Funding conditions, transaction costs and the dynamic performance of anomalies

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Abstract

Transaction costs have declined over time but they can increase considerably when funding liquidity becomes scarce, investors' fears spike or other frictions limit arbitrage. We estimate bid-ask spreads of thousands of firms at a daily frequency and put forward these large movements for several of these episodes in the last 30 years. While small firms and high volatility firms have larger transaction costs, the relative increase in trading costs in crisis times is more pronounced in large firms and low-volatility firms. The gap between the respective trading costs of these high- and low-quality groups also increases when financial conditions deteriorate, which provides evidence of flight to quality. We build anomaly-based long-short portfolios and estimate their average and dynamic alphas adjusted for rebalancing costs based on our security-level transaction cost estimates. Several dynamic performance configurations across periods and anomalies are featured.

1 Introduction

The drastic reduction in average trading costs over time has been amply documented in the literature[1]. The introduction of decimalization in 2000 played an important role, but automation and algorithmic trading accentuated the trend. The latter factor helps reduce the part of trading costs that is related to a firm's specific information since news is instantly reflected in its security price. However, effective bid-ask spreads, as measures of liquidity, share some commonality. Chordia et al. (2000) are early contributors to the study of common aggregate factors affecting quoted spreads, quoted depth, and effective spreads. They show that these security-level measures of liquidity co-move with market- and industry-wide liquidity[2]. More recently, Weller (2019) extracts a measure of tail risk from the cross-section of bid-ask spreads. In these studies, common factors are obtained by averaging individual liquidity measures or computing principal components of a cross-section of such measures. Identification of the sources of commonality is therefore left to the interpretation of these statistical factors.

Our goal is to link daily measures of trading costs at the individual firm level to aggregate funding liquidity conditions. This is theoretically supported by the model of Brunnermeier and Pedersen (2009), whereby market liquidity and funding liquidity cause each other and are mutually reinforcing, potentially leading to liquidity spirals. When funding liquidity conditions are tight, traders are reluctant to take on capital intensive positions in high-margin securities, which lowers market liquidity and increases the effective spread. Similarly, when market liquidity is low, it becomes riskier to finance a trade and intermediaries ask for higher margins.

Ideally, we would like a measure at the individual firm level that can accommodate a conditioning on funding conditions. The current literature proposes low-frequency measures of the effective spread based on observed daily prices. While trade and quote-based measures

[1]For a recent historical perspective, see Novy-Marx and Velikov (2016). Their Figure 1 features the mean effective spreads across market capitalization ranks for various historical periods.

[2]Other early references are Hasbrouck and Seppi (2001) and Huberman and Halka (2001). The first paper shows that commonality in the order flows explains about two-thirds of the commonality in returns. The second documents the presence of a systematic, time-varying component of liquidity.

are often more accurate, low-frequency estimates avoid the challenges and costs of obtaining comprehensive quote data across various markets and asset classes. Ardia et al. (2024a) develop an asymptotically unbiased estimator with minimum variance (called EDGE for Efficient Discrete Generalized Estimator) by accounting for discretely observed prices and optimally considering the complete information set of open, high, low, and close prices[3]. Their empirical analysis uses the CRSP U.S. stock database to compute bid–ask spread estimates from daily prices. They also compute a high-frequency benchmark effective spread from the trade and quote (TAQ) database according to the methodology developed by Holden and Jacobsen (2014) (hereafter HJ)[4]. They show that among several low-frequency estimators, EDGE is the closest to the high-frequency benchmark both in terms of time series and cross-sectional correlations and other evaluation metrics[5]. These measures do not readily lend themselves to a natural linkage with funding conditions in a structural econometric model.

Since market liquidity is defined as the difference between the transaction price and the fundamental value, a conditional version of the Bayesian Gibbs approach in Hasbrouck (2009) appears more promising to make the effective spread of individual stocks dependent on funding conditions. Indeed, the unconditional model of Hasbrouck (2009) seems to be a good starting point. Over a sample from 1993 to 2005 and for about 300 firms per year the CRSP-Gibbs estimate of average effective cost has a correlation of 0.965 with the high-frequency trade and quote (TAQ) value. Our first task will be to confirm that this Bayesian approach delivers estimates of the effective spread that are competitive with the best low-frequency estimator EDGE recently proposed and the high-frequency benchmark HJ.

We estimate the effective cost of trading for all selected securities[6] in the CRSP database

[3] By minimizing the estimation variance, EDGE also minimizes the upward bias that arises in small samples due to the methods employed to guarantee non-negativity of the spread estimates, as shown by Jahan-Parvar and Zikes (2023).

[4] The HJ benchmark is estimated using the mid-point effective spread. However, they also estimate it with the weighted mid-point methodology proposed by Hagströmer (2021) and find a correlation of 99.1% between the two monthly benchmark measures.

[5] In particular, the estimator EDGE performs better than the two low-frequency estimators of Corwin and Schultz (2012) and Abdi and Ranaldo (2017). While Roll (1984) and Hasbrouck (2009) use only the daily closing price, Corwin and Schultz (2012) retain the daily low and high prices and Abdi and Ranaldo (2017) the high, low and close prices.

[6] See the data section for the selection criteria.

from January 1986 to June 2018 with the Hasbrouck (2009) unconditional model (hereafter referred to as HASB). A thorough comparison is done with the EDGE and HJ estimators in terms of cross-sectional and time-series correlations. Overall, the Bayesian estimator HASB holds well with respect to both EDGE and HJ. This is also true for the size decile levels of EDGE and HASB. We provide average estimates of transaction costs for equal-weighted decile portfolios built according to 34 characteristics for EDGE and HASB. We obtain very close estimates for all anomalies. Different patterns are observed for the trading costs depending on the characteristics. We observe monotone patterns for a number of characteristics: for size, price per share, long-term and short-term reversals, trading costs decrease monotonically across deciles, while we observe the reverse pattern for stocks sorted according to realized volatility. For others, especially for rankings based on momentum measures, we often see a U-shape pattern, with a decrease followed by an increase. Finally, little variation is observed for some characteristics such as leverage or standardized unexpected earnings.

To motivate empirically the conditioning of the HASB model with funding liquidity, we explore the relationship of the high-frequency HJ estimator with the TED spread, the difference between the three-month LIBOR (London Interbank Offered Rate) in US dollars and the three-month Treasury bill rate[7]. An increase in the TED spread signals that lenders believe default risk is increasing and funding conditions are getting tight. Figure 4 illustrates the heightened correlations between the two series during episodes of tight funding conditions[8].

We then extend the unconditional model to make the transaction cost of security i at the daily frequency conditional on the TED spread[9]. The conditional Hasbrouck (2009) model can be expressed as follows:

[7]This measure of funding liquidity has been used by Frazzini and Pedersen (2014) and Brunnermeier (2009). Other interest-rate spreads have been used in the literature. Garleanu and Pedersen (2011) measure the shadow cost of capital by the LIBOR - general collateral (GC) repo interest-rate spread, while Park (2015) use the Libor-Overnight Index Swaps (OIS) spread. Several other measures are available at lower frequency (see Fontaine and Garcia (2012), Hu et al. (2013), and Golez et al. (2018)).

[8]See section 4.5 for a discussion of these correlations.

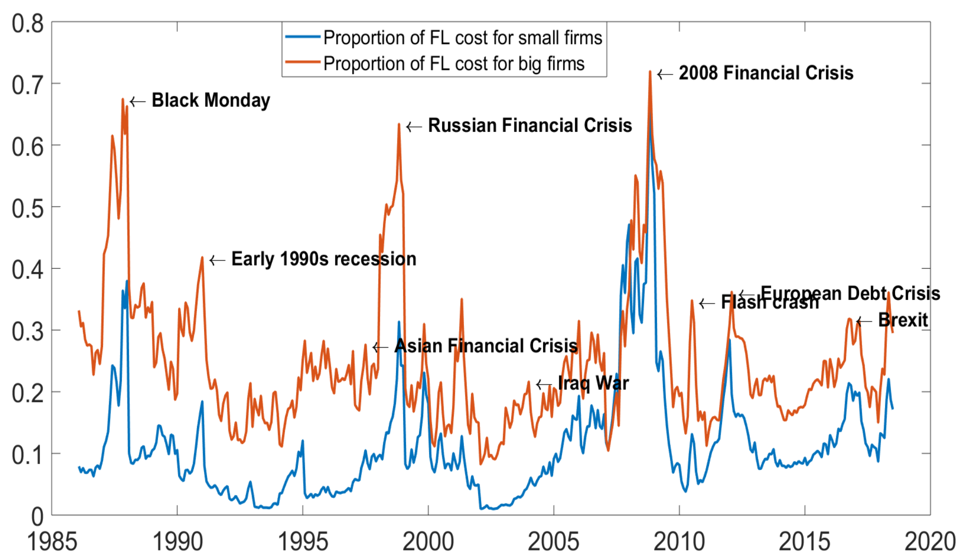
[9]A conditional model is suggested in section VI of Hasbrouck (2009) to add variation in the estimation of the effective spread. The author rejects the simple strategy consisting of forming estimates over smaller subsamples than a year, since it will give a large weight to the prior of the effective cost, which in many situations will be unacceptably biased.

$$\Delta p_t^i = (c_0^i + c_1^i.TED_t)\Delta q_t^i + \beta_m^i r_{mt} + \varepsilon_t^i \tag{1}$$

where p_t^i is the log trade price, q_t^i is a random indicator for the direction of the trade that takes the value one (minus one) if the trade took place at the ask (bid), r_{mt} denotes the market return, ε_t^i is a random disturbance reflecting public information about the stock, and $c_t^i = c_0^i + c_1^i.TED_t$ is the effective cost of trading which depends on the measure of funding liquidity.

To illustrate the potentially important role played by funding conditions, most notably in crisis periods, Figure 1 plots the time series of the proportion of transaction costs attributable to funding liquidity for large and small firms. For each big financial market event between 1986 and 2018, the proportion jumps to about 60-70 % for large firms. Overall, large firms are relatively more impacted by funding conditions than small firms since their transaction costs are small in normal times. However, in the 2008 financial crisis that raised considerably liquidity risk, the proportion for small and large firms are about the same.

Figure 1: **Proportion of transaction cost due to funding liquidity for small firms and big firms**



A stock's spread will be affected by general funding conditions in the market and therefore by global trading activity. This common source of time variation in transaction costs will therefore capture some of the time variation in inventory risk and price impact of large trades for institutional investors (see Chordia et al. (2000); Hasbrouck and Seppi (2001)).

We estimate the conditional HASB model and find statistical support for the TED spread as a common conditioning factor of transaction costs. A test based on the ratio of the marginal likelihoods[10] favors the funding liquidity conditional model over the Hasbrouck (2009) unconditional model for 73% of firm-years. The estimated transaction costs are in average 24% higher for the conditional model compared to the unconditional model. However, the main interest of the conditioning is to see how the transaction costs are affected by the TED spread dynamically.

The model of Brunnermeier and Pedersen (2009) implies that market liquidity not only has commonality across securities but is also subject to flight to quality. Our estimated transaction costs provide evidence of flight to quality. The quality of a particular stock is positively related to the size of the firm (Lang and Lundholm (1993)) and negatively related to the stock's volatility (Brunnermeier and Pedersen (2009)). We will say that there is evidence for flight to quality if the differential in transaction costs between high and low quality stocks increases when funding conditions deteriorate. We find that the differentials in transaction costs between small and large firms and high- and low-volatility firms indeed increase when the TED spread increases.

Given these daily estimates of transaction costs for all securities in our sample, we can measure more precisely the net returns after-trading costs of long-short strategies that arbitrageurs are pursuing by building portfolios sorted on firm characteristics. We consider a subset of 17 anomalies for which the portfolios are rebalanced monthly (since this is where the more frequent trading can reduce most the alpha of the strategy) and measure their after-trading-cost performance. We follow the usual portfolio-formation procedure by ranking stocks, each month, according to the value of the anomaly. Stocks are then grouped into equally-weighted or value-weighted deciles. The long-short portfolio is then obtained by

[10] See Appendix A for a description of the test.

going long on the stocks in the highest decile and short on the stocks in the lowest decile or inversely, depending on the anomaly. To stay exposed to the anomaly, the portfolios need to be rebalanced and transaction costs are incurred. We find that a proper accounting of transaction costs eliminates the profits of most anomaly-based long-short portfolios for both the unconditional and conditional models, except for standardized unexpected earnings (SUE), sales growth (SG) and price per share (PRICE)[11].

To capture the dynamic performance of these anomaly-based strategie, we compute a time-varying alpha for each strategy based on the nonparametric methodology of Ang and Kristensen (2012). We report the numbers of significant positive and negative alphas and non-significantly different from zero alphas for the gross returns and net returns (after trading costs) of each strategy. We also plot the evolution of the time-varying alpha to isolate the periods over which the gains and losses occur. For the three profitable strategies (SUE, SG and PRICE), the numbers of statistically negative alphas are relatively small and cluster around the late 1990s and early 2000s, periods where the TED spread was particularly volatile.

Measuring performance dynamically and conditionally to funding conditions complements the analysis of Novy-Marx and Velikov (2016) conducted with the original Hasbrouck (2009) unconditional methodology, as well as the recent study of Patton and Weller (2019). The latter introduces market liquidity and funding liquidity variables to determine whether characteristic-based trading strategies are implementable in practice.

For robustness purposes, we conduct the same analyses with two other variables available at the daily frequency, the VIX and the tail risk measure of Weller (2019). These two measures are certainly correlated with funding conditions but they can also vary on their own following investors' fear episodes or extreme events. The estimated transaction costs are higher with the VIX and lower with the tail risk but most results in terms of profitable strategies and flight to quality remain.

[11] These results are consistent with a recent paper by Chen and Velikov (2023) that assesses the expected returns of long-short portfolios based on 204 stock market anomalies and concludes that the average net return after trading costs is negative if the strategies are implemented according to the original papers.

For completeness, we also consider the estimation of transaction costs with the model of Lesmond et al. (1999) that requires only the time series of daily returns to endogenously estimate by maximum likelihood the effective transaction costs for any firm. The feature of the data that allows for the estimation of transaction costs is the incidence of zero returns. An important advantage of the method is to allow for an asymmetry in estimating the trading cost for buying or selling a security, while the cost is symmetric in Hasbrouck (2009). We introduce funding liquidity in this model and perform a likelihood ratio test with respect to a model without funding frictions. The model with funding liquidity is preferred to the model without funding liquidity for a third of the firms. For the performance of the long short-strategies we arrive at very similar conclusions.

The rest of the paper is structured as follows. After reviewing the literature on the measurement of transaction costs, we describe in Section 2 the estimation methodology of transaction costs based on the model of Hasbrouck (2009) and its conditional version with funding liquidity. We also describe the low-frequency estimators of Corwin and Schultz (2011), Abdi and Ranaldo (2017), and Ardia et al. (2024a). Section 3 describes the data used for estimation and for comparison purposes. In Section 4, we conduct a comparative analysis of low-frequency estimators of the effective spread and the high-frequency benchmark. Section 7 studies the dynamics of transaction costs with respect to firm size, volatility and momentum and provides evidence of flight to quality. In Section 6, we report the after-trading-cost performances of anomaly-based strategies for equally-weighted and value-weighted portfolios. Robustness analyses are included in Section 7. Section 8 concludes.

Related literature

Conceptually, a direct way to measure transaction costs is to add commissions to the bid-ask spread. However, several problems arise in practice. Grossman and Miller (1988) argue that, for a given trade, it is unlikely that the seller and the buyer arrive at the same time on the market and thus the spread cannot serve as a measure of the transaction cost. Moreover, Roll (1984) points out that since commissions are negotiated, they depend on a number of hard-to-quantify factors such as transaction size, amount of business done by the investor, and time of day or year. Another issue raised by Ng et al. (2008) is that the bid-ask spread does not take into account relevant elements such as price impact or opportunity costs and therefore underestimates the real transaction cost. Finally, the bid-ask spread may not be always available for all firms and time periods[12].

To overcome the issues associated with a direct measure of bid-ask spreads based on trades and quotes, Roll (1984) proposed a model to estimate the transaction cost by a so-called effective bid-ask spread. The suggested measure rests on the fact that transaction costs induce negative serial dependance in successive observed market price changes. However, it is not always the case that this covariance is negative in the data. To address this problem, Hasbrouck (2004) proposes to estimate Roll's model with daily closing prices using a Gibbs-sampling methodology. Hasbrouck (2009) further extends the methodology by including a market return factor in the estimation equation and shows that the estimated effective spreads have a 96.5% correlation with the ones estimated from actual trades from the trade and quote (TAQ) dataset. Goyenko et al. (2009) confirms that the effective bid-ask spread is a good proxy for the bid-ask spreads estimated with intra-daily trade-and-quote data.

The Bayesian procedure proposed by Hasbrouck (2009) necessitates long time series, leaving some firms without a transaction cost estimate. A solution is to rely on proxies[13]. Novy-Marx and Velikov (2016) use the fact that market capitalization and idiosyncratic volatility explain around 70% of the cross section of transaction costs to assign transaction costs to stocks with insufficient observations.

Lesmond et al. (1999) propose a model of security returns that avoids the limitations of the transaction cost proxies. The effect of transaction costs is modeled through the incidence of zero returns. If the value of the information signal is less than the trading cost, the marginal investor will not trade, causing a zero return. Lesmond et al. (2004) use this

[12] Ardia et al. (2024a) also mention the difficulties and costs of obtening quote data for international markets, historical data samples, and asset classes other than stocks.

[13] Karpoff and Walkling (1988) and Bhushan (1994) use price, trading volume, firm size, and the number of shares outstanding, variables assumed to be negatively related to transaction costs. Proxy variables may capture effects not due to transaction costs and cannot be used to compute net returns of a portfolio.

methodology to compute the after-transaction-cost returns of different momentum trading strategies and show that the apparent profits generated by these strategies are in fact illusory. The implementation costs of financial market anomalies have also been studied recently by Patton and Weller (2019). They estimate the transaction costs of mutual funds strategies by relying on Corwin and Schultz (2012)'s methodology to estimate bid-ask spreads based on daily high and low prices.

We also relate to the literature on the link between market liquidity (as measured by the bid-ask spread) and financial risk measures such as funding liquidity (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Kondor and Vayanos (2019))[14], the VIX (Nagel (2012)) or tail risk (Weller (2019)). Aragon and Strahan (2012) link the market liquidity of stocks held by hedge funds exposed to Lehman Brothers to funding liquidity shocks during the bankruptcy.

2 Methodology

To overcome the issues associated with a direct measure of bid-ask spreads based on trades and quotes, Roll (1984) proposed a model to estimate the transaction costs by a so-called effective bid-ask spread from daily security prices. In this section we describe the estimation procedures to arrive at a measure of transaction costs that fluctuates with a measure of aggregate funding conditions.

2.1 Measuring the effective bid-ask spread from daily prices

To incorporate funding liquidity into the measure of the effective bid-ask spreads of firms, we extend the Bayesian procedure of Hasbrouck (2009). We start by describing the model of Roll (1984) on which the procedure is based, then the Bayesian estimation and finally the incorporation of the funding liquidity variable in the procedure.

[14]This is part of a larger literature about the limits of arbitrage (Shleifer and Vishny (1997); Geanakoplos (2010); Gromb and Vayanos (2010)). Tight funding conditions increase transaction costs and therefore prevent arbitrageurs from taking advantage of mispriced assets.

2.1.1 The model of Roll (1984)

Transaction prices are composed of a random-walk and a noise component, as follows:

$$m_t = m_{t-1} + \varepsilon_t \tag{2}$$

$$b_t = m_t - c$$

$$a_t = m_t + c$$

where m_t is the efficient price, b_t the bid price and a_t the ask price, all expressed in logarithms, ε_t a random disturbance reflecting public information about the security, and c is the half-spread, presumed to reflect the quote-setter's cost of market making.

The model introduces a random indicator q_t to capture the direction of the trade. It takes the value one with probability 0.5 if the trade takes place at the ask, and minus one with probability 0.5 if it does at the bid. The observed transaction price can be written as $p_t = m_t + c.q_t$ and:

$$\Delta p_t = c\Delta q_t + \varepsilon_t, \tag{3}$$

which yields $Cov(\Delta p_t, \Delta p_{t+1}) = Cov(c.\Delta q_t + \varepsilon_t, c.\Delta q_{t+1} + \varepsilon_{t+1})$. In most implementations of the Roll model, it is assumed that the direction of the trade is independent of the efficient price movement i.e. q_t is independent of ε_t. With this assumption, we obtain $Cov(\Delta p_t, \Delta p_{t+1}) = c^2.Cov(\Delta q_t, \Delta q_{t+1})$. Given that q_t is equal to $+1$ or -1 with equal probabilities, $Cov(\Delta p_t, \Delta p_{t+1}) = -c^2$. Therefore, the half-spread is equal to $c = \sqrt{-Cov(\Delta p_t, \Delta p_{t+1})}$.

This way of estimating c is infeasible when we have positive auto-covariances between daily changes in stock prices, which happens often in practice[15]. Hasbrouck (2009) adds that another problem arises when there is no trade on a particular day since it leads to a downward bias in the estimated cost[16].

[15] Roll (1984) finds that auto-covariance estimates based on 21 daily returns are positive for almost half the cases. Harris (1990) studies the statistical properties of the Roll bid-ask spread estimator and shows that positive auto-covariances are more likely for low values of the spread.

[16] When there is no trade on a particular day, CRSP reports the midpoint of the closing bid and ask. If these days are retained in the sample, the estimated cost will generally be biased downward, because the midpoint realizations do not include the cost. If these days are dropped from the sample, heteroscedasticity may arise since the efficient price innovations may span multiple days.

2.1.2 The Bayesian procedure of Hasbrouck (2004, 2009)

To overcome this issue, Hasbrouck (2004) proposes a Bayesian approach. In this approach, Hasbrouck (2004) makes two key assumptions: the spread is positive and ε_t is $i.i.d. \sim N(0, \sigma_\varepsilon^2)$. The model parameter set is $\Theta = \{\sigma_\varepsilon^2, c\}$. If we denote the prior parameter density $\pi(\Theta)$, the posterior will be given by $f(\Theta/p) = \frac{f(p/\Theta).\pi(\Theta)}{f(p)}$, where $p = \{p_1, p_2, ..., p_T\}$ is the vector of observed prices over the sample.

This posterior cannot be directly evaluated because the data likelihood function $f(\Theta/p)$ involves the unobserved $q = \{q_1, q_2, ..., q_T\}$. The problem is solved by considering $f(\Theta, q/p)$ and then by integrating out the q with a Markov-Chain Monte-Carlo (MCMC) approach. Hasbrouck (2009) extends the model by including a market return factor in the Roll model:

$$\Delta p_t = c\Delta q_t + \beta_m r_{mt} + \varepsilon_t. \tag{4}$$

With this addition the data likelihood function becomes $f(\Theta, q/p, r_m)$ but the estimation method remains unchanged.

2.2 The Hasbouck model with funding liquidity

In the model of Hasbrouck (2009), the transaction cost of an individual firm is usually estimated at a yearly frequency since any smaller sample will deliver biased estimates as explained by Hasbrouck (2009) and documented by Goyenko et al. (2009). Indeed, if we were to consider a monthly estimate, we will have about 20 daily observations and the posterior for such a small sample will closely resemble the prior, which will produce biased estimates. Solutions suggested by Hasbrouck (2009) include building informative priors or incorporating time variation directly into the model. This is the solution we adopt by linking the transaction cost to a daily measure of funding conditions, the TED spread.

We write the transaction cost as an affine function of TED_t and make the notation more precise than in the previous sections. We distinguish the time scales for the various coefficients and identify the firm since we will be forming anomaly portfolios in the second part of the paper.

$$m_t^i = m_{t-1}^i + \varepsilon_t^i \tag{5}$$

$$p_t^i = m_t^i + (c_{0,t_p}^i + c_{1,t_p}^i.TED_t)q_t^i,$$

where m_t^i is the underlying log efficient value, p_t^i is the log trade price, q_t^i is a random indicator for the direction of the trade that takes the value one (minus one) if the trade took place at the ask (bid), ε_t^i is a random disturbance reflecting public information about the stock, and $c_t^i = c_{0,t_p}^i + c_{1,t_p}^i.TED_t$ is the effective cost of trading. The subscript t corresponds to the daily frequency, while t_p denotes the time period over which we estimate the transaction cost (monthly or yearly). The coefficients c_{0,t_p} and c_{1,t_p} are two coefficients that are constant over each period p but vary from period to period. The effective cost of trading for firm i will be time varying at the daily level. The number of firms will be different each day and will be denoted by n_t.

By generalizing the previous equation to include a market return factor, as in Hasbrouck (2009), we obtain the following equation:

$$\Delta p_t^i = (c_{0,t_p}^i + c_{1,t_p}^i.TED_t)\Delta q_t^i + \beta_m^i r_{mt} + \varepsilon_t^i \tag{6}$$

2.2.1 Estimation by Gibbs Sampling

As in Hasbrouck (2009), we follow a Bayesian approach to estimate this model since q_t^i, the random indicator for the direction of the trade, is unknown. We also assume that ε_t^i is i.i.d $N(0, \sigma_{\varepsilon^i}^2)$. The parameters that will be estimated are c_0^i, c_1^i, β_m^i and $\sigma_{\varepsilon^i}^2$.

We follow the simulation steps described in Hasbrouck (2009) and detail them for our model in Appendix A. It consists of simulating the parameters of our regression model in equation (6) with normal priors and conjugate normal posteriors for the coefficients and an inverted Gamma distribution for the prior and posterior of the variance of the error term. For the trading direction indicators, we follow a sequential procedure with conditional draws. We described the steps of the Gibbs sampling procedure in Appendix A.

2.3 Low-frequency Estimators of the effective spread

Several estimators of the effective spread have been proposed to include more prices than the close price as in the original Roll (1984) model. Corwin and Schultz (2012) propose an estimator based on high and low prices with smaller variance than the Roll (1984) estimator. The underlying assumption is that high prices are almost always buy trades while low prices are sell trades. The estimator of Abdi and Ranaldo (2017) uses both close and high-low prices to achieve a smaller variance than the Roll (1984) estimator and a smaller bias than the Corwin and Schultz (2012) estimator. Both these estimators model the fundamental price as a geometric Brownian motion with zero mean returns and rest on the assumption that prices are observed continuously.

Ardia et al. (2024a) propose an estimator that improve both bias and variance of the Abdi and Ranaldo (2017) estimator. The new estimator reduces the bias by accounting for the discrete nature of trades and lowers the variance by using the full information set of open, high, low, and close prices. The derivation of the mean squared spread of the estimator from close-to-open and open-to-mid return is detailed in section 3 of Ardia et al. (2024a). The authors go further by using the same methodology to construct other estimators from other combinations of prices. In the last step they optimally combine four such estimators to minimize the estimation variance and obtain an efficient estimator called EDGE[17].

In Section 4, we will compare our unconditional Hasbrouck (2009) estimator to the EDGE estimator, a generalized version of the Abdi and Ranaldo (2017) estimator called CHL, and the benchmark high-frequency model of Holden and Jacobsen (2014) called HJ, all computed in Ardia et al. (2024a).

[17]See section 3.1 in Ardia et al. (2024a) for the details of the GMM procedure used to minimize the estimation variance.

3 Data

As detailed in the previous section, we need daily returns of all selected stocks and of the market as well as a daily series of the funding liquidity measure, to estimate the transaction costs of all firms[18]. We obtain the individual stock and market returns from the Center for Research in Security Prices (CRSP) database where each security has a unique identifier (PERMNO). For comparison with the estimators EDGE, CHL and HJ, we use the monthly estimates provided by Ardia et al. (2024a) for individual stocks based on their PERMNO and for various samples[19].

Our measure of finding conditions is the TED spread, but we also use in the robustness section the VIX and the risk measure proposed by Weller (2019) as conditioning variables. The TED spread and the VIX were downloaded from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis. The TED spread series (TEDRATE) spans the period from January 1986 to June 2018, while the VIX series (CBOE Volatility Index) runs from January 1990 to June 2018. The daily tail risk measure was obtained by aggregating the hourly tail risk measures in Weller (2019) from January 2008 to December 2014[20]. Therefore, we will estimate the series of daily transaction costs corresponding to these three financial variables over three different samples.

To compute performance of long-short anomaly-based portfolios, we first construct anomalies following Novy-Marx and Velikov (2016) and Kozak et al. (2019) from two data sources: COMPUSTAT (North America - Fundamentals Quarterly) and CRSP. The list of anomalies and their brief description is provided in Table 1 and a more detailed version is included in the online Appendix. While the number of available anomalies is extensive, we selected a subset of 34 anomalies covering well the major categories identified in Hou et al. (2015), that is momentum, value-versus-growth, investment, profitability, and trading frictions. This

[18]We select all available securities in the CRSP database with a minimum price of 5 US$ and with at least 60 observations in a given year. The first criterion is to avoid the influence of micro firms on the estimation of the transaction costs of the various portfolios. For the second, we follow the recommendation of Hasbrouck (2009) for the Gibbs-sampling methodology used to estimate the transaction costs.

[19]We thank the authors for making available their replication package in Ardia et al. (2024b).

[20]We are thankful to Brian Weller for providing us with the hourly series of tail risk.

has the advantage of being conceptually comprehensive while remaining empirically parsimonious to avoid excessive redundancy. The value of the paper rests on the proposed dynamic analysis of the performance of the long-short strategies and not on the exhaustive review of the profitability of all available characteristic-based strategies.

To build portfolios for each anomaly, we start from the set of all firms[21] for which the anomaly value is available at each date t[22] and sort them according to this value. We separate the firms into decile portfolios and compute the average value-weighted or equally-weighted return for each decile at a monthly frequency . If the value of the anomaly is available at a frequency lower than a month, say a year, the composition of each decile portfolio is kept the same for all the months in this year. The before-trading-cost performance of the portfolios is measured using the *alpha* from the Fama-French three-factor model[23].

4 A comparative analysis of low-frequency and high-frequency estimators of the effective spread

This section documents how the effective spreads of individual stocks or portfolios estimated with the Hasbrouck (2009) model compare with the EDGE effective spreads and with the HJ high-frequency spreads. We consider average transaction costs for all stocks and for size deciles. We also look at time-series and cross sectional correlations for the same measures. Last, we center the comparison between the Hasbrouck (2009) and the EDGE and HJ estimators on the average transaction costs for three deciles of the 34 anomalies .

4.1 Descriptive statistics - All stocks

In Table 2, we report the average transaction costs for all stocks that are common to Hasbrouck (2009) and EDGE estimators over the period from June 1992 to June 2018. The

[21]Our sample counts about 260,000 firm-years with 27,000 firms traded on the NYSE, AMEX and NASDAQ stock exchanges.

[22]Date could be a year, a month, or a quarter, depending on the anomaly.

[23]Data on Fama-French 3 factors are obtained from the Data Library of Kenneth French website.

average transaction costs are almost identical at 2.7%, but the EDGE median (1.3%) is lower than the HASB one (1.9%). The EDGE standard deviation is also higher than the HASB (4.2% instead of 2.7%). For skewness and kurtosis, the usual estimators based on the third and fourth moments are extremely noisy. Therefore, we report robust measures described in Kim and White (2004) based on quantiles. For skewness, we report the measure of Hinkley (1975)[24]:

$$SK_{(}\alpha) = \frac{F^{-1}(1-\alpha) + F^{-1}(\alpha) - 2 * Q_2}{F^{-1}(1-\alpha) - F^{-1}(\alpha)}, \tag{7}$$

with α chosen between 0 and 1. The denominator re-scales the coefficient so that its maximum value is 1 (extreme right skewness), and its minimum value -1 (extreme left skewness). The computed values indicate a sizable right skewness around 0.48 and 0.65 for HASB and EDGE respectively, when $\alpha = 0.1$.

For kurtosis, we compute the robust measure proposed by Crow and Siddiqui (1967):

$$KR = \frac{F^{-1}(0.975) + F^{-1}(0.025)}{F^{-1}(0.75) + F^{-1}(0.25)}. \tag{8}$$

The value of KR for a N(0, 1) is 2.91. The respective values for the transaction-cost distributions, 4.17 and 5.20, of the HASB and EDGE estimators indicate excess kurtosis with respect to the normal distribution. For the quantiles, the lower ones tend to be larger for the HASB model, while the opposite is true for the higher ones.

4.2 Means and correlations of size deciles

Table 3 provides the effective spread means for the size deciles of the low-frequency estimators HASB and EDGE and the high-frequency benchmark HJ. The number of stock-months is above 160,000 for the first seven deciles and declines slightly for the last three till 137,831 for decile 10. The HASB mean is very close to the HJ mean for the small firms in the first two deciles, while the EDGE average tends to overestimate the spread for these two deciles. For the remaining deciles, both HASB and EDGE are above the HJ benchmark, and much more so for the largest firms in the last three ones. However, the HASB mean is somewhat higher than the EDGE one with a value of 1.25% versus 0.74% for decile 10, compared to a

[24] It generalizes the original measure proposed by Bowley (1920) with $\alpha = 0.25$.

benchmark HJ value of 0.22%.

The correlations between the HASB estimator and EDGE monotonically decrease from 0.77 for the first decile to 0.53 for the last one. The same pattern is observed for the correlations between HASB and HJ but it must be noted that for deciles 1, 9 and 10 the values are higher than the EDGE ones. Figure 2 is more telling. The upper panel plots the decile correlations between the benchmark HJ and EDGE, CHL and HASB. While all three exhibit a similar declining pattern from small to large firms, with EDGE ranking above CHL, and CHL above HASB, it should be noticed that for the first decile as well as for deciles 9 and 10 the correlation HJ-HASB is higher than the correlations of HJ with EDGE and CHL. This is an interesting result since characteristic-based strategies are usually built with the extreme deciles. In the lower panel, the reference estimator is HASB and we compute the correlations with EDGE, CHL, and HJ. The ranking is now CHL, EDGE and HJ, but for the smallest firms, the correlation with HJ is the highest with a value close to 0.8. For the larger firms in deciles 9 and 10 the HASB-HJ correlations are higher than the HASB-EDGE ones but lower than the HSB-CHL ones. Overall the largest difference between the EDGE and HJ correlations with HASB in the middle deciles is 0.0617.

4.3 Time series correlations

Figure 3 features the time-series correlations for all available stocks between the various effective spread estimators. In the upper Panel A, we plot the correlations between the benchmark HJ and EDGE, CHL and HASB. Overall, we confirm that EDGE is the most highly correlated with HJ as exhibited in Ardia et al. (2024a), but both HJ-CHL and HJ-HASB follow closely the HJ-EDGE pattern. The correlation levels are highest and closer together before 2000, the year when decimalization was introduced. Afterwards, they trend down with more volatility until the end of 2006, where the financial crisis hits. The correlation levels increase abruptly and the gaps between the estimators narrow. In the post-financial crisis period and until the end of our sample in mid-2018, the correlation levels are a lot more volatile, with several sharp drops, and the HJ-HASB correlation tends to be lower than the other two pairs while sharing their trends.

In the lower panel B, we plot the time-series correlations of HASB with EDGE, CHL and HJ. The main observation is that the three lines comove closely to each other until the end of 2012, where the level of the HASB-HJ correlation drops compared to the other two pairs. Looking at it more attentively, we notice that the HASB-HJ correlation was generally above HASB-EDGE and HASB-CHL from 1993 until the end of 2003. Also, large dips in correlation appear in the HASB-EDGE and HASB-CHL series in the later part of the sample. These dips were also visible in the upper panel for the HJ-EDGE and HJ-CHL, which indicates that they are caused by the EDGE and CHL estimators.

4.4 Anomaly Portfolios

Since we want ultimately to measure the impact of transaction costs on investment strategies based on stock characteristics, we compare the EDGE, HJ and HASB estimators for decile portfolios built on these so-called anomalies. This will provide a good assessment of the Hasbrouck (2009) model in dimensions other than size as we did in the former sections. The average of the round-trip transaction costs for the 34 sets of anomaly-based decile portfolios are reported in Table 4. For each portfolio we take the simple average of the estimated transaction costs of the firms included in the portfolios for the two extreme deciles and for the middle one.

The most important message that we draw from Panel A is that the two estimators EDGE and HASB provide very similar values for all anomalies and deciles. This is a new result in support of the Hasbrouck (2009) model among the low-frequency estimators. In Panel B, we report for completeness the equivalent trading costs for HASB and HJ. The patterns of the costs across the different deciles are similar between the estimators, albeit at a lower level for HJ.

Given this similarity we will comment generically on the size of the spread for the various anomalies and their deciles for the low-frequency estimators. For certain anomalies, we can see a large difference in the transaction costs between the extreme decile portfolios. For three anomalies that are related to the size of the firm (SIZE or market capitalization, PRICE and NOA or Net Operating Assets), there is a difference of 400-500 basis points between the portfolio of small firms (D1) and the portfolio of large firms (D10)[25].

For the realized volatility portfolios, we observe that the high-volatility portfolios have a much higher transaction cost (around 8%) than the low-volatility portfolio (less than 1%)[26]. Another sizable difference between the extreme decile portfolios is noted for momentum anomalies. The losers portfolio (D1) exhibit a larger effective bid-ask spread than the winners (D10), with a difference for EDGE of 330 basis points for MOM11 and 270 basis points for MOM6. For momentum as well as for other strategies (e.g. sales growth or investment growth), it should be noticed that the pattern of transaction costs is not monotonic, with the middle decile having a lower cost than the two extreme portfolios. The long-term reversal (LTREV), momentum reversal (MOMREV) and return on assets (ROAA) anomalies have moderately important differences in transaction costs between the extreme portfolios in the order of 200 to 300 basis points. Overall, for the other anomalies, there are smaller differences between the effective bid-ask spreads of the extreme decile portfolios.

4.5 Discussion

In this section, we have established that the Hasbrouck (2009) estimator provides estimates of the effective spread that are in line with the EDGE estimator, the low-frequency estimator that is the closest to the high-frequency benchmark HJ and the most efficient among the low-frequency estimators. Over the 1993-2018 sample, its time-series correlation with EDGE remains consistently above 0.6. The cross-sectional correlation with EDGE (HJ) varies between 0.77 (0.79) for the smallest firms and 0.53 (0.55) for the largest ones. The closeness between EDGE and HASB extends to the 34 characteristics that we selected to evaluate the

[25] Hirshleifer et al. (2004) document that high normalized net operating assets is associated with a rising trend in earnings that is not subsequently sustained. High Net Operating Assets stocks are more attractive thus have a higher market liquidity than low Net Operating Assets stocks. The inverse relationship between the transaction cost and the price are consistent with Bhushan (1994) who uses share price to proxy for the inverse of transaction costs.

[26] High-volatility stocks for a given year are the stocks that fall in the highest decile when we rank all stocks according to their realized volatility while low-volatility stocks are the stocks that fall in the lowest decile.

transaction costs of anomaly decile portfolios.

The time-series correlations that we plotted in Figure 3 for all the estimators show that market liquidity has varied considerably over the sample due to significant economic and financial events. In the next section we want to explore the conceptual and empirical relationship between the effective bid-ask spread and funding liquidity. When funding liquidity deteriorates, dealers, market makers, and high-frequency traders who rely on short-term funding face higher capital costs. They may widen their bid-ask spreads to reduce inventory risk and compensate for funding constraints. Consequently, the effective spread in financial markets increases. Brunnermeier and Pedersen (2009) provide a theoretical foundation for this relationship, whereby market liquidity and funding liquidity are mutually reinforcing. When funding is tight, market liquidity dries up, which worsens funding constraints — a feedback loop.

As mentioned in the introduction, we measure funding liquidity at the daily frequency by the TED spread, that is the difference between the three-month LIBOR (London Interbank Offered Rate) in US dollars and the three-month Treasury bill rate. To illustrate the relationship we plot in Figure 4 the time-series of the aggregate benchmark HJ and the TED spread at the monthly frequency. While the overall correlation over the full sample from 1993:1 to 2018:12 is relatively weak at 0.25, there are episodes where it is much higher. Between 1998:1 and 2003:12, which includes the Asian and the Russian financial crises as well as the dotcom bubble, the correlation goes up to 0.64. Between 2008:1, the beginning of the great financial crisis, and the end of the sample, which encompasses the first and second Greece bailouts and the oil and China sell-off, for the peaks, and the concomitant low periods in between, the correlation is even higher at 0.71.

To capture precisely the time variation in the relationship between market liquidity and funding liquidity, we need an econometric model at a daily frequency that links the effective bid-ask spread to the TED spread. This is the rationale behind the model described in Section 2.2. With this model, we will be able to address the dynamic behaviour of the transaction costs in various dimensions.

5 The dynamics of transaction costs

The averages we discussed in the previous sections hide strong trends in historical transaction costs and marked spikes around crisis periods where trading frictions occur. In Figure 5, we plot the evolution of the average transaction cost for all firms. We split the cost into its fixed part and its time-varying part. We plot the time series of c_0, which is fixed for a year, and of $c_1 \cdot TED_t$, which varies with the level of the TED spread. We see clearly the downward trend in the fixed part, which was accentuated after 2000, year of the introduction of decimalization. The time-varying cost is computed by averaging $c_1 \cdot TED_t$ where c_1 stays constant for a year and the TED spread changes monthly. When funding conditions are really tight, as during the 2008 crisis, the part of the transaction cost that depends on the TED spread becomes dominant.

We start by analyzing the dynamics for three anomaly characteristics, size, realized volatility and momentum. The average differences between the trading costs of the two extreme decile portfolios are among the largest for these characteristics[27]. Size and realized volatility also explain close to 70% of the cross-section of transaction costs according to Novy-Marx and Velikov (2016). Two common patterns are present among these three sets of long and short portfolios. First, the fall in transaction costs is present for all six anomaly portfolios. Second, the conditioning on funding conditions affects relatively more the low-trading cost portfolios that the high-trading cost ones. We conclude the section by providing empirical support for the relationship between transaction costs and flight to quality securities.

5.1 Transaction costs and firm size

Before aggregating firms according to their capitalization value, it is important to gauge what the introduction of the TED spread changes in the estimation of the trading cost of individual firms. We choose one large firm COCA COLA CO, with a market capitalization

[27] In the internet Appendix, we include a table similar to Table 2 where we compare the average transaction costs estimated by the unconditional and conditional Hasbrouck (2009) model for the 34 characteristics and provide the proportion of firms where the test described in A.5 favors the conditional model over the unconditional one.

of 200 billions US dollars in 2018, and one small firm ROCKY MOUNTAIN CHOCOLATE FACTORY, with a market capitalization of 22 millions US dollars in 2018. In Figure 6, we plot the transaction costs estimated with the Hasbrouck model at an annual frequency and the extended model with funding liquidity, which shows the monthly movements associated with the TED spread. These two individual securities capture both the historical trends in transaction costs and the large fluctuations associated with trading frictions and captured by the TED spread. For both the large firm, COCA-COLA, and the small firm, ROCKY MOUNTAIN, we observe a declining trend over time in transaction costs, from around 200 to 50 basis points for COCA-COLA and from about 750 to 100 basis points for ROCKY MOUNTAIN. This fact is known, but what is less documented are the huge spikes that occur when tight funding conditions impair trading. In the market crash of 1987 and the financial crisis of 2008, the transaction costs spiked at values between 500 and 650 basis points for COCA-COLA and between 1000 and 1500 basis points for ROCKY MOUNTAIN. The annual average estimates of the Hasbrouck (2009) model obscure these large fluctuations in trading costs.

Figure 7 features the evolution over the 1986 to 2018 period of the transaction costs estimated monthly with both models for size portfolios (D1 for small firms and D10 for large firms). Panel (a) confirms the downward time trend for the average of small firms from 10% in 1986 to about 2% in 2018. Two large spikes appear. The 2008 financial crisis is of course one of the two but the largest one occurred in April 1992. In fact it is a culmination since it follows the recessionary period of 1990-1991 that brought the transaction cost to a level of 18% at the end of 1992 from a level of around 10% at the beginning of 1990. Monthly estimates from both models follow closely each other, with the liquidity estimate above the fixed cost of Hasbrouck (2009).

In Panel (b) for large firms, a downward is also apparent between the beginning and the end of the sample, but during the decade 1990-2000 we observe a steady increase from 1992 to the beginning of 2000 for the liquidity model estimate of the transaction cost. It corresponds to an increase of 0.7 in the TED spread from the end of 1992 to the middle of year 2000. The peak at around 350 basis points for the liquidity model and 300 basis points for the HASB model occurred in the first months of the year 2000, coincident with the large jump in valuation during the tech bubble.

5.2 Transaction costs and volatility

Brunnermeier and Pedersen (2009) link market liquidity (that is the transaction price minus the fundamental value, in other words our measured transaction cost) to fundamental volatility. The link is connected with margin constraints and is stronger when funding conditions are tight. High-volatility securities are more affected by intermediaries' wealth shocks.

Figure 8 shows the average transaction costs for high-volatility stocks and low-volatility stocks over time. We note the same declining trend in the transaction cost of the high-volatility stocks from about 10% in 1986 to 4% in 2018. However, as already noted for the small firms, we observe a large increase from the end of 1987 to 1994. The crash plus the recession of 1990-1991 and the jump in the funds rate in 1994 made high-volatility firms more expensive to trade (to more than 20%). The second peak appears of course during the 2008 financial crisis. For the low-volatility firms, the relative difference between the two models is more pronounced than for the high-volatility firms and varies between 20 and 50 basis points except for the crash of 1987 and the financial crisis of 2008, with spreads of 90 and 150 basis points respectively.

5.3 Transaction Costs and Momentum

Several papers have studied the profitability of momentum long-short strategies, which consist of buying winners and selling losers over a six- or twelve-month period. However, the academic literature is less abundant about the proper accounting of implied transaction costs. While Jegadeesh and Titman (1993a) maintain that the momentum portfolio returns exceed the cost of trading, Lesmond et al. (2004) provide a thorough analysis of what it costs to implement such strategies. They measure the trading costs with all the methods available, some based on using transaction cost data directly, others based on price data[28]. The period they investigate extends from January 1980 to December 1998. Their conclusion is clear, no profits are to be expected from such strategies because they draw disproportionately from among stocks with large trading costs. Figure 9 shows that the transaction costs have considerably fallen after the decimalization in 2000 for both the winner and loser portfolios. Of course, as seen with other strategies, the costs feature several peaks that affect potentially the profitability of the strategy.

5.4 Transaction Costs and Flight to Quality

Stocks of large firms and of low-volatility firms can be characterized as high-quality securities. In Brunnermeier and Pedersen (2009), flight to quality occurs when the market liquidity differential between high- and low-quality securities is larger when speculator funding is tight. To rephrase this assertion, we can say that the flight to quality is the fact that the transaction cost differential between high- and low-quality securities (stocks of big and small firms or low-volatility and high-volatility stocks) is larger when funding conditions are tight.

In the conditional model, the transaction cost for a firm i is obtained by $c_t^i = c_{0,t_p}^i + c_{1,t_p}^i.TED_t$. To estimate the transaction cost of two stocks i and j for a given time period t_p, we will estimate the parameters c_{0,t_p}^i and c_{1,t_p}^i for stock i and c_{0,t_p}^j and c_{1,t_p}^j for stock j. If $c_{1,t_p}^i > c_{1,t_p}^j$, the transaction cost differential between stock i and stock j will increase with the TED spread.

Table 5 presents the average value of parameters c_1 for size and realized volatility decile portfolios. The values for c_1 decrease with size and increase with volatility, supporting the flight-to-quality condition. The other columns in Table 5 confirm that the transaction cost decreases with size and increases with volatility in absolute terms, but that it increases with size and decreases with volatility in percentage, which is consistent with what was apparent in the time-series evolution of the size and volatility portfolios.

[28] They use in particular a limited dependent variabe (LDV) procedure based on the presence of zero returns that we explore in section 6 for robustness purposes.

6 After-trading-cost performance of anomalies

After analyzing the average transaction costs of anomaly strategies and the dynamic evolution for several of them, we need to evaluate their impact on the corresponding returns that such strategies generate. Each month, stocks are ranked based on the value of the anomaly variable and placed accordingly in one of the decile portfolios. Given this way of proceeding, each month or each year depending on the trading frequency, the stocks included in a given decile are not necessarily the same as in the previous month or year. Therefore, to stay exposed to the anomaly, the long-short portfolio needs to be rebalanced and transaction costs are incurred.

6.1 Gross returns and Net returns of Anomalies

To compute the alpha of a long-short strategy we need the returns of the corresponding portfolio. The gross returns of a portfolio are obtained by computing either an equal-weighted or a value-weighted average of the individual returns of the stocks included in the portfolio. To compute the net returns, we proceed as Lesmond et al. (2004) or Brandt et al. (2009). For an anomaly-based portfolio, transaction costs are incurred only when the portfolio is rebalanced. For example, if we compute the monthly returns of a portfolio that is rebalanced once a year say in June, the net return will be equal to the gross return for all months except June. For the latter, we will subtract the transaction costs associated with the rebalancing from the gross return. However, if we rebalance monthly, we need to take the transaction costs out of the monthly gross returns of the portfolio.

Fos space considerations, we will limit ourselves to assessing the performance of monthly rebalanced long-short strategies since this is where transaction costs will matter the most. To explain how to compute the rebalancing costs, we take the example of an equally-weighted portfolio P. It consists of a set A_{t-1} of n stocks $\{s_1, s_2, ..., s_n\}$ with weights $\frac{1}{n}$ at month $t-1$. At month t, the portfolio is rebalanced and consists of a set A_t of m stocks with weights $\frac{1}{m}$. Then the net return of portfolio P at time t is:

$$netR_t = \sum_{i=1}^{m} R_{t,z_i} - \text{Transaction costs}, \quad (9)$$

where R_{t,z_i} is the return of stock z_i at t, and,

$$\begin{aligned} \text{Transaction costs} = & \frac{1}{n} \sum_{v \in A_{t-1} \setminus A_t} \text{t-cost for selling } v \\ & + \frac{1}{m} \sum_{v \in A_t \setminus A_{t-1}} \text{t-cost for buying } v \\ & + \mathbf{1}_{n>m} (\frac{1}{m} - \frac{1}{n}) \sum_{v \in A_{t-1} \bigcap A_t} \text{t-cost for buying } v \\ & + \mathbf{1}_{m>n} (\frac{1}{n} - \frac{1}{m}) \sum_{v \in A_t \bigcap A_{t-1}} \text{t-cost for selling } v \end{aligned} \quad (10)$$

The first line of the above formula refers to the selling of the stocks that were in the set A_{t-1} and are not in the set A_t, while the second line accounts for the buying of the stocks that were not in the set A_{t-1} and are now in the set A_t. The two other lines are due to the reweighting of the stocks that remain in the portfolio from $t-1$ to t. If $n > m$ the weight of these common stocks will increase at time t and then we will need to buy more of these stocks, while we will sell them if $m > n$.

6.2 Performance of long-short strategies: constant alphas

The performance of these long-short anomaly-based strategies will be measured by the *alpha* of the portfolio with respect to the Fama-French 3-factor model. This choice is consistent with the fact that many anomalies were uncovered with this benchmark set of factors. It is also a choice that will lean towards a more generous assessment of the performance before accounting for trading costs. The *alpha* of the strategy portfolio is obtained as the intercept of the following regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_1.(R_{Mt} - R_{ft}) + \beta_2.SMB_t + \beta_3.HML_t + \epsilon_{it}, \quad (11)$$

where R_{it} is the total return of the strategy portfolio i, R_{ft} is the risk-free rate of return, R_{Mt} is the total market portfolio return, $R_{it} - R_{ft}$ is the excess return of the strategy, $R_{Mt} - R_{ft}$

is the excess return on the market portfolio, SMB_t is the size premium (small minus big), HML_t is the value premium (high minus low), all evaluated in month t, and β_1, β_2, and β_3 denote the factor loadings of the strategy portfolio.

In Table 6 we report the alphas of the anomaly strategies that are rebalanced monthly, 17 overall. It features the gross returns, the returns net of the transaction costs estimated with the unconditional (HASB) and conditional (FLH) models, for both equally weighted and value-weighted portfolios[29],[30].

We confirm the favorable performance results reported in the literature since 12 of the 17 strategies produce significantly positive gross returns (10 at the 5% level and 2 at the 10% level) over the large sample period from January 1986 to December 2018 for the equally-weighted portfolios. The gross returns for the remaining five strategies are not significantly different from zero. However, transaction costs erase the apparent profits of the positive strategies except for three of them. The first is earnings surprises (measured by Standardized Unexpected Earnings, SUE, defined in the online appendix). After accounting for the conditional trading costs, the monthly net returns remain at 1.7%. The price per share (PRICE) delivers a 1% net return per month after deducting trading costs that include the TED spread. For the third one, sales growth (SG), the conditional net returns are 0.36% with a t-statistic of 2.46.

For the value-weighted portfolios, only six strategies produce significantly positive gross returns and only two of the three anomalies (SUE, PRICE and SG) remain profitable for the unconditional model. The positive performance for SUE is not significant after the inclusion of funding conditions. The after-cost performance for SG is slightly higher than for the equally-weighted portfolios.

The strategies that we studied are based on the high-minus-low decile sort that is most commonly employed in academic studies. Novy-Marx and Velikov (2016) stress that they

[29] All long-short portfolios are computed by excluding all stocks with a share value less than 5$.

[30] For completeness, we also report the alphas associated with the annually-rebalanced strategies in the online appendix. It is of secondary interest to contrast the conditional and unconditional models since funding conditions at the annual frequency are already captured by the unconditonal model. Despite the low-frequency rebalancing, only a third of the strategies provide a significant positive profit net of transaction costs.

significantly overstate the actual cost of trading these anomalies. First, because in practice, large institutional investment firms devote considerable resources to reduce the costs of executing trades. Second, because these strategies were designed ignoring trading costs, and therefore generate too much trading and too high trading costs. They propose three simple, rule-based methodologies to mitigate the incurred trading costs, in particular limiting the universe of traded stocks to the cheap-to-trade ones, and significantly reduce turnover without significantly reducing exposure to the anomaly. We keep the study of cost-mitigating trading strategies in the presence of time-varying trading costs for the robustness section of the paper[31].

6.3 Performance of long-short strategies: time-varying alphas

While constant alphas are informative about the performance of a strategy over a given period, they do not tell us how the performance varies over time and how the strategy fares in periods of tight funding conditions. To compute the time-varying alphas, we rely on Ang and Kristensen (2012). This paper proposes nonparametric techniques to estimate alphas and betas period by period. The model considered to compute the alpha is the same three-factor model as in equation (11) except that all coefficients are time-varying:

$$R_{i,t} - R_{f,t} = \alpha_i(t) + \beta_{1,i}(t).(R_{M,t} - R_{f,t}) + \beta_{2,i}(t).SMB_t + \beta_{3,i}(t).HML_t + w_{ii}(t) z_{i,t}, \quad (12)$$

Ang and Kristensen (2012) propose the following local least-squares estimators of the coefficients in equation (12) at any point in time $t = 1, 2, \dots, T$:

$$[\hat{\alpha}_i(t), \hat{\beta}_i(t)]' =$$
$$arg\min_{\alpha,\beta} \sum_{t'=1}^{T} K_{h_i T}(t'-t).\left[(R_{i,t'} - R_{f,t'}) - \alpha - \beta_1.(R_{M,t'} - R_{f,t'}) - \beta_2.SMB_{t'} - \beta_3.HML_{t'}\right]^2 \quad (13)$$

[31] Another point is that we consider each strategy individually. DeMiguel et al. (2020) consider several anomaly portfolios at a time and investigate how transaction costs change the number of characteristics that are jointly significant for an investor's optimal portfolio. They find that transaction costs increase the number of significant characteristics since the trades in the underlying stocks required to rebalance different characteristics often cancel out, which reduces trading costs. We keep this analysis for future work.

where $\beta_i(t) = [\beta_{i,1}(t), \beta_{i,2}(t), \beta_{i,3}(t)]$ and $K_{h_iT} \equiv K(z/(h_iT))/(h_iT)$ with $K(.)$ being a kernel and $h_i > 0$ a bandwidth. The optimal estimators are simply kernel-weighted least squares:

$$[\hat{\alpha}_i(t), \hat{\beta}_i(t)]' = \left[\sum_{t'=1}^{T} K_{h_iT}(t'-t)X_{t'}X'_{t'}\right]^{-1} \left[\sum_{t'=1}^{T} K_{h_iT}(t'-t)X_{t'}(R_{i,t'} - R_{f,t'})\right] \quad (14)$$

Ang and Kristensen (2012) provide the optimal bandwidth for the estimation of $\alpha(t)$ in terms of mean-square error[32] and show that, for any $t = 1, 2, \ldots, T$[33]:

$$\sqrt{Th_i}(\hat{\alpha}_i(t) - \alpha_i(t)) \sim N(0, \kappa\sigma_i^2(t)) \quad (15)$$

We use this result to test the statistical significance of $\alpha_i(t)$.

In Table 7 we report the results of our estimations for the anomaly-based portfolios, both equally-weighted and value-weighted. For each characteristic and type of returns considered (gross returns, net returns from the unconditional model (HASB-Model), and net returns from the model conditional on funding conditions (FLH-Model)), we include the number of alphas that are significantly positive, significantly negative and not significant, in columns (1) to (3) respectively. Given that the transaction costs increase with the conditional model, the number of alphas that are significantly positive decreases and the number of alphas that are significantly negative increases for all anomalies and the two weighting schemes.

If we consider the three anomalies for which we obtained positive average alphas – Standard Unexpected Earnings (SUE), Sales Growth (SG) and Price per share (PRICE)– we observe that they naturally exhibit among the highest numbers of significant positive alphas for gross returns. When we account for transaction costs, the number of significant negative and unsignificant alphas increases, especially when we condition on funding liquidity and for the value-weighted portfolios. The lower number of statistically positive alphas for the conditional value-weighted portfolios is the result of the relatively higher increase in trading costs for larger firms.

For a number of anomalies – ROME, ROBE, CISS, LTREV and SHVOL – that produce statistically zero or negative alphas on average, we also observe a large number of positive

[32] See all details regarding the consistency and the optimality properties of the estimators.
[33] $Th_i \to \infty$ and $Th_i^5 \to 0$. We chose $\tilde{h}_i$ from 0 to 1 with a step equal to 0.001.

alphas over the sample. Their lack of average performance is due to the presence of a comparable high number of statistically negative alphas. Again, it is the inclusion of the TED spread in trading costs that reduces the number of significant positive and increases the number of significant negative alphas in both the equally- and value-weighted portfolios.

The timing of these effects is visible in Figures 10 and 11 for the equally-weighted and value-weighted portfolios, respectively. We plot the dynamic evolution and the significance of the conditional-model alphas for the three profitable anomalies, as well as for ROME and SHVOL. For SUE, the number of statistically negative alphas remains relatively small and corresponds to the late 1990s and early 2000s periods where the TED spread was particularly volatile, but the effect is more pronounced for the value-weighted portfolio. The volatility of the TED spread also affects the equally-weighted SG portfolio in the same period as SUE, but it has a higher impact on the value-weighted portfolio with a large cluster of negative alphas around the financial crisis period (2007-2010). For the price per share, the performance pattern is similar for the equally-weighted and the value-weighted portfolios, where the highest numbers are for the non-significant alphas.

For both return-on-market equity (ROME) portfolios, the negative alphas are spread out over the sample and do not exhibit any lengthy sub-period over which a positive performance is sustained. On the contrary, the two portfolios for the volume of shares traded (SHVOL) exhibit very different patterns. For the equally-weighted one, the performance was mainly negative in the part of the sample ending in 2010 and mainly positive afterwards[34]. A few important peaks had an important influence on the average performance considered in the analysis. For the value-weighted portfolio, we count less significant negative alphas but a large number of non-significant alphas.

These analyses show clearly that the alpha averages that are mainly used in the academic literature to evaluate the performance of anomaly strategies hide important information regarding the periods over which they generate actual profits. It suggests that even strategies that appear unprofitable in average may be generating profits over sub-samples, which helps

[34] This is quite interesting since the anomaly was published at the end of the nineties by Datar et al. (1998).

understanding the conditions that sustain such profits. In most instances the TED spread plays a significant role in the time-varying performance of the strategies by increasing the transaction costs relatively more for the larger firms.

7 Robustness analysis

While the transaction-cost model of Hasbrouck (2009) is widely used as a benchmark and could be extended easily to include a conditioning variable to account for the impact of funding conditions, we would like to determine whether the magnitude of trading costs we estimated is robust to other specifications since it conditions our performance assessment of the anomaly-based strategies. First, we repeat our analysis with two different conditioning variables that measure volatility risk (VIX) or tail risk (measure of Weller (2019)). Second, we consider another model proposed by Lesmond et al. (1999) to estimate transaction costs. It is rooted in the adverse selection framework of Glosten and Milgrom (1985) and Kyle (1985). In this model, a marginal informed investor will trade on new or accumulated information only if the trade leads to a profit net of transaction costs. We repeat our analysis of the performance of long-short anomaly-based strategies using these new estimates of trading costs. Last, we submit our conclusions about the profitability of the long-short anomaly portfolios to a rebalancing strategy that reduces trading costs.

7.1 Transaction costs with other conditioning financial variables

In this section, we summarize the main results associated with two risk measures that potentially affect the magnitude of the transaction cost. We estimate the time-varying part of the transaction cost $c_1^i \cdot FR_t$, where FR_t is in turn the VIX and the Weller (2019) measure of tail risk. For space considerations we report all detailed results in the online appendix companion to this paper, namely the tables corresponding to the transaction costs computed with the conditional model of Hasbrouck (2009) with the TED spread over the period January 1986 to December 2018. In terms of robustness of the results we will have two different sub-samples, January 1990 to June 2018 for the VIX and January 2008 to December 2014 for the tail risk measure.

7.1.1 Transaction costs and the VIX

The Chicago Board Option Exchanges (CBOE) Market Volatility Index, or VIX is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options. The VIX is often referred to as the fear gauge (Whaley, 2000) for asset markets. It is also closely related to the state of funding conditions. Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predict that a higher market volatility tightens funding constraints of market makers and thereby reduces their liquidity-provision capacity. Nagel (2012) argues that when the VIX is high, market makers are financially constrained and therefore require a higher premium. More concretely, a higher market volatility makes stock prices move further away from their fundamental value, and therefore increase transaction costs.

All descriptive statistics, mean, standard deviation, skewness and kurtosis, of the transaction costs obtained with the conditional model with the VIX are of a significantly higher magnitude than the ones with the TED spread. The mean is 0.0575 instead of 0.0335, while the standard deviation (0.2755) is seven times higher. The skewness is now 0.6372 and the kurtosis 7.41[35]. These average statistics will translate into higher estimates for the transaction costs of the anomaly portfolios. For example, for the SUE D1 and D10 portfolios, the transaction costs with the VIX are 0.052 and 0.048 respectively, compared with 0.035 and 0.034 for the TED spread[36]. It is not a sample effect since the unconditional transaction costs are similar to the ones obtained with the TED spread over a longer period. Such higher estimates are obtained for all portfolios. Strong evidence is also found for flight to quality.

The main question remains about the effect of such high estimates on the after-cost average returns of the long-short anomaly portfolios. Do the few profitable strategies that we have identified with the TED spread remain profitable? Perhaps surprisingly, the conclusions

[35] For the TED spread statistics we refer to Table 1 of the online appendix since the estimates are computed with the full set of securities. In Table 2 of the paper, the statistics have been computed with the subset of firms used for the EDGE estimator in Ardia et al. (2024a).

[36] See Table 3 in the online appendix.

are exactly the same as with the TED spread. For the constant alphas, the anomalies SUE, SG and PRICE have significant positive alphas for the equally-weighted portfolios, and SUE and PRICE for the value-weighted portfolios. Of course, the alphas are all smaller since the transaction costs are higher. Also the patterns observed with the TED spread for the time-varying alphas are similar in terms of significant positive, significant negative and unsignificant alphas.

7.1.2 Transaction costs and tail risk

Market participants and regulators can rely on two prominent measures of high-frequency tail risk developed by Bollerslev and Todorov (2011) and Weller (2019). The first paper uses high-frequency intra-daily data and short maturity out-of-the-money options on the S&P 500 index to construct an Investors Fears index. The second paper stresses the potential limitations imposed by the rarity of liquid, deep out-of-the-money options and proposes a new methodology that relies on the cross-section of bid-ask spreads. In terms of risk factors associated with extreme events, the second measure captures the aggregate economic shocks and the potential systemic threats underlying the cross-section of realized stock returns, while the first measure picks up the risk factors extracted from liquid options on the S&P 500 index.

The Weller (2019) tail risk measure is a very good candidate for a conditional model of transaction costs since it is an extreme risk factor extracted from high-frequency quote data for thousands of U.S. stocks. Moreover it will give another series of estimates for a period that covers the 2008 financial crisis and its aftermath (January 2008 to December 2014). With respect to the relative importance of the VIX and tail risk to measure financial risk, Bollerslev et al. (2015) decompose the VIX into a jump tail risk component and normal-sized price fluctuations. They show that the compensation for jump tail risk makes up a larger part of the variance risk premium. Therefore, it will be interesting to measure the transaction costs associated with a tail risk measure.

The mean estimates of the transaction costs with the tail risk measure are lower than for the two other measures but this is mainly due to the estimation period corresponding mainly to the aftermath of the 2008 crisis. Figures 7 and 8 for the TED-spread estimates show that this period corresponds to the lowest transaction costs. The standard deviation, the skewness and the kurtosis are also smaller to the estimates obtained with the VIX and the TED spread. The resulting average transaction costs for the anomaly decile portfolios are in general lower than what we have found with the TED spread and the VIX. However, for the value-weighted portfolios, we do not find any significant positive alpha. For the equally-weighted portfolios, SUE, PRICE and SHVOL exhibit significant positive net returns for the conditional tail risk model. Results for the time-varying alphas are similar to the TED-spread and VIX ones, but they are not as clear due to the small size of the sample. Flight to quality is still strongly supported with the tail risk measure.

7.2 The Lesmond et al. (1999) Model (LOT Model)

In Glosten and Milgrom (1985), an informed investor trades with a market maker and decides to:

$$\begin{aligned} \text{Buy if} \quad & Z_{jt} > A_{jt}, \\ \text{Sell if} \quad & Z_{jt} < B_{jt}, \\ \text{Not trade if} \quad & B_{jt} < Z_{jt} < A_{jt}, \end{aligned} \tag{16}$$

where A_{jt} and B_{jt} represent respectively the bid and ask prices of a security j and Z_{jt} is the value assigned to the security given her information set I_{jt}. For a security to reflect new information, the security return has to exceed the transaction cost. A zero-return day means that traders know that it would be non-profitable for them to trade after accounting for the transaction costs. Therefore, a high transaction-cost security will count more zero-returns days than a low-transaction cost security. On can therefore infer the true returns from the observed ones net of transaction costs.

Lesmond et al. (1999) propose a limited-dependent variable (LDV) model of the relationship between the observed return R_{jt} and the true one R^*_{jt}. They assume that the true return of a security j is given by price responses to both contemporaneous market return and firm-specific information through the following equation:

$$R^*_{jt} = \beta_j R_{mt} + \epsilon_{jt}, \tag{17}$$

where R_{mt} is the market return, β_j is the sensitivity of the true return to the market return and ϵ_{jt}, assumed to be normally distributed, captures the price response to firm-specific information. The relationship between the observed return R_{jt} and the true one R^*_{jt} is given by:

$$\begin{aligned} R_{jt} = R^*_{jt} - \alpha_{1j} \text{ if } & \quad R^*_{jt} < \alpha_{1j} \\ R_{jt} = 0 \text{ if } & \quad \alpha_{1j} \leq R*_{jt} \leq \alpha_{2j} \\ R_{jt} = R^*_{jt} - \alpha_{2j} \text{ if } & \quad R^*_{jt} > \alpha_{2j} \end{aligned} \tag{18}$$

where $\alpha_{1j} < 0$ represents the cost of selling and $\alpha_{2j} > 0$ the cost of buying. The costs α_{1j} and α_{2j} are not supposed to be equal since studies like Berkowitz et al. (1988) and Huang and Stoll (1994) have provided evidence that the selling cost exceeds the buying cost.

We extend the model of Lesmond et al. (1999) by making the costs of selling and buying dependent on funding conditions FL_t measured by the TED spread:

$$\begin{aligned} \alpha_{1jt} &= \alpha_{01j} + \alpha_{1j} FL_t \\ \alpha_{2jt} &= \alpha_{02j} + \alpha_{2j} FL_t. \end{aligned} \tag{19}$$

The parameters $\alpha_{01j}, \alpha_{1j}, \alpha_{02j}, \alpha_{2j}$ are obtained by maximizing the log-likelihood function in equation (23) in the appendix. The roundtrip transaction cost is given by $\alpha_{2FLjt} - \alpha_{1FLjt}$. To assess whether the model with time-varying transaction costs is preferred to the fixed-cost model, we use a likelihood ratio test for the nullity of the parameters α_{1j} and α_{2j} (see section B of the appendix).

7.2.1 Estimated transaction costs of anomaly-based portfolios

In Table 8, we report, for the two extreme decile portfolios and the centre one, the average selling transaction cost (α_1 and α_{1FL}) and the average buying transaction cost (α_2 and α_{2FL}), as well as the proportion Pr of firm-years for which the likelihood ratio test preferred the LOT model with funding liquidity to the LOT model without funding liquidity.

The results presented in Table 8 are consistent with the findings of Berkowitz et al. (1988) and Huang and Stoll (1994). The asymmetry, $|\alpha_1| \geq |\alpha_2|$ and $|\alpha_{1FL}| \geq |\alpha_{2FL}|$, is verified for each anomaly and each decile portfolio. Table 8 also shows that the transaction costs are higher when estimated with funding liquidity, since in average $|\alpha_1| \leq |\alpha_{1FL}|$ and $|\alpha_2| \leq |\alpha_{2FL}|$ for each anomaly-based portfolio. Overall, adding funding liquidity to the LOT model increases the transaction costs on average by 10%.

The patterns detected for the decile portfolios with the effective bid-ask spread approach are confirmed for all anomalies. In terms of magnitude, estimated trading costs are higher with this model than with the Hasbrouck (2009) model. The likelihood ratio test rejection rate is more modest compared to what we obtained with the effective bid-ask approach. For the whole sample, it rejects the LOT model for 27% of firm-years at the 5% level, and 40% at the 10% level. We have to remember that, unlike the Hasbrouck (2009) model, the LOT model takes in account zero-trading days. When funding conditions worsen, the marginal investor may not trade and this will be reflected in the estimation of the transaction costs. To check this conjecture, we run the regression of Z_t, the proportion of stocks for which we have zero trading, on the TED spread. The adjusted R^2 is 17% and the slope is significant at 1% significant level. By accounting for the incidence of zeros-trading days, the LOT model implicitly accounts for funding conditions.

7.2.2 Performance of long-short anomaly-based strategies

We report in Table 9 the alphas associated with the 17 long-short strategies rebalanced monthly that we already studied in Table 6. Given the higher estimated transaction costs that we obtained with the latent dependent variable model compared with the effective bid-ask spread approach, we can safely infer that all unprofitable strategies will produce even more negative net returns. Among the very few strategies that generated significantly positive returns, SUE and PRICE remain profitable for the equally-weighted strategies and only PRICE survives with the value-weighted portfolios.

The conclusions are clear and very similar to what we obtained with the Hasbrouck (2009) model with and without funding liquidity. This robustness check with another model to compute transaction costs shows that the anomaly profits disappear when transaction costs are taken into account. Our results clearly demonstrate that research about anomalies cannot be conducted without considering transaction costs and their dynamic behavior according to aggregate financial risks prevalent in the economy.

7.3 Cost-mitigating trading strategies

In computing the after-trading-cost performance of anomaly-based strategies, we strictly applied so far the rebalancing considered in the academic literature and did not allow for mitigating strategies employed by practitioners in financial institutions. Novy-Marx and Velikov (2016) consider several strategies to reduce transaction costs. The simplest one consists in trading only the stocks that are expected to be relatively cheap to trade. In the second one, the investor rebalances only a fraction of the portfolio at each rebalance point. For example, rebalancing can be done at a quarterly frequency but only one-third of the portfolio will be rebalanced each month. The last strategy is based on a buy/hold spread. Novy-Marx and Velikov (2016) describe a 10%-20% buy/hold spread as a rule whereby a trader buys stocks when they enter the top decile of the stock selection signal, and holds these stocks until they fall out of the top quintile. Similarly, a trader sells stocks when they enter the bottom decile, and cover these short positions when they fall out of the bottom quintile. Both the staggered partial rebalancing and the buy/hold spread reduce turnover significantly and yield similar transaction cost reductions.

In Table 10, we report the average alphas obtained with a staggered 3-month rebalancing with a third of the portfolios rebalanced each month. We use our benchmark unconditional and conditional Hasbrouck (2009) models and report the gross and net returns for the equally-weighted and value-weighted portfolios. The reduced turnover does not change our main conclusions about the profitable strategies. The alphas for the anomalies SUE, SG and PRICE remain positive and significant for the value-weighted portfolios, but SG is not significant for the equally-weighted portfolios while it was with more frequent trading. Also its alpha is reduced with less rebalancing. Two anomalies become profitable with ROME providing a significant 1.1% monthly for both types of portfolios with the conditional model, and ROBE a 0.3% for equally-weighted portfolios. We also confirm the robustness of the results with the VIX and the tail risk measure as well as with the Lesmond et al. (1999) model for the less frequent rebalancing in the online appendix.

8 Conclusion

We have proposed extensions to the two main models used to compute transaction costs from daily returns on individual securities, the effective bid-ask spread model of Hasbrouck (2009) and the asymmetric bid-ask spread of Lesmond et al. (1999). We introduced measures of financial risk in the estimation of these costs and showed how they can increase considerably in crisis times, whether these large shocks result from tight funding conditions, investors' fears signaled by the VIX or extreme events captured by tail risk. The estimation results are telling. Transaction costs feature large jumps at event times for portfolios built on firm size, realized volatility or momentum, but increase for many other firm characteristics. Our analysis also confirms the technological downward trend in transaction costs over the last 35 years or so, measures precisely how firm characteristics such as size and volatility affect the magnitude of the trading costs at a high frequency, and provides evidence about the flight-to-quality behavior that occurs in hard market times. Finally, the profitable long-short strategies that the academic literature has put forward based on some firm characteristics become either non-profitable or losing propositions. Over the many anomalies considered, only three related to unexpected earnings, sales growth and price per share yield a significant positive profit. The dynamic analysis of time-varying alphas with transaction costs shows that all anomaly-based strategies alternate periods of positive and negative performance, which questions the validity of using the average alpha as a measure of profitability.

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A Simulation Procedure

A.1 Simulating the Coefficients in a Linear Regression

The standard Bayesian normal regression model is $y = Xb + e$ where y is a column vector of n observations of the dependent variable, X is an $(n \times k)$ matrix of fixed regressors, b is a vector of coefficients, and the residuals are zero-mean multivariate normal $e \sim N(0, \Omega_e)$. Given Ω_e and a normal prior on b, $b \sim N(\mu_b, \Omega_b)$, the posterior is $b \sim N(\mu_b^*, \Omega_b^*)$, where $\mu_b^* = (X'\Omega_e^{-1}X + \Omega_b^{-1})^{-1}(X'\Omega_e^{-1}y + \Omega_b^{-1}\mu_b)$ and $\Omega_b^* = (X'\Omega_e^{-1}X + \Omega_b^{-1})^{-1}$.

In our framework, the linear regression we have is $\Delta p_t^i = c_0^i.\Delta q_t^i + c_1^i \cdot FR_t \cdot \Delta q_t^i + \beta_m^i r_{mt} + \varepsilon_t^i$. Non-negativity is imposed on c_0^i and c_1^i in order to keep the transaction cost $c_t = c_0^i + c_1 \cdot FR_t$ positive, since any of the financial risk measures considered is positive.

A.2 Simulating the Error Covariance Matrix

We also make the same assumption for $\Omega_e = \sigma^2 I$ than Hasbrouck (2009). The prior distribution for σ^2 is an inverted gamma distribution: $\sigma^2 \sim IG(\alpha, \beta)$. The posterior distribution will also be an inverted gamma $\sigma^2 \sim IG(\alpha^*, \beta^*)$, where $\alpha^* = \alpha + \frac{n}{2}$ and $\beta^* = [\beta^{-1} + \sum \frac{e_i}{2}]^{-1}$.

A.3 Simulating the Trade Direction Indicators

The remaining step in the sampler involves drawing $q = q_1, ..., q_T$ when c_0, c_1, β_m, and σ^2 are known. The procedure is the same as the one used in Hasbrouck (2009). The procedure is sequential. The first draw is $q_1/q_2, ..., q_T$, the second draw is $q_2/q_1, q_3, q_4, ..., q_T$, the third draw is $q_3/q_1, q_2, q_4, ..., q_T$, etc., where the "/" stands for the conditional draw.

A.4 Steps of the sampling procedure

For the sampler, we follow the steps and simulation parameter choices used in Hasbrouck (2009).

- Step 0 (initialization). Although the limiting behavior of the sampler is invariant to starting values, "reasonable" initial guesses may hasten convergence. The trade direction indicators q_t that do not correspond to midpoint reports are set to the sign of the most recent price change, with q_1 set (arbitrarily) to +1 and those corresponding to midpoint reports are set to 0; σ_ε^2 is initially set to 0.0004[37]. No initial values are required for c_0, c_1 and β_m, as they are drawn first.

- Step 1. Based on the most recently simulated values for σ_ε^2 and the set of q_t, compute the posterior for the regression coefficients (c_0, c_1 and β_m) and make a new draw.

[37]This roughly corresponds to a 30% annual idiosyncratic volatility

- Step 2. Given c_0, c_1 and β_m, and the set of q_t, compute the implied ε_t, update the posterior for σ_ε^2, and make a new draw.

- Step 3. Given c_0, c_1, β_m and σ_ε^2 , make draws for $q_1, q_2, ..., q_T$. q_t that correspond to midpoint reports are not drawn and are equal to 0. Go to Step 1.

Each sampler is run for 1,000 sweeps[38]. Of the 1,000 draws for each parameter, the first 200 are discarded to burn in the sampler by removing the effect of starting values. The average of the remaining 800 draws (an estimate of the posterior mean) is used as a point estimate of the parameter.

A.5 The Bayes factor

The Bayes factor is the ratio of the marginal likelihoods of both models. Let $M_{1,i,y}$ and $M_{2,i,y}$ denote the marginal likelihoods of the Hasbouck model and the extended model, respectively, and D the data set. For a firm i and a year y, the ratio can be written as:

$$BF_{i,y} = \frac{P(M_{2,i,y}/D)}{P(M_{1,i,y}/D)} = \frac{P(M_{2,i,y}).P(D/M_{2,i,y})}{P(M_{1,i,y}).P(D/M_{1,i,y})} \tag{20}$$

Once again, the presence of the latent variable q_t complicates the computation of the marginal likelihoods. For this purpose, we use the reciprocal importance sampling of Gelfand and Dey (1994).

Let the prior density of Θ_k (assumed to be proper) be given by $\pi(\Theta_k/M_{k,i,y})$ and let $\Theta_k^{(m)} = \{\Theta_k^{(1)}, ..., \Theta_k^{(M)}\}$ be M draws from the posterior density $\pi(\Theta_k/D, M_{k,i,y})$ obtained using a Gibbs sampler. Gelfand and Dey (1994) show that

$$\widehat{m}_{GD,k} = \left\{ \frac{1}{S} \sum_{s=1}^{S} \left(\frac{p(\Theta_k^{(s)})}{f(\Theta_k/D, M_{k,i,y}).\pi(\Theta_k/M_{k,i,y})} \right) \right\}^{-1}, \tag{21}$$

converges to $m(D/M_{k,i,y})$.

Therefore, we compute the Bayes factor with the following formula:

$$BF_{i,y} = \frac{\widehat{m}(D/M_{2,i,y})}{\widehat{m}(D/M_{1,i,y})}. \tag{22}$$

By referring to Jeffreys (1998), there is strong evidence for $M_{2,i,y}$ against $M_{1,i,y}$ if $BF_{i,y} > 10^{\frac{3}{2}}$.

We report the ratio of firms for which the funding liquidity model is preferred to the base model according to this criterion.

[38] We ran the estimation with 5,000 and 10,000 sweeps and obtained similar results.

B Maximum likelihood estimation of Lesmond et al. (1999) model with funding liquidity

Given the normality assumption about ϵ_{jt}, the log-likelihood can be written as:

$$\begin{aligned}\log L(\alpha_{01j}, \alpha_{1j}, \alpha_{02j}, \alpha_{2j}, \beta_j, \sigma_j | R_{jt}, R_{mt}) = \sum_{R_1} \ln \frac{1}{(2\pi\sigma_j^2)^{1/2}} + \\ \sum_{1} \frac{1}{2\sigma_j^2}(R_{jt} + \alpha_{1FLjt} - \beta_j R_{mt})^2 + \\ \sum_{R_2} \ln \frac{1}{(2\pi\sigma_j^2)^{1/2}} + \\ \sum_{2} \frac{1}{2\sigma_j^2}(R_{jt} + \alpha_{2FLjt} - \beta_j R_{mt})^2 + \\ \sum_{R_0} \ln \left(\left[N\left(\frac{\alpha_{2FLjt} - \beta_j R_{mt}}{\sigma_j}\right) - N\left(\frac{\alpha_{1FLjt} - \beta_j R_{mt}}{\sigma_j}\right) \right] \right),\end{aligned} \tag{23}$$

The parameters $\alpha_{01j}, \alpha_{1j}, \alpha_{02j}, \alpha_{2j}, \beta_j$ and σ_j are obtained by maximizing the log-likelihood function in equation (23) in the appendix. The roundtrip transaction cost is given by $\alpha_{2FLjt} - \alpha_{1FLjt}$.

A key element in this model is how to define the three regions R_0, R_1 and R_2. The region R_0 is the set of days where we have zero returns. In the original paper of Lesmond et al. (1999), R_1 and R_2 are defined based on R_m, the market return. So R_1 is the set of days where R_m is negative and R_2 is the set of days where R_m is positive. However, Goyenko et al. (2009), who is concerned with market liquidity of individual securities, defines R_1 and R_2 based on R_j, the daily return of firm j. So R_1 is the set of days where R_j is negative and R_2 is the set of days where R_j is positive. This is the procedure we follow to measure the transaction costs of individual securities.

We complete the analysis by adding a likelihood ratio test to assess whether the model with time-varying transaction costs is preferred to the fixed-cost model. This amount to the following test:

$$\begin{aligned} H_0 &: \alpha_{01j} = 0 \;\text{ and }\; \alpha_{02j} = 0 \\ H_1 &: \alpha_{01j} \neq 0 \;\text{ or }\; \alpha_{02j} \neq 0 \end{aligned} \tag{24}$$

The likelihood ratio statistic is given by:

$$LR = -2(l_1 - l_0) \tag{25}$$

$$LR \sim \chi(2)$$

where l_0 is the logarithm of the likelihood of the LOT model without funding liquidity and l_1 is the logarithm of the likelihood of the LOT model with funding liquidity.

C Tables

Table 1: **The anomalies**

Column 1 list the anomalies while Column 2 provides the corresponding references. Column 3 reports the signal used for sorting. The last two columns indicate the frequency of rebalancing and the time-period used (01/1986 - 06/2018). Each anomaly is coloured according to the categories identified in **?**: Momentum, Value-versus-growth, Investment, Profitability, Trading Frictions. See the appendix and/or the references for further details on the construction of the anomalies.

Anomaly	**References**	**Signal**	**Rebalanced**	**Period**
Size	Fama and French (1993)	Market Equity	Annualy	01/1986 - 06/2018
Realized Volatility	Ang et al. (2006)	Standard Deviation of the daily returns over a year	Annualy	01/1986 - 06/2018
Investment to capital	Xing (2007)	Investment to Capital	Annualy	01/1986 - 06/2018
Investment Growth	Xing (2007)	Investment Growth	Annualy	01/1986 - 06/2018
Net Operating Asset	Hirshleifer et al. (2004)	Net Operating Asset	Annualy	01/1986 - 06/2018
Asset Growth	Cooper et al. (2008)	Asset Growth	Annualy	01/1986 - 06/2018
Investment to Asset	Chen et al. (2011)	Investment to Asset	Annualy	01/1986 - 06/2018
Leverage	Bhandari (1988)	Total assets to Market value of Equity	Annualy	01/1986 - 06/2018
Return on Asset	Chen et al. (2011)	Return on Asset	Annualy	01/1986 - 06/2018
Gross Profitability	Novy-Marx (2013)	Gross Profitability	Annualy	01/1986 - 06/2018
Gross Margins	Novy-Marx (2013)	Gross Margins	Annualy	01/1986 - 06/2018
Piotroski's F-score	Piotroski (2001)	Piotroski's F-score	Annualy	01/1986 - 06/2018
Asset Turnover	Soliman (2008)	Sales to total assets	Annualy	01/1986 - 06/2018
Sales to Price	Barbee Jr et al. (1996)	Sales to Price	Annualy	01/1986 - 06/2018
Accruals	Sloan (1996)	Accruals	Annualy	01/1986 - 06/2018
Growth in LT NOA	Fairfield et al. (2003)	Growth in Long term net operating assets	Annualy	01/1986 - 06/2018
Share issuance (annual)	Pontiff and Woodgate (2008)	Change in real number of shares outstanding over a year	Annualy	01/1986 - 06/2018
Standardized Unexpected Earnings	Foster et al. (1984)	Standardized Unexpected Earnings	Monthly	01/1986 - 06/2018
Return on Market Equity	Chen et al. (2011)	Return on Market Equity	Monthly	01/1986 - 06/2018
Return on Book Equity	Chen et al. (2011)	Return on Book Equity	Monthly	01/1986 - 06/2018
Sales Growth	Lakonishok et al. (1994)	Sales Growth	Monthly	01/1986 - 06/2018
Industry momentum	Moskowitz and Grinblatt (1999)	Industry past month's return	Monthly	01/1986 - 06/2018
Composite Issuance	Daniel and Titman (2006)		Monthly	01/1986 - 06/2018
Momentum 6months	Jegadeesh and Titman (1993b)	Prior 6-m stock return skipping the most recent month	Monthly	01/1986 - 06/2018
Momentum 11 months	Jegadeesh and Titman (1993b)	Prior year stock return skipping the most recent month	Monthly	01/1986 - 06/2018
Long-term reversal	De Bondt and Thaler (1985)	Cumulative returns from over the past 5 year by skipping the most recent year	Monthly	01/1986 - 06/2018
Short-term reversal	Jegadeesh (1990)	Return in the previous month	Monthly	01/1986 - 06/2018
Seasonality	Heston and Sadka (2008)	Average monthly return in the same calendar month over the last 5 years.	Monthly	01/1986 - 06/2018
Momentum Reversal	Jegadeesh and Titman (1993b)	Buy and hold returns.	Monthly	01/1986 - 06/2018
Share issuance (monthly)	Pontiff and Woodgate (2008)	Change in real number of shares outstanding over a month	Monthly	01/1986 - 06/2018
Industry Relative Reversal	Da et al. (2013)	Difference between prior month return of a stock and of its industry	Monthly	01/1986 - 06/2018
Price	Blume and Husic (1973)	Log of stock price	Monthly	01/1986 - 06/2018
Share Volume	Datar et al. (1998)	Average number of shares traded over the previous three months scaled by shares outstanding.	Monthly	01/1986 - 06/2018

Table 2: **Summary statistics of the effective spread estimators**

The H-Model costs are based on a year-by-year analysis for the period January 1986 to June 2018. Estimations are done using daily returns and daily equally-weighted market index returns following the transaction cost model of Hasbrouck (2009). The EDGE effective spread is computed with the efficient estimator developed by Ardia et al. (2024a) using daily prices from the CRSP U.S. Stock database. The skewness and kurtosis coefficients are robust measures proposed by Hinkley (1975) and Crow and Siddiqui (1967) (see section 4.1).

	H-Model	**EDGE**
Period	Jun 1992 - Jun 2018	Jun 1992 - Jun 2018
Moments		
Mean	0.02657	0.02660
Standard deviation	0.02683	0.04211
Skewness ($SK_{(0.1)}$)	0.47770	0.65346
Kurtosis (KR)	4.16763	5.19762
Quantiles		
Q(5%)	0.00409	0.00224
Q(10%)	0.00594	0.00329
Q(25%)	0.01035	0.00612
Q(50%)	0.01881	0.01340
Q(75%)	0.03373	0.03099
Q(90%)	0.05523	0.06164
Q(95%)	0.07452	0.09148

Table 3: **Means and correlations of size deciles**

The HASB-Model costs are based on a year-by-year analysis for the period January 1986 to June 2018. Estimations are done using daily returns and daily equally-weighted market index returns following the transaction cost model of Hasbrouck (2009). The EDGE effective spread is computed with the efficient estimator developed by Ardia et al. (2024a) using daily prices from the CRSP U.S. Stock database. Effective spread HJ is computed with respect to the quoted midpoint as described in Holden and Jacobsen (2014). This measure is precomputed by WRDS Intraday Indicators using the Monthly TAQ database in the period 1993-2003, and Daily TAQ onwards.

DEC	nb stock-months	HASB Mean	EDGE Mean	HJ Mean	Corr EDGE-HASB	Corr HJ-HASB
1	177629	0.0569	0.0724	0.0560	0.7702	0.7895
2	191274	0.0386	0.0432	0.0370	0.7341	0.7202
3	192120	0.0305	0.0320	0.0262	0.7300	0.6785
4	187493	0.0253	0.0245	0.0185	0.7240	0.6664
5	180456	0.0223	0.0201	0.0137	0.6789	0.6295
6	172828	0.0202	0.0170	0.0104	0.6645	0.6028
7	163023	0.0183	0.0143	0.0076	0.6257	0.5678
8	153152	0.0164	0.0117	0.0055	0.5714	0.5299
9	144077	0.0144	0.0094	0.0038	0.5181	0.5471
10	137831	0.0125	0.0074	0.0022	0.5272	0.5532

Table 4: **Average HASB, EDGE and HJ transaction costs for anomaly-based decile portfolios**

Panel A: Average EDGE and HASB transaction costs. The results are based on a year-by-year analysis for the period January 1986 to June 2018. For each anomaly, we rank firms by using data on characteristics from CRSP and COMPUSTAT. HASB estimations are done using daily returns and daily equally-weighted market index returns following the transaction cost model of Hasbrouck (2009). The EDGE effective spread is computed with the efficient estimator developed by Ardia et al. (2024a) using daily prices from the CRSP U.S. Stock database.

Anomalies rebalanced annually					**Anomalies rebalanced monthly**				
Anomaly	Bid-Ask	D1	D5	D10	Anomaly	Bid-Ask	D1	D5	D10
SIZE	HASB	0.057	0.022	0.013	SUE	HASB	0.030	0.030	0.028
	EDGE	0.072	0.020	0.007		EDGE	0.030	0.030	0.027
REALVOL	HASB	0.007	0.019	0.073	ROME	HASB	0.014	0.010	0.011
	EDGE	0.006	0.018	0.081		EDGE	0.009	0.007	0.008
IK	HASB	0.040	0.027	0.035	ROBE	HASB	0.033	0.026	0.034
	EDGE	0.044	0.026	0.033		EDGE	0.034	0.025	0.035
IG	HASB	0.041	0.026	0.036	SG	HASB	0.039	0.024	0.036
	EDGE	0.043	0.024	0.037		EDGE	0.040	0.024	0.035
NOA	HASB	0.046	0.029	0.013	INDMOM1	HASB	0.031	0.026	0.031
	EDGE	0.048	0.029	0.008		EDGE	0.030	0.027	0.030
AG	HASB	0.046	0.023	0.031	INDMOM6	HASB	0.031	0.026	0.031
	EDGE	0.047	0.023	0.029		EDGE	0.030	0.027	0.030
IA	HASB	0.044	0.029	0.030	CISS	HASB	0.017	0.021	0.036
	EDGE	0.046	0.027	0.028		EDGE	0.016	0.020	0.034
LEV	HASB	0.022	0.018	0.024	MOM11	HASB	0.053	0.020	0.029
	EDGE	0.017	0.015	0.024		EDGE	0.057	0.020	0.024
ROAA	HASB	0.050	0.021	0.027	MOM6	HASB	0.050	0.021	0.032
	EDGE	0.051	0.023	0.025		EDGE	0.054	0.021	0.027
GPROF	HASB	0.043	0.027	0.033	LTREV	HASB	0.048	0.018	0.022
	EDGE	0.040	0.025	0.032		EDGE	0.051	0.018	0.019
GMARGINS	HASB	0.043	0.027	0.030	STREV	HASB	0.046	0.022	0.037
	EDGE	0.042	0.026	0.028		EDGE	0.049	0.022	0.034
FSCORE	HASB	0.045	0.024	0.023	SEASON	HASB	0.040	0.019	0.031
	EDGE	0.046	0.023	0.022		EDGE	0.040	0.019	0.030
ATURNOVER	HASB	0.037	0.029	0.033	MOMREV	HASB	0.047	0.021	0.031
	EDGE	0.036	0.027	0.033		EDGE	0.048	0.021	0.029
SP	HASB	0.029	0.016	0.028	NISSM	HASB	0.032	0.026	0.028
	EDGE	0.024	0.013	0.025		EDGE	0.030	0.025	0.028
ACC	HASB	0.043	0.025	0.034	INDRREV	HASB	0.046	0.021	0.037
	EDGE	0.045	0.023	0.033		EDGE	0.049	0.021	0.035
GLTNOA	HASB	0.025	0.038	0.015	PRICE	HASB	0.061	0.019	0.014
	EDGE	0.021	0.041	0.010		EDGE	0.068	0.017	0.009
NISSA	HASB	0.024	0.025	0.026	SHVOL	HASB	0.032	0.026	0.034
	EDGE	0.025	0.025	0.025		EDGE	0.041	0.026	0.025

Panel B: Average HJ and HASB transaction costs. The results are based on a year-by-year analysis for the period January 1986 to June 2018. For each anomaly, we rank firms by using data on characteristics from CRSP and COMPUSTAT. HASB estimations are done using daily returns and daily equally-weighted market index returns following the transaction cost model of Hasbrouck (2009). The HJ effective spread is a high-frequency benchmark effective spread from the trade and quote (TAQ) database according to the methodology developed by Holden and Jacobsen (2014).

Anomalies rebalanced annually					**Anomalies rebalanced monthly**				
Anomaly	Bid-Ask	D1	D5	D10	Anomaly	Bid-Ask	D1	D5	D10
SIZE	HASB	0.052	0.022	0.013	SUE	HASB	0.027	0.027	0.025
	HJ	0.056	0.014	0.002		HJ	0.019	0.019	0.017
REALVOL	HASB	0.007	0.018	0.066	ROME	HASB	0.014	0.009	0.010
	HJ	0.006	0.012	0.051		HJ	0.002	0.002	0.001
IK	HASB	0.036	0.024	0.033	ROBE	HASB	0.030	0.024	0.031
	HJ	0.031	0.016	0.021		HJ	0.023	0.017	0.023
IG	HASB	0.039	0.023	0.032	SG	HASB	0.035	0.022	0.032
	HJ	0.031	0.014	0.025		HJ	0.026	0.016	0.022
NOA	HASB	0.043	0.027	0.013	INDMOM1	HASB	0.027	0.024	0.028
	HJ	0.033	0.021	0.003		HJ	0.019	0.020	0.019
AG	HASB	0.042	0.022	0.028	INDMOM6	HASB	0.027	0.024	0.028
	HJ	0.031	0.016	0.018		HJ	0.018	0.020	0.019
IA	HASB	0.039	0.026	0.027	CISS	HASB	0.016	0.019	0.032
	HJ	0.030	0.017	0.016		HJ	0.012	0.012	0.019
LEV	HASB	0.021	0.017	0.023	MOM11	HASB	0.048	0.019	0.027
	HJ	0.006	0.007	0.020		HJ	0.035	0.015	0.014
ROAA	HASB	0.047	0.020	0.024	MOM6	HASB	0.045	0.019	0.029
	HJ	0.033	0.018	0.015		HJ	0.033	0.015	0.016
GPROF	HASB	0.040	0.025	0.030	LTREV	HASB	0.044	0.017	0.020
	HJ	0.026	0.015	0.021		HJ	0.034	0.012	0.010
GMARGINS	HASB	0.039	0.024	0.027	STREV	HASB	0.041	0.020	0.033
	HJ	0.027	0.017	0.017		HJ	0.030	0.016	0.021
FSCORE	HASB	0.042	0.022	0.021	SEASON	HASB	0.036	0.018	0.028
	HJ	0.032	0.016	0.013		HJ	0.026	0.013	0.018
ATURNOVER	HASB	0.033	0.026	0.029	MOMREV	HASB	0.042	0.019	0.028
	HJ	0.022	0.016	0.022		HJ	0.030	0.015	0.017
SP	HASB	0.028	0.016	0.026	NISSM	HASB	0.029	0.024	0.024
	HJ	0.011	0.005	0.015		HJ	0.017	0.016	0.019
ACC	HASB	0.039	0.022	0.031	INDRREV	HASB	0.041	0.020	0.033
	HJ	0.029	0.014	0.021		HJ	0.030	0.015	0.021
GLTNOA	HASB	0.023	0.036	0.015	PRICE	HASB	0.057	0.019	0.014
	HJ	0.011	0.030	0.004		HJ	0.048	0.012	0.004
NISSA	HASB	0.022	0.023	0.025	SHVOL	HASB	0.030	0.023	0.032
	HJ	0.017	0.018	0.015		HJ	0.039	0.016	0.013

Table 5: **FLH-Model: Transaction costs and flight to quality**

The table features the average absolute change and the average change in percentage between the transaction costs estimated with the Hasbrouck (2009) model with funding liquidity (FLH model) and the Hasbrouck model (HASB model). For the two anomalies, size and volatility, we report the changes in the ten decile portfolios. We also compute the average parameter c_1 per portfolio since this parameter measures the sensitivity of the portfolio transaction cost to funding liquidity. We perform an ANOVA to test the difference of all these values across the deciles.

	Size			Volatility		
	Absolute change	Change in percentage	Parameter c_1	Absolute change	Change in percentage	Parameter c_1
Dec1	0.0046	09.01	0.5250	0.0026	39.27	0.2647
Dec2	0.0045	11.22	0.5407	0.0030	32.94	0.3377
Dec3	0.0044	13.55	0.5253	0.0034	29.28	0.3905
Dec4	0.0041	15.45	0.4945	0.0038	25.46	0.4345
Dec5	0.0041	17.32	0.4842	0.0041	22.93	0.4712
Dec6	0.0039	18.82	0.4613	0.0043	20.17	0.4998
Dec7	0.0037	20.65	0.4388	0.0044	16.95	0.5268
Dec8	0.0036	22.26	0.4242	0.0046	14.18	0.5604
Dec9	0.0034	24.52	0.4061	0.0046	10.66	0.5685
Dec10	0.0032	26.99	0.3887	0.0041	05.42	0.5205
Number of periods	390 months	390 months	33 years	395 months	395 months	33 years
Anova: F stat	56.87***	6.97***	5.21***	139.67***	14.34***	12.57***
Anova: DF Columns	9	9	9	9	9	9
Anova: DF Errors	3890	3890	320	3940	3940	320

Table 6: **Alphas (in %) of anomaly portfolios with HASB-Model and FLH-Model transaction costs (January 1986 to June 2018)**

The performance of a strategy is measured by its *alpha*, that is the intercept in the regression $R_{it} - R_{ft} = \alpha_i + \beta_1.(R_{Mt} - R_{ft}) + \beta_2.SMB_t + \beta_3.HML_t + \epsilon_{it}$, where R_{it} is the total return of the strategy portfolio i, R_{ft} is the risk-free rate of return measured by the T-bill rate, R_{Mt} is the total market portfolio return, $R_{it} - R_{ft}$ is the excess return of the strategy, $R_{Mt} - R_{ft}$ is the excess return on the market portfolio, SMB_t is the size premium (small minus big), HML_t is the value premium (high minus low), all evaluated in month t, and β_1, β_2, and β_3 denote the factor loadings of the strategy portfolio. Fore each strategy, we report α_i (in %) and its t-statistic.

Anomaly		Equally-weighted			Value-weighted		
		Gross return	HASB-model net return	FLH-model net return	Gross return	HASB-model net return	FLH-model net return
SUE	α	3.0429	1.9444	1.7146	1.1181	0.3872	0.1807
	$t-stat$	27.8092	15.7584	12.9469	7.6592	2.4791	1.1135
ROME	α	0.2988	-0.6853	-0.8661	0.8183	0.0321	-0.1691
	$t-stat$	0.7799	-1.7388	-2.1686	1.4221	0.0533	-0.2756
ROBE	α	0.8432	-0.1509	-0.3309	0.0845	-0.5574	-0.7180
	$t-stat$	4.1602	-0.7168	-1.5468	0.3603	-2.3063	-2.9362
SG	α	1.4407	0.5268	0.3583	1.4648	0.8657	0.7157
	$t-stat$	10.4910	3.6879	2.4579	7.4527	4.3332	3.5429
INDMOM1	α	1.2684	-3.0480	-3.8462	0.5641	-1.8249	-2.4166
	$t-stat$	4.4448	-10.0521	-12.3486	1.7272	-5.5706	-7.3439
INDMOM6	α	1.1726	-1.0556	-1.4536	0.3938	-0.9612	-1.2842
	$t-stat$	3.7934	-3.3922	-4.6355	1.0736	-2.6261	-3.5005
CISS	α	0.4092	-0.4070	-0.5719	0.2801	-0.4450	-0.6328
	$t-stat$	4.9883	-4.6310	-6.3972	2.1340	-3.2953	-4.6417
MOM11	α	-0.0784	-1.3999	-1.6475	0.4310	-0.7529	-1.0215
	$t-stat$	-0.2800	-4.9549	-5.8052	1.2193	-2.1146	-2.8566
MOM6	α	0.1057	-1.6113	-1.9313	0.3347	-1.1923	-1.5408
	$t-stat$	0.3794	-5.7579	-6.8719	0.9681	-3.4551	-4.4527
LTREV	α	0.3181	-0.3412	-0.4748	-0.0529	-0.6229	-0.7625
	$t-stat$	2.3504	-2.5527	-3.5380	-0.2656	-3.1494	-3.8506
STREV	α	0.4677	-3.3072	-3.9839	-0.2248	-3.2189	-3.8953
	$t-stat$	1.7769	-12.2311	-14.5932	-0.7275	-10.2461	-12.3139
SEASON	α	-0.1319	-3.2248	-3.8483	-0.0598	-2.6371	-3.2484
	$t-stat$	-1.2505	-27.2181	-30.9268	-0.3346	-13.9815	-16.8011
MOMREV	α	0.3136	-1.3101	-1.6197	0.1474	-1.3249	-1.6708
	$t-stat$	1.9837	-8.3211	-10.2042	0.6585	-5.9604	-7.4936
NISSM	α	-0.0344	-0.5709	-0.6874	-0.1250	-0.5195	-0.6306
	$t-stat$	-0.3434	-5.5879	-6.6577	-0.9395	-3.8807	-4.6932
INDRREV	α	1.2512	-2.9456	-3.6816	0.4091	-3.0286	-3.7645
	$t-stat$	4.2219	-9.8829	-12.3193	1.3746	-10.1313	-12.4965
PRICE	α	2.0986	1.1822	1.0345	2.0756	1.2320	1.0910
	$t-stat$	10.1228	5.8066	5.1080	9.2761	5.4725	4.8346
SHVOL	α	0.3056	-0.5455	-0.7094	0.5373	0.0250	-0.0915
	$t-stat$	1.6986	-2.9263	-3.7617	2.6121	0.1234	-0.4530

Table 7: **Time-varying Alphas (in %) of anomaly portfolios with HASB-Model and FLH-Model transaction costs**

The time-varying alphas are computed according to the nonparametric method of Ang and Kristensen (2012) described in section 6.3. The HASB net returns are computed with the Hasbrouck (2009) unconditional model while the FLH net returns are based on the conditional version of the model with the TED spread.

[1]: Number of significant $\alpha > 0$

[2]: Number of non significant α

[3]: Number of significant $\alpha < 0$

Level of significance: 5%

	Gross returns			HASB net returns			FLH net returns			Gross returns			HASB net returns			FLH net returns		
	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]	[1]	[2]	[3]
	EQUALLY-WEIGHTED PORTFOLIO									VALUE-WEIGHTED PORTFOLIO								
SUE	349	46	7	296	95	11	244	131	27	168	184	50	166	187	49	120	200	82
ROME	140	83	179	131	85	186	118	75	209	168	85	149	162	86	154	143	80	179
ROBE	216	50	136	207	46	149	175	51	176	207	45	150	199	50	153	175	44	183
SG	179	195	28	175	186	41	123	214	65	167	197	38	168	192	42	126	217	59
INDMOM1	73	286	43	8	203	191	6	153	243	48	295	59	17	269	116	10	235	157
INDMOM6	40	336	26	22	297	83	14	256	132	11	336	55	10	309	83	8	277	117
CISS	176	134	92	156	122	124	90	118	194	152	152	98	140	147	115	97	132	173
MOM11	30	322	50	19	291	92	7	249	146	31	335	36	24	324	54	14	312	76
MOM6	21	335	46	15	261	126	7	210	185	19	343	40	8	304	90	7	265	130
LTREV	126	219	57	114	233	55	64	224	114	98	197	107	94	200	108	74	191	137
STREV	24	375	3	1	241	160	0	191	211	23	376	3	5	299	98	6	222	174
SEASON	88	212	102	5	80	317	2	37	363	89	229	84	23	165	214	15	106	281
MOMREV	98	278	26	30	279	93	13	214	175	49	309	44	18	298	86	8	262	132
NISSM	130	151	121	136	140	126	78	140	184	142	142	118	148	149	105	91	154	157
INDRREV	166	202	34	44	174	184	31	146	225	144	192	66	39	204	159	20	172	210
PRICE	171	216	15	140	246	16	85	278	39	159	228	15	134	247	21	89	267	46
SHVOL	123	191	88	115	175	112	83	168	151	124	208	70	126	212	64	87	219	96

Table 8: **Average LOT selling and buying transaction costs for anomaly-based decile portfolios**

The results are based on a year-by-year analysis for the period January 1986 to June 2018. For each anomaly, we rank firms by using data on characteristics from CRSP and COMPUSTAT. For each anomaly and each firm, we estimate the parameters $\hat{\alpha}_{01j}, \hat{\alpha}_{1j}, \hat{\alpha}_{02j}$, and $\hat{\alpha}_{2j}$ by using daily returns and daily equally-weighted market index returns. The selling transaction cost is given by $\alpha_{1\hat{F}Lj} = \hat{\alpha}_{01j} + \hat{\alpha}_{1j} * FL$ and the buying one by $\alpha_{2\hat{F}Lj} = \hat{\alpha}_{02j} + \hat{\alpha}_{2j} * TED$. Pr is the proportion of firm-years for which the likelihood ratio test $H_0 : \alpha_{01j} = 0, \alpha_{02j} = 0$ versus $H_1 : \alpha_{01j} \neq 0, \alpha_{02j}$ rejects the constrained LOT model without liquidity.

Anomalies rebalanced annually					**Anomalies rebalanced monthly**				
Anomaly	T-cost	D1	D5	D10	Anomaly	T-cost	D1	D5	D10
SIZE	α_1	-0.098	-0.024	-0.014	SUE	α_1	-0.032	-0.034	-0.032
	α_2	0.087	0.022	0.013		α_2	0.029	0.031	0.028
	α_{1FL}	-0.101	-0.025	-0.014		α_{1FL}	-0.033	-0.035	-0.033
	α_{2FL}	0.088	0.022	0.013		α_{2FL}	0.030	0.031	0.029
	Pr	0.280	0.286	0.262		Pr	0.287	0.267	0.254
REALVOL	α_1	-0.011	-0.024	-0.097	ROME	α_1	-0.017	-0.010	-0.012
	α_2	0.011	0.022	0.081		α_2	0.016	0.010	0.012
	α_{1FL}	-0.012	-0.025	-0.121		α_{1FL}	-0.021	-0.010	-0.012
	α_{2FL}	0.012	0.023	0.098		α_{2FL}	0.016	0.010	0.011
	Pr	0.265	0.255	0.312		Pr	0.489	0.341	0.446
IK	α_1	-0.065	-0.029	-0.042	ROBE	α_1	-0.040	-0.030	-0.040
	α_2	0.057	0.026	0.038		α_2	0.036	0.027	0.036
	α_{1FL}	-0.067	-0.029	-0.043		α_{1FL}	-0.041	-0.030	-0.041
	α_{2FL}	0.058	0.026	0.038		α_{2FL}	0.036	0.027	0.036
	Pr	0.289	0.264	0.263		Pr	0.281	0.264	0.275
IG	α_1	-0.058	-0.028	-0.044	SG	α_1	-0.051	-0.026	-0.044
	α_2	0.051	0.025	0.039		α_2	0.045	0.024	0.039
	α_{1FL}	-0.060	-0.028	-0.044		α_{1FL}	-0.052	-0.026	-0.045
	α_{2FL}	0.052	0.025	0.039		α_{2FL}	0.045	0.024	0.039
	Pr	0.282	0.263	0.271		Pr	0.278	0.266	0.270
NOA	α_1	-0.071	-0.032	-0.014	INDMOM1	α_1	-0.023	-0.016	-0.025
	α_2	0.062	0.029	0.014		α_2	0.021	0.015	0.023
	α_{1FL}	-0.073	-0.033	-0.014		α_{1FL}	-0.023	-0.016	-0.026
	α_{2FL}	0.064	0.029	0.014		α_{2FL}	0.022	0.015	0.023
	Pr	0.267	0.268	0.277		Pr	0.269	0.272	0.258
AG	α_1	-0.060	-0.028	-0.036	INDMOM6	α_1	-0.022	-0.016	-0.027
	α_2	0.051	0.025	0.031		α_2	0.020	0.015	0.025
	α_{1FL}	-0.061	-0.028	-0.036		α_{1FL}	-0.022	-0.017	-0.028
	α_{2FL}	0.053	0.026	0.032		α_{2FL}	0.021	0.016	0.026
	Pr	0.288	0.267	0.265		Pr	0.305	0.279	0.230
IA	α_1	-0.061	-0.033	-0.036	CISS	α_1	-0.021	-0.024	-0.043
	α_2	0.053	0.030	0.033		α_2	0.019	0.022	0.038
	α_{1FL}	-0.063	-0.033	-0.037		α_{1FL}	-0.021	-0.024	-0.044
	α_{2FL}	0.055	0.030	0.033		α_{2FL}	0.020	0.022	0.039
	Pr	0.283	0.257	0.272		Pr	0.280	0.258	0.278
LEV	α_1	-0.025	-0.018	-0.024	MOM11	α_1	-0.074	-0.023	-0.032
	α_2	0.022	0.017	0.022		α_2	0.063	0.021	0.028
	α_{1FL}	-0.025	-0.019	-0.025		α_{1FL}	-0.077	-0.023	-0.032
	α_{2FL}	0.022	0.017	0.023		α_{2FL}	0.065	0.021	0.028
	Pr	0.288	0.300	0.371		Pr	0.305	0.279	0.257
ROAA	α_1	-0.068	-0.025	-0.029	MOM6	α_1	-0.069	-0.024	-0.037
	α_2	0.058	0.023	0.026		α_2	0.060	0.022	0.032
	α_{1FL}	-0.070	-0.025	-0.029		α_{1FL}	-0.073	-0.024	-0.037
	α_{2FL}	0.060	0.023	0.027		α_{2FL}	0.062	0.022	0.032
	Pr	0.288	0.276	0.246		Pr	0.305	0.280	0.262
GPROF	α_1	-0.054	-0.030	-0.034	LTREV	α_1	-0.072	-0.020	-0.021
	α_2	0.047	0.027	0.030		α_2	0.062	0.019	0.020
	α_{1FL}	-0.055	-0.030	-0.035		α_{1FL}	-0.074	-0.020	-0.022
	α_{2FL}	0.047	0.027	0.031		α_{2FL}	0.064	0.019	0.020
	Pr	0.280	0.265	0.252		Pr	0.279	0.268	0.259
GMARGINS	α_1	-0.057	-0.030	-0.039	STREV	α_1	-0.058	-0.030	-0.044
	α_2	0.049	0.027	0.035		α_2	0.050	0.028	0.038
	α_{1FL}	-0.058	-0.031	-0.040		α_{1FL}	-0.060	-0.030	-0.045
	α_{2FL}	0.050	0.028	0.036		α_{2FL}	0.051	0.028	0.038
	Pr	0.285	0.261	0.259		Pr	0.295	0.277	0.267
FSCORE	α_1	-0.050	-0.030	-0.028	SEASON	α_1	-0.053	-0.022	-0.036
	α_2	0.044	0.026	0.026		α_2	0.047	0.020	0.032
	α_{1FL}	-0.051	-0.030	-0.029		α_{1FL}	-0.055	-0.022	-0.037
	α_{2FL}	0.044	0.027	0.026		α_{2FL}	0.048	0.020	0.033
	Pr	0.283	0.256	0.254		Pr	0.270	0.269	0.262
ATURNOVER	α_1	-0.055	-0.033	-0.036	MOMREV	α_1	-0.067	-0.024	-0.036
	α_2	0.049	0.029	0.032		α_2	0.058	0.022	0.032
	α_{1FL}	-0.057	-0.033	-0.037		α_{1FL}	-0.069	-0.024	-0.036
	α_{2FL}	0.050	0.030	0.034		α_{2FL}	0.059	0.022	0.033
	Pr	0.292	0.257	0.260		Pr	0.281	0.278	0.267
SP	α_1	-0.032	-0.017	-0.029	NISSM	α_1	-0.033	-0.029	-0.029
	α_2	0.027	0.016	0.026		α_2	0.029	0.026	0.026
	α_{1FL}	-0.033	-0.017	-0.029		α_{1FL}	-0.034	-0.029	-0.030
	α_{2FL}	0.027	0.016	0.026		α_{2FL}	0.030	0.026	0.026
	Pr	0.325	0.304	0.335		Pr	0.290	0.267	0.273
ACC	α_1	-0.059	-0.028	-0.040	INDRREV	α_1	-0.058	-0.026	-0.045
	α_2	0.050	0.026	0.035		α_2	0.050	0.024	0.039
	α_{1FL}	-0.060	-0.029	-0.041		α_{1FL}	-0.060	-0.026	-0.045
	α_{2FL}	0.052	0.026	0.035		α_{2FL}	0.051	0.024	0.039
	Pr	0.281	0.263	0.267		Pr	0.293	0.278	0.267
GLTNOA	α_1	-0.026	-0.053	-0.016	PRICE	α_1	-0.058	-0.019	-0.013
	α_2	0.023	0.047	0.016		α_2	0.047	0.018	0.012
	α_{1FL}	-0.027	-0.054	-0.017		α_{1FL}	-0.060	-0.019	-0.013
	α_{2FL}	0.024	0.047	0.016		α_{2FL}	0.048	0.018	0.012
	Pr	0.271	0.267	0.271		Pr	0.303	0.277	0.261
NISSA	α_1	-0.030	-0.043	-0.032	SHVOL	α_1	-0.064	-0.027	-0.030
	α_2	0.027	0.039	0.029		α_2	0.060	0.024	0.026
	α_{1FL}	-0.030	-0.043	-0.032		α_{1FL}	-0.066	-0.027	-0.030
	α_{2FL}	0.027	0.039	0.028		α_{2FL}	0.060	0.024	0.027
	Pr	0.274	0.289	0.289		Pr	0.274	0.273	0.276

Table 9: **Alphas (in %) of anomaly portfolios with LOT-Model and LOT-Model plus funding liquidity (FLLOT-Model) transaction costs (January 1986 to June 2018)**

The performance of a strategy is measured by its *alpha*, that is the intercept in the regression $R_{it} - R_{ft} = \alpha_i + \beta_1.(R_{Mt} - R_{ft}) + \beta_2.SMB_t + \beta_3.HML_t + \epsilon_{it}$, where R_{it} is the total return of the strategy portfolio i, R_{ft} is the risk-free rate of return measured by the T-bill rate, R_{Mt} is the total market portfolio return, $R_{it} - R_{ft}$ is the excess return of the strategy, $R_{Mt} - R_{ft}$ is the excess return on the market portfolio, SMB_t is the size premium (small minus big), HML_t is the value premium (high minus low), all evaluated in month t, and β_1, β_2, and β_3 denote the factor loadings of the strategy portfolio. Fore each strategy, we report α_i (in %) and its t-statistic.

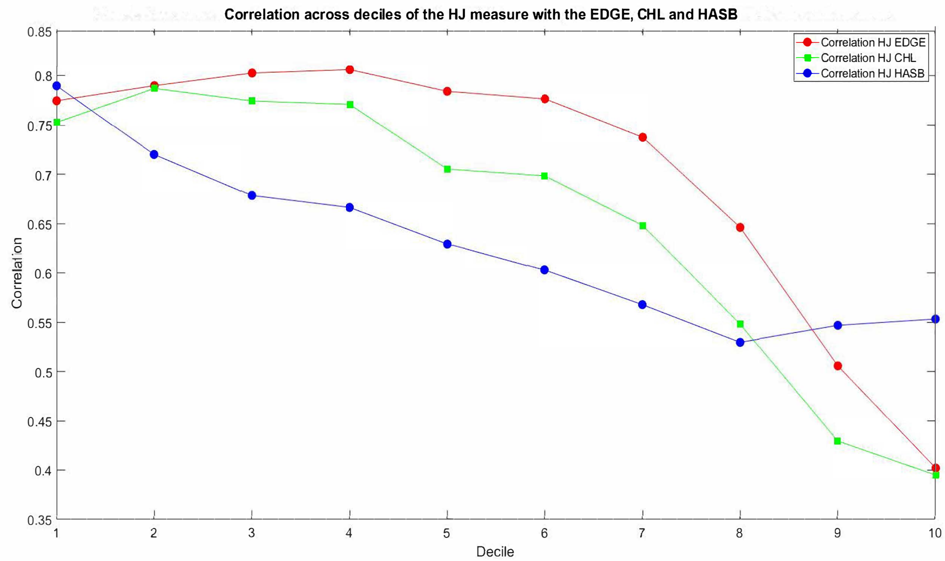
Anomaly		Equally-weighted			Value-weighted		
		Gross return	LOT-model net return	FLLOT-model net return	Gross return	LOT-model net return	FLLOT-model net return
SUE	α	3.0429	1.0293	0.9821	1.1181	-0.3345	-0.3818
	$t-stat$	27.8092	6.1486	5.8061	7.6592	-1.8222	-2.0497
ROME	α	0.2988	-1.5812	-1.6486	0.8183	-0.7742	-0.8420
	$t-stat$	0.7799	-3.7478	-3.8514	1.4221	-1.1967	-1.2586
ROBE	α	0.8432	-0.8617	-0.8961	0.0845	-1.0948	-1.1243
	$t-stat$	4.1602	-3.8032	-3.9305	0.3603	-4.2824	-4.3721
SG	α	1.4407	-0.1260	-0.1552	1.4648	0.3622	0.3279
	$t-stat$	10.4910	-0.7750	-0.9473	7.4527	1.7169	1.5404
INDMOM1	α	1.2684	-5.2200	-5.2408	0.5641	-4.2542	-4.2989
	$t-stat$	4.4448	-17.4114	-17.5093	1.7272	-12.7267	-12.8269
INDMOM6	α	1.1726	-1.9934	-2.0028	0.3938	-2.1225	-2.1420
	$t-stat$	3.7934	-6.3062	-6.3580	1.0736	-5.7435	-5.7974
CISS	α	0.4092	-1.0816	-1.0980	0.2801	-1.0556	-1.0706
	$t-stat$	4.9883	-11.6226	-11.6957	2.1340	-7.6054	-7.6978
MOM11	α	-0.0784	-2.5157	-2.5401	0.4310	-1.7691	-1.7938
	$t-stat$	-0.2800	-8.7737	-8.7786	1.2193	-4.9264	-4.9446
MOM6	α	0.1057	-3.0991	-3.1270	0.3347	-2.5603	-2.5867
	$t-stat$	0.3794	-10.9318	-10.9066	0.9681	-7.3806	-7.3841
LTREV	α	0.3181	-0.8849	-0.8955	-0.0529	-1.0697	-1.0764
	$t-stat$	2.3504	-6.6654	-6.7417	-0.2656	-5.4190	-5.4615
STREV	α	0.4677	-6.7958	-6.8669	-0.2248	-6.2993	-6.3765
	$t-stat$	1.7769	-23.9176	-24.4480	-0.7275	-19.2769	-19.6371
SEASON	α	-0.1319	-6.1803	-6.2230	-0.0598	-5.3181	-5.3562
	$t-stat$	-1.2505	-44.6477	-44.2184	-0.3346	-25.7069	-25.4611
MOMREV	α	0.3136	-2.7322	-2.7485	0.1474	-2.6463	-2.6586
	$t-stat$	1.9837	-17.1033	-17.1736	0.6585	-11.8432	-11.9281
NISSM	α	-0.0344	-0.9623	-0.9727	-0.1250	-0.8375	-0.8503
	$t-stat$	-0.3434	-9.3128	-9.3482	-0.9395	-6.1879	-6.2838
INDRREV	α	1.2512	-6.6137	-6.7103	0.4091	-6.5284	-6.6464
	$t-stat$	4.2219	-21.2125	-21.8664	1.3746	-21.0006	-21.7787
PRICE	α	2.0986	0.5282	0.4914	2.0756	0.5628	0.5194
	$t-stat$	10.1228	2.6009	2.4114	9.2761	2.4594	2.2509
SHVOL	α	0.3056	-1.1474	-1.1589	0.5373	-0.3560	-0.3668
	$t-stat$	1.6986	-6.0086	-6.0294	2.6121	-1.7723	-1.8326

Table 10: **Alphas (in %) of "staggered partial rebalancing" anomaly portfolios with HASB-Model and FLH-Model transaction costs (January 1986 to June 2018).**

The "staggered partial rebalancing" strategy entails rebalancing only a fraction of the portfolio at each rebalancing point. The portfolio is rebalanced at a relatively low frequency, with the rebalancing applied to only a portion of the portfolio at a higher frequency (e.g., quarterly rebalancing, but on only one-third of the portfolio each month). The performance of a strategy is measured by its *alpha*, that is the intercept in the regression $R_{it} - R_{ft} = \alpha_i + \beta_1.(R_{Mt} - R_{ft}) + \beta_2.SMB_t + \beta_3.HML_t + \epsilon_{it}$, where R_{it} is the total return of the strategy portfolio i, R_{ft} is the risk-free rate of return measured by the T-bill rate, R_{Mt} is the total market portfolio return, $R_{it} - R_{ft}$ is the excess return of the strategy, $R_{Mt} - R_{ft}$ is the excess return on the market portfolio, SMB_t is the size premium (small minus big), HML_t is the value premium (high minus low), all evaluated in month t, and β_1, β_2, and β_3 denote the factor loadings of the strategy portfolio. Fore each strategy, we report α_i (in %) and its t-statistic.

Anomaly		Equally-weighted			Value-weighted		
		Gross return	HASB-model net return	FLH-model net return	Gross return	HASB-model net return	FLH-model net return
SUE	α	2.5939	1.9453	1.8191	1.0599	0.6588	0.5495
	$t-stat$	24.9961	18.7192	17.3896	8.8133	5.3849	4.4692
ROME	α	1.8917	1.2803	1.1718	1.6371	1.2142	1.1094
	$t-stat$	6.4554	4.3839	3.9777	3.8582	2.8655	2.6131
ROBE	α	1.3654	0.4847	0.3444	0.2869	-0.2406	-0.3637
	$t-stat$	8.6854	3.0806	2.1855	1.5271	-1.2611	-1.8995
SG	α	1.1079	0.3277	0.1920	1.1414	0.6820	0.5627
	$t-stat$	9.2426	2.6872	1.5675	5.9288	3.5072	2.8947
INDMOM1	α	0.1871	-0.4926	-0.6202	0.0462	-0.3738	-0.4838
	$t-stat$	0.7597	-1.9740	-2.4817	0.1570	-1.2576	-1.6264
INDMOM6	α	0.2692	-0.4243	-0.5525	0.5092	0.1001	-0.0125
	$t-stat$	0.9861	-1.5311	-1.9883	1.5109	0.2934	-0.0366
CISS	α	0.1692	-0.4320	-0.5527	-0.0389	-0.4629	-0.5763
	$t-stat$	2.1761	-5.2828	-6.7082	-0.2880	-3.3541	-4.1622
MOM11	α	-0.0471	-0.8256	-0.9628	0.4599	-0.0696	-0.1890
	$t-stat$	-0.2031	-3.5008	-4.0773	1.6500	-0.2466	-0.6685
MOM6	α	0.2365	-0.5377	-0.6753	0.5458	0.0234	-0.0991
	$t-stat$	0.9762	-2.1865	-2.7420	1.8485	0.0783	-0.3316
LTREV	α	0.0360	-0.5844	-0.7140	-0.2564	-0.7004	-0.8184
	$t-stat$	0.2817	-4.5371	-5.5224	-1.2867	-3.4770	-4.0630
STREV	α	-0.1117	-0.9122	-1.0492	-0.3214	-0.8500	-0.9695
	$t-stat$	-0.6189	-4.9221	-5.6470	-1.2903	-3.3614	-3.8348
SEASON	α	-0.2319	-0.8477	-0.9728	-0.3334	-0.8124	-0.9234
	$t-stat$	-2.8182	-10.0136	-11.3982	-2.2037	-5.2667	-5.9775
MOMREV	α	0.1065	-0.6132	-0.7460	0.2008	-0.3162	-0.4392
	$t-stat$	0.8378	-4.8079	-5.8445	0.9749	-1.5288	-2.1265
NISSM	α	0.0811	-0.5334	-0.6558	-0.1915	-0.5894	-0.6950
	$t-stat$	0.8588	-5.4857	-6.6793	-1.5283	-4.6211	-5.4347
INDRREV	α	-0.1215	-0.9657	-1.1067	-0.2890	-0.8886	-1.0141
	$t-stat$	-0.7081	-5.4631	-6.2468	-1.3249	-4.0326	-4.6062
PRICE	α	2.3287	1.6033	1.4693	2.8927	2.3141	2.1879
	$t-stat$	14.1792	9.8178	8.9931	12.6929	10.1274	9.6101
SHVOL	α	0.4303	-0.2827	-0.4152	0.6084	0.1173	0.0019
	$t-stat$	2.7197	-1.7208	-2.5082	3.0721	0.5886	0.0098

D Figures



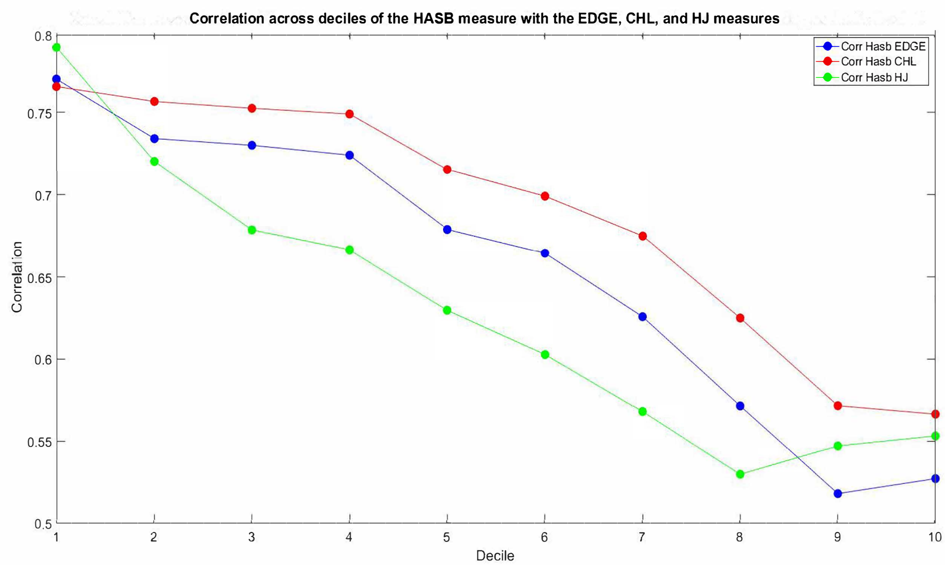
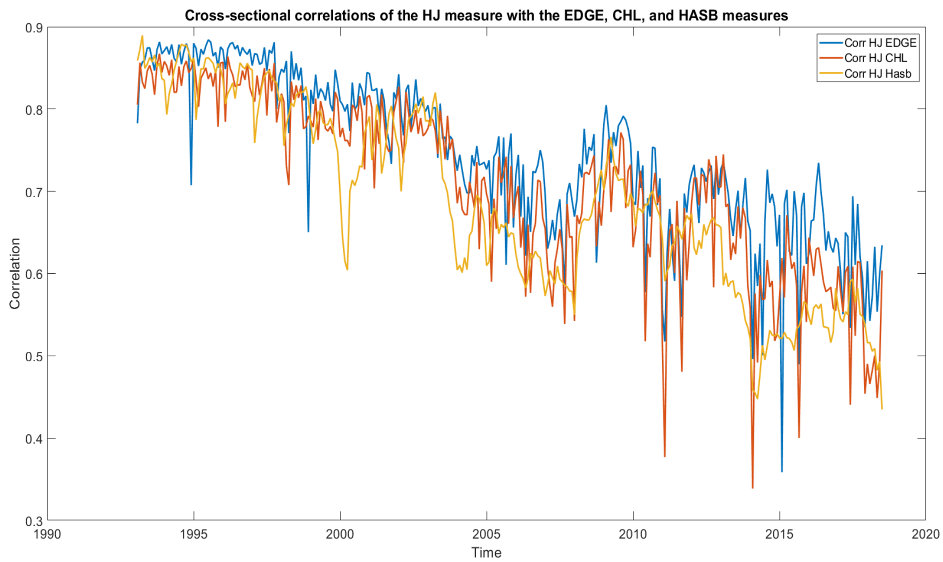


Figure 2: **Correlations of size deciles**



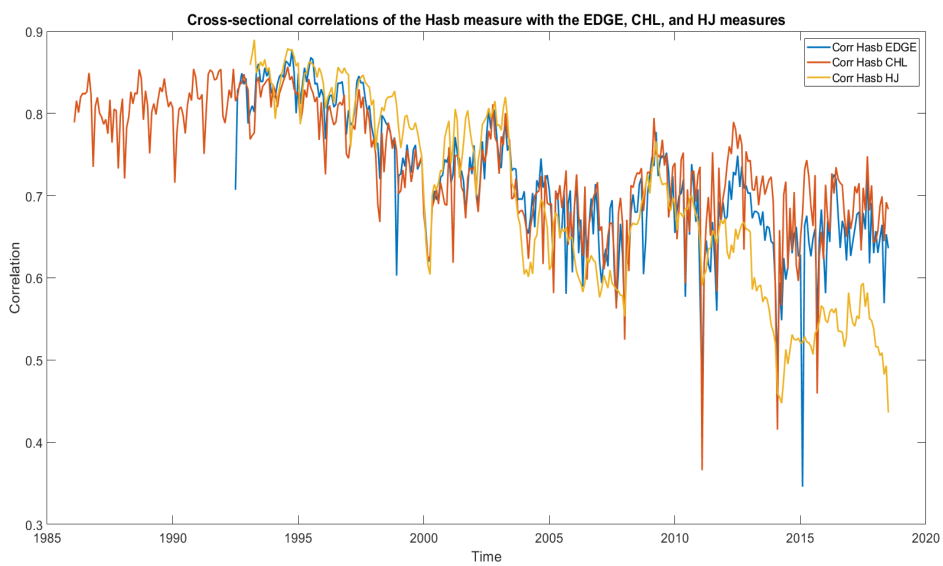


Figure 3: **Time series correlations**

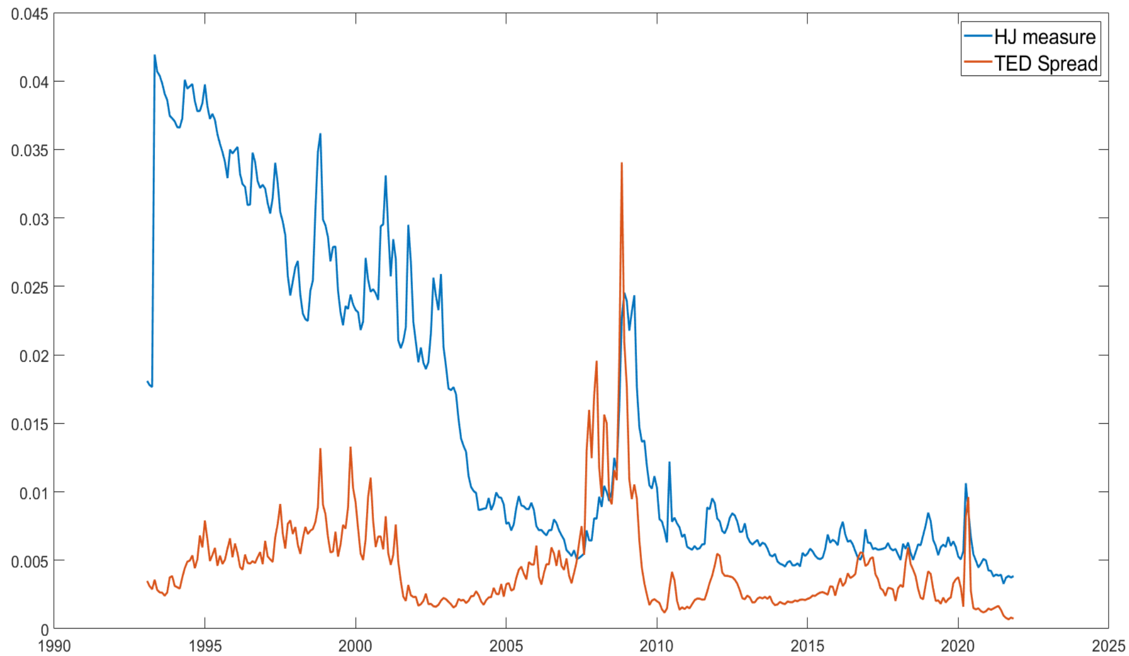


Figure 4: **Time-series of the benchmark HJ and the TED spread**

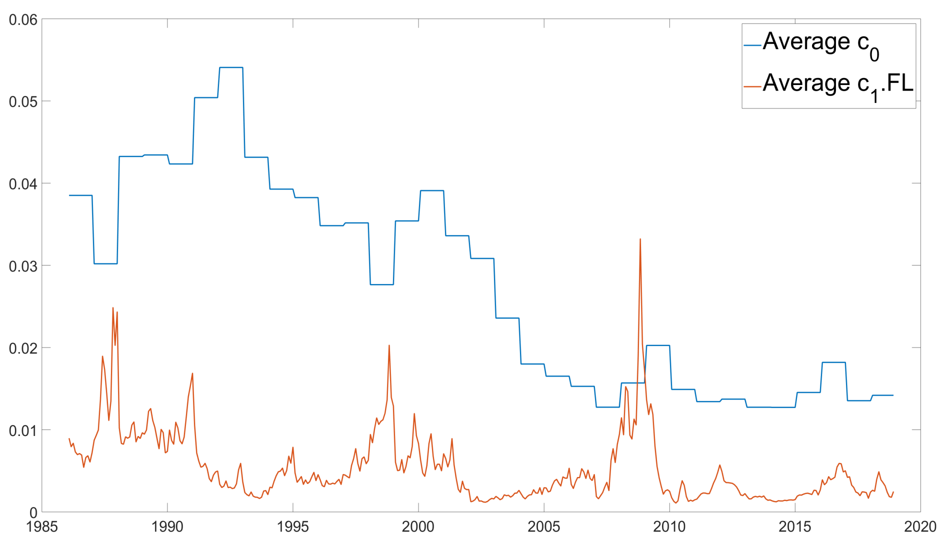
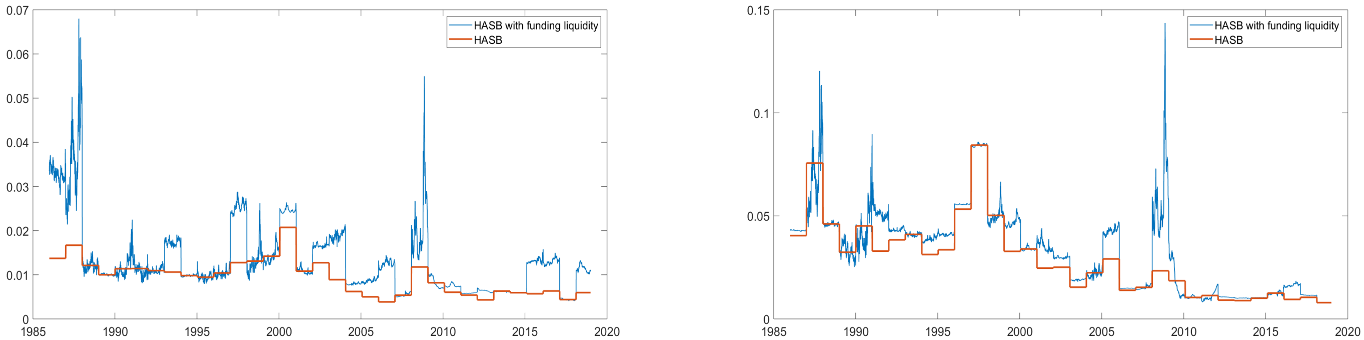
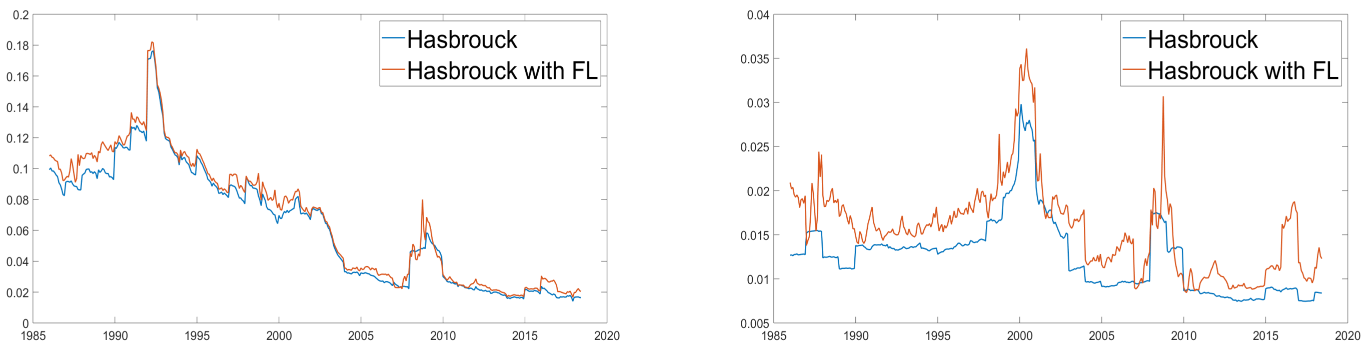


Figure 5: **Separating the transaction cost into its fixed component and its time-varying TED-spread component**



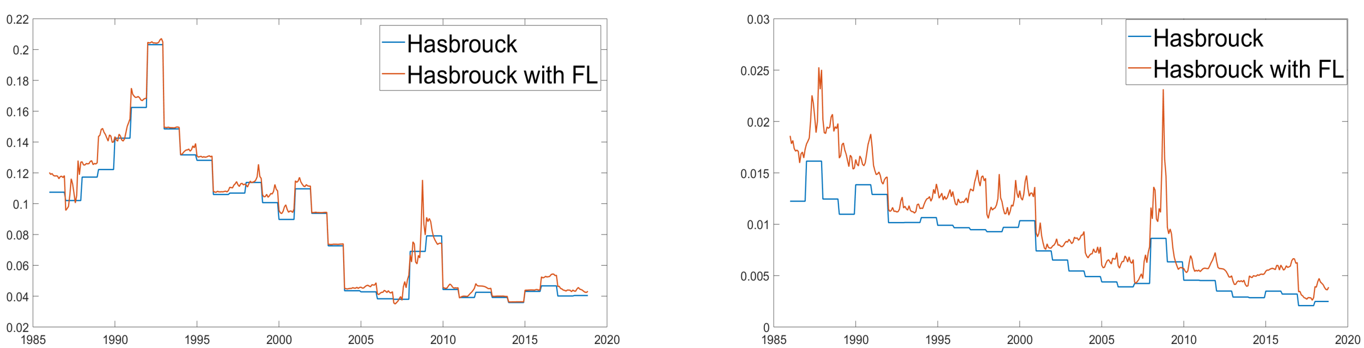
(a) COCA COLA CO (b) ROCKY MOUNTAIN CHOCOLATE FACTORY

Figure 6: **Dynamics of transaction costs for individual stocks**



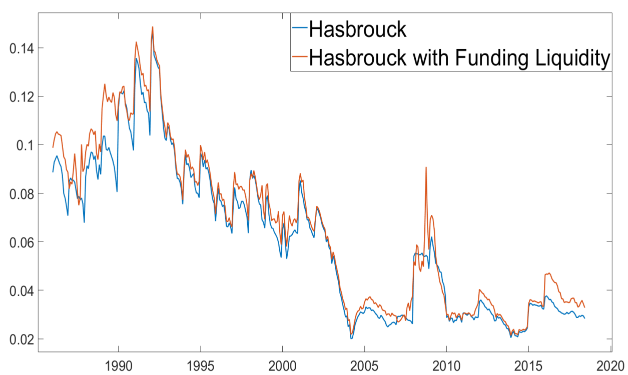
(a) Small firms (b) Large firms

Figure 7: **Dynamics of transaction costs for small and large firms**

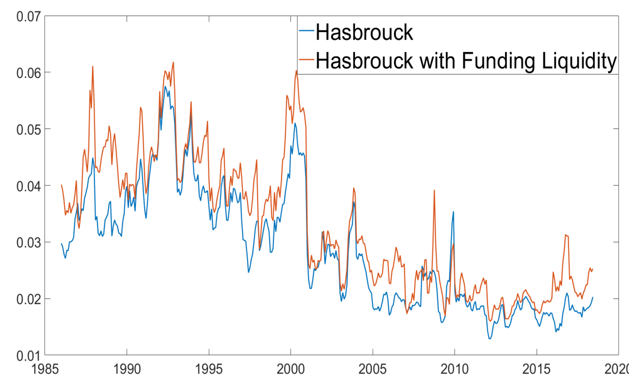


(a) High-volatility firms (b) Low-volatility firms

Figure 8: **Dynamics of transaction costs for high- and low-volatility firms**

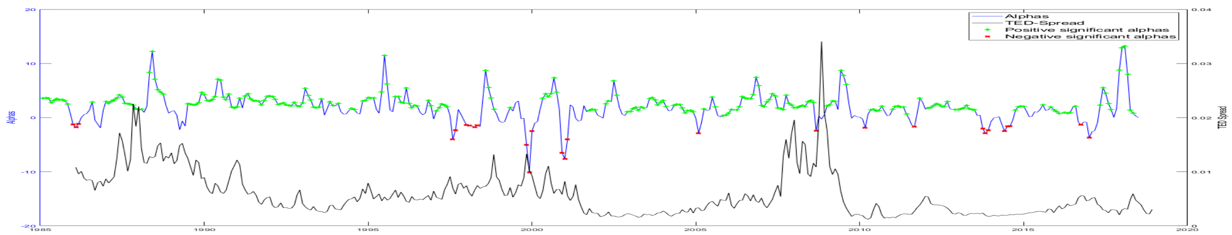


(a) Loser firms

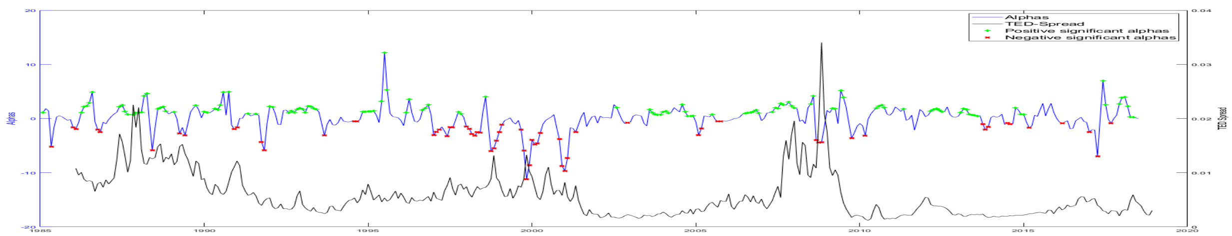


(b) Winner firms

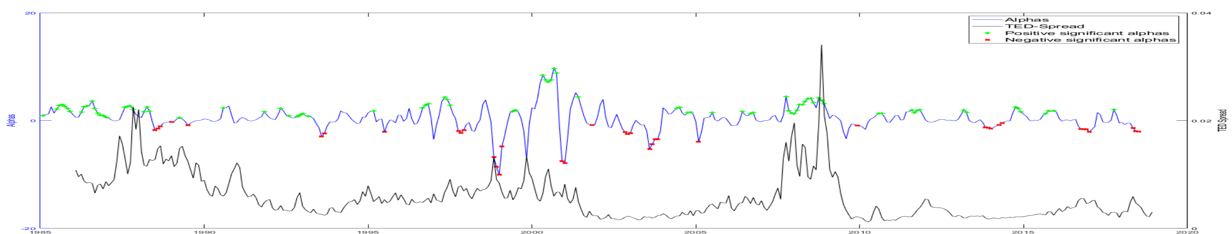
Figure 9: **Dynamics of transaction costs for Momentum strategies**



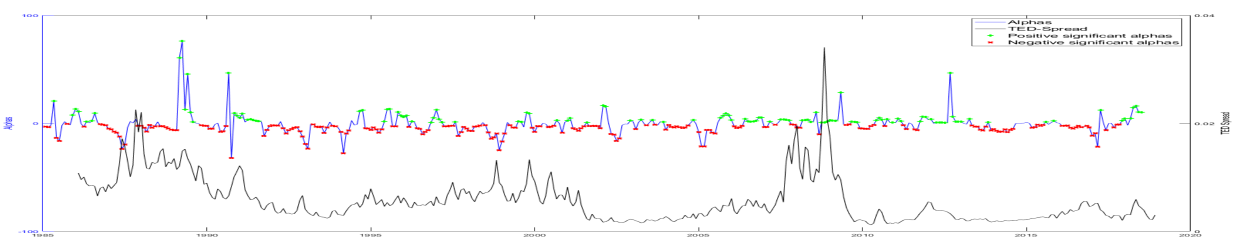
(a) SUE



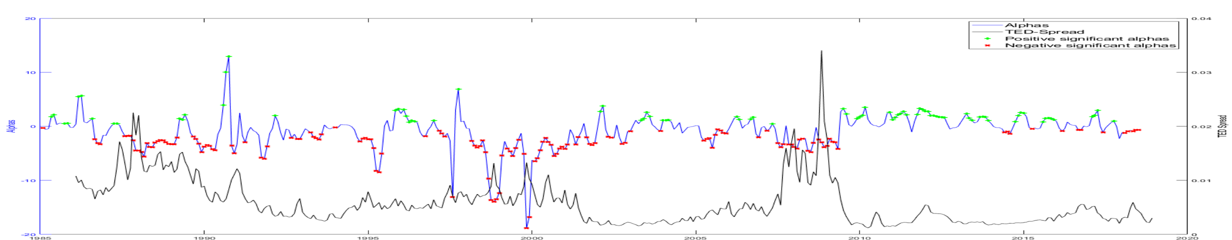
(b) SG



(c) PRICE

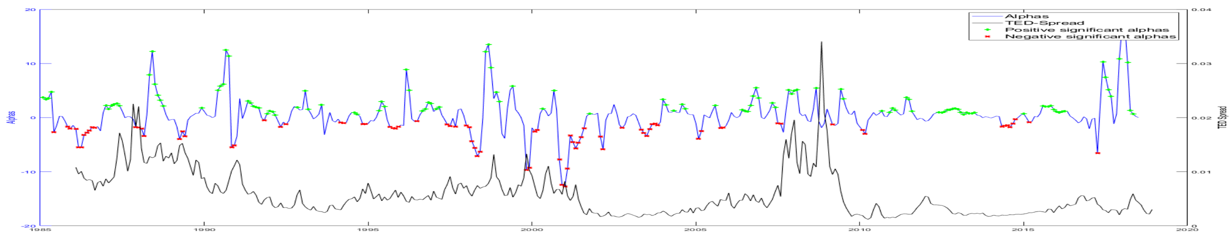


(d) ROME

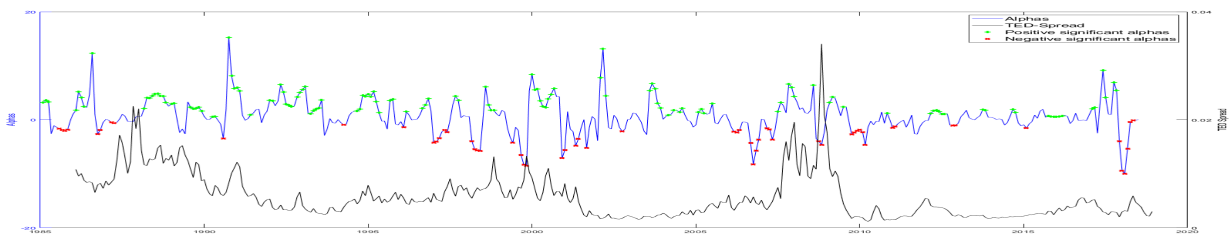


(e) SHVOL

Figure 10: **Time-varying alphas for equally-weighted portfolios**



(a) SUE



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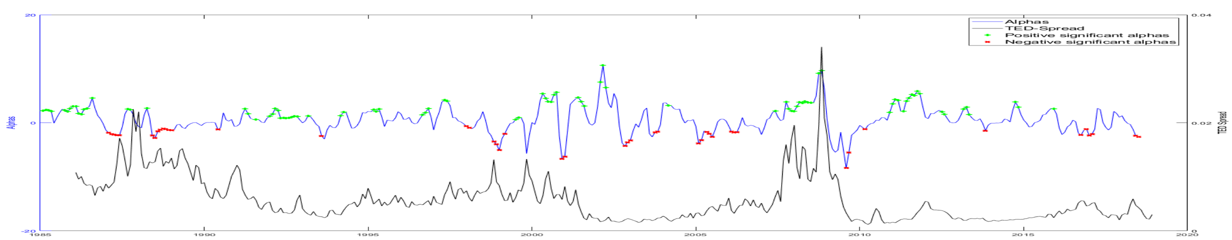
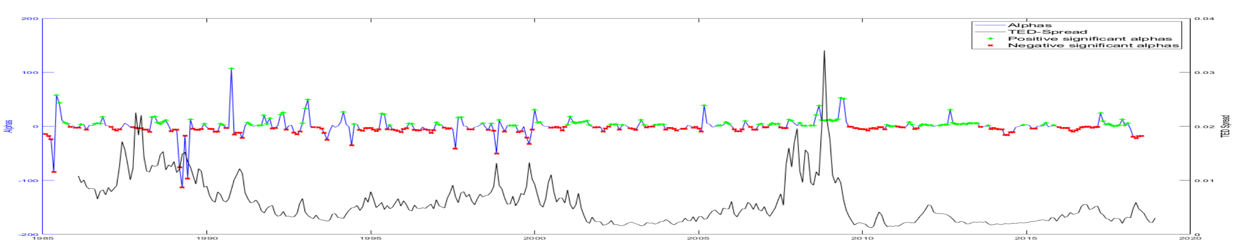
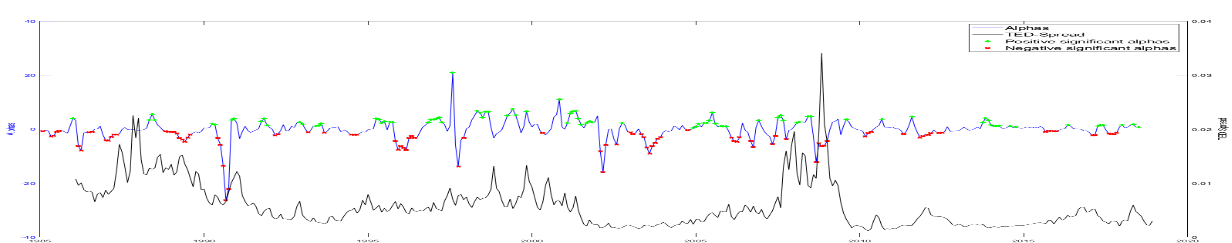


(c) PRICE



(d) ROME



(e) SHVOL

Figure 11: **Time-varying alphas for value-weighted portfolios**