Institutional Investors' Intrinsic Trading Frequency and the Cross-Section of Stock Returns*

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Abstract

We show a novel relation between the institutional investors' intrinsic trading frequency—a commonly used proxy for the investors's investment horizon— and the cross-section of stock returns. We show that the 20% of stocks with the lowest trading frequency earn mean returns that are 6 percentage points per year higher than the 20% of stocks that have the highest trading frequency. The magnitude and predictability of these returns persist or even increase when risk-adjusted by common indicators of systematic risks such as the Fama-French, liquidity or momentum factors. Our results show that the characteristics of stock holders affect expected returns of the very securities they hold, supporting the view that heterogeneity among investors is an important dimension of asset prices.

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1 Introduction

Heterogeneity among investors is a prevalent feature of financial markets. Investors differ in many dimensions such as their preferences, their types, their constraints, their information, the markets they participate in and their investment horizon. However, depending on the environment, heterogeneity may play little or no role in equilibrium asset prices. For example, in a world with complete markets, diversity in investors' characteristics is irrelevant. In particular, all financial claims can be priced through a representative agent's stochastic discount factor that is uniquely determined irrespective of the underlying heterogeneity of investors. Most leading asset pricing models[1] ignore heterogeneity, yet successfully match the observed patterns of a wide range of macroeconomic and financial variables. Rubinstein (1974), Constantinides (1982), Grossman and Shiller (1982), Krusell and Smith (1998) and many others provide conditions under which aggregation, or at least approximate aggregation, obtains even in the presence of heterogeneous agents and incomplete markets. On the empirical side, the literature has downplayed the importance of heterogeneity in investors characteristics as a source of information to understand stock prices in a systematic way. In general, a standard approach is to explain the cross-section of stock returns using variables that are inherent to the underlying firm, such as size or book-to-market ratio, and not to the type of investor holding the stock. Nevertheless, there are many theoretical models in which heterogeneity of investors is a key determinant of asset prices. Examples include heterogeneity of beliefs (Geneakoplos (2010), Scheinkman and Xiong (2004)), information (Allen, Morris and Shin (2006), Angeletos, Lorenzoni and Pavan (2010)) and preferences (Constantinides and Duffie (1996), Kogan and Chan (2002)).

This paper exploits institutional investors' intrinsic trading frequency as a source of heterogeneity to answer the following question: Do the returns of a given security differ in a systematic way when held by investors with different trading frequency? We find that the answer is yes. We show that, even after controlling for exposure to the Fama-French factors, liquidity and momentum risks, the return of portfolios held by investors with different intrinsic trading frequency differ significantly. Moving from

[1] Both, consumption-based models such as Bansal and Yaron (2004)'s long-run risk model, Barro (2005) and Gabaix (2008)'s rare disasters and Campbell and Cochrane (1999)'s habit-formation, and factor models like the Capital Asset Pricing Model (CAPM)

the first to the last quintile in the distribution of trading frequency —that is, moving from more to less frequently traded stocks— is associated with an expected gain in returns of 6 percentage points over the next year. As such, this paper highlights the importance of information about stock ownership to successfully explain asset prices.

We tackle our main question with a three-step methodology: (i) We construct a measure that captures the intrinsic trading frequency for the group of large US financial institutions. (ii) Then, for each security, we construct a security-specific trading frequency index by taking the weighted average of the intrinsic trading frequencies of the institutional investors holding that security. The construction of both institution- and security-specific trading frequency measure in (i) and (ii) follow the procedure introduced in Parsa (2010). Finally, we (iii) explore the relation between the trading frequency index and the cross-section of stock returns.

We use the Thomson-Reuters Institutional Holdings dataset to get stock positions for large US financial institutions, also named the 13-F institutions after the report they are required to file. Our data spans the period 1980-2005 and is available at the quarterly frequency. As defined in Parsa (2010), we construct a measure for the institution's intrinsic trading frequency using the investor's fixed effect in a model of investors' change in their positions. Concretely, we estimate a regression of institutions' turnover of securities on a time fixed effect, a security fixed effect, their interaction, and an institution fixed effect. The institution's fixed effect captures the institutions' intrinsic trading frequency by controlling for any security and market characteristics which could influence the investor's change in its position across time and across securities. In this way, changes in institutional holdings due to events like an increase in market-wide volatility or the hiring of a new CEO do not in themselves affect our measure of investors' intrinsic trading frequency.

Once we have a trading frequency fixed effect for each institution, we construct a security-specific trading frequency index for each security traded in the NYSE, Nasdaq and Amex and held by 13-F institutions. This index is the weighted average of the trading frequency of institutions holding the security. We then explore the relation between the security specific trading frequency index and the cross-section of stock returns.

To that purpose, for each quarter, we form portfolios by sorting stocks on their trading frequency of the previous year. We find that the relation between expected mean returns and trading frequency is monotonically decreasing. This pattern holds independently within subgroups of securities that are sorted on size, book to market, liquidity and past performance. In addition, the spread in the returns between the trading frequency portfolios is not accounted for by common indicators of systematic risk, including the three Fama-French factors, two different measures of liquidity introduced by Sadka (2006) and Pastor and Stambaugh (2003), and the momentum factor of Jegadeesh and Titman (1993). The risk-adjusted difference in the returns between the low trading frequency and the high trading frequency portfolios is approximately 3% per year. Since all portfolios are formed using past information only, we conclude that trading horizon is a strong predictor of future stock returns.

To summarize, the contribution of this paper is twofold. First, we highlight a new characteristic—the trading frequency index of securities—that brings new information about the cross-sectional distribution of stock returns. Second, our research suggests that a complete understanding of asset prices must rely not only on ”supply side” characteristics of firms but also on ”demand side” characteristics of investors who hold firm's stocks.

The remainder of the paper is organized as follows. Section 2 provides a brief description of the literature. Section 3 describes the data as well as the methodology. Section 4 provides the results. Section 5 concludes.

2 Literature Review

This paper is most closely related to and complements Parsa (2010), who is the first to suggest the importance of intrinsic trading frequency. However, this paper explores a fundamentally different source of variation as it focuses on the extent to which the intrinsic trading frequency of a security forecasts stock prices in the *cross-section* of returns.

Otherwise, this paper connects and contributes to three different strands of the existing literature. First, this paper adds to the vast literature on the relationship between the institutional investors and stock prices. This literature documented a positive contemporaneous relation between institutional investors' buying and stock returns; Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Wermers (1999, 2000), Nofsinger and Sias (1999). It has also been highlighted that institutional buying is positively related to short-term expected return, where the expected returns are higher (lower) for stocks experiencing a significant institutional buying (selling); see Daniel, Grimblatt, Titman and Wermers (1997), Gompers and Metrick (2001). Most of this literature considers the group of institutional investors as a homogeneous group. In line with Parsa (2010), this paper contributes to the previous literature by considering the group of institutional investors as a heterogeneous group and exploiting the heterogeneity among the institutional investors in order to understand stock prices. As much as Parsa (2010) focuses on the time series dimension of the data through a predictability exercise, this paper exploits the intrinsic trading frequency of the institutions as the source of heterogeneity that matters in understanding the cross section of stock return. Thus, this paper contributes to a subset of the literature which explores the heterogeneity of investors. Grinblatt and Keloharju (2001) explores a dataset of the shareholdings in FSCD stocks and documents differences in the buy and sell behavior as well as the performance of different types of investors, such as households, foreign investors, financial institutions and insurance companies. Wermers (1999) focuses on the mutual fund industry and provides evidence on the "herding" behavior of mutual funds as well as their impact for the stock prices. Cohen, Polk and Vuolteenaho (2002) study the difference between the trading behavior of institutional investors as opposed to individual investors in their reaction to cash flow news using the VAR-return decomposition at the firm level. In general, the approach in these studies consists in exploring a source of heterogeneity in the type of investors, i.e. mutual funds, retail investors, institutional investors, etc. on the equilibrium investors' trading behavior. In this paper, the heterogeneity is the intrinsic investor trading behavior, measured by the trading frequency fixed effect.

Second, this paper is connected to previous studies which have examined the portfolio turnover rate of institutional investors and its interaction with financial markets motivated by the effect of the investment horizon of institutional investors; see Gaspar, Massa and Matos (2005), Ke, Ramalingegowda and Yu (2006), Jin and Kogan (2007), Khan, Kogan and Serafeim (2010), Parsa (2010), Yan and Zhang (2009). Gaspar, Massa and Matos (2005) look at the corporate controls market and show that firms with shareholders having a higher portfolio turnover are more likely to get an acquisition bid, but at a lower premium. Yan and Zhang (2009) find that the trading of institutional investors with a high portfolio turnover rate forecasts future stock returns. This paper is related and adds to the previous studies as it uses the institution's equity portfolio churning information. However, following Parsa (2010), it focuses on the institutions' intrinsic trading characteristic as opposed to their equilibrium trading behavior to find evidence on the relation between the institution's investment horizon and stock prices. We exploit the variation in the trading behavior intrinsic to the institution by using the fixed effect trading frequency of the investors. Furthermore, in contrast to earlier studies, the main focus of this study is on the differential response of the stock prices to the interaction of the trading frequency fixed effect rather than on the effects of the demand by institutional investors on stock prices. In this manner, the study is related to Jin and Kogan (2007) as well as Parsa (2010). Jin and Kogan (2007) use the variation in the portfolio turnover rate of the mutual fund managers and its interaction with a measure of investor impatience, defined as the sensitivity of money flows into and out of the fund in response to the short-term performance of the fund. They find that mutual fund managers tend to focus on short horizon investments due to the short horizon of their investors (and not the other way around). Their evidence suggests that this behavior may result in abnormal returns as it leads to an inflated demand of short horizon investment opportunities at the expense of longer horizon alternatives. However, Jin and Kogan (2007) differs in several points with respect to this study. Similar to Parsa (2010), the measure we construct for the institutional investors' trading frequency is a "black box", which captures the component of the institution's turnover, which is explained by the institution's intrinsic characteristics as opposed to the market and/or characteristics of the securities they invest in. Thus, we do not focus exclusively on one particular channel through which the higher trading frequency of the institutions may affect stock prices. Institutional investors can have different horizons for many reasons: different levels of patience (subjective discount factor), liquidity needs, administrative costs, legal restrictions, competitive pressures related to the performance based pay; see Dow and Gorton (1997), Shleifer and Vishny (1997), Bolton, Scheinkman and Wei (2006). Instead, the measure used in this study allows us to focus on the whole set of institutional investors and the interaction of their trading frequency with stock prices, as the only information required is the holdings of the investors. Similar to the findings in Jin and Kogan (2007), we provide evidence that the institution's trading frequency matters for the behavior of stock prices. Finally, this paper complements

Parsa (2010), which focuses on the source of the volatility in stock prices between its cash flow and discount factor component as a function of the trading frequency index. Parsa (2010) highlights that the movements of the prices of the securities held by investors trading more frequently is backed out by the long run cash flow of the securities. In this paper we demonstrate that the portfolio of the securities held by investors trading more frequently are closer to their risk adjusted return.

Finally, this paper connects to the literature on the cross sectional behavior of stock returns. This literature has documented a number of empirical patterns unsupported by a standard Capital Asset Pricing Model.[2] The firm size, the book to market ratio (Basu (1981), Fama-French (1993)), the firm's prior performance (Jegadeesh-Titman (1993)) and the liquidity (Pastor-Stambaugh (2003), Sadka (2006)) have each been established as an important dimension in order to understand stock prices. This paper contributes to the previous literature as it underlines a new variable that brings information about stock prices, the trading frequency index. However, in contrast to previous work, the role of the trading frequency index in understanding stock prices suggests a new way of looking at asset pricing as it exploits the heterogeneity of the investors characteristics. Not only do we show that the cross-sectional return of the trading frequency portfolio is not explained by their respective market risk or the usual variables (Fama-French factor, liquidity factor, momentum factor), but the dimension of interest is related to a characteristic of the securities, which is embedded in their ownership.

3 Data Description and Methodology

In order to study the relation between the investors' trading frequency and the cross-section of stock returns, (i) We construct an investor-specific measure of the intrinsic frequency of trading; then (ii) We construct a security-specific measure of the composition of the intrinsic trading frequency of the investors holding the security at a given moment in time. Finally, (iii) We use the security level measure constructed in (ii) to study the relation between the aforementioned security-specific characteristic and the cross-section of stock returns. In what follows, we start with a brief description of the different data sources. We then describe, step by step, each of the three former points as well as the results on the relation between the investors' trading frequency and the cross-section stock returns.

[2] The Capital Asset Pricing Model, introduced by Sharpe (1964), Lintner (1965), Mossin (1966), Treynor (1961), implies that the expected stock returns are determined by their level of beta risk through a positive and linear relation

3.1 Data Description

The information used in this study comes mainly from three sources: (i) The Thomson Reuters Ownership Data, (ii) The Fama-French factors (iii) The Center for Research in Security Prices (CRSP). In addition, the one-month Treasury Bill Rate at monthly frequency gives the risk-free interest rate from Ibbotson Associates.

In order to study the institutional investor's trading frequency, we use information about the quarterly equity holdings of all the institutions provided by the Thomson Reuters Ownership dataset.[3] The dataset results from the 1978 amendment to the Securities and Exchange Act of 1934 which requires all institutions with greater than $100 million of securities under discretionary management to disclose their holdings on all their common-stock positions greater than 10,000 shares or $200,000 on the SEC's form 13F. The institutions included are divided into 5 categories: Banks, Insurance Companies, Investment Companies and Their Managers (e.g. Mutual Funds), Investment Advisors, which includes the large brokerage firms, and all Others (Pension Funds, University Endowments, Foundations). It reports a total of 4382 managers. The data coverage increased in terms of both the security and manager dimension from a total of 573 managers and 4451 securities in 1980 to 2617 managers and 13125 securities in 2005. The institutional investors represented initially 16% of the market they invested in ($954 millions) in 1980 but this number increased to about 44% ($17,500 millions) in 2005. [4]

The Fama-French and momentum factors come from Kenneth French's website at Dartmouth[5]. The Sadka liquidity measures are described in Sadka (2006). The measure captures non-traded, market-wide, undiversifiable liquidity risk. Finally, the Pastor and Stambaugh (2003) liquidity factor is based on the turnover of the securities.

The monthly market information—i.e. return, price, shares outstanding—about each security is taken from the Center for Research in Security Prices (CRSP). The set of securities included corre-

[3] The dataset was previously known as the CDA/Spectrum 34 database. The institutions in the sample are also referred to as the 13F institutions in reference to the form they are required to fill at a quarterly basis.

[4] Some of this growth is due to an increase in the value of the equity market throughout the sample period, which forced more institutions to fill the 13-F forms as the rising market pushed their portfolio across the nominal threshold level of $100 million. For more details about the dataset, I refer you to Gompers and Metrick (2001).

[5] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` We are thankful to Kenneth French.

sponds to the intersection of our two main data sources, i.e. the securities that belong to the portfolio of the 13-F financial institutions and the market information available in the CRSP. We restrict our attention to securities traded in the NYSE, the AMEX and the NASDAQ, provided they are held by more than 25 institutions, or that the institutions hold at least 10% of the shares outstanding. Our sample has 12455 securities represented and a total of 288760 data points.

3.2 Methodology

After having introduced briefly the dataset used, the remainder of this section describes each step of the methodology. We start with the institution-specific trading frequency measure. Then we construct the security specific trading frequency measure as the composition of the trading frequency of the institutions holding the security. Finally, we explain the methodology used to study the relation between the security-specific measure and the cross section of stock returns. The trading frequency measures follow closely Parsa (2011) where more detailed information about the respective measures can be found.[6]

3.2.1 Institutional Investors Intrinsic Trading Frequency

Define s_{ijt} as the number of shares institution i is holding in security j at quarter t. We capture the trading frequency of institution i in each security j at quarter t as the absolute value of the percentage change in the position of institution i in security j at quarter t: [7]

$$y_{ijt} = abs\left(\frac{s_{ijt} - s_{ijt-1}}{1/2(s_{ijt} + s_{ijt-1})}\right). \tag{1}$$

If an institution i is holding the same number of securities at quarter t and $t-1$, then $y_{ijt} = 0$. If on average y_{ijt} is bigger for institution i than institution i', then the institution i is rebalancing its portfolio more frequently than institution i' during a given period of time.

In order to construct a measure that captures an investor's idiosyncratic tendency to change its

[6] More details are provided in the appendix found at http://econ-www.mit.edu/grad/sparsa/research

[7] I am using in the denominator the average number of shares in quarter t and quarter t-1 instead of the number of shares in quarter t-1. The main reason is to keep y_{ijt} from being forced to a missing value when the number of shares moves from 0 to a positive number. However, notice that as the number of shares increase from 0 to a positive number y_{ijt} will be equal to 2. Hence, part of the information is clearly missing as a change of an institution's position is treated differently whether it was holding a positive number at $t-1$ or 0 at $t-1$.

position, once any security or market effects have been partialled out, we exploit y_{ijt}'s three dimensions in a three-way fixed effect model. In particular, we estimate by ordinary least squares, for each year T=1980,...,2005 a regression of the form:

$$y_{ijt}^T = a^T + h_i^T + g_{jt}^T + \beta X_{ijt}^T + \epsilon_{ijt}^T \tag{2}$$

where y_{ijt}^T is the absolute value of the change in the holding of institution i in security j in quarter t of year T, h_i^T is the institution fixed effect; g_{jt}^T is the time-security interaction fixed effect and X_{it}^T controls for the size of the portfolio of investor i as well as the size of each security in the portfolio of investor i.[8] The estimates of h_i^T in equation (2) provide an annual measure of the investor's trading frequency that does not confound any security or time effects. The two latter effects are fully absorbed by the term g_{jt}. We allow the measure of the institution's trading frequency (h_i^T) to change annually in order to capture changes across time that could be driven by investor characteristics, such as the investment horizon associated to changes in its corporate governance, its objective, its CEO, the regulation or its preferences. An investors's intrinsic trading frequency is defined by the fixed effect h_i^T in regression (2). A larger institution's fixed effect h_i^T is associated to investors who change their positions more often and hence have a higher idiosyncratic trading frequency. Ultimately, h_i^T provides a measure comparable to a portfolio turnover rate. However, by exploiting the three dimensions of the data (institutions, security and quarter), it combines the changes in an institution security holdings in one churning rate, which summarizes only the trading behavior that results from the institution.

3.3 Security Specific Trading Frequency

For each 13-F institution, the Thomson Reuters ownership data reports the securities the investor is holding in its portfolio and their respective position in the securities. For each year T, quarter t and security j held by a group of institutions I_j, the security j's trading frequency index at year T and end of quarter t is defined as the weighted average of the fixed effects of the institutions in I_j:

$$H_{jtT} = \sum_{i \in I_j} \omega_{ijtT} h_{iT} \tag{3}$$

[8] Concretely, the fixed effect measures are computed with respect to the following normalization: $\sum_t \sum_j \delta_{jit} g_{jt} = \sum_i \delta_{jit} h_i = 0$ where $\delta_{jit} = 1$ if y_{jit} is non missing and 0 otherwise.

where the weights are $\omega_{ijtT}=\frac{s_{ijtT}}{\sum_{i\in I_j} s_{ijtT}}$, and s_{ijtT} is the number of shares outstanding of security j held by institution i at year T quarter t and h_{iT} is the fixed effect of institution i at year T. The weight ω_{ijtT} captures the relative importance of investor i for security j at year T and quarter t, in terms of the number of shares investor i holds relative to the total number of shares the group of institutional investors is holding. It implies that the trading frequency of an investor holding 90% of the shares of a security should have a larger effect than the trading frequency of an investor holding only 10% of the shares of a security. The security's trading frequency index will give more weight to the former investor's fixed effect than to that of the latter.

H_{jtT} maps the institutional investors' trading frequency, h_i^T, to the security. H_{jtT} is interpreted as the average trading frequency of the population of institutional investors holding the security j at year T. A security j will have a high trading frequency index if, on average, the institutional investors holding the security are characterized by a short investment horizon, proxied by a large h. Overall, the institutions are weighted by their relative size with respect to the institutions holding the security. As a consequence, the variation in H can be traced back to one of two sources: (i) For a given pool of investors, the investors with a lower value of the fixed effect are holding a higher share of the security. In other words, the high trading frequency investors represent a higher share of the security, i.e. higher weight ω_{ijtT} on the high h_{jT} (the high trading frequency investors). (ii) For a given weight, the institutions holding the security have a higher institution's trading frequency. Both sources of variation, translate in a security having higher trading frequency investors than another security or having a higher trading frequency across time.[9] Finally, it is important to note that even though the trading frequency fixed effects at the institution level are orthogonal to any security and market characteristics by construction, there is a correlation between the securities characteristics and the trading frequency index. This dependence arises from the portfolio selection of the investors, which ultimately defines the weights ω_{ijtT}.

[9] The variation of H_{jtT} through time is either the result of : (i) investors selling or buying the security characterized by different horizon, (ii) the investors experiencing a change in their characteristics to trade (which could come from a change in the CEO or a merger), or (iii) both. The variation of H_{jtT} across security mainly comes from different securities being held by a population of investors characterized by different horizons at a given moment in time.

3.4 Cross-Section of Expected Stock Return

In order to analyze the effects of trading frequency on the cross-section of expected stock return, we first sort all the securities for each time period into 5 or 10 portfolios based on their measure of trading frequency. For the 5 portfolios case, the portfolios are built based on the quintiles in the following way: the first portfolio is the value-weighted portfolio of the 20 percent of the stocks with the lowest trading frequency index the previous year, the second portfolio is the value-weighted portfolio of the 20 percent of the stocks with the next highest trading frequency index the past year, and so on. For the 10 portfolios case, the quintiles are simply replaced by the deciles. The main exercise will consist in comparing the average excess return along the trading frequency dimension. Given that the trading frequency fixed effects use all the information for the whole year in which it was estimated, we consider only the trading frequency measure lagged by one year. This assures that we are using exclusively past information in our cross-sectional regression in order to predict the cross section of stock returns. All of the remaining sorting exercises follow the same precept that an investor could have reproduced our study in real time.

Descriptive Statistics

Table I summarizes the descriptive statistics of the main characteristics of the securities in our sample, which consists of $12,455$ securities and $288,760$ data points. Table I reports the means and the standard deviations for the excess return, the size, the book to market ratio, the past performance, the liquidity and the trading frequency index. For each statistic, we also report a number for 2 groups of securities, the securities held in the previous year by the low and high trading frequency investors. Notice from the last line that the trading frequency index ranges from -0.18 (for the low trading frequency group of securities) to 0.18 (for the high trading group of securities) while it is close to zero for the full sample, giving a relatively easy benchmark to understand the magnitude of the trading frequency measure. There is more variation within the high trading frequency group than low trading frequency group. Looking at the column of the mean, one can notice that the high trading frequency securities have a lower excess returns, are substantially more liquid and are larger than the low trading group of securities. Interestingly, from the momentum line, one can observe that the securities held by the low trading group of securities also exhibit a lower past performance. However, one should notice the substantial difference in the standard deviation across the two groups of securities for the liquidity as well as the size, highlighting a difference in the heterogeneity within the groups in terms of the characteristics of the securities. We will show in the next section that after we control for the heterogeneity in all of these dimensions in several ways, the portfolios still show the spread in returns stemming from their different trading horizons.

4 Results

In this section, we explore the extent to which the ownership matters in explaining differences in expected returns in the cross-section of stock by exploiting the heterogeneity in investors' trading frequency.

4.1 Is there a relation between trading frequency and returns?

Figure I illustrates the empirical relation between the realized return and the trading frequency index by reporting the average annualized return for the different trading frequency portfolios. The only difference between Figure I (a) and Figure I (b) is that the number of portfolios formed increased[10] from 5 to 10. Independently of the number of portfolios considered, there is a clear negative relation between the horizon and the realized return. The higher is the average trading frequency of the institutional investors holding the security the previous year, the smaller is the realized return this year. The spread in the realized returns is economically significant: The low trading frequency portfolio exhibits an average annualized return of approximately 11 percentage points and the high trading frequency portfolio is exhibiting an average annualized return of approximately 5.4 percentage points.

Table II shows the relation exists within sub-groups of different types of securities by double-sorting portfolios with respect to their size, book-to-market ratios, liquidity and past performance. The double sorting is done as follows: (i) We sort all the securities into 5 groups based on their trading frequency. (ii) We independently sort all the securities into 3 groups based on each of the dimensions mentioned above. (iii) We construct 15 different portfolios for each trading frequency and characteristic

[10] Our results still hold when forming 25 portfolios, although the statistical inference becomes more challenging because, especially in the double sorts, some portfolios end up having a small number of firms.

combination.

Table II shows that a strategy that consists in buying low and selling high trading frequency securities generates an annual return close to 5 percentage points. This difference is statistically significant at the 5% level as can be noticed from the t-statistic of the last column. The same pattern remains when looking at stocks divided by any of the other characteristics considered. The difference is the smallest for the group of small securities, which is mainly driven by a higher average return for the high trading group of securities. However, in terms of the statistical significance, the relation remains relatively stable even for the small securities.

The natural next step consists in exploring these spreads and the extent to which it can be explained by the characteristics or the risk exposures of the portfolios, and not by their institutional ownership.

4.2 Can we explain trading frequency returns by systematic risks?

The first step in exploring the relation highlighted in Figures I is to confront the data to the Fama-French factors. Figure II reports the mean annualized excess return of the different trading frequency portfolios as a function of the mean excess return predicted by the standard Fama-French model. For each portfolio p, we run the following time-series regression:

$$R_{p,t} - r_t^f = \alpha_p + (R_{m,t} - r_{f,t})\beta_p^m + SMB_t\beta_p^{SMB} + HML_t\beta_p^{HML} + \varepsilon_t \quad (4)$$

$$t = 1, ..., T \quad (5)$$

where (i) $R_m - r_f$ is the excess return on a broad market portfolio, (ii) SMB (small minus big) is the difference between the return on a portfolio of small and large stocks, and (iii) HML (high minus low) is the difference between the return on portfolios of high and low book-to-market stocks, and the time variable t refers to quarters. The OLS estimates are $\hat{\alpha}_p$ and $\hat{\beta}_p$. Figure II plots $E\left[R_{p,t} - R_t^f\right] = \frac{1}{T}\sum_{t=1}^{T}\left(R_{p,t} - R_t^f\right)$ in the y-axis and $E\left[X_t\hat{\beta}_p\right] = \frac{1}{T}\sum_{t=1}^{T} X_t\hat{\beta}_p$ on the x-axis. Each portfolio is represented by a triangle as well as a number that denotes the quintile of the trading frequency index (increasing from 1 (low trading frequency) to 5 (high trading frequency)). Figure III summarizes the pricing error (alpha) of the different portfolios as a function of the trading frequency index. The average trading frequency within each portfolio ranges from -0.15 for the low trading frequency group to 0.16 for the high trading frequency group.

Figure II shows a discrepancy between realized and predicted returns. This divergence is more pronounced for the low trading group of securities. Overall, the portfolio defined by the low trading group of institutions exhibit a realized return of 12 percentage points, from which approximately 9 percentage points has been accounted for by the model. Figure II suggests that the ownership matters and it matters specifically for the low trading frequency group of securities. Figure III shows that the pricing error is a linear and monotonically decreasing function of the trading frequency index. As such, the higher the trading frequency of the institutional investors holding a security, the smaller the underlying alphas.

A more econometrically precise picture of Figures II and III is given in Table III. This table reports the characteristics of trading frequency portfolios from the lowest trading frequently portfolio to highest trading frequency portfolio divided into 5 value-weighted portfolios. The table reports the Fama-French factor sensitivities, i.e. the slope coefficients in the Fama-French three-factor model time-series regressions as well as the alphas and the R^2 (from the left to the right). From table III, one can notice that overall it seems that apart from the low trading group of securities, the model seems to do a fair job from the R^2 point of view. However, the market risk does not help explain the difference in the return as the coefficients of the different portfolios are roughly constant. The risk adjusted return from the first column (alpha) shows that the portfolio that shorts the high trading frequency securities and buys the low trading frequency securities earns approximately 4 percentage points on an annual basis. The bottom line from Table III is that there is a substantial risk-adjusted average return from the trading frequency strategy that can be implemented.

Given the particular nature of our portfolios, there are two other dimensions of portfolios highlighted in the literature that could account for our results: liquidity and momentum. More liquid securities are naturally associated to a higher trading frequency index. This high correlation is expected as investors trading more frequently might select more liquid security. Conversely, investors trading more frequently might increase the liquidity of the securities they invest in by the activities they engage in. For these two reasons, it is necessary to control for the liquidity of these portfolio to make sure that the results are not completely driven by the liquidity risk. Likewise, for the momentum, one could expect that high trading frequency securities might be more correlated to the momentum factor as high trading frequency investors could potentially care more about the short-term price movements and engage in momentum strategies. Figures IV and V illustrate the results after accounting for the two factors. Specifically, for each portfolio, we estimate:

$$R_{p,t} - r_t^f = \alpha_p + (R_{m,t} - r_{f,t})\beta_p^m + SMB_t\beta_p^{SMB} + HML_t\beta_p^{HML} \tag{6}$$

$$+ MOM_t\beta_p^{MOM} + LIQ_t\beta_p^{LIQ} + \varepsilon_t,\ \text{t} = 1,...,\text{T}. \tag{7}$$

where in addition to the variables from (5), we have added the liquidity factors based on Sadka (2006) and Pastor and Stambaugh (2003) and the momentum factor. Interestingly, from Figure V one can notice that the introduction of the new factors actually increases the pricing errors. As such, the spread highlighted in Figure II is not confounding these two characteristics. As in Figure III, Figure V shows that the pricing error (alpha) decreases monotonically with the trading frequency.

Table IV summarizes the results for all the cases considered. It reports the statistical significance of the figures just discussed. It compares the estimates of the pricing error, $\hat{\alpha}$, for the regressions (5) and (7) as well as the simple CAPM model and a model controlling for the long run and short run reversal. The t-statistic is computed using a Newey-West estimator with 3 lags, which is robust to correlation of the error terms across portfolios, within portfolios and across time. Furthermore, we report in the column labeled GRS, the "GRS test statistic" for the hypothesis that all $\hat{\alpha}_p$ are jointly zero. It is nothing but an F-test adjusted for finite samples and is F-distributed, $F[M, T-M-1]$, with M and T-M-1 degrees of freedom, where M is the number of factors in X_t. From table IV, even though the alpha of each portfolio is not statistically significant on its own, the null hypothesis that all the $\hat{\alpha}$ are jointly zero is rejected. Our results show that an investor can earn on average 3.3 percent per year without being exposed to any source of the common systematic risks considered here.

4.3 Can we explain trading frequency returns by a trading frequency index?

So far, we have highlighted a relation between trading frequency and stock returns. We showed that the relation can not be accounted for by the usual factors or variables used in the literature. Can this difference be explained by a trading frequency "factor"? In the previous section, Figures III and IV suggest a linear and monotone negative relation between the trading frequency index and the pricing error. In other words, the higher the trading frequency index, the closer is the return from its fundamentals or from the return predicted by a standard cross-sectional model.

In order to explore this further, we build a trading frequency factor as the difference between the return of the portfolio of the bottom 20% trading frequency group of securities and the top 20% trading frequency group of securities. We then try to explain the extent to which adding this extra factor helps us account for the pricing error. A first answer to this exercise is summarized in Figure VI and VII. Figure VI illustrates the relation between the realized excess return and the predicted return and Figure VII illustrates the relation between the pricing error and the predicted return after controlling for the trading frequency factor. In particular, for each portfolio, we estimate:

$$R_{p,t} - r_t^f = \alpha_p + (R_{m,t} - r_{f,t})\beta_p^m + SMB_t\beta_p^{SMB} + HML_t\beta_p^{HML} \tag{8}$$

$$+ MOM_t\beta_p^{MOM} + LIQ_t\beta_p^{LIQ} + TF_t\beta_p^{TF} + \varepsilon_t, \text{ t} = 1,...,\text{T}. \tag{9}$$

where in addition to the variables from (7), we have added the trading frequency factor TF as defined above. Figure VI shows that the realized return aligns more naturally with the 45 degree line. The difference between the realized and the predicted excess return is by and large accounted for by the inclusion of the trading factor. This is also reported in Figure VII, which shows that the new pricing errors from a model that internalizes the trading frequency factor are smaller and do not have a systematic correlation with the trading frequency measure. Table V shows the related statistical information. On one hand, even though the $\hat{\alpha}$'s are smaller and they do not exhibit a specific relation with the trading frequency, one can still reject the null of all $\hat{\alpha}$'s being jointly zero. On the other hand, from an economic point of view, the return an investor will make exploiting the trading frequency difference are now substantially smaller after accounting for the trading frequency return. Hence, adding the trading frequency factor, even though it adds new information, provides a mixed response to the spread in return of the different trading frequency portfolios.

5 Conclusion

In this paper, we show that stock returns are predicted by the intrinsic frequency of trading of its institutional holders, as introduced by Parsa (2010). Moving from the first to the last quintile in the distribution of the security-specific trading frequency is associated with an expected gain in returns of 6 percentage points over the next year. The magnitude and predictability of these returns persist or even increase when risk-adjusted by measures of systematic risks such as the Fama-French factors.

The result that stock returns depend on who holds them is at odds with two standard views in finance. The first one is that a stock's price is frictionlessly determined by the discounted sum of its dividends. If two institutional investors are not large enough to directly affect the aggregate discount factor and do not have a controlling stake in the firms it invests in, then the fact that one of them owns the stock —and not the other— should make no difference in the stock's return. The second standard view that is challenged by our results is that of the representative agent whose stochastic discount factor prices any given cash flow. In such an economy, the identity and heterogeneous characteristics of stock owners should provide no information about the cross-section of stock returns.

Our study has several limitations that open new avenues for research. An interesting question to study is the effect of trading frequency on stock returns at different horizons. Is it the very-long term investors who are capturing the spread in returns we document? Is it that the short-termists are indeed earning higher returns that are missed by looking at quarterly data instead of high frequency data? Another limitation of our results is that, even though the relation between trading horizon and stock returns is empirically strong and pervasive among different subgroups of stocks, there is no theoretical explanations for why this is the case. A complete understanding of the effects of heterogeneous investors' on asset prices would require complementing our empirical results with a concrete mechanism that originates them.

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Table I

Descriptive statistics

The table shows the annualized mean and standard deviation of excess returns $R - R^f$, market capitalization (Size), Book-to-Market ratio (B/M), volume per number of shares outstanding (Liquidity), last quarter's excess returns (Momentum) and Trading Frequency. Excess returns are from CRSP. Market capitalization is measured as price multiplied by the number of shares outstanding reported in CRSP. The trading frequency of a security is constructed following Parsa (2010). The first column shows the statistics for the full sample of securities, while the last two columns show the statistics for stocks in the lowest and highest quintile of the trading frequency distribution, respectively.

	Full sample		Low trading frequency		High trading frequency	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
$R - R^f$	0.0310	0.278	0.0348	0.253	0.0212	0.311
Size	1.62	1.62	1.62	1.62	0.754	2.96
B/M	0.723	0.723	0.723	0.723	0.723	0.723
Liquidity	3.29	3.29	3.29	3.29	5.21	5.21
Momentum	0.0305	0.304	0.0381	0.294	0.0286	0.310
Trading Frequency	-0.0176	0.137	-0.177	0.0646	0.171	0.130

Table II

Mean Returns and t-Statistics of Sorted Portfolios

The table shows annualized mean excess returns and the corresponding t-statistics of value-weighted portfolios formed by sorting on the characteristics defined in Table I. The first row is a single sort on quintiles of trading frequency for each quarter t. The next rows perform a double sort by independently placing each stock into one of five trading frequency quintiles and one of three size, book-to-market, liquidity or momentum groups. Portfolios are formed by grouping stocks that belong to the interesction of two groups. The reported mean returns are the time-series averages of the annualized returns of each portfolio. The column High-Low constructs a zero-investment portfolio by buying the portfolio in the High trading frequency group and shorting the portfolio in the Low frequency group.

	Trading Frequency					
	Low	2	3	4	High	High-Low
Single-sort	0.129	0.112	0.108	0.0939	0.0789	0.0505
	[3.37]	[2.89]	[2.62]	[2.03]	[1.53]	[2.18]
Size						
Small	0.143	0.132	0.139	0.105	0.107	−0.0366
	[3.41]	[2.75]	[2.69]	[1.95]	[1.98]	[−1.60]
Medium	0.114	0.108	0.101	0.0923	0.0638	−0.0505
	[3.23]	[2.75]	[2.30]	[1.89]	[1.21]	[−1.94]
Big	0.111	0.105	0.0878	0.0789	0.0528	−0.0583
	[3.41]	[3.21]	[2.52]	[1.85]	[1.07]	[−1.62]
Book-to-Market						
High Growth	0.0843	0.0821	0.0342	0.00407	−0.0454	−0.130
	[2.25]	[2.15]	[1.12]	[0.002]	[−0.392]	[−3.42]
Medium	0.0102	0.0244	0.00783	−0.00807	−0.0181	−0.0283
	[1.03]	[1.35]	[0.00532]	[−0.0031]	[−0.47]	[0.0001]
High value	0.148	0.132	0.137	0.0639	0.0353	−0.113
	[9.78]	[5.13]	[3.35]	[2.68]	[1.35]	[2.53]
Liquidity						
More illiquid	0.0163	0.0133	0.00959	0.00648	0.00597	−0.0104
	[1.95]	[1.54]	[1.13]	[0.70]	[0.633]	[−2.90]
Medium	0.0398	0.0225	0.0216	0.021	0.0135	−0.0263
	[3.53]	[2.3]	[2.23]	[2.00]	[1.17]	[−5.98]
More liquid	0.125	0.0838	0.0618	0.0449	0.0406	−0.084
	[6.78]	[5.31]	[3.95]	[2.78]	[2.25]	[−6.74]
Momentum						
High past returns	0.169	0.121	0.118	0.11	−0.0928	−0.262
	[2.29]	[1.93]	[1.36]	[1.22]	[−1.19]	[−2.87]
Medium	0.105	0.077	0.0179	0.101	0.0407	−0.0642
	[0.994]	[1.55]	[0.151]	[0.952]	[0.379]	[−0.363]
Low past returns	0.0119	0.236	0.0972	0.0342	0.0547	0.0428
	[0.0829]	[4.23]	[1.84]	[0.357]	[1.03]	[1.02]

Table III

Time-Series Regressions of Returns of Trading Frequency Portfolios on Fama-French Factors

The table shows estimates of the intercept, coefficients and R^2 of time series regressions of excess returns on the Fama-French factors. Each row corresponds to one of the portfolios constructed by sorting on trading frequency as explained in table II. t-statistics are reported in brackets.

	$\widehat{\alpha}$	$\hat{\beta}^{MKT}$	$\hat{\beta}^{SMB}$	$\hat{\beta}^{HML}$	R^2
Trading Frequency					
Low	−0.0131	1.10	−0.312	0.488	0.926
	[−0.86]	[20.9]	[−4.72]	[6.40]	
2	−0.0005	1.12	−0.113	0.24	0.965
	[0.0516]	[35.8]	[−2.89]	[5.30]	
3	0.0156	1.01	−0.0226	−0.0587	0.944
	[1.66]	[30.8]	[−0.554]	[−1.25]	
4	0.0195	1.01	0.181	−0.103	0.918
	[1.83]	[27.6]	[3.92]	[−1.94]	
High	0.0261	0.923	0.302	0.0758	0.796
	[1.59]	[16.3]	[4.24]	[0.921]	
High-Low	0.0392	−0.007	0.0246	−0.0165	0.513
	[1.51]	[−1.96]	[5.44]	[−3.17]	

Table IV

Pricing Errors of Different Models When Pricing Frequency-Sorted Portfolios

The table shows the performance of different factors when pricing 5, 10 and 25 portfolios constructed by sorting on stock's trading frequency as described in Table II. As factors, we consider the market excess return (CAPM), the Fama-French factors (FF), Jegadeesh and Titman's momentum (UMD), long-term return reversal (Rev) and liquidity factors of Sadka and Pastor/Stambaugh (Liq). All the reported statistics are obtained from regressions of the excess return of the 5, 10 or 25 trading frequency portfolios on the different pricing factors. Mean $|\widehat{\alpha}|$ is the average across regressions of the absolute value of the estimate of the intercept in annualized percentage points. GRS is the Gibbons-Ross-Shanken test-statistic (an F-statistic adjusted for finite sample bias) of the null hyphothesis that the $\widehat{\alpha}$ for all portfolios are jointly zero, for which we also report its p-value. The Mean R^2 is the average value of the R^2 across regressions.

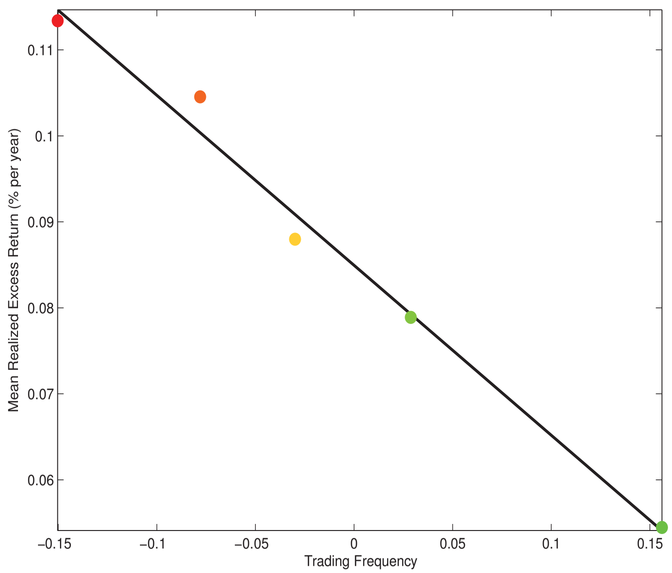
	CAPM	FF	FF+UMD+Liq	FF+UMD+Rev+Liq
5 portfolios				
Mean $|\widehat{\alpha}|$	0.0324	0.015	0.0221	0.0327
GRS	15.9	15.5	14.2	12.1
p-value	0.00	0.00	0.00	0.00
Mean R^2	0.885	0.910	0.910	0.914
10 portfolios				
Mean $|\widehat{\alpha}|$	0.0307	0.0161	0.0215	0.0310
GRS	12.3	11.4	8.38	8.1988
p-value	0.00	0.00	0.00	0.00
Mean R^2	0.808	0.831	0.877	0.837
25 portfolios				
Mean $|\widehat{\alpha}|$	0.0342	0.0215	0.0278	0.0339
GRS	25	25.9	37.5	30.1
p-value	0.00	0.00	0.00	0.00
Mean R^2	0.635	0.685	0.812	0.707

Table V

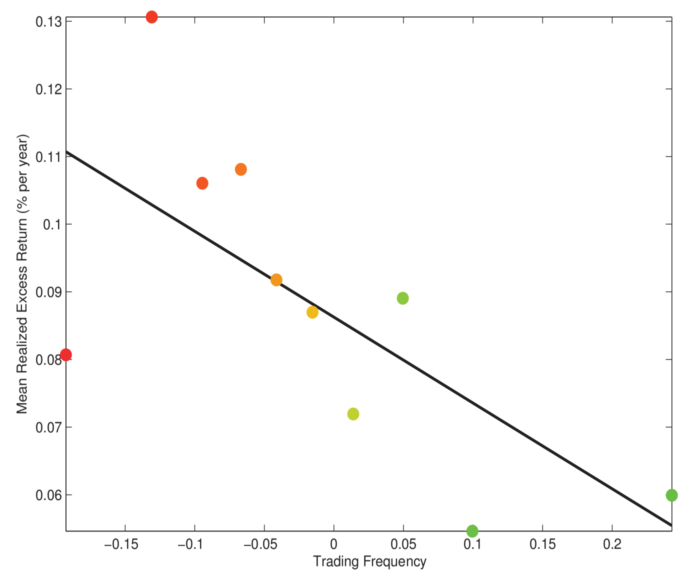
Time-Series Regressions of Returns of Trading Frequency Portfolios on Fama-French and a Trading Frequency Factor

The table shows estimates of the intercept, coefficients and R^2 of time series regressions of excess returns on the Fama-French factors and a the High-Low portfolio. Each row corresponds to one of the five portfolios constructed by sorting on trading frequency as explained in table II. t-statistics are reported in brackets.

	$\widehat{\alpha}$	$\hat{\beta}^{FREQ}$	$\hat{\beta}^{MKT}$	$\hat{\beta}^{SMB}$	$\hat{\beta}^{HML}$	R^2
Trading Frequency						
Low	0.0054	47.2	1.02	−0.0220	0.294	0.974
	[0.591]	[13.2]	[31.8]	[−0.488]	[6.14]	
2	0.0043	9.91	1.06	−0.0525	0.199	0.968
	[0.494]	[2.88]	[35.8]	[−1.21]	[4.34]	
3	0.0131	−6.51	1.01	−0.0626	−0.0319	0.945
	[1.39]	[−1.77]	[30.9]	[−1.35]	[−0.651]	
4	0.0092	−26.3	1.10	0.0194	0.0053	0.952
	[1.11]	[−8.13]	[36.7]	[0.475]	[0.122]	
High	0.0054	−52.8	1.01	−0.0220	0.294	0.938
	[0.591]	[−14.7]	[31.8]	[−0.488]	[6.14]	



(a) Figure I.a



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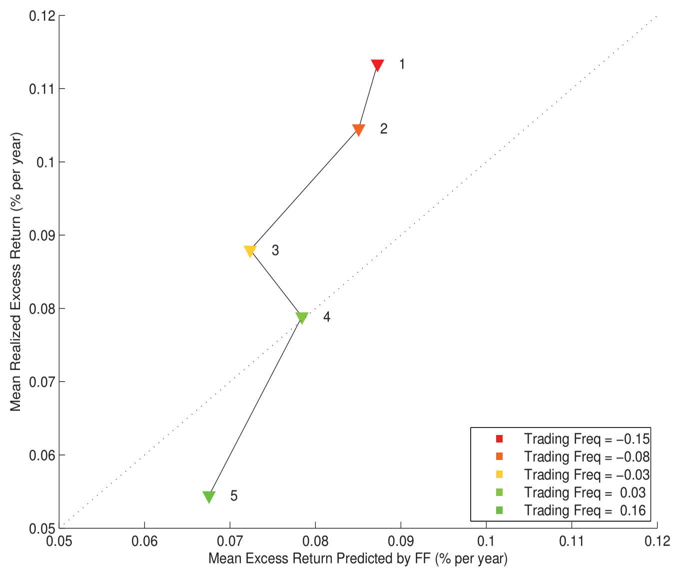
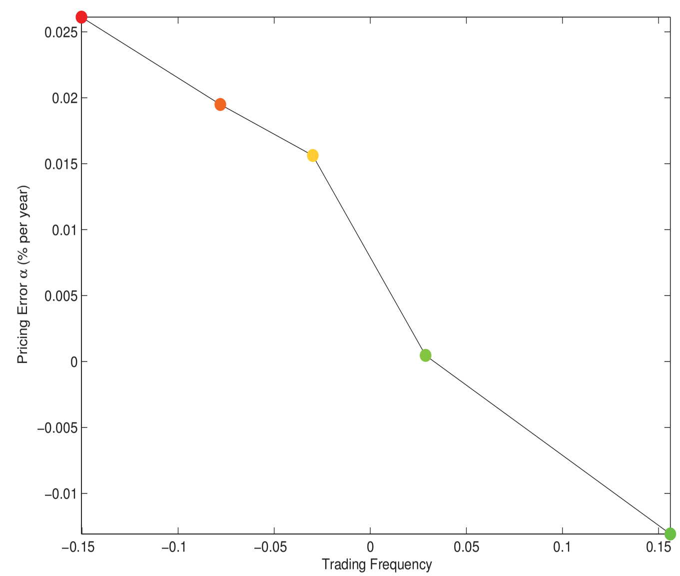
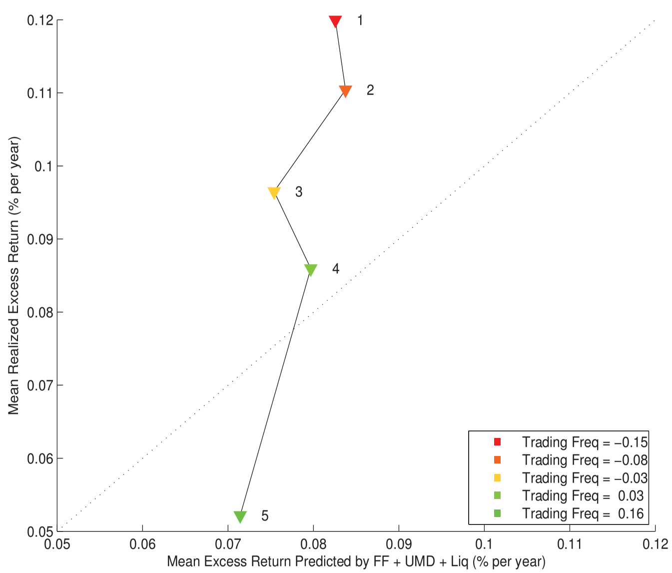


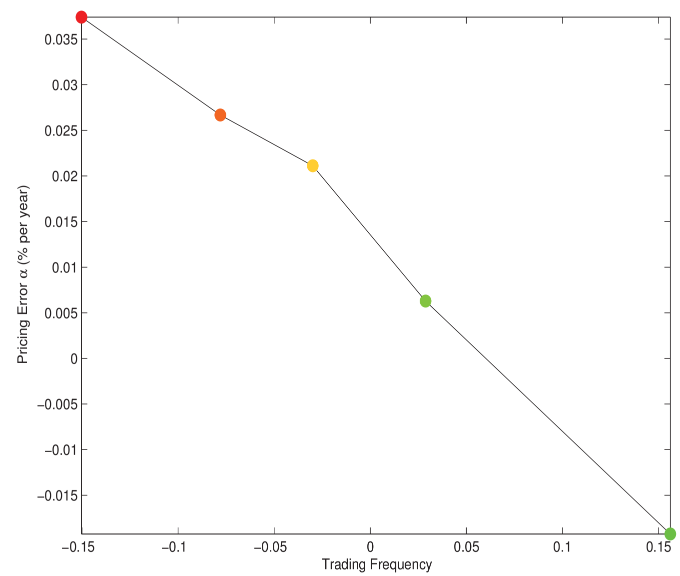
(c) Figure II



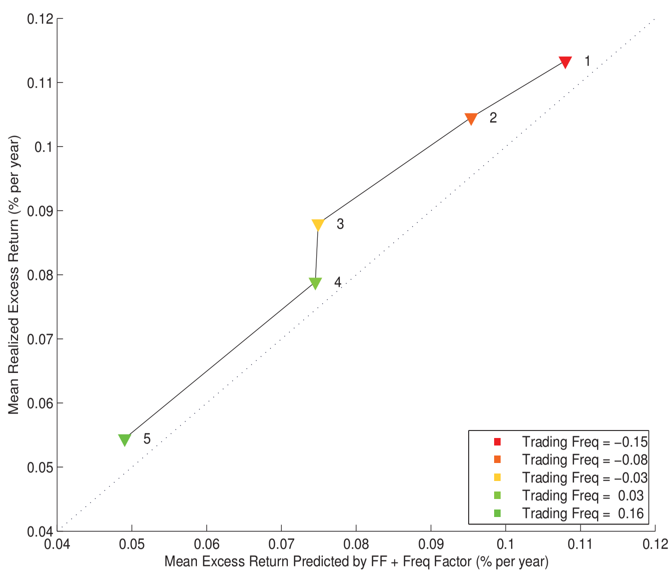
(d) Figure III



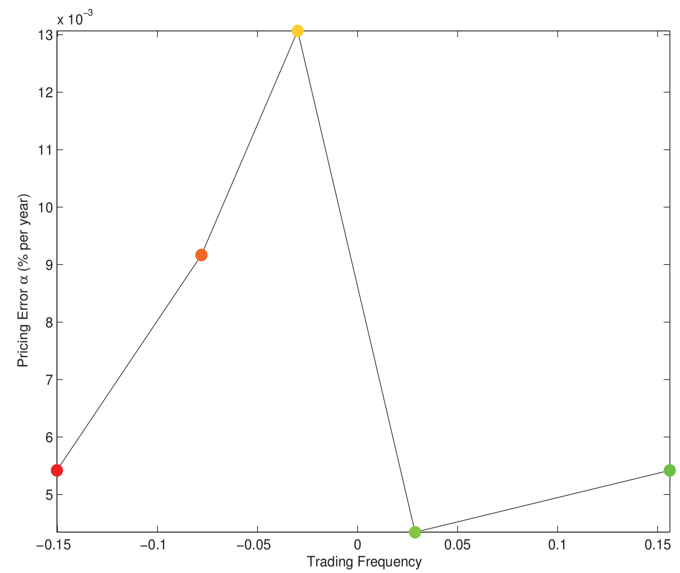
(e) Figure IV



(f) Figure V



(g) Figure VI



(h) Figure VII