Trading Frequency and Asset Pricing on the London Stock Exchange: Evidence from a New Price Impact Ratio

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1. Introduction

As recent events in financial markets have demonstrated, illiquidity appears to be one of the most important market frictions that influence asset prices. Despite the considerable attention that this issue has attracted during the past two decades, it remains an elusive concept (Amihud (2002), Pastor and Stambaugh (2003)).[1] This has led to the emergence of a vast literature proposing a series of measures for particular aspects of illiquidity (e.g. trading costs, trading quantity, trading speed and price impact). These measures include the bid-ask spread (Amihud and Mendelson (1986a)), relative spread (Amihud and Mendelson (1986b), Loderer and Roth (2005)), effective spread (Lee (1993), Heflin and Shaw (2000)), amortized spread (Chalmers and Kadlec (1998)), Kyle's lambda (Kyle (1985), Brennan and Subrahmanyam (1996)), trading volume (Brennan, Chordia and Subrahmanyam (1998)), turnover rate (Datar, Naik and Radcliffe (1998), Chordia, Subrahmanyam, Anshuman (2001)), number of zero-return days (Bekaert, Harvey and Lundblad (2005)) and price sensitivity to order flow (Pastor and Stambaugh (2003)).[2]

The most commonly used measure in the recent empirical literature is the price impact ratio of Amihud (2002), which is defined as the average monthly ratio of daily absolute returns to daily trading volume in monetary terms (henceforth, *RtoV*) (see e.g. Acharya and Pedersen (2005), Korajczyk and Sadka (2008), Goyenko and Ukhov (2009)). This measure is appealing because it is easy to compute for long time periods given the wide availability of returns and trading volume data. In addition, it is intuitively attractive because the average

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[1] For example, the seminal theoretical studies of Constantinides (1986), Heaton and Lucas (1996) and Vayanos (1998) address the impact of transaction costs on asset prices. Jacoby, Fowler and Gottesman (2000) develop a liquidity adjusted CAPM, where systematic and liquidity risk are inseparable, and find that the true measure of systematic risk when considering liquidity costs is based on net (after bid-ask spread) returns. More recently, Lo, Mamaysky and Wang (2004) propose a dynamic equilibrium model of asset prices and trading volume where agents face fixed transaction costs. They show that even small fixed costs can give rise to large "no-trade" regions for each agent's optimal trading policy. Liu (2004) re-affirms the findings of Lo et al. (2004) in the presence multiple risky assets. On the empirical side, research in asset pricing has shown that liquidity risk generates substantial higher cost of capital for the least liquid stocks (see Amihud, 2002, Pastor and Stambaugh (2003), Acharya and Pedersen (2005) among others).
[2] O' Hara (2003) and Amihud, Medelson and Pedersen (2005) provide a comprehensive review of the literature on illiquidity and asset pricing.

daily price response associated with a dollar of trading volume renders it a good proxy for the theoretically founded Kyle's price impact coefficient (Hasbrouck (2005), and Goyenko, Holden and Trzcinka (2009)).

Despite its popularity, Amihud's price impact ratio is not free of limitations. In the cross-sectional dimension, *RtoV* ratio builds in a size effect because trading volume in monetary terms is by construction positively correlated with market capitalization and, as a result, it is by no means comparable across stocks with different market values. This shortcoming has been firstly highlighted by Cochrane (2005a), who argues that the *RtoV* ratio is expected to be much higher for small capitalization stocks, forcing the conclusion that small capitalization stocks are more illiquid than big capitalization stocks. Another important limitation of *RtoV* is that it neglects the trading frequency dimension of liquidity; this may be inappropriate given that actual stocks' trading frequency exhibits considerable time-series as well as cross-sectional variation (Datar et al. (1998)).

This study contributes to the literature by proposing an alternative, more appropriate, price impact ratio defined as the average monthly ratio of daily absolute stock return to its turnover ratio (henceforth *RtoTR*), essentially replacing the trading volume of a stock with its turnover ratio in the denominator of Amihud's ratio. Given that information on turnover ratios is easily accessible in the public domain, the proposed measure inherits the simplicity and data availability that characterizes Amihud's ratio, while it is free of any size bias. This is because turnover does not necessarily exhibit an inherent size-related pattern (Brown, Crocker, Foerster (2009)). Therefore, the proposed measure is more suitable to insulate the price impact from the size effect.

More importantly, the *RtoTR* ratio is not just a methodological contribution. Using turnover rates to calculate price impact ratios helps control not only for the importance of trading costs but also for that of trading frequency on asset pricing. The role of trading frequency, which can be effectively approximated by turnover rate, is highlighted by the

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fundamental theoretical result of Amihud and Mendelson (1986a, p.228) stating that for a risk-neutral investor with trading intensity μ, the required return on security i is given by:

$$E(r^i) = r^f + \mu \frac{C^i}{P^i}$$

where C^i stands for the illiquidity cost of asset i and P^i denotes its price. In other words, while it is true that higher transaction costs command higher expected returns ceteris paribus, it is also the case that expected returns increase with the asset's trading frequency. This proposition implies that even small transaction costs may lead to a high premium if they are very frequently incurred, leading to the conclusion that it is the compound effect of trading frequency and transaction costs that matters for asset pricing, not each aspect in isolation. By introducing a price impact ratio that attempts to control for such a compound effect, we extend earlier studies on the subject that have examined the two effects independently.

The particular emphasis of our price impact ratio, *RtoTR*, on trading frequency has another merit. Trading activity of dominant stock market participants has considerably increased through time. This is a well-known development that is manifested by the existence of institutional investors who hold substantial levels of stock and take actions characterized by short-termism and short holding horizons (Bogle (2005), French(2008)). At the same time, transaction costs have been driven down due to technological innovations and implementation of effective microstructure mechanisms in organized exchanges (Chordia, Roll and Subrahmanyam (2001), French (2008), Ben-rephael, Kadan and Wohl (2008)). As a consequence, the development of a price impact ratio that explicitly considers the impact of trading frequency on required premia is of utmost importance because stocks actually exhibit a considerable cross-sectional variability in their turnover ratios.

Using *RtoTR* as well as *RtoV* for comparison purposes, we rank stocks listed on the London Stock Exchange (LSE) and construct portfolios to examine the issue whether these price impact ratios affect the cross-section of stock returns for the period 1991-2008. Previewing our results, we find that stocks with high *RtoV* values lead to higher expected

returns compared to stocks with low *RtoV* values. This result, which is consistent with the findings of other studies that utilize the *RtoV* ratio, suggests that stocks with high stock price reaction to a British pound of trading volume yield higher returns (see e.g. Amihud (2002) and Liu (2006)). Interestingly, however, we find a striking reversal of the portfolio returns' ordering once the trading-frequency adjusted price impact ratio (i.e. *RtoTR*) is used as a ranking criterion. Specifically, stocks with low *RtoTR* values are the ones that yield much higher risk-adjusted returns as compared to stocks with high *RtoTR* values. Put differently, stocks with very high turnover ratios, and hence very low *RtoTR* values, command high abnormal returns even if the price impact of this trading activity is relatively low. These findings support the view that the trading frequency effect overwhelmingly dominates the transaction cost effect in the determination of the corresponding premium, leading to the result that low *RtoTR* stocks outperform high *RtoTR* stocks.

Moreover, confirming the built-in size bias of Amihud's measure, our findings suggest that the extra returns yielded by stocks with high *RtoV* values relative to stocks with low *RtoV* values evaporate once we account for the size factor in multi-factor models. Crucially, the new price impact ratio suggested in this paper does not suffer from such a bias, since the premium that low *RtoTR* stocks earn is present in all multi-factor model specifications. We then construct a price impact (PI) factor via our measure to further examine whether the size and momentum anomalies can be explained through a PI-adjusted asset pricing model. The results indicate that augmenting the CAPM with the PI factor helps partly explain the momentum but not the size anomaly. Finally, this factor is also shown to be valuable for a mean-variance portfolio optimizer. These results are robust to a series of further checks.

The remainder of the paper is structured in the following way. Section 2 provides the motivation, discussing the shortcomings of the Amihud ratio and introduces the new price impact ratio, *RtoTR,* which controls for the trading frequency effect. Section 3 describes the data and the construction of the portfolios based on the *RtoV* and *RtoTR* measures. The empirical results in a time-series and cross-sectional framework are presented in Section 4.

Section 5 conducts varies robustness tests of the empirical analysis in terms of momentum and size premia. Furthermore, we examine the value of the PI factor in a simple asset allocation setup. Finally, Section 6 concludes.

2. Motivation, related literature and the new price impact ratio

2.1. Amihud's price impact ratio and its shortcomings

The ratio proposed by Amihud (2002) is widely accepted as one of the most appropriate and straightforward price impact measures to construct. Formally, it is calculated by the following ratio:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{V_{itd}} \qquad (1)$$

where R_{itd} and V_{itd} are, respectively, the return and monetary volume of stock i on day d at month t and D_{it} is the number of valid observation days in month t for stock i.

This ratio has several advantages compared to the traditional proxies that capture specific aspects of illiquidity. Firstly, it has a very intuitive meaning. Specifically, by directly measuring the impact of a (monetary) unit of trading volume on stock's return, it implies that the greater the response of returns, the more illiquid this stock is considered to be. While there is already a large number of existing studies arguing that trading volume is related to liquidity (e.g. Brennan et al. (1998), Chordia et al. (2001)), the contribution of this ratio is to capture the impact of trading volume on stock price movements and translate it into transaction cost (Acharya and Pedersen (2005)).

Secondly, *RtoV* is a good empirical proxy for the theoretically fine concept of Kyle's (1985) lambda (see Hasbrouck (2005)). This aspect of illiquidity is tangential to the order imbalance effect studied by Pastor and Stambaugh (2003). In particular, large buy/ sell orders for illiquid stocks lead to wide short-term stock price movements due to adverse selection and inventory costs that partly "bounce back" the following day as this large order shock is being

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absorbed (Amihud and Mendelson (1980), O'Hara (2003)).[3] Moreover, as Cochrane (2005a) notes, Amihud's ratio also has a "price discovery" component due to the fact that trading activity may be motivated by information or expectations regarding future stock price movements (see also Daniel, Hirshleifer and Subrahmanyam (1998)). In addition, this ratio can be interpreted as a measure of disagreement among investors (Amihud (2002)). When investors agree about the implication of news, stock prices change with a low trading volume, while large stock price movements associated with excessive trading volume reveal underlying heterogeneous beliefs

It should be further noted that *RtoV* is closely related to the Aminvest measure, which is very popular among professional investors (Khan and Baker (1993)). Aminvest is roughly the inverse of the *RtoV* ratio, given by the sum of daily volume to the sum of the absolute return and it has been employed by Amihud, Mendelson and Lauterbach (1997) and Berkman and Eleswarapu (1998). To this end, *RtoV* has become very popular for practical issues. It is easy to calculate for long periods because volume and returns data are widely available without resorting to detailed, high quality microstructure data that are difficult to obtain for long periods. For example, the highly sophisticated PIN (probability of informed trading) measure of Easley, Hvidkjaer and O'Hara (2002) and Easley, Hvidkjaer and O' Hara (2010) requires transactions data that are hard to acquire for long time periods and for most of the international markets.

Finally, even though Amihud's ratio does not exactly measure transaction costs, it is still very useful and convenient as compared to traditional measures of transaction costs, such as the bid-ask spread (Amihud and Mendelson (1986a), Amihud and Mendelson (1991)). Bid-ask spreads obtained at a daily frequency may be uninformative because they are noisy and they usually refer to end-of-day transactions. As Acharya and Pedersen (2005) note, larger

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[3] Similar is the intuition underlying the price impact measure of Brennan and Subrahmanyam (1996). In particular, they implement Kyle's model by estimating the price response to both the signed order size and the fixed cost of trading.

bid-ask spreads are indicative of illiquidity but do not provide us with any information regarding the "depth" of the market and, most importantly, regarding the magnitude of price impact due to a trade. In particular, Peterson and Fialkowski (1994) show that the quoted spread is a poor proxy for actual transaction costs. Moreover, closing price bid-ask spreads may be more easily manipulated by market makers, rendering them uninformative. There is the additional problem that in some databases (e.g. Thomson Datastream), bid-ask spreads appear as symmetric around the close price for most of the stocks, making relative spreads uninformative too.[4]

Despite its insightfulness, Amihud's ratio does not come without its shortcomings. Focussing on the properties of this measure from a cross-sectional asset pricing perspective, two major issues arise:

i) RtoV is by no means comparable across stocks with different market capitalization and, therefore, carries a significant size bias. Small cap stocks are bound to exhibit lower trading volume (in monetary terms) than big cap stocks even when they exhibit the same turnover ratio. In other words, based on the *RtoV* ratio, small cap stocks are automatically characterized as "illiquid" only due to their size. Cochrane (2005a, p. 5) explicitly states this bias, warning researchers that use *RtoV* to draw conclusions that the size premium is due to illiquidity. While this conclusion may still be generally valid, it becomes a tautology when this particular ratio is employed.

ii) RtoV neglects investors' stock holding horizons. More specifically, even though this ratio attempts to proxy the cost of transacting in a rather intuitive way, it is uninformative with respect to the frequency at which this cost is incurred. As a result, Amihud's ratio implicitly assumes that trading frequency is similar across stocks, and hence it should not affect liquidity premia. Nevertheless, as we discuss in the following subsections, trading frequency has become and dominant issue and it is expected to significantly affect asset

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[4] Relative and effective spreads are affected by the same data-quality problems, since they are based on bid-ask prices. Chalmers and Kadlec (1998, p.163) analyze some further limitations of these spreads measures.

pricing due to its considerable cross-sectional as well as time-series variation (see Datar et al. (1998)).

2.2. A new price impact ratio

The shortcomings of Amihud's ratio motivate us to introduce a new price impact ratio. This is formally given by the following expression:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{itd}|}{TR_{itd}} \tag{2}$$

where TR_{itd} is the Turnover Ratio of stock i at day d and D_{it} and R_{itd} are as previously defined.

Comparing our measure to *RtoV*, we essentially replace trading volume with turnover ratio in the denominator. *RtoTR* has a similar intuitive interpretation showing how much stock price responds to one percent of turnover rate. The focus on *TR*, a measure of trading activity, enables comparability across assets. Therefore, the proposed measure not only inherits the conceptual advantages of Amihud's ratio, but it also introduces some additional appealing features. More specifically, the proposed measure is easy to calculate, being also comparable across different stock markets and countries, because it does not include a monetary variable and it does not require price level or exchange rate adjustments. Most importantly, it is free of any size bias because there is no mechanical reason why big capitalization stocks should exhibit by construction higher turnover ratios. This fact renders it more appropriate for cross-sectional asset pricing studies and it enables us to disentangle price impact and size effects.

Crucially, our measure is not just a quick fix to overcome the size bias of Amihud's ratio. It actually has a very neat theoretical foundation, highlighting the importance of trading frequency and holding periods. To support this argument, we resort to Proposition 1 of Amihud et al. (2005, p. 281) that iterates Proposition 2 of Amihud and Mendelson (1986a).

This proposition states that for a risk-neutral investor with trading intensity μ, the required return on security i is given by:

$$E(r^i) = r^f + \mu \frac{C^i}{P^i} \tag{3}$$

where C^i stands for the illiquidity cost of asset i and P^i denotes its price. In other words, Amihud and Mendelson (1986a) state that expected excess returns depend not only on the transaction cost of the asset but also on its trading intensity, i.e. the probability according to which this cost is incurred.

The previous statement has an obvious implication; it is the combined effect of transaction costs and trading frequency that determines the required premium, not each aspect in isolation. This is also true in the model of Acharya and Pedersen (2005) that deals with the case of a risk-averse investor (see their discussion in p. 392-393). This is a crucial point because if trading frequencies, and hence turnover ratios, vary considerably across stocks, then they may well dominate transaction costs in determining the overall effect. It is surprising that this aspect of liquidity asset pricing is rarely mentioned in the literature, with the notable exception of Chalmers and Kadlec (1998). This is presumably because theoretical models have been developed within a single risky asset framework. For example, in their empirical investigation, Acharya and Pedersen (2005) assume that trading intensity, and hence turnover ratio is either fixed and exogenously given or an estimated constant that applies uniformly to the cross-section of stocks. Such an assumption is clearly invalid given the cross-sectional variation in stocks' turnover ratios (Datar et al. (1998)).

By controlling for both the trading frequency and the transaction cost effects via the proposed price impact ratio, our analysis also helps explain the mixed evidence in prior literature regarding the relationship between turnover ratios and stock returns. For example, Datar et al. (1998) and Nguyen, Mishra, Prakash and Ghosh (2007) document a negative relationship by arguing that stocks with higher turnover ratio are characterized by greater trading speed and are thought to be more liquid, dictating a lower expected return as

compared to stocks exhibiting low turnover ratios. On the other hand, Brown et al. (2009) report that stocks with high turnover ratios exhibit higher returns.[5] We argue that using *RtoTR* is more appropriate than solely considering trading activity measures, exactly because it is the combined effect of trading costs and frequency that matters rather than trading activity in isolation.

Finally, our ratio contributes to the literature by providing an alternative to the amortized spread of Chalmers and Kadlec (1998), which also attempts to measure the combined effect of trading frequency and transaction costs. Their empirical results provide strong evidence in favour of this combined effect in determining premia, since amortized spreads are found to be more strongly priced as compared to unamortized spreads. In particular, their analysis confirms that stocks with similar spreads exhibit vastly different turnover ratios, so the spread alone cannot be a fully informative proxy for illiquidity. The main shortcoming of Chalmers and Kadlec's (1998) measure, however, is that it requires data on bid and ask prices. As a result, it inherits the problems that we previously discussed for other spreads-based measures and refer to the quality of data and the difficulty in acquiring informative quotes at a daily frequency.[6] Therefore, drawing the analogy with the usefuleness of Amihud's ratio, we argue that *RtoTR* could be more practical than the amortized spread for empirical purposes.

2.3. Trends in transaction costs and trading frequency

In addition to its theoretical foundations and methodological advantages, the suggested price impact ratio is also appealing due to the recently observed trends in trading costs and frequency. This subsection discusses these trends confirming the importance of incorporating

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[5] Chan and Faff (2005) also report mixed evidence on the pricing of a liquidity factor using turnover ratios as proxies for liquidity in Australian stocks.

[6] It should be mentioned that Chalmers and Kadlec (1998) overcome this problem by utilizing high quality intraday data on bid-ask prices. Such detailed datasets are hardly available in international markets for long time series.

trading frequency in a price impact ratio. In particular, French (2008) demonstrates that total trading costs paid by investors in the U.S. market have been reduced from 146 basis points in 1980 to a tiny 11 basis points in 2006. At the same time, the annual turnover ratio has risen from 20% in 1975 and 59% in 1990 to an astonishing 215% in 2007. Similar is the case for U.K. stock market. According to the World Federation of Exchanges, the turnover ratio in the LSE has increased from 40.5% in 1995 to 152.7% in 2008.[7]

A series of important developments are associated with these trends. Trading costs have been driven down due to several institutional and technological changes. For example, there is a continuous effort by organized exchanges to improve their market microstructure mechanisms in order to enhance liquidity (Biais, Glosten and Spatt (2005), O' Hara (2007)).[8] Moreover, technological innovation enabled the introduction of electronic trading systems. There is ample empirical evidence that electronic computerized trading systems improve market liquidity (Jain (2005)). Naik and Yadav (2004) find that liquidity is significantly increased for FTSE 100 stocks, which account for approximately 80% of total trading volume in the LSE, once they are traded on an electronic limit-order trading system.[9] Confirming this finding, Chakravarty, Panchagesan and Wood (2005) argue that the decline in trading commissions can be attributed to the growth of alternative, automated trading systems.

The introduction of online brokerage accounts intensified the competition among brokers and other providers of trading services, driving down costs (Barber and Odean (2002)). At a macro level, there is fierce competition among international stock markets for

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[7] Data on share turnover are available for a series of international stock markets at http://www.world-exchanges.org/statistics/annual/equity-markets.

[8] For example, Venkataraman (2001) documents a trend towards automation of auction trading mechanisms. More recently, Venkataraman and Waisburd (2007) show the beneficial effects for Paris Bourse liquidity due to the introduction of designated market makers.

[9] Along the same lines, Barclay et al. (1999) document that liquidity has risen on the NASDAQ following the introduction of the electronic trading system. Domowitz (2002) finds for a sample of 42 countries that a screen system increases market liquidity by reducing trading costs and increasing trading volume.

attracting new listings. This competition is associated with mergers of exchanges to exploit economies of scale and the emergence of cross-country trading platforms.[10] Moreover, the observed proliferation of trading venues has led to the fragmentation of order flow, which in turn reduces transaction costs (O'Hara and Ye (2009)). It should be mentioned that regulatory initiatives for greater transparency (e.g., the Markets in Financial Instruments Directive in the European Union) may have also contributed to the reduction of transaction costs, given that asymmetric information is an important determinant of bid-ask spreads. Finally, another potential reason for this development is financial innovation. As Ben-Rephael et al. (2008) note, index funds, Exchange Traded Funds (ETFs) and other collective investment vehicles that offer economies of scale with respect to transaction costs, have enabled individual investors to invest indirectly in stocks that would be otherwise expensive to trade.

The second important trend is the increase in trading activity. The most obvious reason is the reduction in trading costs that we previously discussed (see also Barber and Odean (2002), Chordia, Roll and Subrahmanyam (2009)). Moreover, it is widely accepted that the domination of financial markets by institutional investors is another reason for the exorbitant increase in trading frequency. Chordia et al. (2009) document that turnover has increased the most for stocks with high levels of institutional ownership, confirming that institutional investors have played an important role in that respect. This trading behaviour can be partly explained by the volatile behaviour of equity fund flows (Chordia et al. 2009), which may have been caused, to an extent, by the abolition of front and back-end loads that were previously charged by a significant portion of equity funds.[11]

This trend has been strengthened by the emergence of particular types of institutional investors, such as hedge funds, that employ quantitative strategies (e.g. algorithmic trading),

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[10] For example, Nielsson (2009) discusses the liquidity effects due to the creation of Euronext. Moreover, Brockman, Chung and Perignon (2009) provide robust evidence for the existence of commonality in liquidity across exchanges on a global basis.

[11] See the Investment Company Institute Factbook 2009 for an analysis of load fees incurred by equity fund holders. The Factbook is available at http://www.icifactbook.org/

heavily relying on intraday trading (Khandani and Lo (2007)).[12] The very short stock holding horizon of certain groups of institutional investors has been repeatedly used as a means of criticism for their passivity and lassitude regarding corporate governance issues (Bogle (2005)). Moreover, the dramatic growth of assets under management by institutional investors during the last decades as well as their increased trading activity had been reflected by the increase in the proportion of equities traded in blocks (Madhavan and Chang (1997), Stapledon (1996)). Nevertheless, as Chordia et al. (2009) and O' Hara and Ye (2009) note, the introduction of electronic markets has allowed institutional investors to break up large orders and execute them in smaller increments but at a higher frequency in the very recent years.

3. Data and Descriptive Statistics

The initial sample we consider consists of all common stocks listed on the London Stock Exchange for the period from January 1991 to December 2008. Our analysis covers both presently listed and dead stocks (i.e. stocks of firms that were de-listed at some point during the sample period), and hence our dataset is free of any potential survivorship bias. We impose several screening criteria to our initial sample to minimize the impact of outliers. In particular, we exclude firms with market value less than £10 million. Furthermore, we exclude stocks for which we cannot obtain price data for at least 36 consecutive months that are necessary to calculate beta values. Finally, following conventional practice in UK stock market studies (see e.g. Fletcher and Kihanda (2005)), we further exclude unit trusts, investment trusts and ADRs. Our final dataset comprises of an average of 933 stocks in each month.

For each share we use Thomson DataStream to obtain daily information on a wide set of variables including trading volume (number of shares traded for a stock on a particular day),

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[12] The financial press commonly refers to the excessive trading of hedge funds. See, for example, the artidle entitled "In Their Prime", Economist, June 1, 2006.

turnover (ratio of trading volume to the number of shares outstanding), market value (share price multiplied by the number of outstanding ordinary shares) and price-to-book value ratio (share price divided by the book value per share). We also collect daily data on the opening, closing, bid, ask and mid share prices. In our study we mainly utilize two alternative price impact ratios: the *RtoV* ratio proposed by Amihud (2002), which is calculated as the monthly average ratio of the absolute daily return to the corresponding British pound trading volume, and the *RtoTR* ratio, which is calculated as the monthly average ratio of the absolute daily return to the corresponding turnover rate.[13]

For the estimation of the asset pricing models we need to construct the size, value and momentum factors. For the size factor, we sort all listed stocks according to their market capitalization at month *t-1* and we assign the top 30% (value-weighted) to the "Big size" portfolio and the bottom 30% to the "Small size" portfolio. The difference between the returns of these two portfolios at month *t* yields the size factor (SMB_t) return. For the momentum factor we rank all available stocks at month *t-1* according to their returns from month *t-13* to *t-2*. The top 30% (value-weighted) of these stocks were classified as "Winners" and the bottom 30% as "Losers". The spread of their monthly returns at month *t* is taken as the momentum factor return (MOM_t). Following Cuthbertson, Nitzsche and O' Sullivan (2008), we calculate the value factor (HML_t) as the spread between the monthly returns of the MSCI UK Growth and the MSCI UK Value indices. Finally, we use FTSE All Share as the market index and the 1-month UK interbank rate as the risk-free rate.

To provide some initial insights on the usefulness of the *RtoTR* ratio and its superior ability to disentangle the size and liquidity effects in comparison to the *RtoV* ratio, we compute and analyze the Spearman rank correlations for the variables *RtoTR*, *RtoV* and Market Value (*MV*) for a typical month of our sample (January 2000).[14] According to our findings, the Spearman correlation coefficient between the *RtoTR* price impact ratio and *MV*

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[13] See sections 2.1 and 2.2 for details.

[14] The results remain qualitatively similar when other months are considered.

is only 0.006, which is not significantly different from zero. On the contrary, *RtoV* is highly correlated to *MV* with a correlation coefficient of -0.846, which is significantly different from zero. These early findings clearly indicate that the price impact ratio proposed in this study does not exhibit the inherent size bias of the *RtoV* ratio.

To check how *RtoTR* relates to traditional measures of trading frequency and trading costs, we also calculate the Spearman rank correlation coefficient between *RtoTR*, *RtoV*, Bid-Ask spread (*BA*) and Turnover Rate (*TR*). The results lead to several interesting conclusions. First, *RtoTR* is positively correlated with *BA*, with a coefficient of 0.324 and negatively correlated with *TR* with a coefficient of -0.581. This finding supports our previous argument that *RtoTR* is likely to capture two different dimensions of illiquidity, namely trading cost (proxied by *BA*) and trading frequency (proxied by *TR*). Interestingly, the results indicate that this is not the case for *RtoV*, which is negatively correlated with *TR* at -0.326 but also negatively correlated with *BA* at -0.114. Another interesting finding refers to the negative but relatively low rank correlation coefficient between *BA* and *TR* (at -0.152). This is consistent with the view that these two variables are likely to capture two different dimensions of liquidity. Therefore, it is argued that *RtoTR* may help capture some important information that conventional spread measures are unable to adequately incorporate in isolation, since this price impact ratio is able to combine the unique information contained in *BA* and *TR* (see also Liu (2006)).

The next step involves classifiying stocks into decile portfolios according to each of the two price impact ratios (*RtoV* and *RtoTR*) and analyzing these portfolios' characteristics (e.g. performance, average market value, beta and price-to-book value ratio). Specifically, at the end of month *t-1*, stocks are alternatively sorted according to their average *RtoV* and *RtoTR* values in that month into ten portfolios. Portfolio 1 (P1) includes stocks with the smallest values of *RtoV* (or *RtoTR*) while Portfolio 10 (P10) contains stocks with the highest values of *RtoV* (or *RtoTR*), and their excess return in month *t* (i.e. post-ranking returns) is calculated.

For robustness, we calculate both equally weighted and value weighted portfolio returns in excess of the risk free rate. Portfolios are rebalanced on a monthly basis.

Table 1 presents the descriptive statistics of the ten portfolios constructed on the basis of *RtoV*. The results presented in Panel A, referring to the period from February 1991 to December 2008, point to the existence of a non-negligible returns' differential, since the spread between P10 and P1 is significantly positive. Moving from P1 to P10, the average portfolio return considerably increases, though not strictly monotonically. This pattern holds both for equally weighted and for value weighted portfolios' returns. The level of this differential is 13.390% p.a. (*t*=3.093) for equally weighted returns and 6.215% p.a. (*t*=1.517) for value weighted returns. We then conduct a sub-period analysis. Panel B presents the portfolios' descriptive statistics for the period from February 1991 to December 1999, while Panel C contains the corresponding results for the period from January 2000 to December 2008. These results suggest that the P10-P1 equally weighted spread is 13.405% p.a. (*t*=2.151) in the first sub-period and 13.375% p.a. (*t*=2.213) in the second sub-period. However, the value weighted spread is economically and statistically significant only for the first sub-period, equal to 9.736% p.a. (*t*=1.717), while during the second sub-period is found to be equal to 2.726% p.a., but statistically insignificant (*t*=0.461).[15]

Another interesting observation from Table 1 is that in all periods under examination, the average market capitalization of stocks in each portfolio decreases almost monotonically as we move from portfolio P1 to portfolio P10. This pattern confirms the previous argument that *RtoV* is by construction highly negatively correlated with market capitalization. The apparent strong relationship between *RtoV* and *MV* raises legitimate concerns about whether the spread observed in Table 1 can be identified as a size or an illiquidity premium. The rest of the findings in Table 1 suggest that portfolios composed of stocks with low *RtoV* values tend to have higher average price-to-book value ratios than those composed of stocks with

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[15] Ben-Rephael et al. (2008) report a similar decreasing trend for the premium yielded by NYSE stocks with high *RtoV* values relative to stocks with low *RtoV* values.

high *RtoV* values. Finally, the average beta of the stocks, calculated using a 36-month rolling window, is close to one and does not considerably vary across the ten portfolios.

Table 2 presents the corresponding characteristics of the ten portfolios constructed on the basis of the *RtoTR* measure. The analysis based on the new price impact ratio produces results that are substantially different from the ones obtained after using the *RtoV* ratio. In particular, portfolio P1 yields a much higher average return (both for equal and value-weighted portfolios) as compared to portfolio P10. The P1-P10 equally weighted spread is 15.395% p.a. (t=5.156) over the whole sample period, 17.575% p.a. (t=4.361) over the period February 1991-December 1999 and 13.235% p.a. (t=2.999) over the period January 2000-December 2008. When value weighted returns are considered, the corresponding premium for these periods is as high as 12.469% p.a. (t=3.896), 11.050% p.a. (t=2.957) and 13.875% p.a. (t=2.668) respectively. These findings are consistent with the view that the trading frequency effect dominates the transaction costs effect and, therefore, stocks with low *RtoTR* values yield ceteris paribus higher average returns relative to stocks that exhibit high *RtoTR* values.

Another finding that deserves emphasis relates to the average market capitalization of the stocks in each of these portfolios. This does not exhibit any monotonic pattern across the ten portfolios, confirming that the *RtoTR* spread does not reflect a size premium. The validity of this argument is further reinforced by the fact that not only the spread P1-P10 is high but the same holds for the spreads P1-P9, P1-P8 and P1-P7, which involve relatively larger stocks on their long side and yield premiums higher than 10% p.a. (in terms of both equally weighted and value weighted returns). These results hold in all time periods considered (see Panels B and C in Table 2). Finally, the results in Table 2 show that stocks in P1 display the highest average price-to-book value ratio, while stocks in P10 exhibit the lowest ones (except for the period January 2000-December 2008). Finally, the differences in average stocks' betas across the ten portfolios are minimal.

Taken as a whole, the descriptive statistics suggest that Amihud's (2002) price impact ratio, despite of it usefulness to capture the transaction costs effect, it has two major

weaknesses: first, it suffers from a severe size bias and, secondly, it fails to capture the trading frequency effect. On the contrary, the *RtoTR* ratio proposed in this study is free of the size bias and controls for both the trading frequency and the trading cost effects. To properly establish the existence of the premium yielded by stocks with low *RtoTR* values relative to stocks with high *RtoTR* values, we examine in the following section the risk-adjusted performance of these portfolios by conducting appropriate asset pricing tests.

4. Asset Pricing Tests

4.1. *Risk-adjusted performance*

We estimate the abnormal performance of the portfolios constructed on the basis of the *RtoV* and *RtoTR* ratios correspondingly using three asset pricing models. Firstly, we estimate Jensen's alpha from the CAPM:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \varepsilon_{it} \tag{4}$$

where r_{it} is the return of portfolio i in month t, r_{ft} is the risk-free rate for month t and MKT_t is the excess market portfolio return, $(r_{mt} - r_{ft})$, in month t. Secondly, we compute Fama-French alpha, i.e. the intercept of the 3-factor Fama-French (1993) model:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{it} \tag{5}$$

where SMB_t and HML_t stand for the size and value risk factors respectively. Thirdly, we estimate Carhart's alpha, i.e. the intercept of the 4-factor Carhart (1997) model:

$$r_{it} - r_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \varepsilon_{it} \tag{6}$$

where MOM_t stands for the momentum risk factor.[16] In order to test for the joint significance of the ten portfolios' alphas and to mitigate potential errors-in-variable problems we use a system-based estimation. In particular, we report alphas estimated via GMM with standard errors corrected for heteroscedasticity and serial correlation.

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[16] Section 3 provides detailed information on how the factors MKT, SMB, HML and MOM have been constructed.

For comparability purposes, we report the results for both the *RtoV* and the *RtoTR*-sorted portfolios. Table 3 reports the alphas of the ten value-weighted portfolios formed on the basis of the *RtoV* ratio. As shown in Panel A, which refers to the period February 1991-December 2008, the CAPM cannot completely account for the premium that relates to *RtoV* premium. Specifically, P1 yields the lowest Jensen alpha (0.90% p.a.), while P10 yields the highest one (7.49% p.a.), leading to a premium of 6.58% p.a. (*t*=1.64). However, this weak evidence for the existence of this premium disappears when Fama-French or Carhart alphas are considered as measures of risk-adjusted performance. In particular, the Fama-French alpha of the P10-P1 spread is 3.83% p.a., while the corresponding Carhart alpha of this spread is 3.84% p.a. The corresponding *t* values of 1.13 and 1.02 denote that, in both cases, these premia are not statistically significant. To identify which of the three added risk factors causes the disappearance of the premium, we successively add them and re-estimate the models. Unreported results indicate that the initially documented premium disappears in any specification that includes the size factor.

In panels B and C of Table 3 we present the corresponding results from the sub-period analysis, covering the periods February 1991-December 1999 and January 2000-December 2008, respectively. The evidence supports the existence of a weak premium under the CAPM specification in the first sub-period (i.e. the P10-P1 spread has an abnormal return of 8.88% p.a., though it is not statistically significant). The premium is almost halved in the second sub-period (i.e. the P10-P1 spread yields an abnormal return of 4.94% p.a. and remains statistically insignificant). The results obtained from the Fama-French and Carhart models also lead to several interesting conclusions. Specifically, the Fama-French alpha of the P10-P1 spread is found to be large and positive at 10.19% p.a. (*t*=2.33) over the February 1991-December 1999 period but negative and insignificant at -2.27% p.a. (*t*=-0.54) over the period January 2000 to December 2008. Similar are the results when the Carhart model is employed.

Table 4 presents the value weighted alphas of the ten portfolios constructed on the basis of the *RtoTR* price impact ratio. Panel A refers to the period from February 1991 to December

2008; P1 is the portfolio that yields the highest estimated alpha for all three asset pricing models considered. Moving from P1 to P10, alpha estimates are substantially reduced, though not monotonically in all cases. P10 yields the lowest Carhart alpha (-6.85% p.a.) and the third lowest Jensen and Fama-French alpha (-3.89% p.a. and -5.78% p.a., respectively). The premium generated by the P1-P10 portfolio is significantly positive and ranges from 12.20% p.a. (t=3.65) under the CAPM specification to 13.58% p.a. (t=4.22) under the Fama-French model. These results confirm, in risk-adjusted terms, the superior performance of stocks with low *RtoTR* values relative to stocks with high *RtoTR* that we initially reported for unadjusted returns in Table 2. To test the joint significance of the estimated alphas for all of the ten portfolios constructed, we use a Wald test that is equivalent to the Gibbons, Ross and Shanken (1989) test. For every model specification considered the Wald test overwhelmingly rejects the null hypothesis of jointly zero alpha estimates. This result shows that portfolios constructed on the basis of the *RtoTR* ratio yield abnormal returns that cannot be accounted for by the commonly used asset pricing models.

As we have previously mentioned, the explanation for the reversal of the portfolios' returns ordering relative to Amihud's ratio is due to the incorporation of trading frequency in the proposed price impact ratio. Our findings clearly indicate that even after adjusting for market, size, value and momentum risk, stocks with very high turnover rates and low *RtoTR* values dictate large premia. This suggests that the trading frequency effect overwhelmingly dominates the transaction costs effect and, also, that even low transaction costs may yield high expected returns if they are frequently incurred. This is in line with the fundamental theoretical result of Amihud and Mendelson (1986a) and, also, consistent with the evidence that transaction costs have been considerably reduced, while trading frequency has dramatically increased during the last two decades. Overall, our findings suggest that neglecting the trading frequency effect will be misleading, while examining each effect in isolation may lead to inconclusive results; one should take into account these two effects jointly in conducting asset pricing tests.

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The previous findings are confirmed when a sub-period analysis is conducted. In particular, the results in Panels B and C point to the existence of a statistically significant P1-P10 risk-adjusted premium in both sub-periods examined and for every asset pricing model employed. In other words, the outperformance of the strategy that sells short stocks with high *RtoTR* values and invests in stocks with low *RtoTR* values cannot be attributed to any of the size, value and momentum risk factors. This result, taken together with the fact that not only the P1-P10 spread but also the P1-P9 and P1-P8 spreads are greater than 9% p.a. and statistically significant under all model specifications and for every period considered, provides further support for the importance of the trading frequency effect and strengthens the case for using the proposed price impact ratio. Moreover, similar to the results presented in Panel A, the Wald tests strongly reject again the null hypothesis of jointly zero alpha estimates for the ten portfolios in every sub-period and model specification considered.

For robustness, we report in Table 5 the risk-adjusted performance of equally-weighted portfolios constructed on the basis of the *RtoTR* ratio. Panel A refers to the whole sample period, while Panels B and C refer to the two sub-periods considered. All of the previously reported results are robust to calculating portfolios' returns using equal weights.

4.2. Cross-sectional evidence

Given the time-series evidence for the abnormal performance of portfolios constructed on the basis of the *RtoTR* price impact ratio (presented in the previous section), we are motivated to examine whether a Price Impact (PI) factor, once added to the traditional asset pricing model, helps explain the cross-sectional variation in these portfolios' returns. We define the PI factor as the spread return of value weighted portfolios P1-P10, constructed on the basis of the *RtoTR* ratio. As a first step, we perform the traditional two-stage Fama-MacBeth (1973) regressions using information from all of the ten *RtoTR*-sorted portfolios. This exercise will shed light on whether the risk premium associated with this factor is positive and statistically significant.

The first stage of the Fama-MacBeth approach involves the estimation of betas from time-series regressions of excess portfolio returns on a set of risk factors. The most general among the model specifications we consider is the augmented Carhart model, given by:

$$r_{pt} - r_{ft} = \alpha_p + \beta_{p,MKT}MKT_t + \beta_{p,SMB}SMB_t + \beta_{p,HML}HML_t + \beta_{p,MOM}MOM_t + \beta_{p,PI}PI_t + e_{pt} \quad (7)$$

where r_{pt} is the return of portfolio p at time t, r_{ft} is the monthly risk-free rate for month t, and MKT, SMB, HML, MOM and PI refer to the market, size, value, momentum and price impact factors, as previously defined. As it is common practice in the literature, in the first stage we estimate a time-series of factor loadings for each of the ten portfolios using rolling windows of 60 monthly observations. However, for the early sample periods we start computing these betas when there are at least 36 observations.

The second stage involves the estimation of monthly cross-sectional regressions of the ten excess portfolios' returns on the corresponding betas that were estimated in the first-stage. The cross-sectional regression model is:

$$r_{pt} - r_{ft} = \lambda_0 + \lambda_{MKT}\hat{\beta}_{p,MKT} + \lambda_{SMB}\hat{\beta}_{p,SMB} + \lambda_{HML}\hat{\beta}_{p,HML} + \lambda_{MOM}\hat{\beta}_{p,MOM} + \lambda_{PI}\hat{\beta}_{p,PI} + w_{pt} \quad (8)$$

where now lambdas represent the risk premium coefficients associated with each beta. The main hypothesis we test is whether the time-series average of the estimated coefficients λ_5 is positive and statistically significant, which is perceived as evidence that the PI factor is priced. For robustness purposes, apart from standard Fama-MacBeth t-statistics for the lambda coefficients, we follow Shanken (1992) to calculate t-statistics using standard errors that have been corrected for the error-in-variables bias, arising due to the fact that the factor loadings used as regressors in (8) are pre-estimated rather than being the true, unobservable ones.

Table 6 presents the estimated lambda coefficients for the ten value-weighted portfolios sorted according to the *RtoTR* ratio. For comparability purposes, we report results for the three asset pricing models that are most commonly used (CAPM, Fama-French and Carhart models), once they have been augmented by the PI factor. Panel A reports the results for the

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unrestricted model where λ_0 can take any value. The results support the existence of a large positive and statistically significant premium (λ_{PI}). Specifically, we find that when we add the PI factor to the CAPM, its estimated coefficient (λ_{PI}) is positive at 0.81 and statistically significant at the 5% level. The coefficient λ_{PI} remains positive and statistically significant at the 1% level when the PI factor is added to the Fama-French and Carhart models, taking values of 0.97 and 0.94, respectively. The statistical significance of these coefficients remains intact even when we use Shanken-corrected standard errors, which are typically larger. Moreover, the fact that none of the models' intercept (λ_0) is found to be statistically significant points to the conclusion that the PI-augmented models are not mis-specified.

The pre-last column in Panel A of Table 6 reports the adjusted R-squared coefficients, while the last column informs us on the increase in the adjusted R-squared coefficients due to the addition of PI factor to the model.[17] Given the commonly reported values in the literature, our results show that the augmented models have a quite good explanatory power over the cross-section of these *RtoTR* portfolios' returns. Standard models that do not include the PI factor would not only be misspecified since λ_{PI} is statistically significant in every case, but they would also have a much lower explanatory power. In Panel B of Table 6, we report the estimated lambda coefficients from the second stage cross-sectional regression under various specifications, once we have restricted λ_0 to be equal to its zero theoretical value. The results are qualitatively similar to the ones reported in Panel A, supporting the existence of a strong and statistically significant premium that reaches the level of 9.70% p.a. for the PI-adjusted CAPM, 11.20% p.a. for the PI-adjusted Fama-French model and 11.10% p.a. for PI-adjusted Carhart model (the corresponding λ_{PI} coefficients are 0.81, 0.93 and 0.92 respectively).

As an alternative to the Fama-McBeth procedure, we also estimate the premium associated with the PI factor via the GMM procedure described in Cochrane (2005b). In particular, defining $\mathbf{r}_t^x$ to be the 10x1 vector containing the excess returns of the ten test

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[17] Results for all the other model specifications considered are available upon request.

portfolios, $\boldsymbol{\beta_0}$ the 10x1 vector of constants, $\mathbf{B} = [\beta_{MKT} \quad \beta_{PI}]$ the 10x2 matrix of portfolios' returns sensitivities to the market and PI factors and $\mathbf{F_t} = [MKT_t \quad PI_t]$ the 2x1 vector containing the realizations of these factors, then the PI-adjusted CAPM can be written as:

$$\mathbf{r_t^x} = \boldsymbol{\beta_0} + \mathbf{BF}_t + \mathbf{e_t} \tag{9}$$

If the test portfolios are priced by their returns' sensitivities to the traded factors, then their expected returns should satisfy:

$$E(\mathbf{r^x}) = \mathbf{B}\boldsymbol{\lambda} \tag{10}$$

where $\boldsymbol{\lambda} = [\lambda_{MKT} \quad \lambda_{PI}]$ is now a 2x1 vector containing the premia on the corresponding factors. Let $\boldsymbol{\theta}$ denote the set of unknown parameters $[\boldsymbol{\beta_0} \; \mathbf{B} \; \boldsymbol{\lambda}]$. The GMM estimator of θ minimizes the quadratic form $g(\boldsymbol{\theta})^T \mathbf{W} g(\boldsymbol{\theta})$, where $g(\boldsymbol{\theta}) = (1/T) \sum_{t=1}^{T} f_t(\boldsymbol{\theta})$,

$$f_t(\boldsymbol{\theta}) = \begin{bmatrix} (\mathbf{r_t^x} - \boldsymbol{\beta_0} - \mathbf{B}\boldsymbol{\lambda}) \\ (\mathbf{r_t^x} - \boldsymbol{\beta_0} - \mathbf{B}\boldsymbol{\lambda}) \otimes \mathbf{F}_t \\ (\mathbf{r_t^x} - \mathbf{B}\boldsymbol{\lambda}) \end{bmatrix} \tag{11}$$

and $\mathbf{W}$ is a consistent estimator of the optimal weighting matrix.[18]

Using the ten *RtoTR*-sorted portfolios as test portfolios, we get a statistically insignificant market risk premium estimate, $\lambda_{MKT} = 0.15$ (*t*-stat=0.47) on a monthly basis. On the other hand, the premium corresponding to the PI factor is positive and statistically significant, $\lambda_{PI} = 1.58$ (t-stat=3.74). This finding highlights the importance of augmenting the CAPM with the PI factor as well as confirms the previous evidence for the high premium it commands. Finally, given these GMM estimates, we plot the actual mean excess returns versus the model predictions in order to show the goodness of fit of the PI-adjusted CAPM. As one can observe from Figure 1, the augmented model does extremely well in pricing the ten *RtoTR*-sorted portfolios, since they lie along the 45^0 line.

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[18] In particular, we have employed the Newey-West procedure for its estimation.

5. Further results

5.1. Momentum and Size premia

A recurrent issue in the asset pricing literature refers to the identification of the underlying risk factors that may explain the well-established size and momentum anomalies.[19] Given that *RtoTR*-sorted portfolios yield abnormal risk-adjusted returns, we are motivated to examine whether the size and momentum anomalies remain intact once the PI factor is added to the commonly used asset pricing models. To this end, we alternatively sort UK listed stocks in month *t-1* on the basis of their market capitalization and past performance (returns from month *t-13* to month *t-2*), construct the corresponding decile portfolios and calculate their value-weighted returns in month *t*. Using these portfolios' returns, we estimate their abnormal performance by adding the PI factor to each of the three asset pricing models we considered in Section 4.1 (see models (4) to (6)). We opt for a system-based approach and estimate these models via GMM with standard errors corrected for heteroscedasticity and serial correlation.

Panel A of Table 7 presents the risk-adjusted performance of the spread strategy that goes long past winners and short past losers (P10-P1) for each of the six asset pricing models considered. Apart from the whole sample period, we have also considered two sub-periods. When we employ the standard CAPM, Fama-French and Carhart models, the P10-P1 momentum strategy delivers a positive and statistically significant abnormal return of 22.78% p.a. (*t*=2.78), 25.12% p.a. (*t*=3.73) and 9.44% p.a. (*t*=1.97) respectively. This evidence confirms the well known momentum anomaly in our sample too. Interestingly, adding the PI factor to each of the model specifications substantially reduces the magnitude of the abnormal returns that this strategy yields. Most importantly, when we employ the augmented Carhart model, the alpha of the P10-P1 strategy is more than halved to 4.67% p.a. and becomes

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[19] For example, it has been recently argued that liquidity risk may well provide a solution to these puzzles. Amihud (2002) and Acharya and Pedersen (2005) argue that the size anomaly evaporates once a liquidity-adjusted asset pricing model is employed. In the same spirit, Pastor and Stambaugh (2003) document that the momentum premium is more than halved when a liquidity factor is added to the Fama-French model.

statistically insignificant. The alphas derived from the PI-augmented CAPM and Fama-French model remain statistically significant but are considerably smaller in comparison to the ones derived from the standard specifications (16.71% p.a. vs. 22.78% p.a. and 19.81% p.a. vs. 25.12% p.a. respectively). Similar are the findings for the sub-period from February 1991 to December 1999. For the second sub-period, January 2000 to December 2008, the momentum anomaly becomes particularly weak. The addition of the PI factor to any considered model reduces further the momentum strategy's alphas and renders them statistically insignificant. In the spirit of Pastor and Stambaugh (2003), these findings support the view that certain aspects of liquidity risk (e.g. trading costs and trading frequency) may explain to a great extent momentum strategies' profits.

Panel B of Table 7 contains the corresponding results for the risk-adjusted performance of the spread strategy that goes long small cap stocks and sells short big cap stocks (P1-P10). For the whole sample period, the CAPM fails to account for the size effect, since the Jensen alpha of this strategy is as high as 17.56% p.a. (t=2.69). As expected, the size premium is substantially reduced under the Fama-French and Carhart specifications but remains statistically significant at 14.66% p.a. (t=2.76) and 11.85% p.a. (t=2.55) respectively. When the PI factor is added to these models, the abnormal performance of the P1-P10 strategy actually increases and varies from 18.86% p.a. (t=3.93) for the PI-augmented Carhart model to 27.02% p.a. (t=4.37) when the PI-augmented CAPM is employed. The results are similar for the sub-periods February 1991 to December 1999 and January 2000 to December 2008. These findings lead to the conclusion that a price impact risk factor constructed on the basis of the *RtoTR* ratio cannot explain the abnormal returns that the size strategy delivers. This may be explained by the fact that the *RtoTR* ratio is free of a size bias.

5.2. An investment perspective

It was documented in Section 4.1 that portfolios constructed on the basis of the *RtoTR* price impact ratio exhibit a superior performance, even when their potential exposure to market,

size, value and momentum risk is taken into account. This result essentially implies that expected returns should reflect an extra dimension of risk and, as a result, if added to an asset universe that already contains the MKT, SMB, HML, MOM factors, the traded PI factor may further increase the maximum Sharpe ratio that a mean-variance investor can achieve. The relationship between multi-beta asset pricing and mean-variance efficiency of some combination of benchmark portfolios is well-established (see Merton (1973) for an early treatment and Cochrane (2005b, Ch. 5) for a rigorous textbook analysis)). Given this observation, in this section we consider a simple mean-variance asset allocation setup to examine how the addition of this PI factor enhances the mean-variance investor's opportunity set.[20]

More specifically, we calculate the weights of the five traded factors (MKT, SMB, HML, MOM and PI) in the ex post tangency portfolio as well as its corresponding ex post Sharpe ratio. Various combinations of these factors are considered in order to identify the marginal contribution of the PI factor. Panel A of Table 8 contains the results for the period February 1991- December 2008. For the trivial case where only the MKT factor is available, the investor assigns 100% of her portfolio to this asset, achieving an ex post Sharpe ratio of $S^*=-0.036$ on a monthly basis. A negative Sharpe ratio may not be appealing, but it is a direct consequence of the fact that the average excess monthly returns of the FTSE All Share, the market index, have been negative for the period under examination. Adding the SMB factor, that bears a positive average monthly premium, leads to a Sharpe ratio of $S^*=0.083$. The addition of the HML factor induces a negligible only increase in the achievable ex post

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[20] As mentioned in Pastor and Stambaugh (2003), utilizing the mean-variance efficiency setup by no means imply that the tangency portfolio is the optimal allocation for an investor operating in a world that gives rise to multi-beta pricing. It is well known since Merton (1973) that in a world with multiple risk factors optimal portfolios may contain additional hedging demands. Nevertheless, the mean-variance framework, being the most studied setup in portfolio choice, is still of interest to many investors; if the addition of this extra traded factor leads to considerable enhancement in mean-variance terms, then one may expect that it will be highly beneficial for more sophisticated asset allocation schemes too.

Sharpe ratio. In this three-factor setup, the SMB factor is the dominant asset in the tangency portfolio, to the extent that the investor holds a leveraged position by selling short the MKT factor. More interestingly, the addition of the MOM factor considerably enhances the opportunity set of the investor. This factor becomes now the dominant asset in the tangency portfolio, since the investor assigns to it 59.18% of her wealth, while the ex post Sharpe ratio increases to $S^*=0.24$.

Proceeding to asset menus that include the PI factor, striking results are obtained. Allowing the investor to combine the PI factor with the MKT factor, the Sharpe ratio becomes $S^*=0.266$, higher than what an investor can achieve in a four-factor universe à la Carhart (1997). The investor assigns almost all of her wealth in the new factor; this is an anticipated outcome given the disappointing negative excess market returns during the examined period. A harder challenge is to modify portfolio choices and increase Sharpe ratios by introducing PI in the presence of the Fama-French or Carhart factors. Facing this challenge, the PI factor plays an important role in the tangency portfolios constructed in these two cases. In particular, the investor allocates to PI 33.11% of her wealth in the presence of MKT, SMB, HML and 17.54% if MOM is also available. Even more intriguing are the corresponding increases in the Sharpe ratios. In the first case, the inclusion of PI quadruples S^* to 0.333, while in the second case S^* is increased by more than half, reaching $S^*=0.398$. There are two main reasons for this striking enhancement in the opportunity set. The first is the attractive mean-variance profile of the PI factor, as presented in Table 2. The second is its correlation structure with the other available factors. Panel A of Table 9 presents the pairwise correlation coefficients of the five available factors, illustrating that the returns of the employed PI factor have a negligible correlation with HML and MOM returns, while they are negatively correlated with MKT and SMB returns. In other words, the premium associated with the PI does not just mimic other factors' premia; it represents genuine outperformance, while the PI factor can also serve as a helpful diversification tool for the mean-variance optimizer. These results show that besides the statistical significance of the premium

documented within an asset pricing framework, there is scope and value in exploiting this premium in a portfolio choice setup, above and beyond the size, value and momentum premia.

Even though it is a direct consequence of the ongoing financial crisis, the existence of negative average monthly excess returns for the market portfolio may cast doubt on the robustness of our previous results. To address this concern, we repeat this asset allocation exercise excluding the last two years of our sample period. Results are reported in Panel B of Table 8. For the sub-period February 1991- December 2006, average returns for MKT are positive, leading to the familiar outcome of a positive ex post Sharpe ratio (S*=0.023) for the trivial case where MKT is the only available risky asset. For the combinations of MKT, SMB, HML and MOM factors, results are analogous to the ones obtained for the whole sample period. The only difference is that the incentive to sell short MKT is now almost neutralized due to the positivity of its premium, while the Sharpe ratios are also slightly higher. Most importantly, our previous conclusions for the role of the PI factor are robust to the exclusion of the last two years of our sample. The mean-variance investor seeks to allocate considerable portions of her wealth to this traded asset even in the presence of MOM (26.67% in the presence of MKT, HML, SMB and 17.45% in case MOM is also available) and the ex post Sharpe ratios become even higher for all of the cases considered.

The previous argument for the diversification role of the PI factor carries through for this sub-period too, given the pairwise correlation coefficients of these factors presented in Panel B of Table 9. As a further robustness check, we alternatively construct the PI factor using equal weighted returns of the portfolios formed on the basis of the *RtoTR* price impact ratio and then repeat the asset allocation exercise. The results, available upon request, point to an even more important role for the equally-weighted PI factor and to a further increase in the ex post Sharpe ratios. These results stem from the even higher premium that the spread of the equally-weighted portfolios P1-P10 yields in comparison to its value-weighted counterpart and its similar correlation structure with respect to the other traded factors.

6. Summary

In this study we propose a new price impact ratio, *RtoTR*, as an alternative to the most commonly used one in the market microstructure literature, Amihud's (2002) return-to-volume ratio (*RtoV*). This new ratio, *RtoTR*, essentially modifies *RtoV* by substituting trading volume in its denominator with the turnover ratio for each security. The rationale behind the development of this measure is twofold. First, the trading volume of each stock in monetary terms is by construction positively related to its market value, implying that it is not comparable across stocks with different market values. This fact leads to a severe size bias that is present in Amihud's measure, limiting its ability to separate illiquidity from size effects in asset pricing. Our measure does not suffer from this size bias because there is no a priori reason why the turnover ratio of a stock should be correlated with its market capitalization. Second, *RtoTR* is not just a quick methodological fix to overcome the shortcomings of *RtoV*. Instead, there is a solid theoretical foundation in attempting to encapsulate stocks' cross-sectional variability in trading frequency. As Amihud and Mendelson (1986a) point out, an asset's expected return is determined by both the cost and the frequency of transactions. Recent developments in financial markets have led to a substantially higher trading activity and correspondingly lower trading costs, rendering necessary the use of a price impact ratio that explicitly takes into account the cross-sectional variation in stocks' turnover ratios.

Using daily data for all listed companies on the London Stock Exchange over the period January 1991- December 2008, we empirically examine the importance of the suggested price impact ratio for asset pricing. In particular, we report that stocks with low *RtoTR* values yield significantly higher post-ranking returns as compared to stocks with high *RtoTR* values. This finding holds even when we control for market, size, value and momentum risk factors, indicating genuinely abnormal performance. Our results support the argument that it is the compound effect of trading frequency and transaction costs that matters for asset pricing, not each feature in isolation.

Strengthening further the case for the adoption of the modified price impact ratio, *RtoTR*, we empirically confirm that it this free of a size bias. On the other hand, Amihud's (2002) ratio is found to be highly negatively correlated with market capitalization. This forces the conclusion that small stocks are necessarily illiquid. We provide ample evidence that the initial differential return between a portfolio of stocks with high *RtoV* and a portfolio of stocks with low *RtoV* is subsumed once an asset pricing model that includes a size factor is employed.

Finally, a Price Impact (PI) factor, defined as the spread between the return of the decile portfolio of stocks with the lowest *RtoTR* values and the return of the decile portfolio of stocks with the highest *RtoTR*, allows us to partly explain the momentum but not the size anomaly. Moreover, this traded factor is found to be of great value for a mean-variance investor, since it can considerably increase the feasible ex post Sharpe ratio of the tangency portfolio. These results are robust to a wide variety of sensitivity tests.

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TABLE 1

Performance and characteristics of decile portfolios constructed on the basis of the Return-to-Volume (RtoV) price impact ratio

This table reports the characteristics of portfolios constructed on the basis of the Return-to-Volume (RtoV) price impact ratio. All stocks listed on the London Stock Exchange during the period January 1991 to December 2008 are sorted at month $t-1$ in ascending order according to the RtoV ratio and they are assigned to ten portfolios. P1 is the decile portfolio containing the stocks with the lowest RtoV ratios and P10 is the decile portfolio containing the stocks with the highest RtoV ratios. The excess returns of these portfolios at month t are calculated (i.e. post-ranking returns). P10-P1 stands for the spread between P10 and P1. Portfolios are rebalanced on a monthly basis. EW returns correspond to the annualized average monthly returns of equal weighted portfolios. VW returns refer to the annualized average monthly returns of value weighted portfolios. MV is the average market value of the stocks in each portfolio (in £m), calculated as the share price multiplied by the number of outstanding ordinary shares. Price-to-Book is the average ratio of the share price divided by the book value per share for the stocks in each portfolio. CAPM beta is the average stocks' beta in each portfolio calculated using a 36-month rolling window. The last column reports values for t-tests referring to the null hypothesis of no difference in means between portfolios' P10 and P1 characteristics.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-test
DECILE PORTFOLIO												
Panel A. February 1991-December 2008												
EW returns (% p.a.)	0.852	0.260	1.670	1.421	3.277	5.247	5.735	6.905	7.344	14.242	13.390	3.093
VW returns (% p.a.)	-0.735	-0.564	0.359	-0.418	0.408	1.593	0.127	1.046	0.665	5.479	6.215	1.517
RtoV ratio (x10^6)	5.97E-04	2.19E-03	6.28E-03	1.63E-02	3.77E-02	7.48E-02	1.37E-01	2.54E-01	5.09E-01	2.50	2.50	15.015
MV(£m)	12005.541	2216.778	1028.539	588.152	366.601	258.182	187.943	136.944	101.645	64.412	-11941.13	-47.977
Price-to-Book	3.414	3.300	3.437	3.458	3.368	3.343	3.203	2.902	2.813	2.542	-0.872	-14.784
CAPM Beta	1.005	1.095	1.062	1.088	1.073	1.045	1.028	1.023	1.021	1.011	0.006	0.290
Panel B. February 1991-December 1999												
EW returns (% p.a.)	7.094	4.563	5.628	9.242	9.016	9.050	12.080	13.727	14.641	20.499	13.405	2.151
VW returns (% p.a.)	6.754	5.470	4.459	7.019	7.078	6.889	8.071	7.477	8.341	16.490	9.736	1.717
RtoV ratio (x10^6)	7.99E-04	2.32E-03	5.34E-03	1.11E-02	2.14E-02	3.97E-02	7.26E-02	1.32E-01	2.60E-01	1.15	1.15	16.46
MV(£m)	9514.635	2573.908	1300.101	776.216	496.561	351.341	255.295	187.895	140.512	86.815	-9427.820	-33.393
Price-to-Book	3.202	3.146	3.232	3.263	3.369	3.494	3.336	2.998	2.907	2.389	-0.813	-10.097
CAPM Beta	1.000	1.043	1.047	1.028	1.020	1.020	0.995	1.000	1.005	1.030	0.030	0.964
Panel C. January 2000-December 2008												
EW returns (% p.a.)	-5.332	-4.003	-2.251	-6.328	-2.408	1.479	-0.552	0.146	0.115	8.043	13.375	2.213
VW returns (% p.a.)	-8.155	-6.542	-3.703	-7.786	-6.201	-3.654	-7.744	-5.325	-6.940	-5.429	2.726	0.461
RtoV ratio (x10^6)	3.97E-04	2.07E-03	7.21E-03	2.13E-02	5.39E-02	1.09E-01	2.02E-01	3.74E-01	7.56E-01	3.84	3.84	14.37
MV(£m)	14473.384	1862.954	759.491	401.829	237.845	165.885	121.214	86.464	63.137	42.217	-14431.16	-63.304
Price-to-Book	3.625	3.452	3.640	3.651	3.367	3.192	3.071	2.807	2.719	2.694	-0.931	-10.799
CAPM Beta	1.009	1.146	1.077	1.148	1.125	1.069	1.061	1.046	1.037	0.992	-0.017	-0.585

TABLE 2
Performance and characteristics of decile portfolios constructed on the basis of the Return-to-Turnover Rate (RtoTR) price impact ratio

This table reports the characteristics of portfolios constructed on the basis of the Return-to-Turnover Rate (RtoTR) price impact ratio. All stocks listed on the London Stock Exchange over the period January 1991 to December 2008 are sorted at month *t-1* in ascending order according to the RtoTR ratio and they are assigned to ten portfolios. P1 is the decile portfolio containing the stocks with the lowest RtoTR ratios and P10 is the decile portfolio containing the stocks with the highest RtoTR ratios. The excess returns of these portfolios at month *t* are calculated (i.e. post-ranking returns). P1-P10 stands for the spread between P1 and P10. Portfolios are rebalanced on a monthly basis. EW returns refer to the annualized average monthly returns of equal weighted portfolios. VW returns refer to the annualized average monthly returns of value weighted portfolios. MV is the average market value of the stocks in each portfolio (in £m), calculated as the share price multiplied by the number of outstanding ordinary shares. Price-to-Book is the average ratio of the share price divided by the book value per share for the stocks in each portfolio. CAPM beta is the average stocks' beta in each portfolio calculated using a 36-month rolling window. The last column reports values for *t-tests* referring to the null hypothesis of no difference in means between portfolios' P1 and P10 characteristics.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	*t*-test
						DECILE PORTFOLIO						
					Panel A. February 1991-December 2008							
EW returns (% p.a.)	13.902	6.357	8.220	2.886	6.032	4.659	3.080	0.645	2.556	-1.493	15.395	5.156
VW returns (% p.a.)	6.551	1.842	1.939	-2.538	-3.239	-1.684	-5.087	-6.487	-7.814	-5.918	12.469	3.896
RtoTR ratio	1.441	2.899	4.131	5.598	7.522	10.203	14.200	20.968	35.425	120.436	-118.996	-42.730
MV(£m)	2719.871	3499.827	3345.892	2313.492	1789.928	1231.784	835.937	579.423	386.894	253.512	2466.359	31.029
Price-to-Book	3.660	3.315	3.219	3.246	3.281	3.203	3.083	2.948	2.956	2.875	0.785	9.966
CAPM Beta	0.952	1.023	1.053	1.081	1.066	1.070	1.060	1.047	1.034	1.073	-0.122	-6.986
					Panel B. February 1991-December 1999							
EW returns (% p.a.)	22.920	13.347	11.892	5.688	12.028	7.488	9.373	7.606	9.705	5.345	17.575	4.361
VW returns (% p.a.)	14.922	10.565	7.103	5.612	6.898	2.775	1.752	2.388	1.996	3.873	11.050	2.957
RtoTR ratio	1.435	3.104	4.467	5.838	7.447	9.648	12.951	18.734	31.132	103.487	-102.053	-33.174
MV(£m)	2109.883	2242.825	2292.215	2114.469	2246.136	1808.805	1224.806	773.567	530.643	342.754	1767.130	24.756
Price-to-Book	3.935	3.231	3.156	3.076	3.181	3.137	3.083	2.935	2.919	2.759	1.175	14.296
CAPM Beta	0.965	0.981	1.006	1.031	1.031	1.016	1.030	1.027	1.032	1.071	-0.106	-5.249
					Panel C. January 2000-December 2008							
EW returns (% p.a.)	4.968	-0.568	4.582	0.110	0.093	1.856	-3.155	-6.251	-4.527	-8.267	13.235	2.999
VW returns (% p.a.)	-1.743	-6.800	-3.178	-10.612	-13.282	-6.103	-11.862	-15.280	-17.533	-15.617	13.875	2.668
RtoTR ratio	1.447	2.696	3.797	5.360	7.597	10.752	15.438	23.181	39.678	137.228	-135.781	-33.633
MV(£m)	3324.211	4745.190	4389.812	2510.672	1337.945	660.105	450.668	387.078	244.477	165.096	3159.115	29.928
Price-to-Book	3.388	3.398	3.281	3.414	3.379	3.268	3.082	2.962	2.992	2.990	0.398	3.222
CAPM Beta	0.938	1.065	1.099	1.132	1.101	1.123	1.089	1.067	1.036	1.075	-0.137	-4.835

TABLE 3
Alphas of value-weighted portfolios sorted by the Return-to-Volume (RtoV) price impact ratio

This table reports the abnormal performance of ten value-weighted portfolios constructed on the basis of the Return-to-Volume (RtoV) price impact ratio. All stocks listed on the London Stock Exchange during the period January 1991 to December 2008 are sorted in ascending order according to the RtoV ratio and they are assigned to ten portfolios. P1 is the decile portfolio containing the stocks with the lowest RtoV ratios and P10 is the decile portfolio containing the stocks with the highest RtoV ratios. P10-P1 stands for the spread between P10 and P1. CAPM alpha is the annualized alpha estimate derived from the Capital Asset Pricing Model. Fama-French alpha is the annualized alpha estimate derived from the Fama-French three-factor model. Carhart alpha is the annualized alpha estimate from the Carhart four-factor model. t-statistics are reported in parentheses. ***, ** and * indicates that the corresponding alpha coefficient is statistically significant at the 1%, 5% and 10% level, respectively. The last column reports the chi-square (χ^2) statistic of the Wald test referring to the null hypothesis that the ten portfolios' alphas are jointly equal to zero; p-values are reported below the statistic.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	Chi-sq.
						DECILE PORTFOLIO						
					Panel A: February 1991-December 2008							
CAPM alpha (% p.a.)	0.90	1.37	2.27	1.64	2.51	3.54	2.05	2.85	2.60	7.49	6.58	19.29
	(1.27)	(0.85)	(1.16)	(0.72)	(1.04)	(1.34)	(0.78)	(0.91)	(0.84)	(2.10)***	(1.64)	(0.037)
Fama-French alpha (% p.a.)	1.49	0.18	0.54	-0.19	0.70	1.62	0.33	0.47	0.58	5.33	3.83	20.12
	(3.19)***	(0.15)	(0.45)	(-0.12)	(0.39)	(0.71)	(0.14)	(0.20)	(0.20)	(1.62)	(1.13)	(0.028)
Carhart alpha (% p.a.)	1.54	0.05	-0.02	0.08	0.93	1.22	0.36	0.61	1.99	5.38	3.84	17.82
	(3.19)***	(0.04)	(-0.02)	(0.04)	(0.50)	(0.50)	(0.15)	(0.24)	(0.65)	(1.49)	(1.02)	(0.058)
					Panel B: February 1991-December 1999							
CAPM alpha (% p.a.)	1.58	-0.19	-1.38	0.84	0.47	0.93	1.97	1.99	2.25	10.46	8.88	22.73
	(1.33)	(-0.11)	(-0.63)	(0.30)	(0.18)	(0.27)	(0.61)	(0.50)	(0.57)	(2.18)**	(1.57)	(0.012)
Fama-French alpha (% p.a.)	1.23	0.60	-0.76	1.62	1.15	1.82	2.76	2.99	3.27	11.41	10.19	24.08
	(2.20)**	(0.05)	(-0.49)	(0.76)	(0.79)	(0.54)	(1.03)	(0.98)	(1.09)	(2.73)***	(2.33)**	(0.007)
Carhart alpha (% p.a.)	1.19	-1.07	-0.71	2.94	2.43	1.76	3.36	3.88	4.94	12.95	11.76	26.17
	(1.67)	(-0.73)	(-0.45)	(1.25)	(1.64)	(0.49)	(1.22)	(1.14)	(1.60)	(2.70)***	(2.30)**	(0.003)
					Panel C. January 2000-December 2008							
CAPM alpha (% p.a.)	0.33	4.17	6.65	3.38	4.82	6.86	2.19	4.40	3.18	5.27	4.94	23.38
	(0.47)	(1.56)	(2.16)**	(0.95)	(1.23)	(1.66)	(0.52)	(0.92)	(0.67)	(1.02)	(0.88)	(0.009)
Fama-French alpha (% p.a.)	1.42	-0.60	1.07	-1.81	-0.76	1.95	-2.54	-2.44	-2.28	-0.85	-2.27	19.24
	(3.10)***	(-0.47)	(0.62)	(-0.84)	(-0.24)	(0.62)	(-0.71)	(-0.68)	(-0.47)	(-0.21)	(-0.54)	(0.037)
Carhart alpha (% p.a.)	1.54	-0.29	0.58	-1.92	-0.78	1.50	-2.68	-2.51	-1.30	-1.26	-2.80	19.29
	(3.49)***	(-0.23)	(0.34)	(-0.90)	(-0.24)	(0.47)	(-0.71)	(-0.70)	(-0.26)	(-0.29)	(-0.63)	(0.037)

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TABLE 4
Alphas of value-weighted portfolios sorted by the Return-to-Turnover Rate (RtoTR) price impact ratio

This table reports the abnormal performance of ten value-weighted portfolios constructed on the basis of the Return-to-Turnover Rate (RtoTR) price impact ratio. All stocks listed on the London Stock Exchange during the period January 1991 to December 2008 are sorted in ascending order according to the RtoTR ratio and they are assigned to ten portfolios. P1 is the decile portfolio containing the stocks with the lowest RtoTR ratios and P10 is the decile portfolio containing the stocks with the highest RtoTR ratios. P1-P10 stands for the spread between P1 and P10. CAPM alpha is the annualized alpha estimate derived from the Capital Asset Pricing Model. Fama-French alpha is the annualized alpha estimate derived from the Fama-French three-factor model. Carhart alpha is the annualized alpha estimate from the Carhart four-factor model. t-statistics are reported in parentheses. ***, ** and * indicates that the corresponding alpha coefficient is statistically significant at the 1%, 5% and 10% level, respectively. The last column reports the chi-square (χ^2) statistic of the Wald test referring to the null hypothesis that the ten portfolios' alphas are jointly equal to zero; p-values are reported below the statistic.

	DECILE PORTFOLIO											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	Chi-sq.
Panel A. February 1991-December 2008												
CAPM alpha (% p.a.)	8.30	3.48	3.66	-0.70	-1.46	0.25	-3.08	-4.53	-5.60	-3.89	12.20	42.23
	(4.46)***	(2.31)**	(1.98)**	(-0.45)	(-0.59)	(0.10)	(-1.07)	(-1.53)	(-1.44)	(-1.32)	(3.65)***	(0.00)
Fama-French alpha (% p.a.)	7.79	3.10	3.87	-0.72	-1.73	-0.31	-3.82	-5.80	-7.74	-5.78	13.58	42.30
	(4.39)***	(2.03)*	(2.12)**	(-0.44)	(-0.71)	(-0.12)	(-1.52)	(-2.08)**	(-2.45)**	(-2.25)**	(4.22)***	(0.00)
Carhart alpha (% p.a.)	6.53	3.07	3.41	-0.99	-1.75	0.88	-4.22	-5.97	-6.85	-6.85	13.38	33.22
	(3.93)***	(1.91)*	(2.03)**	(-0.63)	(-0.72)	(0.34)	(-1.62)	(-1.96)**	(-2.16)**	(-2.26)**	(3.77)***	(0.00)
Panel B. February 1991-December 1999												
CAPM alpha (% p.a.)	8.87	5.55	1.22	0.01	1.85	2.66	-4.16	-2.62	-4.33	-2.67	11.54	68.31
	(6.17)***	(2.34)**	(0.68)	(-0.01)	(0.93)	(-1.20)	(-2.03)**	(-0.98)	(-0.84)	(-0.75)	(3.19)	(0.000)
Fama-French alpha (% p.a.)	8.92	5.71	1.26	0.16	1.60	-2.67	-4.29	-2.42	-3.45	-1.95	10.87	65.07
	(6.16)***	(2.37)**	(0.73)	(0.10)	(0.87)	(-1.21)	(-2.11)**	(-0.98)	(-0.95)	(-0.74)	(3.82)***	(0.000)
Carhart alpha (% p.a.)	6.67	6.21	-0.49	-0.32	2.34	-1.82	-3.84	-1.49	-2.39	-2.66	9.33	39.99
	(4.83)***	(2.44)**	(-0.33)	(-0.20)	(1.24)	(-0.86)	(-1.78)*	(-0.52)	(-0.63)	(-1.01)	(3.11)***	(0.000)
Panel C. January 2000-December 2008												
CAPM alpha (% p.a.)	6.65	1.83	5.28	-0.83	-3.42	4.94	-5.36	-3.65	-5.18	-5.36	12.01	20.92
	(2.04)**	(0.95)	(2.02)**	(-0.30)	(-0.87)	(1.22)	(-0.16)	(-0.74)	(-0.83)	(-1.04)	(2.12)**	(0.022)
Fama-French alpha (% p.a.)	3.82	-0.14	6.86	-0.20	-6.03	2.87	-4.38	-8.48	-12.02	-11.16	14.98	27.26
	(1.36)	(-0.08)	(3.09)***	(-0.06)	(-1.65)	(0.72)	(-1.12)	(-1.82)*	(-2.42)**	(-2.46)**	(2.58)***	(0.002)
Carhart alpha (% p.a.)	3.46	-0.20	6.82	-0.46	-6.13	3.87	-4.79	-8.94	-11.34	-11.88	15.34	26.25
	(1.26)	(-0.11)	(3.06)***	(-0.16)	(-1.64)	(0.96)	(-1.15)	(-1.91)*	(-2.36)**	(-2.42)***	(2.61)***	(0.003)

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TABLE 5
Alphas of equal-weighted portfolios sorted by the Return-to-Turnover Rate (RtoTR) price impact ratio

This table reports the abnormal performance of ten equal-weighted portfolios constructed on the basis of the Return-to-Turnover Rate (RtoTR) price impact ratio. All stocks listed on the London Stock Exchange during the period January 1991 to December 2008 are sorted in ascending order according to the RtoTR ratio and they are assigned to ten portfolios. P1 is the decile portfolio containing the stocks with the lowest RtoTR ratios and P10 is the decile portfolio containing the stocks with the highest RtoTR ratios. P1-P10 stands for the spread between P1 and P10. CAPM alpha is the annualized alpha estimate derived from the Capital Asset Pricing Model. Fama-French alpha is the annualized alpha estimate derived from the Fama-French three-factor model. Carhart alpha is the annualized alpha estimate from the Carhart four-factor model. t-statistics are reported in parentheses. ***, ** and * indicates that the corresponding alpha coefficient is statistically significant at the 1%, 5% and 10% level, respectively. The last column reports the chi-square (χ^2) statistic of the Wald test referring to the null hypothesis that the ten portfolios' alphas are jointly equal to zero; p-values are reported below the statistic.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	Chi-sq.
						DECILE PORTFOLIO						
					Panel A. February 1991-December 2008							
CAPM alpha (% p.a.)	16.62	8.10	10.15	4.89	8.03	6.56	5.09	2.61	4.57	0.62	15.00	67.94
	(5.61)***	(3.92)***	(4.22)***	(1.85)*	(2.96)***	(2.24)**	(1.47)	(0.88)	(1.43)	(0.15)	(4.14)***	(0.000)
Fama-French alpha (% p.a.)	14.14	6.51	8.46	3.06	6.43	4.66	3.13	0.64	2.51	-1.85	15.99	81.81
	(5.90)***	(4.11)***	(4.73)***	(1.73)*	(3.38)***	(2.22)**	(1.18)	(0.28)	(1.05)	(-0.56)	(4.84)***	(0.000)
Carhart alpha (% p.a.)	12.69	5.76	7.98	2.82	6.18	4.54	3.79	1.41	2.97	-1.84	14.53	80.13
	(6.31)***	(3.66)***	(4.73)***	(1.53)	(3.03)***	(2.01)**	(1.33)	(0.57)	(1.20)	(-0.52)	(4.26)***	(0.000)
					Panel B. February 1991-December 1999							
CAPM alpha (% p.a.)	17.03	7.81	5.94	-0.44	5.82	1.77	3.17	1.65	3.27	-1.41	18.44	127.64
	(5.80)***	(3.20)***	(2.02)**	(-0.14)	(1.97)**	(0.53)	(0.86)	(0.44)	(0.73)	(-0.24)	(4.17)***	(0.000)
Fama-French alpha (% p.a.)	17.45	8.31	6.63	0.33	6.52	2.55	3.98	2.52	4.35	-0.13	17.58	156.48
	(7.06)***	(4.16)***	(3.00)***	(0.18)	(3.31)***	(1.16)	(1.58)	(0.90)	(1.60)	(-0.03)	(5.05)***	(0.000)
Carhart alpha (% p.a.)	15.10	7.78	5.61	0.97	7.29	3.51	5.32	4.84	5.62	0.51	14.59	104.14
	(5.96)***	(3.59)***	(2.27)**	(0.50)	(3.52)***	(1.41)	(2.01)**	(1.65)*	(1.93)*	(0.11)	(3.68)***	(0.000)
					Panel C. January 2000-December 2008							
CAPM alpha (% p.a.)	13.19	8.43	14.98	11.04	10.69	12.30	7.54	4.31	5.89	2.69	10.49	56.70
	(3.61)***	(2.53)**	(4.99)***	(2.96)***	(2.46)**	(2.94)***	(1.33)	(0.94)	(1.19)	(0.42)	(1.94)*	(0.000)
Fama-French alpha (% p.a.)	7.87	2.59	10.01	5.69	6.46	6.80	2.14	-1.35	0.57	-3.39	11.26	49.03
	(3.39)***	(1.34)	(4.40)***	(2.06)**	(1.95)*	(2.06)**	(0.50)	(-0.38)	(0.14)	(-0.69)	(2.26)**	(0.000)
Carhart alpha (% p.a.)	7.34	2.16	9.84	5.25	5.96	6.39	2.47	-1.24	0.65	-3.61	10.95	49.68
	(3.17)***	(1.08)	(4.15)***	(1.88)*	(1.75)*	(1.92)*	(0.55)	(-0.34)	(0.16)	(-0.70)	(2.15)**	(0.000)

TABLE 6
Cross-sectional asset pricing tests

This table reports the mean of the risk premium coefficients λ_i estimated from the second stage of the Fama-MacBeth (1973) methodology. This involves monthly cross-sectional regressions of ten value-weighted excess portfolio returns on the corresponding risk factor loadings estimated in the first stage of the procedure (see Section 4.2 for details). These ten portfolios have been constructed by sorting all listed stocks in ascending order according to their Return-to-Turnover Rate (RtoTR) ratio. The sample period is February 1991- December 2008. The risk factor loadings used as regressors in the second stage are betas estimated from time-series regressions of excess portfolio returns on several risk factors using rolling windows of 60 monthly observations. However, for early sample periods we start computing betas when there are at least 36 observations. The reported results refer to augmented versions of the Capital Asset Pricing Model, the Fama-French model and the Carhart model (see equation (8)). The additional factor is the price impact (PI) factor that goes long the value-weighted decile portfolio P1 containing the stocks with the lowest RtoTR ratios and goes short the value-weighted decile portfolio P10 containing the stocks with the highest RtoTR ratios. In Panel A we report results from the unrestricted model, while in Panel B we report results from the restricted model where λ_0 is set equal to its zero theoretical value. Fama-MacBeth t-statistics are reported in parentheses. We also report in brackets t-statistics using Shanken (1992)-corrected standard errors to mitigate the error-in-variables bias. ***, ** and * indicates that the coefficient is statistically significant at the 1%, 5% and 10% level, respectively. The pre-last column in Panel A reports the adjusted R-squared coefficient for each model, while the last column reports the increase in the adjusted R-squared coefficient due to the addition of the PI factor to the plain version of the model.

	λ_0	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{PI}	Adj. R^2	ΔR^2
Panel A. Unrestricted Model								
	0.99	-1.24				0.81		
1. CAPM&PI	(1.15)	(-1.24)	-	-	-	(2.34)**	0.14	0.06
	[1.08]	[-1.18]				[2.30]**		
	2.02	-2.41	0.21	-0.32		0.97		
2. Fama-French&PI	(1.63)	(-1.70)*	(1.24)	(-0.44)	-	(2.96)***	0.20	0.05
	[1.33]	[-1.40]	[1.06]	[-0.36]		[2.82]***		
	1.74	-2.16	0.29	-0.59	0.25	0.94		
3. Carhart&PI	(1.19)	(-1.32)	(1.02)	(-0.76)	(0.68)	(2.94)***	0.25	0.05
	[0.96]	[-1.07]	[0.84]	[-0.62]	[0.56]	[2.82]***		
Panel B. Restricted model: λ_0 is set to equal zero								
		-0.19				0.81		
4. CAPM&PI	set to 0	(-0.62)	-	-	-	(2.25)**	-	-
		[-0.62]				[2.23]**		
		-0.21	0.08	0.29		0.93		
5. Fama-French&PI	set to 0	(-0.68)	(0.57)	(0.50)	-	(2.79)***	-	-
		[-0.67]	[0.55]	[0.48]		[2.75]***		
		-0.19	-0.13	0.18	0.63	0.92		
6. Carhart&PI	set to 0	(-0.62)	(-0.75)	(0.32)	(2.22)**	(2.83)***	-	-
		[-0.61]	[-0.68]	[0.28]	[1.97]**	[2.74]***		

TABLE 7
Momentum and size alphas from PI-augmented asset pricing models

This table reports the abnormal performance of momentum (Panel A) and size (Panel B) strategies derived from the Capital Asset Pricing Model, the Fama-French and the Carhart model as well as their augmented versions, where the additional price impact PI factor. This PI factor is constructed by going long the value-weighted decile portfolio P1 containing the stocks with the lowest Return-to-Turnover Rate (RtoTR) ratios and goes short the value-weighted decile portfolio P10 containing the stocks with the highest RtoTR ratios. To calculate the returns of the momentum strategy in month t, we sort all listed stocks at month $t-1$ according to their returns from month $t-13$ to month $t-2$ and assign them to ten portfolios. The momentum strategy goes long the value-weighted decile portfolio P10 containing the stocks with the highest prior returns (winners) and goes short the value-weighted decile portfolio P1 containing the stocks with the lowest prior returns (losers). To calculate the returns of the size strategy in month t, we sort all listed stocks at month $t-1$ according to their market capitalization and assign them to ten portfolios. The size strategy goes long the value-weighted decile portfolio P1 containing the stocks with the smallest market capitalization and goes short the value-weighted decile portfolio P10 containing the stocks with the highest market capitalization. t-statistics for the alpha coefficients are reported in parentheses. ***, ** and * indicates that the alpha coefficient is statistically significant at the 1%, 5% and 10% level, respectively.

	February 1991-December 2008	February 1991-December 1999	January 2000-December 2008
Panel A. Momentum alphas			
1. CAPM alpha	22.78 (2.78)***	29.35 (2.73)***	11.57 (1.08)
2. CAPM&PI alpha	16.71 (2.10)**	16.88 (1.87)*	9.57 (0.83)
3. Fama-French alpha	25.12 (3.73)***	27.35 (3.57)***	17.43 (1.68)*
4. Fama-French&PI alpha	19.81 (2.96)**	18.99 (2.71)***	14.34 (1.25)
5. Carhart alpha	9.44 (1.97)**	12.93 (2.30)**	5.80 (0.77)
6. Carhart&PI alpha	4.67 (0.98)	7.84 (1.32)	1.29 (0.17)
Panel B. Size alphas			
7. CAPM alpha	17.56 (2.69)***	13.40 (1.51)	22.44 (2.90)***
8. CAPM&PI alpha	27.02 (4.37)***	20.68 (2.41)***	32.66 (4.63)***
9. Fama-French alpha	14.66 (2.76)***	14.78 (2.07)**	15.64 (2.53)**
10.Fama-French&PI alpha	21.69 (4.19)***	16.16 (2.39)**	25.99 (4.49)***
11.Carhart alpha	11.85 (2.55)**	9.40 (1.66)	14.20 (2.31)**
12.Carhart&PI alpha	18.86 (3.93)***	11.47 (1.90)*	24.65 (4.09)***

TABLE 8
Percentage weights in the ex post tangency portfolio

Each column in this table reports the percentage weights of the available assets in the ex post tangency portfolio as well as the ex post monthly Sharpe ratio of the corresponding tangency portfolio. The asset universe in each case is consisted of various subsets of five traded factors: excess market returns (MKT), size (SMB), value (HML), momentum (MOM) and the price impact (PI) factor that goes long the value-weighted decile portfolio P1 containing the stocks with the lowest Return-to-Turnover Rate (RtoTR) ratios and goes short the value-weighted decile portfolio P10 containing the stocks with the highest RtoTR ratios. Panel A contains the results for the period February 1991- December 2008, while Panel B presents the corresponding results for the subperiod February 1991- December 2006.

Panel A. February 1991- December 2008							
MKT	100	-22.85	-21.95	-2.89	2.74	-1.67	-0.21
SMB	…	122.85	113.02	31.72	…	68.93	42.76
HML	…	…	8.94	11.99	…	-0.38	5.76
MOM	…	…	…	59.18	…	…	34.14
PI	…	…	…	…	97.26	33.11	17.54
Sharpe Ratio	-0.036	0.083	0.084	0.240	0.266	0.333	0.398
Panel B. February 1991- December 2006							
MKT	100	1.47	-0.04	1.22	19.76	2.89	2.52
SMB	…	98.53	89.63	35.53	…	68.44	47.97
HML	…	…	10.41	12.13	…	2.00	5.79
MOM	…	…	…	51.13	…	…	26.27
PI	…	…	…	…	80.24	26.67	17.45
Sharpe Ratio	0.023	0.123	0.128	0.251	0.268	0.381	0.422

TABLE 9
Correlations of traded factors' returns

This table presents the pairwise correlation coefficients of monthly returns for five traded factors: excess market returns (MKT), size (SMB), value (HML), momentum (MOM) and the price impact (PI) factor that goes long the value-weighted decile portfolio P1 containing the stocks with the lowest Return-to-Turnover Rate (RtoTR) ratios and goes short the value-weighted decile portfolio P10 containing the stocks with the highest RtoTR ratios. Panel A contains the correlation matrix for the period February 1991- December 2008, while Panel B refers to the subperiod February 1991- December 2006.

Panel A. February 1991- December 2008					
Correlation Matrix					
MKT	1.00				
SMB	0.19	1.00			
HML	0.16	0.03	1.00		
MOM	-0.15	-0.18	-0.37	1.00	
PI	-0.16	-0.43	0.02	0.09	1.00
Panel B. February 1991- December 2006					
Correlation Matrix					
MKT	1.00				
SMB	0.13	1.00			
HML	0.19	0.06	1.00		
MOM	-0.15	-0.11	-0.37	1.00	
PI	-0.16	-0.46	-0.02	0.13	1.00

FIGURE 1
Goodness of fit of the PI-adjusted CAPM
This Figure shows the goodness of fit of the PI-adjusted CAPM, utilizing the ten value-weighted *RtoTR*-sorted portfolios as test portfolios. In particular, it plots the annualized actual mean excess returns of these portfolios for the period February 1991- December 2008 versus the corresponding returns predicted by the PI-adjusted CAPM, given in equation (10). The estimation of the portfolios' returns sensitivities to the traded factors and their premia has been performed via a GMM estimator as explained in Section 4.2.