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Three Essays in Quantitative Asset Management

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Chapter 1

Introduction

Quantitative asset management integrates methods and tools from finance, economics, applied mathematics, statistics, data science and computer programming, with the aim to predict financial instruments' future returns and build portfolios that generate attractive risk-adjusted investment performance for end-investors. It started to develop in a significant manner in the late 1980s, as both financial data and computing power became readily available. Indeed, quantitative investors (“quants”) are evidence based: before deploying a given strategy, they typically want to back-test it over long historical periods. Quantitative investing models, being rooted in statistics and probabilities, generally require large sample size to be effective (i.e. to exhibit confidence intervals that are narrow enough). Quant funds therefore usually hold a higher number of securities than actively managed funds. Running back-tests on hundreds or thousands of assets for multiple decades requires important amounts of data and computing power.

Quantitative asset management also grew hand in hand with academic research in finance, in particular the strand of behavioral finance that documents “anoma-

lies” in an effort to illustrate the economic consequences of behavioral biases and disprove the efficient market hypothesis. If past data can, on average, predict future prices, then quantitative investment strategies can generate “alpha”, in other words attractive risk-adjusted returns that are not explained by sensitivities to known risk factors.

Other features of quantitative asset management have helped its growth. First, quant trading decisions are made automatically through pre-defined algorithmic rules. As such they are not influenced by human emotions, that have been shown to often lead to departure from rational choices. Second, thanks to systematization, data analysis capabilities and computing power, small teams of quantitative investors can cover very large number of securities and many different investment strategies. Investment analysis is therefore cheaper on a per security or per investment signal basis.

As a result of the above, quants have grown to represent a significant portion of total hedge fund assets. Quant hedge funds are estimated to manage close to USD 1 trillion, which is a large portion of the total assets managed by hedge funds (around USD 3 trillion)¹.

Quants have also expanded outside the hedge fund complex by applying their techniques to build long only portfolios and package them into mutual funds or exchange traded funds (ETFs), where such strategies are often known as *smart beta*. There also, they have come to represent an important proportion of assets under management: for instance, equity smart beta ETFs is estimated to represent around 30% of equity ETFs in the United States².

¹See the Financial Times article written by Robin Wigglesworth in January 2018 “Quant hedge funds set to surpass \$1tr management mark”.

²See The Economist article published in October 2019 “The stockmarket is now run by computers, algorithms and passive managers”.

This growth has not been without challenges. For instance, in August 2007, many equity quant hedge funds experienced significant losses at the same time (Khandani and Lo (2007)). This crisis likely started with emergency unwinds by a quant fund that experienced liquidity pressures due to margin calls and / or capital withdrawals. This led to a liquidity spiral *à la* Brunnermeier and Pedersen (2008). This 2007 Quant Crisis scarred quant equity investors for a long time and led to significant asset outflows. More recently, between 2018 and 2020, factor-based equity strategies exhibited poor returns, explained in great part by a significant under-performance of the value factor. Market observers have dubbed this period the “quant winter”. This period led to large outflows from factor based quant strategies: during that period, AQR, one of the largest factor based quant manager, lost more than a third of its assets, which fell from 226 billion USD to 140 billion USD³.

There are three key aspects to quantitative investing.

First, finding trading signals that are predictive of future returns. These signals are often referred to as “alphas” as they exhibit positive Jensen (1968) alpha versus various risk factors. A large body of the finance literature documents such signals or characteristics, often with the aim to contribute to asset pricing and the debate on market efficiency. For asset managers, finding these predictive characteristics is critical for their pursuit of investment performance.

Second, building portfolios that can extract performance from these signals while respecting risk management features such as diversification, liquidity and constraints on sensitivities to various risk factors (e.g. sectors, countries, equity

³See the Financial times article written by Robin Wigglesworth and Laurence Fletcher in April 2021 “‘Quant winter’ thaw ends long spell of drab returns for funds”.

factors, macro factors etc.). Ever since its beginnings, the literature on portfolio choice has indeed been about optimizing **risk**-adjusted returns. In that respect, it is important to define, estimate and control risk appropriately. Failure to do so can have serious consequences for asset managers, such as capital outflows or even failures.

Finally, implementing these portfolios in the most efficient way. Quantitative investment processes generally require leverage, and their underlying signals are dynamic which often leads to a much higher portfolio turnover than passive investment styles. Implementation costs can therefore represent an important portion of gross expected returns. As such, delivering positive risk-adjusted investment performance **net** of these costs requires a good understanding and estimation of liquidity and the various costs and frictions attached to trading financial assets.

This thesis consists of three essays, each of them contributing to specific topics of interest for these three key aspects of quantitative asset management: alpha generation, risk management and implementation. In this introduction, I will present each of the above three key aspects and the strands of academic literature related to them. Finally, I will introduce the three essays composing my thesis, explaining how they relate and contribute to these aspects.

1.1 Generating Investment Performance

This section examines important facets of alpha generation. What are the sources of alpha? Why is alpha not arbitrated away? And what are the methodological pitfalls faced by researchers looking for predictive signals?

1.1.1 Risk Premia vs Market Anomalies or the Efficient Market Hypothesis Debate

Investment performance (or the predictability of future asset returns) can be interpreted in two different ways. It can be seen as a remuneration for taking risk: the term often used for such investments is “risk premia”. It can also be perceived as the result of market inefficiencies, leading to trading signals that exploit mispricings and are therefore not associated with any particular risk: these signals are referred to as “market anomalies” - predictability that seems to be inconsistent with (typically risk-based) theories of asset prices. Signals exploiting mispricings generate positive excess returns as prices eventually move towards their fundamental values, for instance when fundamental data is released, leading market participants to realize they might have been over- or under-pricing a given asset. The categorization of signals into risk premia or market anomaly is not always clear cut, as it is generally relatively easy to propose either risk or anomaly interpretations to explain their positive performance.

And the way one categorizes a given signal often depends on which side one stands on arguably one of the largest debate in modern academic finance research: the debate around the plausibility of the efficient market hypothesis. This debate

has led academics to document a multitude of signals that appear to be predictive of future asset returns⁴, resulting in a fertile exchange between academia and quant asset management. This exchange goes both way. When originated in academia, the ideas are used by quant asset managers as sources of performance. Ideas can also originate from quants’ own proprietary research, and are then used by academics in their publishing endeavours. It is therefore worth summarizing the debate on market efficiency, which we do in the following paragraphs.

Markowitz (1952)’s work on portfolio theory and the link between security risk and return paved the way for Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966) to develop the Capital Asset Pricing Model (CAPM), a model in which there is a relationship between expected returns and security risk as measured by “market risk”, the beta of individual securities to the market. This was followed by Fama (1970) proposing the efficient market hypothesis, a theory suggesting that asset prices reflect all available information, either because economic agents are fully rational, or, if they are not, because enough arbitrage capital instantaneously chases away mispricings. In such a construct, investment returns can only be a remuneration for risk. A generalization of CAPM was introduced by the research of Lucas (1978): the consumption-based capital asset pricing model (CCAPM). The CCAPM uses a more realistic multi-period set-up than the static one-period setting of CAPM. The main result of CCAPM is that the expected return of an asset is related to its consumption risk. More formally, the CCAPM states that the expected return of an asset in excess of the risk free rate is proportional to the covariance of its return and consumption.

The plausibility of CAPM was put in question by discoveries such as the “low

⁴A large majority of this research are focused on predicting the cross section of stock returns.

beta” anomaly: empirical research (amongst which [Black et al. \(1972\)](#)) showed that high beta stocks performed much less than predicted by CAPM. An extension of CAPM, named Arbitrage Pricing Theory (APT), was put forward by [Ross \(1976\)](#). APT proposes that financial asset returns can be modeled as a linear function of various factors, where sensitivity to changes in each factor is represented by a factor-specific beta coefficient. If prices diverge from the model, arbitrage should bring them back into line (hence its name). The linear factor model structure of APT has been used as the basis for many of the commercial risk systems employed by asset managers. [Fama and French \(1992, 1993\)](#) also based their well-known three factor asset pricing model on APT: they argued that sensitivity to market risk (the sole factor in CAPM) is not the only determinant of stock returns. They added additional factors to the initial model, including size and value. This multi-factor model does a better job than CAPM at explaining the cross-section of stock returns. Fama and French, both proponent of the efficient market hypothesis, argued that size and value are both risk factors. According to them, value and small-cap stocks face higher cost of capital and greater business risk: these stocks should therefore exhibit higher returns to compensate investors for risk.

In parallel, behavioral economics emerged. It began with a questioning of one of the main assumptions behind neoclassical economics and the efficient market hypothesis, namely that economic agents are perfectly rational. As early as the mid 1950s, [Simon \(1957\)](#) proposed bounded rationality - the idea that rationality is limited when individuals make decision - as an alternative. In the 1970s, [Kahneman and Tversky \(1979\)](#) studied decision making, and found that human beings were subject to numerous cognitive biases (such as anchoring and base rate

neglect). Thaler then proceeded to show that these departures from rationality materialized themselves in the real economy. In that respect, financial markets were a good research hunting ground: stock prices and firm-level balance sheet data were available, with relatively long history. Thaler discovered several market anomalies, such as the “January effect” (Thaler (1987): stock prices tend to rise in January, in particular those of small stocks who had declined in previous years). He was followed by many other researchers looking to document more of these anomalies⁵, often with the aim to disprove the efficient market hypothesis. Other articles focused on showing that characteristics, such as those used in Fama and French (1993) were more likely anomalies than risk factors: for instance, Daniel and Titman (1997)’s results indicated that there was no discernible risk factor associated with high or low book-to-market firms. Of course, behavioral finance is not only about looking for asset pricing anomalies: it has many other aims, which include integrating behavioral biases in economic modeling in order to design better, more efficient policies. For a good survey on behavioral finance and its application, see Barberis (2018).

The debate on the efficiency of markets is still ongoing. But some argue that, for asset managers, whether a signal performs because it bears risk or is the result of behavioral biases is not that important. As Ang et al (2009) assert in their study for the Norwegian Government Pension Fund, these signals “are of potential interest [...] because they may indicate sources of return - whether these are factor-based or based on the pricing inefficiency”. The literature on asset pricing has continued to be prolific in recent years. For example, Fama and French (2015)

⁵Harvey et al. (2016) make a list of factors that have been proposed by academic researchers as predictive of the cross-section of stock returns. They use relatively stringent selection criteria but still end up with 313 articles, and 316 factors. They note that this is only a subset of those studied in the literature.

have augmented their model by integrating two additional factors: profitability and investment patterns. Also, new techniques, such as machine learning, have been successfully applied to that field (see, e.g., [Gu et al. \(2020\)](#)).

1.1.2 Limits to Arbitrage

Behavioral finance argues that financial asset returns predictability can be interpreted as deviations from risk-based asset pricing models and that these come from the presence of economic agents that are not fully rational. A long-standing critique to this view is that rational arbitrageurs will chase away any mispricings ([Friedman \(1953\)](#)), thereby making markets efficient. Said differently, the fact that a set of market participants are biased might not lead to inefficient markets as long as arbitrageurs can trade freely, without constraints. The question then becomes: are arbitrageurs truly unconstrained? The answer to this question is that they do face limitations. Academic works studying these are known as the “limits to arbitrage” literature.

For instance, **noise trader risk** refers to the possibility that the mispricing being exploited worsens. This idea was introduced by [De Long et al \(1990\)](#) and studied further by [Shleifer and Vishny \(1997\)](#). This risk is an important consideration because it can force arbitrageurs to early liquidate their positions at a loss. There are two main real-world reasons why arbitrageurs might be coerced into early unwinding their positions. The first one is that arbitrage activity often requires leverage: creditors, after seeing arbitrageurs lose money, can call their loans and trigger forced liquidations. One of the well known example of an arbitrageur falling victim to such risk is Long-Term Capital Management. The second one is the fact that arbitrageurs are often managing third-party investors’ money.

These investors may not be able to evaluate well the arbitrageurs' trading strategies other than by looking at their returns. They might withdraw their funds after negative returns, leading again to forced liquidations.

Another element preventing arbitrageurs from fully chasing away market anomalies is **implementation costs**. Commissions, market impact, bid-offer spreads, borrowing spread, dividend with-holding taxes all make it less attractive to exploit mispricings. Short-sales constraints, such as the fee charged for borrowing stocks, the existence of stocks that cannot be borrowed at all or the risk that borrowed stocks are recalled by lenders, are also important impediments for arbitrageurs (see, e.g., [D'Aviolo \(2002\)](#)).

The early works cited above were followed by many articles carefully studying the process and constraints of arbitrage. [Gromb and Vayanos \(2010\)](#) offer a survey on theoretical developments in this literature, and propose a model that nests most of them.

1.1.3 Data Snooping, Over-Fitting and Multiple Testing

Quant asset managers' researchers, in their pursuit of new sources of performance, face many pitfalls. These pitfalls are the same as those faced by academic researchers that are trying to document new anomalies and risk factors. But the consequences are different. For quant asset managers, mis-selecting signals will lead to poorer performance over the long run. For academic researchers, it could lead to their research being somewhat discredited once it appears that the effect they documented does not hold out of sample. Below, we describe some of these pitfalls.

Data snooping refers to the misuse of data analysis to find patterns in data

that can be presented as statistically significant, thus increasing the risk of false positives. This is generally done by performing many different tests on the data and only reporting those that exhibit significant results. It is therefore related to **multiple hypothesis testing** (MHT): the more candidate signals a researcher tries, the more likely he is to find one that looks statistically significant, even if it is not. Another related pitfall that leads to false positives is **over-fitting**. It generally takes the form of an overly complex signal definition (e.g. with a lot of parameters), that leads to attractive back-tested performance (because the parameters chosen happen to be fitting past data well), but poor out of sample predictive ability.

The premise that finance applications are exposed to MHT dates from the 1990s. [Lo and MacKinlay \(1990\)](#) made a first attempt at estimating the data-snooping bias in asset pricing applications. Other attempts at incorporating MHT adjustments have followed, such as [Ferson and Harvey \(1999\)](#). More recently, a number of papers have applied MHT correction methods to address two main questions in finance: fund performance and the statistical significance of market anomalies. One complication arising for the latter is the fact that one does not know all the tests that have been done, but only observes those that are published, i.e. that passes a certain conventional statistical significance threshold.

There are ways to mitigate selection biases induced by these pitfalls. Defining ex-ante a small number of hypotheses to be tested before analyzing a given dataset helps to reduce this risk. A number of papers are interested in adjusting thresholds for statistical significance when several hypothesis tests are carried out at the same time, such as [Romano and Wolf \(2005\)](#). More recently, [Lopez de Prado \(2019\)](#) and [Harvey et al. \(2020\)](#) both propose methods to improve statistical

inference in financial economics, when faced with multiple testing. This generally requires some honesty from the researcher on the number of independent trials he has done. Also, keeping signal definition as simple as possible and ensuring there is a plausible economic explanation behind its performance can reduce the risk of over-fitting. Finally, splitting the data sample into two, one for initial research, one for out-of-sample analysis can lower the probability of false positives. Machine learning techniques, the use of which has recently spread in finance, are particularly prone to the risk of over-fitting. They typically propose to split the sample available into training and validation samples to alleviate this risk.

There is currently a debate on whether financial economics faces a “replication crisis”, as there is a concern that a large set of studies cannot be replicated or are the result of multiple testing. The extent of the selection bias issue in finance is documented in various papers. One of them is [McLean and Pontiff \(2016\)](#), who study a large set of factors published in academic journals and show they exhibit a large deterioration in performance post-publication. On the other hand, [Jensen et al. \(2021\)](#) offer some reassurance: they show that a majority (rather than a minority) of asset pricing factors can be replicated and work out of sample.

1.2 Risk Management

This section inspects risk management. It first looks at the typical risks associated with a portfolio of financial assets. In order to be controlled, these need to be appropriately estimated. It is also important to take into account the endogenous nature of financial markets: market participants, through their trading behaviours, impact prices. This feature makes crowding, which is studied next, an important risk.

1.2.1 Estimating and Controlling Risk

Many risks are affecting a portfolio of financial assets: its overall volatility, its sensitivity (or beta) to the broader market or to other risk factors (e.g. equity or macro factors), sector, industry and country exposures, concentration and liquidity risks etc. Controlling for these risks makes the portfolio optimization complex, and often requires the help of optimization softwares.

What are the most relevant risks? [Markowitz \(1952\)](#) uses mean returns, variances and covariances to derive an efficient frontier where every portfolio on the frontier minimizes the variance for a given expected return. In his framework, portfolio variance is the risk that is controlled. [Roy \(1952\)](#) states that an investor will prefer safety first and will set some minimum acceptable return, essentially implying that the risk to control is downside risk. A number of important works focus on downside and tail risk, such as, to cite a few recent ones, [Kelly and Jiang \(2014\)](#) and [Langlois \(2018\)](#). The CAPM argues that the main risk in a financial asset is its beta to the broader market, as idiosyncratic risk can be diversified away. [Fama and French \(1992, 1993\)](#) add value and size as equity risk factors in

their three-factor model. [Amihud \(2002\)](#) proposes an illiquidity measure which is based on the daily ratio of absolute stock return to dollar volume, and shows that expected stock returns are affected by an illiquidity premium. Many works build on this, including [Acharya and Pedersen \(2004\)](#), who propose a liquidity-adjusted CAPM that is consistent with empirical findings of how liquidity risk affects asset prices. [Lo \(2001\)](#) argues that dynamic risk analytics, liquidity and non-linearities are important risk consideration for hedge fund managers and investors, as more traditional measures such as mean-variance analysis, beta and value at risk do not capture all risks associated with hedge fund strategies.

Estimating properly these risk inputs is therefore a critical element in the construction of a well risk-controlled portfolio. These estimations often come with more complexity than can initially seem.

For instance, estimating the covariance matrix of stock returns can be tricky. A straightforward method is to calculate the sample covariance matrix from the history of past stock returns. But this creates issues such as documented in [Jobson and Korkie \(1980\)](#). Essentially, when the number of stocks under consideration is large relative to the number of historical observations - which is usually the case for quant equity portfolios, the sample covariance matrix is estimated with a lot of errors. This issue is particularly acute for the most extreme coefficients of the matrix, which is problematic as portfolio optimization will place large bets on those coefficients. To address such problems, [Ledoit and Wolf \(2004\)](#) propose a linear transformation of the covariance matrix they call “shrinkage”. This transformation helps to pull the extremes coefficients towards more central values, thereby reducing estimation error. In more recent work on the topic, [Ledoit and Wolf \(2017\)](#) propose a non-linear shrinkage which improves over the earlier linear

transformation.

1.2.2 Crowding: From Alpha to Risk Factor

The predictive ability of a given signal is not constant through time. Endogenous effects are at play. A signal that exhibits alluring risk-adjusted returns attracts more arbitrage capital. This additional capital, through price impact on the underlying financial assets traded, reduces the risk-adjusted returns of the signal. It also increases the probability of large negative returns when this capital is suddenly removed. This effect is referred to as “crowding” and has been the topic of numerous papers. One of them is [Hanson and Sunderam \(2014\)](#): it infers crowding of some of the well-known quant equity strategies from short interest data and studies its impact. Its key findings are consistent with the above, in particular: (i) attractive strategy performance are followed by higher crowding (more arbitrage capital) and (ii) high levels of crowding are followed by lower strategy returns.

Another strand of literature is interested in the relationship between crowding and draw-down risk. [Khandani and Lo \(2007\)](#) and [Pedersen \(2009\)](#) aim to explain the Quant Crisis of 2007: they infer that this event was triggered by the simultaneous removal of large amounts of arbitrage capital, which illustrate the dangers of crowding. These works are related to the limits to arbitrage literature, such as [Shleifer and Vishny \(1997\)](#) who show that arbitrage is risky because capital can be removed when performance is poor and [Brunermeier and Pedersen \(2008\)](#) who show how the use of leverage can be destabilizing and lead to “liquidity spirals”, events during which liquidity dries up across securities and arbitrageurs are suffering losses while safe assets are bid up.

Finally, some papers are focused on alpha decay. For instance [McLean and](#)

[Pontiff \(2016\)](#) show that post-publication performance is reduced significantly versus pre-publication performance. They attribute this decay to the fact that academic publication leads to increase in capitals arbitraging the documented signals.

The above discussion points to a natural evolution for investment signals (see [Lo \(2004\)](#) and his “adaptive market hypothesis”). They start as anomalies - well performing signals with limited sensitivity to broader liquidity shocks. When known and adopted by a large set of investors, they become risk factors, signals with limited out-performance and with frequent draw-downs. [Cho \(2020\)](#) shows empirically that arbitrage activity indeed exposes market anomalies to endogenous risks, thereby “turning alphas into betas”. Faced with such an evolving environment, it is critical for quant investment managers to develop the appropriate tools to monitor signal-level crowding and decay measures.

1.3 Implementation

This section presents the important topic of implementation. Market anomalies are often studied in the literature with little care given to implementation considerations. But these are in fact crucial for determining whether these anomalies have actual economic significance, i.e, whether they can be implemented profitably and at significant scale by arbitrageurs.

1.3.1 Liquidity

As mentioned earlier, quant asset managers, in order to increase the risk-adjusted profitability of the signals they trade, look to deploy them on a large universe of individual securities. By increasing the number of positive-expected-returns bets they take, they reduce, through diversification and the law of large numbers, the probability and range of adverse outcomes. But there is a limit to how much a (not too small) investor can diversify: liquidity.

Indeed, certain financial assets cannot be included in investable universes because their liquidity is not large enough. The size one can trade might be too small to matter, or the price impact of trading the required amount might be prohibitive.

What are the best measures of liquidity? The finance literature has proposed various measures, that can be broadly grouped in two categories. “Spread” measures are computed from bid, offer and traded prices, such as in [Huang and Stoll \(1996\)](#). “Price impact” measures look at how much traded volume impacts prices. Some well-known price impact liquidity measures are proposed by [Amihud \(2002\)](#) and [Pastor and Stambaugh \(2003\)](#). [Goyenko et al. \(2009\)](#) provide a good summary

of both intraday measures and proxies based on daily data. Liquidity also constrains “capacity”, the amount of capital that can be allocated to a given trading strategies without deteriorating its net performance beyond certain levels.

1.3.2 Trading Costs

The vast majority of the empirical asset pricing research dedicated to documenting anomalies does not take into account trading costs. Instead, this literature aims to show that certain signals correlate with future returns (gross of any costs) in a statistically significant way. As alluded to in **1.1.1**, the interpretation of such findings is either a failure of the efficient market hypothesis, or the discovery of a new risk factor.

It is important to consider implementation costs for multiple reasons. First, as we have discussed above, limits to arbitrage such as transaction costs are crucial when analyzing market efficiency. Market anomalies do not put market efficiency into much question if they can not attract arbitrage capital because they are not implementable profitably in the real world. Second, arbitrageurs will be interested in any techniques that help them implement their strategies in the most efficient manner (in other words, reduce their “implementation shortfall” as defined by [Perold \(1988\)](#)). A pre-requisite for this is to properly account for and estimate trading costs. A large body of research has contributed to this important topic.

A set of papers (such as [Almgren et al. \(2005\)](#) and [Frazzini et al. \(2018\)](#)) are interested in estimating market impact - a financial asset’s price movement caused by trades in that asset. These works generally use proprietary equity execution databases and all come broadly to the same conclusion: market impact follows a power function of trade size. More recent papers (see, e.g. [Farmer et al.](#)

(2013) and [Bucci et al. \(2019\)](#)) have analysed theoretically and empirically the subsequent behavior of market impact (i.e. in the days following the trade causing such impact): they show that market impact decays slowly. This fact pattern will be an important ingredient for the third chapter of this thesis.

Other papers have focused on analysing various market anomalies net of trading costs. For instance, [Novy-Marx and Velikov \(2016\)](#) run such analysis on a large number of anomalies and show that transaction costs reduce significantly the strategies' profitability and associated statistical significance. Consistent with intuition, this is especially true for high turnover strategies. [Drechsler and Drechsler \(2014\)](#) focus on shorting fees and show that eight of the largest and most well-known equity cross-sectional anomalies disappear when applied to the stocks that have low fees (and are therefore easier to short).

Another set of papers are interested at devising optimal trading rules in the presence of trading cost. Works from [Constantidines and Magill \(1976\)](#), [Constantidines \(1986\)](#) and [Dumas and Luciano \(1991\)](#) look at transaction costs in the context of their impact on portfolio choice. These works show that it is optimal to avoid trading unless portfolio weights leave a “region of no transactions” around the frictionless target. Many papers on portfolio choice in the presence of costs followed. For example, [Garleanu and Pedersen \(2013\)](#) derive a closed-form optimal dynamic portfolio policy in the presence of quadratic trading costs.

1.4 Research Work Presentation

The aim of this dissertation is to contribute to all three aspects of quantitative asset management described above. These contributions are of both empirical and theoretical natures.

On the empirical front, an important part of the work is devoted to confirming, in the data, hypotheses or theoretical predictions such as the inattention of stock prices to currency movements, the tendency of crowded trading strategies to suffer upon the occurrence of liquidity shocks, the much lower effective capacity of trading strategies when market impact “memory” is taken into account. From a methodological point of view, a great care is given to ensuring the soundness of the results. For instance, T-statistics are appropriately adjusted for complicating factors such as cross-sectional dependencies or generated regressor bias. The universe of financial assets studied include both North American and Developed Europe stocks, and a wide array of firm-level datasets are used.

A theoretical framework is developed in the third chapter: its aim is to make predictions on crowded strategy by modeling the interaction of different types of arbitrageurs. Its results are then confirmed in the empirical work. Additionally, a synthesis of the relevant theoretical literature is proposed for each essay, and helps elaborate hypotheses that can be tested subsequently. For example, in the second chapter, bounded rationality (inattention) is offered as an explanation for the lack of immediate reaction of stock prices to currency movements.

Finally, this work can hopefully be of interest to quantitative asset managers: it offers tools to monitor risks such as crowding, as well as methods to better estimate capacity, both important considerations for practitioners.

1.4.1 Currency and Stock Returns: An Example of Market Inattention

The second chapter of the thesis, co-written with Augustin Landier and Yonglei Wang, studies the impact of currency movements on the cross section of stock returns. Indeed, currency shocks offer an interesting laboratory to analyze the extent to which markets deviate from efficiency and whether investors tend to under-react to new information.

We use an original dataset that provides firm-level geographical revenue splits by country. By combining this information with currency returns, we are able to construct a measure of firm-level “currency pressure” that should impact stock prices. Consistent with a bounded rationality interpretation, we show that stock prices fail to integrate rapidly small and medium sized currency shocks; but integrate efficiently larger, more salient shocks.

This deviation from market efficiency is a typical market anomaly (as described in the first section of this introduction): it cannot be explained by risk-based theories of asset prices, but rather by the existence of behavioral frictions - in this case, inattention. Such anomaly can be exploited by arbitrageurs seeking to generate alpha.

This article contributes in several ways. First, it documents that analysts fail to integrate currency information in their firm-level forecasts. In that respect, it adds to the literature documenting analyst biases, that started with [Abarbanell \(1991\)](#). Second, it shows that stock prices also fail to respond immediately to currency movements: they take about two weeks to integrate past currency shocks. But prices **do not** under-react to larger shocks, in line with our hypothesis of bounded

rationality and inattention. Finally, it studies a long/short trading strategy that aims to arbitrage this anomaly. It confirms that such a strategy delivers significant positive alpha. But it also shows that more arbitrage capital have been chasing it in the past few years, shedding light on alpha decay and the “adaptive” nature of markets (Lo (2004)).

1.4.2 Crowding and Liquidity Shocks

The third chapter, co-written with Tony Tan, studies the link between crowding and liquidity shocks, both of which are important topics in finance (as discussed in 1.2).

This work starts by developing a model where biased “naive” investors trade with two different groups of arbitrageurs, each observing different signals that give information on these biases. This set up enables to study crowding and reach the following results. First, crowding measures can be inferred from arbitrageurs’ aggregated positions (similar to Hanson and Sunderam (2014)). Second, arbitrageurs’ overall profits suffer V-shape drawdowns upon the occurrence of exogenous liquidity shocks. Third, crowded strategies suffer larger losses during these shocks.

The second portion of the chapter confirms these results empirically. It uses short interest as a proxy for arbitrageurs’ aggregated positions and confirms that a strategy following these aggregated positions suffers large drawdown during liquidity shocks such as the 2007 Quant Crisis and the 2020 Quant Deleverage. It then computes crowding measures for some well-known equity factors and verifies that the more a strategy is crowded the more it tends to suffer during liquidity shocks.

This article contributes to the crowding and risk literature by formally and empirically establishing that crowding is associated with an adverse exposure to broad liquidity shocks.

1.4.3 Market Impact Decay and Capacity

The final chapter of this dissertation is dedicated to estimating the capacity of trading strategies by taking into account a recently discovered feature of market impact: the fact that it takes weeks to decay, rather than immediately reverts as previously assumed (see, e.g., [Farmer et al. \(2013\)](#) and [Bucci et al. \(2019\)](#)).

The capacity of trading strategies such as market anomalies is an important topic, both for asset managers who need to carefully estimate it, and for academic researchers: in order to establish the economic significance of a given anomaly, it is indeed critical to evaluate the amount of arbitrage capital that can profitably exploit it.

This article contributes to the cost and capacity literature in two major ways. First, it proposes a numerical methodology to estimate capacity. The advantage of such a methodology is that it can incorporate any specification of market impact, including its slow decay through time. Second, it estimates the capacity of some well-known equity long/short strategies for both large and medium market capitalization stocks in North America. It finds that capacity is orders of magnitude lower than previously thought. The intuition is that as trades tend to become more auto-correlated when capital increases, the fact that market impact decays slowly leads to an increase in trading costs.

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Chapter 2

Currency and Stock Returns: An Example of Market Inattention

Joint work with Augustin Landier (HEC) and Yonglei Wang (AXA IM Chorus)

Abstract: Currency shocks affect future corporate earnings: companies exporting in countries with an appreciating currency see their earnings increase. Using company-level data on geographic sales for US and Canadian firms, we document that analysts fail to fully integrate currency shocks into their forecasts: their forecast errors can therefore be predicted by past currency movements. We also show that stock prices do not respond immediately to currency shocks: prices take about two weeks to integrate them. This is true for small to medium size shocks but not for larger shocks, in line with a bounded rationality interpretation. Finally, we find some evidence that arbitrage capital exploiting this anomaly has increased in recent years.

2.1 Introduction

A major function of financial markets is to ensure that prices incorporate information in real time. Under the efficient market hypothesis, the reaction of prices to public news should be immediate: at any given time, prices should reflect expected fundamental values conditional on available information. This idealized view of markets imperfectly represents reality. A large body of literature documents that markets sometimes over-react (typically, when information is “salient”), and sometimes under-react (typically to small news that are not attention-grabbing). Understanding the conditions under which people over-react and under-react to news remains an open problem in social sciences.

Currency shocks offer an interesting laboratory to analyze (i) the extent to which markets deviate from the efficient market hypothesis and (ii) when investors tend to under-react to new information. Indeed, companies’ earnings and value are, on average, affected in a predictable manner by exchange rate movements once the split of their international sales by country is taken into account. Furthermore, currency returns offer the econometrician a large spectrum of intensity that can be used to ascertain the reaction of market participants. Small currency returns might be too small to grab the attention of investors, thus leading to under-reaction. In contrast, large shocks could be highly visible in the news and might be integrated into prices efficiently.

The aim of this paper is to analyze how exchange rate fluctuations are incorporated in analysts’ earnings forecasts and stock prices.

Firms are exposed to currency movements for the following reasons. First, they are exposed to exchange rate movements through mismatches between the

currency denomination of their assets and liabilities. For instance, a firm with significant foreign sales (an exporting firm) would generally have an important proportion of its expected cash flows denominated in foreign currencies, whereas most of its production costs would be in local currency. As a result, absent any currency hedging, the profitability and value of exporting firms increase (decrease) with the depreciation (appreciation) of its country's currency. Companies often try to reduce such exchange rate sensitivity, either through derivatives hedging transactions (such as FX forwards) or by directly reducing their currency mismatches, for example by moving production and costs to the countries where it generates foreign currency sales. Second, the depreciation of a country's currency also makes its exporting firms more competitive as they can offer lower prices in foreign currencies and can thereby increase their market share. Finally, an appreciating foreign currency might be correlated with a stronger economic environment in that foreign country, thus increasing demand for the products of companies that export in that country.

Here is an illustration of the above. Apple Inc. derives the majority of its net sales from abroad (63% in 2017, according to the firm's 10-K for the fiscal year 2017), and is therefore expected to be impacted by exchange rate movements. In the risk factors of the company's filings, we find the following passage:

The Company's primary exposure to movements in foreign currency exchange rates relates to non-U.S. dollar-denominated sales and operating expenses worldwide. Weakening of foreign currencies relative to the U.S. dollar adversely affects the U.S. dollar value of the Company's foreign currency-denominated sales and earnings, and generally leads to the Company to raise international pricing, potentially reducing demand for the Company's products. The use of [...] hedging

activities may not offset any, or more than a portion, of the adverse financial effects of unfavorable movements in the foreign exchange rates.

Further, in the business highlights of the same filing, Apple Inc. reports:

The weakness of foreign currencies relative to the U.S. dollar had an unfavourable impact on net sales during 2017 compared to 2016.

The impact of currency fluctuations on companies has long been documented. For instance, [Jorion \(1990\)](#) looks into the exposure of US firms to foreign currency risk and shows that the co-movement between stock returns and the value of the dollar is positively related to their percentage of foreign operations. [Allayanis and Ofek \(2001\)](#) confirm the results of [Jorion \(1990\)](#) and, in addition, show evidence that firms use foreign currency derivatives to reduce their sensitivity to exchange rate movements (rather than to speculate). [Dominguez and Tesar \(2006\)](#) examine the relationship between exchange rate movements and firm market value across eight industrialized and emerging countries. They find that exchange rate movements are impacting a significant fraction of firms, but that these exposures are time varying, suggesting that firms dynamically adjust their behaviors by using tools such as currency hedging. On the particular topic of hedging and risk management by corporations, [Froot et al. \(1993\)](#) develop a theoretical framework to determine optimal hedging and discuss, amongst other, exchange rate hedging strategies for multinationals.

We focus our analysis on the 1,000 largest US and Canadian stocks at any given time. Our analysis consists of the following. We obtain, for each firm-year in our sample, the split of foreign sales by country. This is provided by the Factset Geographical Revenue Exposure database and is available since January 2007. We are then able to compute, for each firm, a measure of “currency pressure”

by applying recent currency returns to these country splits: we call this measure FX Shock. A positive FX Shock means that recent currency returns have been favourable for the company (for example, because its local currency has recently depreciated, thereby increasing the value of its foreign sales), and should therefore lead to better earnings and an increase of the firm's value. We confirm in the data that there is a positive relationship between our measure and firms' earnings. We also develop a methodology to distinguish between small and large currency shocks.

Equipped with this measure of firm-level currency pressure, we then proceed to various tests. We find the following. First, we document that analysts fail to fully integrate currency shocks in their firm-level forecasts. Their forecast errors can therefore be predicted by currency shocks. We show that analysts under-react systematically to all shocks, small or large. Second, we document that stock prices fail as well to respond immediately to currency movements: they take about two weeks to integrate past currency shocks. But markets **do not** under-react to larger shocks, in line with a bounded rationality interpretation. Finally, we look at a trading strategy that goes long (short) stocks that are subject to positive (negative) currency shocks. The strategy exhibits a positive and significant Sharpe ratio and has continued performing strongly since the first version of the paper was disseminated more than two years ago. We then try to detect whether capital allocated to such a strategy has increased in recent years. We do so by looking at the negative impact on strategy performance of trading on information lagged by a few days. This impact has increased in the past few years, giving some evidence that more arbitrage capital is chasing this anomaly.

Our work is related to the large body of literature on behavioral finance, and in

particular to under-reaction and inattention. [Barberis and Thaler \(2003\)](#) and [Hirshleifer \(2015\)](#) provide detailed surveys on behavioral finance. [Hong et al. \(2000\)](#) give evidence that firm-specific information, especially negative information, diffuses only gradually across the investing public and prices. They contend that this slow diffusion of information is one explanation for momentum in stock returns. It is also well documented that analysts forecasts exhibit biases (see e.g. [Abarbanell \(1991\)](#) and [Kothari et al. \(2016\)](#)). On the more specific subject of inattention (which is often cited as one of the main causes for under-reaction), [Gabaix \(2018\)](#) provides an in-depth review. More recently, a few papers have contributed to the debate on under- versus over-reaction. [Bordalo et al. \(2020\)](#) show that professional forecasters tend to over-react to their individual news, while consensus forecasts are sluggish and show signs of under-reaction. They reconcile these seemingly contradictory empirical findings by formulating a diagnostic expectations model. [Kwon and Tang \(2020\)](#) identify substantial heterogeneity in reaction to news. To explain this, they propose a model of stock price reaction to corporate news in which investors use significant past observations to evaluate new information.

A few previous studies have used geographic segment data. One of them is [Li et al. \(2014\)](#) who combine firm-level exposures to country with macro economic forecasts of country-level performance to generate superior forecasts for firm fundamentals.

This paper is also related to the literature on the decay of trading strategies. [McLean and Pontiff \(2016\)](#) show that many market anomalies disappear as soon as research papers documenting them are disseminated to the public, suggesting that arbitrage capital moves in quickly and decays their performance. In earlier works, [Johnson and Schwartz \(2000\)](#) and [Green et al. \(2011\)](#) document, respectively on

the post-earnings drift and the accruals anomalies, a decline in anomaly returns following academic publication. More recently, [Caluzzo et al. \(2019\)](#) show that institutional investors trade on stock anomalies once they become publicized and participate in the decay of these anomalies.

Finally, this work is connected to papers who look at the interaction between markets and analysts. Recent examples include [Bouchaud et al. \(2019\)](#) who propose a theory of the “profitability” anomaly by documenting that analysts are on average too pessimistic regarding future profits of high-profit firms. [Chen et al. \(2018\)](#) show that when analyst coverage drops, sophisticated investors scale up information acquisition and mitigate the market efficiency impairment caused by that drop.

Our paper adds to the strand of research that investigates under-reaction and inattention in financial markets. We document that analysts fail to integrate exchange rate fluctuations in their forecasts of company earnings. Markets do a better job at integrating this information in stock prices, but still take around two weeks to do so. Markets do not under-react to larger, more visible currency shocks, consistent with a bounded rationality interpretation.

We also contribute to the literature that investigates the relationship between currency movements and stock prices. Most of these earlier studies focused on longer window contemporaneous co-movement between stock prices and currencies. Our work analyses higher frequency returns (weekly). Consistent with previous work, stock prices co-move with currencies, but with a lag of about two weeks.

Finally, we add to the debate on the attenuation of anomalies. We show that a quantitative equity long/short strategy that aims to benefit from this slow diffusion

of exchange rate fluctuations in stock prices needs to be implemented quicker than a few years ago, which implies an increase in arbitrage capital devoted to this strategy in recent years.

The remainder of this paper is organized as follows. **Section 2.2** describes the data used. **Section 2.3** explains how we construct our measure of firm-level currency pressure *FXShock* and confirms that there is a positive relationship between this measure and both net sales and earnings. **Section 2.4** establishes that analysts fail to properly take into account the past dynamic of currency prices when they issue their firm-level forecasts. In **Section 2.5**, we show that the market is much quicker than analysts at integrating currency movements in stock prices. However, this reaction is not instantaneous: we find that FX shocks predict future stock returns for around two weeks. **Section 2.6** analyses a long-short trading strategy that benefits from stock prices' initial under-reaction to currency shocks. **Section 2.7** offers our conclusions.

2.2 Data

We merge firm-level data from Datascope for currency and equity data, Factset Geographic Revenue Exposure for geographic sales splits, Worldscope for balance sheet data and I/B/E/S for analyst forecasts. The study covers a more than 12-year period starting in January 2007 and ending in June 2020. The last quarterly financial period covered by balance sheet and forecast data is the first quarter of 2020.

Data used in subsequent regressions are winzORIZED at the 1% and 99% level, to deal with possible outliers.

2.2.1 Stock Sample Selection

The sample of firms used in this paper consists of the top 1,000 US and Canadian firms at any given time, based on market capitalization. We thus restrict our attention to stocks that have a certain size and liquidity. At the beginning of each month, the largest 1,000 US and Canadian firms by market capitalization are selected and used for that month. In order to avoid any survivorship bias, the set of firms amongst which the stocks are selected includes securities that were subsequently de-listed.

2.2.2 Fundamental and Forecasts Data

We obtain firm-level net sales data from Worldscope. From this data, we compute the year-on-year growth rate of quarterly sales, $SalesGr_{i,t}$, for company i and quarter t .

We also use analysts' forecasts data from I/B/E/S. Here, we are interested in earnings surprises versus consensus. Specifically, for a given fiscal quarter t and company i , we observe the “Standardized Unexpected Earnings” $SUE_{i,t} = (E_{i,t} - F_{i,t})/SD_{i,t}$, where $E_{i,t}$ is quarter t realized earnings per share reported by firm i , $F_{i,t}$ is the latest consensus forecast regarding $E_{i,t}$ and $SD_{i,t}$ is the standard deviation of these forecasts across analysts. SUE therefore measures the intensity and significance of the surprise at the time of earnings publication versus the latest analyst consensus. A positive SUE means that analysts are positively surprised by the earnings announced by the company.

2.2.3 Geographic Revenue Exposure

This data comes from the Factset Geographic Revenue Exposure database. For each firm-year, it provides the split of sales by countries. To compile the data, Factset uses information publicly disclosed by firms via regulatory filings and investor reports. As companies' geographic segment reporting is disparate (some report by regions, others by countries etc.), geographic revenues to regions and countries that companies did not explicitly disclose are allocated by algorithms built by the data provider.

2.2.4 Summary Statistics

Table 2.1 provides summary statistics for some of the stock-level variables used in this paper. Number of Foreign Countries provides, for each firm-year, the number of foreign countries for which a firm has non-zero geographical exposures. The mean is 55 and the median 45, reflecting the fact that firms in our sample are on

average selling their products or services in many countries. Non Domestic Sales focuses on the sub-set of firms that have non-zero foreign sales. The number of firm-year observations is close to 30% lower than for Number of Foreign Countries, which is in line with the fact that close to a third of the firm in the sample are purely domestically focused and have no foreign sales. On average 43% of the sales of exporting firms come from abroad. *SalesGr* shows quarterly year-on-year sales growth. Our sample of firms have an average *SalesGr* of 9.7% and a median of 6%. *SUE* shows quarterly earning surprises (as defined above). On average during our sample, analysts have been positively surprised by 1.37 times the analyst forecasts standard deviation for a given firm-quarter, which is consistent with anecdotal evidence that earnings have exceeded expectations in the past two decades or so. Finally, we show the market capitalization statistics (in billion USD) over our sample. We have more than 3 million firm-day observations, with a mean of 20.47 and a median of 7.86. The smallest firm has a market capitalization of slightly less than 300 million USD and the largest firm more than 1.5 trillion USD.

Table 2.2 offers a more detailed view on the international exposure of firms in our sample. Here, we focus on firms that have non-zero foreign sales and split our sample across various criteria: firm size, country and sector. First, we split the sample between Large Cap and Mid Cap. Large Cap (Mid Cap) are firms above (below) the market capitalization median at any point in time. We find no major differences between the two groups with both having slightly more than 40% of sales on average derived internationally. Next, we split the sample by country: Canada and US. Around 90% of firms in our sample are US companies. Canadian firms tend to export more than US firms (61% vs 41%). Finally, we split our sample by sectors (GICS1), with some variability in average foreign sales: the

sector which exports the less is Utilities (24%) and the one that exports the most is Information Technology (57%).

Table 2.1

Summary Statistics

	N	Mean	Median	Min	Max	SD
Number of Foreign Countries	15,244	55	45	0	195	55
Non Domestic Sales	10,863	0.43	0.41	0.01	1.00	0.27
<i>SalesGr</i>	49,936	0.097	0.060	-0.509	1.457	0.260
<i>SUE</i>	49,203	1.3668	0.964	-8.303	14.697	3.205
Market Capitalization (\$B)	3,378,219	20.47	7.86	0.29	1,588.66	46.41

This table reports summary statistics for some of the stock-level variables used in this paper. Non Domestic Sales (expressed as a fraction of total sales) is the sum of all non-domestic geographical exposures for the sub-set of firms with non-zero foreign sales. Number of Countries is the number of foreign countries for which a firm has non-zero geographical exposures. $SalesGr_{i,t}$ is the year-on-year quarterly sales growth. $SUE_{i,t}$ is the quarterly standardized unexpected earning. The table also shows Market Capitalization. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time.

Table 2.2**Foreign Sales by Size, Country, Sector**

	N	Mean	Min	5%	Median	95%	Max	SD
Full	9,794	0.43	0.00	0.05	0.41	0.92	1.00	0.27
By Size								
Large Cap	4,911	0.43	0.00	0.05	0.44	0.90	1.00	0.26
Mid Cap	4,883	0.42	0.00	0.04	0.38	0.93	1.00	0.28
By Country								
Canada	820	0.61	0.01	0.09	0.67	1.00	1.00	0.31
US	8,974	0.41	0.00	0.04	0.39	0.89	1.00	0.26
By Sector (GICS1)								
Communication Services	38	0.39	0.00	0.01	0.39	0.98	0.99	0.25
Consumer Discretionary	1,477	0.37	0.00	0.06	0.31	0.91	1.00	0.25
Consumer Staples	654	0.39	0.00	0.04	0.37	0.97	1.00	0.28
Energy	709	0.41	0.00	0.04	0.37	0.87	1.00	0.27
Financials	1,277	0.34	0.00	0.02	0.31	0.87	1.00	0.25
Health Care	1,041	0.39	0.00	0.03	0.42	0.79	1.00	0.24
Industrials	1,537	0.39	0.00	0.06	0.38	0.84	1.00	0.23
Information Technology	1,898	0.57	0.01	0.12	0.56	0.94	1.00	0.26
Materials	879	0.54	0.00	0.05	0.58	1.00	1.00	0.29
Real Estate	72	0.47	0.02	0.02	0.50	0.91	0.92	0.30
Telecommunication Services	53	0.32	0.00	0.01	0.13	1.00	1.00	0.38
Utilities	157	0.24	0.00	0.02	0.16	0.80	0.96	0.25

This table reports statistics for Non Domestic Sales, for the sub-set of firms in the sample with non-zero foreign sales. Non Domestic Sales (expressed as a fraction of total sales) is the sum of all non-domestic geographical exposures for each firm-year. The table reports this data split across various dimensions: by firm size, where Large Cap (Mid Cap) are firms above (below) the market capitalization median at any point in time, by country (US and Canada) and by sector (GICS1). The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time.

2.3 Measuring Firm-Level Currency Pressure

2.3.1 FX Shocks

We start by constructing a measure of whether firms are under positive or negative currency pressure. We define $s_{i,C,t}$ as the fraction of sales that company i generates in country C . This information is available at time t in the Factset Geographic Exposure database. We then compute, for each firm, $FXShock_{i,t}$, the sum-product of country exposure $s_{i,C,t}$ with the corresponding currency return (computed versus the domestic currency). This measure essentially aggregates shocks coming from currency movements in countries where the firm has foreign sales:

$$FXShock_{i,t} = \sum_C s_{i,C,t-3m} FX_{C,[t-3m, t]} \quad (2.1)$$

Where $FX_{C,[t-3m, t]}$ is the 3-month currency return of country C up to time t versus the home country.

All else equal, when there is a shock on the local currency, $FXShock_{i,t}$ will be larger in absolute terms for firms that have a higher fraction $\sum_C s_{i,C,t-3m}$ of international sales. When a shock impacts a foreign currency, $FXShock_{i,t}$ will take larger absolute values for firms that derive a higher proportion of their sales in the impacted country.

2.3.2 FX Shocks, Sales Growth and Earnings Growth

We first proceed to a check on the data: if the Geographical Revenue Exposure data is accurate, we should be able to see a strong link between contemporaneous FX Shocks and firms' net sales (given one key input into firm-level FX shocks is the fraction of sales derived in foreign countries).

To do this check, we regress firms' year-on-year quarterly net sales growth on contemporaneous quarterly FX shocks, with controls such as firm size, fixed effects and lagged FX Shocks. Our baseline regression is as follows:

$$SalesGr_{i,t} = \alpha + \beta FXShock_{i,t} + controls + \epsilon_{i,t} \quad (2.2)$$

$SalesGr_{i,t}$ is the year-on-year quarterly sales growth rate as of quarter t . We therefore have one observation per firm-quarter in the regression. Results are reported in **Table 2.3** (columns 1 and 2) and confirm that there is a positive and statistically significant relationship between firms' year-on-year sales growth and contemporaneous quarterly FX shocks (positive coefficient in front of $FXShock$, significant at the 1% level for both specifications). These regressions are controlled for firm fixed effects (which control for heterogeneity in individual sales growth rate) and time fixed effects. FX shocks lagged by one quarter also have effects on a firm's earnings, possibly reflecting the fact that some currency shocks are permanent rather than temporary. These results give some assurance that the geographical exposures used in the rest of this paper are on average accurate.

We then analyze the relationship between FX shocks and earnings growth. The relationship is expected to be less mechanical (and therefore weaker) than for sales growth. Indeed, companies hedge their exchange rate exposure through cur-

currency derivatives transactions (Dominguez and Tesar (2006)), thereby offsetting part of their earnings' sensitivity to exchange rate movements. Additionally, it is well documented in the corporate finance literature that companies use accounting discretion to "smooth" their earnings, (see, for example, Chaney and Lewis (1995)).

We run the same regression as above but replacing $SalesGr_{i,t}$ by $EPSGr_{i,t}$, the year-on-year quarterly earnings per share (EPS) growth of firm i for quarter t (to deal with negative earnings firms, observations for which the previous year's quarterly EPS were negative are removed).

$$EPSGr_{i,t} = \alpha + \beta FXShock_{i,t} + controls + \epsilon_{i,t} \quad (2.3)$$

As expected, results (columns 3 and 4 of **Table 2.3**) show a positive relationship between earnings growth and FX shocks, but coefficients are smaller and less significant than for sales growth. This is consistent with firms hedging (partially) their exchange rate exposures, and possibly smoothing the volatility of their earnings, thereby lowering the sensitivity of their earnings to currency movements.

Table 2.3**Net Sales Year-on-Year Growth vs. Past Quarterly FX Shocks**

	<i>SalesGr</i>	<i>SalesGr</i>	<i>EPSGr</i>	<i>EPSGr</i>
	(1)	(2)	(3)	(4)
<i>FXShock</i>	0.63***	0.65***	0.58**	0.42*
	(7.60)	(7.94)	(2.32)	(1.70)
<i>FXShock</i> _{lag1}		0.22***		0.40
		(2.58)		(1.61)
<i>Log(MarketCap)</i>		0.10***		0.23***
		(32.39)		(24.54)
Stock Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	49,936	48,848	45,577	43,753
R ²	0.26	0.27	0.13	0.14

This table reports results from regressing firm-level year-on-year quarterly sales growth *SalesGr* (columns 1 and 2) and year-on-year quarterly EPS growth *EPSGr* (columns 3 and 4) on contemporaneous and lagged quarterly FX shocks. *FXShock*, *FXShock*_{lag1} correspond respectively to contemporaneous and past quarterly FX shocks lagged by 1 quarter. Time fixed effects correspond to year-quarter dummies. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

2.3.3 Distinguishing Small and Large FX Shocks

A useful feature of currency movements is that they can vary greatly in intensity, thereby offering a wide spectrum that can be used to assess whether analysts and market prices react differently to smaller and less attention-grabbing news versus larger, more salient information.

We therefore split FX shocks into two disjoint sub-sets: small and large shocks. Specifically, we define a binary variable $LargeShock_{i,t}$ that is equal to 1 if $FXShock_{i,t}$ is in L , the sub-set of FX shocks that are in the bottom 5% or top 5% of the set of non-zero FX shocks:

$$LargeShock_{i,t} = 1 \text{ if } FXShock_{i,t} \in L \text{ else } LargeShock_{i,t} = 0$$

$$SmallShock_{i,t} = 1 - LargeShock_{i,t}$$

There are many other ways to split FX Shocks into attention-grabbing versus not. We tested and confirmed the robustness to alternative definitions of large and small shocks of all results in this paper. We used different % thresholds (e.g. 2.5% instead of 5%). We also used another definition of salient shocks, the idea being that market participants could pay more attention to FX shocks for firms who are exposed to currencies which have exhibited a particularly large move in the recent past. More details are provided in the Appendix, as well as the results of some of the robustness checks.

2.4 Are Analysts Attentive to Currency Movements?

Financial analysts are professional forecasters who produce, inter alia, estimates of companies' future earnings per share for different horizons. Various biases have been documented in the literature: in particular, analysts tend to be over-optimistic and to react too slowly to past information (see for example, [Abarbanell and Bernard \(1992\)](#)).

If analysts' forecasts were perfectly rational, they would integrate all information available at the time they are issued. Thus, the sign and magnitude of the standardized unexpected earnings SUE (described in Section 2) should not depend on anything that has happened prior to the forecast issuance. Our goal is to test whether analysts integrate past currency movements in their forecasts. To do so, we regress $SUE_{i,t}$ (the standardized unexpected earnings for stock i and quarter t), on past quarterly FX shocks and various controls such as firm size and fixed effects. Regressing earnings surprises on certain past information is typical of investigations into whether analysts efficiently incorporate this information in their forecasts (see for example [Bradshaw et al. \(2001\)](#) or, more recently, [Bouchaud et al. \(2019\)](#)).

$$SUE_{i,t} = \alpha + \beta FXShock_{i,ct-1m} + controls + \epsilon_{i,t} \quad (2.4)$$

We use the quarterly $FXShock$ calculated one month before ct , the date at which the consensus used to compute the quarterly SUE was taken by I/B/E/S. We do so because we do not want our results to be driven by staleness in ana-

lyst forecasts: in our specification, analysts are given one month to react to the information contained in $FXShock_{i,ct-1m}$.

Columns 1 to 3 of **Table 2.4** report results from this regression for various set of controls (stock fixed effects, time fixed effects, sector*time fixed effects, size and lagged FX Shock). For all three specifications, the coefficient in front of FX Shock is positive and significant at the 1% level. Quantitatively, a beneficial FX shock of 10% leads to a SUE which is on average higher by around 0.5, which represents about 15% of the standard deviation of SUE : FX shocks that are positive for firms lead to larger positive earnings surprises. These results show that analysts fail to integrate past currency movements in their forecasts.

Next, we test whether analysts under-react less for companies that have more analyst coverage, which would give credence to an inattention interpretation of their failure to incorporate past currency movements in earnings forecasts. To do so we add the interaction between $FXShock$ and $Log(Coverage)$, the logarithm of the number of analyst covering a firm at a particular point in time as provided by I/B/E/S. The results are shown in column 4 of **Table 4** and confirms this hypothesis. The coefficient in front of $FXShock * Log(Coverage)$ is negative and significant at the 1% level: the under-reaction of analysts to past currency movements tends to be lower for companies that have higher analyst coverage.

We then investigate if, in line with bounded rationality, analysts pay more attention to FX shocks when they are relatively large (and thus possibly more visible and attention-grabbing). To do so, we use large and small FX shocks as described in **Section 2.3.3**.

The hypothesis would be that analysts are more attentive to large shocks, whose causes (e.g. large domestic currency movements) are more likely to be

covered in the media. We test this by running the following regression:

$$\begin{aligned} SUE_{i,t} = & \alpha + \beta_1 FXShock_{i,ct-1m} * SmallShock_{i,ct-1m} \\ & + \beta_2 FXShock_{i,ct-1m} * LargeShock_{i,ct-1m} + controls + \epsilon_{i,t} \quad (2.5) \end{aligned}$$

Columns 5 to 7 of **Table 2.4** shows results for this regression with the same set of controls as the regression in columns 1 to 3. The coefficient in front of both small and large shocks are positive and significantly different from zero at the 1% level: analysts under-react to both small and large shocks. We can therefore conclude that analysts generally over-look currency movements when making their forecasts. In un-tabulated regressions, robustness of these results to alternative specifications of large shocks were confirmed.

Table 2.4**Past FX Shocks Predict Earnings Surprise**

	<i>SUE</i>	<i>SUE</i>	<i>SUE</i>	<i>SUE</i>	<i>SUE</i>	<i>SUE</i>	<i>SUE</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>FXShock</i>	4.38*** (3.53)	4.64*** (3.71)	5.08*** (3.75)	19.59*** (3.50)			
<i>FXShock * SmallShock</i>					4.76*** (2.57)	5.09*** (2.74)	4.63*** (2.32)
<i>FXShock * LargeShock</i>					4.15*** (2.76)	4.36*** (2.87)	5.34*** (3.36)
<i>FXShock*Log(Coverage)</i>				-5.58*** (-2.68)			
<i>Log(Coverage)</i>				-0.23*** (-3.97)			
<i>FXShock</i> _{lag1}		5.00*** (3.97)	4.61*** (3.39)	4.51*** (3.32)		5.02*** (3.98)	4.59*** (3.37)
<i>Log(MarketCap)</i>		0.04 (1.04)	-0.00 (-0.06)	0.03 (0.71)		0.04 (1.04)	-0.00 (-0.06)
Stock Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	-	-	Yes	Yes	-
Sector*Time Fixed Effects	-	-	Yes	Yes	-	-	Yes
N	49,203	48,129	48,129	48,110	49,203	48,129	48,129
R ²	0.18	0.18	0.22	0.22	0.18	0.18	0.22

This table reports results from regressing firm-level quarterly sales *SUE* on *FXShock*. *FXShock* is the quarterly FX Shock taken one month before the date of the consensus used to compute *SUE*, to account for possible staleness in analysts' forecasts. *SmallShock* (*LargeShock*) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. *Log(Coverage)* is the logarithm of the number of analysts covering a firm at a particular time, as provided by I/B/E/S. Time fixed effects correspond to year-quarter dummies and sector*time fixed effects correspond to year-quarter-GICS2 (sector classification) dummies. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

2.5 Does the Market Under-react?

We now investigate whether the market efficiently integrates currency movements in stock prices.

2.5.1 No Under-Reaction at Earnings Announcement

In a first step, we run a similar test to the one used for analysts. This time, we look at the relationship between past FX shocks and **price** surprises (as opposed to **earnings** surprises) at time of earnings publication. We run this analysis to investigate whether it is earnings announcements that lead prices to integrate past currency movements, or if they have already done so prior to announcements. Indeed, numerous papers show that, for various anomalies, prices do catch up on earnings announcement. A recent such paper is [Engelberg et al. \(2018\)](#): the authors use a sample of 97 stock return anomalies and find that their returns are on average 6 times higher on earnings announcement days.

The left hand side of the regression is the Cumulative Abnormal Return ($CAR_{i,t}$): the cumulative beta-adjusted stock return computed over a two days window starting at the day of earnings announcement for stock i and quarter t . Betas are estimated through rolling 1-year regressions of stock returns on market returns. We define the market as a value weighted basket of the stocks in our universe at a given time. $FXShock$ is the quarterly FX shock contemporaneous with the financial quarter.

The regression is as follows:

$$CAR_{i,t} = \alpha + \beta FXShock_{i,t} + controls + \epsilon_{i,t} \quad (2.6)$$

Beyond our usual controls, we add firm characteristics which are known to affect returns: mtb is the market-to-book value of equity and $R212$ is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2.

In contrast with analysts, the market appears to have already integrated past currency movement information into prices by the time earnings are announced. The coefficients in front of $FXShock$ are indeed insignificant for all three specifications (columns 1 to 3 of **Table 2.5**). Columns 4 to 6 show that this is also the case for small and large shocks (coefficients in front of $FXShock * SmallShock$ and $FXShock * LargeShock$ are also insignificant). By the time of earnings, prices have therefore already integrated past quarterly FX shocks: the market is quicker and more efficient than analysts.

Table 2.5**Absence of Price Surprises at Earnings Announcements as a Function of Past FX Shocks**

	<i>CAR</i>	<i>CAR</i>	<i>CAR</i>	<i>CAR</i>	<i>CAR</i>	<i>CAR</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>FXShock</i>	-0.03 (-1.42)	-0.03 (-1.16)	-0.01 (-0.25)			
<i>FXShock * SmallShock</i>				-0.04 (-1.07)	-0.03 (-0.79)	0.02 (0.51)
<i>FXShock * LargeShock</i>				-0.03 (-1.09)	-0.03 (-0.96)	-0.02 (-0.68)
<i>FXShock</i> _{lag1}		0.01 (0.51)	0.03 (1.19)		0.01 (0.51)	0.03 (1.17)
<i>Log(MarketCap)</i>		-0.01*** (-17.54)	-0.02*** (-18.55)		-0.01*** (-17.54)	-0.02*** (-18.55)
<i>mtb/10,000</i>		0.14 (0.57)	0.23 (0.87)		0.14 (0.57)	0.23 (0.87)
<i>R212</i>		0.40 (1.44)	0.46 (1.53)		0.40 (1.44)	0.46 (1.53)
Stock Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	-	Yes	Yes	-
Sector*Time Fixed Effects	-	-	Yes	-	-	Yes
N	48,259	47,117	47,117	48,259	41,117	41,117
R ²	0.05	0.06	0.09	0.05	0.06	0.09

This table reports results from regressions on *FXShock* of cumulative abnormal returns *CAR*, computed over a two-day window starting the day of quarterly earnings announcement. Thus, there is one observation by firm-quarter. *SmallShock* (*LargeShock*) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. *mtb* is the market-to-book value of equity and *R212* is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2. Time fixed effects correspond to year-quarter dummies and sector*time fixed effects correspond to year-quarter-GICS2 (sector classification) dummies. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

2.5.2 Under-Reaction to Recent Currency Shocks

We then attempt to measure precisely the speed at which markets integrate past currency movements. In perfectly efficient markets, the reaction of prices to information should be immediate. However, a large body of behavioral finance literature has documented abnormally slow price reactions to public information (see, for example, [Hong et al. \(2000\)](#)).

In **Table 2.6**, we regress weekly cumulative beta-adjusted stock returns $AdjR_{i,t}$ on past weekly FX shocks $FXShockWeekly_{i,t}$ with several lags. We use shorter windows to compute FX shocks as we have established that prices react faster than analysts. As is customary in asset pricing regressions, we use [Fama and Macbeth \(1973\)](#)'s methodology to obtain standard errors that are adjusted for cross-sectional dependence.

$$AdjR_{i,t} = \alpha + \beta FXShockWeekly_{i,t} + controls + \epsilon_{i,t} \quad (2.7)$$

Where:

$$FXShockWeekly_{i,t} = \sum_C s_{i,C,t-1w} FX_{C,[t-1w, t]}$$

There is one observation per firm-week in this regression. We use a rich set of firm-level controls, including *mtb*, *R212*, firm size and a dummy *domestics* which is equal to 1 if 100% of the revenues of a particular firm come from domestic sales. In a perfectly efficient market, we expect the coefficient β to be equal to zero as $FXShockWeekly_{i,t}$ captures information already available at time t .

The results, reported in **Table 2.6**, columns 1 to 3, show a positive coefficient β , significant at the 1% level for all three specifications, indicating market under-

reaction. The economic magnitude can be interpreted as follows: a 10% FX shock experienced by a firm implies roughly a 1.5% abnormal return for the stock of that firm the following week.

This market under-reaction is driven by small shocks. In columns 4 to 6 of **Table 2.6**, we split shocks between small and large (defined as previously as the bottom and top 5% of the set of non-zero FX shocks). The coefficients in front of $FXShockWeekly * SmallShock$ are slightly larger (than those in front of $FXShockWeekly$) and are all significant at the 5% level. In contrast, we find a lesser and non-significant under-reaction to large shocks: the coefficients in front of $FXShockWeekly * LargeShock$ are smaller and not significantly different from zero. This is in line with a bounded rationality interpretation whereby the market pays more attention to effects that are large enough. Coefficients in front of one-week lagged FX shocks ($FXShockWeekly_{lag1}$) are also significant at 5%, and have a magnitude of about two third that of the non lagged shocks. In further regressions not reported in this paper, we included further lags, which appear insignificant and economically negligible. This indicates that a couple of weeks is the order of magnitude of time it takes for stock prices to fully integrate currency movements.

We also test the robustness of our results to alternative definitions of large FX shocks. First, we look at shocks that are in the bottom or top 2.5% (instead of 5%) of the set of non-zero FX shocks. Next, we focus on shocks for which at least one currency experience a 5-day return of more than 5% or 10% in the past 3 months. Here, the idea is to assume that market participants will pay more attention to the impact of FX moves if one currency to which a particular company is exposed has exhibited a large move in the recent past. Results, shown in the Appendix,

are robust: the market does not under-react to large shocks; the under-reaction is driven by smaller, less attention-grabbing currency movements.

Given that prices are a lot more efficient than analysts, it is unlikely that this few weeks under-reaction of prices depends on analyst coverage. In untabulated regressions, we checked that this was indeed the case: prices' under-reaction to past weeks FX Shocks do not depend on analyst coverage.

Figure 2.1 offers an illustration. Towards the end of April 2018, the EUR started to depreciate gradually against the USD. This information was quickly integrated in the stock price of ManpowerGroup Inc, a company with 46% of its revenues coming from the Eurozone (larger FX shock). In contrast, the stock price of Lear Corp, which has a smaller portion of its revenues coming from there (24%), under-reacted to the move in EUR/USD.

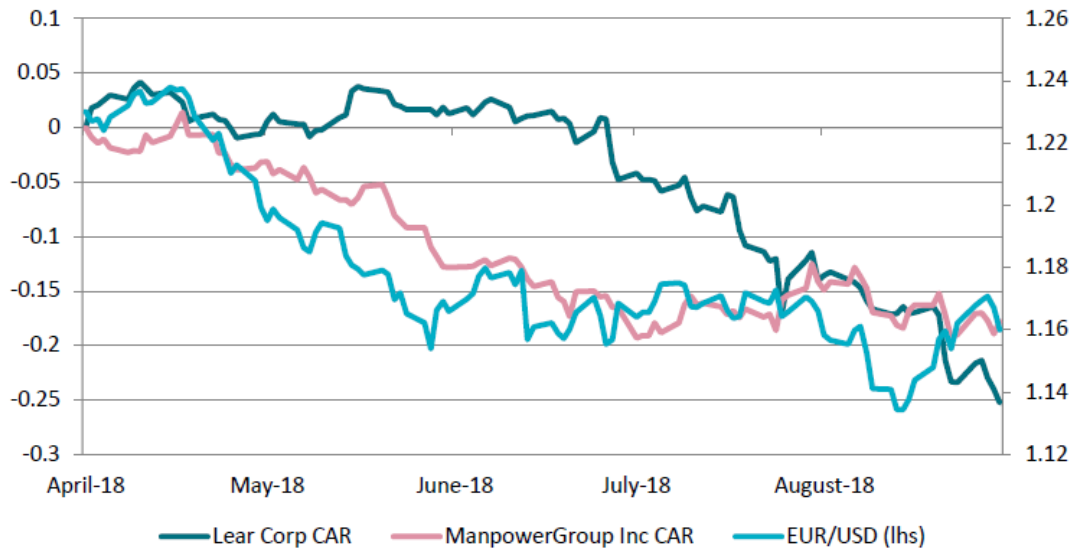
Table 2.6**Stock Returns vs. Past One Week FX Shocks**

	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>FXShockWeekly</i>	0.13*** (2.72)	0.12*** (2.79)	0.13*** (2.74)			
<i>FXShockWeekly*SmallShock</i>				0.15** (2.37)	0.14** (2.43)	0.13** (2.13)
<i>FXShockWeekly*LargeShock</i>				0.07 (1.22)	0.06 (1.10)	0.08 (1.31)
<i>Log(MarketCap)/10,000</i>		0.45 (0.37)	0.44 (0.37)		0.45 (0.38)	0.44 (0.37)
<i>mtb/10,000</i>		0.48*** (2.96)	0.50*** (3.04)		0.48*** (2.95)	0.49*** (3.02)
<i>R212</i>		0.14 (0.65)	0.14 (0.65)		0.14 (0.65)	0.14 (0.66)
<i>domestics/1,000</i>		-0.09 (-0.34)	-0.28 (-1.13)		-0.07 (-0.28)	-0.24 (-0.97)
<i>FXShockWeekly</i> _{lag1}			0.099** (2.10)			0.10** (2.16)
Intercept/100	-0.09*** (-4.47)	-0.25 (-0.87)	-0.23 (-0.81)	-0.09*** (-4.42)	-0.25 (-0.88)	-0.24 (-0.82)
N	673,268	654,664	654,444	673,268	654,664	654,444
R ²	0.00	0.00	0.00	0.00	0.00	0.00

This table reports Fama-Macbeth regression results of cumulative beta-adjusted stock returns computed over a five-day window *AdjR* on the preceding week FX shocks *FXShockWeekly*. *SmallShock* (*LargeShock*) is a binary variable equal to 1 if the corresponding FX Shock is large (small) as defined in the text above, 0 otherwise. *mtb* the market-to-book value of equity, *R212* is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2 and *domestics* is a dummy equal to 1 if 100% of the revenues of a particular firm come from domestic sales. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

Figure 2.1

EUR/USD, Lear Corp and ManpowerGroup Inc



This figure plots the EUR/USD (right hand scale) and the cumulative beta-adjusted returns of Lear Corp and ManpowerGroup Inc (left hand scale) between April and August 2018. Lear Corp and ManpowerGroup Inc have respectively 24% and 46% of their revenues coming from the Eurozone.

2.6 Long-Short Trading Strategy

We next turn to designing and analyzing a trading strategy that exploits the under-reaction of stock prices to past currency movements.

The trading strategy is daily re-balanced and buys stocks of companies that have experienced positive currency shocks and sells stocks of those who have been subject to negative shocks.

Every day t , each stock i is ranked according to its past two-week FX shock. These ranks are then transformed into uniformly distributed values between -0.5 (for the stock with the most negative shock) and 0.5 (for the stock with the most positive shock). These resulting values $w_{i,t}$ are the weights assigned to stock i on day t .

The weights $w_{i,t}$ can be computed by the close of markets in t (currencies closing prices are all available, except for a few Latin American currencies). We assume that these weights are achievable via a re-balancing at the closing prices of that day t . The daily returns r^{strategy}_t of the long-short trading strategy are then obtained by multiplying the subsequent returns of each stock $r_{i,t+1}$ (the return computed between the closing prices at t and those at $t + 1$) by their weight $w_{i,t}$ and summing across all stocks in the universe.

$$r^{\text{strategy}}_t = \sum_i w_{i,t} r_{i,t+1} \quad (2.8)$$

Figure 2.2 shows the cumulative return of the trading strategy during our sample (January 2007 to June 2020). The strategy performs strongly, exhibiting a Sharpe ratio of 1.04. The first version of this paper was made public on SSRN

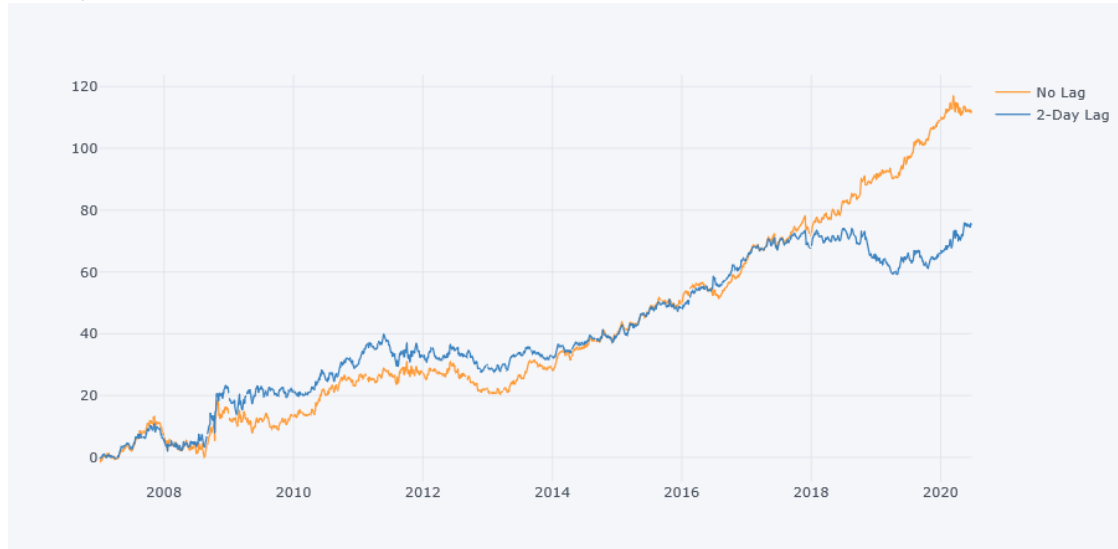
in 2018 and used a sample ending in October 2017. We therefore have close to three years of out of sample data for this market anomaly. As can be seen on the graph, the strategy continued performing out of sample, with a Sharpe ratio of 1.00 during the period from October 2017 to June 2020. This out of sample performance increases the likelihood that the anomaly we are documenting in this paper is not the result of data snooping.

Figure 2.2 also plots the same trading strategy, but with weights lagged by two days. The idea here is to see what is the impact of trading with a 2-day lag. Both graphs are quite similar before 2017, after which the lagged version starts diverging and performing less. Why is that the case? One possible explanation is that more arbitrage capital has been devoted to trading this strategy, thereby impacting stock prices in the first few days after portfolio formation and making the lagged implementation less profitable.

Figure 2.3 illustrates this point further. It plots for each year, the 2-day lagged strategy's rolling 3-year Sharpe ratio normalized by the non-lagged strategy's rolling 3-year Sharpe ratio. This number becomes smaller as the lagged strategy's performance deteriorates versus the original (non-lagged) strategy. The graph shows that the decay has grown on average over the past years, consistent with an increase in arbitrage capital exploiting the under-reaction of stock prices to currency movements.

Figure 2.2

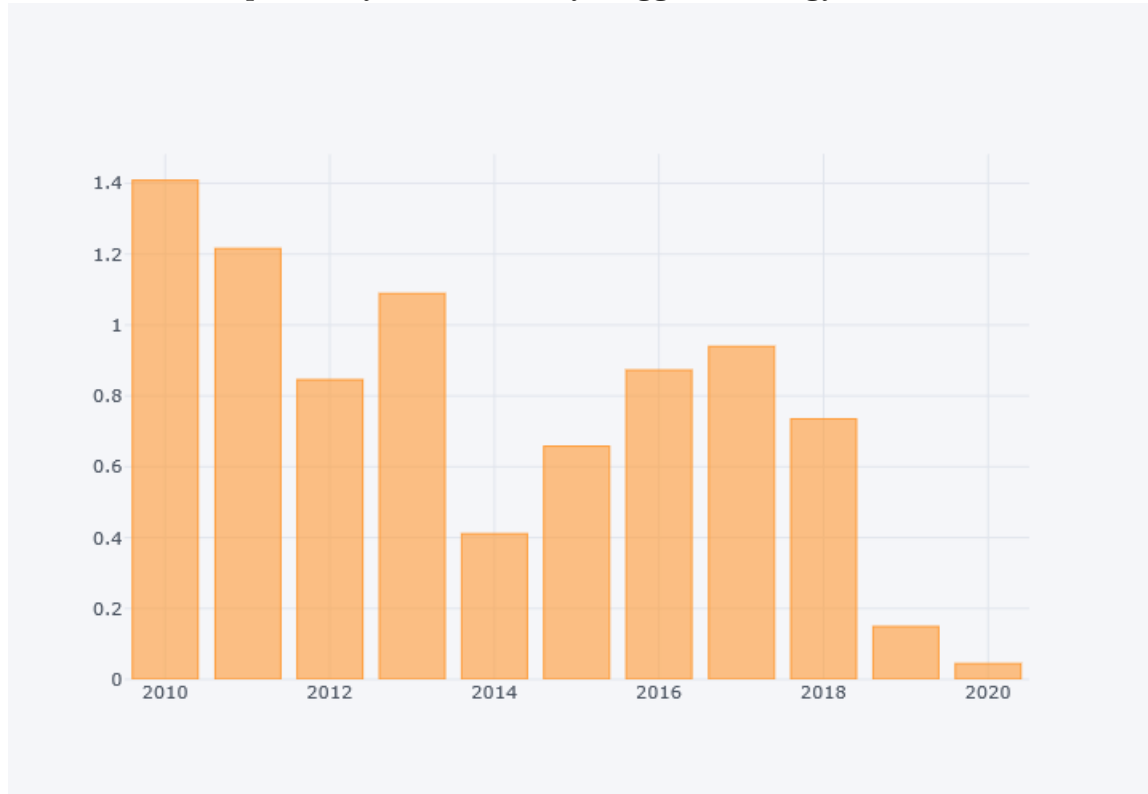
Long/Short Trading Strategy, Cumulative Returns



This figure plots the cumulative performance of a daily re-balanced trading strategy that goes long stocks with positive past 2-week FX shocks and short those with negative shocks. The weights of each stock in the portfolio are described in details in the paper. The figure also shows the same strategy with weights lagged by two days. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time.

Figure 2.3

Increase in Sharpe Decay for the 2-Day Lagged Strategy



This figure plots for each year the rolling 3-year Sharpe ratio of the 2-day lagged long/short strategy normalized by the rolling 3-year Sharpe ratio of the non-lagged strategy. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time.

2.7 Conclusion

It is well documented that exchange rate movements affect the value of firms, particularly those with significant foreign sales. How efficiently do analyst forecasts and stock prices integrate currency fluctuations? This paper answers this question through an empirical exploration of the reaction of stock-level financial analysts' estimates and prices to past currency movements.

Under the efficient market hypothesis, market prices should fully and immediately reflect all available information. In contrast, we report strong evidence that financial analysts **under-react** to FX shocks. The market is more efficient (quicker) at integrating exchange rate fluctuations in stock prices, but still takes around two weeks to do so. Also, prices **do not under-react** to larger FX shocks, in line with a bounded rationality interpretation.

A long-short trading strategy that benefits from the under-reaction of stock prices to currency movements is profitable (Sharpe ratio of 1.04). Further, such a strategy has continued performing out of sample (since the first version of this paper), showing that the under-reaction we are documenting is probably not the result of data snooping. Finally, we show that arbitrage capital exploiting this under-reaction has likely increased in the past few years.

These results shed light on market participants' behavior: a similar type of information, depending on its intensity, can either be over-looked or taken into account. Over-looked information leads to price under-reaction. Arbitrage capital moves in to exploit such under-reaction, helping prices integrate quicker the information.

2.8 Appendix

2.8.1 No Market Under-Reaction to Salient FX Shocks: Robustness Checks

In this sub-section of the Appendix, we test the robustness of results shown in **Table 2.6** to alternative definitions of salient FX shocks.

First, we look at shocks that are even larger: in the bottom or top 2.5% (instead of 5%) of the set of non-zero FX shocks. **Table 2.7** confirms that market does not under-react to these shocks with coefficients in front of $FXShockWeekly * LargeShock2.5$ even less significant than in **Table 2.6**.

Next, we test another specification for salient shocks. We focus on shocks for which at least one currency experiences a 5-day return of more than 5% (binary variable $Salient5$) or 10% ($Salient10$) in the past 3 months. Here, the idea is to assume that the market will pay more attention to the impact of FX moves if one currency to which a particular company is exposed has exhibited a large move in the recent past. Results, reported in **Table 2.8**, confirm that the market does not under-react to more salient shocks, and that the under-reaction is driven by smaller, less attention-grabbing currency movements. Furthermore, coefficients in front of $FXWeeklyShock * Salient10$ are negative and nearly significantly so for some of the specifications, which indicates that for shocks that are salient enough, the market could even **over-react**.

Table 2.7

Stock Returns vs. Past One Week FX Shocks (Top and Bottom 2.5% FX Shocks)

	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>
	(1)	(2)	(3)
<i>FXShockWeekly * SmallShock2.5</i>	0.15** (2.73)	0.14** (2.90)	0.13** (2.57)
<i>FXShockWeekly * LargeShock2.5</i>	-0.00 (-0.05)	0.01 (0.16)	0.03 (0.39)
<i>Log(MarketCap)</i>		0.00 (0.38)	0.00 (0.38)
<i>mtb</i>		0.00*** (2.95)	0.00*** (3.00)
<i>R212</i>		0.14 (0.64)	0.14 (0.65)
<i>domestics</i>		-0.00 (-0.28)	-0.00 (-1.01)
<i>FXShockWeekly</i> _{lag1}			0.11** (2.21)
Intercept	-0.00*** (-4.46)	-0.00 (-0.89)	-0.00 (-0.83)
N	673,268	654,664	654,444

This table reports Fama-Macbeth regression results of cumulative beta-adjusted stock returns computed over a five-day window *AdjR* on the preceding week FX shocks *FXShockWeekly*. *SmallShock2.5* (*LargeShock2.5*) is a binary variable equal to 1 if the corresponding FX Shock is in bottom (top) 2.5% of the sub-set of non-zero FX shocks, 0 otherwise. *mtb* is the market-to-book value of equity, *R212* is Carhart's momentum, i.e. the cumulative stock return between month -12 and month -2 and *domestics* is a dummy equal to 1 if 100% of the revenues of a particular firm come from domestic sales. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

Table 2.8**Stock Returns vs. Past One Week FX Shocks (Salient FX Shocks)**

	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>	<i>AdjR</i>
	(1)	(2)	(3)	(4)	(5)	(6)
<i>FXShockWeekly</i> * <i>NonSalient5</i>	0.13*** (2.64)	0.12*** (2.69)	0.13*** (2.68)			
<i>FXShockWeekly</i> * <i>Salient5</i>	20.18 (1.04)	20.14 (1.15)	20.93 (1.10)			
<i>FXShockWeekly</i> * <i>NonSalient10</i>				0.13*** (2.70)	0.12*** (2.71)	0.14*** (2.76)
<i>FXShockWeekly</i> * <i>Salient10</i>				-6.97 (-1.24)	-9.4 (-1.63)	-9.99* (-1.71)
<i>Log(MarketCap)</i>		0.00 (0.37)	0.00 (0.36)		0.00 (0.40)	0.00 (0.39)
<i>mtb</i>		0.00*** (2.98)	0.00*** (3.05)		0.00*** (2.96)	0.00*** (3.03)
<i>R212</i>		0.14 (0.64)	0.14 (0.64)		0.14 (0.66)	0.14 (0.66)
<i>domestics</i>		-0.00 (-0.35)	-0.00 (-1.12)		-0.00 (-0.41)	-0.00 (-1.19)
<i>FXShockWeekly</i> _{lag1}			0.09** (1.96)			0.10** (2.13)
Intercept	-0.00*** (-4.45)	-0.00 (-0.87)	-0.00 (-0.80)	-0.00*** (-4.39)	-0.00 (-0.89)	-0.00 (-0.82)
N	673,268	654,664	654,444	673,268	654,664	654,444

This table reports Fama-Macbeth regression results of cumulative beta-adjusted stock returns computed over a five-day window *AdjR* on the preceding week FX shocks *FXShockWeekly*. *Salient5* (*NonSalient5*) is a binary variable equal to 1 if at least one currency to which a firm is exposed had a 5-day return of at least 5% in the preceding 3 months, 0 otherwise. *Salient10* and *NonSalient10* are similarly defined but for 5-day returns of at least 10%. *mtb* is the market-to-book value of equity, *R212* is Carhart's momentum and *domestics* is a dummy equal to 1 if 100% of the revenues of a particular firm come from domestic sales. The sample runs from January 2007 to June 2020 and contains the largest 1,000 US and Canadian firms at any given time. For each explanatory variable, two numbers are reported: in the first row, the coefficient of the regression, and in the second row (in parentheses) the t-statistic. *, ** and *** next to the coefficients indicate respectively that these coefficients are significantly different from zero at the 10%, 5% and 1% significance levels.

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Chapter 3

Crowding and Liquidity Shocks

Joint work with Tony Tan (AXA IM Chorus)

Abstract: We develop a model whose aim is to study the relationship between crowding and liquidity shocks. One of the main results of that model is that crowding is associated with a larger exposure to broader liquidity shocks on arbitrageurs. We confirm this link empirically by studying equity long/short strategies. We use short interest data both to identify liquidity shocks impacting sophisticated equity investors and to infer crowdedness for some of the well-known long/short equity factors. When liquidity shocks (such as the 2007 Quant Crisis or the more recent 2020 COVID-19 induced Quant Deleverage) occur, crowded strategies indeed tend to under-perform.

“Likely factors contributing to the magnitude of the losses of this apparent unwind were: [...] the enormous growth of assets devoted to long/short equity strategies over the past decade [...]; the general lack of awareness [...] of just how crowded the long/short equity category had become.”

Khandani and Lo (2007) on the 2007 Quant Crisis.

“For a broad class of quantitative trading strategies, an important consideration for each individual arbitrageur is that he cannot know in real-time exactly how many others are using the same model and taking the same position as him. This inability of traders to condition their behavior on current market-wide arbitrage capacity creates a coordination problem and [...] can result in prices being pushed further away from fundamentals.”

Stein (2009) on “crowding”.

3.1 Introduction

“Crowding” – a significant overlap of positions between a large set of investors – has become an important subject over the past years. Investors want to understand its impact on future performance and risk, and whether it can be measured in real-time, so as to take appropriate investment decisions. Regulators are concerned about the systemic risks posed by crowded trades. Of particular interest to researchers, in addition to helping investors and regulators address their concerns, are the implications of crowding on market efficiency. Our aim in this paper is to address a subset of these issues: we are in particular focused on the relationship between crowding and liquidity shocks.

We start by developing a model in order to show that (i) crowding measures for a given arbitrage trading strategy can be inferred from arbitrageurs’ aggregated positions, (ii) arbitrageurs’ overall profits suffer V-shape drawdowns upon the occurrence of exogenous liquidity shocks and (iii) more crowded strategies suffer larger losses during these shocks. In our model, biased “naive” investors trade with two different groups of arbitrageurs, each observing different signals that gives them information on these biases. By having these two groups of arbitrageurs, we can analyze aggregated positioning measures (which is the type of data we have in practice, e.g., short interest) and vary the fraction of each group of arbitrageur to understand how crowding measures for a given strategy change as a result. Furthermore, the settings of our model enable to exogenously shock down arbitrageurs’ capital and get our main results.

We then move on to confirm empirically our main result, i.e. that crowded strategies suffer during liquidity shocks. In order to infer trading strategies’ crowd-

ing levels, a key ingredient is needed: positioning data, preferably aggregated at the sophisticated investor level, and ideally available at daily frequency. In that respect, the short interest data we are using for this paper (IHS Markit¹ Securities Finance database) is an ideal candidate. Because short-sellers are generally hedge funds and other arbitrageurs, short interest is a good proxy for the aggregated short single stock positions of sophisticated investors, many of whom implement quant equity strategies. The other advantage is that the data is available daily and with little lag (a few days): the crowding measure inferred from this data is therefore near-real-time. From this data, we infer crowding measures of some well-known equity factors and show that sophisticated investors have continued to crowd in some of these strategies. We also proxy arbitrageurs overall profits from this data, by constructing what we subsequently call the Short Interest strategy: the returns of this strategy will help us identify liquidity shocks. We define the Short Interest strategy as buying stocks with low short interest and selling stocks with high short interest. This strategy can be thought of as “mimicking” sophisticated investors’ aggregate positions. It is a good indicator for deleveraging activity amongst arbitrageurs (Richardson et al (2017)). Indeed, if short sellers deleverage their positions, they will sell the stocks they were long and buy back stocks they were shorting: high short interest stocks will therefore rally, and low short interest stocks will sell off, causing the strategy to under-perform. Confirming this intuition, the strategy had its largest drawdowns on the sample studied,

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during the well-documented 2007 Quant Crisis as well as the recent 2020 Quant Deleverage. In both cases, it rebounded very quickly thereafter, highlighting that the price impact generated by large deleverage episodes are mostly temporary. Finally, we confirm the link between crowding and liquidity shocks in the data: when a liquidity shock impacts short-sellers, the strategies that are crowded at that moment tend to under-perform.

The main contribution of this paper is to establish, both theoretically and empirically, the positive relationship between crowding and exposure to broad liquidity shocks. We show that when liquidity shocks on short sellers occur, crowded strategies tend to under-perform. Crowding is therefore associated with higher exposure to systemic risk. To the best of our knowledge, no previous work has focused on establishing, both theoretically and empirically, this relationship.

This work is closely related to the literature on crowding. We provide below a summary of these papers.

Crowding received some academic attention in the aftermath of the 2007 Quant Crisis and the 2008 Global Financial Crisis. [Khandani and Lo \(2007 and 2011\)](#) analyse the Quant Crisis of August 2007. They simulate the performance of equity trading strategies likely used by quantitative investors and find evidence of large unwinding of factor-based portfolios and of sharply declining liquidity at that time. [Pedersen \(2009\)](#) also focuses on the Quant Crisis to illustrate the nature of liquidity crises: crowding combined with leverage can generate “liquidity spirals”. [Stein \(2009\)](#), when considering whether the increased presence of sophisticated investors in stock market trading would ultimately lead to greater market efficiency, identifies two complicating factors, the first being crowding and the second leverage. For him, the main complication with crowding is that at any

point in time, no individual arbitrageur knows exactly how much arbitrage capacity has been taken by others. [Pojarliev and Levich \(2011\)](#) estimate crowdedness of currency strategies by looking at the fraction of currency managers that have significant loadings on several well-known currency strategies. [Hanson and Sunderam \(2014\)](#), thereafter [HS](#), propose a crowding measure based on short interest, that we use in this paper. They also document that the amount of capital devoted to Value and Momentum strategies has grown significantly since the late 1980s. They then proceed to confirm empirically fact patterns that are consistent with theories of limited arbitrage. In the empirical section of this paper, we also look at what has happened since the end of [HS](#)' sample (2011). We document some interesting patterns. First, the rise in arbitrage capital, as measured by average short interest levels, has not continued since the 2008 Global Financial Crisis and is much lower than the heights reached before 2008. Second, quant equity investors have continued to crowd in well-known equity factors such as Momentum, Value and Low Volatility. We extend the analysis to European equities, where we find broadly similar patterns as in North America.

More recently, the subject of crowding attracted some further attention, in part because equity factor-based strategies have exhibited lacklustre performance in recent years. [Marks and Shen \(2019\)](#) study the link between crowding and liquidity and show that correlated trading among investors can affect the liquidity and risk of the securities they trade. [Brown et al. \(2019\)](#) use hedge fund long equity holdings data from the SEC 13F quarterly filings to measure security level crowdedness (defined as hedge funds' aggregate position in a stock divided by its average daily volume) and show that stocks with higher exposure to crowdedness experienced large drawdowns during the 2008 crisis. [Benzaguen et al. \(2020\)](#)

propose crowding measures by looking at the fluctuations in the imbalance of trades executed in the market. Based on these metrics, they show evidence that Momentum has become more crowded in recent years. On a more optimistic note, [DeMiguel et al. \(2021\)](#) show that institutions exploiting different equity factors lead to “trading diversification”, which helps offset, through a lowering of market impact, some of the decay due to crowding.

Our work is also related to the relatively large literature on short selling and the stock lending market. Just to cite a few, [Desai et al \(2002\)](#) study short interest in the Nasdaq market and find that high short interest ratios forecast low future returns. [Asquith et al \(2005\)](#) show that large stocks, given their low level of short interest and high level of institutional ownership are generally not subject to short selling constraints. [Saffi and Sigurdsson \(2011\)](#) establish that price efficiency is hindered by short-sale constraints. More recently, [Hong et al \(2015\)](#) show that days-to-cover (number of stocks shorted divided by daily average number of stocks traded) is a better measure than short interest as it implicitly considers trading costs. [Callen and Fang \(2015\)](#) find that short interest is positively related to one-year ahead stock price crash risk. [Richardson et al \(2017\)](#) show that high short interest stocks experience large positive returns around periods of funding capital scarcity. Finally, [Engelberg et al \(2018\)](#) argue that stocks with more short-selling risk have lower returns.

The paper is organized as follows. **Section 3.2** exposes our model and its results, the most important one being that crowding is associated with a larger risk exposure to liquidity shocks. **Section 3.3** presents our empirical set-up. It starts by introducing the data used (short interest data, amongst other) and computes the Short Interest strategy’ returns as a “barometer” for liquidity shocks impacting

sophisticated equity long/short investors. Such an indicator will be particularly useful to identify liquidity shocks subsequently. As illustration, it shows that the strategy was indeed a good indicator for both the 2007 Quant Crisis and the more recent COVID-19 induced 2020 Quant Deleverage, that we document in this paper. It then presents the crowding measure and its evolution – over our sample and for some of the better-known equity factors – in both North America and Developed Europe. **Section 3.4** confirms empirically the link between crowding and liquidity shocks found in the theoretical part of the paper (**Section 3.2**). **Section 3.5** concludes.

3.2 Theoretical Framework

In this section, we present a model whose aim is to explicit the link between crowding and unexpected exogenous liquidity shocks on arbitrageurs.

3.2.1 Model Settings

The basic settings of the model are inspired from [HS](#).

There are two types of arbitrageurs: A1 and A2, respectively representing a fraction a_1 and a_2 of investors. The remaining $1 - a_1 - a_2$ are “naive” investors (N) that have biased beliefs about future stock returns: these beliefs could be explained, for instance, by behavioral biases as documented by the large literature on behavioral finance.

Stocks are indexed by $i = 1, 2, \dots, I$ and each stock has a fixed positive supply w_i , where $\sum_i w_i = 1$. At time 2, stocks pay terminal dividends. At time 0, investors trade and returns between time 0 and time 2 are determined. We use time 1 solely to shock parameters a_1 and a_2 and understand the impacts such shocks have. Note that in the absence of any changes in a_1 or a_2 , no trading would happen in $t = 1$, as we make the assumption that agents take a_1 and a_2 as fixed and therefore do not anticipate the shocks).

Naive investors incorrectly believe that the expected return of stock i , $E_N[r_i] = E^*[r_i] + b_{1,i} + b_{2,i}$. $b_{1,i}$ and $b_{2,i}$ represent two distinct sources of overpricing of stock i : these could be any of the many market anomalies documented in the empirical asset pricing literature. Arbitrageurs have an advantage over naive investors: each type (resp. A1 and A2) observes one of the sources of naive investors’ over-pricing before trading (resp. $b_{1,i}$ and $b_{2,i}$). This means that they are biased only by

the source of mispricing that they do not observe: $E_{A1}[r_i] = E^*[r_i] + b_{2,i}$ and $E_{A2}[r_i] = E^*[r_i] + b_{1,i}$

For simplicity, we assume no aggregate mispricing, $\sum_i w_i b_{1,i} = 0$ and $\sum_i w_i b_{2,i} = 0$. This assumption has no impact on our results as we are focused on the cross-section of expected stock returns. It implies that all three types of investors expect the same excess returns r_M on the market portfolio. We also assume that all investors perceive the same exogenously given variance-covariance matrix of returns \mathbf{V} . Without too much loss of generality and to simplify the analysis, we put some structure on this matrix and assume that \mathbf{V} is diagonal and that the variance of each stock is inversely related to its size w_i , such that each diagonal element of \mathbf{V} is equal $\frac{c}{w_i}$ where c is a constant².

Finally, we assume that all investors maximize mean-variance utility over terminal wealth and have all same risk aversion λ . Such maximization leads to the following stock demand functions³ \mathbf{q} at time 0 (in vector notation for compactness), for $X = A1, A2, N$.

$$\mathbf{q}_X = \lambda^{-1} \mathbf{V}^{-1} E_X[\mathbf{r}] \quad (3.1)$$

The difference between our model and HS's are the addition of the following features. First, we decompose the bias of naive investors into two elements, \mathbf{b}_1 and \mathbf{b}_2 . Second, instead of one type of arbitrageurs that have full information, we include two types of arbitrageurs, each of which only observes one of the elements

²This proposed specification helps keep the exposition simple and enables to express results in terms of the correlation between \mathbf{b}_1 and \mathbf{b}_2 . Had we kept a more general matrix \mathbf{V} , subsequent results would have also depended on second-order cross terms. Results would only be impaired for some very specific (and probably unrealistic) \mathbf{V} that would exhibit strong structural cross-dependencies between its terms, \mathbf{b}_1 and \mathbf{b}_2 .

³These demand functions are obtained from first order conditions of the maximization of mean-variance utility $\mathbf{q}_X^T E_X[\mathbf{r}] - \lambda \mathbf{q}_X^T \mathbf{V} \mathbf{q}_X$, for each investor type ($X = A1, A2, N$).

of this bias. This is an important addition to (i) better represent reality where a set of arbitrageurs are trading a particular signal in the presence of other arbitrageurs that are trading other signals and (ii) as a result, better understand the impact of the two groups of arbitrageurs' interaction on the proposed crowding measure and its connection with liquidity shocks. Finally, we focus on a 3-period model ($t = 0, 1, 2$) so that we can study the impact of unanticipated exogenous liquidity shocks on arbitrageurs and study its link with crowding. We focus on exogenous shocks as evidence suggests that the recent largest liquidity events impacting equity long/short arbitrageurs, namely the 2007 Quant Crisis and the 2020 Quant Deleverage, were triggered by shocks unrelated to the quantitative long/short equity sector.

3.2.2 Equilibrium

At equilibrium, supplies and demands for all stocks are equal: $\mathbf{w} = a_1 \mathbf{q}_{A1} + a_2 \mathbf{q}_{A2} + (1 - a_1 - a_2) \mathbf{q}_N$, which implies that⁴:

$$E^*[\mathbf{r}] = -(1 - a_1) \mathbf{b}_1 - (1 - a_2) \mathbf{b}_2 + \frac{Cov[\mathbf{r}, r_M]}{Var[r_M]} E^*[r_M] = \boldsymbol{\alpha} + \boldsymbol{\beta} E^*[r_M] \quad (3.2)$$

Each stock has a CAPM alpha of $-(1 - a_1)b_{2,i} - (1 - a_2)b_{2,i}$. The alpha is negative for positive b_i and is decreasing in $b_{1,i}$ and $b_{2,i}$. This makes intuitive sense: the higher the bias of the naive investors on a stock, the more they will over-demand this stock and push its time 0 price up, thereby reducing its excess return. The CAPM alpha's absolute value is decreasing in a_1 and a_2 . The alpha related to bias $b_{1,i}$ ($b_{2,i}$) tends to 0 as a_1 (a_2) tends to 1. Again, this makes sense: the more arbitrageurs exploiting a given bias, the smaller the alpha related to this bias.

At equilibrium, arbitrageurs' positions are \mathbf{q}_{A1}^* and \mathbf{q}_{A2}^* , which can be obtained by substituting equilibrium excess returns $E^*[\mathbf{r}]$ (2) in demand functions (1). We obtain for arbitrageurs A1 (it is symmetrical for arbitrageur A2):

$$\mathbf{q}_{A1}^* = \mathbf{w} + \lambda^{-1} \mathbf{V}^{-1} (a_1 \mathbf{b}_1 + a_2 \mathbf{b}_2 - \mathbf{b}_1) \quad (3.3)$$

These positions deviate from the market portfolio \mathbf{w} in a way that is decreasing

⁴Developing and re-arranging, we get $(E^*[\mathbf{r}] + (1 - a_1) \mathbf{b}_1 + (1 - a_2) \mathbf{b}_2) = \lambda \mathbf{V} \mathbf{w}$. Taking the i^{th} element, we have $E^*[r_i] + (1 - a_1)b_{1,i} + (1 - a_2)b_{2,i} = \lambda \sum_j Cov(r_i, r_j) w_j = \lambda Cov(r_i, r_M)$, where r_M is the return on the market portfolio. Using this we can compute $E^*[r_M]$ as $E^*[r_M] = \sum_j (E^*[r_j] + (1 - a_1)b_{1,i} + (1 - a_2)b_{2,i}) w_j = \lambda \sum_j w_j Cov(r_i, r_M) = \lambda Var[r_M]$. This yields an expression for λ : $\lambda = E^*[r_M] / Var[r_M]$. Substituting in the previous expression, we get equation (2).

in \mathbf{b}_1 . Indeed, arbitrageurs A1 know that naive investors have biases and tend to over-value high \mathbf{b}_1 stocks (and under-value low \mathbf{b}_1 stocks). They underweight these stocks (assign less weights than the market portfolio) as they have lower expected excess returns. For some parameters (large enough \mathbf{b}_1 , small enough a_1 and a_2), they even short-sell some of these over-valued stocks. On the other hand, the positions are increasing in the interaction terms $a_1\mathbf{b}_1$ and $a_2\mathbf{b}_2$. Indeed, if a stock is initially over-valued by naive investors (high \mathbf{b}_1 or high \mathbf{b}_2), but there is a lot of arbitrage capital (high a_1 or high a_2) chasing this over-valuation, it will end up being less over-valued at equilibrium, and arbitrageurs will demand more of that stock.

The total aggregated arbitrageurs' positions, expressed as ratios of market capitalization \mathbf{P}^*_A are equal to $(a_1\mathbf{q}^*_{A1} + a_2\mathbf{q}^*_{A2})/\mathbf{w}$, which becomes after using (3) and re-arranging:

$$\mathbf{P}^*_A = (a_1 + a_2)1 - \lambda^{-1}\mathbf{V}^{-1}(1 - a_1 - a_2)(a_1\mathbf{b}_1 + a_2\mathbf{b}_2)/\mathbf{w} \quad (3.4)$$

Furthermore, we take into account our assumption that \mathbf{V} is diagonal and that the variance of each stock is inversely related to its size \mathbf{w} . Equation (6) then simplifies into:

$$\mathbf{P}^*_A = (a_1 + a_2)1 - \tilde{\lambda}(1 - a_1 - a_2)(a_1\mathbf{b}_1 + a_2\mathbf{b}_2) \quad (3.5)$$

Where $\tilde{\lambda}$ is a constant equal to $\frac{1}{c*\lambda}$.

3.2.3 Results

Result 1: an ordinary least square cross-sectional regression of aggregated arbitrageurs positions \mathbf{P}^*_A on a given anomaly signal (\mathbf{b}_1 or \mathbf{b}_2) recovers information about the amount of arbitrage capital (a_1 or a_2) devoted to this given signal. Intuitively, if there are more arbitrageurs A1, low \mathbf{b}_1 stocks, which these arbitrageurs over-weight because they appear to them as under-valued, will on average tend to show up as over-weighted in aggregated arbitrageurs' positions (that is, unless arbitrageurs A2 tend to have opposite views on these stocks). The coefficient k_{A1} obtained from this univariate cross-sectional regression is:

$$k_{A1} = \frac{Cov[\mathbf{P}^*_A, \mathbf{b}_1]}{Var[\mathbf{b}_1]} = \tilde{\lambda}(1 - a_1 - a_2)(a_1 + a_2\rho\frac{\sigma_2}{\sigma_1}) \quad (3.6)$$

Where ρ , σ_1 and σ_2 are defined, respectively, as the size-weighted correlation between \mathbf{b}_1 and \mathbf{b}_2 , standard deviation of \mathbf{b}_1 and standard deviation of \mathbf{b}_2 ⁵). For small enough a_1 and a_2 , the coefficient k_{A1} is increasing in a_1 . This result is similar to HS and shows it is possible to infer capital allocated to a given trading strategy through this regression. As we have two sources of market anomalies and two types of arbitrageurs, we also investigate what is the impact of a_2 on this coefficient. This impact depends on the sign and magnitude of $\rho\frac{\sigma_2}{\sigma_1}$. If it is positive (i.e. the two anomaly signals are positively correlated) and above a certain threshold, the coefficient will also be increasing in a_2 , which makes sense as both types of arbitrageurs will tend to trade in the same direction. If the two anomaly signals \mathbf{b}_1 and \mathbf{b}_2 are negatively correlated, a_2 's impact will be to reduce the coefficient. A high crowding measure for anomaly \mathbf{b}_1 can therefore come from

⁵We therefore have $\sigma_1^2 = \sum_i w_i b_{1,i}^2$, $\sigma_2^2 = \sum_i w_i b_{2,i}^2$, $\rho = \frac{\sum_i w_i b_{1,i} b_{2,i}}{\sigma_1 \sigma_2}$.

(i) a high number of arbitrageurs exploiting this anomaly (high a_1) and/or (ii) a high number of arbitrageurs exploiting the other anomaly (\mathbf{b}_2) and this other anomaly being positively correlated to the first anomaly.

Result 2: in most cases, arbitrageurs generate positive excess returns (at the expense of naive investors). The excess returns generated by arbitrageurs A1 are $\boldsymbol{\alpha}^T \mathbf{q}_{A1}$ (again, results for A2 are symmetrical), where $\boldsymbol{\alpha}$ is the alpha for each stock obtained in equation (2). After simplification, we obtain:

$$\boldsymbol{\alpha}^T \mathbf{q}_{A1} = \tilde{\lambda} \sigma_1^2 \left[(1 - a_1)^2 - a_2(1 - a_2) \frac{\sigma_2^2}{\sigma_1^2} + (1 - 2a_2)(1 - a_1) \rho \frac{\sigma_2}{\sigma_1} \right] \quad (3.7)$$

From (7), we can see that for small enough values of a_1 and a_2 the sum of the first two terms inside the bracket, $(1 - a_1)^2 - a_2(1 - a_2) \frac{\sigma_2^2}{\sigma_1^2}$, is positive as long as the variance of \mathbf{b}_2 is not orders of magnitude higher than the variance of \mathbf{b}_1 . The second term's sign is the same as the covariance between \mathbf{b}_1 and \mathbf{b}_2 and will be small compared to the first term when the correlation between \mathbf{b}_1 and \mathbf{b}_2 , ρ , and the ratio of standard deviation $\frac{\sigma_2}{\sigma_1}$ are not too high. Note that in a particular case where ρ is very negative and the ratio of the standard deviation $\frac{\sigma_2}{\sigma_1}$ is high, arbitrageurs A1 could be generating negative returns. Intuitively, if \mathbf{b}_2 is more informative (higher standard deviation than \mathbf{b}_1) and negatively correlated with \mathbf{b}_1 , then A1's signal will tend to have limited or even negative predictive power⁶.

⁶In an extreme case where \mathbf{b}_1 and \mathbf{b}_2 are perfectly negatively correlated and $\sigma_2 > \sigma_1$, then arbitrageurs A1 are more biased than naive investors.

Result 3: when there is an un-anticipated, exogenous liquidity shock on a type of arbitrageurs at $t = 1$ (e.g., in the case of A1, a reduction of a_1), these arbitrageurs generally suffer mark-to-market losses (that are recouped at $t = 2$). This can be seen by looking at $\frac{\delta}{\delta a_1} \boldsymbol{\alpha}^T \mathbf{q}_{A1}$. A negative number means that arbitrageurs A1's terminal excess returns are increasing at the time of the shock, and therefore that they are suffering losses versus the previous period.

$$\frac{\delta}{\delta a_1} \boldsymbol{\alpha}^T \mathbf{q}_{A1} = \tilde{\lambda} \sigma_1^2 (-2(1 - a_1) - (1 - 2a_2) \rho \frac{\sigma_2}{\sigma_1}) \quad (3.8)$$

From (8), it can be seen that $\frac{\delta}{\delta a_1} \boldsymbol{\alpha}^T \mathbf{q}_{A1}$ is indeed negative, except again in particular cases where the correlation between \mathbf{b}_1 and \mathbf{b}_2 is very negative and \mathbf{b}_2 is much more informative than \mathbf{b}_1 .

An un-anticipated, exogenous liquidity shock on the other type of arbitrageurs also impacts A1's excess returns:

$$\frac{\delta}{\delta a_2} \boldsymbol{\alpha}^T \mathbf{q}_{A1} = \tilde{\lambda} \sigma_1^2 \left(-(1 - 2a_2) \frac{\sigma_2^2}{\sigma_1^2} - 2(1 - a_1) \rho \frac{\sigma_2}{\sigma_1} \right) \quad (3.9)$$

The first term in expression (9) is negative: less arbitrageurs A2 at time $t = 1$ means, all else equal, more naive investors who push prices against all arbitrageurs (including A1). The second term represent the effect of possible correlation between \mathbf{b}_1 and \mathbf{b}_2 . A positive correlation will lead to a more negative impact on A1, whereas a negative correlation will actually help A1.

Result 4: when there is an un-anticipated, exogenous liquidity on both types of arbitrageurs (a_1 and a_2 both decrease by a multiplicative factor γ), arbitrageurs suffer losses overall (this follows from **Result 3**), and strategies that are more crowded (as measured before the shock) generally suffer more. The change in

excess returns upon such a shock is shown in equation (10) below. For small a_1 and a_2 , this change is indeed positive (negative mark-to-market for A1) and can be shown, in most cases, to have same sign sensitivities to a_1 and a_2 as k_{A1} . The change in excess returns is therefore generally increasing in k_{A1} : the more crowded a given strategy, the larger the mark-to-market loss it will suffer upon a liquidity shock.

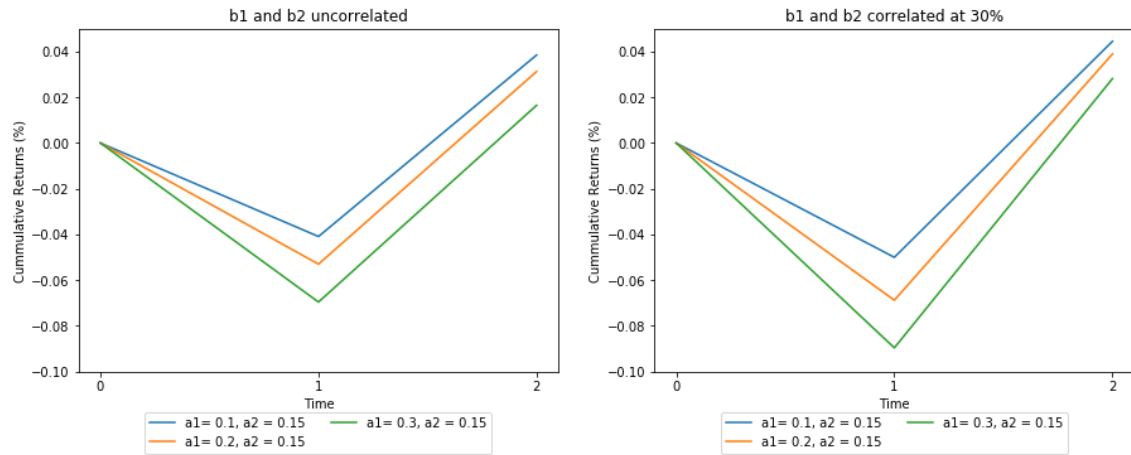
$$\begin{aligned} \boldsymbol{\alpha}^T \mathbf{q}_{A1}[a_1(1 - \gamma), a_2(1 - \gamma)] - \boldsymbol{\alpha}^T \mathbf{q}_{A1}[a_1, a_2] &\approx -(a_1\gamma)\delta(\boldsymbol{\alpha}^T \mathbf{q}_{A1})/\delta a_1 - (a_2\gamma)\delta(\boldsymbol{\alpha}^T \mathbf{q}_{A1})/\delta a_2 \\ &= \gamma\tilde{\lambda}\sigma_1^2[2a_1(1 - a_1) + (a_1 + 2a_2 - 4a_1a_2)\rho\frac{\sigma_2}{\sigma_1} + a_2(1 - 2a_2)\frac{\sigma_2^2}{\sigma_1^2}] \end{aligned} \quad (3.10)$$

3.2.4 Illustration

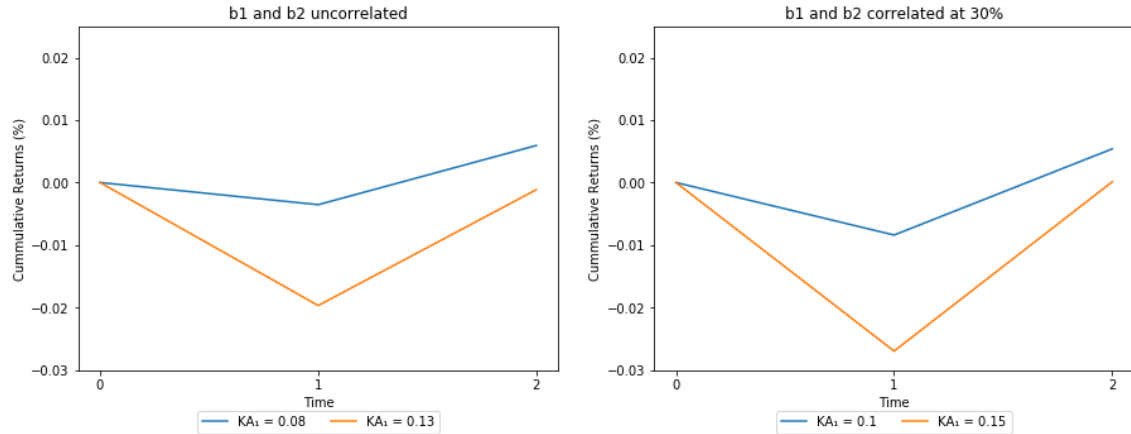
Figure 3.1 and **Figure 3.2** illustrate **Result 4**. **Figure 3.1** plots, for a given set of parameters, the cumulative profits of arbitrageurs upon a liquidity shock. As can be seen from the graph, for a given shock, these cumulative profits exhibit a V-shape drawdown, which is more severe when arbitrageurs represent a higher fraction of total investors (higher $a_1 + a_2$) and when the anomaly signals **b1** and **b2** are positively correlated. At time $t = 1$, arbitrage capital is reduced leading to an unwind in arbitrageurs' positions which exerts adverse price pressure: over-valued and under-valued stocks become even more over-valued and under-valued, thereby inflicting losses on arbitrageurs. The fraction of arbitrageurs who lose their capital unwind their positions and crystallize their losses, while arbitrageurs that keep operating generate a profits at time $t = 2$ as the dislocated stock prices converge to their terminal values. This result will be particularly useful in the

empirical section, as it will help us identify liquidity shocks (from the drawdowns of the short interest strategy, which is a good proxy for arbitrageurs aggregated returns). **Figure 3.2** plots, for a given set of parameters, cumulative profits of arbitrageurs A1 upon a liquidity shock. The difference between the left-hand side and right-hand side graphs are the correlation between **b1** and **b2** (respectively 0 and 0.3). On each graph, we plot, two cases: one where A1 is not crowded ($a_1 = 0.05$ and $a_1 = 0.35$) and one where it is crowded ($a_1 = 0.35$ and $a_1 = 0.05$). In both graphs, the crowded case exhibits a more severe drawdown. Also, when **b1** and **b2** are positively correlated, the drawdowns are larger, which makes sense as arbitrageurs A1 suffer both from the shock on themselves but also from the shock on A2⁷.

⁷Note how this positive correlation also increases the crowding measure k_{A1} . Crowding comes from the capital devoted to the strategy A1 but also from capital devoted to strategies that are correlated, as explained in **Result 1**.

Figure 3.1**Arbitrageurs' Profits Exhibit V-Shape Drawdown Upon Liquidity Shock**

This figure plots the cumulative profits of arbitrageurs A1 and A2 (combined) upon liquidity shock, as per the model presented in this section. Parameters used are the following: $\gamma = 0.9$, $\sigma_1 = \sigma_2 = 0.15$, $\tilde{\lambda} = 1$, ρ (the correlation between **b1** and **b2**) is set to 0 (left hand-side graph) or 0.3 (right-hand side graph), and a_1 and a_2 are set as indicated at the bottom of the graphs. Larger initial arbitrage capital (higher $a_1 + a_2$) and higher correlation ρ both lead to higher drawdowns.

Figure 3.2**More Crowded Strategies Exhibit Larger Drawdowns Upon Liquidity Shock**

This figure plots the cumulative profits of arbitrageurs A1 upon liquidity shock, as per the model presented in this section. Parameters used are the following: $\gamma = 0.9$, $\sigma_1 = \sigma_2 = 0.15$, $\tilde{\lambda} = 1$, ρ (the correlation between **b1** and **b2**) is set to 0 (left hand-side graph) or 0.3 (right-hand side graph), and a_1 and a_2 are set at respectively 0.05 and 0.35 (corresponding to a low crowding measure k_{A1} for A1's trading strategy), and 0.35 and 0.05 (corresponding to a high crowding measure k_{A1}). Higher crowding as measured by k_{A1} is associated with larger drawdown upon liquidity shock.

3.3 Empirical Set-Up

We now turn to testing empirically the results obtained in **Section 3.2**. We focus on some of the well-know long/short equity factors. A key advantage of doing so is the availability of stock-level short interest data. This data is a good proxy for arbitrageurs' aggregated positions: indeed short-sellers are typically sophisticated investors or arbitrageurs⁸. We proceed as follows. First, we describe the data used. Second, we analyze the Short Interest strategy, and confirm that it is likely a good indicator for liquidity shocks (its two largest drawdowns coincide with the largest liquidity shocks during that period). Finally, we compute crowding measures for the well-known long/short equity strategies studied in this paper (Momentum, Value, Low Volatility, Return on Asset). These will be important ingredients for **Section 3.4** where we will confirm that crowded strategies suffer larger drawdowns upon the occurrence of liquidity shocks.

3.3.1 Data

We combine daily equity finance data from IHS Markit, with equity data from Datascope and stock-level fundamental data from Worldscope, as described in detail below. The study covers a nearly 14-year period from July 1, 2006 through April 23, 2020.

⁸One shortcoming of short interest data is that it provides information on short positioning, not on long positioning. Nevertheless, in the absence of accurate long positioning data aggregated at the sophisticated investor level, we believe that short interest is the best data available. [HS](#) use as well short interest data to approximate for arbitrageurs' aggregated positions.

Stock Sample Selection

We focus on stocks listed in North America and Developed Europe⁹ that are likely to be included in quantitative equity market neutral portfolios. These strategies use leverage, deploy equity anomalies that require frequent rebalancing and, given fixed costs associated (including data, ability to short via prime brokers or derivatives, fund set-up costs...), need to have reasonable assets under management – and therefore capacity.

We thus restrict our attention to stocks that have a certain size and liquidity. Based on an extract from Datascope, we select stocks based on market capitalization and turnover (median for the past 3 month) thresholds. The stock selection is performed monthly, on the first day of the month. This results in two regional pools that, after cleansing detailed in the next paragraphs, average, at any point in time, approximately 1,100 stocks for North America and 540 stocks for Developed Europe over the time horizon studied. In order to avoid any survivorship bias, the set of firms amongst which the stocks are selected includes securities that were subsequently de-listed.

Equity Finance Data

This data comes from the IHS Markit Securities Finance database. It is sourced daily from a variety of industry participants that include beneficial owners, custodian and agents, sell side brokers (such as investment banks' prime brokerage arms) and buy side investors (such as hedge funds who are borrowing stocks to be able to short them). The data is collected globally and covers the largest de-

⁹North America: Canada and United States. Developed Europe: Belgium, Denmark, France, Finland, Germany, Italy, Ireland, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

veloped world equity markets, the two largest regions being North America and Developed Europe.

The data has been collected daily since July 1, 2006. The historical depth of the data-set is shorter than more traditional short interest data-sets such as Compustat. The data is made available by IHS Markit on a daily basis, one day after the settlement date of the underlying stock lending transactions. Stock lending settlement cycles are typically similar to those for stocks: for most markets, transactions are settled 2 business days after execution. The data is therefore close to real time (only 3 days between the time stocks are borrowed and data delivery). Such features (daily availability, near real-time) compare positively with Compustat (available monthly, with a larger lag).

Many stock-level lending variables are included in this database. We use the following:

- *Share Supply*: number of shares available to be borrowed divided by shares outstanding. This number is an indication of the supply of shares that are available for short sellers to borrow.

- *Short Interest*: number of shares borrowed divided by shares outstanding. This number gives the percentage of shares that are borrowed (the majority of which is likely shorted).

- *Utilization*: Short Interest divided by Share Supply.

- *Daily Cost of Borrow Score (DCBS)*: a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on IHS Markit Securities Finance proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. High DCBS indicate that the corresponding stocks are “Hard-To-Borrow”.

To deal with possible outliers, we remove, in each cross-section, observations

corresponding to the top and bottom percentile in Short Interest, Share Supply and Utilization. Additionally, there are well-known dividend with-holding tax optimization activities that lead short interest ratios to increase artificially around dividend ex-dates. To deal with that, we remove data 5 business days before and after dividend ex-dates. **Table 3.1** displays summary statistics for both the North America (Panel A) and Developed Europe (Panel B) stock samples. For the average North America stock in our sample, around 3% of outstanding shares are on loan and close to 28% are available to be borrowed. The mean utilization is around 13%. The average DCBS is close to 1, which indicates that most stocks in the sample are cheap to borrow. In Developed Europe, both average short interest and share supply are lower at around 1.8% and 17% respectively. Mean utilization is similar at around 13%. The average DCBS is slightly higher than in North America, but still very close to 1.

Panel A of **Figure 3.3** shows that short interest ratios rose significantly at the beginning of the sample and declined significantly during the Global Financial Crisis, stabilising thereafter. This is consistent with what is documented in [HS](#). They use monthly short interest data from Compustat (available since 1988) and show that short interest ratios trended upward during the mid-1990s, rose dramatically from 2001 to 2007 and registered a marked drop in September 2008 when the SEC imposed a ban on the shorts sales of financial stocks. Their sample ends in 2011. Since then, as can be seen from the graph, short interest ratios have remained relatively stable, at around half of the top reached in 2008. Overall, this shows that the rise in arbitrage capital (as measured by short interest ratios) has not continued post crisis. In fact, it is still quite far away from the levels reached in the years immediately preceding the 2008 Global Financial Crisis.

In Panel B of **Figure 3.3**, we show an alternative measure of arbitrage capital, normalizing by stock liquidity rather than by market capitalization. We define Days to Cover as the number of shares borrowed divided by median 3-month daily number of shares traded¹⁰. Indeed, turnover as a fraction of market capitalization has declined since the Global Financial Crisis, and it is therefore logical to check how arbitrage capital has evolved as a percentage of market liquidity. Similar trends as in Panel B can be seen. The difference is that average Days to Cover has decreased less than average Short Interest since their peaks in 2008.

Similar patterns in short interest ratios can be observed for Developed Europe (Panel C and D of **Figure 3.3**). One additional notable feature of European short interest ratios is that they experience annual seasonal spikes around dividends, likely due to with-holding tax optimization activity¹¹.

In all panels of **Figure 3.3**, equal-weighted short interest ratios are larger than value-weighted ratios, pointing to more short-selling in smaller stocks than in larger stocks. Panel A and C of **Figure 3.4** show the relationship between size and short interest and confirms this pattern in both North America and Developed Europe: smaller stocks have on average higher short interest ratios than larger stocks. Panel B and D show the relationship between stock volatility and short interest: higher volatility stocks tend to be more shorted than lower volatility stocks (again this is true both in North America and Developed Europe).

¹⁰Markets have fragmented over the period, with more and more trading taking place outside primary exchanges. For each stock, we use primary exchange turnover, multiplied by a year and country dependent factor to consider this fragmented liquidity. This multiplier is estimated for each year and each regional pool. For example, in the United States, the multiplier is 1.5 for 2008 and 2.1 for 2018, consistent with an increased fragmentation of liquidity.

¹¹Dividends are generally paid annually in Europe (versus quarterly in US and Canada). Tax optimization benefits are therefore higher and market participants that are shorting stocks to optimize with-holding taxes can afford to do so for longer periods than in North America.

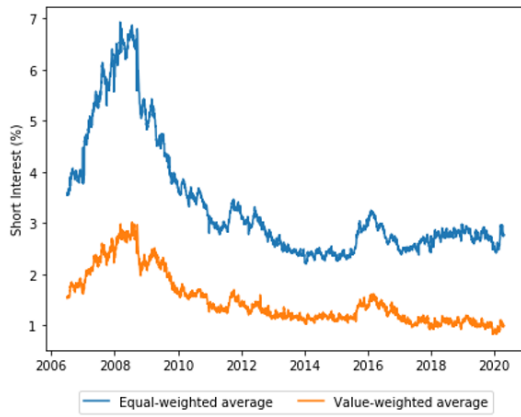
Table 3.1**Summary Statistics**

Panel A: North America Sample (firm-days, 2006-2020)						
	N	Mean	Median	Min	Max	SD
Short Interest	3,950,044	0.0339	0.0187	0.0000	0.3082	0.0397
Share Supply	3,950,044	0.2780	0.2787	0.0259	0.5671	0.0787
Utilization	3,950,044	0.1259	0.0701	0.0003	0.8747	0.1433
DBCS	3,949,673	1.04	1	1	8	0.33
Market Capitalization	3,950,044	\$14.97B	\$4.96B	\$0.06B	\$1,435.26B	\$38.82B
Daily Volatility	3,950,044	0.0218	0.0192	0.0072	0.1016	0.0103
Panel B: Developed Europe Sample (firm-days, 2006-2020)						
	N	Mean	Median	Min	Max	SD
Short Interest	1,924,673	0.0180	0.0110	0	0.1899	0.0195
Share Supply	1,924,673	0.1715	0.1721	0.0033	0.9870	0.0744
Utilization	1,924,673	0.1252	0.0715	0.0001	0.8917	0.1406
DBCS	1,918,108	1.14	1	1	8	0.54
Market Capitalization	1,924,673	\$16.35B	\$6.83B	\$0.05B	\$354B	\$26.76B
Daily Volatility	1,924,673	0.0195	0.0175	0.0073	0.0857	0.0078

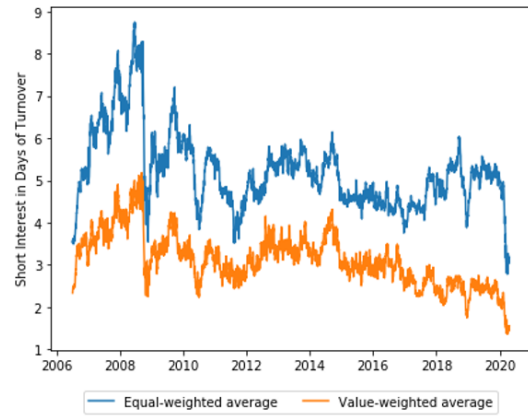
This table reports summary statistics for stock-level lending variables used in this paper. Share Supply is number of shares available to be borrowed divided by shares outstanding. Short Interest is number of shares borrowed divided by shares outstanding. Utilization is Short Interest divided by Share Supply. DBCS (Daily Cost of Borrow Score) is a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on IHS Markit Securities Finance proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. The table also shows Market Capitalization and Daily Volatility, computed as the exponentially-weighted standard deviation of daily stock returns, with a half-life of 126 business days. Panel A shows these summary statistics for our North America sample and Panel B for our Developed Europe sample.

Figure 3.3

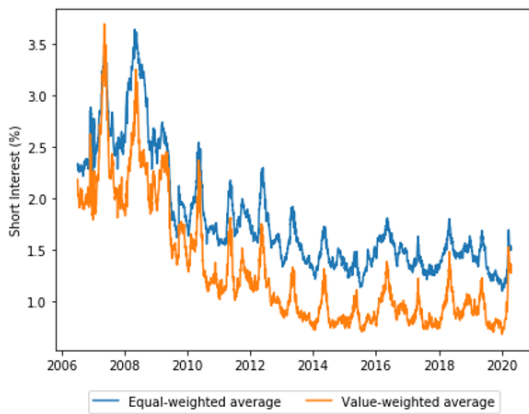
Average Short Interest and Days to Cover, 2006-2020



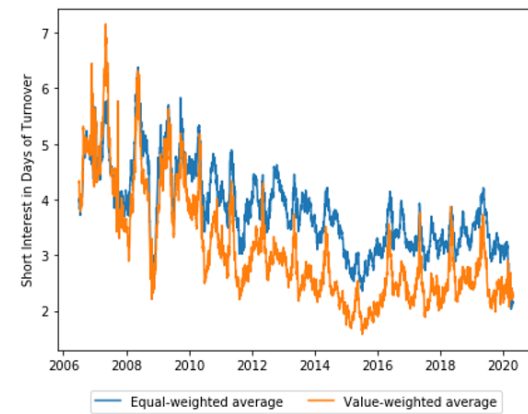
Panel A: Short Interest (North America)



Panel B: Days to Cover (North America)



Panel C: Short Interest (Developed Europe)

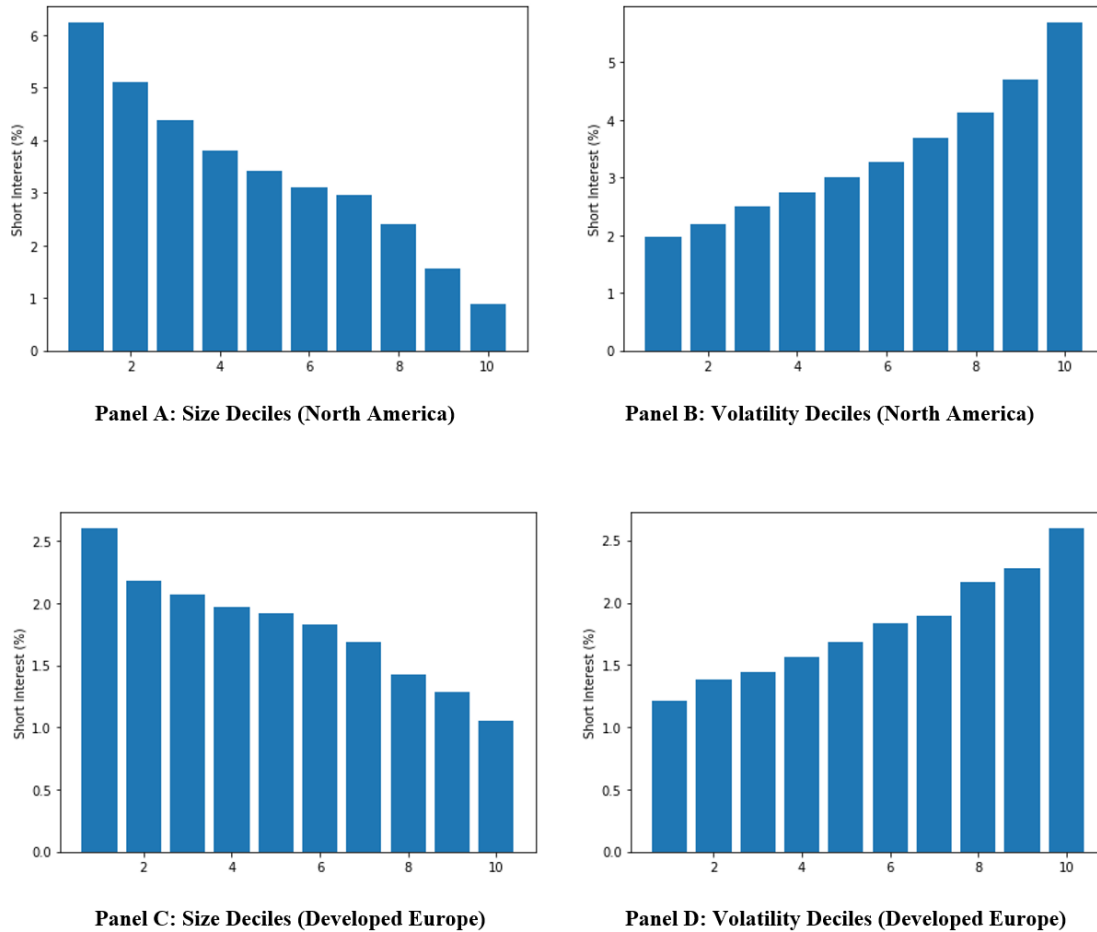


Panel D: Days to Cover (Developed Europe)

Panel A and C plot the daily equal- and value-weighted average short interest for all stocks in our North America and Developed Europe samples. Short interest is number of shares borrowed divided by shares outstanding. Panel B and D plot the daily equal- and value-weighted average days to cover ratio for all stocks in our North America and Developed Europe samples. Days to cover is the number of shares borrowed divided by median 3-month daily number of shares traded.

Figure 3.4

Mean Short Interest by Size and Volatility Deciles, 2006-2020



Each day, stocks in the North America pool are sorted into size and volatility deciles. For each decile, mean Short Interest are computed. Panel A (C) shows the average over the sample period of the daily mean Short Interest by size decile for our North America (Developed Europe) sample. Panel B (D) shows the average over the sample period of the daily mean Short Interest by volatility decile for our North America (Developed Europe) sample. Short interest is number of shares borrowed divided by shares outstanding.

Equity Factor Strategies Data

We primarily focus on Momentum, Value, Low Volatility and Return on Assets strategies because of their long histories among both academics and practitioners. We also add the Short Interest strategy given the focus of this paper.

The definitions used for these strategies and the corresponding data sources are shown in the **Appendix**.

For each of these strategies, every day t , each stock i is ranked in the cross-section according to the measures above. These ranks are then transformed into a strategy score s_{it}^{strategy} uniformly distributed on $[-1, 1]$. For example, the stock with the lowest Momentum measure at date t will be assigned a score s_{it}^{momentum} of -1 , and the one with the highest Momentum measure a score of 1 .

We also study a combination of these four strategies, as a good approximation to how factor-based equity market neutral funds invest. These funds have grown in popularity and assets in the previous decade and have more recently (since 2018) suffered outflows after lacklustre performances¹². The strategy combination score $s_{it}^{\text{composite}}$, which we call *composite* is the uniform transformation on $[-1, 1]$ of the following aggregated score:

$$\frac{1}{3}s_{it}^{\text{value}} + \frac{1}{3}s_{it}^{\text{momentum}} + \frac{1}{6}s_{it}^{\text{lowvolatility}} + \frac{1}{6}s_{it}^{\text{roa}}$$

It is essentially an equi-weighted strategy combination of Value, Momentum and Defensive (itself an equi-weighted combination of Low Volatility and Return on Assets). From information we have gathered on factor-based equity market neutral funds (also known as “risk premia” or “style premia”), we believe it is a

¹²Barrett and al. (2020), in a Kepler industry publication, document the lackluster performance of systematic equity market neutral funds and corresponding outflows.

good approximation of the trading strategy followed by these funds¹³.

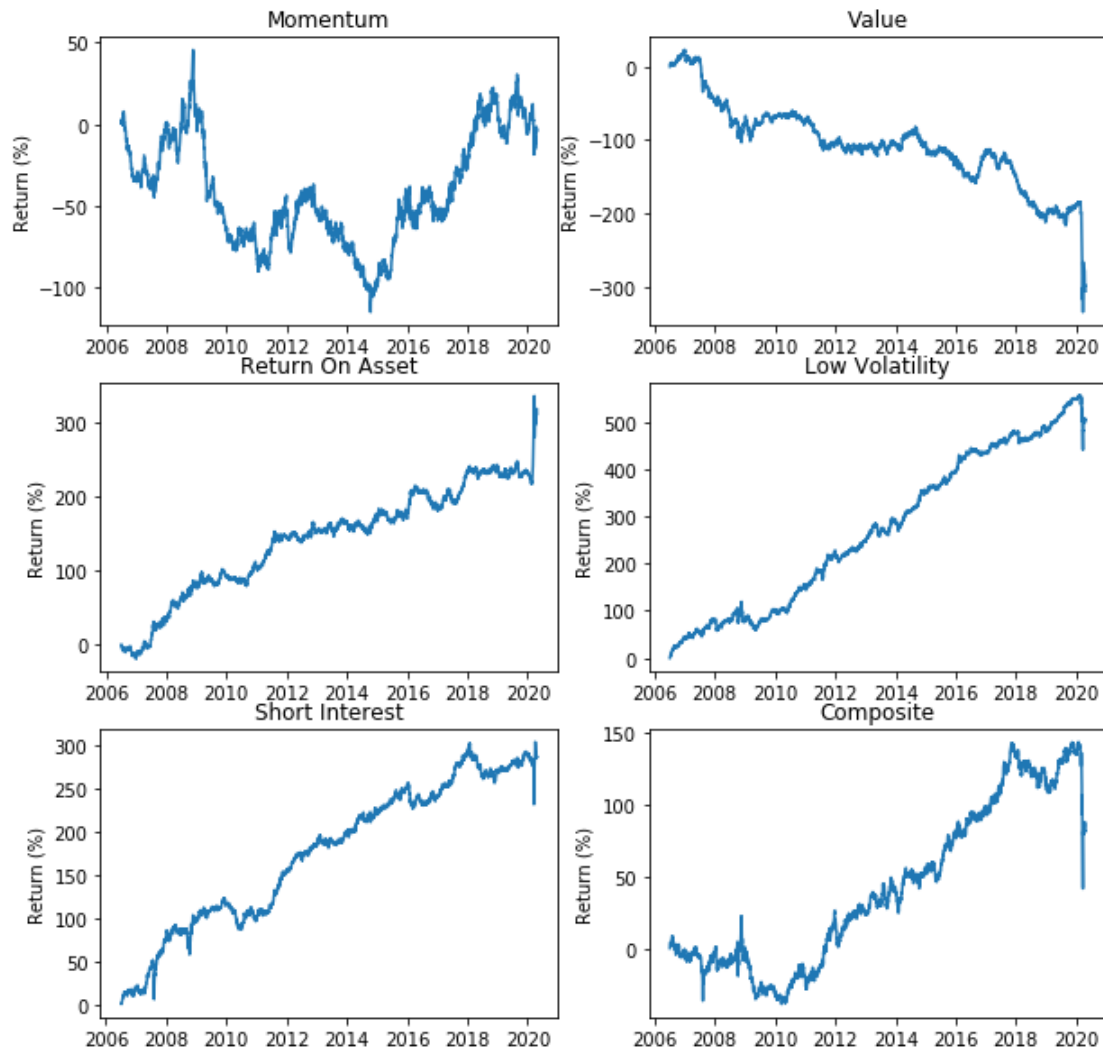
We then compute strategy daily returns, by constructing long-short strategy portfolios following a more sophisticated portfolio construction than the traditional quantile sorting methodology. This construction is closer to how real-life arbitrageurs construct their portfolio, and we believe it is therefore preferable for our empirical analysis of actual crowding levels. It is described in details in the **Appendix**. Note that a number of widely cited papers use factor constructions that differ from the quantile sorting methodology (see, for example, [Asness et al. \(2013\)](#)).

Figure 3.5 (North America) and **Figure 3.6** (Developed Europe) plot the cumulative returns for Momentum, Value, Low Volatility, Return on Asset, Short Interest and the Composite strategies. These strategies all behave consistently with academic or anecdotal evidence. Momentum exhibits the well documented “2009 Momentum Crash” ([Daniel and Moskowitz \(2016\)](#)) and performs relatively well since 2015. Value performs poorly over the sample, particularly in the past few years, and experiences a very significant drawdown during the COVID-19 crisis. This poor performance has been the subject of both market commentaries and academic research in the past years and months ([Lev et al \(2019\)](#), [Asness \(2020\)](#)). Return on Assets performs well. Low Volatility exhibits a strong performance. Short Interest, consistent with several papers in the short-selling literature (see, e.g. [Desai et al \(2002\)](#)), exhibits positive alpha.

¹³AQR, one of the largest investment managers by assets for this type of funds, describe the investment approach of their Style Premia Equity Market Neutral UCITS Fund in their prospectus as follows: “The Fund is actively managed and will seek [...] to provide exposure to three separate investment styles [...]: value, momentum, and defensive, using both “long” and “short” positions.”

Figure 3.5

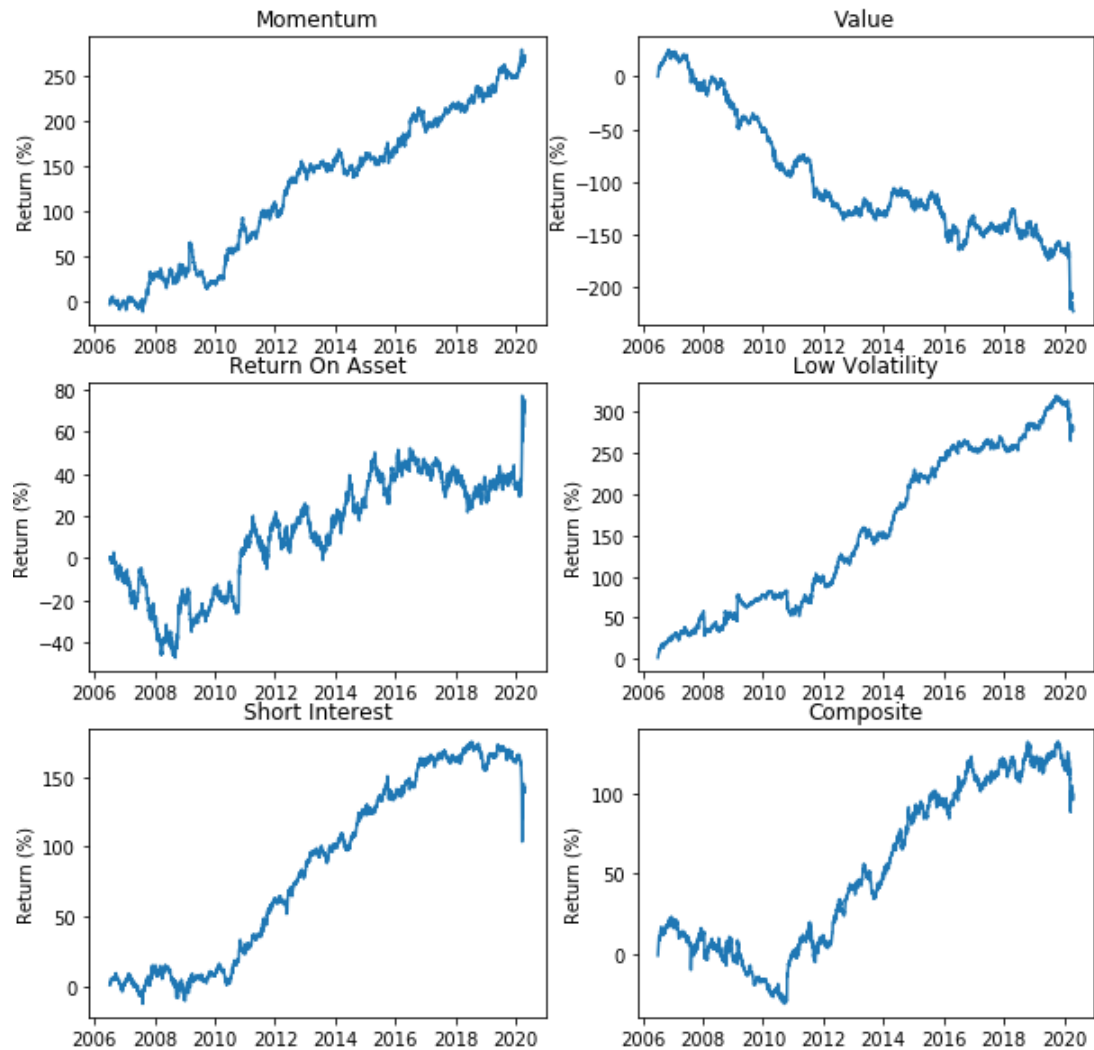
Equity Strategies Cumulative Returns, 2006-2020 (North America)



Momentum, Value, Return on Asset, Low Volatility, Short Interest and Composite cumulative returns for our North America sample. Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

Figure 3.6

Equity Strategies Cumulative Returns, 2006-2020 (Developed Europe)



Momentum, Value, Return on Asset, Low Volatility, Short Interest and Composite cumulative returns for our Developed Europe sample. Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

3.3.2 The Short Interest Strategy as an Indicator for Delever- age Episodes

The Short Interest strategy consists in shorting high short interest stocks (e.g. stocks that tend to be sold short by sophisticated investors such as hedge funds) and buying low short interest stocks. The strategy therefore “mimics” short-sellers’ aggregate short positions and can therefore be thought of as “piggy-backing” on sophisticated investors’ skills in generating alpha. In **Section 3.2**, we have seen that arbitrageurs, on aggregate, generate positive excess returns because they have an informational advantage over “naive” investors¹⁴. We have also seen that arbitrageurs suffer V-shaped drawdowns when they are hit by exogenous liquidity shocks. This last result is helpful because it can help us identify empirically these shocks, by looking at the returns of the Short Interest strategy.

Confirming this intuition in the data, the two sharpest draw-downs for the strategy actually coincided with the well-documented 2007 Quant Crisis and the more recent 2020 Quant Deleverage, both of which represented significant exogenous liquidity shocks on equity long/short arbitrageurs. The following analyses both crises and the corresponding performance of the Short Interest strategy.

The 2007 Quant Crisis was described at length by [Khandani and Lo \(2007 and 2011\)](#). Here is the abstract of their 2007 paper for reference: “During the week of August 6, 2007, a number of quantitative long/short equity hedge funds

¹⁴The profitability of the Short Interest strategy (or, in other words, the negative relationship between short interest and subsequent stock returns) has been the subject of a relatively large set of papers, such as [Desai et al \(2002\)](#). One of the perspectives offered to explain the profitability of the Short Interest strategy is the following: given shorting costs, informed traders are more likely to engage in short-selling, leading high short interest to signal adverse information that is not yet reflected in stock prices. Such an explanation is consistent with our model.

experienced unprecedented losses. [...] we hypothesize that the losses were initiated by the rapid “unwind” of one or more sizeable quantitative equity market-neutral portfolios. Given the speed and price impact with which this occurred, it was likely the result of a forced liquidation [...]. These initial losses then put pressure on a broader set of long/short and long-only equity portfolios, causing further losses by triggering stop/loss and deleveraging policies. A significant rebound of these strategies occurred on August 10th, which is also consistent with the unwind hypothesis. This dislocation was apparently caused by forces outside the long/short equity sector – in a completely unrelated set of markets and instruments [...].”

More than a decade later, in March 2020 (at the height of the COVID-19 induced market panic), a significant deleverage of quantitative equity strategies took place. Financial markets had recently become extremely volatile. Investors started to understand the negative economic impact of the COVID-19 pandemic related lock-downs. Governments and central banks, surprised themselves, had not yet announced the massive shock-offsetting monetary and fiscal measures that would later ease the panic. In the first two weeks of March, quant equity market neutral funds were resisting quite well to the market turmoil (they were only slightly negative for the year)¹⁵. Then, between March 13 and March 18, a large deleverage by quant equity hedge funds followed¹⁶. The deleverage started the day some European regulators announced short-selling bans, as a response to the market volatility caused by the COVID-19 pandemic.

¹⁵According to a Goldman Sachs daily report, they were down -2.7% year to date as of March 12, 2020.

¹⁶According to a Goldman Sachs weekly report published on March 20, 2020, Systematic Equity Long/Short managers reduced significantly their gross equity exposures during the preceding week.

A mix of factors were likely making any leveraged strategies vulnerable to a sudden shift in expectations: investors hitting their value at risk limits following the sharp increase in volatility, impaired liquidity, losses in other asset classes, increased probability of generalized short bans, the self-fulfilling fear that other investors would deleverage and that it was therefore better to be the first to do so. Once it started, quant equity managers started experiencing severe losses and a liquidity spiral followed.

This recent deleverage shared a lot of similarities with the 2007 Quant Crisis. It lasted only a few days, with sharp price reversals thereafter. It spilled-over across regions. The shocks triggering both were likely external, rather than endogenous. Indeed, leading to the recent deleverage, quant equity strategies' performance was not particularly negative; and quant equity investors did not appear to be leverage constrained. Similarly, as pointed out by [Khandani and Lo \(2007\)](#), the 2007 Quant Crisis “was apparently caused by forces outside the long/short equity sector – in a completely unrelated set of markets and instruments [...]”.

The main difference between the two episodes is that while the 2007 Quant Crisis happened under relatively benign market conditions (at a time where funding markets had just started to seize and more than a year before the Lehman bankruptcy), the recent deleverage occurred in much more volatile markets, pretty much at the height of the market panic caused by the COVID-19 pandemic. Another difference is that the 2007 Quant Crisis started in US equity markets and then spilled over to Europe, whereas the recent Quant Deleverage seems to have originated in Europe (and then spilled over to North America).

Figure 3.7 plots the cumulative performance of the Short Interest strategy (our unwind “barometer”) for North America and Europe, during both the 2007

Quant Crisis and the 2020 Quant Deleverage. We can see the following:

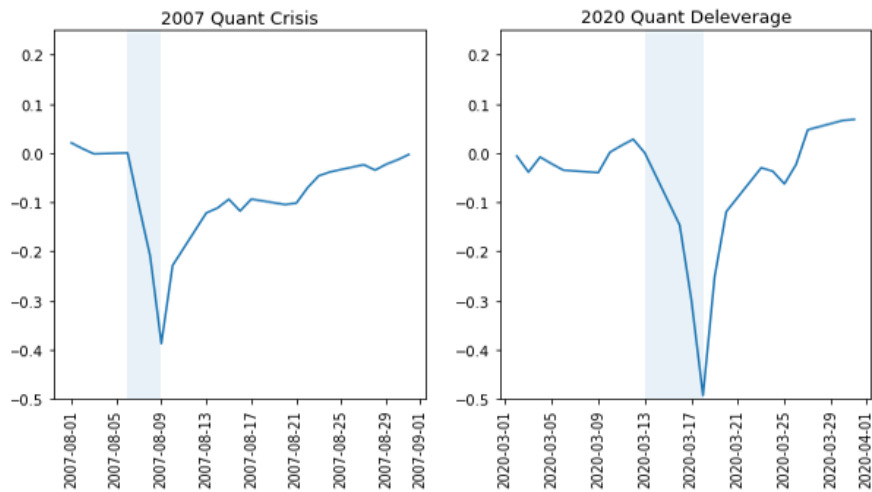
As expected, the Short Interest strategy exhibits a V-shape cumulative performance during both these crises and in both regions: the strategy suffers sharp drawdowns and rebounds quickly right after, consistent with the unwind hypothesis (temporary large price pressures that are not linked to fundamentals).

In 2007, the drawdown starts earlier and is more severe in North America. Europe does get affected, but to a lesser extent and a day later. This is consistent with what has been documented for the 2007 episode: the crisis was triggered in the US, and then impacted other international markets.

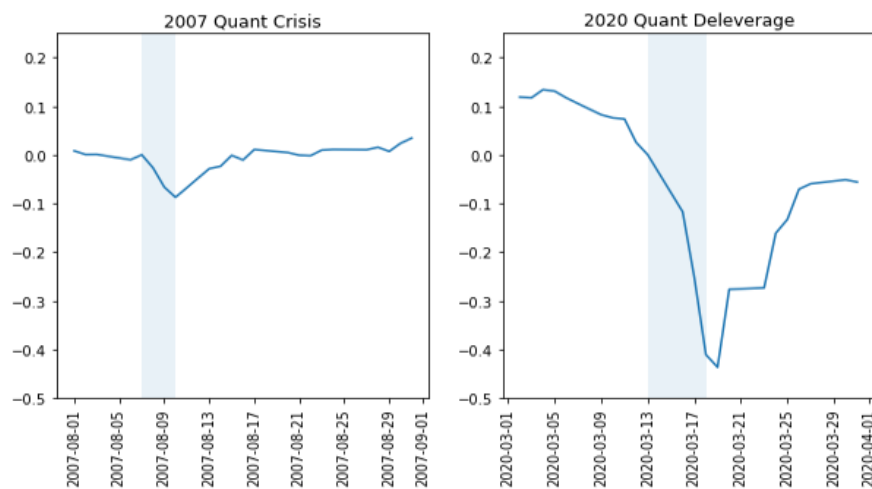
For both regions, the drawdown is more severe in 2020 than in 2007, showing how violent the shock was. There is one caveat. Markets were very volatile during the 2020 episode. In contrast, the 2007 Quant Crisis happened at the onset of the Global Financial Crisis, at a time where equity markets were less volatile.

Figure 3.7

Short Interest Strategy Cum. Returns (2007 Quant Crisis, 2020 Quant Deleverage)



Panel A: Short Interest Cumulative Returns (North America)



Panel B: Short Interest Cumulative Returns (Developed Europe)

Short Interest strategy cumulative returns for our North America (top, panel A) and Developed Europe (bottom, panel B) samples, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

3.3.3 Crowding Measure

In this section, we provide details on the computation of a near real-time crowding measure. This crowding measure will be an important ingredient for **Section 3.4**, which shows that trading strategies with high crowding measures tend to suffer upon the occurrence of liquidity shocks. We show the evolution of this crowding measure through time for the quant equity trading strategies studied in this paper.

Crowding Measure Methodology

[HS](#) develop a methodology to infer from short interest data the amount of capital allocated to quantitative arbitrage strategies. Their key insight is that “each cross-section of short interest reveals how intensely arbitrageurs are using a quantitative equity strategy at a given time”. We have also shown in **Section 3.2** why this was the case. Intuitively, if a lot of arbitrageurs are allocating capital to a given long-short equity strategy, short interest should be higher for stocks shorted by that strategy (in our setting, those with negative s_{it}^{strategy}).

We run daily cross-sectional regressions of stock-level short interest SI_{it} on strategy scores s_{it}^{strategy} , controlling for stock volatility¹⁷ and size (as we have shown above, both are correlated to short interest):

$$SI_{it} = k_t^{\text{strategy}}(-s_{it}^{\text{strategy}}) + \text{controls} + \epsilon_{it} \quad (3.11)$$

The coefficient obtained through this regression, k_t^{strategy} , is the estimated difference in short interest between the most shorted stock (that has a score of

¹⁷For the low volatility strategy, we do not control for volatility. All other strategies, including the composite, are controlled for both size and volatility.

-1) and the median score stock (that has a score of 0). It can be interpreted as a proxy for crowdedness of the strategy-level arbitrage capital.

Our crowding measure differs from [HS](#)' in the following aspects:

1. Short Interest Data: we use IHS Markit, available daily and based on aggregating data from various institutions involved in the equity finance market. [HS](#) use Compustat which is monthly and based on exchange data.
2. We focus on a tradeable stock sample. [HS](#) study a larger sample that includes a lot of smaller stocks.
3. [HS](#) regress short interest on strategy decile dummies, omitting the 5th decile, whereas we regress on a uniformly distributed strategy score.

Results

Table 3.2 shows the average coefficients, t-statistics and R^2 of k_t^{strategy} in the daily cross-sectional regressions for Value, Momentum, Low Volatility, Return on Assets and the Composite. With the exception of Value in North America and Return on Assets in both regions, coefficients are positive and significant. Low Volatility has the highest average coefficients and t-statistic, suggesting highest level of crowded-ness. Average R^2 are in the 0.1 to 0.2 range.

Figure 3.8 (North America) and **Figure 3.9** (Developed Europe) further show the evolution over time of k_t^{strategy} as well as the corresponding t-statistics.

Low Volatility seems to be the most significantly crowded strategy with $k_t^{\text{low volatility}}$ showing a steady increase over the past 8 years or so, in both regions. This result is consistent with the findings in **Figure 3.4** which shows that higher volatility stocks are associated with higher short interest ratios. At the other end of the spectrum, Return on Assets is not very crowded over the sample, except on the

lead up to the Global Financial Crisis. Value and Momentum are in between, with average k_t^{strategy} that are positive but not always significant. Value is more crowded in North America than in Developed Europe while Momentum is more crowded in Developed Europe than in North America. $k_t^{\text{composite}}$ is generally positive and significant. It increased a lot since 2016 and peaked at the end of 2017 before decreasing meaningfully, quite consistently with the rise and fall in assets of factor-based equity market neutral strategies. Most strategies were crowded pre Global Financial Crisis and experienced large drops in crowding in September 2008 (Lehman default, SEC short ban). One exception is Value, which was not crowded in the build up to the crisis.

Table 3.2

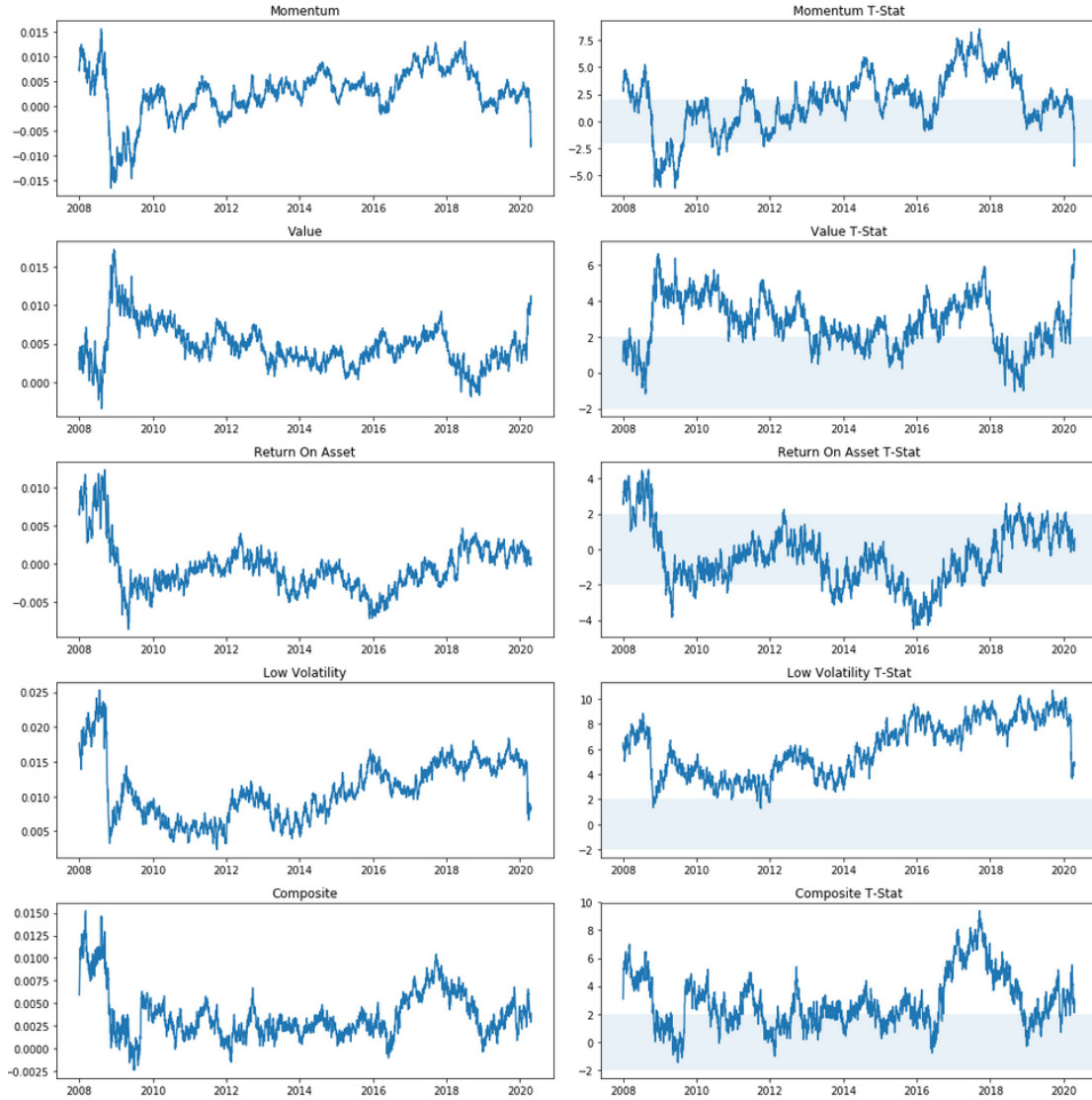
Summary Statistics of Crowding Measures

Panel A: North America					
	Momen- tum	Value	Low Vol	ROA	Compos- ite
Average Coefficients	0.0033	0.0043	0.0115	0.0005	0.0039
Average T-Stats	[1.97]	[2.49]	[6.13]	[0.00]	[2.92]
Average R ²	0.20	0.20	0.18	0.20	0.20
Panel B: Developed Europe					
	Momen- tum	Value	Low Vol	ROA	Compos- ite
Average Coefficients	0.0044	0.0004	0.0055	-0.0009	0.0022
Average T-Stats	[3.33]	[0.36]	[4.03]	[-0.66]	[2.36]
Average R ²	0.12	0.10	0.09	0.10	0.11

The crowding measure k_t^{strategy} is estimated daily via the following cross-sectional regression: $SI_{it} = k_t^{\text{strategy}}(-s_{it}^{\text{strategy}}) + \text{controls} + \epsilon_{it}$ where SI_{it} is the short interest for stock i and s_{it}^{strategy} is the score for the quantitative equity strategy studied, uniformized on $[-1, 1]$. Strategy include Value, Momentum, Low Volatility, Return on Assets and the Composite. The regression is controlled for size (log of market capitalization) and volatility. Average crowding measure, t-statistic and regression R² are shown.

Figure 3.8

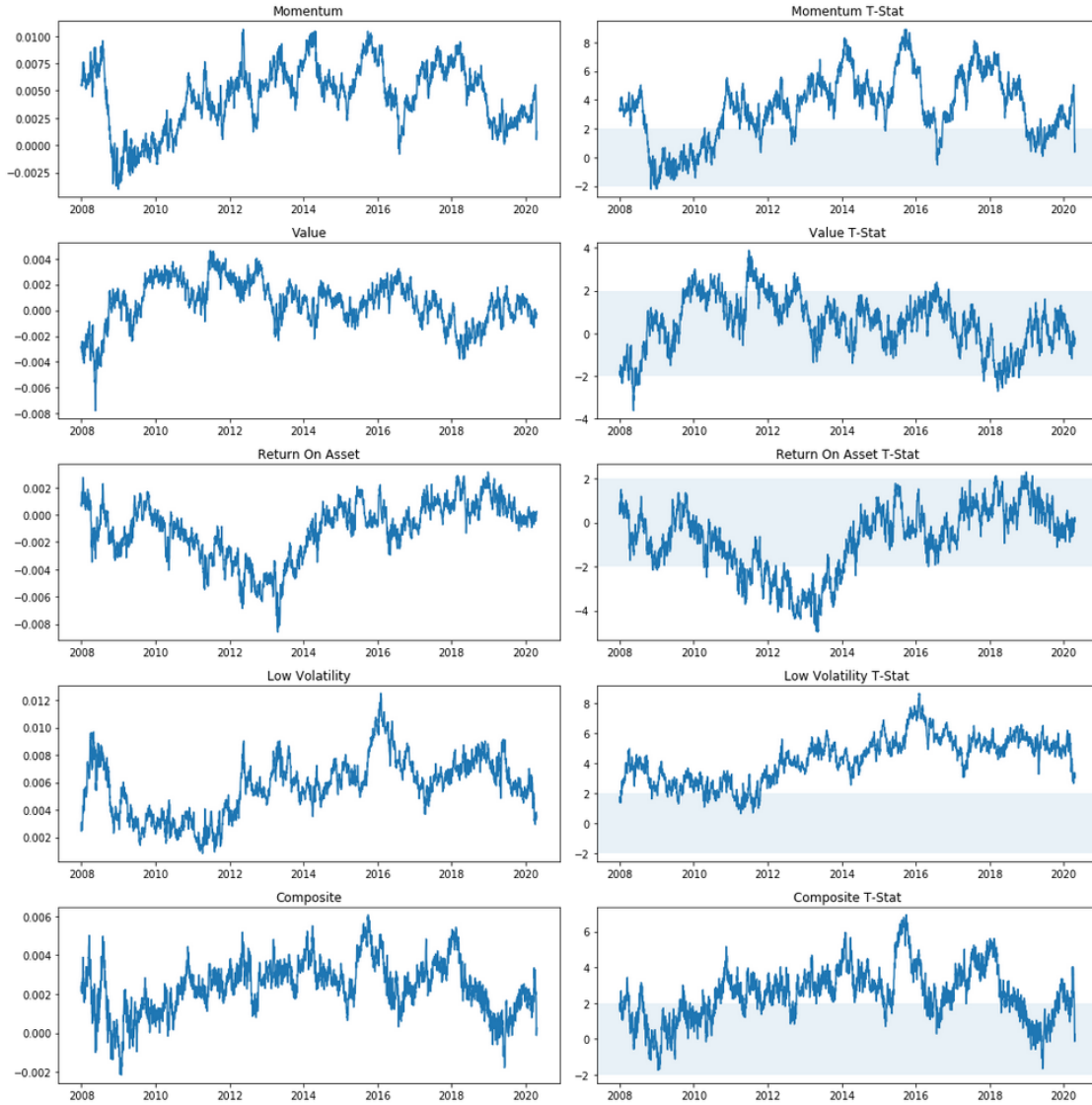
Evolution of Crowding Measures k_t^{strategy} , 2008-2020 (North America)



The crowding measure k_t^{strategy} is estimated daily via the following cross-sectional regression: $SI_{it} = k_t^{\text{strategy}}(-s_{it}^{\text{strategy}}) + \text{controls} + \epsilon_{it}$ where SI_{it} is the short interest for stock i and s_{it}^{strategy} is the score for the quantitative equity strategy studied, uniformized on $[-1, 1]$. Strategy include Value, Momentum, Low Volatility, Return on Assets and the Composite. The regression is controlled for size (log of market capitalization) and volatility. The evolution though time of the coefficient k_t^{strategy} is shown on the left-hand side, that of the t-statistic of the regression on the right-hand side (where the shaded portion corresponds to non-significant values).

Figure 3.9

Evolution of Crowding Measures k_t^{strategy} , 2008-2020 (Developed Europe)



The crowding measure k_t^{strategy} is estimated daily via the following cross-sectional regression: $SI_{it} = k_t^{\text{strategy}}(-s_{it}^{\text{strategy}}) + \text{controls} + \epsilon_{it}$ where SI_{it} is the short interest for stock i and s_{it}^{strategy} is the score for the quantitative equity strategy studied, uniformized on $[-1, 1]$. Strategy include Value, Momentum, Low Volatility, Return on Assets and the Composite. The regression is controlled for size (log of market capitalization) and volatility. The evolution though time of the coefficient k_t^{strategy} is shown on the left-hand side, that of the t-statistic of the regression on the right-hand side (where the shaded portion corresponds to non-significant values).

3.4 Empirical Link Between Crowding and Liquidity Shocks

In this section, we check what happens to crowded strategies upon the occurrence of a liquidity shock, as identified from the largest drawdowns of the Short Interest strategy. Consistent with the results in **Section 3.2**, we confirm that crowded strategies tend to suffer larger drawdowns upon the occurrence of liquidity shocks. We then provide some illustration for these results.

3.4.1 Empirical Results

As we have discussed in previous sections, the short interest strategy can be seen as a barometer for liquidity shocks affecting short-sellers: the strategy will exhibit drawdowns when short sellers' positions are subject to broad-based deleveraging episodes.

The causes for these unwinds can be multiple, as widely documented in the limits to arbitrage literature ([Schleifer and Vishny \(1997\)](#), [Brunnermeier and Pedersen \(2009\)](#)). They may be the consequence of voluntary risk reductions following increases in broader market volatility, as many sophisticated investors want to maintain a certain level of ex-ante risk (one of the plausible factors that led to the 2020 Quant Deleverage). They can also be due to economy-wide liquidity shocks that trigger hedge funds' clients to withdraw their capital, and brokers to reduce the leverage available by increasing margining requirements (as happened during the 2008 Global Financial Crisis). Finally, they can be the result of losses triggering a deleveraging spiral (2007 Quant Crisis, where the initial loss was likely

the result of one large fund unwinding its positions).

In **Section 3.2**, we have shown theoretically that crowded strategies generally tend to suffer larger drawdowns upon the occurrence of liquidity shocks. The aim of this sub-section is to confirm this link empirically, equipped with (i) a way to identify these liquidity shocks (using the drawdowns of the short interest strategy) and (ii) crowding measures through time for the well-known strategies studied in this paper.

To confirm this result, we proceed to the following empirical analysis. First, we focus on the largest short interest strategy drawdowns for each of our Europe and North America samples. We define these periods as the bottom 20, 30 and 40 non-overlapping 5-day returns of the short interest strategy. For each of these periods and for each of the five quant equity trading strategies studied in this paper (Momentum, Value, Low Volatility, Return on Assets and Composite), we compute crowding levels k_t^{strategy} (as defined in **Section 3.3.3**) at the beginning of the period, as well as the contemporaneous 5-day returns $r_{t,t+5}^{\text{strategy}}$. We then pool across strategies and periods and regress crowding level on strategy returns. A statistically significant negative coefficient would confirm our hypothesis.

$$r_{t,t+5}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t,t+5}^{\text{strategy}} \quad (3.12)$$

In this regression, the right hand variable k_t^{strategy} was itself derived through a regression and is therefore a “generated regressor”. This leads to under-estimation of standard errors as the regressor was estimated with sampling errors. To correct for this bias, we follow [Green \(2017\)](#). We bootstrapped 100 samples when calculating the crowding measures k_t^{strategy} , with each sample randomly drawing

50% of data points. The resulting mean and standard deviation of bootstrapped samples of β are then used to compute t-statistics.

To deal with outliers, we run two types of regressions. First, a standard ordinary least square regressions where we have first removed the top and bottom 1% of both strategy returns and crowding levels. We also examined results after removing top and bottom 0.5% and 2.5% of strategy returns as well as removing outliers based on mean absolute deviation measure. These alternatives lead to similar conclusion. Second, a “robust” regressions with Huber loss.

Table 3.3 shows the results for each region, as well as for both regions pooled together and for the two types of regressions. It also shows results for various numbers of short interest strategy draw-downs (20, 30 and 40). There are therefore a total of 18 regressions (3 pools of stocks, 3 different numbers of draw-downs, ordinary OLS and ”robust” regressions). Coefficients for the Combined pool of stocks and for Developed Europe are both negative and significant across all 6 specifications. In North America, all coefficients are negative as well but results are weaker with only 2 out of the 6 specifications significant at the 1% level.

Overall (in the majority of cases), coefficients are negative and statistically significant. This confirms empirically our hypothesis: crowding is associated with an increased exposure to liquidity shocks.

We tested the robustness of these results to the traditional decile construction of the factors studied (results in **Appendix**). Results are in line with negative and significant coefficients for the Combined and Developed Europe pools. Results in North America appear weaker in this specification.

Table 3.3
Crowding and Strategy Drawdowns

Panel A: Standard OLS									
	Top 20 Drawdowns			Top 30 Drawdowns			Top 40 Drawdowns		
	EU	AM	Combined	EU	AM	Combined	EU	AM	Combined
Intercept	-0.01	-0.02	-0.01	-0.01	-0.02	-0.01	-0.00	-0.01	-0.01
	[-5.56]	[-6.69]	[-8.36]	[-6.52]	[-10.14]	[-11.35]	[-4.86]	[-9.58]	[-10.67]
Capital	-2.35	-0.69	-1.44	-2.13	-0.28	-1.05	-2.10	-0.37	-0.92
	[-3.82]	[-1.25]	[-3.39]	[-4.81]	[-0.79]	[-3.60]	[-6.17]	[-1.46]	[-4.51]

Panel B: Robust Regression with Huber Loss									
	Top 20 Drawdowns			Top 30 Drawdowns			Top 40 Drawdowns		
	EU	AM	Combined	EU	AM	Combined	EU	AM	Combined
Intercept	-0.01	-0.03	-0.02	-0.01	-0.02	-0.01	0.01	-0.02	-0.01
	[-7.66]	[-8.00]	[-10.80]	[-7.45]	[-7.66]	[-10.25]	[-6.87]	[-7.65]	[-10.36]
Capital	-2.08	-0.44	-1.48	-2.17	-1.50	-2.00	-2.17	-1.25	-1.66
	[-2.74]	[-0.60]	[-3.05]	[-3.54]	[-2.88]	[-5.42]	[-4.83]	[-3.40]	[-6.32]

Panel A reports coefficients and t-statistics for the standard ordinary least square regression $r_{t,t+5}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t,t+5}^{\text{strategy}}$ where $r_{t,t+5}^{\text{strategy}}$ is the cumulative return of strategies (Value, Momentum, Return on Asset, Low Volatility and Composite) between days t and t+5, during the bottom 20, 30 and 40 non-overlapping 5-day returns of the short interest strategy. k_t^{strategy} is the strategy-level crowding measure calculated as described in section 3. Developed Europe (EU), North America (AM) and pooled results are reported. Top and bottom 1% of both strategy returns and crowding level are removed before regression. Panel B displays the results for Robust Regression with Huber Loss function. Coefficients and t-statistics are calculated from bootstrapped mean and standard deviations of 100 sampled regressions.

3.4.2 Case Study: 2007 Quant Crisis and 2020 Quant Delever- age

To illustrate this empirical link between crowding and liquidity shocks, **Figure 3.10** (North America) and **Figure 3.11** (Developed Europe) plot, for both the 2007 Quant Crisis and the 2020 Quant Deleverage, strategy level crowding and strategy cumulative returns for Momentum, Value, Low Volatility, Return on Asset. Here are some observations.

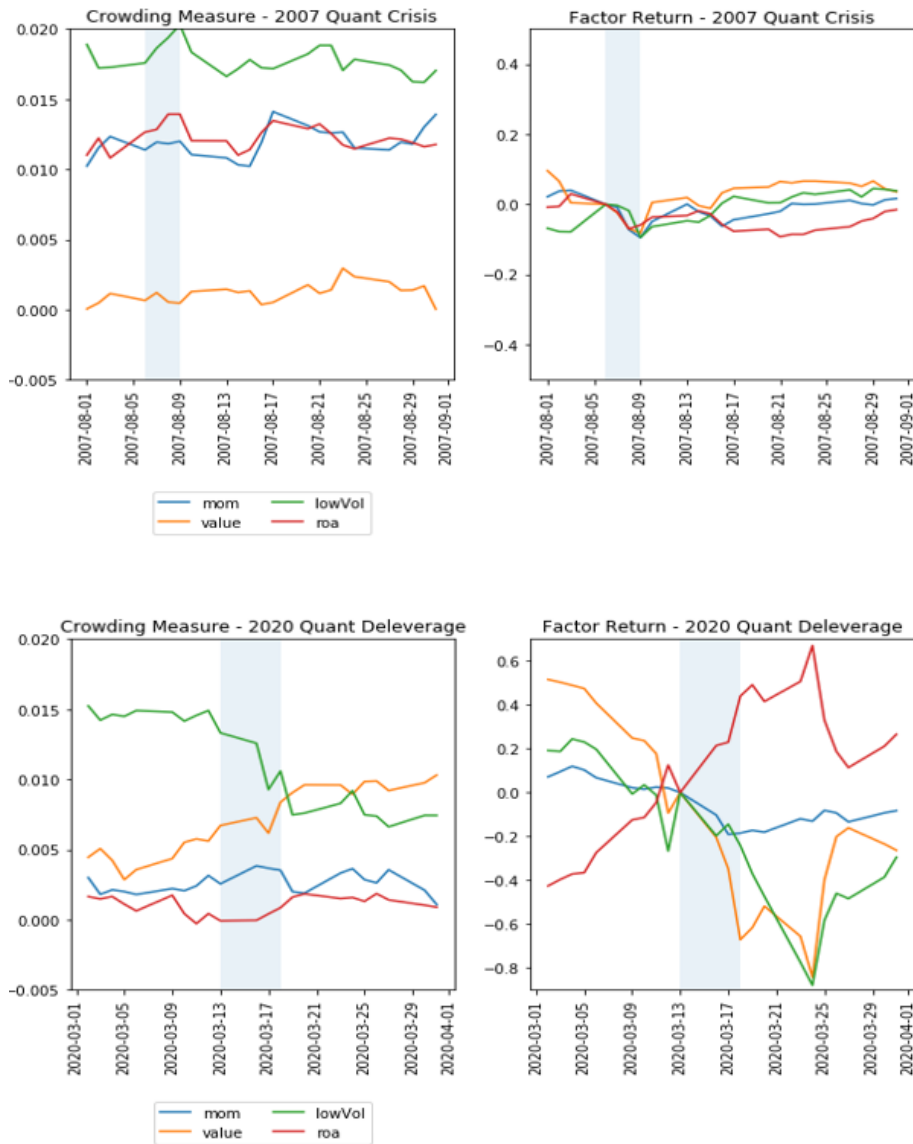
Markets were very volatile during the 2020 episode. In contrast, the 2007 Quant Crisis happened at the onset of the Global Financial Crisis, at a time where equity markets were less volatile. This can be seen in the range of strategy returns, which is much larger in 2020 than in 2007.

Strategies that were crowded generally suffered in the 2020 episode. Momentum and Low Volatility were crowded and under-performed in both regions, Return on Asset was not crowded and performed. Value is less clear, it suffered the most in both regions but was only crowded in North America. Given the volatility at the time, other factors than crowding were likely at play and added noise in the strategy returns.

In 2007, crowded strategies under-performed in North America: Momentum, Low Volatility, Return on Assets were all crowded and suffered. Value was not crowded but suffered as well. In Europe where the Quant Crisis was much less pronounced, the picture is less clear: Value and Momentum both suffered but only Momentum was crowded. Low Volatility was crowded but did not under-perform.

This case study shows patterns consistent with the results of **3.4.1**: crowded trading strategies tend to draw-down during liquidity events.

Figure 3.10
Crowding and Factor Performance, 2007 Quant Crisis and 2020 Quant Deleverage (North America)



Crowding measures (left) and factor (Momentum, Value, Low Volatility, Return on Asset) cumulative returns (right) for our North America sample, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

Figure 3.11

Crowding and Factor Performance, 2007 Quant Crisis and 2020 Quant Deleverage (Developed Europe)



Crowding measures (left) and factor (Momentum, Value, Low Volatility, Return on Asset) cumulative returns (right) for our Developed Europe sample, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

3.5 Conclusion

In this paper, we propose a model to understand the link between crowding and exogenous liquidity shocks. In this model, two different types of sophisticated investors arbitrage the biases of a majority of “naive” investors. When a liquidity shock affects them, arbitrageurs unwind their positions, resulting in price pressures that impact negatively their profits; these price pressures subsequently abate, leading to a rebound in profits. Also, the more crowded type of arbitrageur tend to suffer more than the less crowded type: crowding is therefore associated with an increased adverse exposure to liquidity shocks.

We then go on to confirm this link between crowding and liquidity shocks empirically. We use sophisticated equity investors’ positioning data for two purposes: first, by approximating their portfolios, as an indicator for liquidity shocks impacting these investors; second, through cross-sectional regressions, as inputs to calculate crowding levels of various quant equity strategies. In that respect, equity finance data is particularly well adapted. It enables to compute short interest ratios for each stock. Although these ratios are aggregated stock-level short position measures across all short-sellers, they are good proxies for arbitrageurs short single stock positions. This is because short-sellers are typically sophisticated investors such as hedge funds and other arbitrageurs.

Our analysis of the Short Interest strategy shows that, consistent with several papers in the short-selling literature, high short interest predicts low future returns. In other words, a strategy that shorts high short interest stocks and buys low short interest stocks exhibits positive alpha. But we also show that this strategy exhibits large V-shaped drawdowns during “liquidity crises”, times dur-

ing which quant arbitrageurs simultaneously unwind their positions. The largest drawdowns for the Short Interest strategy coincided with the 2007 Quant Crisis and, more recently, the 2020 Quant Deleverage.

Next, we use short interest data to infer near real-time levels of crowdedness for some of the best-known quantitative equity strategies, by regressing cross-sectionally short interest on strategy-level scores. Such a method can be used for any other type of quant equity strategy. We show that quantitative investors are still crowding significantly in some of these, though there is important time variation in the levels of crowding.

What are the consequences of crowding? This paper establishes a link between crowding and liquidity shocks: crowded strategies tend to suffer when liquidity shocks affect short sellers. All else equal, sophisticated investors and arbitrageurs should therefore try to avoid crowded trades.

Why, then, are sophisticated quant investors crowding in the same strategies? Perhaps, as explained by [Stein \(2009\)](#), because they cannot measure in real-time how much capital other investors are simultaneously deploying in these strategies. In this paper, we show that near real-time crowding can be inferred from short interest data. Such measures are surely available to sophisticated investors. Maybe, then, are quant investors crowding in the same strategies because these, even crowded, remain good bets? This is possible, as (in results that we left for the **Appendix**) we find no clear empirical link between levels of crowding and future returns: alpha decay, factor timing skills and flow effects probably cancel each other out on average. On the one hand, more crowding for a trading strategy should lead to lower returns as the strategy's capacity becomes saturated, but on the other hand, sophisticated investors might be skilled at timing strategy returns,

thereby increasing their positions on strategies that will perform better.

Possible alternative explanations, which are outside the scope of this paper but could be the topic of future investigations include the following. Perhaps are quant managers not all that sophisticated. Some might not measure crowding at all. Others might grossly over-estimate the overall capacity available to the strategies they trade, as argued recently by [Chan \(2021\)](#). Or maybe there are principal agent issues: as liquidity crises are rare, it might be rational for some managers to crowd in strategies that are well known and fashionable with end-clients. The strategies are therefore easy to implement and sell and will generate fees for the managers until the risk materializes.

3.6 Appendix

3.6.1 Strategy Definitions

- *Momentum*: cumulative returns from months $t - 12$ to $t - 1$ (stock returns are taken from Datascope).
- *Value*: common equity divided by market capitalization lagged by 21 business days (Worldscope for common equity and Datascope for market capitalisation).
- *Low Volatility*: 1 divided by stock returns volatility, calculated as the exponentially-weighted standard deviation of daily stock returns, with a half-life of 126 business days (Datascope).
- *Return on Assets*: EBIDTA / Average Total Assets (Worldscope)
- *Short Interest*: minus short interest (IHS Markit)

3.6.2 Strategy Weights Computation

We detail in this sub-section how we compute portfolio weights for the trading strategies studied in this paper. Each day t , for each stock i in the sample, optimal weights w_{it}^* are computed by performing the following optimization:

$$\begin{aligned} & \text{Max} \sum_i w_{it}^* s_{it}^{\text{strategy}} \\ & \text{s.t.} : \sigma_{P,t} = 0.1, \text{ and } \sum_i w_{it}^* \beta_{it} = 0 \end{aligned}$$

$\sigma_{P,t}$ is the volatility of the portfolio constructed and β_{it} is the beta of stock i .

Essentially, we maximise $\sum_i w_{it}^* s_{it}^{\text{strategy}}$, which can be seen as the expected returns of the portfolio, subject to volatility and beta neutrality constraints. If the

strategy indeed generates alpha, a high score stocks should be followed by high excess returns and vice versa. We constrain the volatility of the portfolio to be 10% and the beta of the portfolio (against an equi-weighted basket of the stocks in the portfolio) to be 0.

$\sigma_{P,t}^2$ and β_{it} are computed from a variance-covariance matrix Ω_t that is estimated over a medium horizon.

[Daniel et al \(2020\)](#) tackle a similar problem (instead of maximising returns for a given volatility, they minimize volatility for a given return) and show that this maximisation program has a simple close form solution.

Finally, we smooth turnover in order to consider real-life concerns about trading costs. We follow [Garleanu and Pedersen \(2013\)](#), who show that an optimal dynamic portfolio policy when trading is costly is to trade partially towards the current aim.

Our final weights w_{it} become:

$$w_{it} = (1 - \tau)w_{it-1} + \tau w_{it}^* \tag{3.13}$$

We choose a τ equal to 0.1, which is on average close to optimal for the strategies studied. Multiplying these weights by daily stock returns yields the strategy daily returns, gross of any trading costs.

3.6.3 Impact of Crowding on Strategy Returns

Here, we investigate whether a higher level of crowding is followed by lower strategy returns (as previously documented by [HS](#)). In **Table 3.4**, we regress strategy returns over the following d business days $r_{t,t+d}^{\text{strategy}}$ on the initial level of crowd-

ing. We look at various values for d : 63, 126 and 252 business days. The equation for the regression is:

$$r_{t,t+d}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t,t+d}^{\text{strategy}}$$

The t-statistics are calculated using Newey-West standard errors because of overlapping returns, allowing for $d+2$ daily lags. We also show results when we control for the increase in the crowding measure during the period for which the returns are computed: $\Delta k_{t,t+d}^{\text{strategy}} = k_{t+d}^{\text{strategy}} - k_t^{\text{strategy}}$. Indeed, strategy inflows and outflows could have some contemporaneous impact on strategy returns.

Results are generally robust to various values of d and to controlling for $\Delta k_{t,t+d}^{\text{strategy}}$, but no clear pattern emerge across strategies and regions. High levels of crowding seem to be followed by higher returns in North America for Momentum, Value and Return on Assets but by lower returns for Low Volatility and the Composite. Developed Europe shows no significant pattern, except for Composite where high levels of crowding are very significantly followed by higher returns, opposite to what we see in North America. Overall and on balance, although the results are mixed, it seems that crowding is associated in more cases to higher future returns, which is at odds with what is found by [HS](#) on their 1973-2011 sample: they showed a negative relationship between crowding and future strategy returns.

A possible explanation is that offsetting effects are at play. On the one hand, more arbitrage capital chasing the same strategy will, all else equal, lead to alpha decay. But on the other hand, some sophisticated investors might have skills in timing factors: these skilled investors increase exposure to a factor when they

(correctly) believe it will have attractive future returns. This increased exposure shows up in short interest data and our crowding measure.

Table 3.4

Crowding and Future Strategy returns

Panel A: North America Sample 2006-2020

	Momentum		Value		Return on Assets		Low Volatility		Composite	
d=63										
Intercept	-0.03	-0.04	-0.07	-0.06	0.05	0.05	0.12	0.11	0.01	0.02
	[-2.01]	[-2.04]	[-2.64]	[-2.24]	[3.69]	[3.73]	[3.47]	[3.29]	[0.84]	[0.93]
k_t^{strategy}	10.16	10.96	5.03	3.96	4.99	3.88	-2.59	-2.09	1.2	0.65
	[3.68]	[3.51]	[1.26]	[0.77]	[1.87]	[1.34]	[-0.97]	[-0.8]	[0.41]	[0.18]
$\Delta k_{t,t+d}^{\text{strategy}}$		2.24		-2.74		-6.51		2.14		-1.55
		[0.55]		[-0.32]		[-1.83]		[0.47]		[-0.38]
d=126										
Intercept	-0.06	-0.07	-0.12	-0.13	0.09	0.09	0.27	0.26	0.06	0.05
	[-1.88]	[-1.95]	[-2.93]	[-2.53]	[4.29]	[4.26]	[5.05]	[4.66]	[2.57]	[1.63]
k_t^{strategy}	19.55	21.81	8.96	11.59	10.91	9.77	-7.34	-6.64	-4.39	-2.16
	[4.03]	[3.58]	[1.28]	[1.32]	[2.75]	[2.08]	[-1.85]	[-1.57]	[-1.01]	[-0.32]
$\Delta k_{t,t+d}^{\text{strategy}}$		3.82		4.12		-3.61		1.86		4.1
		[0.81]		[0.42]		[-0.76]		[0.44]		[0.55]
d=252										
Intercept	-0.08	-0.1	-0.25	-0.31	0.18	0.18	0.63	0.6	0.18	0.18
	[-1.30]	[-1.44]	[-3.44]	[-2.99]	[5.43]	[5.48]	[8.58]	[6.78]	[4.17]	[3.39]
k_t^{strategy}	29.24	36.13	20.17	32.71	18.84	22.52	-23.27	-20.27	-20.02	-21.82
	[4.24]	[3.17]	[1.56]	[1.94]	[3.31]	[3.71]	[-3.78]	[-2.75]	[-2.81]	[-1.68]
$\Delta k_{t,t+d}^{\text{strategy}}$		7.69		15.98		6.95		6.2		-1.88
		[1.08]		[0.83]		[1.4]		[0.92]		[-0.17]

Panel B: Developed Europe Sample 2006-2020

	Momentum		Value		Return on Assets		Low Volatility		Composite	
d=63										
Intercept	0.06	0.05	-0.03	-0.03	0.01	0.01	0.03	0.02	-0.01	-0.02
	[2.20]	[1.92]	[-2.83]	[-2.75]	[0.72]	[0.53]	[1.05]	[0.63]	[-0.93]	[-1.79]
k_t^{strategy}	-2.19	-1.62	-4.57	-11.17	-1.82	-3.44	3.46	5.71	13.15	18.72
	[-0.49]	[-0.32]	[-0.72]	[-1.82]	[-0.47]	[-0.74]	[0.77]	[1.22]	[2.72]	[3.26]
$\Delta k_{t,t+d}^{\text{strategy}}$		1.72		-17.59		-4.63		7.96		12.57
		[0.38]		[-3.37]		[-0.83]		[1.08]		[2.61]
d=126										
Intercept	0.09	0.1	-0.07	-0.06	0.01	0.01	0.08	0.04	-0.01	-0.04
	[1.72]	[1.63]	[-3.38]	[-3.37]	[0.85]	[0.67]	[1.50]	[0.62]	[-0.45]	[-1.68]
k_t^{strategy}	1.43	-0.8	2.37	-13.13	-3	-5.75	4.04	12.24	21.13	35.51
	[0.16]	[-0.07]	[0.22]	[-1.06]	[-0.47]	[-0.76]	[0.49]	[1.34]	[2.27]	[3.35]
$\Delta k_{t,t+d}^{\text{strategy}}$		-3.89		-26.16		-6.16		18.26		22.31
		[-0.69]		[-3.24]		[-0.74]		[1.79]		[4.08]
d=252										
Intercept	0.2	0.17	-0.15	-0.13	0.04	0.03	0.16	0.06	-0.04	-0.12
	[2.38]	[1.75]	[-4.30]	[-4.40]	[1.23]	[0.89]	[1.59]	[0.68]	[-0.82]	[-2.69]
k_t^{strategy}	-1.67	4.94	16.04	-7.45	-3.05	-12.82	9.39	26.48	50.53	85.42
	[-0.12]	[0.27]	[1.31]	[-0.45]	[-0.42]	[-1.2]	[0.59]	[1.63]	[3.44]	[5.42]
$\Delta k_{t,t+d}^{\text{strategy}}$		8.04		-38.57		-18.3		27.97		40.53
		[0.82]		[-2.82]		[-1.6]		[1.89]		[4.16]

This table reports coefficients and t-statistics for the regression $r_{t,t+d}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t,t+d}^{\text{strategy}}$ where $r_{t,t+d}^{\text{strategy}}$ is the cumulative strategy return between days t and $t+d$, k_t^{strategy} is the strategy-level crowding measure calculated as described above (section 6.3) and strategy include Value, Momentum, Return on Asset, Low Volatility and the Composite strategies. T-statistics are shown in brackets and calculated using Newey-West standard errors, allowing for serial autocorrelations up to $d+2$ daily lags. We show results for both our North America (Panel A) and Developed Europe (Panel B) samples.

3.6.4 Link Between Crowding and Liquidity Shocks Using Factor Deciles

Here, we conduct a robustness test for the results shown in **Section 3.4.1**. Instead of the construction described in **Section 3.6.2** (which we believe is more appropriate for this paper, as closer to how arbitrageurs construct their portfolios), we build trading strategy weights using the more traditional decile construction. We find that the hypothesis is generally supported: there is a link between crowding and exposure to liquidity crises (although results in North America appear even more insignificant than in **Section 3.4.1**).

To elaborate, the daily crowding measure k_t^{strategy} is computed following a similar fashion as in [HS](#), i.e.

$$SI_{it} = k_t^{\text{strategy}}(I_{\text{Decile } 1, it}^{\text{strategy}}) + \sum_{j \in [2, 10] \setminus \{5\}} k_{j, t}^{\text{strategy}}(I_{\text{Decile } j, it}^{\text{strategy}}) + \text{controls} + \epsilon_{it}$$

where $I_{\text{Decile } j, it}^{\text{strategy}}$ is a dummy variable and takes on the value of 1 when a strategy score of stock i is in the j^{th} decile at time t .

Factor returns are computed daily, as the spread between market capitalization weighted average return of stocks in the top decile versus those in the bottom.

The resulting crowding measures and factor returns are utilized in the regression model of [Section 4.2](#):

$$r_{t, t+5}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t, t+5}^{\text{strategy}}$$

To handle the generated regressor bias, we again bootstrapped 100 samples

when calculating the crowding measures k_t^{strategy} , with each sample randomly drawing 50% of data points. The resulting mean and standard deviation of bootstrapped samples of β are then used to compute t-statistics. To deal with outliers, we follow the same methodology as in **Section 3.4.1** and run a standard ordinary least square regression with outliers removed and a “robust” regression with Huber loss.

Table 3.5 shows the results for each region, as well as for both regions pooled together and for the two types of regressions. Results are significant for all 6 specifications for the combined pool. When splitting the sample by regional pools, we see similar patterns as in **Section 3.4.1**: results are significant for Europe but not for North America.

Table 3.5

Crowding and Strategy Drawdowns from Regressions Using Decile Dummies

Panel A: Standard OLS									
	Top 20 Drawdowns			Top 30 Drawdowns			Top 40 Drawdowns		
	EU	AM	Combined	EU	AM	Combined	EU	AM	Combined
Intercept	0.00	-0.02	-0.00	0.00	-0.02	-0.01	-0.00	-0.01	-0.01
	[2.60]	[-5.68]	[-2.25]	[2.36]	[-8.04]	[-4.55]	[-0.43]	[-7.61]	[-6.01]
Capital	-2.07	-0.13	-1.18	-1.66	0.18	-0.71	-1.04	-0.03	-0.49
	[-6.05]	[-0.36]	[-5.30]	[-6.87]	[0.69]	[-3.98]	[-4.83]	[0.17]	[-3.64]

Panel B: Robust Regression with Huber Loss									
	Top 20 Drawdowns			Top 30 Drawdowns			Top 40 Drawdowns		
	EU	AM	Combined	EU	AM	Combined	EU	AM	Combined
Intercept	0.01	-0.04	-0.01	0.00	-0.03	-0.01	-0.00	-0.02	-0.01
	[2.39]	[-6.04]	[-3.03]	[1.29]	[-6.86]	[-4.60]	[-0.12]	[-6.83]	[-5.66]
Capital	-2.54	-0.09	-1.52	-1.66	-0.19	-1.05	-1.10	-0.31	-0.81
	[-4.80]	[-0.18]	[-4.41]	[-4.64]	[-0.49]	[-3.89]	[-4.03]	[-1.10]	[-4.32]

Panel A of Table 2 reports coefficients and t-statistics for the standard ordinary least square regression $r_{t,t+5}^{\text{strategy}} = \alpha + \beta k_t^{\text{strategy}} + \epsilon_{t,t+5}^{\text{strategy}}$ where $r_{t,t+5}^{\text{strategy}}$ is the cumulative return of strategies (Value, Momentum, Return on Asset, Low Volatility and Composite) between days t and t+5, during the bottom 20, 30 and 40 non-overlapping 5-day returns of the short interest strategy. k_t^{strategy} is the strategy-level crowding measure calculated as described in this section. Developed Europe (EU), North America (AM) and pooled results are reported. Top and bottom 1% of both strategy returns and crowding level are removed before regression. Panel B of Table 2 displays the results for Robust Regression with Huber Loss function. Coefficients and t-statistics are calculated from bootstrapped mean and standard deviations of 100 sampled regressions.

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Chapter 4

Market Impact Decay and Capacity

Abstract: Recent studies have documented that market impact decays slowly through time. We study the impact of such slow decay on trading strategies' capacity. To do so, we propose a numerical methodology to estimate capacity. A key benefit of such a procedure is its flexibility in incorporating any specification of market impact. In particular, as trades tend to be more auto-correlated when capital devoted to a trading strategy increases, capacity is sensitive to assumptions on market impact decay. The slow decay of market impact leads to trading strategy capacity estimates that are significantly lower than shown in previous capacity studies.

4.1 Introduction

In the past few decades, academic research has documented a large set of equity “anomalies”, variables that have been shown to predict the cross-section of stock returns in a statistically significant manner. The interpretation of many of these results is a failure of the efficient market hypothesis: if current data can predict future prices, then prices are not efficiently integrating all available information. One possible critique that can be made to this literature is that most of the research is done without taking into account trading costs associated with arbitraging these anomalies away, despite the fact that friction costs have long been an important topic in the finance research literature (starting from [Constantidines and Magill \(1976\)](#)). As highlighted by [Novy-Marx and Velikov \(2016\)](#), “*these so called anomalies do not test market efficiency if they cannot attract arbitrage capital because they are not actually profitable to trade*”. In a similar vein, [Bonelli et al. \(2019\)](#) argue that “*in order to assess the economic significance of an asset-pricing anomaly, it is crucial to determine the amount that can be effectively invested in it, i.e. its capacity*”.

Incorporating trading costs and estimating trading strategies’ capacity are also critical tasks for quantitative asset managers - who have been trying, with more or less success, to exploit some of these cross-sectional equity anomalies in order to deliver superior investment performance. Failing to properly take into account trading frictions such as fixed costs, market impact, partial execution of orders, shorting costs etc. can lead to greater “implementation shortfall” ([Perold \(1988\)](#)), possibly to a point where a trading strategy can become a loss making proposition. And asset managers who over-estimate the amount of capital their trading strategy

is able to withstand (i.e. their capacity) will tend to grow their assets under management to levels where such strategy is no longer profitable.

Capacity is a topic closely related to trading costs: in order to assess the capacity of a trading strategy, one needs to have a good estimate of trading costs. For large enough order sizes, the main component of trading costs in single stocks is market impact - a financial asset's price movement caused by trades in that asset. A few recent papers (see e.g. [Bucci et al. \(2019\)](#)) have shown that market impact decays slowly (over multiple days) and incompletely reverts once a large order is completed. This has significant implications for estimating capacity. Indeed, the larger the capital allocated to a particular strategy, the more trades need to be split over multiple days, thereby causing auto-correlation in trading. Ignoring the slow decay of market impact will then lead to under-estimated trading costs and over-estimated capacity.

Here is an illustration. Let us assume that a particular anomaly suggests to buy stock A. Let us further assume that for large enough amounts of capital, the liquidity of stock A does not allow the suggested trade to be completed in one day at a reasonable cost. Instead, the order needs to be split equally over two days, with an estimated market impact for each day of 10bps. A "naive" transaction cost model - one that would assume that market impact reverts fully after an order is executed - would compute total market impact costs of 10bps on the total amount of stock A bought over the two days ($50\%*10\text{bps} + 50\%*10\text{bps}$). This estimate is overly optimistic: in fact, the second day cost will be more than 10bps, because the first day buy orders will have impacted stock A's price and this impact will have only slightly reverted. For the sake of this illustration, let us assume that by the time the second day trade is initiated, the price pressure from the previous day

trade has reverted by 2bps. The actual market impact cost of buying stock A the second day is therefore $10 - 2 + 10 = 18$ bps. The total market impact cost to do the whole trade is therefore 14bps ($50\% * 10$ bps + $50\% * 18$ bps), which is significantly higher than 10bps.

Ignoring the “memory” of prices to past trades - equivalently ignoring the slow decay of market impact - therefore leads to under-estimating trading costs. But it will also lead to wrong decisions about scheduling trades. For an investment signal that is persistent enough (i.e. for which the opportunity cost in trading tomorrow versus today is not too large), a quantitative investor that ignores memory will erroneously give too much benefit to splitting the execution over a few days. Indeed, market impact is an increasing function of trade size as a fraction of daily volume. By splitting his execution over a few days, he has reduced the average ratio of trade size on daily volume. But once memory is taken into account, his cost has actually not decreased by nearly as much.

This work is, to the best of our knowledge, the first paper on trading strategies’ capacity that takes into account the slow decay of market impact. We propose a numerical methodology to estimate the capacity of trading strategies. A key benefit of such procedure is its flexibility in incorporating any specification of market impact, including its slow decay over subsequent days. Following the intuition illustrated above, the slow decay of market impact leads to trading strategy capacity estimates that are significantly lower than shown in previous capacity studies (by between 3.5x and 10x for the anomalies considered).

This paper is related to the literature on transaction costs. Pioneering articles from [Constantidines and Magill \(1976\)](#), [Constantidines \(1986\)](#) and [Dumas and Luciano \(1991\)](#) look at transaction costs in the context of their impact on portfolio

choice. These works essentially show that it is optimal to avoid trading unless portfolio weights leave a “region of no transactions” around the frictionless target. They also demonstrate that transaction costs only have a second-order effect on welfare as investors accommodate them by reducing the frequency and volume of trade. Many papers on portfolio choice in the presence of costs followed. For example, [Garleanu and Pedersen \(2013\)](#) derive a closed-form optimal dynamic portfolio policy in the presence of quadratic trading costs. We make use of their closed-form solution in this paper.

Several papers study transaction costs and capacity associated with trading equity anomalies. Some of them tend to put in question the economic significance of anomalies, by showing that once transaction costs are taken into account, their profitability disappears or is substantially reduced. [Korajczyk and Sadka \(2004\)](#) find that momentum can only be exploited in relatively modest scale. [Novy-Marx and Velikov \(2016\)](#) study the performance of various equity anomalies net of trading costs. They show the extent to which increased capital reduces strategy profitability is inversely related to strategy turnover. [Chen and Velikov \(2019\)](#) study the post-publication net of transaction costs profitability of 120 equity anomalies and show that it is quite low.

In contrast, other papers offer a more optimistic view on capacity. [Frazzini et al. \(2015\)](#) argue that trading costs are smaller than previously estimated and “therefore the potential scale of these strategies is more than an order of magnitude larger than previous studies suggest”. [Bonelli et al. \(2019\)](#) derive closed-form formulas in order to estimate the capacity of trading strategies. They apply their framework to well-known equity strategies and find that capacity has increased in recent decades due to improved liquidity. One caveat to their analysis

(which they do mention) is that they assume market impact reverts instantaneously, likely making their capacity estimates too optimistic. [DeMiguel et al. \(2020\)](#) and [DeMiguel et al. \(2021\)](#) study in details the benefits on trading costs and capacity of “trading diversification”, the fact that combining signals reduces transaction costs because trades in the underlying stocks required to re-balance different signals often cancels out¹: the first one shows that such diversification increases the number of significant signals while the second one argues that it alleviates crowding concerns and increases capacity by close to 50%.

[O’Neill and Warren \(2019\)](#) provide a survey on methods involved in evaluating capacity, directed at investment industry practitioners. They list all the determinants of trading strategies’ capacity at the investment manager level, some increasing with size (economies of scale and scope) and others decreasing with size, the main one being dis-economies in trading and portfolio construction, which is the focus of this paper. They also provide an overview of transaction cost modeling, which they consider critical to predicting capacity.

None of the above mentioned papers integrate the slow decay of market impact, which we show in this paper to be an important determinant of capacity.

Our work also builds on the results from the strand of literature that analyzes and estimates market impact. It is now well documented that the market impact of large trading orders that are split into small pieces and executed incrementally during the trading day (called *metaorders* in many papers) is proportional to the square root of the trade size, expressed as a fraction of liquidity of the asset traded. [Almgren et al. \(2005\)](#), [Gomes and Waelbroeck \(2015\)](#), [Frazzini et al.](#)

¹This point was already made previously in a few papers such as [Frazzini et al. \(2015\)](#) and [Barroso and Santa-Clara \(2015\)](#)

(2018), Said et al. (2019) to name a few, all reach this conclusion by analyzing various equity execution data-sets. Donier and Bonart (2015) find similar results for Bitcoin/USD, through an empirical analysis of more than one million metaorders in that relatively new asset, implying that this square-root relationship holds beyond single stocks. Another segment of the market impact literature studies the persistence of the price movement after a meta-order is executed, commonly called either “permanent market impact” or “slow decay of market impact”. Farmer et al. (2013) formulate a model of an execution service and derive a fair pricing condition, which leads to market impact following a square root specification, and average permanent impact relaxing to two thirds of peak impact. Two empirical studies confirm Farmer et al. (2013) fair pricing condition and its implications for permanent market impact: Bershova and Rakhlin (2013) via an empirical study of a set of large institutional orders executed in the US equity market and, more recently, Said et al. (2019) through an analysis of a proprietary database of limit metaorders. Finally, Brokmann et al. (2015), using a proprietary data-set and Bucci et al. (2018) using the ANcerno execution data-set, show that relaxation takes place as soon as the metaorder ends: by the end of the trading day it is on average two thirds of the peak impact. They show that the decay continues the next days, but slowly.

We proceed as follows. **Section 4.2** presents our methodology for deriving capacity estimates for trading strategies. First, we explain how we construct portfolios that are close to how real-life arbitrageurs implement equity long/short trading strategies. Then, we describe how we compute market impact, and in particular how we take into account its slow decay. This enables us to calculate strategy returns net of market impact costs for various levels of capital, which is the

measure we use to estimate capacity. In **Section 4.3**, we use this methodology to compute capacity on three well known equity anomalies. Results show that capacity estimates are orders of magnitude lower when taking into account the slow decay of market impact and the memory of past trades. **Section 4.4** concludes.

4.2 Methodology

In this section, we describe our proposed methodology to estimate the capacity of equity long/short trading strategies. We start by explaining how we determine, every day, each stock's weight in the portfolio. Given the focus of our study, we want to use a portfolio construction that resembles the way real-life quantitative investors build their positions (rather than the more academic decile approach²). We then give a description of how capacity will be estimated. First, by estimating trading costs and subtracting them from the gross returns of the strategies in order to obtain net Sharpe ratio. Second, by choosing, for a given amount of capital allocated to the strategy, the trading speed parameter τ that will yield the optimal net Sharpe ratio. The capacity estimate will then become the level of capital for which the net Sharpe ratio is above a certain threshold (in our case, a value relative to the net Sharpe ratio of the strategy for small amounts of capital).

4.2.1 Building Tradeable Portfolios

We first compute trading strategies daily returns gross of trading costs, by constructing long-short equity portfolios following a more sophisticated portfolio construction than the traditional quantile sorting methodology. This construction is closer to how real-life arbitrageurs construct their portfolio: it is therefore more relevant for the task at hand, which is to estimate how much capital arbitrageurs can devote, in practice, to profitably exploit anomalies. It is described in the following paragraphs.

²Note that in recent the years, a number of papers in finance have moved away from the decile approach. A widely cited such paper is [Asness et al. \(2013\)](#).

Portfolio Optimization

Every day t , each stock i in the trading universe considered by a particular trading strategy, is ranked in the cross-section according to a particular trading signal (for example, minus its past one-month return). These ranks are then transformed into a strategy score s_{it} uniformly distributed on $[-1, 1]$. For example, the stock with the lowest signal measure at date t will be assigned a score s_{it} of -1, and the one with the highest Momentum measure a score of 1.

Each day t , for each stock i in the sample, optimal friction-less weights w_{it}^* are computed by performing the following optimization:

$$\begin{aligned} & \text{Max} \sum_i w_{it} s_{it} & (4.1) \\ \text{s.t.}: & \sigma_{P,t} = 0.1, \text{ and } \sum_i w_{it} \beta_{it} = 0 \end{aligned}$$

$\sigma_{P,t}$ is the volatility of the portfolio constructed and β_{it} is the beta of stock i against an equal weighted long basket of the stocks considered by the trading strategy.

Essentially, we solve for the weights w_{it}^* that maximize $\sum_i w_{it} s_{it}^{\text{strategy}}$. This latter term can be interpreted as the expected returns of the portfolio, subject to volatility and beta neutrality constraints. If the anomaly is indeed predictive of stock returns, high scores should be followed on average by high excess returns and vice versa: the portfolio should therefore aim to have larger long positions on higher scores stocks and larger short positions on lower scores stocks. We constrain the ex-ante volatility of the portfolio to be 10%³ and the beta of the portfolio

³Note that the choice of this number is of no importance as it is just a scaling factor. It also means that the capacity estimates we will obtain are for portfolio that have an ex-ante volatility of 10%.

(against an equal weighted long basket of the universe of stocks considered by the strategy) to be 0.

$\sigma_{P,t}$ and β_{it} are computed from a variance-covariance matrix that is estimated over a medium term horizon.

[Daniel et al \(2020\)](#) tackle a similar problem (instead of maximizing returns for a given volatility, they minimize volatility for a given return) and show that this maximisation program has a simple close form solution.

Trading Smoothing Parameter τ

Next, we smooth turnover in order to consider real-life concerns about trading costs. We follow [Garleanu and Pedersen \(2013\)](#), who show that an optimal dynamic portfolio policy when trading is costly is to trade partially towards the current aim. Their results are obtained from inter-temporal optimization: investors optimally smooth trading in order to reduce transaction costs.

Our final weights w_{it}^f become:

$$w_{it}^f = (1 - \tau)w_{it-1}^f + \tau w_{it}^* \tag{4.2}$$

Multiplying these weights by daily stock returns yields the strategy daily returns, gross of any trading costs.

The parameter τ can be interpreted as trading speed. At the extreme, a τ of 1 corresponds to an immediate implementation of the signal. It will generally lead to higher gross returns, as the latest predictive information is fully expressed in the weights of the portfolio. But it also generates higher costs as trading is not smoothed. A τ between 0 and 1 corresponds to only partially trading to the

friction-less optimal weights w^* : the implementation of the strategy is therefore partially lagged. This will reduce the returns gross of trading costs of the strategy, but also reduce portfolio turnover and trading costs associated.

The parameter τ will be critical in the next sections, as it will be used to obtain the optimal trading speed as a function of the capital allocated to a particular trading strategy. Generally speaking, the higher the capital, the lower the optimal τ (which corresponds to a higher degree of smoothing) as this will lead to lower turnover and therefore to less transaction costs (but also to a slower implementation, with corresponding opportunity costs). It is also important to note that a lower τ will help reducing turnover in part by smoothing trades through time, and therefore increasing the auto-correlation of trades.

The trade-off in setting the right level for this parameter is between higher gross returns and lower trading costs. It is therefore key to define how to estimate trading costs. This is what we explain next.

4.2.2 Trading Costs

There are many costs involved in implementing a long/short equity strategy, such as leverage costs (funding spreads paid on long positions and shorting fees paid on short positions), dividend with-holding taxes (that negatively impact long positions) and trading costs (commissions paid to brokers and market impact).

Among all these costs, market impact is the only one that increases more than proportionally to the capital allocated to a trading strategy. It is therefore the driver in limiting capacity to finite amounts. All the other costs are proportional to the capital allocated⁴ and shift down net returns by the same %.

⁴Note that shorting fees will depend on the liquidity of the stocks studied. Indeed, mid-caps

solely on market impact in this paper.

Market Impact

The empirical estimation of market impact is an important subject for both academics and practitioner. The main empirical papers on that topic and the corresponding data-sets are the following: [Almgren et al. \(2005\)](#) (Citigroup US equity trading data between December 2011 to June 2013), [Moro et al. \(2009\)](#) (UK and Spanish equity execution data from January 2001 to December 2004), [Bershova and Rakhin \(2013\)](#) (Alliance Bernstein US equity execution data from January 2009 to June 2011), [Gomes and Waelbroeck \(2015\)](#) (equity metaorders from an order management system between July 2009 and March 2012), [Frazzini et al. \(2018\)](#) (live execution data from a large money manager from August 1998 to June 2016), [Said et al. \(2019\)](#) (execution on the European equity market between January 2016 and December 2017) and [Bucci et al. \(2019\)](#) (ANcerno database, January 2007 to June 2010).

All these works come broadly to the same conclusion: market impact, typically measured as the difference, expressed in basis points, between the average execution price of a metaorder and the price prevailing before the start of the order, follows a power function of trade size divided by daily volume (thereafter $Trade\%DV$). Many of the above papers estimate the power to be $1/2$ and call this relationship the *Square Root Law*.

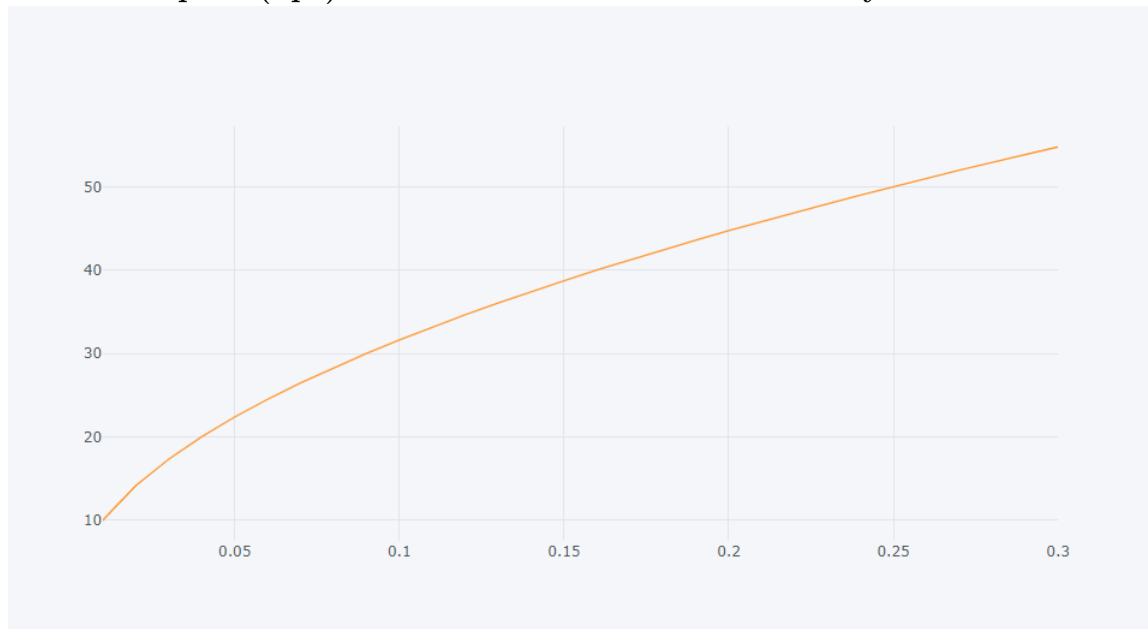
$$MI = \alpha * (Trade\%DV * 100)^{0.5} \tag{4.3}$$

are more likely to be “hard to borrow” and therefore more expensive to short than large-caps. [Bonelli et al. \(2019\)](#) check that for sufficiently large amounts traded, this effect is second order compared to price-impact concerns.

We choose $\alpha = 10$, which is consistent with recent empirical estimates of market impact such as [Frazzini et al. \(2018\)](#). **Figure 4.1** plots market impact in basis points as a function of $Trade\%DV$. A metaorder representing 10% of the daily volume will lead to a market impact of 31.6 basis points. In contrast, a smaller metaorder representing 0.5% of daily volume will lead to a market impact of 7.1 basis points.

Figure 4.1

Market Impact (bps) vs Trade Size as Fraction of Daily Volume



This figure plots market impact, expressed in basis points, as a function of trade size, expressed as a fraction of daily volume.

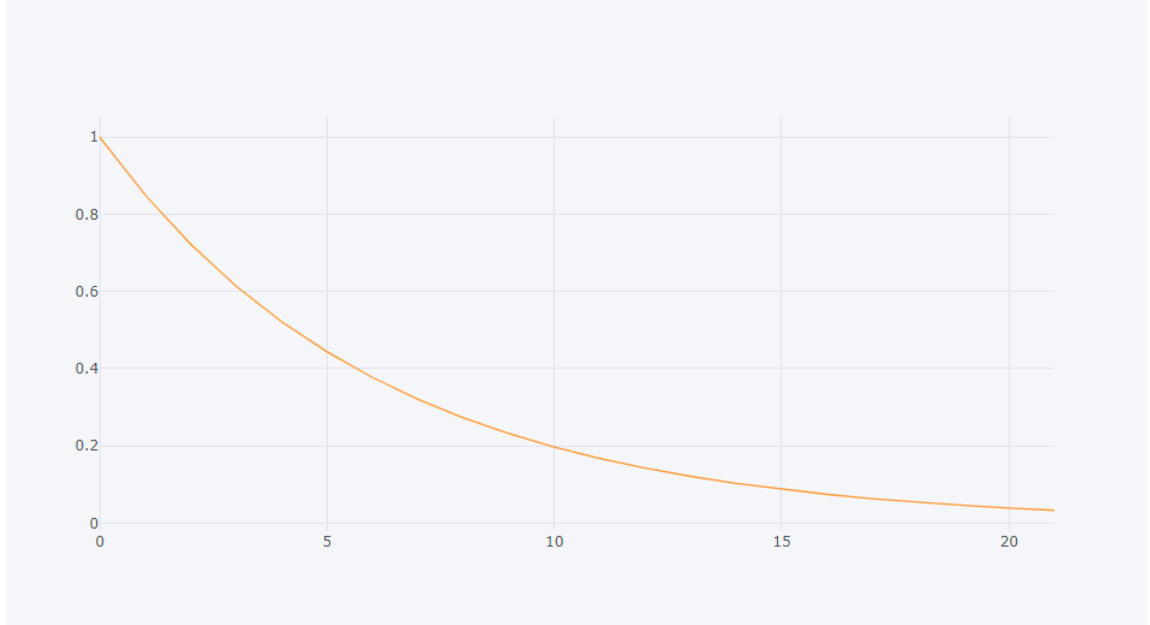
Slow Decay of Market Impact

More importantly, a sub-set of the above mentioned papers, focus on what happens to this price pressure in the days and weeks following a metaorder. All these papers show that market impact reverts slowly and asymptotically converges to a fraction of the first day impact (the “permanent” impact). In the remainder of this paper, we show that this slow decay of market impact leads to significantly lower capacity estimates for trading strategies. We broadly follow [Brokmann et al. \(2014\)](#)’s empirical results to calibrate our market impact decay $MIDecay_t$, the proportion of market impact that has not yet reverted t days after a metaorder:

$$MIDecay_t = Permanent + (1 - Permanent) * \gamma^t \quad (4.4)$$

Essentially, $MIDecay_t$ converges to *Permanent*. γ is a parameter that controls for how slowly that convergence occurs. **Figure 4.2** plots $MIDecay_t$ as a function of the t , the number of days since the trade has occurred, for *Permanent* equal to 0 and γ equal to 0.85. These parameters closely fit empirical data shown in [Brokmann et al. \(2014\)](#), and will therefore be used in the remainder of this paper⁵. Furthermore, on any given day and in order to ease numerical computation, we will only consider trades that have occurred in the past month (last 21 business days). As can be seen on **Figure 4.2**, most of the market impact is gone by that time.

⁵A lot of papers argue that there is a permanent impact of around 0.3-0.5, especially when trades are “informed” and are therefore helping push prices back to their fundamental values. We choose a permanent impact of 0 for computational simplicity (else market impact would depend on all previous trades, even those that occurred multiple years ago). In non-tabulated results, we have tested using non-zero permanent impact and going back multiple months. The key results are the same: capacity estimates are orders of magnitude lower when taking into account the slow decay of market impact.

Figure 4.2
Market Impact Decay vs Days Since Trade


This figure plots market impact decay $MIDecay_t$, the proportion of market impact that has not yet reverted t days after a metaorder, as a function of t .

Computing Market Impact Costs and Portfolio Net Returns

Equipped with both market impact and decay functions, we can now compute market impact costs and subtract them from portfolio gross returns to obtain net returns, which will be key for determining capacity estimates of trading strategies.

For a particular strategy, total market impact costs for date t will be the sum of the individual market impact across all stock i :

$$MICost_t = \sum_i \Delta w_{i,t}^f * C * \sum_{j=t-x}^t sign_{i,j} * MIDecay_{t-j} * MI_{i,j} \quad (4.5)$$

$\Delta w_{i,t}^f$ is the change in weights for stock i between $t - 1$ and t : it corresponds to a buy (sell) order if positive (negative). When multiplied by the USD capital C allocated to the strategy, it becomes the trade in USD. $sign_{i,t}$ is a dummy variable

equal to 1 if $\Delta w_{i,t}$ is positive (buy order) and -1 if it is negative. $MI_{i,t}$ is the same day market impact, expressed in basis points, generated by the trade $\Delta w_{i,t}^f * C$, and follows the square root law described above. $MIDecay_t$ is the decay of market impact. Finally x is the number of past days that we consider when computing the total market impact.

Because market impact does not fully revert on the trade day, we need to take into account the memory of past trades to determine market impact costs. For example, if we buy the same stock two days in a row with same day market impacts of 10bps on the first day and 12bps on the second day, the second day cost will be $12\text{bps} + 10\text{bps} * MIDecay_1$, leading to increased costs. Conversely, if we buy a stock on the first day and sell it the second day, with respective same day market impacts 5bps and 7bps, the second day cost will be $7\text{bps} - 5\text{bps} * MIDecay_1$, leading to reduced costs: indeed, the buy impact of the first trade is still there on the next day, at which time the stock can therefore be sold at a higher price.

Net USD returns at time t for a capital C allocated to a strategy are gross returns minus market impact costs:

$$NetReturn_t = C * \sum_i w_{i,t}^f * r_{i,t} - MICost_t \quad (4.6)$$

4.2.3 Deriving Capacity Estimates

To derive capacity estimates for a given trading strategy, we go through the following steps.

First, we compute target weights for a range of parameter τ through the portfolio optimization described in **Section 4.2.1**.

Next for a range of capital values C and the range of parameter τ we compute market impact costs, net returns and the corresponding net Sharpe ratio.

Then, for each capital value, we select the τ for which the net Sharpe ratio is the highest, thereby assuming that investors adapt the speed of their trading to the in-sample optimal value. This is an optimistic assumption (that will lead to higher capacity estimates), first because of this in-sample choice of optimal τ , but also because it entails that investors coordinate their choice of trading speed, which is likely not the case (see, e.g. [Stein \(2009\)](#)).

Finally, the capacity estimate is the capital for which the net Sharpe ratio is below a certain threshold. For this paper, and without loss of generality, we will set the threshold at half of the net Sharpe ratio for a small amount of capital (USD 10 million).

4.3 Empirical Study

In this section, we apply the methodology described in **Section 4.2** to three well-known equity anomalies. For each of them, we compute capacity estimates and compare them to “naive” capacity estimates that only consider same day market impact. We show that capacity estimates are significantly lower when the slow decay of market impact is taken into account. To understand the impact of liquidity, we run this analysis on two different pools of stocks in North America: large caps and mid caps.

4.3.1 Data

We combine equity data from Datascope, stock-level fundamental data from Worldscope and short interest data from Markit. Our sample covers a more than 20-year period from January 2000 to March 2021⁶.

We focus on stocks listed in North America (Canada and United States), that are likely to be included in quantitative equity market neutral portfolios. These portfolios typically use leverage and exploit equity anomalies that require frequent re-balancing and, given fixed costs associated (including data, ability to short via prime brokers or derivatives, fund set-up costs...), need to have reasonable assets under management.

We thus restrict our attention to stocks that have a certain size and liquidity. From Datascope, we select stocks based on market capitalization and daily trading volume thresholds. The stock selection is performed monthly, on the first day of the month. In order to avoid any survivorship bias, the set of firms amongst which

⁶Short interest data starts later, in June 2004.

stocks are selected includes securities that were subsequently de-listed. This results in a universe of stocks that includes on average 1,200 stocks at any point in time. We further split the sample into large caps (the most liquid 600 stocks at a given time) and mid caps (the remaining stocks).

4.3.2 Definition of Equity Anomalies Studied

We focus on three equity long-short strategies: 1-month reversal, short interest and quality (also known as profitability). We selected these three equity anomalies for two reasons. First, because they have different trading horizons: 1-month reversal exhibits the highest turnover, quality the lowest and short interest lies in between. Considering anomalies with various levels of persistence will be of interest for our empirical analysis of capacity. The second reason for selecting these three anomalies is that they are well documented in the literature. The evidence that short horizon stock returns exhibit serial correlation (i.e. a reversal effect) has been documented as early as in the 1960s ([Fama \(1965\)](#)) and subsequently widely studied (see, e.g., [Jegadeesh \(1990\)](#)). The negative relationship between short interest and subsequent stock returns has been the subject of many papers (see, e.g., [Asquith et al. \(2005\)](#)). Finally, the quality anomaly is also widely discussed in many papers such as [Novy-Marx \(2013\)](#) and, more recently, [Bouchaud et al. \(2019\)](#).

The definition for each of these are the following. 1-month reversal is minus the cumulative returns for the past month (taken from Datascope). Short interest is minus the short interest ratio (taken from IHS Markit Equity Finance). Finally, quality is defined as net operating cashflow divided by total assets (both taken from Worldscope).

Figure 4.3 plots the cumulative returns, gross of trading costs, for each of the three strategies, for both North American large and mid caps, and with no turnover control ($\tau = 1$). All exhibit positive gross returns over the sample studied. **Table 4.1** presents their gross Sharpe ratios as well as average annualized turnover (defined as average absolute sum of trades divided by the average absolute sum of weights). As expected, 1-month reversal is the fastest signal with a turnover of around 80, followed by short interest at around 20 and quality at around 13.

Figure 4.3

Cumulative Gross Returns: 1-Month Reversal, Short Interest, Quality



This figure plots cumulative gross returns for the strategies studied in this paper (1-month reversal, short interest and quality) for both the large cap and the mid cap samples. No turnover control is applied ($\tau = 1$).

Table 4.1

Statistics: 1-Month Reversal, Short Interest, Quality

		Reversal (Large)	Reversal (Mid)	Short Interest (Large)	Short Interest (Mid)	Quality (Large)	Quality (Mid)
Gross	Sharpe	1.74	1.28	0.87	0.89	0.74	1.02
Ratio							
Turnover		79.7	79.1	24	20.2	12.9	12.8

This table shows gross Sharpe ratio (defined as annualized gross returns divided by annualized volatility) and turnover (defined as average absolute sum of trades divided by the average absolute sum of weights) for the strategies studied in this paper (1-month reversal, short interest and quality), for both the large cap and the mid cap samples. No turnover control is applied ($\tau = 1$).

4.3.3 Results

We follow the methodology described in **Section 4.2**. For each anomaly and pool of stock, we construct portfolios based on various trading speed and compute their gross Sharpe ratio. For each anomaly, pool of stock and trading speed, we compute costs based on various amount of USD capital and use these to calculate net Sharpe ratios. We do so for both our specification of market impact (e.g. with slow decay and therefore impact from previous days trades) and the “naive” specification (only taking into account same-day market impact).

Table 4.2 shows the results for 1-month reversal, with Panel A showing net Sharpe ratios for our proposed market impact specification and Panel B showing net Sharpe ratios for the “naive” specification. The small capital (10 million USD) optimal speed is the same for both panels: full speed. This is expected as market impact costs for small capitals are close to negligible: reducing trading speed (i.e. reducing τ) leads to lower Sharpe ratios - as discussed, it is equivalent to lagging the signal and generally leads to lower gross performance. As capital increases, the optimal trading speed decreases: lowering trading speed will reduce turnover and corresponding market impact costs. As expected, the net Sharpe decreases a lot quicker with capital when the decay of market impact and past trades are taken into account. This is because lowering trading speed has less benefit than in the “naive” specification: it will lead to splitting trades over a few days (thereby increasing the positive auto-correlation of trades), the benefit of which is not that high given prices revert only slowly. The USD capitals for which the net Sharpe is halved versus a 10 million USD capital is 400 million USD for our specification. This is significantly lower (around ten times) than the estimate for the “naive”

specification (4 billion USD).

Table 4.3 shows the same for a lower turnover strategy: short interest. Capacity estimates are 2 billion USD for Panel A versus 14 billion USD for Panel B, which again is significant (seven times lower).

Even for very low turnover strategies such as quality (**Table 4.4**), capacity estimates are five times lower for Panel A when compared to Panel B (10 billion USD versus 50 billion USD).

Table 4.2: 1-month Reversal, North American Large Caps
 Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.77	0.97	1.09	1.16	1.23	1.30	1.37	1.42	1.48	1.52	1.55	1.58
200	0.70	0.83	0.85	0.84	0.87	0.91	0.96	0.99	1.02	1.03	1.03	1.02
400	0.66	0.75	0.73	0.67	0.68	0.71	0.74	0.76	0.77	0.77	0.75	0.72
600	0.63	0.70	0.63	0.53	0.53	0.55	0.57	0.58	0.59	0.57	0.54	0.49
800	0.60	0.65	0.55	0.42	0.41	0.42	0.43	0.43	0.43	0.40	0.36	0.29
1,000	0.58	0.60	0.48	0.33	0.30	0.30	0.31	0.30	0.29	0.25	0.20	0.12
1,200	0.56	0.57	0.41	0.24	0.20	0.19	0.19	0.18	0.16	0.12	0.06	-0.04
1,400	0.54	0.53	0.35	0.16	0.11	0.10	0.09	0.08	0.05	-0.00	-0.08	-0.18
1,600	0.52	0.50	0.30	0.08	0.02	0.00	-0.01	-0.03	-0.06	-0.12	-0.20	-0.31
1,800	0.51	0.46	0.25	0.01	-0.06	-0.08	-0.10	-0.12	-0.16	-0.23	-0.32	-0.44
2,000	0.49	0.44	0.20	-0.05	-0.13	-0.16	-0.18	-0.21	-0.26	-0.33	-0.42	-0.55

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.79	1.00	1.13	1.21	1.28	1.35	1.40	1.45	1.49	1.52	1.55	1.56
400	0.76	0.94	1.02	1.02	1.01	1.00	0.98	0.94	0.89	0.81	0.71	0.59
800	0.74	0.91	0.96	0.92	0.88	0.83	0.77	0.69	0.59	0.46	0.30	0.11
1200	0.73	0.89	0.92	0.85	0.78	0.70	0.61	0.49	0.36	0.19	-0.01	-0.25
1600	0.72	0.87	0.89	0.79	0.69	0.59	0.47	0.33	0.16	-0.04	-0.28	-0.56
2000	0.71	0.85	0.85	0.73	0.62	0.49	0.35	0.19	-0.01	-0.24	-0.51	-0.84
2400	0.70	0.84	0.83	0.69	0.55	0.41	0.24	0.06	-0.16	-0.42	-0.72	-1.08
2800	0.69	0.82	0.80	0.64	0.49	0.33	0.14	-0.06	-0.31	-0.59	-0.92	-1.31
3200	0.69	0.81	0.78	0.60	0.43	0.25	0.05	-0.18	-0.44	-0.74	-1.10	-1.52
3600	0.68	0.80	0.75	0.56	0.37	0.18	-0.04	-0.28	-0.56	-0.89	-1.27	-1.72
4000	0.68	0.78	0.73	0.52	0.32	0.11	-0.12	-0.38	-0.68	-1.03	-1.43	-1.91

Net Sharpe ratios for the 1-month reversal long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American large capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

Table 4.3: Short Interest, North American Large Caps
 Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.49	0.57	0.64	0.71	0.74	0.76	0.77	0.79	0.80	0.80	0.81	0.82
1,000	0.42	0.46	0.49	0.49	0.49	0.49	0.48	0.48	0.47	0.45	0.44	0.41
2,000	0.39	0.42	0.42	0.40	0.38	0.37	0.35	0.34	0.32	0.29	0.26	0.22
3,000	0.37	0.38	0.36	0.32	0.29	0.27	0.25	0.23	0.20	0.17	0.13	0.08
4,000	0.35	0.35	0.32	0.26	0.22	0.19	0.16	0.14	0.10	0.07	0.02	-0.04
5,000	0.33	0.32	0.28	0.20	0.16	0.12	0.09	0.06	0.02	-0.03	-0.08	-0.15
6,000	0.31	0.29	0.24	0.15	0.10	0.06	0.02	-0.02	-0.06	-0.11	-0.17	-0.25
7,000	0.30	0.27	0.21	0.11	0.05	0.00	-0.04	-0.08	-0.13	-0.18	-0.25	-0.34
8,000	0.29	0.25	0.17	0.07	0.00	-0.06	-0.10	-0.15	-0.20	-0.25	-0.33	-0.42
9,000	0.27	0.23	0.14	0.03	-0.05	-0.11	-0.16	-0.21	-0.26	-0.32	-0.40	-0.50
10,000	0.26	0.21	0.12	-0.01	-0.09	-0.16	-0.21	-0.26	-0.32	-0.38	-0.46	-0.57

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.50	0.58	0.66	0.72	0.75	0.77	0.78	0.79	0.80	0.81	0.81	0.82
2,000	0.45	0.52	0.57	0.58	0.56	0.52	0.48	0.43	0.37	0.31	0.23	0.14
4,000	0.43	0.49	0.53	0.52	0.47	0.41	0.35	0.27	0.18	0.08	-0.03	-0.16
6,000	0.42	0.47	0.50	0.47	0.41	0.33	0.24	0.14	0.04	-0.09	-0.23	-0.39
8,000	0.40	0.46	0.48	0.43	0.35	0.26	0.15	0.04	-0.09	-0.23	-0.39	-0.59
10,000	0.39	0.44	0.46	0.40	0.30	0.20	0.08	-0.05	-0.19	-0.35	-0.54	-0.76
12,000	0.38	0.43	0.44	0.37	0.26	0.14	0.01	-0.13	-0.29	-0.47	-0.67	-0.91
14,000	0.37	0.42	0.42	0.34	0.22	0.09	-0.05	-0.21	-0.38	-0.57	-0.79	-1.05
16,000	0.37	0.40	0.40	0.31	0.18	0.04	-0.11	-0.28	-0.47	-0.67	-0.90	-1.18
18,000	0.36	0.39	0.39	0.28	0.15	-0.01	-0.17	-0.35	-0.54	-0.76	-1.01	-1.30
20,000	0.35	0.38	0.37	0.26	0.11	-0.05	-0.22	-0.41	-0.62	-0.85	-1.11	-1.42

Net Sharpe ratios for the short interest long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American large capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

Table 4.4: Quality, North American Large Caps
Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.47	0.52	0.58	0.63	0.65	0.67	0.68	0.69	0.70	0.71	0.72	0.73
2,000	0.42	0.45	0.49	0.51	0.53	0.54	0.55	0.55	0.55	0.56	0.55	0.55
4,000	0.40	0.42	0.45	0.46	0.47	0.48	0.48	0.49	0.49	0.49	0.48	0.47
6,000	0.38	0.40	0.42	0.42	0.43	0.43	0.44	0.44	0.44	0.43	0.42	0.41
8,000	0.37	0.38	0.39	0.39	0.39	0.40	0.40	0.40	0.39	0.39	0.38	0.36
10,000	0.36	0.36	0.37	0.36	0.36	0.36	0.36	0.36	0.36	0.35	0.33	0.31
12,000	0.35	0.35	0.34	0.34	0.33	0.33	0.33	0.33	0.32	0.31	0.30	0.27
14,000	0.34	0.33	0.33	0.31	0.31	0.30	0.30	0.30	0.29	0.28	0.26	0.24
16,000	0.33	0.32	0.31	0.29	0.28	0.28	0.28	0.27	0.26	0.25	0.23	0.20
18,000	0.32	0.31	0.29	0.27	0.26	0.25	0.25	0.24	0.23	0.22	0.20	0.17
20,000	0.31	0.30	0.27	0.25	0.24	0.23	0.23	0.22	0.21	0.19	0.17	0.14

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.47	0.53	0.58	0.63	0.65	0.67	0.68	0.70	0.71	0.71	0.72	0.72
5,000	0.43	0.47	0.51	0.54	0.54	0.54	0.53	0.51	0.49	0.47	0.45	0.41
10,000	0.41	0.45	0.48	0.50	0.49	0.48	0.46	0.43	0.40	0.37	0.33	0.27
15,000	0.39	0.43	0.46	0.47	0.45	0.43	0.40	0.37	0.33	0.29	0.24	0.17
20,000	0.38	0.41	0.44	0.44	0.42	0.39	0.36	0.32	0.27	0.22	0.16	0.08
25,000	0.37	0.40	0.43	0.42	0.39	0.36	0.32	0.27	0.22	0.16	0.09	0.00
30,000	0.36	0.39	0.41	0.40	0.37	0.33	0.28	0.23	0.18	0.11	0.03	-0.07
35,000	0.35	0.38	0.40	0.38	0.34	0.30	0.25	0.20	0.13	0.06	-0.03	-0.13
40,000	0.34	0.37	0.38	0.36	0.32	0.28	0.22	0.16	0.09	0.01	-0.08	-0.19
45,000	0.33	0.36	0.37	0.35	0.30	0.25	0.19	0.13	0.05	-0.03	-0.13	-0.25
50,000	0.32	0.35	0.36	0.33	0.28	0.23	0.17	0.10	0.02	-0.07	-0.18	-0.30

Net Sharpe ratios for the quality long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American large capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

Detailed results for mid cap stocks are shown in **Appendix** and show similar patterns.

Table 4.5 summarizes the results for the three anomalies in both large and mid cap samples (six portfolios). Capacity estimates when taking into account the slow decay of market impact and past trades are significantly lower for all six portfolios (between 3.5x and 10x lower). Capacities are generally much lower for the mid cap sample, which makes sense given the lower liquidity of these stocks. The only exception is short interest, where capacity for mid caps is significantly higher than for large caps. An investigation into the Sharpe ratio for 10 million USD of capital for various trading speed (first row of **Table 4.3** above and **Table 4.7** in the **Appendix**) can help explain this apparent inconsistency. The Sharpe ratio for mid caps decreases only slowly with a reduction in trading speed. This means that there is no urgency to trade: trades can be split over multiple days without any performance opportunity cost. This not the case for large caps, where the signal has to be traded a lot quicker.

Table 4.5

Capacity Estimates (million USD): 1-Month Reversal, Short Interest, Quality

	Reversal (Large)	Reversal (Mid)	Short Interest (Large)	Short Interest (Mid)	Quality (Large)	Quality (Mid)
With MI Slow De- cay	400	62.5	2,000	10,000	10,000	4,500
Without	4,000	250	14,000	35,000	50,000	16,000
Multiplier	10x	4x	7x	3.5x	5x	3.5x

This table shows capacity in million USD for the strategies studied in this paper (1-month reversal, short interest and quality). It shows these capacity estimates for both large and mid cap samples as well as for two market impact specifications: one taking into account the slow decay of market impact and past trades (“With MI Slow Decay”), the other ignoring these effects (“Without”). Multiplier is the ratio between the capacity estimates Without and With Mi Slow Decay.

4.4 Conclusion

The asset pricing literature has documented a large set of anomalies in the past decades. But one could argue that the economic significance of anomalies is important only if significant amount of arbitrage capital can profitably exploit them. In this paper, we have shown that taking into account the slow decay of market impact through time leads to capacity estimates that are significantly smaller than previously thought (between 3x and 10x for the anomalies considered), possibly meaning that markets are less inefficient than they might have appeared to be.

Higher turnover anomalies such as 1-month reversal have very little capacity (400 million USD for North American large caps, 62.5 million USD for mid caps): they are not implementable at large scale. Slower anomalies, if their Sharpe ratio gross of cost is high enough, can absorb relatively large amount of capital: quality, for example, can withstand 10 billion USD of assets invested in a North American large cap portfolio targeting an ex-ante volatility of 10%, before seeing its net Sharpe ratio halved. Nevertheless, this is not a lot versus the current size and liquidity of markets, and much lower than previously thought.

This paper can also serve as a guide for practitioners. The main result of this paper seems confirmed by recent anecdotal evidence: equity quantitative asset managers who gathered very large amounts of assets under management have struggled to perform: they might have over-estimated the capacity available to the trading strategies they deploy.

4.5 Appendix

In this section, we present similar tables as in **Section 4.3.3**, but for the mid caps sample. **Tables 4.6, 4.7 and 4.8** show net sharpe ratios for various trading speed and capitals (in million USD) for respectively 1-month reversal, short interest and quality.

Table 4.6: 1-month Reversal, North American Mid Caps
 Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.33	0.48	0.56	0.59	0.64	0.70	0.76	0.81	0.86	0.90	0.94	0.97
25	0.30	0.43	0.48	0.48	0.52	0.57	0.62	0.67	0.71	0.74	0.77	0.79
50	0.27	0.37	0.38	0.36	0.38	0.42	0.47	0.51	0.54	0.56	0.58	0.59
75	0.25	0.33	0.31	0.26	0.28	0.31	0.35	0.38	0.41	0.43	0.43	0.43
100	0.23	0.29	0.25	0.18	0.19	0.22	0.25	0.28	0.30	0.31	0.31	0.30
125	0.21	0.26	0.20	0.11	0.11	0.13	0.16	0.19	0.20	0.21	0.20	0.18
150	0.20	0.23	0.15	0.04	0.04	0.06	0.08	0.11	0.12	0.12	0.11	0.08
175	0.18	0.20	0.10	-0.01	-0.03	-0.01	0.01	0.03	0.04	0.03	0.02	-0.02
200	0.17	0.18	0.06	-0.07	-0.09	-0.07	-0.06	-0.04	-0.04	-0.04	-0.07	-0.11
225	0.16	0.16	0.02	-0.12	-0.15	-0.13	-0.12	-0.11	-0.11	-0.12	-0.15	-0.19
250	0.15	0.13	-0.01	-0.17	-0.20	-0.19	-0.18	-0.17	-0.17	-0.19	-0.22	-0.27

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.36	0.54	0.66	0.71	0.75	0.79	0.83	0.86	0.89	0.91	0.92	0.93
100	0.33	0.49	0.56	0.54	0.53	0.51	0.48	0.45	0.40	0.35	0.27	0.17
200	0.31	0.46	0.50	0.44	0.39	0.34	0.27	0.20	0.11	0.00	-0.13	-0.29
300	0.30	0.43	0.45	0.37	0.29	0.20	0.11	0.01	-0.12	-0.26	-0.43	-0.64
400	0.29	0.41	0.41	0.30	0.20	0.09	-0.02	-0.15	-0.31	-0.48	-0.69	-0.94
500	0.28	0.39	0.38	0.24	0.12	-0.01	-0.14	-0.30	-0.47	-0.68	-0.92	-1.21
600	0.27	0.37	0.35	0.19	0.05	-0.09	-0.25	-0.43	-0.63	-0.86	-1.13	-1.44
700	0.26	0.36	0.32	0.14	-0.01	-0.18	-0.35	-0.55	-0.77	-1.02	-1.32	-1.66
800	0.25	0.34	0.29	0.10	-0.07	-0.25	-0.44	-0.66	-0.90	-1.17	-1.49	-1.87
900	0.25	0.33	0.27	0.06	-0.13	-0.32	-0.53	-0.76	-1.02	-1.32	-1.66	-2.06
1,000	0.24	0.32	0.25	0.02	-0.18	-0.39	-0.61	-0.86	-1.13	-1.45	-1.81	-2.24

Net Sharpe ratios for the 1-month reversal long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American mid capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

Table 4.7: Short Interest, North American Mid Caps
 Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.80	0.81	0.81	0.81	0.80	0.81	0.81	0.82	0.82	0.83	0.83	0.82
1,000	0.68	0.64	0.58	0.50	0.45	0.42	0.39	0.37	0.35	0.32	0.28	0.23
2,000	0.63	0.56	0.47	0.36	0.28	0.24	0.20	0.16	0.13	0.08	0.03	-0.04
3,000	0.59	0.51	0.39	0.25	0.16	0.10	0.05	0.00	-0.04	-0.10	-0.16	-0.25
4,000	0.55	0.46	0.32	0.16	0.05	-0.02	-0.08	-0.13	-0.18	-0.25	-0.32	-0.43
5,000	0.52	0.41	0.26	0.07	-0.04	-0.12	-0.19	-0.25	-0.31	-0.38	-0.47	-0.58
6,000	0.50	0.37	0.21	0.00	-0.12	-0.21	-0.28	-0.35	-0.42	-0.50	-0.59	-0.72
7,000	0.47	0.34	0.15	-0.07	-0.20	-0.30	-0.37	-0.45	-0.52	-0.61	-0.71	-0.85
8,000	0.45	0.30	0.11	-0.13	-0.27	-0.37	-0.46	-0.54	-0.62	-0.71	-0.82	-0.97
9,000	0.43	0.27	0.06	-0.19	-0.34	-0.45	-0.54	-0.62	-0.71	-0.80	-0.92	-1.08
10,000	0.41	0.24	0.02	-0.24	-0.40	-0.52	-0.61	-0.70	-0.79	-0.89	-1.02	-1.18

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.80	0.82	0.83	0.82	0.82	0.82	0.82	0.83	0.83	0.83	0.83	0.82
5,000	0.66	0.64	0.59	0.46	0.33	0.20	0.06	-0.07	-0.22	-0.39	-0.58	-0.80
10,000	0.60	0.57	0.49	0.30	0.11	-0.07	-0.26	-0.46	-0.67	-0.91	-1.17	-1.48
15,000	0.55	0.51	0.41	0.18	-0.05	-0.28	-0.51	-0.75	-1.01	-1.29	-1.61	-1.99
20,000	0.51	0.46	0.35	0.08	-0.19	-0.45	-0.71	-0.99	-1.29	-1.61	-1.97	-2.41
25,000	0.48	0.42	0.29	-0.01	-0.31	-0.60	-0.89	-1.20	-1.53	-1.89	-2.28	-2.76
30,000	0.44	0.38	0.23	-0.09	-0.41	-0.73	-1.05	-1.39	-1.75	-2.13	-2.55	-3.08
35,000	0.41	0.34	0.19	-0.16	-0.51	-0.85	-1.20	-1.56	-1.94	-2.35	-2.80	-3.36
40,000	0.39	0.31	0.14	-0.23	-0.60	-0.96	-1.33	-1.71	-2.12	-2.55	-3.02	-3.61
45,000	0.36	0.28	0.10	-0.29	-0.68	-1.06	-1.45	-1.85	-2.28	-2.73	-3.22	-3.84
50,000	0.34	0.25	0.06	-0.35	-0.76	-1.16	-1.56	-1.99	-2.43	-2.90	-3.41	-4.05

Net Sharpe ratios for the short interest long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American mid capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

Table 4.8: Quality, North American Mid Caps

 Net Sharpe for Various Capitals (USD million) and Trading Speed τ

Panel A: With Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.63	0.70	0.78	0.85	0.89	0.92	0.94	0.95	0.97	0.98	0.99	0.99
500	0.58	0.64	0.69	0.73	0.76	0.79	0.80	0.82	0.82	0.83	0.83	0.82
1,000	0.56	0.60	0.64	0.68	0.71	0.72	0.74	0.75	0.75	0.75	0.75	0.74
1,500	0.54	0.58	0.61	0.64	0.66	0.68	0.69	0.70	0.70	0.70	0.69	0.68
2,000	0.52	0.56	0.58	0.61	0.62	0.64	0.65	0.65	0.65	0.65	0.64	0.62
2,500	0.51	0.54	0.56	0.57	0.59	0.60	0.61	0.62	0.61	0.61	0.60	0.58
3,000	0.50	0.52	0.53	0.55	0.56	0.57	0.58	0.58	0.58	0.57	0.56	0.54
3,500	0.49	0.51	0.51	0.52	0.53	0.54	0.55	0.55	0.55	0.54	0.52	0.50
4,000	0.47	0.49	0.49	0.50	0.51	0.51	0.52	0.52	0.51	0.50	0.49	0.46
4,500	0.46	0.48	0.48	0.48	0.48	0.49	0.49	0.49	0.49	0.47	0.46	0.43
5,000	0.46	0.47	0.46	0.45	0.46	0.46	0.47	0.46	0.46	0.45	0.43	0.40

Panel B: Ignoring Market Impact Slow Decay												
	0.025	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	0.64	0.71	0.78	0.85	0.89	0.92	0.94	0.96	0.97	0.98	0.98	0.99
2,000	0.57	0.63	0.68	0.72	0.74	0.74	0.73	0.72	0.70	0.67	0.64	0.59
4,000	0.53	0.59	0.64	0.67	0.67	0.65	0.64	0.61	0.57	0.53	0.48	0.41
6,000	0.51	0.56	0.61	0.62	0.61	0.59	0.56	0.53	0.48	0.43	0.36	0.28
8,000	0.49	0.54	0.58	0.58	0.57	0.54	0.50	0.46	0.40	0.34	0.26	0.16
10,000	0.47	0.52	0.55	0.55	0.53	0.49	0.45	0.39	0.33	0.26	0.17	0.06
12,000	0.46	0.50	0.53	0.52	0.49	0.45	0.40	0.34	0.27	0.19	0.09	-0.03
14,000	0.44	0.48	0.51	0.49	0.46	0.41	0.35	0.29	0.21	0.12	0.01	-0.11
16,000	0.43	0.47	0.49	0.47	0.43	0.37	0.31	0.24	0.16	0.06	-0.05	-0.19
18,000	0.41	0.45	0.47	0.44	0.40	0.34	0.27	0.19	0.10	0.00	-0.12	-0.26
20,000	0.40	0.44	0.45	0.42	0.37	0.31	0.23	0.15	0.06	-0.05	-0.18	-0.33

Net Sharpe ratios for the quality long/short strategy that targets an ex-ante annualized volatility of 10%, investing in North American mid capitalization stocks. Rows correspond to different USD amounts of capital invested in the strategy. Columns correspond to various trading speeds, as represented by the parameter τ . For each USD amount of capital, the net Sharpe ratio corresponding to the optimal trading speed is highlighted in yellow. The capacity of the strategy is highlighted in green. Panel A shows results for our proposed specification of market impact that takes into account the impact of previous days trade (slow decay of market impact). Panel B shows results for a specification of market impact that ignores previous days trade.

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RÉSUMÉ

Cette thèse se compose de trois essais indépendants qui examinent certains aspects clés de la gestion quantitative d'actifs : l'alpha, le risque de crowding, les coûts de transaction et le sujet connexe de la capacité. Le premier essai étudie l'anatomie d'une stratégie de trading quantitative sur actions typique. En utilisant des données de répartitions géographiques des ventes des entreprises, nous montrons que les cours des actions ne réagissent pas immédiatement aux chocs de change : les prix prennent environ deux semaines pour les intégrer. Cela est vrai pour les chocs de petite à moyenne ampleur, mais pas pour les chocs plus importants, conformément à une interprétation de "bounded rationality". Le deuxième essai développe un modèle dont le but est d'étudier la relation entre le "crowding" et les chocs de liquidité. L'un des résultats principaux de ce modèle est que le "crowding" est associé à une exposition aux chocs de liquidité sur les arbitrageurs. Nous confirmons ce lien empiriquement en étudiant certaines stratégies equity long/short. Nous utilisons les données de short interest afin d'identifier les chocs de liquidité qui impactent les investisseurs sophistiqués et de mesurer le "crowding". Quand surviennent des chocs de liquidité, les stratégies "crowdées" tendent en effet à sous-performer. Dans le dernier essai, j'étudie l'impact de l'intégration du "slow decay" du market impact, récemment documenté, sur la capacité des stratégies de trading d'actions long/short. Les estimations de capacité qui en résultent sont des ordres de grandeur inférieurs à ceux indiqués dans les études précédentes.

MOTS CLÉS

Anomalies de marché, gestion du risque, capacité, crowding, chocs de liquidité, market impact, inattention.

ABSTRACT

This dissertation consists of three independent essays that examine key aspects of quantitative asset management: alpha, crowding risk, trading costs and the related topic of capacity. The first essay studies the anatomy of a typical equity quantitative trading strategy. Using company-level data on geographic sales, we show that stock prices do not respond immediately to currency shocks: prices take about two weeks to integrate them. This is true for small to medium size shocks but not for larger shocks, in line with a bounded rationality interpretation. The second essay develops a model whose aim is to study the relationship between crowding and liquidity shocks. One of the main results of that model is that crowding is associated with a larger exposure to broader liquidity shocks on arbitrageurs. We confirm this link empirically by studying equity long/short strategies. We use short interest data both to identify liquidity shocks impacting sophisticated equity investors and to infer crowdedness for some of the well-known long/short equity factors. When liquidity shocks occur, crowded strategies indeed tend to under-perform. In the last essay, I investigate the impact of integrating the recently documented "slow decay" of market impact on the capacity of long/short equity trading strategies. Resulting capacity estimates are orders of magnitude lower than shown in previous studies.

KEYWORDS

Market anomalies, risk management, capacity, crowding, liquidity shocks, market impact, inattention.