms' operating performances decline following large listing events in the same industry.

According to the argument of Hou and Robinson (2006), product market structure has risk implications for firm stock returns, which is not captured by market risk premium, size, value and momentum. In the sense that IPOs help issuing firms gain market share and shift competitive advantages toward issuing firms, incumbent firms face enhanced competition subsequently and should exhibit higher risk premium.

Hypothesis 3 (H3): Incumbent firm's stock exhibit positive abnormal return post large listing events relative to CAPM and Fama-French (3 or 4) factor models.

To explore whether this abnormal return is consistent with a risk based explanation, I study the time-series properties of incumbents' abnormal returns. I apply the ICAPM (inter-temporal CAPM) setting and examine how incumbent firms' returns vary with macroeconomic conditions. It is known that inflation rate, term premium, default premium, dividends yield, and t-bill rates are closely related to macroeconomic conditions. As these variables are very persistent, I use the

[13] Hsu et al. (2011) show that both the filing dates and listing dates have information content and argue that there is still lots of uncertainty in the market when IPOs are filed and completion of these IPOs solve these uncertainty and thus have new information embedded.

innovation terms of these variable as proxy for expected future economic conditions. Within the ICAPM framework, risk means lower returns during bad times, which transfer wealth from bad times to good times and is undesirable for investors who prefer smooth consumption. If incumbent firms' positive abnormal returns originate from risks, I expect that incumbent firms' returns exhibit features of 'procyclical'. In particular, incumbent firms should have lower returns during recessions, but higher returns during expansions.

Hypothesis 4a (H4a): Returns of industry incumbents' co-vary positively with macro-economic conditions.

In addition, if incumbent firms' abnormal returns are the results of increased risk caused by newly listed firms, within the ICAPM framework, incumbent firms' stock should become more 'procyclical' after large IPO events (higher risk) compared to prior-IPO period.

Hypothesis 4b (H4b): Returns of industry incumbents' co-vary even more positively with macro-economic conditions during post-issuance periods.

According to Hou and Robinson (2006), increased competition risk in the industry is associated with higher default probabilities for firms in the industry. If large IPOs increase competition risk in the industry, industry incumbents should have higher default probability after large IPO events in the same industry.

Hypothesis (H5): Incumbent firms have higher default probability after large IPO events.

If increased returns are attributable to the competitive effects of IPO events, IPO events that can exert more negative impacts on incumbents firms should be accompanied by higher returns of industry incumbents subsequent to listings. I propose that industry concentration is related to the strength of the competitive effects. However it is ambiguous to which direction industry concentration affects such competitive effects. On the one hand, monopolistic firms (higher concentration) have more market power, and can employ tactics, such as price increase, to drive out competitors. On the other hand, they lack experience in fair market competition.[14]

Hypothesis 6a (H6a): Industry concentration affects the cross-sectional variation in incumbent firms' long-term stock returns.[15]

Karuma (2007) argues that industry competition is multi-dimensional instead of the single dimension capture by industry concentration. He argues that after controlling industry concentration, several industry characteristics are related to competition. Specifically, higher degree of product similarity (lower differentiability), larger market size, and lower barrier to entry (entry cost) all indicate intense competition conditional on industry concentration.[16] Each of these measures captures a piece of the relative competitiveness of each industry and more importantly, variation in the level of competition across different industries. In industries where competition is more intense, additional competitive advantages can impose more threat for existing firms, whose risk will increase more as a result. Following Karuna (2007), I measure product market competition with level of product substitutability, market size, entry cost, together with number of public firms to examine how these measures relate to the long-term stock returns of industry incumbents[17].

Hypothesis 6b, 6c, 6d, 6e (H6b, H6c, H6d, H6e): Given industry concentration, the degree of product similarity, number of public firms, and market size both correlate positively with

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[14] Previous studies that investigate industrial effects of corporate events have provided evidence for both situations. Hoberg and Phillips (2010) show that negative spillover effect is more severe for competitive industry. In contrast, Sarkissian and Wang (2013) show that negative impact of foreign IPOs is more severe for concentrated industries.

[15] As pointed above, the prediction regarding how industry concentration affects incumbent firms' ability to response to the threats of new listed firms is ambiguous, so the hypothesis here is non-directional.

[16] Specifically, Karuna (2007) and other related studies (Raith (2003)) argue that industry concentration is endogenously determined by market fundamentals such as substitutability of product, market size, or firms' cost to enter the market. Concentration could indicate either intense competition or low competition.

[17] I will explain more in detail in later subsections regarding cross sectional tests for each proxy.

incumbent firms' long term stock returns. Barrier to entry is negatively associated with incumbent firms' long term stock returns.

The weakness of the fore-mentioned measures is that they all capture the competition at the industry level. Firms in the same industry can still face different levels of competition due to their different positions in the market. To capture intra-industry difference in competition level, I use market share as proxy for market power. Intuitively, firms that occupy more market share are likely to have stronger market power and less competition (e.g., Nickell, Wadhwani, and Wall, 1992, and Nickell, 1996). Firms with greater market shares are more likely to be financially flexible, which enable them to take advantages of information disclosed during the IPO process and mitigate the competitive threats imposed by newly issued firms. In contrasts, firms with smaller market share (industry followers) bear more of the negative impacts from newly listed firms. This suggests a negative relationship between incumbent firms' market share and post-issuance stock returns.

Hypotheses 7 (H7): incumbent firms' long term expected stock returns are negatively correlated with incumbent firms' market share after controlling for other related factors.

4. Sample and Data

I constrain the current study to large IPO events for reasons stated in section II. I obtain my initial IPO sample from the Securities Data Company (SDC) New Issue database, which consists of 2079 completed US industrial IPOs over the sample period from 1998 to 2013[18]. To minimize the effect of errors in data on my results, I correct for mistakes in SDC's database following Jay Ritter's "Correction to Security Data Company's IPO database". [19] I exclude from the sample unit offerings, foreign issues, REITs, closed-end funds, reverse LBOs, spin-offs, ADRs. I extract the

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[18] In 1997 the SFAS131 replaced the SFAS14 and firms changed their segment reporting. Since I use Compustat Segment files do calculate measures related to industry competition, to maintain consistency, my sample period starts from 1998.

[19] It is available online at http://bear.cba.ufl.edu/ritter/ipodata.htm.

accounting information for my IPO sample from Compustat database, stock market information from CRSP database. Since my analysis request clear identification of industry, so I further require the SIC codes of issuing firms are identifiable from Compustat, CRSP and/or prospectus retrieved from Edgar Online. The filtered sample includes 1882 IPO events with information available and identified Fama French 49 industry from 1998 to 2013.

To select the most influential IPOs to purge out the contamination of small IPO events, I follow the method used in Hsu et al. (2010), and McGilvery et al. (2012). Specifically, I use the most recent sales available prior to going public (usually one-year prior) as a measure of size. If sales are not available for the year before the IPO, then I use sales in the year of the IPO, adjusted by industry sales growth, to get the estimation of prior-IPO sales. [20] For the 1476 IPO events have sales data on Compustat and CRSP either for one year before the IPO or for the IPO year. I select large IPO event firms as those have the largest sales during the surrounding seven-year-window (three years before and after IPOs). The final IPO sample comprises of 109 IPO events.

The advantage of this sample selection is that it makes good use of available data. The Seven-year-window can distinguish clearly post-IPO periods from prior-IPO periods, and help purge out the contamination from small IPOs better[21]. But, on the other hand, filtering criteria that is too stringent makes the sample less representative and limits the generality of results. The present study weighs the pros and cons and adapts different filtering processes which are less exclusive while still attempting to weed out noise associated with confounding small IPOs. I repeat my tests

[20] I calculate the sales growth for all the IPO firms during that year for each industry first, and then divide sales for the IPO year (year 0) with 1+sales growth rate from year-1 to year 0.

[21] It might involve some look-ahead bias, but even when I use other sample selection criteria, For example, IPO firms with prior-IPO sales in the top 10% among all IPO firms in the same industry in the same year. The results are qualitatively similar.

for several alternative samples with much more observations[22]. Results of different samples are qualitatively similar and are discussed briefly in the subsequent section on robustness of tests.

I identify industry incumbents as existing public firms primarily operating in the same Fama French 49 industry as the IPO event firms. Incumbent firms must be publicly tradable at least three years before IPO event year so that I can get sufficient prior-IPO data to make reliable comparison with post-IPO periods. Accounting information and stock returns of industry incumbents have to be available from the Compustat and CRSP. I impose no requirement on either the listing exchanges of incumbents or how many years they survive after corresponding listing events, as these requirements are likely to generate survivorship bias. The final incumbent firm sample includes 5327 IPO event-firm observations covering 3302 unique incumbent firms.

Table 2.1 reports descriptive statistics for the universe of IPO firms that have data available from CRSP and Compustat, and the final sample of large IPO events respectively. It also provides summary statistics for the sample of industry incumbents. Market capitalization of IPO firms is measured using the first available stock price from CRSP, while market capitalization of incumbents is measured at the end of the IPO event month. Sales and assets are measured using the first available data post listing dates from Compustat. The results show that issuing firms are on average much smaller than existing public firms, which are about 10 times large in terms of sales (342 vs. 3662) and total assets (447.8 vs. 4266.7). But, as the first two columns show that sizes of IPO firms are positively skew. This suggest while on average IPO firms are much smaller than industry incumbents, there do has some large firms going public.

[22] But results from different samples do suggest that the more firms included in the IPO sample, the smaller the IPO event firms, the less strong the results are. This confirms that it is necessary to restrain sample to large IPO event firms.

Selected IPO event firms are much larger than the average IPO firms. They even have a significantly higher sales (671 vs. 417) and assets (593 vs. 421) when compared with industry incumbents using a Wilcoxon Z test. This is consistent with previous documented results in Hsu et al. (2010). It indicates that while on average IPO firms are much smaller than existing incumbents, which makes their competitive effects susceptible, those large IPO firms are more capable of exerting competitive pressure on industry incumbents.

Since IPO firms and existing incumbents share the same industry environment, if IPO firms could gain additional competitive advantages through IPOs, then successful IPO events should contain bad information for incumbent firms in the same industry. Consequently, market should react negatively to incumbent firms' stocks around IPO event dates, i.e a negative valuation effect. I replicate the finding of short term valuation effect documented in Hsu, Reed and Rocholl (2010) in Table 2.2. Specifically, I calculate cumulative abnormal returns of incumbent firms around relevant IPO dates using CAPM, the Fama-French three-factor model, and the four-factor model that includes the momentum factor. All three models are estimated using an estimation window beginning 255 days and ending 42 days prior to the IPO dates. Incumbent firms must have at least 50 daily observations during the estimation window available from CRSP so that model parameters can be reasonably estimated. Cumulative abnormal returns during each event window are the sum of daily equally weighted average abnormal returns across all incumbent firms.

Table 2.2 shows that stock prices of incumbent firms drop significantly around successful large IPO events in their industries. Cumulative abnormal returns across various event windows are almost always significantly negative. Cumulative abnormal return in the three-day window around the listing date is a statistically significant -0.13% (-0.20%, -0.17%) with CAPM (Fama French 3 factor, 4 factor) model. When extending backwards, CARs starting 5 days before the IPO till one day after are significant at -0.12% (-0.13%, -0.12%) with CAPM (Fama French 3 factor, 4 factor) model. when extending the window backwards more to includes 10-20 days prior to the listing date, we still observe negative significant returns. This suggests that the price of industry incumbents begin to fall before the actual IPO dates, consistent with that market can predict the success of the deal before the actual trading dates. When we extend the event windows to cover 10-20 days after the IPOs, the stock prices of industry incumbents continue to drop. CARs amount to -1.04% (-0.56%, -0.44%) during the 21 days around IPO dates, close to monthly return between -0.44% and -1.04% , which is economically significant. This also indicates that the negative stock response persists for a relative long time after IPOs. In untabulated results, I calculate the CARs around IPO filing dates. Stock prices of industry incumbents also fall significantly around IPO file dates. The magnitudes of negative CAR across various event windows are similar to those documented in Hsu, Reed and Rocholl's (2010) study[23].

Overall, results in Table 2.2 indicate that incumbent firms experience a significant drop in their stock price when a large firm in the same industry files for IPO and when the IPO event successfully completes. Price declines persist for several days (at least 20 days as shown in the table) after the event dates. This implies that market on average perceives successful large IPO events as bad information for industry incumbents. In the next section, I will explore in more detail whether this negative valuation effect comes from unexpected negative cash flow shocks, or comes from increases in the risk of industry incumbents (or both).

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[23] I also examine the CARs of incumbent firms for several alternative samples, provided in appendix. Cumulative abnormal returns of incumbent firms are quite similar in magnitude using two-digit SIC industry definition, three-digit SIC industry definition and using Fama-French 49 industry definition. All the returns are significant at 1% level across the assorted event windows. For other empirical tests, I also examine it for those alternative samples, some results are also included in appendix. All results are qualitatively similar.

5. Empirical Results

I investigate first whether the short term negative valuation effect implies decline in operating performances for industry incumbents after the IPO events. Then, I will examine how the risk of industry incumbents change after the IPO events

5.1. Long-Term Operating Performance

It is possible that the short term valuation effect originates from investors' expectation about future cash flow declines for industry incumbents due to intensified competition. To investigate this problem, I examine directly how operating performances of industry incumbents change over time. Table 2.3 Panel A reports the univariate changes of incumbent firms' operating performances, changes in their KZ financial constraint index (Kaplan and Zingales, 1997) and Altman's Z-score after large IPO events in the same industry. The result shows that incumbents exhibit declined sales growth and asset growth. They also experience increases in their KZ index and decreases in Altman Z score, indicating they face stricter financial constraint subsequent to IPO events than before.

I examine whether large IPO events significantly affect incumbents' performances even after controlling for related factors that are known to be related with performances. Specifically, I estimate the following model of performances as a function of firm size, valuation, and past performances. $Performance_{i,t} = \alpha + \beta * IPO_{i,t} + \gamma * controls_{i,t} + \epsilon_i + \theta_t + \varepsilon_{i,t}$, where performance is measured as sales growth, operating income growth and investment growth (capital expenditure) in each year t for every incumbent firm i. $IPO_{i,t}$ is an indicator variable that equals to 1 if year t is within the 3 years post to a sample IPO events in firm i's industry, and zero otherwise. The above equation is estimated for incumbent firms that has data from both pre-IPO years and post-IPO years. I include industry and year fixed effects to control for unobserved heterogeneity. Estimated coefficient of IPO measures to what extent IPO contribute to the decline of incumbent firms' operating performance. Table 2.3 Panel B reports the results.

As shown in Panel B, sales growth is significantly affected by size, and valuation. These relationships also hold for other growth. Firms with higher market valuation on average perform better than firms with lower market valuation. Estimated IPO indicator variables are negative and significant across all performance measures. Specifically, it shows that incumbents firms 10% decline in sales growth after a large IPO occurs in the same industry. Similarly, operating income growth will decline by 11.9%, and capital expenditure growth decline by 12.7%, both of which are also highly significant. The last column of panel B shows that R&D intensity (R&D/sales) even increases by about 15.3%. But in untabulated results, I find R&D growth rate actually declines after large IPOs. This implies that sales decline more compared with R&D investment, which is consistent with that incumbents firms don't cut their R&D investment dramatically following declined sales in order to compete with newly listed firms better. This is also consistent with Hsu et al. (2010) results, which document that incumbent firms with higher R&D intensity performs relatively better subsequent to large IPO events. The increase in R&D intensity also suggests that the innovation risk is likely to increase after large IPO events in the same industry, consistent with Hou and Robinson (2006)'s argument that greater competition is involved with more innovation.

5.2. Long-Term Stock Performance

In this section I assess the competitive effect of large IPO listing events on industry incumbents by examining the long run stock performance of incumbent firms post-listing. To measure the long-term stock return of incumbent firms, I apply the calendar-time portfolio approach. Fama(1998) and Mitchell and Strafford (2001) recommend a monthly calendar-time portfolio approach for measuring long-term abnormal performance for three reasons. First, the cross-correlations of firm abnormal returns are automatically accounted for in the portfolio variance. Second, the monthly returns of portfolios are less susceptible to the problems in the model. Last, the distribution of the estimator is better approximated by the normal distribution, allowing for more powerful statistical inference. Following previous studies on post IPO underperformance, I create both IPO-firm portfolios and similarly incumbent portfolios to measure the stock performances of IPO and incumbent firms within three years post IPO events respectively. Specifically, return for a specific firm is included in the IPO portfolio for that month, if it went public within the past 37 months till one month before[24]. Return for an incumbent firm is included in the incumbent portfolio if an IPO happened in the same industry within the past 37 months till one month before. Table 2.4 reports returns for these calendar time portfolios. T-statistics are corrected using Newey-West with 5 lags of autocorrelation for past returns.[25]

As we can see from Table 2.4, long-term returns for IPO sample firms are always negative. After controlling for existing factors, their monthly alphas range from -0.284% to -0.188%. This is consistent with the extensive previous literature documenting IPO underperformance within 3 to 5 years after their public listing. However, none of these negative returns are significant. This could be reasonably explained with the large size of IPO event firms in my sample. As one could see from the descriptive statistics included in Table 2.1, the average market capitalization of IPO event firms included in my sample is 1223.58 million (median 668.50 million), which is almost twice as large as the universal IPO (mean 773.58 million. median 361.56 million). Previous studies consistently document that the scale of IPO underperformance declines with size of the listing

[24] I skip the first month after the IPO for the IPO portfolio to mitigate the effect of initial prices increase after the IPOs. To make it consistent, I also skip the first month after IPO to form the incumbent portfolio.
[25] All t-statistics included in this study are already corrected for 5-lag of autocorrelation for past returns using Newey-West correction.

firms[26]. Thus, as the size of the listing firm increased greatly, the underperformances became less severe.

In contrast, alphas for corresponding incumbent firm samples are always positive and significant at 1% even after controlling for market risk, size, value and momentum factors. These range from 0.634% with the Fama French 3 factor model to 0.881% with CAPM. The differences of alphas between IPO portfolio and industry incumbent portfolio are always significant, ranging from -1.055% to –1.139% monthly and equivalent to over 10% annually.

The differences in alphas suggest that either incumbent firms have different risk exposure from IPO firms, or investors have problem valuing incumbent firms (but not IPO firms), contributing to their positive abnormal returns. The latter explanation seems less plausible, as industry incumbents exist in the public market for a much longer time than IPO firms (at least three years before the IPOs). Intuitively, there is more information about industry incumbents in the market than the newly listed firms. Even if there is any mis-valuation, the mis-valuation should be stronger for IPO firms than for industry incumbents. Thus, a risk explanation is more probable.

However, people might still argue that large IPO events are more likely to happen for industries that have a higher valuation ratio, as suggested by various previous studies such as Pagano et al. (1998), Subrahmanyam and Titman (1999), Lowry (2002), and etc. Although the abnormal return measured here already control for market to book ratios, it is possible (though unlikely) that the positive abnormal returns are attributable to investor sentiment and/or growth opportunities that are not captured by market-to-book ratios[27]. But neither growth opportunities nor investor

[26] For example, Ritter (1991) and Loughran and Ritter (1995)

[27] It is unlikely in the sense that higher market valuation should increase the return of IPO firms and industry incumbents at the same time, however what we observe in the data is that incumbent firms have positive abnormal return, but IPO firms on average underperform (e.g., Ritter, 1991, 1993, 1995, and Loughran and Ritter 1993, 1995). Even for the current sample of large IPO events, we can still observe negative and insignificant abnormal returns.

sentiment uncaptured by market-to-book ratios can reconcile with the different return patterns between IPO firms and their industry incumbents. If increased industry valuation signals improved growth opportunities and firms respond by going public (Subrahmanyan and Titman (1999), Schultz (2000)), then positive alphas of industry incumbents can be explained as contagion effect, where higher price in IPOs reveals growth opportunities for that industry and investors increase their valuation for industry incumbent following listing. This explanation implies that IPO firms should also have positive abnormal returns post listing, inconsistent with the documented underperform after going public (at least no positive alphas). Also it is unlikely that some industries can have persistent improvement in growth opportunities, and thus hardly explain why positive alphas exist for a long period.

Alternatively, several studies have found that firms are more likely to go public following a period of favorable investor sentiment, and eventually earn a lower returns as the market cools down (Baker and Wurgler (2000), Lowry (2002), Lowry and Schwert (2002)). But this predicts that incumbents should exhibit lower returns during the post-issuance period when the market cools down, not positive alphas observed in the data, in this sense, market valuation doesn't help to explain the positive alphas of industry incumbents.

A risk explanation would suggest that industry incumbents are exposed to some additional risk uncaptured by included factors (market risk, size, value, and momentum). To examine whether a risk explanation is more plausible than mis-valuation story, I apply the time-series method employed by Hou and Robinson (2006), which is similar to an ICAPM method. Within the ICAPM framework, risk means loss during bad times. Specifically, I investigate whether returns of industry incumbents during the post-issuance period exhibits time variation across different business cycles, i.e. when macro-economy turns downwards, are incumbent firms more likely to experience loss.

I estimate the following time-series regression of monthly return from incumbent portfolio on several macro-economic variables which are commonly accepted as indicators of business cycle, controlling for existing factors:

$$r_t = a + \sum_{j=1}^{J} \beta_j F_{j,t} + \sum_{k=1}^{K} \gamma_k X_{k,t} + \varepsilon_t \ ,$$

where dependent variable r_t is the monthly return for incumbent firm portfolio in month t. $F_{j,t}$ is the return to the factor-mimicking portfolio of risk factor j in month t, and $X_{k,t}$ is the month-t value of the macro-economic variable k (J is the number of risk factors in total, K is the number of economic variables in total). a is the intercept of the above regression.

Several macro-economic variables which are generally acceptable as having predictive power for stock returns are included in the above regression. First, monthly inflation rate (INF), which is calculated using the Current Consumer Price Index published monthly by the Bureau of Labor Statistics (BLS). Term Spread (TERM) is the difference between the 10-year and 1-year treasury constant maturity rates. Default premium (DEF) is the difference between Moody's Baa and Aaa monthly bond yield. These data (also include T-bill rate) are obtained from the Federal Reserve Bank of St. Louis through FRED. Dividend yield is obtained from Goyal and Welch's (2008) dataset. Since inflation rate, term spread, default premium and dividend yield are quite persistent over time, I use the innovation term of these five variables as indicators of business cycles, which is the difference between the current value and lagged value one period before (Chen, Roll and Ross, 1986). When ΔINF is high, or ΔDIV, ΔTerm and ΔDEF are low, economy is more likely to be in expansion. In contrast, when ΔINF is low, ΔDIV, ΔTerm and ΔDEF is high, economy is likely to be in recession. I also include monthly returns of SMB, HML and UMD portfolio (from Ken French's data library). Table 2.5 Panel A reports results for the above regression of incumbent portfolio returns on existing factor and macro-economic variables. Post refers to the incumbent portfolio returns during month [+1, +37] subsequent to large IPO events. Prior refers to the returns of portfolio constructed by included returns from industry incumbent firms during month [-37, -1] before large IPO events.

Panel A shows that monthly incumbent portfolio returns are negatively related to changes default spread and dividends yield. Since term premium, default spread and dividends yield tend to increase during economic recession, this means that incumbent firms are likely to generate loss during recessions. Loadings on ΔDEF and ΔDIV are significant, while the estimated coefficient for ΔTerm is insignificant. Changes in inflation rate is significantly positively related to incumbent portfolio returns, implying that incumbent portfolio tend to have higher return during economic expansion, but declined return when the economy takes a downturn. Estimated coefficient for ΔTbill is positive but insignificant. Generally, these results show that incumbent firms tend to have higher return during good times, but in contrast, perform worse during downturns. This is consistent with H4a, and suggests that the abnormal returns are likely to be explained with additional risk.

It might be that my sample filtering criteria generate incumbent firms that happened to be more sensitive to economic conditions than the average firms (though it is not clear why it might be the case). To investigate in more detail whether IPO events actually influence incumbent firms' performance, I compare the loadings on these economic factors during the prior-issuance period for industry incumbents with loadings during the post-issuance period. If IPOs can exert competitive pressure to industry incumbents and increase their risk, then I expect that incumbent firms become more sensitive to economic conditions after large IPO events in the same industry (H4b).

In the second last column of panel A, I report the estimated coefficient from the same regression for each economic variable, but now the dependent variable changes to incumbent firm returns before the IPO from month [-37, -1], instead of during the post-issuance period during [+1, +37][28]. The very last column I document the differences and t-statistics between the post-issuance loading and pre-issuance loading on each macroeconomic factors.

The results show that compared with prior-IPO period, incumbents firms now become more sensitive to surprises in term premium, default premium, dividend yield and T-bill rate. In particular, the significant change of -0.059 on the estimated coefficients of dividend yield suggest that after large IPO events incumbent firms have even lower returns during economic recession. The negative loadings on dividend yield more than tripled (0.024 prior, vs. 0.083 post). During prior-issuance period, increase in dividend yield by one standard deviation (0.078) is only related to decrease in monthly returns by -0.19%. In comparison, during the post-issuance period, increase in dividend yield by the same amount is associated with decrease in monthly returns by -0.65%. The difference suggests that during economic downturns, now incumbent firms have even lower returns, which are economically significant at over -5% annually. The implication from increased negative loadings on default spread and term premium is similar. Overall, H4b is supported.

Panel B of Table 2.5 replicates the same regressions as included in panel A but substitute macro-economic variables with their traded factor mimicking portfolio. In brief, all results in Panel A continue to hold. Incumbent portfolio returns are always significantly positive related to inflation surprises and T-bill surprises, negative significantly related to surprises in default spread and dividend yield. Compare the changes in loadings before and after large IPO events, we can

[28] For brevity, I don't document the loadings on SMB, HML, UMD and Mktrf, since the purpose of the current study is to show incumbent firms become more sensitive to economic conditions after large IPO events in the same industry.

see that loadings on inflation rate increased significantly after large IPO events, suggesting incumbent firms become more sensitive to economic conditions. While the decrease in the loading on term premium is close to marginal significant, the other changes in loadings are with expected signs but insignificant. One explanation of the insignificant results may be that there are only mild correlation between the actual economic variables and returns to the factor mimicking portfolio. In Appendix table A1, I provide the correlation among the macro economic variables and their factor mimicking portfolio returns. The correlations between the actual economic variable and their factor mimicking portfolio returns ranges only from 0.4 to 0.626.

The top panel of Panel C of Table 2.5 documents results from regression incumbent portfolio returns during both prior- issuance period and post-issuance period on all macroeconomic variables altogether, while the bottom panel reports regression on all factor mimicking portfolios. It also reports the changes in loading during the post-issuance period compared with before IPO events. The results are consistent with findings in Panel A and Panel B. Specifically, performances of incumbents load more negatively on changes in term premium, default premium and dividends yield. Changes in term premium and default premium are only significant with factor mimicking portfolio regression, while changes in dividend yield are only significant with macroeconomic variable regressions. Performances also loaded more positively with inflation rate surprises using factor mimicking portfolio. The changes in loading on T-bill rate surprises are ambiguous.

It is worth nothing from results in panel B and the bottom part of panel C, that even after controlling for macro-economic conditions using factor mimicking portfolio returns, intercept reported for post-IPO issuance period are still positive and significant. For example, in bottom part of Panel C, intercept for post-issuance period is a significant 0.7%. One explanation is that, as Hou and Robinson (2006) suggest, risk associated with increased competition is not captured by existing factors and economic variables. In comparison, intercept for prior-issuance period are much smaller at 0.37%, and only marginal significant. This suggests that risk related with competition are much larger during post-issuance period compared with prior-issuance period. Hou and Robinson (2006) further suggest that this competition risk is positive related to distress risk and innovation risk. In the following subsection, I investigate directly how the default probability changes for industry incumbents after large IPO events.

6. Changes in Default Probability of Industry Incumbent after Large IPO Events

If industry incumbents' positive returns during the post-issuance period come from enhanced within-industry competition, I should observe a higher default risk for industry incumbents during the post-issuance period (H5). To accomplish this, I examine whether IPO events are related to the probability of failure of industry incumbents. Specifically, I use the default probability model developed by Campbell, Hilscher and Szilagyi (2008), and estimate a dynamic logistic regression with an IPO indicator to predict the default probability for all incumbent firms over the period between 1995 and 2013. The estimated coefficient on the IPO indicator measures the incremental explanatory power of IPO events to the distress probability of industry incumbents. According to H5, I expect the coefficient on IPO indicator to be positive.

I define failure using CRSP delisting codes following Demers and Joos (2007). Firms with delisting code for liquidation (400) and involuntary delistings (500, 520, 550, 551, 552, 560, 561, 570, 573, 574, 580, 581, 582, 583, 584, 585), excluding firms that switch exchanges (501) or voluntary delist (503), are defined as failure. For the purpose of predicting firm failure, I follow the firm failure model of Campbell, Hilscher and Szilagyi (2008), where the dependent variable is a dichotomous outcome variable that equals to one if the firm fails in a particular year. The model includes the following predictor variables: NIMTA is the ratio of net income to the market value of assets, and is used to measure profitability; TLMTA is the ratio of total liability to the market value of asset; CASHMTA is the ratio of a firm's cash and short-term assets to the market value of its asset; MB is the firm's market-to-book ratio; RSIZE measures the relative size of each firm as the log ratio of its market capitalization to the total market value of the S&P 500 index; SIGMA is the annualized standard deviation of daily stock return over the previous three months; EXRET is the monthly log excess return on each firm's equity relative to the S&P 500 index.

Table 2.6 reports the estimated coefficients, odds ratio, and t-statistics from the dynamic logistic regressions. An odds ratio larger than 1 implies a positive relationship between the variable value and probability of default, while an odds ratio smaller than 1 implies a negative relationship between the variable and probability of default. In column (1), I use the predictor variables proposed by Campbell et al. (2008) to estimate the probability of failure for all firms during my sample period. I find that profitability (NIMTA), cash holding (CASHMTA), relative size (RSIZE) and excess returns (EXRET) are negative related to a firm's probability of failure, while leverage (TLMTA) and volatility (SIGMA) are positive related to a firm's probability of failure. All coefficients are significant with the expected sign. The model has a pseudo-R square of 0.3023. The results are similar to that documented in Campbell et al. (2008).

In column (2), I replicate Campbell et al's model for the incumbent firm sample. The results are similar to those documented in column (1) except that estimated coefficient of cash holding (CASHMTA) and volatility (SIGMA) become insignificant, though they still have the right sign. One reason might be that incumbent firms included in my sample are established firms that have relative stable cash holdings and less volatility (by my sample filtering criteria, they have stay public for at least four years), and thus CASHMTA and SIGMA has little cross sectional predictive power for their default probability.

In column (3), I add in the model an indicator variable, IPO, which equals to one for a firm-year observation if a large IPO event happened in the same industry as the firm during the past four years, otherwise it is equal to zero. The estimated coefficient of the IPO indicator is a significantly positive 1.21. This demonstrates that IPO indicator contain failure-related information that is not captured in the existing predictor variables and default probability for industry incumbents increases after large IPO events, consistent with H5. The odds ratio of 3.36 implies the probability of default during the post-issuance period is more than doubled compared with pre-IPO period. Compared with the actual default probability in the incumbent sample, which is 1% (=428/41415), the default probability increases by 2.36% after large IPO events[29]. In untabulated result, I estimate the model using IPO indicator alone, without other predictor variables to investigate whether the interaction between the predictor variables and the IPO indicator drives the previous results in column (3). Estimated coefficient of IPO indicator (1.27) continues to be positive and significant with an odd ratio of 3.55, confirming earlier result. In sum, it suggests that industry incumbents have higher default probability after large IPO events in their industry.

One may argue that results in previous section simply because IPO is correlated with some omitted variables that increase firms' default probability, i.e. the IPO indicator simply capture the mean reversion of industry growth. To address this concern, I conduct cross sectional tests based on the characteristics of industry incumbents. TO the extent that I find evidence consistent with theoretical predictions in which incumbents are expected to be affected more by IPO firms and are

[29] The absolute magnitude of default probability is small since incumbent firm sample include large and established firms. But even in such cases, we can still observe the impact of IPO events which are generally smaller firms. This confirm the existence of IPO related competitive advantages.

more likely to have increased default probability, the endogeneity concern due to omitted variables reflecting firms' default risk should be mitigated.

Intuitively, the investment flexibility and growth opportunities that incumbent firms possess can help mitigate the enhanced competition imposed by newly-listed firms. I consider the following moderating factors: Tobin's Q which captures firms' growth opportunity, leverage and Altman Z score capture the investment flexibility a firm has (the higher leverage, and more constrained firms have less investment flexibility), and profitability, which capture performances. The underlying intuition is that the more financial flexibility and growth opportunity the firm has, and the better performed the firm is, then the less increase in their default probability after large IPO events.

In Panel B of Table 2.6, I estimated the same default probability prediction model with IPO indicators for different subsamples of industry incumbents. Specifically, for each IPO events, industry incumbents are sorted according to their most recent prior-IPO profitability, leverage, Tobin's Q and Altman Z score. Firms in the bottom 30% of each measure are assigned to the low portfolio, while firms in the top 30% are assigned to the high portfolio. I expect that industry incumbent with higher profitability, Tobin's Q and Altman Z-score but lower leverage will have less increase in their default probability after large IPO events (smaller loading on the IPO indicator).

The results documented in Table 2.6 Panel B are consistent with my prediction. For example, industry incumbents with the lowest Altman Z-score (the least financial flexibility) will have more than tripled default probability after large IPO events (odds ratio=4.3), while firms with highest Altman Z-score (the most investment flexibility) will only exhibit a 1.8 times increase in their default probability (odds ratio=2.84). Similarly, firms with higher profitability and more growth opportunities but lower leverage also experience less increases in their default probability.

The above results from cross sectional tests alleviate the endogeneity concern that my results are driven by omitted variables that capture the mean reversion of industry growth. If this endogeneity concern is valid, I should expect that those have better performances (further away from the mean) have larger increases in their default probability rather than firms that have lower profitability, less growth option, higher leverage. But the above results indeed show it is firms with lower profitability, higher leverage, lower Tobin's Q that exhibit a greater increase in their default probability.

7. Cross-Sectional Analysis of Incumbent Firms' Positive Abnormal Return

Evidence documented above is consistent with the explanation that large IPO events enhance the competition, exert higher competition pressure to incumbents, and increase their default risk. If greater competition contributes to the risk and abnormal returns of industry incumbents observed in the data, then I expect industry competition is related to incumbent firms' expected stock returns. In this section, I try to shed more lights on how differences across industries affect IPO-related competitive effects by examining how various aspects of competition relate to incumbent stock returns.

7.1. Industry Concentration/Competitiveness

Hou and Robinson (2006) show that product market structure (i.e. industry concentration), affects cross sectional firm returns. Firms in concentrated industry with high Herfindahl Index earn on average lower return than firms operating in competitive industries with low Herfindahl Index. And the differences in returns cannot be explained by existing factors such as size (SMB), book-to-market (HML) and momentum (UMD). On one hand, this supports my story of increased competition risk for industry incumbents. On the other hand, it might be the case that my previous results overlap with theirs, and is not associated to IPO-related advantages. To rule out this possibility, I estimate the effect of IPO events on incumbent firms' cost of equity using an IPO dummy and controlling for industry concentration (measured with Herfindahl Index) and existing factors that affect firm returns. Specifically, I estimate the following regressions:

$$R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * HHI_{i,t-1} + \beta_2 * IPO_{i,t} * HHI_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t}$$

Where $R_{i,t}$ is monthly return for incumbent firm i in calendar month t. IPO is a dummy variable that equals to 1 if month t is within the 36 months post large IPO events in incumbent firm i's industry, and zero otherwise. $HHI_{i,t}$ denotes the Herfindahl index for firm i's industry at month t, which is calculated as the sum of squared market share for all firms in that industry. [30] The lower the value of Herfindahl Index is, the more competitive the industry is. [31] $X_{k,t}$ is the month-t value of the control variable X, which is known to be related to stock return. Xs include beta, size, market-to-book ratios, and past six-month returns. In addition, since the probability of firm's to go public is related to market liquidity, I also control for stock liquidity with Roll (1984) measure. a is the intercept of the above regression. Firms' market beta is estimated as in a Fama Macbeth regression. Specifically, market beta is estimated as the sum of the coefficients of regressions of individual firms' monthly stock returns on contemporaneous and lagged market returns over the past three years.

I also include the interaction term of IPO dummy and industry competitiveness in my regression, in order to examine specifically the effect of IPOs on incumbents for different

[30] I am aware of the data availability that constrains the calculation of Herfindahl Index, but this is the most commonly used index to measure industry competition.

[31] I also use Four-Firm concentration ratio as an alternative, the results are quite similar with those estimated with Herfindahl Index

industries. To rule out unobservable industry heterogeneity and to control for serial correlation, I estimate the above model using Fama-Macbeth regression with industry dummies. Note that the explanatory variables are all lagged by one period, so that the estimated results can be explained as the effects of IPOs on incumbent firms' expected returns.

Table 2.7 Panel A documents the summary statistics of all the competition measures used in this section; Panel B documents the Pearson correlation among all competition measures. Generally speaking, the distribution of my calculated measures and their correlations are similar to those documented in Karuma (2007). Table 2.8 reports the estimated results of the above equation. Column one shows that industry incumbents in concentrated industries on average earn lower returns than those in less concentrated industries, as suggested by the significantly negative loading on Herfindahl index of -0.0243. In column 3, I add the IPO indicator, which is equal to one for incumbent observations that are within 36 months after corresponding large IPO events. The result shows that incumbent firms experience a significant increase of 5.4% in their stock returns after large IPO events. The negative interaction between IPO indicator and industry Herfindahl index shows that the associated increase in returns is less for concentrated industries but larger for competitive industry. However, the difference is insignificant. One plausible explanation for the insignificance is that industry concentration is a noise measure of product market competition (Karuma, 2007), which imply either strong competition or less competition[32]. Karuma (2007) further show that conditional on industry concentration, market size, entry cost, product differentiability are also related to competition. Thus to explore the relationship between

[32] Firms in concentrated industry usually face weak competition, and thus are less experienced in dealing with competitors. But they have more market power, and relative immune to the small listing firms. Therefore, generate the overall insignificant differences between concentrated industries and competitive industries.

competition and incumbent firms' expected return in more detail, I use other measures (as in Karuma, 2007) in following cross sectional regression of expected returns on industry competition.

7.2. Other Competition Measures

The average level of product substitutability (or differentiability) in each industry is related to product market competition. Product substitutability refers to the likelihood of one product being substituted by another product that is similar and close. Higher level of product substitutability implies lower level of product differentiability, and higher level of price competition. I expect that expected returns of existing incumbents in industries with high level of product substitutability increase more (H6b).

Following studies in industrial organization, I use price-cost margin to measure product substitutability in an industry, which is exactly the negative reciprocal of price elasticity of demands (Nevo, 2001)[33]. Intuitively, a lower price-cost margin (closer to 1) implies that the price approaches to the true production cost, thus the industry is more close to perfect competition. In such industries, demand is more sensitive to price change (high price elasticity). Thus lower price cost margin reflects higher level of product substitutability. I first calculate price-cost margin for each 4-digit SIC code[34], and then average them across each Fama-French 49 industry.[35] I add into the previous regression a measure of product substitutability, and an interaction term between IPO

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[33] The higher the price elasticity is (in absolute value), the lower price-cost margin is.

[34] On June, 1, 1998, IAS 14 Segment Reporting requires reporting of financial information by business or geographical area. While before 1998, data of segment sales are generally available from Compustat Segment File, the data related to operating costs (i.e. segment COGS, segment SGA, and segment depreciation and amortization) are almost missing. To minimize the problem caused by missing data, my analysis starts from year 1998. See Appendix B for how to calculate each competition measure

[35] The reason for doing this two-stage average instead of averaging over the whole industry directly is to mitigate the effect of extreme value. Price-cost margin might differ within a 'wider' industry, where price-cost margins of sub-industries differ greatly. For example, taken from Nevo (2001), the profit margin of ready-to-eat cereal industry (with SIC code 2043) is 64.4%, while the whole food industry with two digit SIC code 20 is only a little bit over 26.5%.

and industry product substitutability. I expect that the interaction term of IPO and product substitutability measure (DIFF) is negative.

Other variables associated with product market competition include market size (MktSize), number of public firms (Fnum) and entry cost (EntCost). Large market size is usually associated with high profitability and growth potential, which attracts firms entering the industry[36]. Since industries with large market size are usually in the growth stage and have higher profit margin, negative competitive effects from IPO firms to existing incumbents can be relatively mitigated by the huge growth potential. This suggests that IPO-related competitive effects should be negatively related with market size (a negative value for the coefficient of the interaction between IPO and market size).

Entry cost measures the start-up cost for entering the industry. Higher entry cost serves as a natural barrier to potential competitors. Firms operating in high entry cost industries are likely to lack experience in competing with potential entrants. Therefore, IPO events will more likely to generate significant negative impacts in industries with higher entry cost.

To explore how IPO related competitive impacts vary across different industries, I apply the same approach as before, adding alternative measures of competition and their interaction with IPO dummy. Since these competition measures are skewed, so I use the log transformation of these competition measure in my regressions. As shown in Table 2.7, these competition measures are correlated with each other, so I start by estimating the above regression for each competition measure respectively. Table 2.8 Panel A reports the estimated results.

Column 1 documents the results of regression on product differentiability, after controlling for industry concentration (HHI). The negative significant loading on the interaction between IPO

[36] Firms keep entering the industry and lower its profit margins, until the profit margin equals to the marginal cost of entry for the next new entrants.

indicator and product differentiability suggest that IPO events in high differentiable industries have smaller competitive impacts, consistent with my expectation. Specifically, everything else equal, firms in industries have lower differentiability (Diff_Q1=1.09) will experience 0.11% more increase in their monthly returns after large listing events. In contrast, firms in industries with higher differentiability (DIFF_Q3=1.19) will experience 0.08% less increase in their monthly stock returns after large listing events. This is because declined expected cash flow out-weighs the effect of increasing expected risk, and the overall effect is a decrease in expected returns.

Similarly, Column 2 shows that incumbent firms' return increases significantly after large listing events, but now the result is weaker as the estimated coefficient on IPO is only close to marginally significant. Estimated coefficient on the interaction between IPO and market size is negative -0.0041, but insignificant. No evidence regarding how market size affects IPO related competitive advantages might be because the offsetting effect of industry sales on the expected cash flow and risk of existing incumbents.

Column 3 offers some evidence that IPO increase incumbent firms' returns, but no evidence regarding how entry cost affects IPO related competitive advantages. This might be because the measure of entry cost calculated using PP&E is not a good measure of competition. It might have been a good proxy years ago, but currently technology cost also accounts for an important part of entry cost, especially in some high-tech industries.

Chemmanur, He and Nandy (2010) show that the number of public firms is associated with industry competition. Industries with higher number of public firms are more competitive. In column 4, we can see that none of the variables of interest are significant, although all the signs are consistent with my expectations. One plausible reason is the concentration measure is highly correlated with number of public firms (-0.513), which might attenuate explanatory power.

In Table 2.8 Panel B, I regress incumbent firms' monthly return on multiple competition measures at the same time. Generally, the sign of each interactions between competition and IPO dummy is the same as in panel A (except for EntCost). The last column includes the estimated results from an all-sink regression.

From Column 5 we can see that after large IPO events, incumbent firms generally experience increase in their expected stock returns, as indicated by the positive and significant coefficient of 0.1748 for IPO indicators. Moreover, such increases in incumbent firms' stock returns is larger for industries with large firm number (significant IPO*Fnum = 0.04), for industries with smaller growth opportunities (marginally significant IPO*Mktsize = -0.0112), and for industries with lower differentiability (close to marginally significant IPO*Diff = -0.0829). In other words, consistent with my conjunction, increase in abnormal returns is higher for industries with great competition. Overall, the results suggest that IPOs can enhance product market competition, which consequently increases expected returns of existing incumbents.

7.3. Market share as proxy for market power

To analyze how IPO affects existing incumbent in more detail, I use each firm's market share as a proxy for their market power. Firms with larger market share have greater market power, and thus more capable of competing with newly listed firms. Thus I expect less negative impacts. I estimate a similar regression as above, but now add the lagged one period market share, and the interaction term of market share and IPO. Particularly, I expect interaction term between IPO and market share to be significantly negative. Table 2.9 documents the estimated results from the regression of incumbent firms' expected returns on market share and its interaction term with IPO dummy.

Column 1 of Table 2.9 shows that neither the IPO indicator nor the interaction between IPO and market share is significant. One potential reason for this is that the relationship between expected return and market share is non-linear. To solve this problem, I define an industry leader dummy variable. If individual firm's market share exceeds certain percentile benchmark, then the leader dummy is equal to one. I use 10% and 30% respectively for column 2 and 3. Column 2 shows a significant positive interaction between IPO and industry leader dummy, suggesting that firms with large market share perform well after IPO. This might as argued before, IPO involves extensive information disclosure, which might benefit some firms. Column 3 shows a similar result.

I construct a similar measure called industry follower if an individual firm's market share is below the bottom 10% or 30% among all firms in the industry. Column 4 shows that for firms with the smallest market share, their returns also increase after IPO events in the same industry. However, the magnitude of increases is much smaller than that for industry leader. This might be explained as that expected cash flow decrease so much which offset partially the increase in expected returns.

8. **Robustness tests**

It might be that the previous documented results are specific to my selected samples. To provide robustness tests, I re-do all the tests for different IPO and industry incumbent samples. Specifically, I have change the industry identification from Fama French 49 industry to 3 and 2 digit SIC code respectively, for IPO firms that have the 10% proceeds and for IPO firms that have the top 30% sales. Results are included in appendix (available upon request). Briefly speaking, results for alternative sample are statistically and qualitatively similar.

8.1 Long-term stock return

It is a quite arguable problem how to measure long term expected returns. But recently much progress has made as which measure is better. In previous sections, I use the calendar time portfolio method recommended by Fama (1998) and Mitchell and Stafford (2001). I create the calendar time portfolio each month, including firms whose industry has a large IPO event during the past 36 month, calculate their monthly return and regress on SMB, HML and UMD to get the abnormal return. But as Mitchell and Stafford (2001) point out, this method also has weakness as it requires constant loadings on SMB, HML and UMD factors. They suggested a method called calendar time abnormal return-CTAR (first used in Jeffe (1976)) as a robustness test. I replicate this method, and get similar significantly positive abnormal returns for my competing firms. The results are briefly listed below. It shows that competing firms have a positive abnormal return within three years after large IPO events in the same industry. Furthermore, the magnitude of these abnormal returns is quite similar to those documented in Table 2.4 for each specific model, confirming that the positive abnormal returns observed for industry incumbents are not an artifact.

	Calendar time portfolio			Robustness- CTAR		
	CAPM	Fama French 3 Factor	Fama French 4 Factor	CAPM	Fama French 3 Factor	Fama French 4 Factor
alpha	0.764%	0.532%	0.652%	0.788%	0.659%	0.706%
	2.40	2.70	3.58	2.85	3.84	4.86

8.2 Cash flow shocks

According to Campbell and Shiller (1988) decomposition, returns are determined by shocks to cash flows and shocks to discount rates. Thus cash flow shocks could be responsible for my previous findings. However, it is unlikely this is the case. Fist, while cash flow shocks is related to positive excess returns, they hardly persist for three years subsequent to IPO events. Moreover, results in Table 2.3 show that operating performance and profitability of incumbents decline subsequent to listing events in the same industry. Thus, post-issuance expected cash flows for industry incumbents are more likely to fall instead of increase. To rule out the possibility formally I examine whether industry incumbents experience persistently positive earnings/profitability shocks in this section.

I measure unexpected profitability for all incumbent firms as the residual from the following earning forecast models, which is similar to the method in Fama and French (2000), Vuolteenaho (2002) and Hou and Robinson (2006).

$$\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t$$

Where E/A measures firm profitability, and is calculated as earnings scaled by the book value of total asset; V/A is the ratio of market value of asset to book value of asset; DD is a dummy variable for non-dividend-paying firms; and D/B is the ratio of dividend payments to book equity. I also add the lagged profitability measure (E/A) as suggested by Vuolteenaho (2002). Expected profitability is the fitted value for the above equation, while regression residual captures unexpected profitability for a firm-year observation.

Table 2.11 panel A reports the average estimated results from Fama-Macbeth regressions of the above equation, which are similar to those reported in Hou and Robinson (2006) and Fama and French (2000). Loadings on D/B and DD are statistically significant, and have the expected sign. The results are consistent with previous findings that dividends-paying firms have higher profitability. Lagged profitability is highly significant and positively related with current profitability. Inclusion of lagged profitability helps improve the regression R^2 to 48.6% as suggested in Vuolteenaho (2002). The only difference from previous results is that the estimated coefficient on V/A reverses its sign. It might be attributable to the fact that my sample period has more weight around internet bubble period.

Panel B of Table 2.11 presents the average and median unexpected profitability for industry incumbents within a three-year period before and after IPO events. The results demonstrate that for industry incumbent firms, average unexpected profitability before the IPO events is an annually 1.68%. It declines to 1.16% annually subsequent to large IPO events, around 30% decrease. The difference in unexpected profitability before and after IPOs is significant with a t-statistic of 2.61. To address this concern that this result might be driven by outliers, I winsorize unexpected profitability for all observations at 1%, and 5% level respectively. Untabulized results are qualitatively same. Panel B also indicates that the median level of unexpected profitability also decreases from 2.54% before IPOs to 2.19% after IPOs., also statistically significant with Wilcoxon rank test.

Table 2.12 panel C directly examines the relationship between unexpected profitability of incumbents and IPO by estimate a regression of unexpected profitability on IPO indicator (defined same as in previous sections). The loading on IPO indicator in column (1) is negative and significant, confirming that unexpected profitability decreases on average by 0.53% after large IPO events for industry incumbents. I include year fixed effect further in the estimation to control for time related factors. Result documents in column (2) shows that IPO indicator continues to be significantly negative, thus the decline in unexpected profitability is not driven by unobserved time effect. I include industry and year fixed effect together in column (3) to control additionally for industry unobservables. Estimator of IPO indicator continues to be significantly negative.

These results suggest that unexpected profitability of industry incumbents actually decrease instead of increasing after large IPO events. This contradicts with the existence of persistent positive cash flow shocks, and it implies that positive return observed for industry incumbents after large IPO events is not driven by persistent shocks in cash flow, but rather attributable to shocks to discount rate.

There might be people argue that results in Table 2.11 are based on the assumption that the profitability prediction model is correct. If the model cannot fully capture the dynamic of firm profitability, then the decreased unexpected profitability could be correlated with other missing variables which might at the same time attribute to the higher returns of industry incumbents after IPO events. To address this concern, I use three alternative measures that don't depend on specific models: earnings surprises. In particular, I estimate earnings surprises using both analyst earnings forecasts and historical earnings as proxies for market expectation. Unexpected earnings are calculated as the differences between actual and expected earnings scaled by price, following Livnatand Mendenhall (2006). The first one is a time-series earnings surprise measure denoted as SUE1. It is computed by the following equation: $SUE1_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{P_{i,t}}$, Where $E_{i,t}$ represents EPS before extraordinary items for firm i in quarter t; $E_{i,t-4}$ represents EPS before extraordinary items for the same quarter in the previous year. $P_{i,t}$ is the stock price of firm i at the end of quarter t. Although for this measure, the benchmark is set to be historical EPS with no adjustment, the advantage of this measure is that it covers the most of Compustat firms. To address the influence of special items, I follow the method used in Bradshaw and Sloan [2002] and Livnatand Mendenhall (2006). Specifically, I subtract from the EPS the amount of special items times 65% divided by the number of shares used to calculate earnings per share. Thus, the estimated measure is after exclusion of special items, and is denoted as SUE2. Last, I estimate earnings surprise with analyst forecasts by substituting $E_{i,t-4}$from the above equation with analysts' expectations, and denote it as SUE3. This measure incorporates more judgment from sophisticated investors and captures market surprises better. However, the requirement for available analyst earnings forecasts makes it less inclusive.

I replicate previous tests in Table 2.11 using SUE. Table 2.12 Panel A reports the average and median earnings surprise for industry incumbents within a seven-year period around IPO events (three years before and three years after IPO events). Briefly speaking, results in Table 2.12 indicate that average earnings surprises of industry incumbents decline after large IPOs in the same industry. For example, unexpected EPS after special items (SUE2) is on average 1.43% (median 0.16%) before IPOs. It declines to -1.05% (median 0.107%) after IPOs. Differences in both median and mean are significant. However, SUE3, which capture the unexpected earnings from analyst expectations, exhibit a relative weak but still significant decline.

In Table 2.12 Panel B, I estimate a regression of the three earnings surprises measures on the IPO indicator. Similar as in Table 2.11, the IPO indicator variable are loaded significantly negative for all three measures, even with year-quarter fixed effect in column (2) and industry fixed effect together in column (3). The estimated coefficients range from -0.0043 for SUE3 to -0.0247 for SUE1, which translate into decline in unexpected earnings range from 0.43% (SUE3) to 2.47% (SUE1), more than 40% decrease when compared to their pre-IPO level. Overall, results in this section show that persistent cash flow shocks are not the reason that industry incumbent firms exhibit positive stock returns after large IPO events.

8.3. Simultaneity

Another concern might arise from the fact that sometimes firms go public because of enhanced product market competition (Chemmanur and He (2012)). If increased product market competition leads firms to go public, then industry incumbents' positive abnormal returns simply capture the fact that their industries are becoming competitive and have nothing to do with competitive threat imposed by IPO firms. But if this is the case, then new listed firms should also have a positive competition premium, inconsistent with non-positive premium for IPO firms in Table 2.4. Moreover, the cross sectional regression estimated above has already included industry dummies, which capture the unobserved industry characteristics that might affect the likelihood of IPO events and incumbent firms' increased expected return at the same time. Thus the estimated results are consistent estimates regarding IPO events' impact on industry incumbents' expected returns.

9. Conclusion

In this study, I analyze how large IPO events affect industry incumbents in terms of their risk. I show that industry incumbents experience significant price decline around the successful large IPO events. But they earn positive abnormal returns within three years' horizon post large IPO events. The positive abnormal return cannot be explained by size, book-to-market and momentum factor. At the same time, their operating performances such as ROA and asset growth decline compared with their prior-IPO level, and their default probability increase. Further, within the ICAPM framework, I provide evidence that their stock performances are now more sensitive to economic condition, suggesting they become more risky. I further show that observed positive returns are not contributable to persistent cash flow shocks. These results consistently suggest that large IPO events can increase the risk of industry incumbents by exerting competitive pressure. Using a set of cross sectional test, I provide some evidence that increases in incumbent firms' expected returns is greater for firms in industries with low differentiability, large number of public firms, and for industries with smaller market size.

References

Akhigbe, Aigbe, Stephen F. Borde, Ann Marie Whyte, 2003, Does an Industry Effect Exist for Initial Public Offerings? Financial Review 38(4): 531-551.

Baginski, Stephen P., 1987, Intraindustry Information Transfers Associated with Management Forecasts of Earnings, Journal of Accounting Research 25(2): 196-216.

Benveniste, Lawrence M., Paul A. Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, Journal of Financial Economics 24(2): 343-361.

Bradshaw, Mark T., and Richard G. Sloan, 2002, GAAP versus The Street: An Empirical Assessment of Two Alternative Definitions of Earnings, Journal of Accounting Research 40(1): 41-66.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In Search of Distress Risk, The Journal of Finance 63(6): 2899-2939.

Carter, Richard B., Frederick H. Dark, Ajai K. Singh, 1998, Underwriter Reputation, Initial Returns, and the Long-Run Performance of IPO Stocks, the Journal of Finance 53(1): 285-311.

Carter, Richard, Steven Manaster, 1990, Initial Public Offerings and Underwriter Reputation, the Journal of Finance 45(4): 1045-1067.

Chemmanur, Thomas J., He Jie, 2011, IPO waves, product market competition, and the going public decision: Theory and evidence, Journal of Financial Economics 101(2): 384-412.

Chemmanur, Thomas J., Shan He, Debarshi K. Nandy, 2010, The Going-Public Decision and the Product Market, Review of Financial Studies 23(5): 1855-1908.

Chen, Nai-Fu, Richard Roll, and Stephen Ross, 1986 , Economic Forces and the Stock Market, Journal of Business 59 (3): 383–403.

Choe, Hyuk, Ronald W. Masulis, Vikram Nanda, 1993, Common stock offerings across the business cycle: Theory and evidence, Journal of Empirical Finance 1(1): 3-31.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, The Journal of Finance 52(3): 1035-1058.

Daniel, Kent, David Hirshleifer, Avanidhar Subrahmanyament, 1998, Investor Psychology and Security Market Under- and Overreactions, the Journal of Finance 53(6): 1839-1885.

Eckbo, B. Espen, Øyvind Norli, 2005, Liquidity risk, leverage and long-run IPO returns, Journal of Corporate Finance 11(1-2): 1-35.

Fama, Eugene F., and Kenneth R. French, 2000, Forecasting profitability and earnings, Journal of Business 73, 161–175.

Hou, Kewei, David T. Robinson, 2006, Industry Concentration and Average Stock Returns, the Journal of Finance 61(4): 1927-1956.

Hsu, Hung-Chia, Adam V. Reed and Jorg Rocholl, 2010, The New Game in Town: Competitive Effects of IPOs, The Journal of Finance 65(2): 495-528.

Ibbotson, Roger G., Jeffrey F. Jaffe, 1975, "HOT ISSUE" MARKETS, the Journal of Finance 30(4): 1027-1042.

Irvine, Paul J., Jeffrey Pontiff, 2009, Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition, Review of Financial Studies 22(3): 1149-1177.

Jain, Bharat A., Omesh Kini, 1994, The Post-Issue Operating Performance of IPO Firms, the Journal of Finance 49(5): 1699-1726.

Jain, Bharat A., Omesh Kini, 1995, Venture capitalist participation and the post-issue operating performance of IPO firms, Managerial and Decision Economics 16(6): 593-606.

Karuna, Christo, 2007, Industry product market competition and managerial incentives, Journal of Accounting and Economics 43: 275-297.

Kim, Yongtae, Michael Lacina, and Myung Seok Park, 2008, Positive and Negative Information Transfers from Management Forecasts, Journal of Accounting Research 46(4): 885-908.

Livnat, Joshua, and Richard R. Mendenhall, 2006, Comparing the Post–Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts, Journal of Accounting Research 44(1): 177-205.

Ljungqvist, Alexander, William J. Wilhelm, 2003, IPO Pricing in the Dot-com Bubble, the Journal of Finance 58(2): 723-752.

Loughran, Tim, Jay R. Ritter, 1995, The New Issues Puzzle, the Journal of Finance 50(1): 23-51.

Loughran, Tim, Jay R. Ritter, 1997, The Operating Performance of Firms Conducting Seasoned Equity Offerings, the Journal of Finance 52(5): 1823-1850.

Lyandres, Evgeny, Le Sun, Lu Zhang, 2008, The New Issues Puzzle: Testing the Investment-Based Explanation, Review of Financial Studies 21(6): 2825-2855.

Maksimovic, Vojislav, and Pegaret Pichler, 2001, Technological Innovation and Initial Public Offerings, The Review of Financial Studies 14(2): 459-494.

McGilvery, Andrew, Robert Faff, and Shams Pathan, 2012, Competitive valuation effects of Australian IPOs, International Review of Financial Analysis 24: 74-83.

Mikkelson, Wayne H., M. Megan Partch, Kshitij Shah, 1997, Ownership and operating performance of companies that go public, Journal of Financial Economics 44(3): 281-307.

Nevo, Aviv, 2001, Measuring Market Power in the Ready-to-Eat Cereal Industry, Econometrica 69(2): 307-342.

Pástor, Ľuboš, Lucian A. Taylor, Pietro Veronesi, 2009, Entrepreneurial Learning, the IPO Decision, and the Post-IPO Drop in Firm Profitability, Review of Financial Studies 22(8): 3005-3046.

Ritter, Jay R., 1991, The Long-Run Performance of initial Public Offerings, the Journal of Finance 46(1): 3-27.

Roll, Richard, 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, The Journal of Finance 39(4): 1127-1139.

Spiegel, Matthew, and Heather Tookes, 2008, Dynamic Competition, Innovation and Strategic Financing, *working paper*.

Spiegel, Matthew, and Heather Tookes, 2014, An IPO's Impact on Rival Firms, *working paper*.

Sarkissian, Sergei, Yan Wang, 2012, Do Foreign Listings in the U.S. Affect U.S. Firms? *working paper*.

Teoh, Siew Hong, Ivo Welch, T. J. Wong, 1998, Earnings Management and the Long-Run Market Performance of Initial Public Offerings, the Journal of Finance 53(6): 1935-1974.

Tookes, Heather E., 2008, Information, Trading, and Product Market Interactions: Cross-sectional Implications of Informed Trading, The Journal of Finance 63(1): 379-413.

Vuolteenaho, Tuomo, 2002, What Drives Firm-Level Stock Returns? The Journal of Finance 57(1): 233-264

Table 2.1: Descriptive Statistics

Table 2.1 reports the descriptive statistics for the three samples of IPO event firms and their incumbent firms. Assets, sales, and market capitalization are reported at the end of the IPO event year. All variables are measured at the end of the IPO event year. Data of accounting information comes from Compustat annual files, and stock market data comes from CRSP. The unfiltered sample includes 1476 IPO event that has data available from CRSP and Compustat. I select 109 large IPO events based on their prior-IPO sales. Incumbent firms are defined as firms operating in the same Fama French 49 industry as the IPO firms which are public traded at least three years before the IPO year. The last column documents the p-value from Wilcoxon z test of equal rank between IPO sample firms and their industry incumbents.

	IPO_all obs=1476		IPO_smpl obs=109		Incumbents obs=5327		differences Wilcoxon z
	mean	median	mean	median	mean	median	*p-value*
Asset ($mil)	447.79	112.26	3538.41	593.42	4266.70	421.50	0.020
Sales ($mil)	342.12	47.92	3725.62	671.66	3661.98	417.08	0.001
Market Capitalization ($mil)	773.58	361.56	1223.58	668.50	3480.36	321.52	0.002
Venture backed	0.64	1	0.18	0			

Table 2.2: Cumulated Abnormal Return of Incumbent Firms around IPO Dates

Table 2.2 reports the cumulative abnormal return of incumbent firms around IPO filing dates and initial trading dates. Competitor firms have to be in the same industry as the IPO firms, and are public at least three years before the IPO year with available data. Abnormal returns are calculated using market adjusted excess return, Fama French 3 factor model and additionally with the momentum factor, which is the difference between actual stock return and the expected model stock return. Three models are estimated using an estimation window between 255 days and 42 days prior to the IPO events. I require the incumbent firms to have at least 50 daily observations during the estimation windows to achieve reasonable parameter estimations. Various event windows are applied.

	CAPM		Fama-French 3 factor		Fama-French 4 factor	
Event Window	CAR	*t-stat*	CAR	*t-stat*	CAR	*t-stat*
(-1, +1)	-0.13%	*-1.80*	-0.20%	*-2.69*	-0.17%	*-2.33*
(-5, +1)	-0.12%	*-1.72*	-0.13%	*-2.08*	-0.12%	*-2.03*
(-5, +5)	-0.14%	*-1.98*	-0.11%	*-1.79*	-0.09%	*1.03*
(-10, +1)	-0.53%	*-3.49*	-0.39%	*-2.58*	-0.33%	*-2.17*
(-10, +5)	-0.55%	*-3.19*	-0.38%	*-2.19*	-0.20%	*-1.99*
(-10, +8)	-0.80%	*-4.21*	-0.49%	*-2.56*	-0.33%	*-1.71*
(-10, +10)	-1.04%	*-5.13*	-0.56%	*-2.80*	-0.44%	*-2.16*
(-15, +10)	-1.11%	*-4.84*	-0.72%	*-3.19*	-0.53%	*-2.30*
(-20, +10)	-1.19%	*-4.75*	-0.75%	*-3.01*	-0.51%	*-2.02*
(-10, +15)	-1.10%	*-4.77*	-0.52%	*-2.28*	-0.28%	*-1.91*
(-10, +20)	-1.48%	*-5.72*	-0.63%	*-2.44*	-0.24%	*-1.90*

Table 2.3: The Effect of IPO Events on Operating Performance of Industry Incumbent Firms

Table 2.3 documents how operating performance changes over time for industry incumbents. Panel A reports how KZ index and Altman's Z- score change for industry incumbents over time. Data used to calculate KZ index and Altman's Z-score come from Compustat. t-statistics and Wilcoxon test statistics are reported. Panel B reports the estimates from a panel regression of incumbent firms' sale growth, operating income growth and capital expenditure growth on an IPO indicator, controlling for firm age, size, valuation, past performance and industry and year fixed effects. Sales growth is the difference between current log sales and previous year log sales. Operating income growth is the difference between the log current operating income and log previous year log income. Capital expenditure growth is the difference between log current capital expenditure and log one-year-prior capital expenditure. R&D intensity is measured as R&D scaled by sales. IPO dummy is an indicator variable which equals to one if year t is within 3 years after a sample IPO events, and zero otherwise. M/B is the market to book ratio. Stardard errors are clustered at firm level. t-statistics are reported in parentheses.

Panel A: Changes of financail constraints for incumbents over time				
mean	Sales growth	Asset Growth	KZ index	Altman Z score
three years before the IPO	19.62%	15.84%	0.066	4.71
three years after the IPO	11.37%	11.34%	0.155	2.67
t-stat	-7.72	-5.76	5.32	-11.29
median	Sales growth	Asset Growth	KZ index	Altman Z score
three years before the IPO	9.06%	8.18%	0.301	3.69
three years after the IPO	6.08%	5.65%	0.346	3.22
Wilcoxon Z test	<.0001	<.0001	<.0001	<.0001

Panel B: Estimated Panel Regression of performance on IPO dummy				
	Sales Growth	Operating Income Growth	Capital Expenditure Growth	R&D Intensity
IPO dummy	-0.100	-0.119	-0.127	0.153
	(-22.73)	(-12.13)	(-11.66)	(4.44)
Lag dependent variable	-0.096	-0.2665	-0.268	0.3712
	(-14.43)	(-33.47)	(-40.38)	(41.20)
Asset	0.150	0.0972	0.294	-0.2164
	(25.80)	(6.68)	(20.75)	(-4.93)
M/B	0.009	0.0187	0.012	-0.0129
	(15.33)	(12.28)	(8.30)	(-3.11)
Industry fixed effect?			*Yes*	
Year fixed effect?			*Yes*	
Clustered Std. error			*Yes*	
N	26,095	20,165	25,799	16,171
Adj. R^2	0.2951	0.2747	0.2114	0.6871

Table 2.4: Long-Term Stock Performance

This table documents the monthly returns of industry incumbents within three years after large IPO events in the same industry. The monthly returns are calculated following the calendar time portfolio method. Mktrf is the market excess return. SMB and HML are size and B/M factor mimicking portfolio returns. UMD is the momentum factor returns. Monthly data of Mktrf, SMB, HML and UMD are available from Ken French's website. T-statistics are adjusted using Newey-West correction for 5-lag of autocorrelations.

	IPO Calendar Time Portfolio			Incumbent Calendar Time Portfolio			IPO - Incumbent		
	CAPM	Fama French 3	Fama French 4	CAPM	Fama French 3	Fama French 4	CAPM	Fama French 3	Fama French 4
alpha	-0.188%	-0.284%	-0.244%	0.881%	0.634%	0.727%	-1.074%	-1.055%	-1.139%
	-0.36	-0.87	-0.85	3.11	3.40	3.58	-2.7	-2.71	-2.99
Mkt-Rf	1.180	1.195	1.146	1.245	1.083	1.001	-0.071	0.071	0.091
	8.83	11.94	10.37	22.80	21.38	16.07	-0.62	0.78	0.91
SMB		0.670	0.724		0.822	0.865		-0.148	-0.169
		5.3	6.00		12.19	12.19		-1.74	-1.74
HML		0.431	0.379		0.115	0.063		0.353	0.374
		3.87	3.58		0.37	0.96		3.35	3.53
UMD			-0.176			-0.166			0.071
			-2.28			-2.37			0.78
R-square	0.5965	0.7040	0.7167	0.7208	0.8742	0.8901	0.0613	0.1256	0.1222

Table 2.5: Time Series Regression of Incumbent Return on Risk Factors and Economic Variables

This table presents the results of times series regression of incumbent firms' monthly returns on various risk factors and economic variables. MktRf is the market excess return. SMB and HML are the returns to size portfolio and value. UMD refers to the momentum factor as in Carhart (1997). Data regarding risk factors come directly from Ken French's website. INF is monthly inflation rate, which is calculated using the Current Consumer Price Index published monthly by the Bureau of Labor Statistics (BLS). Term Spread (TERM) is the difference between the 10-year and 1-year treasury constant maturity rates. Default premium (DEF) is the difference between Moody's Baa and Moody's Aaa monthly bond yield. These data, along with T-bill rate is obtained directly from the Federal Reserve Bank of St.Louis through FRED. Dividend yields come from Welch and Goyal's (2008) dataset. ΔINF, ΔTerm,ΔDEF, ΔDIV, and ΔT-bill refer to the innovations between the current value and the lagged value one period before for all economic variables. ΔINF_F, ΔTerm_F, ΔDEF_F, ΔDIV_F, and ΔT-bill_F represent the factor mimicking portfolio, constructed by regressing change in macroeconomic variables on the 25 size and B/M portfolio returns, and getting the fitted part. Post refer to the portfolio returns of incumbent firms during month [+1, +37] subsequent to large IPO events; prior refer to the portfolio constructed by included returns from industry incumbent firms during month [-37, -1] before large IPO events. Panel A documents the estimated results using raw numbers; Panel B documents the results using factor-mimicking portfolios. In the second last column of Panel A and Panel B, I report the estimated coefficient from the same regression but with incumbent firm returns before the IPO as the dependent variable. The last column of Panel A and Panel B document the differences and t-statistics between the post-issuance loading and pre-issuance loading on each macroeconomic factors and factor mimicking portfolios. Panel C documents the results using several macro-economic variables and factor-mimicking portfolios all together, and the differences of coefficient loadings before the IPO and after the IPOs. T-statistics are reported

Panel A:	Time Series Regression on Macro Economic Variables											
					Post						Prior	
Intercept	Mkt-Rf	SMB	HML	UMD	ΔINF	ΔTerm	ΔDEF	ΔDIV	ΔT-bill	Adj. R^2	Coefficient	diff
0.0072	1.0015	0.8569	0.0702	-0.1654	1.1817					0.8953	1.010	0.172
3.76	17.5	12.52	1.17	-2.56	2.69						2.46	1.28
0.0072	0.9983	0.8679	0.0581	-0.1705		-0.3269				0.8911	0.936	-1.263
3.59	16.22	12.34	0.9	-2.57		-0.49					2.55	-1.75
0.0074	0.9734	0.8560	0.0436	-0.1689			-3.8279			0.8961	-3.276	-0.552
4.00	17.57	11.9	0.69	-2.46			-3.86				-2.92	-1.85
0.0077	0.9406	0.8568	0.0144	-0.1510				-0.0829		0.8983	-0.024	-0.059
4.24	16.54	12.06	0.22	-2.15				-4.34			-1.18	-2.34
0.0077	0.9827	0.8664	0.0505	-0.1771					1.7045	0.8933	-0.183	1.796
4.05	18	12.06	0.83	-2.66					1.49		-0.2	1.7

Panel B: Time Series Regression on Factor Mimicking Portfolio Returns

					Post						Prior	
Intercept	Mkt-Rf	SMB	HML	UMD	ΔINF_F	ΔTerm_F	ΔDEF_F	ΔDIV_F	ΔT-bill_F	Adj. R^2	Coefficient	diff
0.77%	1.012	0.836	0.119	-0.150	5.042					0.9051	3.059	2.648
4.19	20.35	14.93	2.17	-2.55	3.53						3.09	2.69
0.73%	1.002	0.884	0.053	-0.169		-1.404				0.9016	1.882	-3.286
3.6	17.96	12.93	0.84	-2.5		-0.89					1.52	-1.63
0.53%	0.947	0.842	0.027	-0.158			-9.997			0.8991	-10.854	0.857
2.65	19.76	12.35	0.42	-2.19			-4.3				-4.99	0.25
0.61%	0.873	0.847	-0.047	-0.130				-0.186		0.9090	-0.125	-0.060
2.92	17.06	12.18	-0.73	-1.57				-2.37			-2.39	-0.86
0.57%	0.952	0.888	0.019	-0.169					8.413	0.9090	6.235	2.251
2.96	20.33	14.26	0.31	-2.41					2.7		3.05	0.77

Panel C: Time Series Regression on Multiple Factors

		Intercept	Mkt-Rf	SMB	HML	UMD	ΔINF	ΔTerm	ΔDEF	ΔDIV	ΔT-bill	Adj. R^2
Macro-Economic Variables	post	0.0081	0.9404	0.8490	0.0235	-0.1619	1.0977	0.9003	-4.0189	-0.0573	1.5119	0.9005
		4.72	18.39	12.11	0.43	-2.47	2.85	0.31	-2.58	-2.72	1.29	
	prior	0.0070	0.9749	0.7288	0.2745	-0.2827	0.8508	0.1834	-1.1269	0.0169	0.4651	0.9062
		4.92	26.84	8.85	4.39	-8.26	1.97	2.33	-1.07	0.68	0.47	
	diff						0.5972	-0.9303	-1.8460	-0.0682	0.9190	
	(t-stat)						1.01	-1.28	-1.53	-2.39	0.76	
		Intercept	Mkt-Rf	SMB	HML	UMD	ΔINF_F	ΔTerm_F	ΔDEF_F	ΔDIV_F	ΔT-bill_F	
Factor Mimicking Portfolios	post	0.70%	0.981	0.837	0.080	-0.141	4.787	-2.295	-7.381	-0.027	-3.308	0.9173
		3.08	16.16	14.53	1.15	-2.12	2.14	-1.22	-1.74	-0.3	-0.62	
	prior	0.37%	0.958	0.685	0.296	-0.279	2.007	2.196	-1.898	0.049	0.156	0.9140
		1.92	18.41	7.58	3.44	-6.94	1.51	1.76	-3.04	0.76	0.04	
	diff						3.630	-4.089	-3.216	-0.078	-3.214	
	(t-stat)						1.77	-2.00	-1.6	-0.72	-0.43	

Table 2.6: Dynamic Logistic Regression of Default Probability with IPO Indicator

This table documents the estimated results from the dynamic logistic regression of default probability model with IPO indicator. The model is estimated with the predictor variables for all industry incumbent firms between year 1995 and 2013. The dependent variable is a dummy variable that equals to one if the firm is delisted in a given year. All independent variables are measured at the year before the failure event. NIMTA is the ratio of net income to the market value of assets, and is used to measure profitability. TLMTA is the ratio of total liability to the market value of asset. SIGMA is the annualized standard deviation of daily stock return over the previous three months. MB is the firm's market-to-book ratio. RSIZE measures the relative size of each firm as the log ratio of its market capitalization to the total market value of the S&P 500 index. CASHMTA is the ratio of a firm's cash and short-term assets to the market value of it asset. EXRET is the monthly log excess return on each firm's equity relative to the S&P 500 index. Numbers on top are the estimated coefficients, numbers in the middle are the corresponding odds ratio, and T-statistics are reported at the bottom.

Panel A: Dynamic Logistic Regression of Default probability			
	all	Incumbents	
	(1)	(2)	(3)
Intercept	-10.691	-11.556	-11.952
			3.355
			(11.35)
NIMTA	-3.573	-4.232	-3.904
	0.028	0.015	0.020
	(-16.57)	*(-8.46)*	*(-7.73)*
TLMTA	1.196	2.245	2.105
	3.308	9.442	8.207
	(14.33)	*(10.36)*	*(9.55)*
MB	0.202	0.212	0.214
	1.223	1.236	1.239
	(15.64)	*(7.47)*	*(7.43)*
RSIZE	-0.433	-0.460	-0.444
	0.648	0.631	0.641
	(-26.75)	*(-12.82)*	*(-12.48)*
CASHMTA	-1.704	-0.021	-0.245
	0.182	0.979	0.783
	(-7.82)	*(-0.04)*	*(-0.49)*
SIGMA	1.018	0.015	1.416
	2.767	1.015	4.121
	(12.82)	*(0.08)*	*(0.46)*
EXRET	-7.034	-4.893	-5.442
	0.001	0.008	0.004
	(-23.03)	*(-6.31)*	*(-6.84)*
# failure	2639	428	
N	104345	41415	
Pseudo R^2	0.3023	0.2396	0.2836

Table 2.6: Dynamic Logistic Regression of Default Probability with IPO Indicator (Cont.)

This table reports the different estimated results from the dynamic default probability model for different portfolio of incumbent firms. It sorts industry incumbent firms first according to their most recent profitability, leverage, Tobin's Q, and Altman Z score. Profitability is defined as net income scaled by total assets. Leverage is defined as long term debt scaled by the market value of asset. Tobin's Q is the ratio of market value of assets to the book value of assets. Altman Z score is defined following the coefficients in Altman (1968) as 3.3* Earnings before interest and taxes / total assets +0.99*sales/total assets +1.4 retained earnings/ total assets+0.6*market capitalization/long term debt+1.2*working capital/total assets. For each IPO events, incumbent firms in the top 30% are included in the high ratio sample, while firms in the bottom 30% are included in the low ratio sample. Estimated coefficients, odds ratio and t-statistics are reported respectively for the same regression as in Panel A.

Panel B:	Dynamic Logistic Regressions for Subsamples							
	profitability		Leverage		Tobin's Q		AltmanZ	
	Low	High	low	High	Low	High	low	High
	(1)	(2)	(5)	(6)	(3)	(4)	(5)	(6)
IPO	1.434	1.118	1.088	1.271	1.362	1.176	1.460	1.044
	4.195	3.058	2.970	3.563	3.903	3.242	4.306	2.841
	(10.70)	*(4.54)*	*(4.94)*	*(8.51)*	*(8.94)*	*(5.60)*	*(10.26)*	*(4.26)*
NIMTA	-3.691	-5.067	-5.769	-3.779	-3.690	-4.678	-3.522	-6.134
	0.025	0.006	0.003	0.023	0.025	0.009	0.030	0.002
	(-5.65)	*(-4.15)*	*(-5.30)*	*(-5.30)*	*(-5.32)*	*(-4.37)*	*(-5.21)*	*(-5.03)*
TLMTA	2.087	3.145	2.627	1.983	1.652	2.169	1.827	1.743
	8.059	23.220	13.831	7.263	5.217	8.749	6.213	5.716
	(7.63)	*(5.36)*	*(5.58)*	*(5.40)*	*(4.78)*	*(5.32)*	*(6.06)*	*(3.22)*
MB	0.242	0.135	0.266	0.197	0.091	0.268	0.166	0.228
	1.273	1.145	1.305	1.218	1.095	1.308	1.180	1.256
	(6.73)	*(1.80)*	*(4.20)*	*(5.14)*	*(1.65)*	*(4.96)*	*(4.54)*	*(2.88)*
RSIZE	-0.485	-0.299	-0.415	-0.433	-0.404	-0.454	-0.448	-0.367
	0.616	0.742	0.660	0.648	0.668	0.635	0.639	0.693
	(-9.79)	*(-4.00)*	*(-5.15)*	*(-8.77)*	*(-7.89)*	*(-6.15)*	*(-9.17)*	*(-4.47)*
CASHMTA	-0.442	2.418	0.535	-0.750	-1.134	0.756	-0.528	0.342
	0.643	11.227	1.708	0.472	0.322	2.130	0.590	1.407
	(-0.69)	*(1.14)*	*(0.56)*	*(-0.96)*	*(-1.61)*	*(0.76)*	*(-0.78)*	*(0.31)*
SIGMA	2.472	-2.114	-0.055	0.396	1.721	2.245	0.164	-0.370
	17.570	0.121	0.947	1.486	5.590	9.443	1.179	0.691
	(0.64)	*(-0.25)*	*(-0.13)*	*(1.47)*	*(0.39)*	*(0.36)*	*(0.63)*	*(-0.79)*
EXRET	-4.877	-6.728	-4.703	-3.946	-6.063	-6.235	-5.080	-6.950
	0.008	0.001	0.009	0.019	0.002	0.002	0.006	0.001
	(-4.94)	*(-3.30)*	*(-2.94)*	*(-3.58)*	*(-4.99)*	*(-4.27)*	*(-4.91)*	*(-3.90)*
# failure	272	72	97	216	209	108	240	77
N	16716	18487	17493	16649	17353	17731	16642	17430
Pseudo R^2	0.3025	0.2098	0.2614	0.2807	0.2447	0.3148	0.281	0.228

Table 2.7: Descriptive Statistics for Industry Concentration and Competition

This table provides descriptive statistics industry concentration and competition measures used in the following analyses. HHI represents the Herfindahl index, calculated as the sum of squared market shares for all firms in each industry. DIFF represents product differentiability, which is calculated as industry sales scaled by operating cost (defined as the sum of cost of goods sold (COGS), selling, general, administrative expenses (SG&A), depreciation and amortization). Market size (MktSize) is calculated as the sum of firm sales in each industry. Entry cost (EntCost), which is calculated as the weighted average of firms PP&E for each industry (weight is individual firm's market share). Fnum denotes number of public firms. All data used come from Compustat Segment files. Panel A documents the distribution of various measures, while Panel B reports their Pearson Correlation coefficients.

Panel A: Summary Statistics of various Competition Measures				
	mean	*median*	*Q1*	*Q3*
HHI	0.54	0.56	0.42	0.67
DIFF	1.39	1.12	1.09	1.19
MKTSIZE ($M)	286269.79	129920.00	54346.29	371075.44
log(MKTSIZE)	11.82	11.77	10.90	12.82
ENTCOST ($M)	9948.46	4792.56	2383.36	9438.72
log(ENTCOST)	8.50	8.47	7.78	9.15
Fnum	209.70	138.00	60.00	291.00
log(Fnum)	4.85	4.92	4.09	5.67

Panel B: Pearson Correlation				
	HHI	DIFF	MKTSIZE ($M)	ENTCOST ($M)
HHI	1.000			
DIFF	**-0.084**	1.000		
MKTSIZE ($M)	**-0.339**	**0.119**	1.000	
ENTCOST ($M)	**-0.193**	0.020	**0.666**	1.000
Fnum	**-0.514**	**0.158**	**0.472**	**0.087**

**bold indicate significant at 5% level*

Table 2.8: Effect of IPOs on Incumbents' Returns, Cross Sectional Regression on Herfindahl Index

This table examines the effect of IPOs on Incumbent firms' returns cross sectionally. It reports estimated results from a panel regression of incumbent firm returns on Herfindahl Index, an IPO dummy variable, and several known existing risk factor that affect firm returns. Specifically, I estimate the regression as following: $R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * HHI_{i,t-1} + \beta_2 * IPO_{i,t} * HHI_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t}$, where IPO dummy variable equals to 1 if month t is within the 36 months of a large IPO events in firm i's industry, and zero otherwise. Herfindahl index is employed to measure industry competition, and is calculated as the sum of squared market share for all the firms in each industry.

IPO			0.054
			1.72
HHI	-0.0243	-0.8263	-1.894
	-2.38	-0.84	-1.11
IPO*HHI			-0.0214
			-0.96
beta	0.0035	0.0043	0.0044
	0.7	0.86	0.87
ln(size)	-0.0003	-0.0001	-0.0001
	-0.44	-0.15	-0.12
ln(M/B)	-0.0123	-0.0128	-0.0128
	-7.18	-8.13	-8.19
past returns	-0.0003	-0.0004	-0.0004
	-1.7	-2.06	-2.03
liquidity	0.0017	0.0017	0.0017
	4.27	3.99	4.03
Industry dummy	No	Yes	Yes

Table 2.9: Cross Sectional Fama-Macbeth Regression on Product Market Competition

This table reports Fama Macbeth estimates for equation in the following form: $R_{i,t} = \alpha + \beta_0 * IPO_{i,t} + \beta_1 * competition_{i,t-1} + \beta_2 * IPO_{i,t} * competition_{i,t-1} + \sum_{k=1}^{K} \gamma_k X_{k,t-1} + \varepsilon_{i,t}$, where IPO dummy variable equals to 1 if month t is within 36 months of a large IPO events in firm i's industry, and zero otherwise. Competition measures include product differentiability (DIFF), which is calculated as industry sales scaled by operating cost (defined as the sum of cost of goods sold (COGS), selling, general, administrative expenses (SG&A), depreciation and amortization), market size (MktSize), which is calculated as the sum of firm sales in each industry, entry cost (EntCost), which is calculated as the weighted average of firms PP&E for each industry (weight is individual firm's market share), and number of public firms. Herfindahl index is calculated as the sum of squared market share for each industry. Market capitalization and market to book ratio is calculated at the end of previous month. Liquidity is measured using Roll (1984) liquidity measure. Panel A documents the estimated results of expected return on each competition measure respectively, while panel B documents the regression results on multiple competition measures. T-statistics adjusted for autocorrelation and heteroskedasticity are reported below each coefficients.

Panel A: Regression on Each Competition Measure

	(1)	(2)	(3)	(4)
IPO	0.102	0.0188	0.0214	0.0427
	2.57	1.52	1.97	0.88
IPO*DIFF	-0.0926			
	-2.77			
IPO*MktSize		-0.0041		
		-1.07		
IPO*EntCost			-0.0017	
			-0.88	
IPO*Fnum				0.0073
				0.98
DIFF	0.044			
	0.45			
MktSize		0.0034		
		1.16		
EntCost			0.0922	
			0.94	
Fnum				-0.0039
				-0.47
beta	0.0044	0.0044	0.0044	0.0044
	0.87	0.87	0.87	0.86
ln(size)	-0.0001	-0.0001	-0.0001	-0.0001
	-0.12	-0.13	-0.12	-0.13
ln(M/B)	-0.0128	-0.00128	-0.0128	-0.0128
	-8.18	-8.19	-8.17	-8.18
past returns	-0.0004	-0.0004	-0.0004	-0.0004
	-2.04	-2.03	-2.03	-2.04
liquidity	0.0017	0.0017	0.0017	0.0017
	4.08	4.07	4.06	4.06
HHI	-0.192	-0.0839	0.9412	0.1659
	-0.56	-0.38	1.9	0.8
IPO*HHI	-0.0128	-0.0085	-0.0235	-0.0137
	-0.61	-0.31	-1.01	-0.63
industry dummy	yes	yes	yes	yes

Panel B: Regression on Multiple Competition Measures

	(1)	(2)	(3)	(4)	(5)
IPO	-0.0187	0.06216	-0.0131	0.0314	0.1748
	-0.32	0.22	-0.31	1.21	1.79
IPO*DIFF	-0.0379	-0.1334	-0.0883	-0.0657	-0.0829
	-0.92	-1.83	-1.52	-0.89	-1.59
IPO*MktSize	-0.0067	-0.0286	-0.0047	-0.0027	-0.0112
	-1.79	-2.29	-0.99	-0.46	-1.63
IPO*EntCost			0.0052	0.004	0.0005
			1.41	1.29	0.14
IPO*Fnum		0.1437		0.0201	0.04
		0.88		0.55	1.85
DIFF	0.0976	0.0926	-0.046		0.0917
	1.36	1.46	-0.51		1.68
MktSize	-0.0025	0.0027	0.0032	-0.105	0.0286
	-0.43	0.54	0.77	-0.92	0.43
EntCost			0.0092	0.0108	0.0519
			1.81	1.09	1.52
Fnum		-0.1241		-0.0387	-0.0599
		-0.77		-1.2	-1.06
beta	0.0044	0.0044	0.0044	0.0044	0.0044
	0.86	0.86	0.86	0.86	0.86
ln(size)	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	-0.13	-0.12	-0.12	-0.12	-0.12
ln(M/B)	-0.0128	-0.0128	-0.0128	-0.0128	-0.0128
	-8.18	-8.17	-8.18	-8.18	-8.18
past returns	-0.0004	-0.0004	-0.0004	-0.0004	-0.0005
	-2.04	-2.04	-2.04	-2.04	-2.04
liquidity	0.0017	0.0017	0.0017	0.0017	0.0017
	4.07	4.06	4.08	4.07	4.08
HHI	-0.1176		0.073		-0.2876
	-1.13		0.91		-1.22
IPO*HHI	0.0062		0.0132		0.0453
	0.26		0.51		0.76
industry dummy	yes	yes	yes	yes	yes

Table 2.10: Cross Sectional Fama-Macbeth Regressions of Returns on Market Share

This table reports the estimated results of regressing incumbent firms expected return on their market share and interaction between IPO and market share. Market share is defined as firm sales scaled by industry sales. Market Leader is a dummy variable which equals to one for observations where individual firms' market share is in the top 10% or 30% of all firms' market share for each industry. Industry follower is defined similarly as firms whose market share is in the bottom 10% or 30%. T-statistics are reported below.

	(1)	(2)	(3)	(4)	(5)
IPO	0.0008	-0.0001	-0.0002	0.0003	0.0002
	0.3	-0.03	-0.07	0.14	0.11
market share	-0.1084				
	-0.39				
IPO* market share	0.1118				
	0.41				
IPO*market leader		0.0029	0.0024		
		1.98	1.9		
IPO*market follower				0.0006	0.0017
				0.28	1.57
beta	0.0042	0.0048	0.0048	0.0048	0.0048
	0.87	0.93	0.94	0.93	0.93
ln(size)	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	-0.31	-0.28	-0.35	-0.29	-0.35
ln(M/B)	-0.0129	-0.0131	-0.0131	-0.013	-0.013
	-8.24	-8.29	-8.29	-8.72	-8.51
past returns	-0.0004	-0.0004	-0.0004	-0.0004	-0.0004
	-2.17	-2.11	-2.1	-2.15	-2.1
liquidity	0.0017	0.0017	0.0017	0.0017	0.0017
	4.02	3.98	3.96	4.08	4.04
industry dummy	yes	yes	yes	yes	yes

Table 2.11: Unexpected Profitability and IPO

This table examines the relationship between unexpected profitability of industry incumbents and IPO events. Panel A represents the average estimated coefficients and R^2 of Fama Macbeth regression of profitability on firm characteristics in the following form: $\frac{E_t}{A_t} = \alpha_0 + \alpha_1 \frac{V_{t-1}}{A_{t-1}} + \alpha_2 DD + \alpha_3 \frac{D_{t-1}}{B_{t-1}} + \alpha_4 \frac{E_{t-1}}{A_{t-1}} + \epsilon_t$, where E/A is earnings scaled by the book value of total asset, which measures firm profitability; V/A is the ratio of market value of asset to book value of asset; DD is a dummy variable for non-dividend-paying firms; and D/B is the ratio of dividend payments to book equity. R^2 is calculated as the average of all cross sectional R^2. T-statistics are included in parentheses. Panel B documents the mean and median unexpected profitability for industry incumbents within three years before and after IPO events, where unexpected profitability is the regression residual. Panel C documents the results for cross sectional regressions of unexpected profitability on IPO indicators. IPO variable is defined to be one for a firm-year observation if a large IPO event happened in the same industry as the specified firm within a three-year period before that particular year; otherwise IPO is equal to zero. T-statistics for each coefficients are reported below.

Panel A: Expected Profitability Regressions

	α_0	$(V/A)_{t-1}$	DD	$(DB)_{t-1}$	$(E/A)_{t-1}$	Adj R^2
E/A	0.012	-0.004	-0.035	0.118	0.719	0.4863
	(2.10)	(-2.35)	(-5.42)	(1.87)	(62.24)	

Panel B: Average Unexpected Profitability before and after IPO Events

before	*mean*	1.680%	*median*	2.536%	t-stat	Wilcoxon
after	*mean*	1.160%	*median*	2.187%	*2.61*	*0.0002*

Panel C: Regression of Unexpected Profitability on IPO

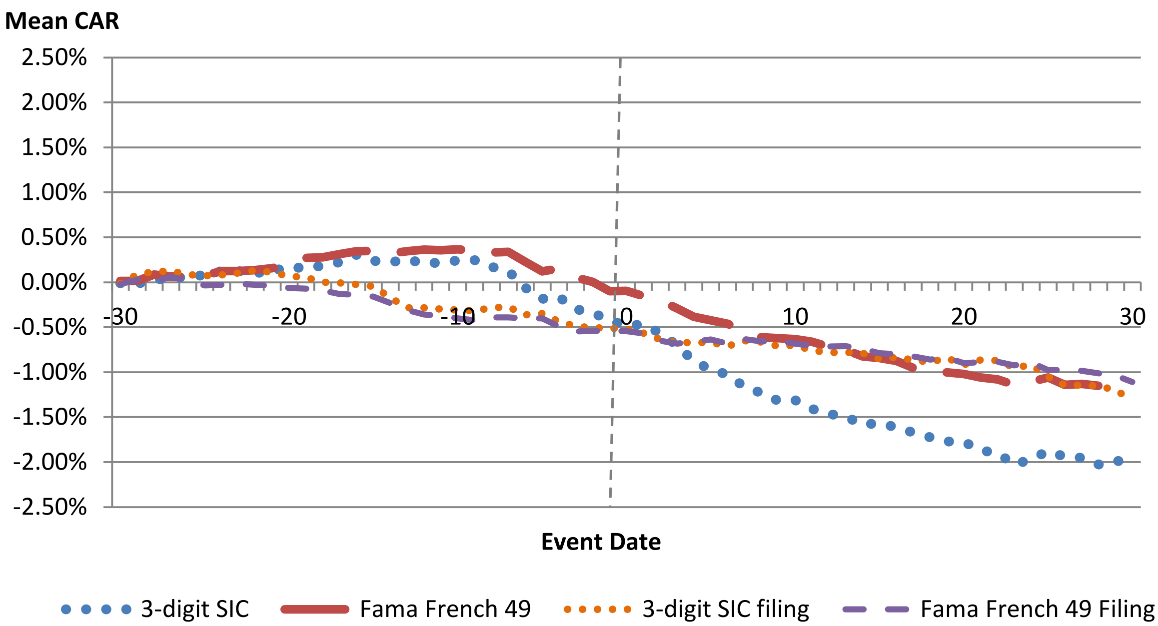
IPO	-0.0053	-0.0056	-0.0023
	-2.69	-2.87	-1.51
R^2	0.0003	0.0072	0.0375
Industry fixed effect	no	no	yes
year fixed effect	no	yes	yes

Table 2.12: Earnings Surprises and IPO

This table examines the relationship between earnings surprises of industry incumbents and IPO events. SUE1 is computed as: $SUE1_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{P_{i,t}}$, where $E_{i,t}$ represents EPS before extraordinary items for firm i in quarter t; $E_{i,t-4}$ represents EPS before extraordinary items in the previous year. $P_{i,t}$ is stock price of at the end of the quarter. I adjust for earnings of special items in the computation of SUE2. Specifically, following Bradshaw and Sloan [2002] and Livnat and Mendenhall (2006), I subtract from EPS the amount of special items times 65% divided by the number of shares used to calculate earnings per share. SUE3 is calculated as the differences between actual and analyst expected EPS, scaled by price. Panel A documents the mean and median earnings surprises around IPO events: three years before and three years after IPO events. Panel B represents the estimated results of regressing earnings surprises on IPO indicator variable, where IPO indicator is set to be one for a firm-year observation if a large IPO event happened in the same industry as the specified firm i within 36 months before IPO month; otherwise IPO is equal to zero.

Panel A: Quarterly Earnings Surprises around IPOs				
		SUE1	SUE2	SUE3
before IPO	*mean*	0.061%	1.430%	-0.108%
	median	0.160%	0.160%	0.047%
after IPO	*mean*	-3.670%	-1.050%	-0.457%
	median	0.100%	0.107%	0.045%
diff	*t-stat*	4.98	2.21	1.94
	Wilcoxon	<.0001	<.0001	0.0373
Panel B: Regression of Earnings Surprises on IPO Indicator				
			SUE1	
IPO		-0.0373	-0.0337	-0.0247
		-2.62	-1.92	-2.55
R^2		0.0001	0.0002	0.0015
industry fixed effect		no	no	yes
time fixed effect		no	yes	yes
			SUE2	
IPO		-0.0248	-0.0232	-0.0226
		-2.21	-2.06	-1.9
R^2		0.0001	0.0002	0.0014
industry fixed effect		no	no	yes
time fixed effect		no	yes	yes
			SUE3	
IPO		-0.0035	-0.0037	-0.0043
		-1.98	-2.04	-2.13
R^2		0.0001	0.0008	0.0049
industry fixed effect		no	no	yes
time fixed effect		no	yes	yes

Figure 2.1 Incumbents' Cumulative Abnormal Return around IPO Completion and Filing



IPO firms are selected according to their proceeds. I only select IPOs that have the largest proceeds in their industry at the IPO year. Industries are defined using three different criteria: 3 digit SIC code, 2-digit SIC code and Fama-French 49 industry. Incumbent firms are defined to be the existing public firms in the same industry as the IPO firm at the time of the IPO. I further require incumbent firms to be public tradable at least three years before IPO year. My sample of incumbent firms included 37768 incumbent firm-year observations corresponding to 1177 IPOs using 3-digt SIC code, and 64585 incumbent firm-year observations corresponding to 563 IPO events using Fama-French 49 industry. Average daily cumulative abnormal returns are shown on y-axis, which are calculated as the equally weighted mean market model adjusted return across all incumbent firms. X-axis shows the timeline in days around an IPO event, where day zero represents the IPO date.

Appendix

A2.1: Correlation of Macroeconomic Variables and Factor Mimicking Portfolio

This table provides the correlation between the macroeconomic variables employed in this paper and their factor mimicking portfolios, which are constructed by regression changes in macro variables on the returns of 25 size and B/M portfolio and getting the fitted part. MktRf is the market excess return. SMB and HML are the returns to size portfolio and value. UMD refers to the momentum factor as in Carhart (1997). Data regarding risk factors come directly from Ken French's website. INF is monthly inflation rate, which is calculated using the Current Consumer Price Index published monthly by the Bureau of Labor Statistics (BLS). Term Spread (TERM) is the difference between the 10-year and 1-year treasury constant maturity rates. Default premium (DEF) is the difference between Moody's Baa and Moody's Aaa monthly bond yield. These data, along with T-bill rate is obtained directly from the Federal Reserve Bank of St.Louis through FRED. Dividend yields come from Welch and Goyal's (2008) dataset. ΔINF, ΔTerm,ΔDEF, ΔDIV, and ΔT-bill refer to the innovations between the current value and the lagged value one period before for all economic variables. ΔINF_F, ΔTerm_F, ΔDEF_F, ΔDIV_F, and ΔT-bill_F represent the factor mimicking portfolio. Bold numbers mean significant correlation at least at 5% level.

	ΔINF	ΔTerm	ΔDEF	ΔDIV	ΔT-bill	ΔINF_F	Δterm_F	ΔDEF_F	ΔDIV_F	ΔT-bill_F
ΔINF	**1.000**									
ΔTerm	0.117	**1.000**								
ΔDEF	**-0.241**	0.033	**1.000**							
ΔDIV	**-0.175**	-0.049	**0.507**	**1.000**						
ΔT-bill	-0.044	**-0.572**	**-0.252**	**-0.148**	**1.000**					
ΔINF_F	**0.457**	0.084	**-0.137**	-0.123	**0.118**	**1.000**				
Δterm_F	0.081	**0.475**	0.003	-0.004	**-0.158**	0.177	**1.000**			
ΔDEF_F	**-0.116**	0.002	**0.538**	**0.415**	**-0.297**	**-0.254**	0.005	**1.000**		
ΔDIV_F	**-0.090**	-0.003	**0.357**	**0.626**	**-0.249**	**-0.197**	-0.006	**0.664**	**1.000**	
ΔT-bill_F	0.135	-0.188	**-0.400**	**-0.390**	**0.400**	**0.295**	**-0.395**	**-0.744**	**-0.623**	**1.000**

A2.2: Calculation of other competition measures

I calculate all competition measures following Karuma (2007).

Price cost margin (DIFF) is measured as industry sales scaled by operating cost, where operating cost is defined as the sum of cost of goods sold (COGS), selling, general, administrative expenses (SG&A), depreciation and amortization. Industry sales are computed as the aggregation of all industrial segment sales, and industry operating cost is the sum of all industrial segment operating costs.

Market size (MktSize) is defined as the sum of firm sales in each Fama French 49 industry. But since industries with large sales usually have great fixed cost, which is confirmed by the high correlation between market size and entry cost (significant 0.686 as in Table 2.6 Panel B). Thus, I scale market size by entry cost in the regression[37].

Entry cost (EntCost) is measured as the weighted average of industry PP&E for all firms in each Fama French 49 industry.

Firm number (Fnum) is calculated as the number of firms that have data from COmpustat for each Fama French 49 industry.

[37] Using market size directly without scaling it, generate pretty similar results.

CHAPTER 3

LIQUIDITY CLIENTELES

1. Introduction

Transaction costs are important to investors because net returns they get from trading equal to their required gross returns subtract transaction costs. Specifically, investors should pay attention to their transaction costs per period in order to maximize their net returns per period, and investors' optimal trading strategy should involve reducing transaction costs per period.

Theoretical works have linked the optimal trading behavior of investors facing transaction costs to the liquidity premium in a stock's returns. In theoretical models where holding periods are endogenous determined, the frequency that investors trade illiquid stocks will determine how transaction costs are amortized over periods, and thus determines liquidity premium. If investors trade illiquid stocks infrequently, for instance as in Vayanos 1998, Constantinides 1988, Heaton and Lucas 1996, then amortized transaction costs will be low, and investors will require a small liquidity premium. If, on the other hand, investors trade frequently due to income shocks (Lynch and Tan 2007), or need to hedge (Lo, Mamaysky and Wang 2005), then the resulting liquidity premium could be large. Thus, understanding of investors' trading behavior is important for us to understand liquidity premium.

In this paper, we focus on one aspect of investors' trading behavior: their holding period. Holding periods are related to investors' optimal trading strategy in the sense that it determines how transaction costs are amortized over each period. It is investors' trading behavior that links transaction costs and the liquidity premium for that stocks. The relationship between holding periods and transaction costs can help us shed more lights on how investors make their trading decisions. However, limited availability of investors' transaction data has made it hard to empirical examine how investors trade facing transaction costs, and it is still a relatively less explored area yet.

This paper investigates the trading behavior of retail investors, specifically the relationship between investors' holding periods and transaction costs, using two unique datasets. One reports the transactions of 66,000 households in the United States between year 1991 and 1996; the other reports the transactions of over 1.3 million retail investors in Finland between year 1995 and 2003. First, we examine how transaction costs affect investors' holding period, and the heterogeneity of this relationship among different investors. Second, we extend this question to look at further whether trading behavior of the aggregate households as a group change over time.

Amihud and Mendelson (1986) show in their seminal work that existence of transaction costs causes investors with long holding periods to select into holding stocks with higher transaction costs, which is called liquidity clientele. We show empirically that transaction costs play an important role in household's trading decisions, and are an important determinant of investors' holding period. After controlling for various investor and stock characteristics, we document that investors hold stocks with higher transaction costs for relatively long periods. This result is consistent with Amihud and Mendelson (1986) hypothesis about liquidity clientele.

Moreover, individual investors differ in how much attention they pay to the transaction costs of the stocks they hold. Investors that are more sophisticated financially tend to pay more attention to transaction costs than other retail investors. This is also consistent with Coval, Hirshleifer, and Shumway (2005) that a subset of investors tend to be more sophisticated and perform better than others in the stock market. We also show further that there is systematic variation in the demand for liquid securities over time. Consistent with the notion of *flight to liquidity*, the demand for liquid assets evidenced by the purchase transaction of aggregate households increases during times of low aggregate market liquidity.

This study is also related to the increased interest in investor rationality, and in particular, to the increasingly popular notion that individual investors overtrade. Odean 1999, Barber and Odean 2000, for instance, show that retail investors trade over frequently and pay too much transaction costs, which greatly hurts their performances. They propose a behavior bias, i.e. overconfidence, as an explanation for individuals' excessive trading. Barber, Odean and Zheng (2005), show that investors pay attention only to the salient costs of mutual funds, but ignore hidden operating costs. In contrary, findings in this paper suggest that the average investor does pay attention to transaction costs when they trade. A number of other papers document that a subset of retail investors display greater financial sophistication and market understanding than the average retail investor, enabling them to persistently earn positive abnormal returns[1]. We show consistently in this paper that sophisticated households are tend to pay attention to transaction costs, and they hold illiquid stocks over longer time periods.

The reminder of this paper is organized as follows. Section 2 describes the empirical question and related literature. Section 3 introduces the individual transaction data we use, and the liquidity and holding period measure. Section 4 documents the empirical results about the relationship between transaction costs and holding periods. Section 5 provides robustness tests, and results related to how exogenous liquidity shocks affect holding period. Section 6 studies the time series variation in investors' systematic preferences to liquidity. The last section concludes.

2. Previous Literature and Hypotheses Development

Amihud and Mendelson (1986) models a security market where risk neutral investors with limited budget and exogenous holding period trade different securities subject to fixed transaction costs in order to maximize their wealth. They show that in equilibrium investors who have longer holding

[1] For example, Grinblatt and Keloharju (2001).

periods select into holding stocks with higher transaction costs, thus more illiquid stocks. In extended models where holding periods are endogenous determined (Constantinides 1986, Vayanos 1998, Vayanos and Vila 1999, and Heaton and Lucas 1996), the predictions about liquidity clienteles remain the same. Specifically, illiquid stocks are associated with longer holding period.

However, there is no empirical evidence regarding liquidity clienteles yet. In this study, we study individual transaction data from the United States[2] and Finland to directly test for the relationship between holding period and transaction costs after controlling for a number of investor and stock characteristics. The results in this paper focus more on the trading behavior of retail investors in the U.S. However, since the U.S. transaction data we study here covers only a proportion of the retail investors in the United States, we perform the same tests using individual transaction data from Finland as a robustness test. In contrast with the U.S. individual transaction data, the Finnish transaction data documents trades for the universe of retail investors (grp=5). Empirical results using the Finnish transaction data are similar to the U.S. results, and are provided in the section of robustness tests (section 5a).

The first hypothesis directly tests the liquidity clienteles, and is stated as follows:

H1: *Holding periods are positively related to measures of transaction costs, after controlling for investor and stock characteristics.*

Since our study investigate the behavior of individual investors, it is also related to previous research on individual trading behavior. Previous studies have shown that individual investors are unsophisticated and unskilled traders. With the same data as us, Barber and Odean (2000), Barber, Odean, Lee, and Liu (2008) show that on average, individual investors trade too frequently, which

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[2] The dataset we use here in this study is the same as used in Barber and Odean (2000, 2001). We thank Terrance Odean for providing the data used in this study.

hurt their performance. Odean (1999) shows that stocks individual investors' purchases underperform stocks they sell by a significant margin. However, there is cross-sectional heterogeneity among individual investors' performances. Some studies provide evidence that there exists a subset of investors who display greater financial sophistication than the rest of individual investors. For instance, Coval, Hirshleifer, and Shumway (2005) document strong persistence in the performances of individual investors' trades, suggesting that some individual investors are able to earn persistent positive abnormal profits. This implies that some investors understand the market better and are much more skillful in trading stocks. Goetzmann and Kumar (2008) find that portfolio diversification is related to investor sophistication. Feng and Seasholes (2005) show that sophisticated investor exhibit less disposition effect. Given previously documented heterogeneity in individual trading performance, we expect the relationship between transaction cost and holding periods exhibit similar cross-sectional differences. Specifically, we expect the relationship between transaction costs and holding periods to increase with investor sophistication and experience.

H2: *The correlation between holding period and transaction costs is higher for sophisticated investors.*

Furthermore, previous research on liquidity has shown that there is a common component of liquidity across stocks (Chordia et al 2000, Hasbrouck and Seppi 2001, and Huberman and Halka 2001). Other related studies show that this common component of liquidity is priced in stock returns (Pastor and Stambaugh 2003, Acharya and Pedersen 2005, Korajczyk and Sadka 2008). However, it is unclear whether this common component of liquidity arises from the supply side (systematic variation in the costs of providing liquidity), or from the demand side (systematic variation in the demand for liquidity due to common shocks). Chordia, Roll, and Subrahmanyam

(2000) provide some empirical evidence that inventory risk and information asymmetry affect the common component of liquidity via systematic variation in the costs of providing liquidity. Comerton-Forde et al. (2010) and Coughenour and Saad (2004) study NYSE stocks overseen by the same specialists, and show consistently that systematic variation in the cost of providing liquidity contribute to the observed common component of liquidity. Huberman and Halka (2001) on the other hand, fail to find support for the supply side view, and suggest that commonality in liquidity come from the demand side, where volatility and uncertainty in the market causes systematic variation in investors' demand for liquidity. Vayanos (2004) develops a model in which changes in market volatility creates correlated trading patterns among investors, and consequently affect systematic liquidity. With individual transaction data, we can directly examine whether there is systematic variation in the demand for liquid assets.

H3: *There is systematic variation in individuals' demand of liquid stocks.*

If investors' demand for liquid asset does vary systematically, then it is interesting to examine whether and how this systematic demand varies over time with aggregate market liquidity. Previous literature generally take individual investors as noise traders, who constantly provide liquidity to the market. Consistent with this, Kaniel, Saar, and Titman (2006), Campbell, Ramadorai, and Schwartz (2007), Stoffman (2008), and Griffin et al. (2003) study the short-term returns and the trade imbalance to both institutional and individual investors, and provide evidence that retail traders provide liquidity to meet institutional investors' demand for immediacy. But these studies focus only on trade imbalances, and do not consider either the liquidity level of the securities bought and/or sold by individual investors, or the variation over time of individual investors' demand for liquidity with market liquidity. We supplement previous studies by examining directly the liquidity level of the stocks that retail investors trade, and whether there is a flight to liquidity among households when market liquidity is low. We expect that when aggregate market liquidity is low, household are more likely to be net demanders of liquid stocks.

H4: *Individuals are net buyer of liquid stocks when aggregate market liquidity is low.*

The correlation of individuals' demand for liquidity with market aggregate liquidity is also likely to exhibit cross-sectional differences. Sophisticated investors can take advantage of investment opportunities during turbulent markets. When market liquidity is low, investors' demand for liquidity will be high, and thus required liquidity premium for holding illiquid stocks will also be high. Illiquid stocks will receive larger drop in their prices due to increased liquidity premium. Sophisticated investors could take advantage of this opportunity to purchase illiquid stocks that are undervalued more, while unsophisticated investors want more liquid stocks. However, it is also possible that even sophisticated retail investors are afraid of trading against the market. If this is the case, then sophisticated investors tend to demand liquidity more.

H5: *Sophisticated individual investors can be net buyers of illiquid stocks when aggregate market liquidity is low.*

3. Individual Transaction Data and Liquidity Measure

3.1. Individual Transaction Data

This study uses two distinct datasets. One documents transactions for a subset of individual investors in the United States, the other documents all transactions for the universe of individual and institutional investors in Finland. The individual trade data for the United States comes from a major U.S. discount brokerage house. It records the daily trading of 78,000 households from January 1991 to December 1996. We focus only on the common stock transaction of households in this study, which account for nearly two-thirds of the total value of household investments. We exclude from the current analysis investments in mutual funds (both open-end and closed-end), American Depositary Receipts (ADRs), warrants, and options. About 66,000 out of the 78,000 households trade common stocks, making about two million trades over the sample period. The transaction record includes number of shares traded, price traded, each household's month-end positions, and value of their position at market close. The dataset also includes demographic information for a sub-sample of households, such as income, age, gender, occupation and marital status. For a more detailed description of this dataset please refer to Barber and Odean (2000, 2001). A comparison of this dataset with Survey of Consumer Finances, IRS and TAQ data has shown it to be representative of U.S. individual investors (Ivkovic, Sialm, and Weisbenner 2006, Ivkovic, Poterba, and Weisbenner 2005, and Barber, Odean, and Zhu 2006).

To address further concerns that our findings are specific to the data we employ, we perform the same tests for a similar dataset from Finland. This dataset comes from the central register in the Finnish Central Securities Depository (FCSD). The register is the official daily recording of trades for all Finnish investors - both individual and institutional from January 1995 to December 2003. For purpose of this current study, we only use record of individual trades, which is identified by investor category (grp=5). Similar as the U.S. data, the Finnish data includes for each transaction, the number of shares traded, daily close price, and the holding for each account starting from January, 1995. It also incorporates individuals' demographic information, such as age and gender. However, it doesn't provide information about income, occupation, and marital status. A more detailed description of the Finnish dataset could be found in Grinblatt and Keloharju (2000, 2001).

3.2. Liquidity Measures

Liquidity is a multi-dimensional concept and is usually defined as transaction costs, which are related to price impact, risk of asymmetric information, and inventory risk. Given multi-faceted and unobservable nature of liquidity, we use several different liquidity measures previously utilized in the literature.

The first measure is the Amihud illiquidity ratio from Amihud (2002), calculated as:

$$Illiq_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d}|}{dvol_{i,t}}$$

where $r_{i,d}$ is the daily return in day d of month t for stock i , $dvol_{i,t}$ is the dollar volume in day d, and $D_{i,t}$ is the number of days in month t for stock i. The Amihud measure is similar to Kyle's lambda and captures the price impact of a trade. We adjust the Amihud measure as in Acharya and Pedersen (2005) to remove outliers and to make it stationary:

$$AdjIlliq_{i,t} = \min\ [0.25{+}0.30{\times}Illiq_{i,t} \times M_{t-1}, 30]$$

where M_{t-1} is the ratio of value-weighted market portfolio at the end of the month *t-1* to that of the market portfolio in July of 1962.

The second measure is the Bayesian version of the Roll (1984) transaction cost measure:

$$c_{i,t} = \begin{cases} \sqrt{-cov(r_{i,t}, r_{i,t-1})} & if cov(r_{i,t}, r_{i,t-1}) < 0; \\ 0 & otherwise. \end{cases}$$

It is based on the model $r_{i,t} = c_{i,t}\Delta q_{i,t} + \varepsilon_{i,t}$ where $q_{i,t}$ is a trade direction indicator, $c_{i,t}$ is the transaction cost measure, and $\varepsilon_{i,t}$ is an error term for stock *i* at time *t*. The Roll's measure is derived under the assumption that buyer- and seller-initiated trades are equally likely. The Bayesian estimation of this cost measure using the Gibbs sampler is described in detail in Hasbrouck (2006).

The third liquidity measure is the Pastor and Stambaugh (2003) reversal Gamma. It is motivated by Campbell, Grossman, and Wang's (1993) model, and is designed to capture the temporary price fluctuation arising from order flow. It is estimated from the following equation:

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d+1,t} + \gamma_{i,t} sign(r^e_{i,d,t}) v_{i,d,t} + \varepsilon_{i,d,t}$$

where $v_{i,d,t}$ is the dollar volume on day *d* in month *t* for stock *i*, $r_{i,d+1,t}$ is the return for stock *i*, in day *d* of month *t*, $r^e_{i,d+1,t}$ is the return in excess of market return. Gamma measures the reverse of the previous day's order flow shock. It has a negative sign. The larger the absolute value of Gamma (the smaller the Gamma is), then the larger the implied price impact.

We also included in the analyses quoted spread and effective spread calculated from intra-day data. We use a 5-second delay to match trades with quotes and apply the same filters as discussed in Hvidkjaer (2006). The relative quoted spread is calculated for each trade as the ratio of the quoted bid-ask spread to the prevailing transaction price. The relative effective (half-) spread is computed for each transaction as the absolute value of the difference between the transaction price and the quoted midpoint, divided by the quoted midpoint.

Since the Finnish transaction data doesn't provide bid and ask information for each trade, these spread measures are excluded for empirical tests using Finnish stocks. We include another liquidity measures instead for tests using Finnish transaction data. We compute zero return frequency introduced by Lesmond, Ogden, and Trzcinka (1999), it represents the proportion of days with zero returns for each stock within each year. The higher the proportion is, the more illiquid the stock is.

Altogether, we include five liquidity measures for transactions in the United States: Adjusted Amihud ratio (*AdjIlliq*), Roll's measure, Pastor and Stambaugh's reversal gamma (*PS Gamma*), quoted spread, and effective spread, and three liquidity measures for analyses in Finland: Adjusted Amihud ratio (*AdjIlliq*), Roll's measure, and zero return frequency (*Zerofreq*). The results across all measure are very much similar to each other. For brevity, we focus on Adjusted Amihud ratio (*AdjIlliq*) in this study, results using other liquidity measures are similar.

There is likely to be endogeneity in the relationship between liquidity and holding period. As trading interest in a stock increases, so does its liquidity. However, we can think of a stock as having a baseline exogenous cost component, which is consistent with the assumption of fixed transaction costs as in Amihud and Mendelson (1986). Although the liquidity for a penny stock, for instance, will increase when more investors begin to trade on it, it can never reach the same level of liquidity as a large cap stock based purely on the increased trading interest. To keep it in line with the assumption in Amihud and Mendelson (1986), we want to capture the baseline component of each stock's transaction cost. Therefore, we use the annual average of each liquidity measure in our analyses. We later incorporate time-series variation in the liquidity level of each security in section 6, which extendedly analyzes the time variation of investors' liquidity preference.

Table 1 reports the summary statistics and correlations of different liquidity measures for stocks traded in the United States. The result shows that our major liquidity measure – adjusted Amihud ratio (*AdjIlliq*) is positive skewed with a mean of 7.23, but a much smaller median of 1.66. The distributions of other liquidity measures are similar to that of adjusted Amihud ratio. Size is also positively skewed, with the average market capitalization almost 10 times as large as the median firm size. Panel B and C in Table 1 show that size is negative correlated with all liquidity measures. The larger the firm is, the more liquid its stock is. Different liquidity measures are positive correlated with each other. The correlation among different liquidity measures are not always large, which supports the multi-dimensional feature of liquidity. Table A1 in Appendix reports the summary statistics and correlations of liquidity measures for stocks traded in Finland, and is similar as in the United States.

4. Empirical Evidence about Holding Periods and Transaction Costs

4.1. Holding Period Measure

To examine the relationship between holding periods and transaction costs, we need to calculate holding period for each transaction in the dataset. The holding period is defined as the number of trading days from the first purchase of a stock to the first sale, following the approach of Seru, Shumway, and Stoffman (2010).[3] This generates 806,404 holding period observations, with an average of 185 trading days and a median of 86 trading days for retail investors in the United States.

4.2. Transaction Level Analysis

To provide a basic picture of how liquidity is related to holding period, we rank and assign the 806,404 holding period observations into ten groups based on their length. The bottom group (1) has the shortest holding periods, while the top group (10) has the longest holding periods. We then calculate the average holding periods, stock liquidity, price, and market capitalization for stocks in each group. Liquidity are measured as of the purchase day, by averaging monthly or daily measures over the previous 12 months. Results in Table 2 show that there is a strong positive relationship between holding period and stock illiquidity. Most of the illiquidity measures increase almost monotonically with holding periods, and are not a simply reflection of price or size. The adjusted Amihud illiquidity measures, for instance, increases monotonically with holding period from 0.91 for the group with shortest holding periods to 1.75 for the group with the longest holding period, and the difference between the top and bottom holding period decile is significant at 1% level. PS Gamma and Roll's measure increase almost monotonically with holding periods. The differences in stock liquidity between the top and the bottom decile of holding period are always significant regardless what liquidity measure is used.

[3] We obtain similar results by alternatively defining the holding period as the number of trading days from first purchase till the day when all positive positions are closed, as in Feng and Seasholes (2005).

Figure 1 shows this relationship graphically. We plot Kaplan – Meier survival probabilities for stocks that are in the highest illiquidity decile (most illiquid) with the adjusted Amihud illiquidity ratio, and for all the rest stocks in the dataset. The x-axis stands for the number of trading days that have passed since the purchase of that stock, and the plotted lines represent the probability of an investor holding a stock conditional on no sale up to a certain point in time. The graph shows that stocks ranked in the highest illiquidity decile have significantly higher survival probabilities, which suggests that investors tend to hold the most illiquid stocks for longer periods of time. This provides another piece of evidence that holding periods are strongly related to measures of transaction costs. We perform more detailed analysis that controls for related stock and investor characteristics in the following sections.

4.3. Hazard Regression

Univariate results above suggest that holding periods are strongly related to measures of transaction costs. In this section, we utilize a hazard framework controlling for stock and investors characteristics to analyze household holding period decisions. We explicitly model an investor's trading decision by considering his sell vs. hold decision each day. We use a Cox proportional hazard model with time-varying explanatory variables. The hazard model takes the following form:

$$\lambda t = \lambda_0 t \times \exp(x_t{}'\beta) + z'\alpha$$

This model describes how long an investor in the dataset will hold a stock before selling it. The left hand variable, λt, is the hazard rate. It represents the probability of selling (vs. hold) a stock at day *t* conditional upon holding that stock until that point in time. The explanatory variables in this model can either be static or time varying. x_t represents time-varying covariates while z represents covariates that are constant over time, such as gender. $\lambda_0 t$ is the baseline hazard rate and describes the average hazard rate when the independent variables are all equal to zero. With the Cox (1972) estimator, we can estimate coefficients for each explanatory variable (α and β) without specifying a baseline hazard rate $\lambda_0 t$.

The explanatory variables used in this paper include stock illiquidity, a set of investor demographic variables, such as gender, marriage status, and professions, as well as pthe related stock characteristics, such as size, book-to-market ratio, and momentum. Momentum is measured with stock returns during the previous 12 months before a stock is sold. We include momentum in the model in an attempt to capture the disposition effect – a behavioral tendency for investors to sell shares whose price has increased while holding stocks whose price has dropped. We also include size, and book-to-market ratio in the model to control for investors' preferences for certain stock characteristics. Since there is also likely to be seasonality in buy and sale decisions, we also include calendar month dummies in the hazard regression. Positions that are not closed by the end of the sample period are treated as censored observations.

Following standard reporting conventions, we report hazard ratios instead of estimated coefficients from the hazard regression in Table 3.3. Also, the hazard ratio is more intuitive to interpret. The hazard ratio is defined as the ratio of two hazard functions when one explanatory variable is changed by one unit holding everything else equal, which is similar to the odds ratio estimated from binary choice model. In the current context, the hazard ratio indicates the marginal effect of explanatory variable on the probability of sell vs. hold. A hazard ratio less than one suggests increase in the explanatory variable will decrease the probability of a sale vs. hold, in other words, higher probability of holding the stock. In the contrary, a hazard ratio larger than one suggests increase in the explanatory variables will increase the probability of a sale vs. hold.

In Table 3, we only reports the estimated results with the adjusted Amihud ratio (*AdjIlliq*) as measure of transaction costs for brevity. Similar results are obtained using Pastor & Stambaugh's

Gamma and Roll's measure. In general, results in Table 3.3 are consistent with the univariate results. Model I shows that the estimated hazard ratio for the adjusted Amihud illiquidity ratio is a significant 0.98, implying the more illiquid the stock is, the less likely it will be sold.

However, investors are different among one another. One way to capture heterogeneity across households within a hazard regression framework is to assume a different baseline hazard rate for each household. This is accomplished by estimating the same hazard model with partial likelihood using the method of stratification, which is analogous to controlling for household fixed effects. We estimate Model II and Model III with stratification of each household, and additionally control for size, book-to-market and momentum in Model III. The estimated hazard ratio for our illiquidity measure in Model III is a significant 0.97. This result indicates that there is variation in holding period for different stocks for a given household. Furthermore, the significant hazard ratio of 0.97 infer that increase in the Adjusted Amihud ratio by one standard deviation decrease the probability of sale by a given household by 30%, which is also significant economically. The above results support the hypothesis that the average investor is aware of liquidity, and pay attention to transaction cost when making trading decisions.

The estimated hazard ratios for momentum in Table 3.3 are always significant and larger than one, which indicates that investors are more likely to sell stocks that exhibit higher past returns, while retaining stocks that exhibit relative lower previous returns. This is consistent with the disposition effect. The estimated hazard ratios for size and book-to-market ratios are always less than one and significant, suggesting that investors tend to hold large and value stocks longer.

To analyze further whether the relationship between holding period and transaction costs is stronger for a subset of investors that are more sophisticated and skillful financially, we include in the hazard model framework several demographic variables that we think are associated with investor sophistication. We assume that financial sophistication is correlated with education and resources available to each investor[4]. Investors who have more wealth, and invest large amount of money in the stock market are likely to be more sophisticated financially, thus we include income, and equity investment as control variable in the hazard model. In addition, we also take into account investors' trading experience. Investors who have ever traded options and/or foreign securities, or have ever shorted a stock are likely to be sophisticated and skillful traders. We construct Option User Dum, Foreign Dum, and Short User Dum respectively for investors who have at least once traded options, foreign securities, or have initiated short positions. We also include a Profession Dum, which is a dummy variable that is equal to one for investors who hold technical and managerial positions. We also control for portfolio diversification which is computed as the sum of the squared value weight of each stock in a household's portfolio. According to Goetzmann and Kumar (2008), the more diversified the household portfolio is, the more sophisticated the investor is. In addition to the above variables, we also control for gender, age, and marriage status, which may be relevant to investors trading behavior.

After we include investor characteristics and the interaction terms of these variables with illiquidity measure in Model V, the results show that investors who are more sophisticated tend to pay greater attention to the transaction costs of the stocks they trade. However, not all hazard ratios for the interaction terms are significant. Individuals who have held short positions, who have traded options, and who invest more money in equity market, have holding periods more positively correlated with transaction costs. Investors who trade stocks with their retirement accounts are also more attentive to transaction costs. The positive relationship between holding periods and

[4] This is consistent with Goetzmann and Kumar (2008).

transaction costs is also stronger for investors who have traded foreign securities, and who are professionals, but the estimated hazard ratio is not significant.

4.4. Investor sophistication

To further explore the role of investor sophistication, we create a finer numeric variables to proxy for the level of investor sophistication. The sophistication measure starts at a value of zero for unsophisticated investors, and increases by one for each investor characteristics associated with sophistication. The top panel of Table 3.3 describes the criteria used to construct the sophistication measure. If an investor satisfy one of the criteria, then his sophistication measure increases by one. The computed sophistication measure ranges from the minimum value of 0 for unsophisticated investor to the maximum value of 7 for the most sophisticated investor. Model VI in Table 3.3 replace investor characteristics associated with sophistication with the constructed sophistication measure in the hazard regression. The estimated hazard ratio for the interaction of sophistication and transaction costs measure is a significant 0.996, suggesting sophisticated investors pay more attention to transaction costs than unsophisticated investors. The results are similar when we use sophistication dummy (where sophisticated investors are defined as investors with sophistication measure larger than 3), or illiquidity dummy (where Illiq Dum is equal to one when liquidity of a stock falls into the bottom 20%).

5. Robustness Tests

5.1. Individual Transactions in Finland

Results in section 4 support our first and second hypotheses. Specifically, we already show that the average individual investor’s holding period is positively related to the illiquidity level of stocks in the United States, and that the relationship between holding periods and stock transaction costs is stronger among sophisticated investors. However, people might be concerned whether the results we get using only a proportion of US investors are representative of all investors. In this section, we provide robustness tests using individual transaction data in Finland. This dataset include every trades made by the universe of Finnish investors. Stock information and firm characteristics are obtained from DataStream and Compustat Global data. Table A1 in Appendix provides the descriptive statistics and correlation for liquidity measures we use for Finnish Stocks. Similar to the U.S, all liquidity measures are positive skewed, and correlated positively with each other. Size is also positive skewed for Finnish stocks.

We use a similar hazard framework to test Hypotheses 1 and 2 for Finnish investors. We estimate another hazard regression of holding periods on measures of stock illiquidity, controlling for stock characteristics to examine the relationship between holding period and transaction costs of stocks. We incorporate investor characteristics, and a sophistication measure constructed similarly to test whether the relationship is stronger among sophisticated investors vs. unsophisticated investors. For brevity, we only include in the paper the results using the adjusted Amihud ratio to be consistent with the U.S. results. Results using other liquidity measures are similar to the results documented here and are available upon request.

Table 3.4 reports the estimated results of the hazard regressions for Finnish investors. As evidenced by the results, the average investor in Finland also tend to hold illiquid stocks for a longer period, consistent with our findings for the United States. This implies that our previous results are not specific for the US data we use. After controlling for household fixed effect in Model II, the estimated hazard ratio for the adjust Amihud ratio is a significant 0.97, suggesting that the average investor are 25% less likely to sell the stock when its illiquidity increase by one standard deviation. The magnitude of the estimated hazard ratio of illiquidity for Finnish stocks is similar to that for the US stocks, and is also significant economically.

To examine the cross-sectional differences in the relationship between holding periods and stock liquidity, we include investor characteristics and its interaction with stock liquidity in our hazard models. We first use all investor characteristics, and later expand our analysis by replacing characteristics associated with sophistication with the single sophistication measure constructed as before in Table 3.3. The top panel of Table 3.4 lists the criteria used to construct the sophistication measure for Finnish investors. Since the Finland transaction data doesn't provide information regarding investors' income and professions, nor information about whether the investor has ever traded any foreign securities, we exclude these criteria in the construction of sophistication measure. Four criteria are applied to construct the sophistication measure, which makes the sophistication measure range from a minimum of 0 for unsophisticated investors to a maximum of 4 for the most sophisticated investors in Finland. The last model in Table 3.4 shows that sophisticated investors pay greater attention to transaction costs, and they tend to hold illiquid stocks for a longer period than unsophisticated investors do. The magnitude of estimated hazard ratio for the interactions between sophistication and transaction costs is smaller than that in the United States in Table 3.3. One reasonable explanation could be that exclusion of investors' income level from the construction of sophistication measure introduce noise.

5.2. Exogenous Liquidity Shock

It is possible that some missing variables are responsible for the covariation of liquidity and holding periods simultaneously. If this is the case, then our empirical finding are subject to endogeneity problem. In this section, we employ a form of exogenous liquidity shock which is unlikely to affect holding periods directly. Specifically, we examine how stock liquidity and holding periods change around stock split events.

People usually think that one of the main reasons for firms to split their stocks is to increase liquidity. Increase in the shareholder base of a company's security can lead to increase in its trading volume, and thus reduce its transaction costs. Previous studies generally find that liquidity increases after stock splits. For example, Schultz (2000) show that the number of trades, especial small trades, increases significantly subsequent to stock splits. Desai, Nimalendran, and Venkataraman (1998) find that both informed trades and noise trades increase after stock splits. Kryzanowski and Zhang (1996) report that absolute trading volume increases for Canadian stocks after splits. Conroy, Harris, and Benet (1990) show a significant reduction in the absolute bid-ask spread and relative bid-ask spread for NYSE stock splits[5]. However, stock splits along are unlikely to affect investors' holding periods for that stock directly. Stock splits can only affect holding periods through reducing transaction costs, which makes trading of the stocks less costly.

Using CRSP data, we find there are 3586 stock splits (distribution code 5523) of all sizes between year 1991 and 1996, including reverse splits. Of these splits, we exclude 1067 observations which have a cash-dividends distribution within +/- 30 days window around the split events to make sure that our results are not influenced by other events happening simultaneously. In order to find "pure" stock split events, we further remove 669 observations that have a split factor less than 0.25[6]. Our final sample includes 1850 pure forward-split events with available data in this period.

Previous studies have documented that stock liquidity increases 6 months subsequent to stock splits. To study the change in liquidity subsequent to stock splits, we estimate an OLS regression

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[5] Empirical results regarding whether liquidity increases subsequent to stock splits are mixed. It is determined by the time frame analyzed, and the liquidity measure used. Also price drops subsequent to stock splits are also likely to bias up the estimate of relative bid-ask spread.

[6] Previous studies examining stock splits events generally impose this restriction to filter out reverse-splits. The results are similar if we use stock splits that have a split factor larger or equal to 0.

of our monthly liquidity measure on a time period indicator – After Dum, controlling for stock characteristics, i.e. size, book-to-market and momentum. We estimate the OLS regression for different time horizons, which compare 6 months, 9 months, and 12 months before and after the stock split events[7]. Table 3.5 reports the estimated results with the adjusted Amihud ratio, and provides evidence that the liquidity of stocks increase after stock splits. We could see that regardless of the comparison horizons, the estimated After Dum is always significantly negative, which suggests that the adjusted Amihud ratio decreases significantly after stock splits events, consistent with previous findings that liquidity increases after stock splits. After controlling for stock fixed effect, column 4 in Table 3.5 reports that average adjusted Amihud ratio decrease by a significant 0.186 for stock that splits, which is more than 10% increase in liquidity compared with the median stock, and is economically meaningful.

If stock liquidity is an important determinant of investors' holding periods of that stock, then we expect that holding periods also shortened for firms that split their stocks. To examine this question, we include the After Dum defined in Table 3.5 in our hazard framework from Table 3.3, keeping everything else the same. An estimated hazard ratio of larger than 1 for the After Dum will suggest that investors are more likely to sell the stock subsequent to its split (reduced holding period), while a hazard ratio smaller than 1 will indicate that investors tend to hold the stock longer subsequent to stock splits. According to results in Table 3.5, stocks become more liquid after splitting, thus we expect the After Dum to have an estimated hazard ratio of larger than one.

Table 3.6 reports the estimated hazard ratio of the After Dum in the hazard regression where the dependent variable is the conditional probability of sale. Panel A includes After Dum as the

[7] We also tried 2-month and 3-month window, during which time stocks don't experience a significant increase in their liquidity. According to Lakonishok and Lev (1987), trading volume tend to increase from 7 months before stock splits, and then decline a little within 2 months subsequent to stock splits, which might help explain our insignificant liquidity increase within the 2 or 3 months window.

only independent variable, while Panel B extend the framework to include all control variables as in Table 3.3. We could see that the estimated hazard ratio for the After Dum is always larger than one, and almost always significant. This suggests that average holding periods decline for stock that splits. We further control for stock split event fixed effect to address clustering in stock splits, and household fixed effect to account for unobservable preferences. The results become a bit weaker, but still significant. The estimated hazard ratio is significant at 1.092 for the 9-month window in Panel B, suggesting that stock are 10% more likely to be sold by the same investor subsequent to its split. This is equivalent to a reduction in holding period by about 20 business days, which is close to one calendar month. This additional piece of evidence prove again that stock liquidity is an important and economically meaningful determinant of investors' holding periods.

6. Time Variation of Liquidity Preference

In this section, we extend previous analysis to consider how households as a group make liquidity decisions over time, in other words, how their preferences to liquidity change systematically over time. As described in Section 2, commonality in liquidity could arise from investors demanding liquidity at the same time, i.e. increase in uncertainty about the future can cause investors to tilt their portfolio towards more liquid assets at the same time. However, a number of papers show that retail investors are generally noise traders, who constantly provide liquidity to the market. It is unclear then how the systematic changes of individual investors' liquidity preferences vary with aggregate market liquidity. With the data we have, we investigate directly whether there is a flight to liquidity during times of low market liquidity (i.e. investors demand liquid assets at the same time), and whether a subset of retail investors provide liquidity to the market by purchasing illiquid stocks.

To test the systematic variation in investors' liquidity preference, we employ a similar methodology as in Kumar and Lee (2006), and Barber, Odean and Zhu (2003), who investigate the correlation among individual trades. Because we compare liquidity over time under different regimes of aggregate liquidity, we use stock liquidity ranks instead of their levels. We rank all stocks based on their adjusted Amihud ratio every month and assign them into percentile ranks. Stocks ranked into the first percentile have the smallest adjusted Amihud ratio, and are the most liquid. Similarly, stocks ranked into the 100th percentile have the largest adjusted Amihud ratio, and are the most illiquid.

To measure households' preferences for liquidity, we define a term called *IlliqBSI*. It is analogous to the buy-and-sell imbalance index in illiquidity for all stocks traded by the household. It is the differences in the liquidity ranks of the stocks they purchase vs. they sold in a given month, calculated as below:

$$IlliqBSI_t = \frac{\sum_{i \in N} BV_t^i \times BAdjIlliqRank_{t-1}^i - \sum_{i \in N} SV_t^i \times SAdjIlliqRank_{t-1}^i}{\sum_{i \in N} BV_t^i \times BAdjIlliqRank_{t-1}^i + \sum_{i \in N} SV_t^i \times SAdjIlliqRank_{t-1}^i}$$

where BV_t^i and SV_t^i are the total value of purchases and sales for household *i* during month *t*. *AdjIlliqRank* stands for the adjusted Amihud percentile rank. B means Buy, while S means sell. $BAdjIlliqRank_{t-1}^i$ and $SAdjIlliqRank_{t-1}^i$ are the weighted average adjusted Amihud illiquidity rank for stocks purchased and sold by household i, respectively. *IlliqBSI* is the weighted average of each household's imbalance, and indicates whether the aggregate retail investors are net buyers or sellers of liquid stocks. To examine the systematic variation of investors' preference for liquidity with market liquidity, we measure monthly market illiquidity (*MktIlliq*) with the equal-weighted average of the adjusted Amihud ratio for all stocks in a given month[8].

[8] We obtain similar results with Pastor and Stambaugh's Gamma. The correlation between adjusted Amihud ratio and PS measure is about 30%

Figure 3.3 plots the aggregate market illiquidity, *MktIlliq*, and *IlliqBSI* over the sample period. In the figure, the period with the low market liquidity corresponds with the Mexican peso crises in 1994. From the figure, we can see that aggregate household's demand for liquid stocks are negatively correlated with market illiquidity, the correlation is a negative -35%.

To examine the variation in more detail, we split the sample period into five time periods based on the aggregate market liquidity. The first time period corresponds to the 14 months with the lowest level of market illiquidity, in other words, the most liquid period; and the last period corresponds to the 14 months with the highest level of market illiquidity, the most liquid months. Table 3.7 reports the illiquidity ranks of stocks bought and sold by households during these five time periods. During the most illiquid months, we can see that stocks that households purchase are more liquid than stocks they sell. The difference is a significant -0.86. During the most illiquid month, June, 1994, stocks that households purchase have a significant 1.13 percentile higher liquidity than the stocks they sell. When considering the fact that more than half of the US household trade very liquid stocks, usually have an average portfolio illiquidity rank in the bottom 8^{th} percentile, the difference of 1.13 percentile is significant both statistically and economically.

We adjusts for the liquidity of each household portfolio in the last column of Table 3.8. We subtract the weighted average illiquidity rank of each household's portfolio from the illiquidity rank of stocks transacted by that household. This is similar to controlling for household fixed effect for liquidity. The results show the differences in the illiquidity ranks of stocks that households purchase and sell. There is a weaker but still significant difference in the liquidity ranks of stocks that households buy and sell. These results generally prove that retail investors tend to purchase more liquid securities when aggregate market is illiquid, which confirms our hypothesis IV (H4) about flight-to-liquidity.

It is also interesting to look at whether sophisticated retail investors take advantage of the opportunities during market turbulence period by purchasing illiquid stocks that are discounted more. For each transaction, we regress the illiquidity ranks of stocks that households purchase in a given month on market illiquidity and investor sophistication. The regression is of the following form:

$$
\begin{aligned}
AdjIlliqrank_{i,k,t} & \\
&= \beta_0 + \beta_1 MktIlliqDum_t + \beta_2 Buy_{i,k} + \beta_3 Sophistication_i + \beta_4 Buy_{i,k} \\
&\times MktIlliqDum_t + \beta_5 Buy_{i,k} \times Sophistication_i + \beta_6 MktIlliqDum_t \\
&\times Sophistication_i + \beta_7 Buy_{i,k} \times MktIlliqDum_t \times Sophistication_i
\end{aligned}
$$

where $AdjIlliqrank_{i,k,t}$ is the illiquidity rank of the underlying stock for transaction k of household *i* in month *t*. To get a more intuitive and consistent interpretation of the estimated results as in Table 3.7, we transform the market illiquidity variable into a dummy variable ($MktIlliqDum_t$), which takes on a value of one for the month in which market illiquidity is at its highest during the sample period. $Buy_{i,k}$ is a dummy variable that takes on a value of one if transaction *k* for household *i* is a purchase, otherwise zero. Sophistication is defined as in Table 3.3, but we use a dummy for sophistication to keep consistency. $Sophistication_i$ takes on a value of one if sophistication measure for household *i* is larger than 3 (the range is between 0 and 7). The variables of interest here are the interaction between the buy dummy and market illiquidity dummy, which measures the purchase behavior of the average household during time of illiquid market, and the interaction among buy, market illiquidity, and sophistication dummy, which captures the trading behavior of sophisticated investors during market turbulence.

Table 3.6 already shows that the average retail investor tends to buy more liquid stocks during illiquid period. We predict the estimated coefficient of the interaction between buy and market illiquidity from the above regression to be negative. If sophisticated investors take advantage of this time period, they should purchase more illiquid stocks than the average household, in other words, the estimated coefficient on the interaction between buy, market illiquid, and sophistication dummy from the above regression should be positive. Table 3.7 reports the estimated results of the above equation. Panel A defines a month to be illiquid if the market illiquidity measure for that month is in the top 10% during the sample period, while Panel B only considers the most illiquid month during the entire period.

The estimated coefficient on the interaction of buy and market illiquid dummy in Model I of Panel A is significantly negative, suggesting that when market is illiquid, the average investor tends to purchase more liquid stocks. Controlling for household fixed effect in Model II reduce the effect a little but it is still significant. However, the estimated coefficient on the interaction among buy, market illiquidity and sophistication dummy is significantly negative, suggesting that sophisticated investors tend to buy even more liquid stock in the turbulent time, instead of providing liquidity to the market. Panel B provides similar evidence regarding the most illiquid month during the entire sample period. The interaction of buy, market illiquidity and sophistication dummy is a significant -3.33. Since we measure illiquidity with their rank, the -3.33 is economically meaning, and suggests that sophisticated investors even pay more attention to transaction costs when market illiquidity is high.

7. Conclusion

This paper studies the trading behavior of individual investors. It provides empirical evidence that transaction costs are an important determinant of investors trading decisions, specifically their holding period decisions. We show that the average investor in the United States tend to hold illiquid stocks for longer periods, consistent with the liquidity clientele proposed by Amihud and

Mendelson (1986). The results are robust after we control for stock characteristics, household fixed effect, as well as disposition effect. This effect is stronger for investors who are sophisticated and skillful financially. We find similar evidence in Finland, which suggests that our results are generalizable to the overall retail investors, instead of driven by sample bias.

Since investors' trading behavior is likely to affect liquidity, we use stock splits as exogenous liquidity shocks that are unlikely to affect holding periods directly to further investigate the relationship between liquidity and holding periods. We do find that holding periods decrease following positive liquidity shocks. This results confirm our hypothesis that liquidity is an important determinant of holding periods.

Last, this paper shows that there is a systematic variation in investors' demand for liquid stocks across time. Specifically, retail investors are net buyers of more liquid stocks when market is illiquid, consistent with the notion of flight-to-liquidity. Interestingly, sophisticated investors are even more sensitive to transaction costs during times of extremely low aggregate market liquidity.

References

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

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

Amihud, Y. and H. Mendelson, 1986, "Asset pricing and the bid-ask spread," Journal of Financial Economics, 17, 223–249.

Atkins, A. B. and E. A. Dyl, 1997, "Transactions costs and holding periods for common stocks,"Journal of Finance, 52, 309–325.

Barber, B. M., and T. Odean, 2000, "Trading is hazardous to your wealth: the common stock investment performance of individual investors," Journal of Finance, 55, 773–806.

Barber, B. M., and T. Odean, 2001, "Boys will be boys: Gender, overconfidence, and common stock investment," Quarterly Journal of Economics, 116, 261–292.

Barber, B. M., T. Odean, and L. Zheng, 2005, "Out of sight, out of mind: The effects of expenses on mutual fund flows," Journal of Business, 78, 2095–2119

Barber, B., T. Odean, and N. Zhu, 2003, "Systematic noise," Working paper, Haas School of Business, University of California at Berkeley.

Barber, B. M., T. Odean, and N. Zhu, 2006, "Do noise traders move markets?," Working Paper, UC Davis.

Barber, B. M., T. Odean, Y. Lee, and Y. Liu, 2008, "Just how much do investor lose from trade?," Working paper, UC Davis.

Campbell, J. Y., S. J. Grossman, and J.Wang, 1993, "Trading volume and serial correlation in stock returns," Quarterly Journal of Economics, 108, 905–939.

Campbell, J. Y., T. Ramadorai, and A. Schwartz, 2007, “Caught on tape: Institutional trading, stock returns, and earnings announcements,” Working paper, Harvard University.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, “Commonality in liquidity,” Journal of Financial Economics, 56, 309–325.

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

Chordia, T., S.Huh, and A. Subrahmanyam, 2007, “Theory-based illiquidity and asset pricing,” Working paper, UC Los Angeles.

Comerton-Forde, C., T. Hendershott, C.M. Jones, P.C. Moulton, and M.S. Seasholes, 2010, “Time variation in liquidity: The role of market maker inventories and revenues,” Journal of Finance 65(1): 295-331.

Conroy, Robert M., Robert S. Harris, and Bruce A. Benet, 1990, “The effects of stock splits on bid-ask spreads,” Journal of Finance 45, 1285-95.

Constantinides, G. M., 1986, “Capital market equilibrium with transaction costs,” Journal of Political Economy, 94, 842–862.

Coughenour, J.F., and M.M. Saad, 2004, “Common market makers and commonality in liquidity," Journal of Financial Economics, 73, 37-70.

Coval, J. D., D. A. Hirshleifer, and T. Shumway, 2005, “Can individual investors beat the market?” Working Paper, University of Michigan.

Cox, D., and D. Oakes, 1984, Analysis of survival data, Chapman and Hall, London; New York.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers, 1997, “Measuring mutual fund performance with characteristic-based benchmarks,” Journal of Finance, 52, 1035–1058.

Datar, V. T., N. Y. Naik, and R. Radcliffe, 1998, “Liquidity and stock returns: An alternative test,” Journal of Financial Markets, 1, 205–219.

Desai, Anand S, M Nimalendran, and S Venkataraman, 1998, “Changes in Trading Activity Following Stock Splits and Their Effect on Volatility and the Adverse- Information Component of the Bid-Ask Spread,” Journal of Financial Research 21,159-83

Easley, D., N. M. Kiefer, and M. O”Hara, 1997, “One day in the life of a very common stock,” Review of Financial Studies, 10, 805–835.

Easley, David, Soeren Hvidkjaer, and Maureen O”Hara, 2002, “Is information risk a determinant of asset returns?,” Journal of Finance, 57, 2185–2221.

Eckbo, E., and O. Norli, 2002, “Pervasive liquidity risk”, Working paper, Tuck School of Business.

Feng, L., and M. S. Seasholes, 2005, “Do investor sophistication and trading experience eliminate Behavioral biases in financial markets?,” Review of Finance, 9, 305–351.

Garleanu, N. and L. H. Pedersen, 2004, “Adverse selection and the required return,” Review of Financial Studies, 17, 643–665.

Goetzmann, W. N., A. Kumar, 2008, “Equity portfolio diversification,” Review of Finance 12(3): 433-463.

Griffin, J. M., J. H. Harris, and S. Topaloglu, 2003, “The dynamics of institutional and individual trading,” Journal of Finance 58, 2285–2320.

Grinblatt, M., and M. Keloharju, 2001, “What makes investors trade?,” Journal of Finance, 56, 589–616.

Hasbrouck, J., 2009, “Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data,” Journal of Finance 64(3): 1445–1477.

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

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

Huberman, G. and D. Halka, 2001, “Systematic liquidity,” Journal of Financial Research, 24, 161–178.

Hvidkjaer, S., 2006, “A trade-based analysis of momentum,” Review of Financial Studies, 19, 457-491.

Hvidkjaer, S., 2008, “Small trades and the cross-section of stock returns,” Review of Financial Studies, 21, 1123-1151.

Ivkovi´c, Z., C. Sialm, and S. J. Weisbenner, 2008, “Portfolio concentration and the performance of individual investors,” Journal of Financial and Quantitative Analysis 43(3): 613-655.

Ivkovi´c, Z., and S. J. Weisbenner, 2005, “Local does as local is: Information content of the geography of individual investors common stock investments,” Journal of Finance, 60, 267–306.

Kaniel, R., G. Saar, and S. Titman, 2008, “individual investor trading and stock returns,” Journal of Finance 63(1): 273-310.

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

Kumar, A. and M.C. Lee, 2006. "Retail investor sentiment and return comovements," Journal of Finance, 61, 2451-2486.

Lakonishok, Josef, and Baruch Lev, 1987, “Stock Splits and stock dividends: Why, who and when,” Journal of Finance 42, 913-932.

Lin, D.Y. and L.J. Wei , 1989, “The robust inference for the cox proportional hazards model,” Journal of the American Statistical Association, 84, 1074–1078.

Lo, A. W., H. Mamaysky, and J.Wang, 2004, “Asset prices and trading volume under fixed transaction costs,” Journal of Political Economy, 112, 1054–1090.

Lynch, A. W. and S. Tan, 2011, “Explaining the magnitude of liquidity premia: The roles of return predictability, wealth shocks and state dependent transaction costs,” Journal of Finance 66(4): 1329–1368.

Naes, R., and B. A. Odegaard, 2008, “liquidity and asset pricing: Evidence on the role of investor holding period”, Working Paper, Norwegian School of Management.

Odean, T., 1999, “Do investors trade too much?,” American Economic Review, 89, 1279–1298.

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

Roll, R., 1984, “A simple implicit measure of the effective bid-ask spread in an efficient market,” Journal of Finance, 39, 1127–1139.

Schultz, Paul, 2000, “Stock Splits, Tick Size, and Sponsorship,” Journal of Finance 55,429-50

Seru, A., T. Shumway, and N. Stoffman, 2010, “Learning by trading”, Review of Financial Studies 23 (2): 705-739.

Shefrin, H., and M. Statman, 1985, “the disposition to sell winners too early and ride losers too long: Theory and evidence,” Journal of Finance, 40, 777–790.

Stiglitz, J.E., 1989, “Using tax policy to curb speculative short-term trading,” Journal of Financial Services Research, 3, 101-115.

Stoffman, N., 2014, “Who trades with whom? Individuals, institutions, and returns,” Journal of Financial Markets 21: 51-75.

Summers, L.H., V.P. Summers, 1989, “When financial markets work too well: A cautious case for a securities transactions tax,” Journal of Financial Services Research 3, 261-286.

Vayanos, D., 1998, “Transactions costs and asset prices: A dynamic equilibrium model,” Review of Financial Studies, 11, 1-58.

Vayanos, D., and J.C. Vila, 1997, “A preferred-habitat model of the term structure of interest rates,” Working paper, London School of Economics.

Vayanos, D., and J.C. Vila, 1999, "Equilibrium interest rate and liquidity premium with transaction costs," Economic Theory, 13, 509-539.

Vayanos, D., 2004, "Flight to quality, flight to liquidity, and the pricing of risk," Working paper, London School of Economics.

Table 3.1: Summary Statistics of Stock and Investor Characteristics for US and Finland

Table 3.1 reports descriptive statistics for stock in the US and Finland, as well as investor and trade characteristics, respectively. Only stocks that are traded by households in the dataset are considered. Summary statistics are calculated by pooling annual observations over the 1991-1996 time period for US, and over the 1995-2003 time period for Finland. All liquidity measures are annual averages and are defined in the text. AdjIlliq is the adjusted Amihud illiquidity ratio. Roll’s C is the Bayesian estimate of Roll’s (1984) transactions cost measure. Price is the annual average of the daily closing prices. Mkt Cap is the average market capitalization value in millions of US dollars. Number of trades is the total number of trades placed by an investor during the sample period. Average portfolio value is the average marked-to-market value of an investor’s portfolio using daily closing prices.Panel A reports the results in United States, and Panel B for Finland.

Panel A: Summary Statistics for the US				
	Mean	P25	Median	P75
	Stock Characteristics			
Price ($)	18.61	5	12.5	24.5
Mkt Cap ($mil)	1045	30	105	452
AdjIlliq	7.23	0.38	1.66	11.64
Roll's C	1.73	0.45	1.06	2.26
ZeroFreq	8.66%	0.00%	8.33%	9.09%
	Investor Characteristics			
Number of years with trades	3.3	2.0	3.0	5.0
Number of securities traded	9.4	2.0	5.0	11.0
Number of trades	21.1	3.0	8.0	20.0
Average value of shares traded, USD	12353	2600	5300	11688
Average Portfolio Value, USD	47334	6163	16210	33741
Portfolio Diversification	0.40	0.19	0.35	0.57
Income	75	45	88	113
Age in 1996	49.6	40	48	58
Professional traders	0.64			
Gender (1=female)	0.21			
Trade Option	0.14			
Trade Foreign Securities	0.22			
Short Position	0.38			

Table 3.1: Summary Statistics of Stock and Investor Characteristics for US and Finland (Cont.)

Panel B: Summary Statistics for Finland				
	Mean	P25	Median	P75
	Stock Characteristics			
Price (€)	12.61	2.69	7.67	16.4
Mkt Cap (€mil)	1132	33	125	498
AdjIlliq	10.61	1.07	6.21	20.12
Roll's C	2.96	0.66	2.30	3.88
ZeroFreq	21.90%	13.50%	20.64%	27.75%
	Investor Characteristics			
Number of years with trades	3.0	1.0	2.0	4.0
Number of securities traded	6.7	2.0	4.0	8.0
Number of trades	33.1	3.0	8.0	22.0
Average value of shares traded, EUR	4229	962	1989	4030
Average Portfolio Value, EUR	10823	1341	2079	5292
Portfolio Diversification	0.20	0.09	0.17	0.27
Age in 1995	39.5	27	40	52
Gender (1=female)	0.33			
Trade Option	0.04			
Short Position	0.003			

Table 3.2: Impact of Liquidity on Investors' Holding Periods in the US, univariate analysis

Table 3.2 presents univariate analysis of the relationship between stock liquidity and average holding periods of individual investors in the US between 1991 and 1996. All transactions in the dataset are ranked according to their holding periods and then are placed into one of ten groups based on this ranking. Holding period is measured in days as the duration between the purchase and sale of an asset by a specific investor. Censored transactions are included in the summary stats, i.e. when a certain purchase can't be assigned to a corresponding sale by its investor the asset is presumed to be sold on the last available date in the dataset. Averages for the various liquidity measures for the underlying securities are then calculated for each group. All liquidity measures are annual averages and are defined in the text. Price is the annual average of the daily closing prices. Mkt Cap is the average market capitalization in millions of dollars. PS Gamma is Pastor and Stambaugh's (2003) reversal gamma. AdjIlliq is the adjusted Amihud illiquidity ratio. Roll's C is the Bayesian estimate of the Roll's (1984) transactions cost measure. High minus Low raw reports the differences for the various liquidity measures between the investor groups with the highest and lowest holding-periods. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

	Holding Period	**Price $**	**Mkt Cap 000s**	**Amihud AdjIlliq**	**Roll's C**	**ZeroFreq**
Low	6	32.89	7,940	0.9142	0.6608	2.51%
2	20	32.04	7,602	0.9943	0.6834	2.59%
3	44	31.28	7,833	1.0893	0.7054	2.67%
4	79	31.52	9,029	1.1265	0.7072	2.67%
5	127	33.96	9,199	1.2606	0.7337	3.00%
6	194	31.21	10,513	1.2421	0.7312	2.94%
7	294	30.36	9,886	1.3535	0.7382	3.26%
8	470	29.47	10,266	1.3819	0.7312	3.65%
9	771	31.74	11,434	1.4889	0.7425	3.76%
High	1225	40.76	11,270	1.7578	0.8182	3.97%
High-Low	1219***	7.87***	3330***	0.8436***	0.1575***	1.46%***

Table 3.3: Impact of Liquidity on Individual Investors' Holding Periods in the US, hazard analysis

Table 3.3 examine the impact of stock liquidity on individual investors' holding period in the US using a hazard model framework. Panel A of Table 3.3 lists the criteria used to measure the sophistication of individual investors in the US between 1991 and 1996. A US investor's sophistication is presumed to cumulatively increase with each of the following criteria met: if the investor has a total household income higher than $75K; if the household ranked in the top 25% of all investors based on equity holdings at any point in time during the sample period; if the investor held either technical or managerial positions and as such is considered a professional; if the investor traded options at least once during the entire sample period; if the investor ever held any short positions during the sample period; if the investor ever traded foreign securities, including ADRs, foreign stocks or mutual funds; and if the investor's portfolio is more concentrated than the median investor's, i.e. if the investor's diversification is less than 0.3 for the US sample. Diversification is defined as in Goetzmann and Kumar (2008), and is equal to the sum of the squared values of the weights of each stock in a household's portfolio. Panel B of Table 3.3 reports hazard ratios from the holding period hazard regressions for the US, between 1991 and 1996, where the conditional probability of sale is the dependent variable. Independent variables consist of the adjusted Amihud illiquidity ratio (our global proxy for transactions costs); firm characteristics; a set of demographic controls; trade variables; as well as the interaction of our proxy for transactions costs with investor characteristics. Our proxy for transactions costs, Illiquidity, is the adjusted Amihud illiquidity ratio calculated over the previous 12 months prior to a transaction. Size is the market value of equity. B/M calculates the book-to-market ratio by dividing previous year end book value by the most recently available market capitalization. Momentum is the cumulative returns over the period between [t-12] to [t-2] months. All stock characteristics are calculated at the beginning of the month that a sale takes place. Age refers to the age of the head of the household. Income is the total annual household income. Married Dum is a dummy variable set to one if the head of the household is married. Male Dum is set to one if the head of the household is male. Professional Dum and Retired Dum are dummy variables that reflect investors' employment status. Professional Dum is set to one for investors who hold technical and managerial positions, and Retired Dum is set to one for investors who are retired. Retirement Account Dum is set to one if the underlying account is a retirement (IRA or Keogh) account. Trade variables are derived from the trades made by investors in the dataset. Short User Dum is set to one if an investor executed at least one short sale during the sample period. Option User Dum is set to one if an investor ever traded options. Foreign User Dum is set to one if an investor made at least one trade in a foreign asset including ADRs, foreign stocks or foreign mutual funds during the sample period. Calendar month dummies (not reported) are twelve dummy variables that take on a value of one if the month of the transaction is equal to the month dummy. Year dummies (not reported) take on a value of one for each year. Clustered robust standard errors are calculated at the household level. Ties are handled using the Efron procedure. Wald test is used for each additional set of regressors. P-values are reported below each coefficient. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Characteristics Used to Determine Investor Sophistication

Criteria	Marginal Sophistication
Income > $75K (mean)	+1
Equity Investment in the top 25%	+1
Investor is a professional	+1
Traded Options	+1
Has held a short position	+1
Traded Foreign Securities	+1
Portfolio Diversification < 0.3 (median)	+1

Panel B: Predicting the Conditional Probability of Sale via Hazard Regressions								
	I	*I-Roll'sC*	*I-Zerofreq*	**II**	**III**	**IV**	**V**	**VI**
AdjIlliq	0.981***	0.982***	0.322***	0.973***	0.981***	0.983***	1.025	1.006
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.134*	0.485
				Firm Characteristics				
Size					0.649***	0.724***	0.725***	0.720***
					<.0001	*<.0001*	*<.0001*	*<.0001*
B/M					0.681***	0.889***	0.887***	0.878***
					<.0001	*<.0001*	*<.0001*	*<.0001*
Momentum					1.135***	1.113***	1.112***	1.113***
					<.0001	*<.0001*	*<.0001*	*<.0001*
				Demographic Variables				
Age						0.997***	0.997***	0.996***
						<.0001	*<.0001*	*<.0001*
Log (Income)						0.927***	0.925***	
						<.0001	*<.0001*	
Married Dum						0.959***	0.956***	0.904***
						<.0001	*<.0001*	*<.0001*
Male Dum						1.103***	1.113***	1.064***
						<.0001	*<.0001*	*<.0001*
Professional Dum						1.001	1.005	
						0.891	*0.633*	
Retirement Acct Dum						0.912***	0.917***	0.853***
						<.0001	*<.0001*	*<.0001*
Retired Dum						1.076***	1.082***	1.245***
						<.0001	*<.0001*	*<.0001*
				Trade Variables				
Foreign securities Dum						1.245***	1.248***	
						<.0001	*<.0001*	
Option user Dum						1.395***	1.406***	
						<.0001	*<.0001*	
Short user Dum						1.877***	1.895***	
						<.0001	*<.0001*	
Log (Total Equity)						1.079***	1.081***	
						<.0001	*<.0001*	
Diversification						3.228***	3.238***	
						<.0001	*<.0001*	
				Interactions				
AdjIlliq * Age							1	1
							0.667	*0.697*
AdjIlliq * Log (Income)							1.002	
							0.329	
AdjIlliq * Married Dum							1.004	1.004

							0.244	*0.212*
AdjIlliq * Male Dum							0.988**	0.990*
							0.028	*0.055*
AdjIlliq * Professional Dum							0.996	
							0.229	
AdjIlliq * Retirement Acct Dum							0.993**	0.995*
							0.029	*0.091*
AdjIlliq * Retired Dum							0.992	0.989***
							0.108	*0.007*
AdjIlliq * Foreign Dum							0.997	
							0.314	
AdjIlliq * Option user Dum							0.989***	
							0.001	
AdjIlliq * Short user Dum							0.989***	
							<.0001	
AdjIlliq * Log (Total Equity)							0.998**	
							0.028	
AdjIlliq * Diversification							0.995	
							0.447	
				Sophistication Measure				
Sophistication								1.116***
								<.0001
AdjIlliq * Sophistication								0.996***
								<.0001
Household effects	No	No	No	Yes	Yes	No	No	No
Firm fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes
Calendar month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes					
N Observation	799469	799469	766168	799469	589794	115147	115147	115147
Wald test	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 3.4: Impact of Liquidity on Individual Investors' Holding Periods in Finland, hazard analysis

Table 3.4 examine the impact of stock liquidity on individual investors' holding period in Finland using a hazard model framework. Panel A of Table 3.4 lists the criteria used to measure the sophistication of individual investors in Finland over the 1996-2003 time period. A Finnish investor's sophistication is presumed to cumulatively increase with each of the following criteria met: if the household ranked in the top 25% of all investors based on equity holdings at any point in time during the sample period; if the investor traded options at least once during the entire sample period; if the investor has ever held any short positions during the sample period; and if the investor's portfolio is more concentrated than the median investor's, i.e. if the investor's diversification is less than 0.1 for the Finnish sample. Diversification is defined as in Goetzmann and Kumar (2008), and is equal to the sum of the squared values of the weights of each stock in a household's portfolio. Panel B of Table 3.4 reports hazard ratios from the holding period hazard regressions in Finland where the conditional probability of sale is the dependent variable. Independent variables consist of the adjusted Amihud illiquidity measure (our global proxy of transactions costs); firm characteristics; a set of demographic controls; trade variables; as well as the interaction of our proxy for transactions costs with investor characteristics. Our proxy for transactions costs, Illiquidity, is measured with the adjusted Amihud illiquidity ratio calculated over the previous 12 months prior to a transaction. Size is the market value of equity. B/M calculates the book-to-market ratio by dividing the previous-year-end book value by the most recently available market capitalization. Momentum is the cumulative returns over the period between [t-12] to [t-2] months. All stock characteristics are calculated at the beginning of the month that a sale takes place. Demographic variables include gender and age. Male Dum is set to one if the head of the household is male. Age [40-64] Dum equals to one if the head of the household ages between 40 and 64. Age 65+ Dum is set to one if the head of the household ages over 64. Trade variables are derived from transactions made by investors in the dataset. Option User Dum is set to one if an investor has traded options. Short User Dum is set to one if an investor executed at least one short-sale during the entire sample period. Year Dummies are dummy variables take the value of one if the year during which the transaction takes place equals to the year dummy. Calendar month dummies (not reported) are twelve dummy variables that take on a value of one if the month of the transaction equals to the month dummy. Robust standard errors are calculated as in Lin and Wei (1989). Ties are handled using the Efron procedure. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Characteristics Used to Determine Investor Sophistication

Criteria	**Sophistication**
Equity Investment in the top 25%	**+1**
Trades Option	**+1**
Has held a Short Position	**+1**
Portfolio Diversification < 0.1 (median)	**+1**

Panel B: Predicting the Conditional Probability of Sale via Hazard Regressions							
	I	*I-Roll's C*	*I-Zerofreq*	**II**	**III**	**IV**	**V**
Illiquidity (Adj. Amihud)							
AdjIlliq	0.984***	0.975***	0.105***	0.976***	0.982***	1.052	1.008***
	<.0001	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*
Firm characteristics							
Size					1.003***	0.999***	1.001***
					<.0001	*<.0001*	*<.0001*
BM					0.993***	0.918***	1
					<.0001	*<.0001*	*0.219*
Momentum					1.014***	1.016***	1.009***
					<.0001	*<.0001*	*<.0001*
Demographic Controls							
Age						0.992***	0.992***
						<.0001	*<.0001*
Male Dum						1.336***	1.263***
						<.0001	*<.0001*
Trade Variables							
Option user Dum						1.581***	
						<.0001	
Short user Dum						1.934***	
						<.0001	
Log (Equity Holding)						1.081***	
						<.0001	
Diversification						10.483***	
						<.0001	
Sophistication							1.490***
							<.0001
Interactions							
AdjIlliq *Age						1.000	1.000**
						0.395	*0.04*
AdjIlliq *Male Dum						0.996	0.993***
						0.388	*<.0001*
AdjIlliq *Option user Dum						1.011*	
						0.098	
AdjIlliq *Short user Dum						1.017***	
						<.0001	
AdjIlliq * Log (Equity Holding)						1.003**	
						0.011	
AdjIlliq *Diversification						0.888*	
						0.066	
AdjIlliq *Sophistication							0.999**
							<.0001
Household fixed effect	No	No	No	Yes	Yes	No	No
Firm fixed effect	No	No	No	Yes	Yes	Yes	Yes
Calendar month dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N Observation	2,304,232	2,304,232	2,304,232	2,304,232	2,131,366	1,522,716	1,522,716
Wald test	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Table 3.5: Change in Liquidity around Stock Splits in the US

Table 3.5 reports the change in liquidity for splitting stocks in the US around their ex-split dates over the 1991-1996 time period. There are 2,729 forward stock splits during our sample period with a split factor larger than or equal to 0.25. We estimate an OLS regression of stock liquidity on a time period indicator – *After*- dummy, controlling for size, book-to-market and momentum. Liquidity is measured with the adjusted Amihud illiquidity ratio. The time period indicator – *After*- dummy equals to one when liquidity for a splitting stock is measured after the split, otherwise the dummy equals to zero. Each coefficient reported below for the –*After*- dummy comes from a single OLS regression. The comparison involves different event windows, namely 6 months, 9 months and 12 months before and after stock splits. Size, book-to-market and momentum are calculated monthly. For brevity, the coefficients for size, book-to-market and momentum are not reported here. For each event window we first report OLS results without firm controls and then in the adjacent columns we report the results with firm controls. Standard errors of estimated coefficients are reported in the row below in *Italic* and in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

Window	6-months		9-months		12-months	
After dummy	-0.193***	-0.186***	-0.250***	-0.248***	-0.293***	-0.289***
	(0.016)	*(0.017)*	*(0.013)*	*(0.014)*	*(0.011)*	*(0.012)*
Adj. R^2	0.005	0.044	0.008	0.046	0.011	0.048
N Obs	31,652	27,703	47,271	40,488	62,744	52,484
Stock Controls	*no*	*yes*	*no*	*yes*	*no*	*yes*

Table 3.6: Change in Holding Periods following US Stock Splits

Table 3.6 examines the change in holding period following stock split events in the US. It reports hazard ratios from the holding period hazard regressions in the US where the conditional probability of sale is the dependent variable over the 1991-1996 time period. Holding period is calculated as previously defined. The – *After*- dummy equals to one if a given stock is sold after it splits, otherwise it is zero. We define three different event windows around the ex-split date, ranging from 6 months to 12 months before and after the stock splits. For each event window, we set the – *After*- dummy equal to one only if we can observe at least one closed or censored transaction for a given household both before and after the ex-split date. Panel A presents the results with the – *After*- dummy as the only independent variable, while Panel B documents the estimated results controlling for size, book-to-market and momentum. All firm characteristics are measured at the closure of a given transaction. For brevity, estimated coefficients for the firm characteristics are not reported. Calendar year and month dummies (not reported) are dummy variables that take on a value of one if the year and month of the transaction is equal to the year and month dummy. Regressions also control for household fixed effects as well as the fixed effect of each specific stock split event. P-values are reported below each coefficient. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

Panel A: Hazard Regression of Holding Period around Stock Splits (split factor>=0.25, w/o firm characteristics)

Window	6-months		9-months		12-months	
After dummy	1.332***	1.042	1.375***	1.039	1.451***	1.061**
	<.0001	*0.1947*	*<.0001*	*0.146*	*<.0001*	*0.0106*
Household fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Event fixed effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Calendar month dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N Observations	*92,740*		*132,702*		*171,480*	
Wald test	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*

Panel B: Hazard Regression of Holding Period around Stock Splits (split factor>=0.25, with firm characteristics)

Window	6-months		9-months		12-months	
After Dum	1.366***	1.084**	1.421***	1.092***	1.479***	1.109***
	<.0001	*0.0228*	*<.0001*	*0.0027*	*<.0001*	*0.0001*
Household fixed effect	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Event fixed effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Calendar month dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N Observations	*75,006*		*106,353*		*137,362*	
Wald test	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*

Table 3.7: Investors' Demand for Liquidity under Varying Aggregate Liquidity Regimes

Table 3.7 reports individual traders' demand for liquidity under varying aggregate market illiquidity regimes over the 1991-1996 time period. Market illiquidity is calculated as the equal-weighted average of the adjusted Amihud illiquidity ratio of all stocks in a given month. The sample period then is broken into five time periods equal in duration, determined by the level of market illiquidity, ranked from *Low* to *High* in the table. *Max* is the month corresponding to the highest (lowest) level of market illiquidity (liquidity). Stocks are then ranked each month based on their respective adjusted Amihud Illiquidity measure and assigned to illiquidity percentile ranks. Then, for every aggregate market illiquidity regime we calculate the average illiquidity percentile for all stock purchases and stock sales separately. Column one specifies the market illiquidity regime, column two merely lists the trade type as a "Buy" or a " Sell transaction, while column three reports the numbers of buy and sell transactions that take place during each market illiquidity regime. In column four, we report the average illiquidity percentiles for stock purchases, stock sales as well as the differences between purchases and sales for each corresponding market regime. The last column shows the differences in illiquidity ranks of stock purchases and sales adjusted for household portfolio level of liquidity. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

Market Illiquidity	Buy/Sell	N Obs	Adj Illiquidity Percentile	HH demeaned Adj Illiquidity Percentile
Low	Buy	188,601	16.71	0.94
	Sell	155,111	16.05	0.24
	Diff		0.66***	0.7***
2	Buy	226,817	15.87	0.29
	Sell	185,471	15.86	-0.03
	Diff		0.01	0.32***
3	Buy	186,929	16.00	0.43
	Sell	155,989	15.44	-0.18
	Diff		0.56***	0.61***
4	Buy	244,573	15.97	0.36
	Sell	201,018	15.44	-0.31
	Diff		0.53***	0.67***
High	Buy	215,823	16.35	0.58
	Sell	174,064	17.21	0.99
	Diff		-0.86***	-0.41***
Max	Buy	11,436	14.94	-0.2
	Sell	7,659	16.06	0.27
	Diff		-1.13***	-0.47*

Table 3.8: Aggregate Market Liquidity, Investor Sophistication, and Demand for Liquidity

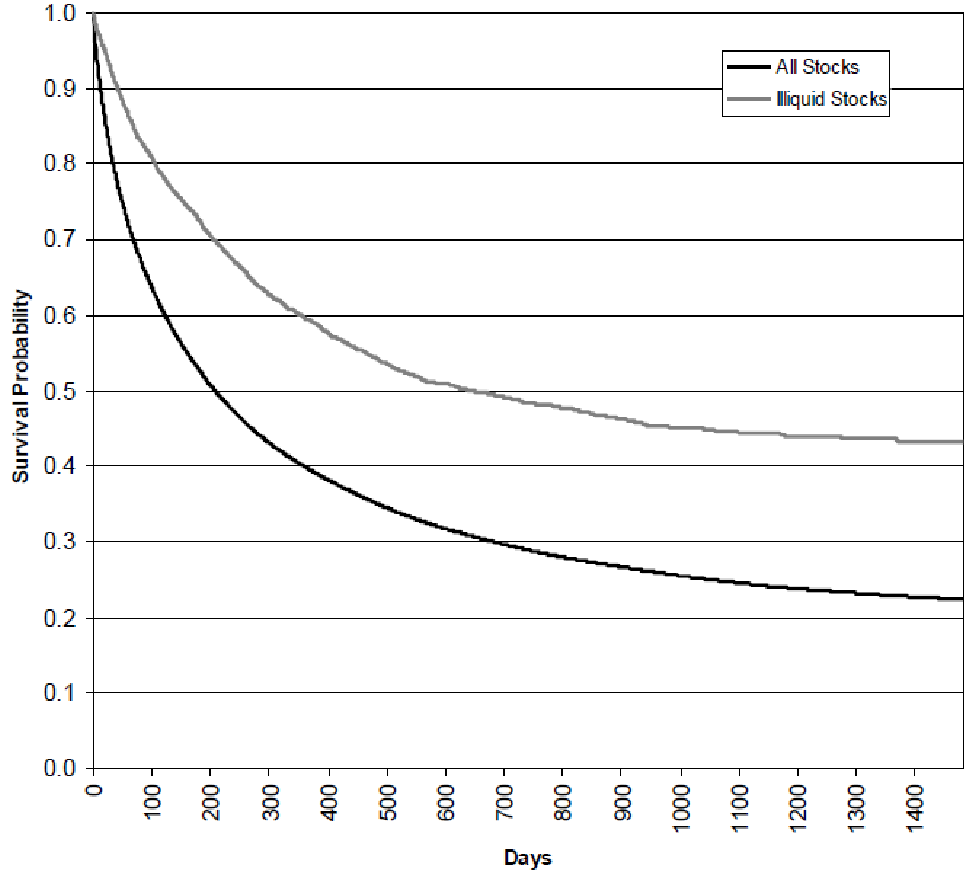
Table 3.8 examines the relationship among aggregate market liquidity, investor sophistication and their demand for liquidity. It reports the results from regressing the percentile illiquidity ranks of stocks purchased or sold in a given month on aggregate market illiquidity and investor sophistication over the 1991-1996 time period. Stocks with the illiquidity percentile rank of one are the most liquid, while stocks with an illiquidity percentile rank of one-hundred are the most illiquid. Market illiquidity is calculated as the equal-weighted average of the adjusted Amihud illiquidity (*AdjIlliq*) ratio of all stocks in a given month. In Panel A, *MktIlliq* is a dummy variable that takes on a value of one if the aggregate market illiquidity is in the top decile over the entire sample period. In Panel B, *MktIlliq* is defined more narrowly as a dummy variable that is equal to one for the month with the greatest aggregate market illiquidity (June 1994) over our sample period. *Buy* is a dummy variable that takes on a value of one if the transaction indicates a purchase. *Sophistication > 3 Dummy* is a dummy variable that takes on a value of one if the trader's sophistication –based on the criteria listed in Panel A of Table 3.3- is larger than 3, otherwise zero. All regressions are estimated at the transaction level. Standard errors of estimated coefficients are reported in the row below in *Italic* and in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

Panel A: MktIlliq equals one for the top ten percent of months with the highest market illiquidity			
	Model I	**Model II**	**Model III**
MktIlliq	0.1826***	0.0266	0.3405
	(0.073)	*(0.065)*	*(0.215)*
Buy	0.2880***	0.3243***	0.3693***
	(0.032)	*(0.028)*	*(0.095)*
Buy * MktIlliq	-0.9753***	-0.5587***	-0.9815***
	(0.098)	*(0.086)*	*(0.298)*
Buy * MktIlliq * Sophistication Dummy			-0.7349*
			(0.434)
Sophistication >3 Dummy			-2.2043***
			(0.103)
Buy * Sophistication Dummy			0.0244
			(0.139)
Sophistication Dummy * MktIlliq			0.3119
			(0.319)
Adj R^2	0.0001	0.326	0.003
Household Effects	No	Yes	No

Table 3.8: Aggregate Market Liquidity, Investor Sophistication, and Demand for Liquidity (Cont.)

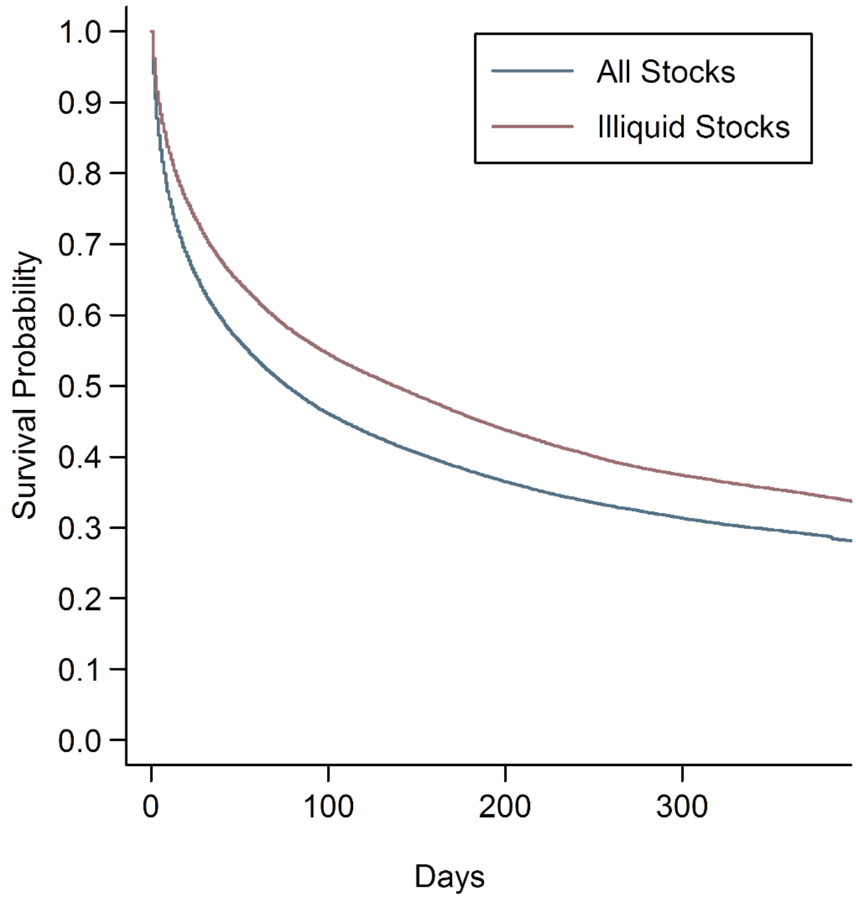
Panel B: MktIlliq equals one for the month with the highest market illiquidity for the entire sample period			
	Model I	**Model II**	**Model III**
MktIlliq	1.8074***	1.6903***	0.7677
	(0.239)	*(0.211)*	*(0.157)*
Buy	0.1977***	0.2734***	0.2740***
	(0.030)	*(0.027)*	*(0.091)*
Buy * MktIlliq	-1.5407***	-1.0595***	-0.6837***
	(0.309)	*(0.271)*	*(1.072)*
Buy * MktIlliq * Sophistication Dum			-3.3327**
			(1.453)
Sophistication >3 Dum			-2.2105***
			(0.098)
Buy * Sophistication Dum			-0.0237
			(0.132)
Sophistication Dum * MktIlliq			3.7603***
			(1.124)
Adj R^2	0.0001	0.326	0.003
Household Effects	No	Yes	No

Figure 3.1: Survival Probabilities for Stocks in the United States



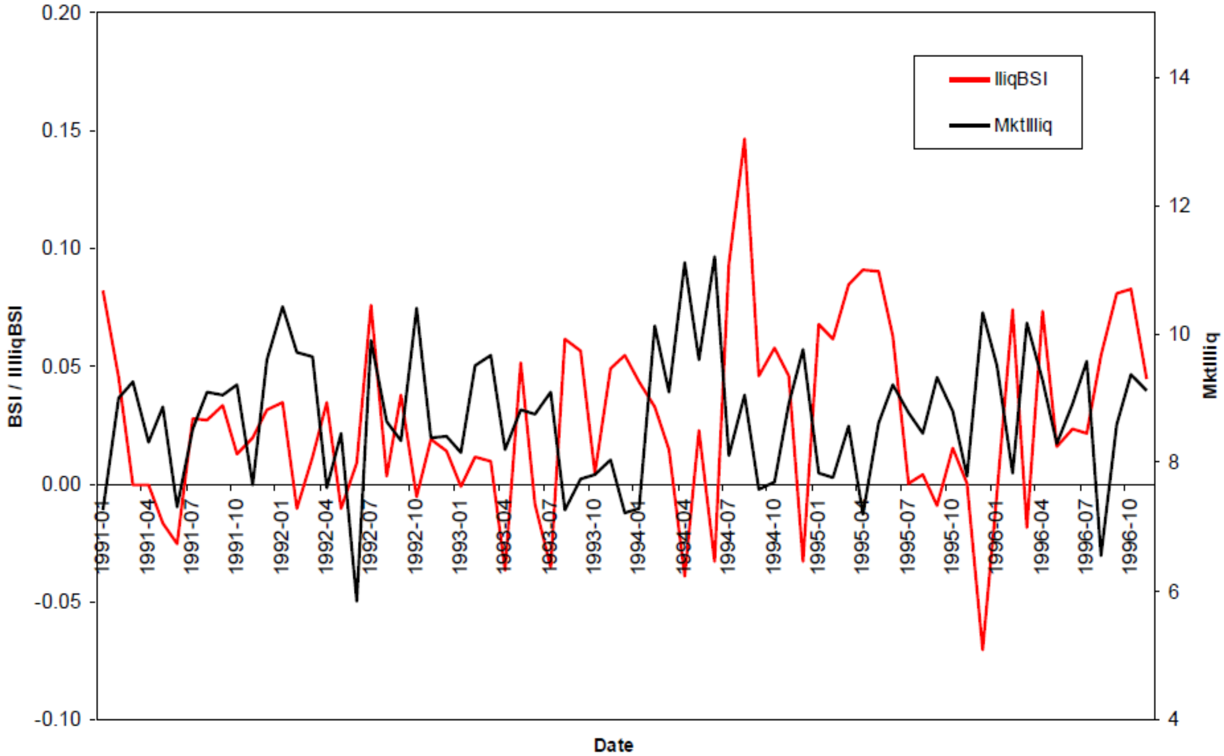
This figure plots Kaplan-Meier survival probabilities for two groups of stocks held by households in the United States over the 1991-1996 time period. Illiquid stocks in the figure are stocks that are in the highest illiquidity decile of stocks ranked according to the adjusted Amihud illiquidity measure. The gray line stands for the probability of holding onto illiquid stocks, and the black line stands for the probability of holding all the rest stocks.

Figure 3.2: Survival Probabilities for Stocks in Finland



These figures plot Kaplan-Meier survival probabilities for two groups of stocks held by households in Finland over the 1996-2003 time period. Illiquid stocks refer to stocks that are in the highest illiquidity decile based on their adjusted Amihud illiquidity measure, while all stocks refer to all the other stocks.

Figure 3.3: Market Liquidity and Illiquidity BSI in the US



This figure plots the difference in the illiquidity ranks of buys and sells (IlliqBSI), and the aggregate level of market illiquidity (Mktilliq) for the United States over the 1991-1996 time period. Market illiquidity is calculated as the equal-weighted average of the adjusted Amihud ratio of all stocks in a given month.