Best Short*

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Abstract

We infer investors' expectations about future stock returns through a measure of short conviction that exploits net short positions disclosed at the investor-stock level for European stock markets. A strategy that sells high-conviction stocks and buys low-conviction stocks, named *Best Short*, generates a risk-adjusted excess return that is larger than 8% per annum and differs from the performance of traditional strategies based on aggregate short interest. Its profitability, moreover, cannot be explained by transaction costs, stock characteristics, frictions in the securities lending market, leverage constraints, and measures of price inefficiency.

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1 Introduction

Short-selling activity came under scrutiny, as a potential source of price distortion, during the global financial crisis in 2007. Many securities markets regulators reacted by banning or limiting certain short sales, ultimately to restore investor confidence and curb excessive price declines. These measures, however, failed to support security prices, were detrimental for liquidity, and impeded price discovery (e.g., Saffi and Sigurdsson, 2011; Beber and Pagano, 2013), consistent with the view that short-sellers have access to valuable information and limiting their market participation can affect the informational efficiency of prices and have significant implications for the real economy (e.g., Engelberg, Reed, and Ringgenberg, 2012; Boehmer, Jones, and Zhang, 2013).

Concerns about the benefits of short-selling bans soon led some financial authorities to introduce greater transparency through disclosure requirements as an alternative and perhaps less invasive policy tool. European Union countries, in particular, took the lead in this approach and adopted in recent years a uniform regime that requires immediate public disclosure of *net short positions* above a certain threshold.[1] Under this pan-European arrangement, an investor must publicize her net short positions larger than 0.5% of a company's issued share capital, including derivatives, by the next business day after the trade. Also, the disclosure must indicate the date of the transaction, the name of the short seller, the instrument sold short, and the size of the holdings. As a result, this regulatory scheme provides on a large scale timely and detailed information about individual investors' short-selling activity beyond the traditional measures of aggregate short interest (e.g., Jones, Reed, and Waller, 2016; Jank, Roling, and Smajlbegovic, 2019).

This paper exploits the granularity of net short positions disclosed at the investor-stock level

[1] Stock exchanges in the US are only required to release aggregate information of short sales at the stock level twice a month despite the Dodd–Frank Act required the SEC to study costs and benefits of real-time disclosures (SEC, 2014). Recently, both NYSE and NASDAQ have filed rulemaking petitions for short-sale disclosures with the SEC (petition numbers 4-689, October 7, 2015; 4-691, December 7, 2015; see https://www.sec.gov/rules/petitions.shtml)

for European stock markets and contributes to the existing literature in several important ways. We first document that short sellers' confidence in each of their holdings is not uniform and short positions tend to be concentrated on relatively few stocks. In our sample, more than 40% of the investors have disclosed positions on a single stock and up to 70% of the investors hold short positions on no more than three stocks. This evidence leads us to hypothesize that short sellers tilt their portfolios towards selected bets in which they have a higher level of short conviction, similar to the findings of Antón, Cohen, and Polk (2021) for mutual fund managers. We then extract forward-looking expectations about asset valuation through a theoretically-motivated measure that aggregates investors' short conviction at the stock level and find that selling high-conviction stocks while buying low-conviction stocks generates a sizeable risk-adjusted excess return. Finally, this strategy, which we label *Best Short*, cannot be rationalized by transaction costs, stock characteristics, frictions affecting the securities lending markets, and measures of price efficiency that capture the speed of price adjustment to market-wide information (e.g., Hou and Moskowitz, 2005; Boehmer and Wu, 2013; Engelberg, Reed, and Ringgenberg, 2018).

Our measure of short conviction can potentially amplify the role of smaller or highly specialized funds. This happens as we first compute portfolio weight at the stock-manager level and then aggregate across managers using a simple average. If larger or less specialized funds had more dispersion in their positions relative to smaller or highly specialized funds, a simple average would then overweight the stocks on which the latter have short positions. This bias is a feature of our data and not a methodological flaw. A plausible explanation for the high concentration of disclosed net short positions could be that funds with limited resources or capacity constraints may choose to specialize and hold fewer positions. As a result, our measure of short conviction is likely to harvest information from highly specialized funds.

Our sample consists of daily disclosed net short positions at the investor-stock level from November 2012 to December 2018. While publicly disclosed net short positions are provided through the national regulators' websites, we have obtained the data from Caretta Data, a consolidated source that assembles disclosed short positions from different national authorities in Europe and provides live updates through a data feed. Our sample contains approximately 1.7 million short positions disclosed by 585 different investors on about 1,400 securities across 15 major European countries. This rich dataset is further complemented with information about inventory of shares available for lending and estimates of borrowing fees collected directly from the securities lending desks of prime brokers, custodian banks, asset managers, and hedge funds by IHS Markit.

Our analysis focuses on hedge fund investors, which are the dominant group in our sample. We make some simplifying assumptions to infer investors' expectations about asset returns from disclosure position using standard portfolio theory. Specifically, we assume that hedge funds are mean-variance investors and build market-neutral portfolios. This enables us to show that their portfolio allocations will be directly proportional to their expectations of information ratios, thus, a larger portfolio weight may signal a higher level of conviction toward a given stock. We aggregate those investor-level expectations into an aggregate measure of *short conviction* at the stock level and construct portfolios sorted on short conviction. As a measure of the economic value of the disclosure data, we use the wedge between the two corner portfolios. This corresponds to a long-short trading strategy, the *Best Short*, that sells high-conviction stocks and buys low-conviction stocks. Best Short delivers a statistically significant and economically large excess return of 8.85% per annum, after controlling for risk exposure to the five Fama and French (2015) and Carhart (1997) momentum factors. Moreover, the performance of Best Short cannot be explained by transaction costs and remains robust to a battery of tests.

In an attempt to shed light on the observed performance of *Best Short*, we examine whether market frictions or other risks may explain our results. Following Engelberg, Reed, and Ringgenberg (2018), we test whether *dynamic* risks associated with short-selling can explain the premium earned by Best Short. We measure unexpected changes in future lending conditions using either daily changes in the cross-sectional variance of borrowing fees or daily changes in the stock market implied volatility skew. With a cross-sectional asset pricing test, we find that Best Short's premium cannot be understood as compensation for the uncertainty over future stock borrowing fees. Building on the work of He, Kelly, and Manela (2017), we also find that Best Short's performance does not reflect leverage constraints, as captured by the intermediary capital risk factor. Next, we test whether Best Short's excess returns are related to short-sale constraints stemming from a tight supply of lendable shares. Loan supply is measured using the number of shares actively available for lending divided by the total number of shares outstanding, and unexpected shocks to loan supply are quantified using daily changes in the cross-sectional variance of stock-level loan supply. Employing the same methodology as in our previous tests, we show that shocks to loan supply is not a priced risk factor in the cross-section of conviction-sorted portfolios, thus, also fails to rationalize our results. An event study of the dynamics of loan supply, total short interest, and borrowing fees around portfolio formation further corroborates our conclusions thus far.

Finally, we estimate panel regressions to assess whether short conviction is related to cross-sectional differences in price efficiency, which could be an indication of limits to arbitrage or market frictions preventing the smooth incorporation of information into asset prices. Our dependent variables are two measures of price delay proposed by Hou and Moskowitz (2005). These delay measures are based on the regression of weekly stock returns on the contemporaneous return of the market and four lags of weekly market returns. We then re-estimate this equation after imposing the constraint the coefficients of lagged market returns are zero. The first delay measure implies that a stock takes longer to incorporate new market information. The second measure examines the size of the lagged market return coefficients relative to the contemporaneous coefficient. While regressions based on the first delay measure yield that short conviction is associated with larger price delays (or, equivalently, less price efficiency), regressions based on the second delay measure reveal that this relationship is statistically and economically insignificant. Taken together, these results suggest that information arising from short conviction is not subsumed by firm characteristics, liquidity, supply and demand of lendable shares, short-selling risk, or investor attention. This would be in line with our hypothesis that short conviction aggregates forward-looking expectations about the distribution of asset returns.

Overall, our empirical results indicate that information gathered from publicly available net short positions in Europe is economically valuable and not entirely subsumed by traditional explanations of risk exposure and limits to arbitrage. Thus, we can contribute to a long-standing policy debate on the trade-off between greater transparency and the potential costs of public disclosure. On the one hand, greater transparency about short sales may improve market efficiency as negative expectations about firms' fundamentals are quickly disseminated among market participants. On the other hand, improving transparency about short-selling activities may weaken the incentives of short sellers to collect and analyse firms' fundamentals as other investors could free-ride the costs of information acquisition. As a result, market efficiency would worsen and the information content of disclosed positions should become less valuable. Our results suggest that ex-ante expectations implied from publicly disclosed net short positions remain informative about future asset price movements.

Our paper is related to two strands of literature. First, we speak to an extensive literature on short-selling activity and stock returns. Asquith and Meulbroek (1995), among others, find that high short interest predicts negative abnormal returns.[2] However, Asquith, Pathak, and Ritter (2005) show that predictability is strongest in stocks with low institutional ownership, and Boehmer, Huszar, and Jordan (2010) find that abnormal returns are limited to the extreme first percentile of the most heavily shorted stocks. Jank and Smajlbegovic (2017) use short position disclosures in Europe to track the performance of short sellers and find that as a group they generate an excess return of about 5.5%, adjusted for the three Fama and French (1993) factors. Nonetheless, the authors also find that this large excess return can be explained by trading on other well-known factors, such as momentum, betting-against-beta, and quality. We contribute to this literature by showing how one could exploit the granularity of the publicly disclosed short positions in Europe to construct a trading strategy with a large excess return that is not captured by the five Fama and French (2015) and Carhart (1997) momentum factors.

[2] Other studies include Diamond and Verrecchia (1987), Aitken, Frino, McCorry, and Swan (1998), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009), Boehmer and Wu (2013), Reed (2013), and Rapach, Ringgenberg, and Zhou (2016).

Second, our work also relates to previous work on the effects of short-selling disclosure. Recent literature has examined the market-wide effects of the short-selling disclosure regime in Europe as well as investors' behavior around the disclosure threshold. Jones, Reed, and Waller (2016), for instance, exploit the staggered introduction of the disclosure regime in different countries and conclude that the obligation to publicly disclose short positions reduces short interest and informativeness of prices but improves liquidity. Furthermore, Jank, Roling, and Smajlbegovic (2019) shed light on how investors behave around the disclosure threshold. Using confidential regulatory data, the authors document that investors accumulate short positions below the publication threshold in order to protect their trading strategies from copycat investors. Kahraman (2020) finds that more frequent disclosure of aggregate short interest in the US improves informational efficiency, suggesting that the type of the disclosure regime (i.e., frequency, aggregated vs disaggregated, etc.) matters. Beyond the effect of disclosure requirements, earlier literature has also examined the impact of short-selling constraints on price efficiency. Saffi and Sigurdsson (2011) document that stocks with higher short-selling constraints, measured by low lending supply, have lower price efficiency, while Beber and Pagano (2013) show that short-selling bans imposed in various countries during the 2007-09 crisis failed to support prices and were detrimental for liquidity. One of the potential costs of disclosure is so-called copycat behaviour. Our paper contributes to the literature on the costs of disclosure by building on the work of Frank, Poterba, Shackelford, and Shoven (2004) who show that copycat funds could potentially erode market share from actively managed funds (in the US mutual funds space) by offering comparable returns net of expenses based on disclosed long-only mutual fund positions. We extend this work to short positions by constructing a long-short trading strategy that exploits disclosed short-positions and can be interpreted as a proxy for a copycat long-short equity fund. Our results similarly raise the prospect of copycat hedge funds that could erode the market share of existing hedge funds.

The remainder of the paper is organized as follows. Section 2 describes the institutional background and the data. Section 3 introduces *short conviction* and documents the large economic premium that can be earned by trading on this measure. Section 4 examines potential explanations of our findings, while Section 5 offers a number of robustness tests. We conclude in Section 6. A separate Internet Appendix provides additional robustness tests and supporting analysis.

2 Data

This section provides a detailed description of the net short positions on European shares, which are publicly disclosed on a daily basis at the stock and investor level. We also summarize all additional data that are key for our empirical analysis, i.e., the amount of share available for lending, borrowing fees, and stock characteristics. Finally, we present the summary statistics before turning to the construction of our *Best Short* trading strategy in the next section.

2.1 Disclosed Short Positions

At the outbreak of the global financial crisis, many countries in Europe adopted various measures to suspend or constrain short-selling activity in response to concerns about market destabilization. These restrictions, however, were imposed and lifted at different dates and one could have avoided short-selling restrictions in one country by trading in another one. To circumvent this lack of coordination in market oversight while dealing with price and liquidity distortions associated with short-selling bans, the European Union (EU) introduced a harmonized regime to regulate the short-selling of securities. This framework, implemented with the Short Selling Regulation (SSR 236/2012), acknowledges the role of short selling in price discovery and market quality, and, thus, largely focuses on reporting and transparency obligations.

Since the beginning of November 2012, all investors must disclose their net short positions on securities traded in EU venues (including countries of the European Economic Area and Switzerland), when certain limits are exceeded. The regulation builds around a two-tier reporting system of individual net short positions that include a *confidential notification* to the regulator activated when a given threshold is crossed, followed by *public disclosure* to the market triggered by a higher threshold. Confidential notifications arise when the net short position on given security at the end of a trading day reaches 0.2% of the issued share capital and each additional 0.1% above the notification threshold. Public disclosure is required when a net short position at the end of a trading day crosses 0.5% of the issued share capital of the company shorted and each subsequent 0.1% above the disclosure threshold. Also, investors must provide an update whenever holdings fall below the notification and disclosure thresholds, which can be amended by the European Securities and Markets Authority (ESMA).[3]

The notification and disclosure requirements apply to all investors irrespective of their domicile and *net short positions* on each reference stock are calculated as the difference between short and long positions held both in cash and derivatives markets at the investor level. The notional value of derivatives must be delta-adjusted to take sensitivity to the underlying share price into account. These requirements also affect short positions held indirectly through baskets or indices (e.g., ADRs, GDRs, and ETFs) and exemptions exist only for those transactions that are essential to market-making activities (e.g., market markers and authorized primary dealers). These provisions, moreover, hold for financial instruments traded in EU venues unless the principal trading venue, determined by ESMA based on turnover, is located in a third country. Short positions that require notification or disclosure must be reported to the national competent authorities, separately for each country, by 3:30 pm local time of the next trading day, meaning that there is a one-day lag between the position date and the reporting date. National authorities then publish the holdings subject to public disclosure on their websites by the end of the same trading day. In the UK, for example, investors

[3]On March 16, 2020 (not in our sample), for instance, ESMA lowered the notification threshold to 0.1% of the issued share capital under the exceptional circumstances caused by the COVID-19 pandemic.

report their short positions to the Financial Conduct Authority (FCA) which makes them available on its website.[4]

The reporting obligation requires to submit the name of the investor, the name of the shorted stock, the International Securities Identification Number (ISIN), the date when the short position hit the relevant thresholds, and the size of the net short position as a percentage of the issued share capital. In our empirical analysis, we work with daily disclosed short positions from November 1, 2012, to December 31, 2018. While publicly disclosed net short positions are provided through the national regulators' websites, we have obtained them from Caretta Data, a consolidated source that assembles disclosed short positions from different national authorities in Europe and provides live updates through a data feed available at https://www.caretta.io. Our sample contains approximately 1.7 million short positions disclosed by 585 different investors on about 1,400 securities. We report the daily number of short positions, unique securities, and individual managers in Figure A1. It reveals a steady and sharp increase in the number of disclosed short positions between 2012 and 2018, driven by a growing number of both managers and shorted securities. From a regulatory perspective, greater transparency about short sales is likely to improve market efficiency, as negative information about company fundamentals is quickly disseminated among market participants. Also, recent literature points out that arbitrageurs face short-sale constraints and may be reluctant to profit from mispricing if the downward price correction takes too long to happen while shorting fees pile up. Increased public disclosure may indeed help arbitrageurs reduce the limits to arbitrage, thus accelerating price discovery (e.g., Ljungqvist and Qian, 2016; Kovbasyuk and Pagano, 2018). Improving transparency on short-selling activities, however, may weaken the incentives of short sellers to collect information about company fundamentals as other investors could free-ride the costs of information acquisition, thus worsening market efficiency (e.g., Grossman and Stiglitz, 1980). One could then expect, everything else being equal, a decline in the number of disclosed short positions over time,

[4]The list of the national authorities and the links to their websites is available on ESMA's website at https://www.esma.europa.eu/sites/default/files/library/ssr_websites_ss_procedures.pdf.

and less valuable information content. *Prima facie*, the pattern recorded in Figure A1 suggests that this is not the case. Also, it seems consistent with the findings of Kahraman (2020) who studies the increased public disclosure for US short positions in response to an SEC amendment to exchange rules. Under the new regime, information embedded in short interest is more rapidly incorporated into prices, price informativeness improves, and short-sellers increase their amount of short-selling activities.

Our sample, moreover, spans 15 major European countries, namely, Austria, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Spain, Sweden, Switzerland, and the UK. Other countries are not included in the dataset compiled by Caretta due to infrequent disclosed short positions at the daily frequency.

2.2 Equity Lending Data

We complement our disclosed net short positions with securities lending data sourced from IHS Markit, a leading data provider. The EU regulation prohibits naked short positions and requires that short positions are either offset by long positions or other arrangements that include share borrowing or an agreement to borrow. The data are collected directly from the securities lending desks of prime brokers, custodians, asset managers, and hedge funds, and provide security-level information on the number of shares borrowed, inventory of shares available for lending, estimates of borrowing fees and rebate rates, and level of utilization for about 90% of the securities lending market in developed countries according to IHS Markit.

The securities lending market operates as an over-the-counter market where a lender temporarily transfers securities to a borrower and the latter is obliged to return the securities on demand or at the end of an agreed term. As protection against counterparty risk, moreover, the lender receives cash or other securities of equal or greater value as collateral. When the transaction is collateralized with securities, the lender receives a borrowing fee from the borrower. If the transaction is undertaken with cash as collateral, in contrast, the lender pays the borrower a rebate rate that is below the market interest rate to capture the cost of borrowing the security.

We employ the following main variables from IHS Markit in our analysis: *Short Loan Quantity* is the number of securities on loan with dividend trading and financing trades removed, *Active Available Quantity* is the number of securities that are actively available for lending, *Average Tenure* is the weighted average number of days with open short positions on a given stock, *Indicative Fee* and *Indicative Rebate* reflect the expected borrowing cost for a security assuming non-cash and cash collateral, respectively, and *Short Interest* is the number of shares on loan as a percentage of shares outstanding. The data provider reports these variables as of the settlement day, which is three days after the actual trading day. We adjust these variables by three days, eliminating the settlement lag so that all of our data reflects trade time. When forming a trading strategy, however, we introduce an appropriate time delay so that the information used is available at the time of trading.

2.3 Data Compilation

For every stock in our sample, we merge Caretta and IHS Markit data with pricing and accounting data from Bloomberg. The set of pricing data includes close prices adjusted for dividends and corporate actions in US dollars, market capitalization in US dollars, and bid-ask spreads computed as a volume-weighted average of intraday bid-ask spreads over a five trading day window. The list of accounting data comprises the *Price-to-Book Ratio*, *Book Value* measured as total common equity, *Debt* defined as short-term and long-term debt, *Operating Income Before Depreciation*, *Total Assets*, *Leverage* corresponding to the debt to book value ratio, and *Profitability* defined as the ratio of operating income before depreciation (or operating income) to total assets. Finally, daily returns for European risk factors are obtained from Kenneth French's data library.

2.4 Descriptive Analysis

We only observe holdings above the disclosure threshold of 0.5% of the issued share capital of a listed company and a natural question to ask is whether our sample is representative as compared to the total short interest, a widely used proxy for short-selling holdings (e.g., Saffi and Sigurdsson, 2011; Jones, Reed, and Waller, 2016; Jank, Roling, and Smajlbegovic, 2019; Gargano, Sotes-Paladino, and Verwijmeren, 2020). Put differently, if the sum of disclosed short positions for each given stock is only a small fraction of the observed short interest, one could argue that we only observe the "tip of the iceberg", thus casting doubts on the informativeness of our data. To address this legitimate concern, we first construct the daily ratio between publicly disclosed net short positions and short interest for each security in our sample and then plot the median value as well as the interquartile range (between the 75th and 25th percentiles) across all countries in Figure 1.

Figure 1 about here

This chart reveals that publicly disclosed short positions represent a substantial part of the observed short interest. The median value of the ratio between disclosed holdings and short interest is above 50% when public disclosure starts in November 2012, jumps to roughly 70% in early January 2013, and then reaches more than 80% towards the end of the sample in December 2018. We also uncover a fair amount of dispersion as shown by the interquartile range, which can be larger than one. This happens as short interest quantifies the percentage amount of shares sold short while regulatory disclosure also includes positions created via derivatives. This evidence, overall, suggests that undisclosed short positions represent a small fraction of the observed short interest and are unlikely to affect the conclusions of our study.

Figure 2 about here

As an illustrative example of our unique dataset, Figure 2 presents the anatomy of short-selling activities on Carillion, a British construction and support services group that collapsed in January 2018. Before its debacle and for about 18 months, Carillion was the most popular security to short on the UK stock market according to a *Financial Times* article (McCrum and Johnson, 2017). The top panel displays the stock price in US dollars from Bloomberg and the corresponding borrowing fee in percentage per annum from IHS Markit whereas the bottom panel presents the net short positions disclosed at the investor level from Caretta and the total short interest extracted from IHS Markit, both expressed as a percentage of the issued share capital of Carillion.

As suggested by the data, short-selling activity on Carillion started to pick up towards the end of 2014 after Balfour Beatty, a competing multinational infrastructure group, rejected the merger offer in August and following the company decision to issue a convertible bond, an expensive form of debt, in December. In March 2015, moreover, UBS analyst Gregor Kuglitsch sparked concerns over Carillion's leverage and the management of its receivables as reported by Bloomberg article (Bryant, 2018). Short interest reached a peak of 30% in 2017 and borrowing fees surged to almost 20%, with hedge funds and institutional investors heavily shorting Carillion up until its collapse and compulsory liquidation on January 15, 2018. Our dataset offers a unique opportunity to observe investors' short positions above the threshold of 0.5% of shares outstanding. In our example, we display the holdings of 40 major different hedge funds, which indicate the existence of a critical source of cross-sectional information that we explore in the next section. This example also reveals that our disclosed short positions capture most of the short interest and only a small fraction of these holdings remain undisclosed, especially after 2015 and for more than three years before Carillon's liquidation.

An additional illustrative example is provided in Figure A2, which displays the net short positions disclosed by Renaissance Technologies, the American hedge founded by Jim Simons and regarded as one of the most secretive and successful hedge funds. The net-short position is translated into US dollars using the stock market closing price from Bloomberg. The figure shows granular information about publicly disclosed net short positions on 44 firms, which belong to different sectors such as financials (e.g., Commerzbank, Deutsche Bank, Unione di Banche Italiane), health care (e.g., Erytech Pharma), industrials (e.g., ASM International, Philips, and Sif Holding), and materials (e.g., Saipem, Thyssenkrupp, and Buzzi Unicem).

2.5 Summary Statistics

2.5.1 By Country and Investor Type

We report descriptive statistics of publicly disclosed net short positions in Table 1 while winsorizing the data at the 99-th percentile to guard against possible extreme values. Recall that our sample ranges between November 1, 2012, and 31 December 2018, and comprises roughly 1.7 million net short positions disclosed by 585 different investors on approximately 1,400 securities corresponding, by issuer's domicile, to 15 major European countries.

Table 1 about here

In Panel A, we aggregate our data by country and display the total number of securities, total number of disclosures, average disclosure per day, and the overall market value in billions of US dollars. We also present the percentage share of each component relative to all countries. In terms of shorted securities, the UK is the most representative market with 528 shorted shares corresponding to 38% of the sample, followed by Germany with 183 shorted shares equivalent to 13.4% of the sample, Sweden with 140 shorted shares akin to 10.1% of the sample, and France with 133 shorted shares or 9.6% of the sample. The ranking remains fairly similar in terms of disclosed positions with the UK and Germany accounting for about 39% and 15% of the sample, and in terms of daily market value with the UK and Germany capturing about 36% and 14% of the sample.

In Panel B, we categorize individual investors into asset managers, banks, non-financial corporate firms, hedge funds, pension funds, and private equity funds. Hence, for each group, we report the total number of investors, the total number of disclosures, average disclosure per day, and the overall market value in billions of US dollars. The sample is dominated by hedge funds with 415 distinct reporting entities accounting for 71% of the sample, followed by asset managers with 132 different reporting entities corresponding to 23% of the sample, and banks with 28 different reporting entities akin to about 5% of the sample. Non-financial corporate firms, pension funds, and private equity funds altogether reach less than 1% of the sample. In addition to having the largest number of reporting entities, the hedge fund group is also the most active one with more than one million (or 69%) disclosed positions in our sample. Asset managers and banks, taken together, then account for half a million (or about 30%) disclosed positions in our sample. We also have information about the investors' domicile in our sample and 56% of the investors are located in North America, 41% in Europe, and only 3% in the Asia-Pacific region. When we inspect the investor type, moreover, we uncover that hedge funds are mostly located in North America (65%) and then in Europe (32%). The majority of asset managers and banks, in contrast, are primarily located in Europe (66% and 64%, respectively) as opposed to North America (32% and 29%, respectively).

2.5.2 By Trade

We also report descriptive statistics at the trade level in Table 2. In particular, we identify a unique trade as follows: when investor i discloses a net short position on a given stock j for the first time, we categorize this trade as a unique trade and assign it a unique identifier until the position falls below the disclosure threshold. If the same investor i in the future discloses a new position on the same stock j, we will regard this trade as a new trade with a new identifier. For each unique trade, we first compute the sample mean for the variable of interest and then calculate the cross-sectional means, standard deviations, and interdecile ranges between the 10th and the 90th percentiles. Moreover, the *Net Short Position (%)* indicates the percentage of total shares outstanding, *Net Short Position ($ million)* is the market value in millions of US dollars, *Market Cap* is the market capitalization in billions of US dollars, *Small Cap Stocks (%)*, *Mid Cap Stocks (%)*, and *Big Cap Stocks (%)* denote the percentage number of small, medium, and big-cap stocks, respectively, based on market capitalization, *Number of Investors* is the number of different investors shorting the same stock on a given day, and *Holding Period* is the number of days from entering to closing a disclosed short position. We also compute the percentage of trades with *Multiple Investors (%)*, positions disclosed by first-movers with *Initiator (%)*, positions with a holding period of up to 10 days with *Holding Period* $<$ *10 days (%)*, and positions disclosed by investors domiciled in the same country as the stock with *Same Country (%)*.

Table 2 about here

In our dataset, the average net short position is about 0.69% of the total issued shares with the 90th percentile larger than 1%. In US dollar terms, the average net short position is worth more than 28 million with the 90th percentile close to 60 million. Based on market capitalization, moreover, 45% of the trades involve stocks from the small-cap universe whereas 55% of the trades concern medium- and large-sized enterprises. The holding period is skewed to the right with a median of 14 days, an average close to 66 days, and a 90th percentile larger than 6 months. Finally, 84% of the trades have multiple investors but only 22% of the trades are disclosed by the first mover.

Figure 3 about here

We also slice net short positions from the perspective of individual investors and display in Figure 3 the distribution of unique holdings held on each given day by an individual investor in our sample. This figure reveals that investors' disclosed short positions are concentrated on relatively few stocks since more than 40% of the investors have a single disclosed net short position, less than 20% of the investors have disclosed positions concentrated on two stocks, and about 10% of the investors have disclosed positions spread on at least three stocks. Only about 10% of the investors, moreover, have disclosed short positions on more than ten stocks in their portfolio.

3 Short Conviction

In this section, we describe how to infer investor's expectations about asset returns through a measure of short conviction that exploits granular information from disclosed net short positions at the stock-investor level. We then show that selling high-conviction stocks and buying low-conviction stocks generates on average sizable excess returns. We conclude by describing the properties of this strategy relative to other existing short-selling strategies.

3.1 Setting

The granularity of the disclosure data allows us to infer investors' conviction on each of their disclosed holdings. To motivate our approach, we assume that investors have mean-variance preferences and build a market-neutral portfolio from a set of N risky assets in the spirit of Antón, Cohen, and Polk (2021).

Each investor i maximizes at time t an expected mean-variance utility function as

$$\max_{\boldsymbol{w}_{i,t}} \boldsymbol{w}'_{i,t}\boldsymbol{\mu}_{i,t} - \frac{\gamma_i}{2}\boldsymbol{w}'_{i,t}\boldsymbol{\Omega}_{i,t}\boldsymbol{w}_{i,t},$$

where $\boldsymbol{\mu}_{i,t} = \mathbb{E}_{i,t}(\boldsymbol{R}^e_{t+1})$ and $\boldsymbol{\Omega}_{i,t} = \mathbb{Cov}_{i,t}(\boldsymbol{R}^e_{t+1})$ denote, respectively, the N-dimensional conditional mean vector and conditional covariance matrix of future excess returns formed by investor i at time t, γ_i is investor's i coefficient of risk aversion, and $w_{i,t}$ is investor's i set of portfolio weights determined at time t using the traditional closed-form solution $\boldsymbol{w}_{i,t} = \gamma_i^{-1}\boldsymbol{\Omega}^{-1}_{i,t}\boldsymbol{\mu}_{i,t}$. This solution, however, can be reversed to infer investor's i expected excess returns in the spirit of Sharpe (1974) and Black and Litterman (1991) as

$$\boldsymbol{\mu}_{i,t} = \gamma_i \boldsymbol{\Omega}_{i,t} \boldsymbol{w}_{i,t}. \tag{1}$$

A few simplifying assumptions can be made in our context. First, we assume that $\boldsymbol{\Omega}_{i,t}$ depends on a single market factor such that

$$\boldsymbol{\Omega}_{i,t} = \boldsymbol{\Sigma}_{i,t} + \sigma_m^2 \boldsymbol{\beta}_i \boldsymbol{\beta}_i', \tag{2}$$

where $\boldsymbol{\Sigma}_{i,t} = diag\{\sigma_{i1,t}^2, \ldots, \sigma_{iN,t}^2\}$ is a diagonal matrix that contains the conditional idiosyncratic variance of each risky asset j on its main diagonal, $\boldsymbol{\beta}_i = (\beta_{i1}, \ldots, \beta_{iN})$ is a vector that comprises the market beta of each risky asset j, and σ_m^2 is the variance of the market portfolio. By combining Equations (1) and (2), we then obtain that

$$\boldsymbol{\mu}_{i,t} = \gamma_i \boldsymbol{\Sigma}_{i,t} \boldsymbol{w}_{i,t} + \gamma_i \sigma_m^2 \boldsymbol{\beta}_i \boldsymbol{\beta}_i' \boldsymbol{w}_{i,t}. \tag{3}$$

Second, we assume that each investor i builds a market-neutral portfolio by setting $\boldsymbol{\beta}_i' \boldsymbol{w}_{i,t} = 0$. Recall that our sample is mostly populated by hedge funds and it is common for these market players to have strategies with a zero market beta exposure aiming at reducing risk and expanding diversification (e.g., Bollen, 2013). Finally, we assume that all investors share the same coefficient of risk aversion γ.

Using these simplifying assumptions, we ultimately obtain that

$$\boldsymbol{\mu}_{i,t} = \gamma \boldsymbol{\Sigma}_{i,t} \boldsymbol{w}_{i,t}, \tag{4}$$

which is equivalent to saying that the investor's i portfolio weight on asset j at time t is proportional to her subjective expectation of the information ratio as

$$w_{ij,t} = \frac{1}{\gamma} \frac{\mu_{ij,t}}{\sigma_{ij,t}^2} \tag{5}$$

and a larger portfolio weight may signal a higher level of conviction toward a given asset at the investor level. By aggregating $w_{ij,t}$ across all investors, one can then gauge forward-looking market's expectations about asset valuations (e.g., Grinold and Kahn, 1999; Litterman, 2003; Johnson and Tiwari, 2019).

3.2 Empirical Measure

Motivated by the previous section, we exploit our short-selling data to measure short conviction aggregated at the stock level. For this exercise, we first compute the *short conviction* of investor i in asset j on day t as

$$C_{ij,t} = \kappa_{j,t} V_{ij,t}, \tag{6}$$

where $V_{ij,t}$ is her dollar exposure in asset j and $\kappa_{j,t}^{-1} = \sum_j V_{ij,t}$ is her total dollar exposure such that $C_{ij,t}$ is proportional to the size of her short position.[5] We then obtain a simple measure of short conviction for asset j on day t by aggregating across all investors N_t with disclosed short positions as

$$C_{j,t} = \frac{1}{N_t} \sum\nolimits_i C_{ij,t}. \tag{7}$$

As mentioned in the introduction, our measure of short conviction tends to over-emphasizes smaller or highly specialized funds. If these funds hold fewer stocks short in their portfolio due to limited resources, higher costs of acquiring information, capacity or leverage constraints, then the simple average across managers would overweight the stocks disclosed by smaller/specialized funds.

Net short positions are generally available to the public with a delay of a business day between the position date (i.e., when the investor shorts the asset) and the publication date (i.e., when the regulator publicizes the short positions). Also, there may exist a lack of

[5]Short conviction may be imperfectly quantified as all of investors' long and short positions are not observed.

synchronization for data release among regulators and investors may require some time to collect and process the data before practically implementing a trading strategy. In our core exercise, we consider a time delay of three days between the position date and the portfolio formation date, i.e., when we implement our strategy based on short conviction. The choice of three days is not random but it is dictated by the fact that stock-level short interest, a popular short-selling indicator among market participants, is made available by IHS Markit with a time delay of three days. Using an identical time delay will then allow us to make a fair comparison between our strategy based on short conviction and a traditional strategy based on aggregate short interest.

As a clarifying example, assume no intra-week holidays for simplicity and consider an investor i that builds a net short position larger than 0.5% of the issued shared capital on asset j on Monday (day $t-3$). This position is subsequently disclosed to the regulator by 15:30 on Tuesday (day $t-2$). While the regulator publishes the net short position on its website at the end of Tuesday (day $t-2$), a third-party investor may collect and process the data on Wednesday (day $t-1$) before executing the strategy on Thursday (day t). To sum up, $C_{j,t}$ denotes our measure of short conviction employed for portfolio construction on day t. This quantity, however, is based on net short positions established by short-sellers on the day t and publicized by regulators on the day $t-2$.

3.3 Trading on Disclosed Short Positions

We employ the measure of short conviction defined in Equation (7) to construct daily rebalanced portfolios as follows. On each day t, we allocate all stocks in our sample to five portfolios based on their short conviction $C_{j,t}$ such that the first portfolio contains stocks with the lowest short convictions and the last portfolio comprises stocks with the highest short convictions. The number of stocks available on each day t varies over time as only stocks with publicly disclosed positions are sorted into portfolios.[6] On day $t+1$, we then take the perspective of a US investor and compute dollar-denominated discrete returns for each asset j as $R_{j,t+1} = (P^*_{j,t+1}/P^*_{j,t}) \times (S_{t+1}/S_t) - 1$, where $P^*_{j,t}$ is the stock price in local currency and S_t is the spot exchange rate that translates $P^*_{j,t}$ in dollars. Finally, we take the equally-weighted average within each basket and obtain dollar-denominated portfolio returns.

The descriptive statistics of these portfolios' returns, in percentage per annum, are presented in Table 3. The average returns decrease monotonically when moving from the first to the last portfolio and this pattern indicates a strong cross-sectional correlation between short conviction and portfolio performance. In particular, stocks in the lowest conviction quantile earn an average return of 7.94% per annum while stocks in the highest conviction quantile generate an average return of −0.07% per annum. These findings are also confirmed by the annualized Sharpe ratio, which is about 0.47 for the first portfolio and drops below zero for the last portfolio. We also find some evidence that low short conviction stocks have a more negative skewness than high short conviction stocks. Finally, all portfolios display a positive return autocorrelation with the first-order serial correlation coefficient ranging between 0.10 and 0.13.

TABLE 3 ABOUT HERE

The return difference between the first portfolio P_1 and the last portfolio P_5 denotes the *Best Short* strategy, namely, a long-short basket that sells stocks with high short conviction and buys shocks with low short conviction. By exploiting the cross-sectional variation underlying investors' conviction, our strategy generates an average excess return of about 8% per annum that translates into an annualized Sharpe ratio of 1.09. In addition to being economically large, the average excess return is also statistically significant since the associated t-statistic

[6] We also discard highly illiquid stocks characterized by a bid-ask spread larger than 5%. They account for less than 1% of all observations.

based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection is larger than 2.60. We also assess downside risk by reporting the Sortino ratio and the maximum drawdown. The former differentiates between volatility due to up and down movements in portfolio returns and measures the excess return per unit of bad volatility (or standard deviation of negative returns). The latter quantifies the loss that a trader would experience from the peak to the next trough in the cumulative returns. In our sample, we report a Sortino ratio of 1.86 per annum and a maximum drawdown of -9.52%, which indicate a low risk of large losses. Put differently, the *Best Short* portfolio is not akin to "picking up nickels in front of a steam roller".

The *Best Short* strategy captures information that arises cross-sectionally from short conviction measured at the investor-stock level. Naturally, one could ask whether this source of granular information, previously unexplored, helps outperform a simple short-only strategy. The latter ignores any cross-sectional variation in short conviction and sells all stocks with disclosed net short positions on each given day as in Jank and Smajlbegovic (2017). This strategy, which we name the *Naïve Short*, is equivalent to selling all five conviction-based portfolios with equal weights while investing in the riskless asset, which we proxy with the one-month US Treasury Bill. The excess return on the *Naïve Short* strategy, i.e., the riskless rate minus the cross-sectional average of all five conviction-based portfolios, is negative and displays a very pronounced drawdown. Specifically, the average excess return is about -3.72% per annum (with a t-statistics of -0.53) and the maximum drawdown is close to -50%. Overall, this suggests that trading on granular short conviction is fundamentally different than unconditionally exploiting short-selling positions.[7]

Figure 4 about here

To further evaluate the economic importance of the *Best Short*, we consider an investor that

[7] The *Naïve Short* strategy can be alternatively implemented by simply taking an equally-weighted short-only strategy on stocks with existing publicly disclosed net short positions. The results would be virtually identical.

uses traditional equity strategies (e.g., Fama and French, 1993; Carhart, 1997; Fama and French, 2015) and verify how her optimal portfolio changes when the *Best Short* enters her menu of available strategies as follows. Consider a portfolio of N strategies with covariance matrix Σ, which we compute ex-post using full-sample information. The global minimum volatility portfolio is the portfolio with the lowest return volatility and represents the solution to a simple optimization problem, i.e., $min\ w'\Sigma w$ subject to the constraint that $w'\iota = 1$, where w is vector of portfolio weights on the risky assets, ι is a vector of ones such that $w'\iota$ denotes the sum of the portfolio weights, and both w and ι are $N \times 1$ vectors. The weights of the global minimum volatility portfolios are given by $w = (\Sigma^{-1}w)(\iota'\Sigma^{-1}\iota)^{-1}$.

The set of traditional strategies includes the value-weighted return on all available stocks minus the one-month Treasury bill rate (MKT), the size factor constructed as the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks (SMB), the value factor computed as the return difference between diversified portfolios of high book-to-market and low book-to-market stocks (HML), the profitability factor constructed as the difference between the returns on diversified portfolios of stocks with robust and weak profitability (RMW), the investment factor computed as the difference between the returns on diversified portfolios of the stocks of low and high investment firms (CMA), and the momentum factor that buys diversified portfolios of past winner stocks and sells diversified portfolios of past loser stocks (WML). These strategies are based on European stock markets and sourced from Ken French's data library.

In our exercise, the optimal weight assigned to the *Best Short* is about 4% and the Sharpe ratio of the minimum volatility portfolio is 1.92 per annum. However, this number drops to 1.70 per annum if the investor is not given access to the *Best Short* and only employs the other six strategies. Figure 4 graphically displays the mean-variance frontier with and without the inclusion of the *Best Short* and shows that average excess returns can substantially improve for a different level of target volatility. For example, an investor with a target volatility of 10% per annum would earn an average excess return of about 16.2% (13.3%) per annum when she is (not) given access to the *Best Short*. Overall, these findings suggest that the

Best Short is also valuable as part of a diversified strategy thanks to its desirable correlation properties.

3.4 Trading on Aggregate Short Interest

We now check whether portfolios sorted on short conviction are different from portfolios sorted on total short interest, i.e., the number of shares on loan as a percentage of shares outstanding. Specifically, on each day t, we sort stocks into five baskets using stock-level total short interest such that P_1 (P_5) contains stocks with the lowest (highest) total short interest. On day $t + 1$, we then construct portfolio returns by taking the equally-weighted average of dollar-denominated returns within each portfolio.[8] We present descriptive statistics of these return portfolios in Table A4 in the Internet Appendix and find that the return difference between P_1 and P_5, i.e., a long-short strategy that sells stocks with high short interest and buys stocks with low short interest, delivers an average excess return that is both economically and statistically indistinguishable from zero. To sum up, extracting information from the cross-sectional variation of short conviction is essentially different from exploiting the cross-sectional variation of total short interest, and these strategies display as little correlation as 21%. We now move to examine possible explanations for the performance of our conviction-based strategy.

4 Understanding the Best Short Strategy

The previous section documents that trading on short conviction, measured at the investor-stock level, generates an average excess return that is economically sizeable and statistically significant. The properties of this strategy, moreover, are different from those of conventional

[8]Recall that IHS Markit discloses data on total short interest three days after the actual data are collected. We thus introduce a time delay of three days such that total short interest is available at the time of the portfolio formation.

short-selling strategies that either sell all stocks with existing net short positions or condition on total short interest. While the main contribution of this paper is empirical and we do not have a formal theoretical model that rationalizes our results, we examine possible mechanisms that could drive our results.

4.1 Exposure to Traditional Risk Factors

We first examine whether the profitability of the *Best Short* strategy can be understood as a compensation for canonical risk by running Fama and French (1993) time-series regressions subsumed by the following specification

$$rx_t = \alpha + \beta' f_t + \varepsilon_t,$$

where rx_t is the daily excess returns on our conviction-based long-short strategy, f_t comprises daily excess returns on canonical traded risk factors (e.g., Fama and French, 1993; Carhart, 1997; Fama and French, 2015), and α is the risk-adjusted average excess return. Excess returns are denominated in US dollars and expressed in percentage per annum.[9]

Table 4 about here

The least-squares estimates of α and β associated with different combinations of risk factors are displayed in Table 4. We report t-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection in brackets. The column labeled CAPM tests the pricing ability of the market excess return but finds no statistical evidence that this is the case. The estimate of β is close to zero and is statistically insignificant (-0.006 with a t-statistic of -0.333) whereas the percentage per annum estimate of α is economically large and statistically significant (approximately 8.04 with a t-statistic larger than 2.6). The

[9]We use the same risk factors employed for the exercise presented in Figure 4.

next two columns FM3 and FM4 verify the pricing ability of the traditional Fama and French (1993) three-factor model and Carhart (1997) four-factor model, respectively. While there is some weak evidence that our conviction-based strategy is negatively correlated with the SMB factor, the percentage per annum estimates of α remain both qualitatively and quantitatively unaltered. The column FM5 presents the estimates for the more recent Fama and French (2015) five-factor model, which becomes a six-factor model in the last column FM6 by adding the momentum factor. Despite expanding the set of factors, we find no evidence that the *Best Short* strategy can be rationalized as compensation for exposure to equity risk. In particular, while the negative correlation with the SMB factor becomes statistically significant at the 5% level, the percentage per annum estimates of α revolves around 8.8 with a t-statistic slightly below 3, thus remaining economically large and highly statistically significant. This empirical evidence is further corroborated by the fact that the goodness of fit is rather poor as the adjusted R^2 turns out to be far below 1%.[10]

Figure 5 about here

Finally, we use all conviction-based portfolios as test assets, run time-series regressions against all equity factors, and plot the estimates of α in Figure 5. The first portfolio is an equally-weighted portfolio that buys stocks with the lowest short conviction whereas the last portfolio is an equally-weighted portfolio that buys stocks with the highest short conviction. The *Best Short* strategy would then sell the high-conviction portfolio and buy the low-conviction one. After controlling for all risk factors, the low-conviction portfolio generates a positive risk-adjusted excess return of about 2% per annum with a t-statistic of 0.87 whereas the high-conviction portfolio delivers a negative risk-adjusted excess return of −6.8% per annum with an absolute t-statistic larger than 2.5. The risk-adjusted performance

[10]We also run Fama and French (1993) time-series regressions using the *Naïve Short* strategy as a test asset and present the least-squares estimates of α and β in Table A5 of the Internet Appendix. We find that the risk-adjusted excess return is economically small and statistically insignificant after controlling for equity risk exposure.

of the *Best Short* strategy is thus driven by the high-conviction portfolio as opposed by the low-conviction portfolio, consistent with our hypothesis that short conviction may capture forward-looking market's expectations about asset valuations of highly specialized funds.[11]

To sum up, we find that traditional risk factors display a significant explanatory power for excess returns to a short-only strategy. In contrast, they fail to rationalize excess returns to a long-short strategy that exploits net short positions at the investor-stock level. Section 5 will describe several additional exercises and show that our results are robust to sorting on a volatility-adjusted measure of conviction, forming value-weighted portfolios, and accounting for trading costs. We now turn to investigate alternative explanations to rationalize our findings.

4.2 Market Frictions in the Securities Lending Market

Due to the decentralized nature of the securities lending market, a short sale is generally completed over-the-counter and visible only to the parties directly involved in the transaction. This aspect of the securities lending market then begs the question of whether the profitability of our short conviction strategy is related to market frictions or other risks that may be associated with holding short positions. The recent literature, for example, has investigated the role of uncertainty about future lending conditions, search costs resulting from market opacity, leverage constraints, and scarcity of lendable shares (e.g., Chen, Hong, and Stein, 2002; Nagel, 2005; Kolasinski, Reed, and Ringgenberg, 2013; He, Kelly, and Manela, 2017; Engelberg, Reed, and Ringgenberg, 2018).

[11] Figure A3 in the Internet Appendix uses net short positions disclosed by other investors (i.e., Asset Managers, Banks, Corporate Firms, Private Equity Funds, and Pension Funds) and uncovers no statistically significant risk-adjusted excess returns between high-conviction and low-conviction stocks.

4.2.1 Uncertainty about Lending Fees and Search Frictions

As the first source of market frictions, we examine whether uncertainty about future stock lending fees may deter investors today from shorting a particular stock irrespective of their beliefs about the stock fundamentals. Also, stock loan contracts are typically subject to a recall clause that allows lenders to recall borrowed stocks at any time, thus forcing short-sellers either to close their short positions or rebuild them at a possibly higher borrowing fee. This impediment to short-selling activity, often labeled short-selling risk or recall risk, finds its theoretical root in D'Avolio (2002), who develops an equilibrium model for the lending market and shows that a short seller is concerned not only with the size but also with the variance of borrowing fees. Engelberg, Reed, and Ringgenberg (2018) build on this work and show that a suitable measure of short-selling risk based on the variance of borrowing fees affects the cross-section of stock returns, and stocks with higher sensitivity to short-selling risk are characterized by lower returns, less short selling, and less price efficiency.[12] Muravyev, Pearson, and Pollet (2020) further show that expected changes in borrowing fees can be quantified from option prices using the implied volatility skew (or implied volatility spread).

The variance of borrowing fees has been also associated with search friction between borrowers and lenders in the equity lending market. Search frictions result from market opacity and imply that short-sellers must first identify security brokers that are willing to lend stocks and then bargain over the lending fee. In this context, Kolasinski, Reed, and Ringgenberg (2013) provide empirical evidence that the dispersion of borrowing fees widens when the average loan fee moves from moderate to high levels, consistent with the hypothesis formulated by Duffie, Garleanu, and Pedersen (2002) that search frictions impact short-selling costs.

Following this literature, we measure unexpected changes in future lending conditions (or

[12] Drechsler and Drechsler (2016) show that borrowing fees are highly informative about the cross-section of stock returns and short-sellers concentrate their positions on a few shocks with high borrowing fees. The resulting excess return is then interpreted as a reward for shorting stocks whose idiosyncratic risk cannot be diversified.

search frictions) using either daily changes in the cross-sectional variance of borrowing fees or daily changes in the stock market implied volatility skew and refer to them as short-selling risk (SSR). The former is based on stock-level indicative borrowing fees from IHS Markit, whereas the latter is simply the implied volatility difference between a one-month 10-delta put option and an at-the-money option on the EURO STOXX 50 index extracted from Bloomberg. We then specify a linear pricing kernel where the conviction portfolios are the test assets, and MKT and SSR act as pricing factors. This specification, in turn, implies a beta pricing model $E[rx_i] = \lambda'\beta_i$, where expected excess return rx_i on each portfolio i depends on factor prices λ and risk quantities β_i.

Table 5 about here

Panel A of Table 5 presents estimates of λ implied from a first-stage GMM with standard errors based on Newey and West (1987) and Andrews (1991), the cross-sectional R^2, and the Hansen and Jagannathan (1997) distance measure for the null hypothesis of zero normalized maximum pricing error.[13] We also report results from the two-pass Fama-MacBeth procedure with Shanken (1992) standard errors together with χ^2 test statistic for the null hypothesis of zero pricing errors. The estimates of λ_{SSR}, i.e., the factor price of risk associated with short-selling risk, turn out to be statistically insignificant irrespective of the proxy for unexpected changes in lending conditions. Panel B reports the least-squares estimates of β but finds no evidence of a significant relationship between short-selling risk and conviction-based portfolios. In economic terms, the short-selling risk premium predicted by the model, i.e., $\lambda_{SSR} \times (\beta_{1,SSR} - \beta_{5,SSR})$, amounts to $0.937 \times (2.800 + 1.059) \approx 3.62\%$ per annum when using the daily changes in the variance of borrowing fees, and to to $0.608 \times (-3.224 + 6.296) \approx 1.87\%$ when using the daily changes in the stock market implied volatility skew. Overall, the performance of the *Best Short* cannot be rationalized

[13]The factor means and covariance matrix μ and Σ are jointly estimated with the factor loadings b by adding the corresponding moment conditions to those implied by the Euler equation. We then compute the factor prices as $\lambda = \Sigma b$ and the corresponding standard errors via delta method (e.g. Cochrane, 2005).

as compensation for binding short sale constraints in the equity lending markets.[14]

4.2.2 Leverage Constraints

The profitability of our conviction strategy could also reflect leverage constraints that ultimately prevent short sellers from monetizing the information revealed through data disclosure. As highlighted by Shleifer and Vishny (1997) in their seminal paper, while textbook arbitrage requires no capital and involves no risk, real-world arbitrage strategies are risky and arbitrageurs need access to a substantial amount of capital to execute trades and cover losses. Also, arbitrage is not frictionless as arbitrageurs have limited access to capital and this constraint affects their ability to exploit price discrepancies in financial markets (Gromb and Vayanos, 2018). In this context, short-sellers can be viewed as specialized arbitrageurs that make risky bets but face financial constraints that can arise from the amount of leverage extended to them by intermediaries. As shown by recent literature, intermediaries act as marginal investors in many asset classes and their marginal value of wealth can explain average returns on a broad cross-section of securities (e.g., He and Krishnamurthy, 2013; He, Kelly, and Manela, 2017). When intermediaries experience a negative shock to their equity capital ratio, their risk-bearing capacity declines, and the marginal cost of leveraged positions increases. A trading strategy that relies on leverage may then be less appealing for arbitrageurs, thus leaving stock prices away from fundamentals for a protracted period of time. This argument may then explain why sorting on conviction would generate positive excess returns.

Table 6 about here

He, Kelly, and Manela (2017) use shocks to the equity capital ratio of primary dealers as a proxy for intermediary capital risk and explain the cross-sectional differences in average

[14] We uncover qualitatively similar results when using daily changes in the stock market implied volatility spread on the EURO STOXX 50 index (i.e., implied volatility difference between one-month 10-delta put and call options) and implied volatility skew/spread on the FTSE 100 index.

returns of several asset classes. We build on their work and test the relationship between leverage constraints and the *Best Short* strategy using a linear asset pricing framework that includes MKT and the (non-traded) intermediary capital risk (ICR) of He, Kelly, and Manela (2017) as pricing factors. We report the estimates of the factor prices λ and risk quantities β_i, using the methodology presented in the previous section, on the left-hand side of Table 6. Panel A reveals that λ_{ICR}, i.e., the factor price of risk associated with intermediary capital risk, is not only statistically insignificant but also economically small. Panel B shows the least-squares estimates of β_i, which are all positive and statistically significant. However, the spread between the corner portfolios is positive, meaning a negative predicted intermediary capital risk premium of -0.19% per annum. This evidence suggests that leverage constraints cannot explain the *Best Short* strategy.

4.2.3 Scarcity of Lendable Shares

Short-sale constraints may arise when securities are hard to borrow in lending market because of a limited supply. As pointed out by Chen, Hong, and Stein (2002), scarcity of lendable shares affects the participation of stock market participants with pessimistic opinions, thus having a significant impact on equilibrium prices and expected returns (e.g., Miller, 1977).[15]

In this section, we test whether Best Short's returns are related to short-sale constraints stemming from a tight supply of lendable shares. We measure the loan supply for each stock in our sample using the number of shares actively available for lending (provided by IHS Markit) divided by the total number of shares outstanding. We then quantify unexpected

[15]To quantify the supply of lendable shares, the authors use the breadth of ownership defined as the number of investors with long positions in a particular stock such that short-sale constraints are tight (relaxed) when few (many) investors have long positions. Nagel (2005), moreover, proposes a modified proxy that builds on the share of stocks owned by institutional investors and finds that loan supply is sparse, short selling is more expensive, and cross-sectional return predictability is more pronounced for stocks with low institutional ownership. Asquith, Pathak, and Ritter (2005) further argue that short-sale constraints occur when there is a strong demand to sell short coupled with a limited supply of shares to borrow. They find that stocks characterized by short-sale constraints, i.e., stocks with high short interest and low institutional ownership, have significantly lower abnormal returns than unconstrained stocks.

and undiversifiable shocks to loan supply (SLS) using daily changes in the cross-sectional variance of stock-level loan supply. Hence, we use a linear asset pricing framework that includes MKT and SLS as pricing factors. We report the estimates of the factor prices λ and risk quantities β_i, using the methodology presented in the previous section, on the right-hand side of in Table 6. The estimates of λ_{SLS} and β_i are both statistically insignificant, meaning that scarcity of lendable shares is unable to rationalize the large excess returns recorded the *Best Short* strategy.

FIGURE 6 ABOUT HERE

Finally, we present a simple event study in Figure 6 using a window that comprises 60 days before and 60 days after the portfolio formation. Over this window, we calculate the cumulative excess returns, the average borrowing fees, average supply of lendable shares, and average total short interest for all stocks grouped into the corner portfolios of the *Best Short* strategy. We only find some weak evidence that borrowing fees tend to increase for high conviction stocks and loan supply tends to decrease for low conviction stocks after the portfolio formation. Overall, this exercise confirms the quantitative results reported in Tables 5 and 6. To sum up, commonly used sources of market frictions in the securities lending market cannot fully explain the excess returns of the Best Short. In the next section, we assess whether a parsimonious measure of market frictions, based on price delays with respect to aggregate market returns, can rationalize our findings.

4.3 Short Conviction and Price Delay

The predictability of short conviction in the cross-section of stock returns may collectively result from a variety of market frictions that limit the ability of the stock market to incorporate information into asset prices. To evaluate whether market frictions have a significant impact on short conviction, we examine the link between short conviction and the speed of information diffusion in the spirit of Hou and Moskowitz (2005), Boehmer and Wu (2013), and Engelberg, Reed, and Ringgenberg (2018). The latter is proxied by the average delay with which a stock price responds to information and can be thought of as a measure of price delay that parsimoniously captures the impact of several potential frictions that range from lack of liquidity to incomplete information on the price process of a stock.

As pointed out by Hou and Moskowitz (2005), the relation between market frictions and the speed of information diffusion is consistent with theories of investor recognition and limited stock market participation (e.g., Merton, 1987; Hirshleifer, 2015; Shapiro, 2002) or theories of neglected firms (e.g., Arbel, Carvell, and Strebel, 1983). In this context, Hong and Stein (1999), for example, develop a model of gradual information diffusion in which news-watchers observe some private information but fail to extract other news-watchers' information from prices, while Peng (2004) shows that information capacity constraints can cause a delay in asset price responses to the news. Price delay may also arise from lack of liquidity resulting from several sources (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). In their paper, Hou and Moskowitz (2005) find that frictions associated with investor recognition rather than traditional measures of liquidity price impact are more consistent with the data on firms experiencing large delays in their price formation process.

To verify whether short conviction masks market frictions, we follow Hou and Moskowitz (2005) and construct two annual measures of relative price efficiency that capture the speed of price adjustment to market-wide information. Specifically, in June of each year t, we first run for each stock j the following regression

$$r_{j,\tau} = \alpha_j + \beta_j r_{m,\tau} + \sum_{\ell=1}^{4} \delta_{j,\ell}\, r_{m,\tau-\ell} + \epsilon_{j,\tau} \tag{8}$$

where $r_{j,\tau}$ denotes the Wednesday-to-Wednesday weekly returns on stock j between July of year $t-1$ and June of year t, $r_{m,\tau}$ refers to the corresponding weekly returns on the market between July of year $t-1$ and June of year t, and ℓ denotes the number of lags on the market return. If stock j reacts immediately to market news, we should then obtain a statistically significant estimate of β coupled with statistically insignificant estimates of $\delta_{j,\ell}$. In contrast, if stock j responds to market news with some lags, some estimates of $\delta_{j,\ell}$ should be statistically different from zero.

For each firm j, we then measure price delay in June of year t using the coefficient estimates of Equation (8). The first measure of price delay $D1$ captures how much of the current return variation is explained by the lagged market returns and is defined as

$$D1_{j,t} = 1 - \frac{R_r^2}{R_u^2}, \tag{9}$$

where R_u^2 is the unrestricted R^2 from Equation (8) and R_r^2 is the restricted R^2 obtained by running a regression that sets all coefficients on the lagged market returns equal to zero. $D1$ is closer to one when $R_u^2 > R_r^2$ and more return variation is captured by the lagged returns. In contrast, $D1$ is closer to zero when the ratio between R_r^2 and R_u^2 approaches one, and the relation between the asset return at time t and the lagged market returns is negligible. A larger price delay $D1$ implies a less efficient stock price, meaning that it takes longer for a given stock to incorporate market-wide information. The second measure of price delay $D2$ further differentiates between shorter and longer lags by capturing the magnitude of the lagged coefficients relative to the magnitude of all coefficients as

$$D2_{j,t} = \frac{\sum_{\ell=1}^{4} |\delta_{j,\ell}|}{|\beta_j| + \sum_{\ell=1}^{4} |\delta_{j,\ell}|}. \tag{10}$$

$D2$ quantifies the fraction of a stock's price movement that can be attributed to a delayed reaction to the market. A larger $D2$ implies a stronger price delay or a less efficient stock price.

Finally, we examine the relationship between price delay and short conviction by running panel regressions similar to Saffi and Sigurdsson (2011) and Engelberg, Reed, and Ringgenberg (2018) as

$$D_{j,t} = \alpha + \beta C_{j,t} + \gamma' X_{j,t} + \alpha_t + \epsilon_j \tag{11}$$

where $D_{j,t}$ is a measure of price delay in June of year t for stock j (i.e., either $D1$ or $D2$), $C_{j,t}$ is the average *Short Conviction* on stock j between July of year $t-1$ and June of year t, $X_{j,t}$ are stock-specific control variables measured daily and then averaged between July of year $t-1$ and June of year t, and α_t denotes year fixed effects. $X_{j,t}$ includes *Loan Supply* defined as the number of shares actively available for lending as a fraction of total shares outstanding, *Short-Selling Risk* as the variance of borrowing fees based on a one-year window, *Log Market Cap* as the market value of a company in logs, *Price-to-Book* as the market value of a company relative to its book value, *Volatility* as the exponentially weighted moving average volatility with a two-month half-life, *Bid-Ask Spread* as the volume-weighted average of intraday bid-ask spreads over a five trading day window, *Amihud Illiquidity* as the absolute return divided by the dollar volume (scaled by 10^5), *Short Interest* as the number of shares on loan as a percentage of shares outstanding, *Borrowing Fee* as the cost of borrowing a share, *Institutional Ownership* as the fraction of shares outstanding owned by institutional investors (scaled by 100), *Analyst Coverage* as the number of analysts covering a stock(scaled by 100), *Leverage* as the (short- and long-term) debt of a company relative to its book value, *Profitability* as the operating income before depreciation relative to total assets, and *Skewness* as the sample skewness based on a three-month window.

Table 7 about here

Table 7 reports panel regression estimates associated with Equation (11) with standard errors clustered by the firm and year dimension (not reported to save space). We include year fixed effects in all specifications to control for possible unobserved factors changing each year but common across firms. In Panel A, we uncover a positive and statistically significant correlation between short conviction and price delay as measured by $D1$. In specification (1), for example, the coefficient on *Short Conviction* is 0.018 and is statistically significant at the 5% level. In economic terms, a one-standard-deviation increase in *Short Conviction* is associated with a 3.73% increase in price delay (or decline in price efficiency) relative to its unconditional mean.[16] The negative coefficient on *Loan Supply*, albeit insignificant, confirms the findings of Saffi and Sigurdsson (2011) that price efficiency improves with a higher supply of lendable shares. In specification (2), we add *Short-Selling Risk*, *Log Market Cap*, *Price-to-Book*, and *Volatility* as in Engelberg, Reed, and Ringgenberg (2018) and the coefficient on *Short Conviction* remains statistically significant at the 10% level. In specification (4), we find that β remains statistically significant and economically sizeable even after controlling, among others, for firm characteristics, liquidity measures, and investor attention variables akin to Hou and Moskowitz (2005). We find that price delay responds to measures of liquidity as well as to frictions associated with investor recognition such as institutional ownership and analyst coverage.

In Panel B, we employ $D2$ as a measure of price delay but the correlation between price delay and short conviction turns out to be statistically insignificant when controlling for frictions in the securities lending market, firm characteristics, liquidity measures, and investor attention variables. In specification (8), for example, the estimate of β is 0.012 with a standard error (unreported) of 0.008. In economic terms, a one-standard-deviation increase in *Short Conviction* is associated with a 1.37% increase in price delay (or decline in price efficiency) relative to its unconditional mean. Taken together, these results imply a weak relationship between high-conviction stocks and price inefficiency. They also suggest that information arising from short conviction is not subsumed by firm characteristics, liquidity, supply and demand of lendable shares, short-selling risk, or investor attention. This would be in line with our hypothesis that short conviction aggregates forward-looking investors' expectations about asset valuations.

Table 8 about here

In Table 8, we study the short conviction portfolios further and present the average values of stock characteristics associated with these portfolios. On each trading day, we first group

[16] The economic value is computed as $(0.018 \times 0.545)/0.263 \approx 3.73\%$, where 0.545 is the standard deviation of *Short Conviction* and 0.263 is the mean of $D1$.

stocks into five portfolios using short conviction as in Table 3. Within each portfolio, we then compute the average value of the corresponding firm characteristics, risk measures, liquidity measures, securities lending market variables, and investor attention variables. Finally, we present the average value of these characteristics across the entire sample. Recall that P_5 comprises stocks with high short conviction and P_1 stocks with low short conviction. Panel A provides results for firm characteristics and shows that stocks in P_5 have lower leverage and higher market cap than stocks in P_1. No pattern emerges for price-to-book ratio and profitability. Panel B focuses on risk measures such as skewness and short-selling risk. The former can be seen as a measure of short squeezes, which lead to sudden and large increases in stock price whereas the latter proxies for uncertainty about future lending conditions. We find that stocks in P_5 have a lower skewness but slightly higher short-selling risk than stocks in P_1. Volatility is instead evenly distributed across the different buckets. Panel C displays results for liquidity measures and shows that stocks in P_5 have a lower bid-ask spread and a lower Amihud Illiquidity than stocks in P_1. In Panel D, we record results for securities lending market variables and find that stocks in P_5 have slightly higher borrowing fees, lower supply, and substantially higher total short interest than stocks in P_1. In Panel E, finally, we show variables that recent literature has associated with investor recognition. While there is no pattern in terms of institutional ownership, we show that stocks in P_5 have higher analyst coverage than stocks in P_1. This evidence largely corroborates our earlier findings on short conviction.

5 Robustness and Extensions

In this section, we consider additional robustness checks. In particular, we test whether the strategy could work with a lower rebalancing frequency or delays in the information.

5.1 Impact of Transaction Costs

A daily rebalanced strategy can be transaction-intensive and, thus, expensive to run in terms of transaction costs. We consider these concerns and compute returns net of transaction costs that include bid-ask spreads collected from Bloomberg and borrowing fees obtained from IHS Markit. We employ a setting in which bid-ask spreads are deducted from returns whenever a stock enters and/or exits one of the corner portfolios, effectively buying at the ask price and selling at the bid price. Regarding the impact of borrowing fees, we assume that the stock borrower provides full cash collateral, pays a borrowing fee, and receives from the stock lender a rebate that partly offsets her borrowing fee. Put differently, the stock loan is an open-term loan that is renegotiated every day such that our investor pays a fee to the lender and the lender pays the overnight riskless rate to the borrower on her cash collateral as in (e.g., Saffi and Sigurdsson, 2011). To minimize the impact of transaction costs and reduce portfolio turnover, fund managers routinely use rebalancing threshold rules that prevent a strategy reweighing by small amounts (e.g., Zilbering, Jaconetti, and Kinniry, 2015). We follow this practice and rebalance our strategy whenever the incremental portfolio weight in absolute terms on a single stock is at least 5% or the overall change in all portfolio weights in absolute terms is at least 10%. As an example, suppose that the current weight of security in a portfolio is 10% and the rebalancing threshold is 5%. If the targeted weight is 12%, the security will not be reweighted since its weight has only drifted by less than the rebalancing threshold.

Table 9 about here

Table 9 displays results for the *Best Short* strategy subject to rebalancing threshold before and after accounting for transaction costs. In Panel A, we present descriptive statistics and find that the average excess return is about 9.95% (with a t-statistic of 3.15) per annum before transaction costs, 7.60% per annum (with a t-statistic of 2.38) after accounting for bid-ask spreads, and 6.00% (with a t-statistic of 1.87) per annum after accounting for both bid-ask spreads and borrowing fees. In Panel B, we run time-series regressions using the set of traded risk factors described in Section 4.1 and present the percentage per annum estimates of α. Our results remain qualitatively similar to those reported in Table 4 since estimates of α remain economically large and statistically significant. Using the six-factor model, for example, the estimate of α is about 8.7% per annum after accounting for bid-ask spreads and larger than 7% per annum after deducting both for bid-ask spreads and borrowing fees.[17]

Table 10 about here

An alternative approach to minimize the impact of transaction costs would be to rebalance the strategy monthly while recording returns daily. Put differently, the composition of the conviction-based portfolios is refreshed at the of each month and the investor pays the transaction costs arising from the bid-ask spreads once per month. The borrowing fees, in contrast, will be charged daily since stock loans are open-term loans that are renegotiated daily. Panel A of Table 10 summarizes the performance of a monthly-rebalanced *Best Short* strategy before and after accounting for transaction costs. The bid-ask spreads and borrowing fees bite approximately 35% of the overall performance and the average excess return drops from 8.83% per annum (before transaction costs) to 5.75% per annum (after transaction costs). The latter figure, however, remains economically sizeable and statistically significant. In Panel B of Table 10, we run time-series regressions using the set of traded risk factors described in Section 4.1 and present the percentage per annum estimates of α. Our results remain qualitatively similar to those reported in Table 4 since estimates of α remain economically large and statistically significant. Using the six-factor model, for example, the estimate of α is about 6.65% per annum after accounting for transaction costs. In summary,

[17]Before accounting for transaction costs, the *Best Short* with rebalancing thresholds performs slightly better than the corresponding one without rebalancing thresholds. This happens as thresholds further reduce trading noise that is likely to arise from an unbalanced panel of stocks. In Figure A4 in the Internet Appendix, we plot the number of long and short positions for both strategies and show that they track each other fairly closely over time, meaning that, they have a nearly identical composition of stocks.

while transaction costs erode part of its performance, our conviction-based strategy seems to maintain its appealing risk-return trade-off.

5.2 Value-Weighted Portfolios

The *Best Short* is constructed as a long-short strategy of equally-weighted portfolios. Therefore, one concern is whether our results are driven by exposure to small or illiquid stocks. Specifically, the concern about small stocks is twofold: first, small stocks tend to be less liquid - thus, transaction costs could be large; and second, even if abnormal returns can be captured by trading small stocks, this anomaly would only represent a small portion of the overall market and would not be scalable due to capacity constraints. The standard way of addressing this issue is to form value-weighted portfolios in which each stock is weighted by its market capitalization.[18] We replicate our key results using value-weighted portfolios and report the evidence in the Internet Appendix. Table A1 presents the summary statistics of value-weighted conviction portfolios and reports an average excess return of 5.90% per annum with an annualized Sharpe ratio of 0.73 for the *Best Short* strategy. Moreover, Figure A5 plots estimates of α obtained by regressing the conviction-based portfolios against all equity risk factors described in Section 4.1. We find that the low-conviction portfolio generates a positive risk-adjusted excess return of about 2.6% per annum with a t-statistic of 1.87 whereas the high-conviction portfolio delivers a negative risk-adjusted excess return of about -4.6% per annum with an absolute t-statistic larger of 1.63. The resulting long-short basket delivers a risk-adjusted excess return larger than 7% per annum with a t-statistic of 2.11.

[18] A value-weighted strategy is unlikely to be implemented by an investor with short positions. This weighting scheme mechanically increases the exposure to stocks with a positive market trend, thus increasing losses and vulnerability to margin calls.

5.3 Risk-Adjusted Short Conviction

In this section, we verify the robustness of findings using a measure of short conviction adjusted for risk. This measure would then reflect investors' beliefs for expected returns rather than information ratio as shown by Equation (5). To illustrate this point, consider two stocks, H and L, with volatility ν_H and ν_L such that $\nu_H > \mu_L$ and assume that an investor holds these stocks with equal weights $w_H = w_L = w$. Under our current definition, the investor exhibits equal conviction on these two stocks, that is $C_H = C_L = w$. However, since stock H is riskier than stock L and the investor holds equal dollar amounts on these stocks, one may argue that conviction on stock H is actually higher than conviction on L. On the basis of these considerations, we infer investors' beliefs for expected returns by altering Equation (6) as follows

$$C_{ij,t} = \nu_{j,t}^2 \kappa_{j,t} V_{ij,t}, \tag{12}$$

where $\nu_{j,t}$ is the volatility of asset j on the day t using an exponentially weighted moving average with a half-life of two months. We then aggregate across all investors and obtain an aggregate *risk-adjusted conviction* using Equation (7). Table A2 in the Internet Appendix presents the summary statistics of equally-weighted portfolios sorted on risk-adjusted conviction portfolios. The average excess return for the *Best Short* strategy is about 10.9% per annum with an annualized Sharpe ratio of 1.10. Figure A6 plots estimates of α and shows that the low-conviction portfolio generates a positive risk-adjusted excess return of about 2.5% per annum with t-statistic of 1.31 whereas the high-conviction portfolio delivers a negative risk-adjusted excess return of about -8.1% per annum with an absolute t-statistic of 2.18. The resulting long-short basket delivers a risk-adjusted excess return larger than 10% per annum with a t-statistic of 2.76. These results confirm the robustness of our earlier findings since they imply that compared to the baseline results in Table 3, the *Best Short* strategy based on risk-adjusted conviction exhibits the same statistical significance and a spread portfolio mean return that is around 2 percent higher.

5.4 Other Exercises

We also examine the country-level exposure of our *Best Short*. Figure A7 in the Internet Appendix displays the holdings of the long and short portfolios underlying our strategy and uncovers that their composition exhibits significant time and country variation.

6 Conclusion

Recently introduced regulation on short selling in Europe requires investors to publicly disclose their short positions (above the threshold of 0.5% of issued share capital) on stocks as soon as the next trading day after the position has been established. We use the public disclosure data to infer investors' level of short conviction in each of their publicly disclosed short positions and show that a long-short strategy based on conviction delivers large risk-adjusted returns. After accounting for transaction costs, the strategy delivers a risk-adjusted excess return of 7.11% per annum that translates into an annualized Sharpe ratio of 0.79. Our results cannot be explained by traditional risk exposure or market frictions. We contribute to the public policy debate (e.g,, Frank, Poterba, Shackelford, and Shoven (2004)) about the costs and benefits of position disclosure since the profitability of our short position based Best Short strateg raises the prospect of copycat funds that may erode the market share of existing hedge funds.

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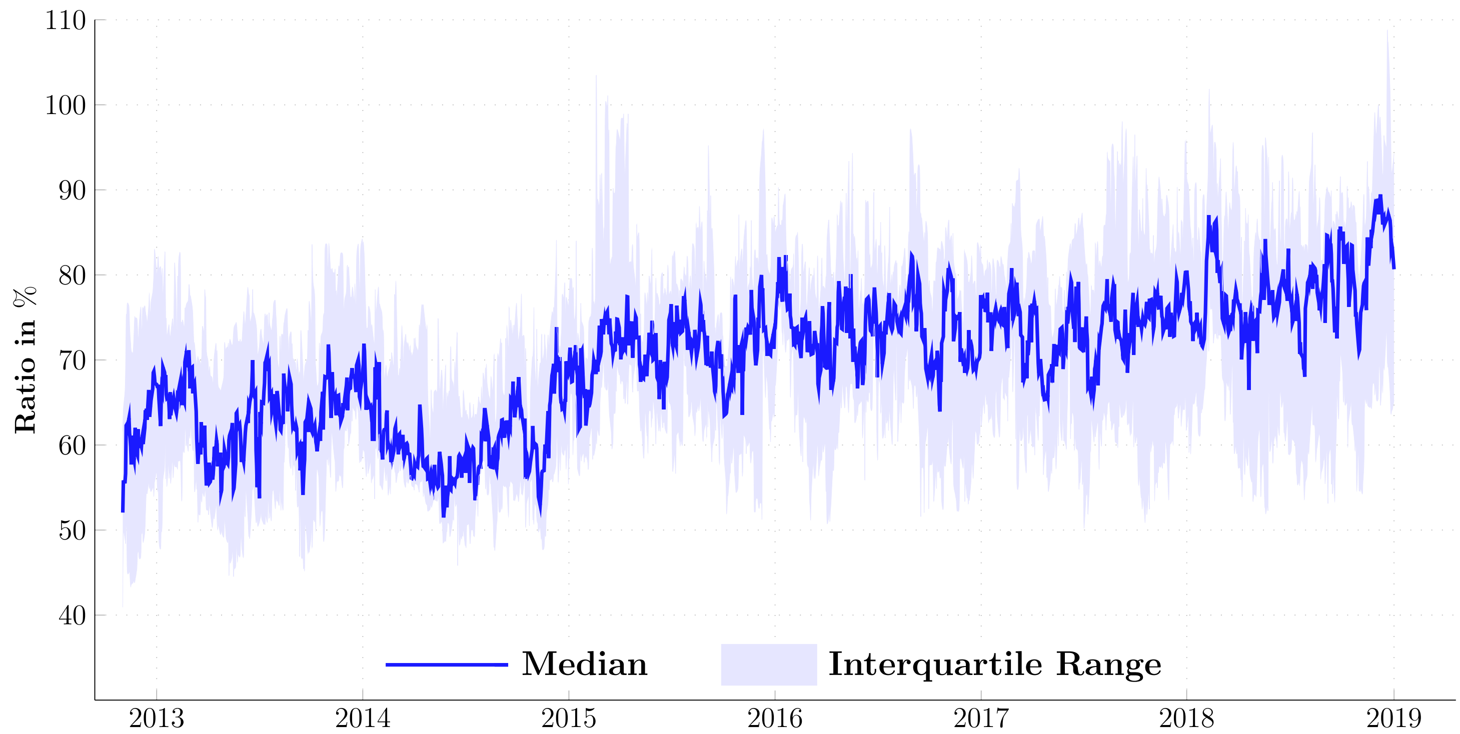

Figure 1. Disclosed Short Positions over Short Interest

This figure compares publicly disclosed net short positions and short interest for major European stock markets. For each security in our sample, we first construct the daily ratio between publicly disclosed net short positions and short interest and then plot the median value and the interquartile range across all countries. Net short positions exceeding 0.5% of the issued share capital of the reference company are publicly disclosed at the investor level under the European Union Short Selling Regulation and calculated by summing up long, short, and delta-adjusted positions in derivatives on each reference stock. Short interest is the percentage of total shares on loan and is collected from the securities lending desks of various market participants. The sample runs at daily frequency between November 2012 and December 2018 for 15 major European stock markets. Data are from Caretta and IHS Markit.

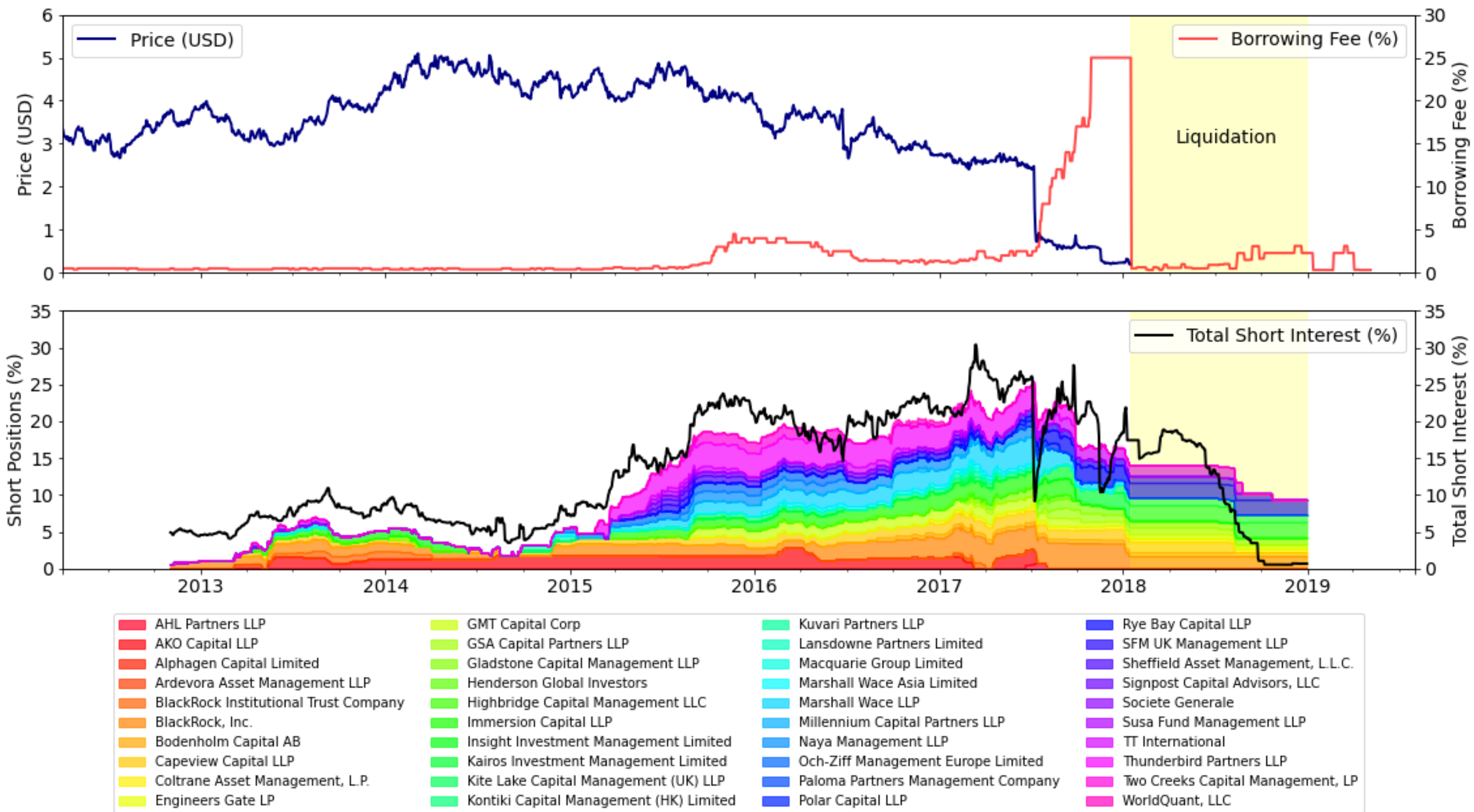

Figure 2. Example: Disclosed Short Positions on Carillion

This figure displays the short-selling activities on Carillion, a British construction and support services group that collapsed on January 15, 2018. The top panel plots the stock price in US dollars and the borrowing fee in percentage per annum. The bottom panel shows net short positions disclosed at the investor level and anonymous short interest, both as percentage of the issued share capital. Net short positions exceeding 0.5% of the issued share capital are publicly disclosed under the European Union Short Selling Regulation and combine long, short, and delta-adjusted positions in derivatives. Short interest and borrowing fee are from the securities lending desks of various market participants. The sample runs at daily frequency between November 2012 and December 2018. Data are from Bloomberg, Caretta, and IHS Markit.

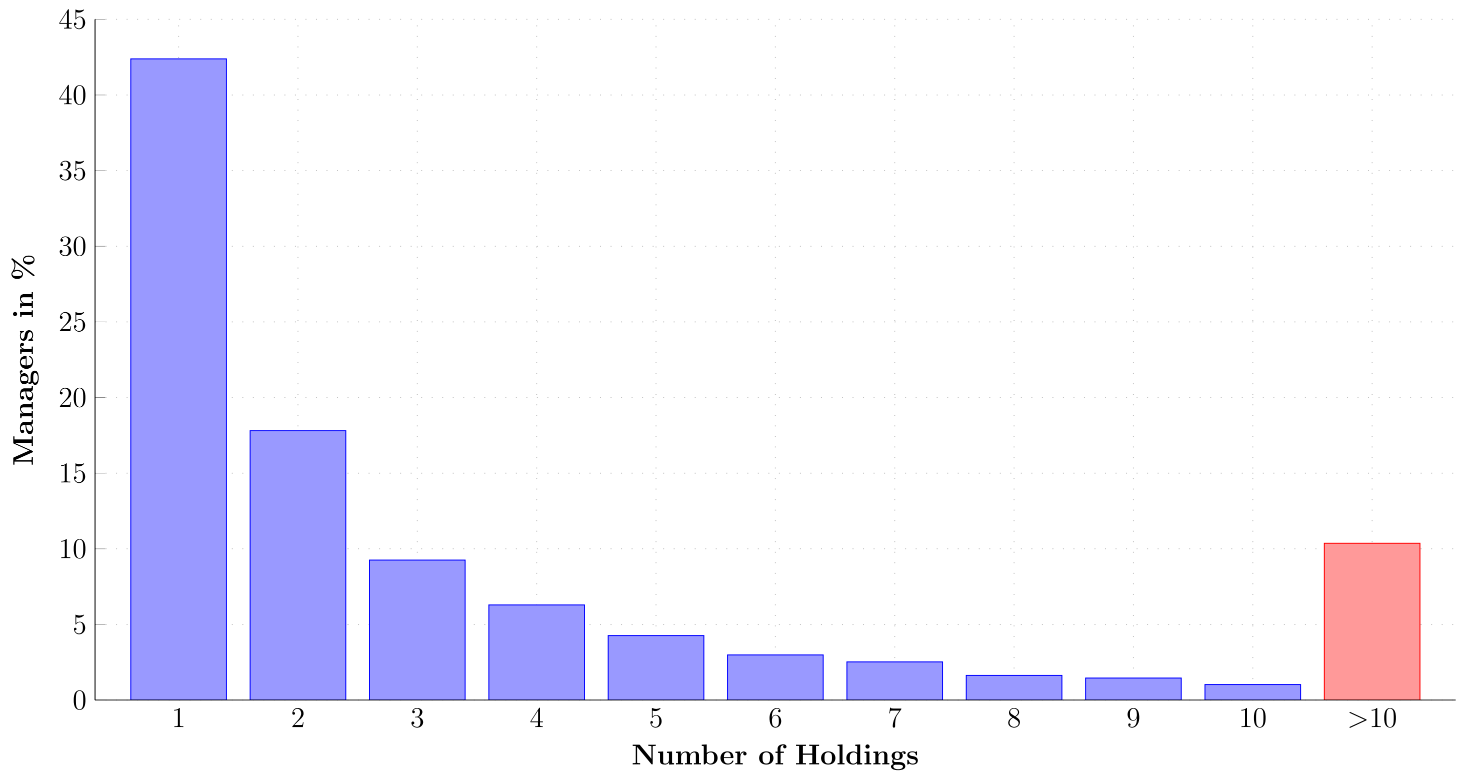

Figure 3. Number of Disclosed Holdings across Managers

This figure illustrates the number of unique security holdings disclosed per manager at each point in time. The sample runs at daily frequency between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Caretta.

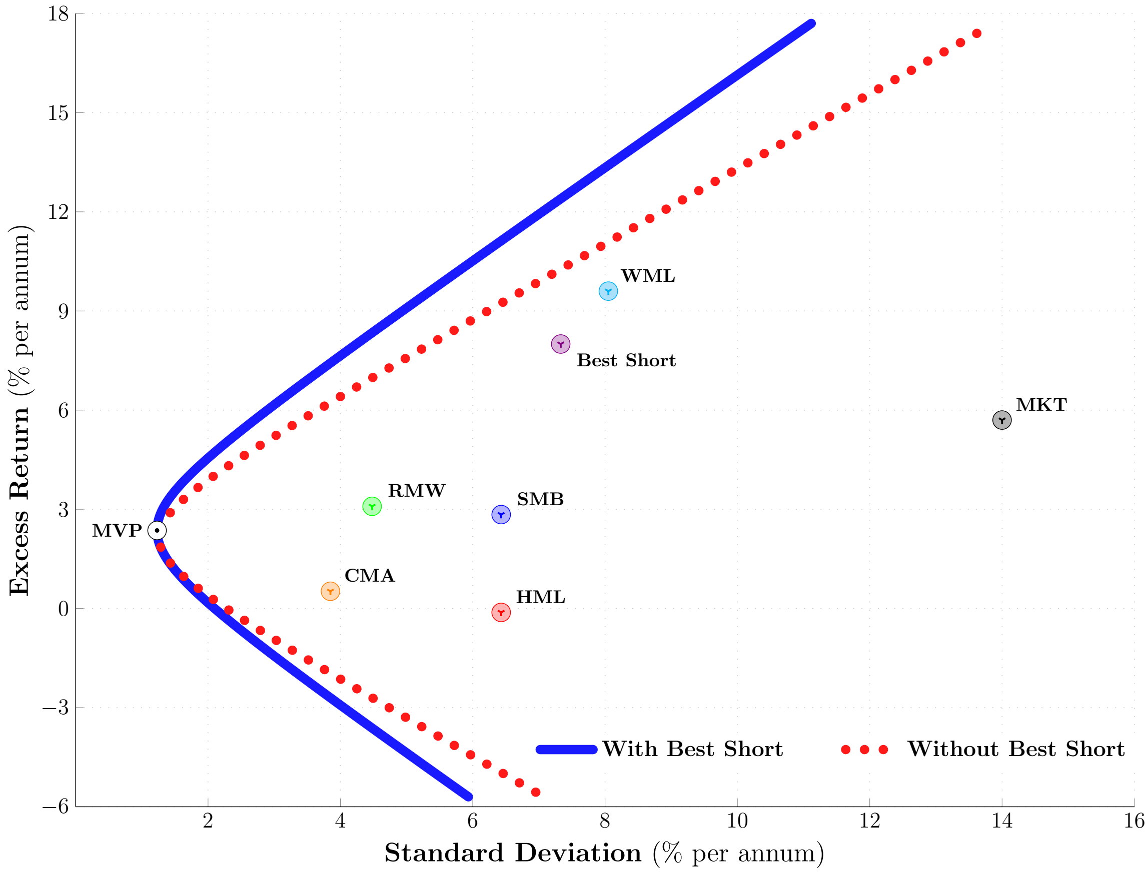

Figure 4. Mean-Variance Frontier

This figure displays the mean-variance frontier with (solid line) and without (dotted line) the *Best Short* to a menu of traditional equity strategies. The *Best Short* is long-short strategy that buys (sells) stocks with the lowest (highest) short conviction. The set of traditional strategies includes the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). MVP denotes the minimum volatility portfolio based on all strategies. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Short conviction is calculated using net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market that are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta. Daily equity factors for European stock markets are from Ken French's data library.

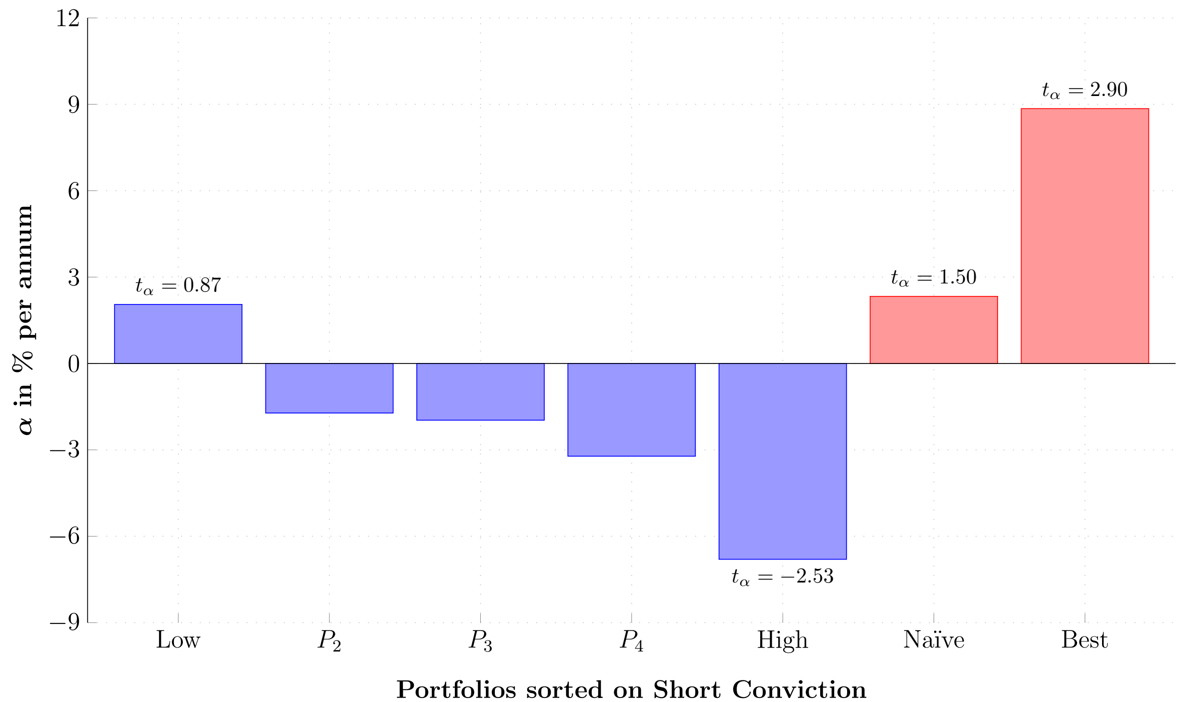

Figure 5. Portfolios Sorted on Short Conviction

This figure displays risk-adjusted excess returns (or alpha) of equity portfolios sorted on short-selling conviction constructed with publicly disclosed net short positions at the investor-stock level. Low (High) Conviction denotes an equally-weighted long portfolio that buys stocks with the lowest (highest) short-selling conviction. *Naïve Short* is a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* denotes a long-short strategy that sells the high-conviction portfolio and buys the low-conviction portfolio. Risk-adjusted excess returns are obtained using six traded factors, i.e., the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). t_α denotes the t-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. Returns are denominated in US dollars using daily spot exchange rates and expressed in percentage per annum. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta. Daily equity factors for European stock markets are from Ken French's data library.

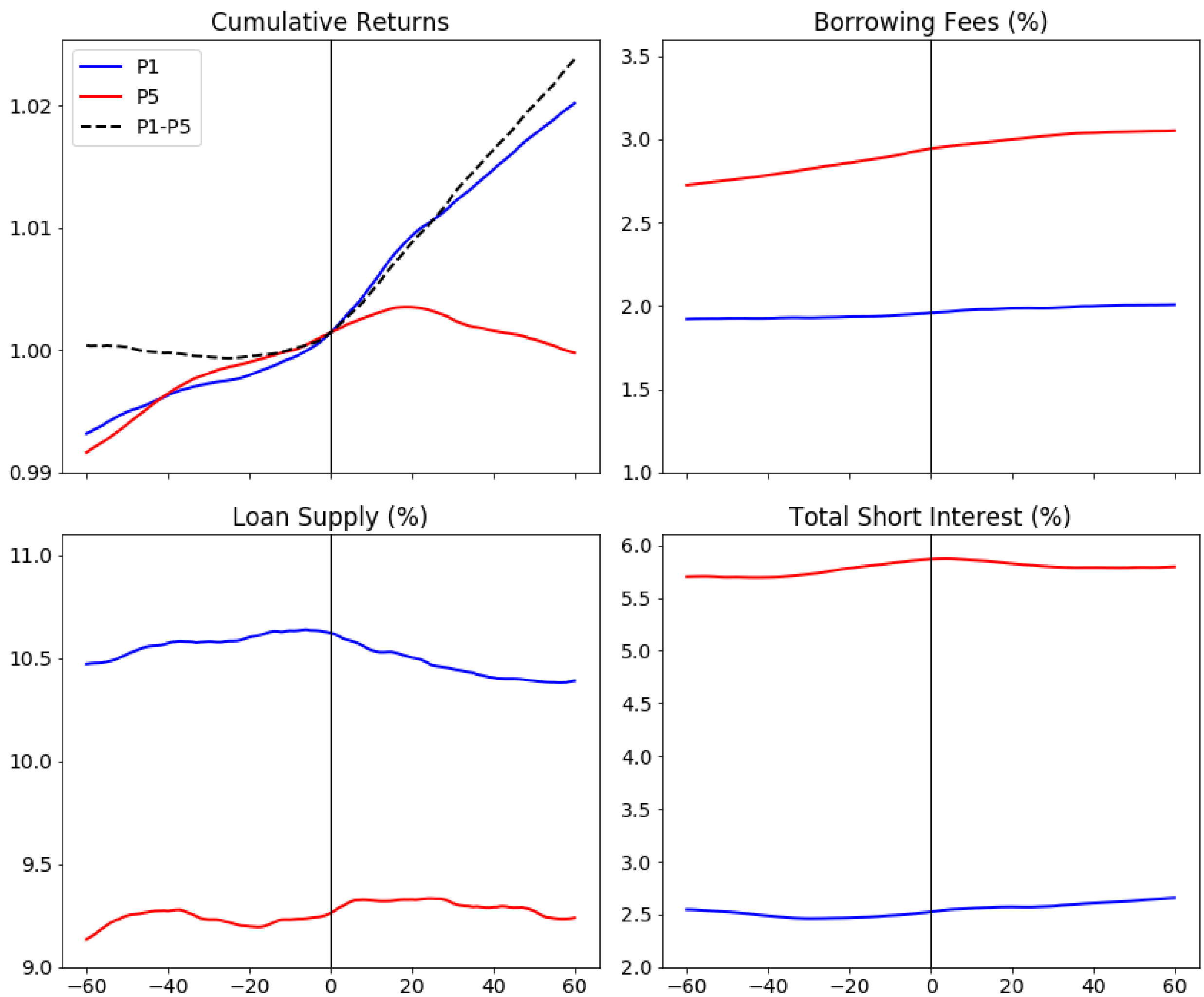

Figure 6. Best Short and Market Frictions: An Event Study

This figure presents the characteristics, i.e., cumulative returns, average borrowing fees, average loan supply, and average total short interest, in event time for the corner portfolios of the *Best Short* strategy. The exercise use a window of 60 days prior and 60 days after portfolio formation. *Best Short* denotes a long-short strategy that sells the high-conviction portfolio and buys the low-conviction portfolio. Returns are denominated in US dollars using daily spot exchange rates and expressed in percentage per annum. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg, Caretta, and IHS Markit.

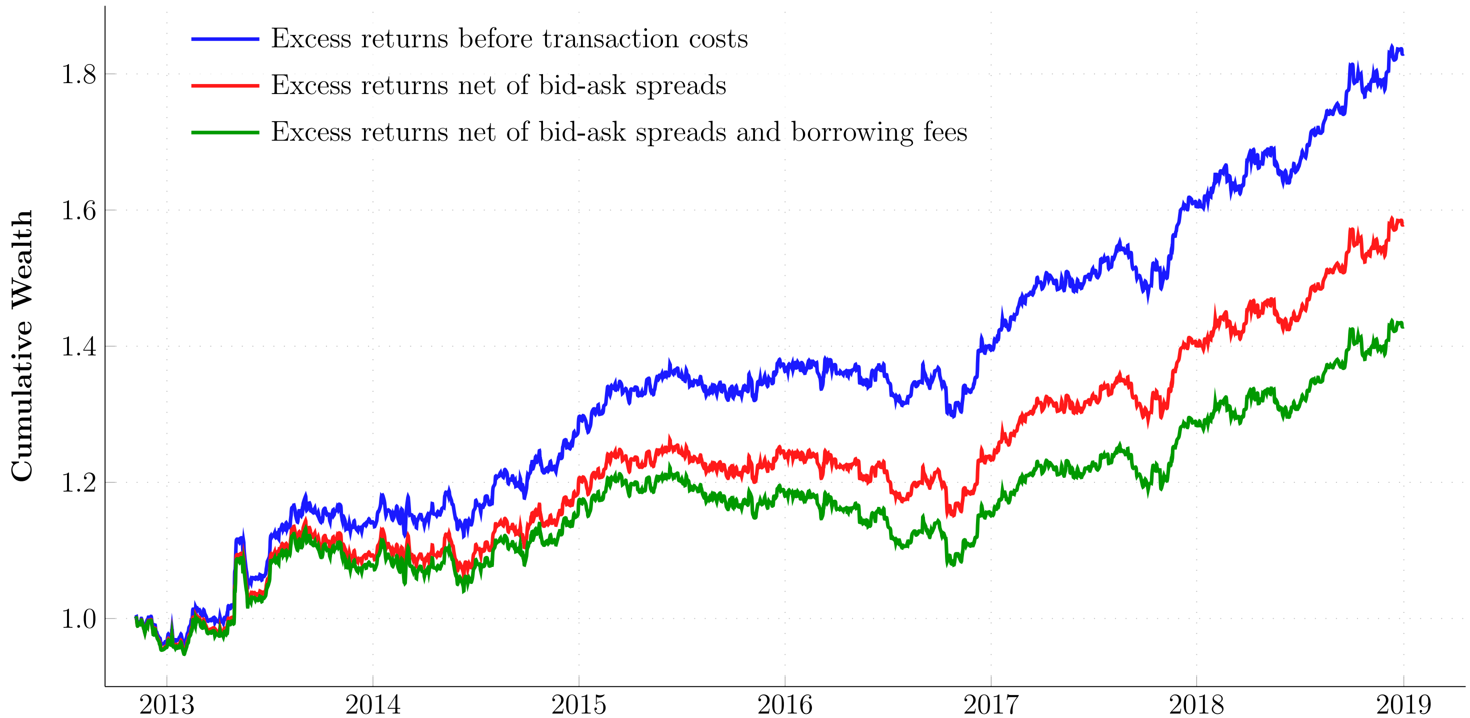

Figure 7. Cumulative Wealth of Best Short Strategies

This figure displays the cumulative wealth from investing in the *Best Short* strategy that sells (buys) an equally-weighted portfolio of stocks with high (low) short-selling conviction. Short-selling conviction is constructed with publicly disclosed net short positions at the investor-stock level. The strategy is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. To minimize portfolio turnover, the strategy incorporates rebalancing thresholds that prevent a reweighing by small amounts, i.e., the strategy is rebalanced whenever the absolute incremental portfolio weight on a single stock is at least 5% or the overall absolute change in all portfolio weights is at least 10%. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are Bloomberg, Caretta, and IHS Markit.

Table 1. Summary Statistics by Country and Investor Type

This table presents summary statistics of publicly disclosed net short positions in stocks by country (issuer's domicile) in Panel A and investor type in Panel B. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Net short positions combine long, short, and delta-adjusted positions in derivatives on each reference stock. *Position per Day* denotes the daily market value of net short positions constructed using the stock market close price. The sample runs at daily frequency between November 2012 and December 2018 for 15 major European stock markets. Data are from Bloomberg and Caretta.

Panel A: Summary Statistics by Country

	Number of Securities		Number of Disclosures		Disclosures per Day		Position per Day ($ billion)	
Austria	22	1.6%	19,097	1.1%	12	1.1%	0.24	0.6%
Finland	41	3.0%	69,269	4.1%	43	4.1%	2.02	5.1%
France	133	9.6%	167,478	9.9%	104	9.8%	5.06	12.8%
Germany	186	13.4%	260,724	15.4%	162	15.3%	5.64	14.3%
Greece	6	0.4%	3,104	0.2%	6	0.5%	0.03	0.1%
Hungary	4	0.3%	7,867	0.5%	5	0.5%	0.22	0.6%
Ireland	4	0.3%	1,289	0.1%	2	0.1%	0.02	0.1%
Italy	123	8.9%	121,949	7.2%	76	7.2%	2.71	6.9%
Netherlands	63	4.5%	91,525	5.4%	57	5.4%	2.09	5.3%
Norway	42	3.0%	40,171	2.4%	25	2.4%	0.50	1.3%
Poland	28	2.0%	16,252	1.0%	10	1.0%	0.34	0.9%
Spain	67	4.8%	87,050	5.1%	54	5.1%	2.67	6.8%
Sweden	140	10.1%	146,953	8.7%	91	8.6%	3.72	9.4%
Switzerland	2	0.1%	875	0.1%	1	0.1%	0.04	0.1%
United Kingdom	528	38.0%	662,103	39.0%	412	38.9%	14.16	35.9%
Total	1,389	100%	1,695,706	100%	1,060	100%	39.47	100%

Panel B: Summary Statistics by Investor Type

	Number of Investors		Number of Disclosures		Disclosures per Day		Position per Day ($ billion)	
Asset Managers	132	22.6%	375,213	22.1%	234	22.1%	4.95	12.5%
Banks	28	4.8%	128,273	7.6%	80	7.5%	2.34	5.9%
Corporate Firms	3	0.5%	9,623	0.6%	7	0.6%	0.07	0.2%
Hedge Funds	415	70.9%	1,169,305	69.0%	729	68.8%	31.88	80.8%
Private Equity	6	1.0%	12,063	0.7%	9	0.8%	0.24	0.6%
Pension Funds	1	0.2%	1,229	0.1%	1	0.1%	0.01	0.0%
Total	585	100.0%	1,695,706	100.0%	1,060	100.0%	39.47	100.0%

Table 2. Summary Statistics by Trade

This table presents summary statistics of publicly disclosed net short positions in stocks by different trades. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Net short positions combine long, short, and delta-adjusted positions in derivatives on each reference stock. When an investor discloses a short position on a given stock for the first time, we categorize it as a new trade with a unique identifier until the position falls below the disclosure threshold. If the same manager, later on, discloses a new position on the same stock, it would count as a new trade. For each unique identifier, we first compute the sample mean for the variable of interest and then report the cross-sectional statistics across trades, i.e., means, standard deviations, and interdecile ranges between the 10th and the 90th percentiles. *Net Short Position (%)* is the percentage of total shares outstanding, *Net Short Position ($ million)* is the market value in millions of US dollars, *Market Cap* is the market capitalization in billions of US dollars, *Small Cap Stocks* is the percentage number of small cap stocks based on market capitalization (and similarly for mid and large cap stocks, respectively), *Number of Investors* is the number of different investors shorting the same stock on a given day, and *Holding Period* is the number of days from entering to closing a disclosed short position. We also quantify the percentage of trades with *Multiple Investors (%)*, positions disclosed by first-movers with *Initiator (%)*, positions with an holding period of up to 10 days with *Holding Period < 10 days (%)*, and positions disclosed by investors domiciled in the same country as the stock with *Same Country (%)*. The sample runs at daily frequency between November 2012 and December 2018 for 15 major European stock markets. Data are from Bloomberg and Caretta.

	N	Mean	Std	10%	25%	50%	75%	90%
Net Short Position (%)	17,522	0.69	0.34	0.50	0.50	0.58	0.73	1.03
Net Short Position ($ million)	17,522	28.58	54.47	3.02	6.75	14.89	32.15	59.44
Market Cap ($ billion)	17,522	4.42	7.75	0.46	1.06	2.31	5.01	9.15
Small Cap Stocks (%)	17,522	44.42	49.69	–	–	–	–	–
Mid Cap Stocks (%)	17,522	47.08	49.92	–	–	–	–	–
Large Cap Stocks (%)	17,522	8.50	27.89	–	–	–	–	–
Holding Period (days)	17,522	65.76	141.20	1.00	2.00	14.00	61.75	181.00
Number of Investors	17,522	4.13	3.14	1.00	2.00	3.15	5.61	8.50
Multiple Investors (%)	17,522	83.79	36.85	–	–	–	–	–
Initiator (%)	17,522	23.33	42.29	–	–	–	–	–
Holding Period < 10 days (%)	17,522	44.49	49.70	–	–	–	–	–
Same Country (%)	17,522	17.09	37.64	–	–	–	–	–

Table 3. Portfolios sorted on Short Conviction

This table reports descriptive statistics of equity portfolios sorted on short conviction measured using investor-stock level net short positions disclosed by hedge funds. P_1 (P_5) denotes the return on an equally-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is the excess return on a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* is the excess return on a long-short strategy that sells P_5 (high-conviction portfolio) and buys P_1 (low-conviction portfolio). t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. AC(1) denotes the first-order serial correlation coefficient. The conviction-based portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redenominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta.

	P_1	P_2	P_3	P_4	P_5	*Naïve Short*	*Best Short*
Mean	7.94	4.25	4.49	3.86	−0.07	−3.72	8.00***
	[1.08]	[0.58]	[0.65]	[0.54]	[−0.01]	[−0.53]	[2.66]
Volatility	16.89	17.26	16.30	16.64	17.17	16.31	7.33
Skewness	−0.89	−0.97	−1.11	−0.67	−0.73	0.96	0.62
Kurtosis	8.62	9.09	9.88	5.08	5.56	8.26	5.59
Sharpe Ratio	0.45	0.22	0.25	0.21	−0.03	−0.23	1.09
Sortino Ratio	0.58	0.29	0.32	0.28	−0.03	−0.37	1.86
Max Drawdown	−34.99	−31.24	−33.86	−36.84	−39.19	−50.54	−9.52
AC(1)	0.13	0.10	0.10	0.10	0.11	0.11	0.05

Table 4. Best Short and Canonical Risk

This table reports least-squares estimates of time-series regressions. The test asset is the excess return on the *Best Short* strategy that sells stocks with high short-selling conviction and buys stocks with low short-selling conviction and described in Table 3. The set of traded factors includes the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). CAPM denotes the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), FM3 is the three-factor model of Fama and French (1993), FM4 is the four-factor model of Carhart (1997), FM5 is the five-factor model of Fama and French (2015), and FM6 is a six-factor model that includes all traded factors. α denotes the risk-adjusted performance in percentage per annum. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The test asset is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redenominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily equity factors for European stock markets are from Ken French's data library. Other data are from Bloomberg and Caretta.

	CAPM	FM3	FM4	FM5	FM6
MKT	−0.006	−0.031	−0.031	−0.035	−0.035
	(0.019)	(0.024)	(0.024)	(0.022)	(0.022)
SMB		−0.070*	−0.070*	−0.076**	−0.075**
		(0.038)	(0.038)	(0.036)	(0.037)
HML		0.048	0.043	0.027	0.023
		(0.033)	(0.033)	(0.061)	(0.064)
RMW				−0.103	−0.103
				(0.080)	(0.080)
CMA				−0.101	−0.099
				(0.074)	(0.073)
WML			−0.012		−0.006
			(0.035)		(0.034)
α	8.039***	8.385***	8.502***	8.790***	8.849***
	(3.033)	(3.043)	(3.051)	(3.045)	(3.055)
R^2 (%)	0.02	0.27	0.22	0.39	0.33
N	1,574	1,574	1,574	1,574	1,574

Table 5. Best Short and Short-Selling Risk

This table presents asset pricing results for a linear model based on the market excess return (MKT) and short-selling risk (SSR), i.e., unexpected changes in future lending conditions. The test assets are excess returns on the five conviction-based portfolios described in Table 3. SSR is measured as the daily changes in the cross-sectional variance of borrowing fees (left panel) or the daily changes in the stock market option implied volatility skew measured as the implied volatility difference between one-month 10-delta put and at-the-money options on the EURO STOXX 50 index. Panel A reports the factor prices λ, and cross-sectional R^2 obtained via first-stage GMM and Fama-MacBeth (FMB) regressions. Standard errors, reported in parentheses, are based on Newey and West (1987) with Andrews (1991) optimal lag selection for GMM and Shanken (1992) adjustment for FMB. HJ is the Hansen and Jagannathan (1997) distance measure (with a simulated p-value in brackets) and χ^2 is a pricing error statistic (with Shanken (1992) p-value in brackets). Panel B reports time-series estimates with standard errors in parentheses based on Newey and West (1987) with Andrews (1991) optimal lag selection. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The test asset is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redenominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily excess returns of the European stock markets are from Ken French's data library, daily borrowing fees are from IHS Markit, and the daily option implied volatilities on the EURO STOXX 50 index are from Bloomberg.

Panel A: Factor Prices

	Borrowing Fees				Option Market			
	λ_{MKT}	λ_{SSR}	HJ	$R^2(\%)$	λ_{MKT}	λ_{SSR}	HJ	$R^2(\%)$
GMM	2.410	0.937	0.063	33.9	6.501	0.608	0.058	36.5
	(6.463)	(0.645)	[0.928]		(6.001)	(0.435)	[0.863]	
	λ_{MKT}	λ_{SSR}	χ^2	$R^2(\%)$	λ_{MKT}	λ_{SSR}	χ^2	$R^2(\%)$
FMB	2.410	0.937	3.324	33.9	6.501	0.608	3.816	36.5
	(6.318)	(0.636)	[0.505]		(5.816)	(0.432)	[0.432]	

Panel B: Factor Betas

	α	β_{MKT}	β_{SSR}	R^2 (%)	α	β_{MKT}	β_{SSR}	R^2 (%)
P_1	1.443	1.059***	2.800	77.0	1.463	1.056***	−3.224	77.0
	(3.065)	(0.029)	(3.176)		(3.109)	(0.032)	(4.693)	
P_2	−2.402	1.107***	0.463	80.4	−2.527	1.102***	−4.439	80.4
	(2.774)	(0.029)	(2.869)		(2.780)	(0.033)	(5.026)	
P_3	−2.137	1.047***	3.501	81.1	−2.010	1.044***	−4.856	81.0
	(2.486)	(0.030)	(2.904)		(2.506)	(0.033)	(4.748)	
P_4	−2.811	1.049***	−0.257	77.9	−2.570	1.043***	−8.152**	77.9
	(2.735)	(0.018)	(3.485)		(2.785)	(0.019)	(3.941)	
P_5	−7.037**	1.062***	−1.059	75.3	−6.430*	1.060***	−6.296	75.5
	(3.304)	(0.021)	(3.180)		(3.305)	(0.023)	(4.813)	

Table 6. Best Short and Other Market Frictions

This table presents asset pricing results for a linear model based on the market excess return (MKT), shocks to intermediary capital ratio (ICR) or shocks to the supply of lendable shares (SLS). The test assets are excess returns on the five conviction-based portfolios described in Table 3. ICR is from He, Kelly, and Manela (2017) whereas SLS is measured as the daily changes in the cross-sectional variance of the number of shares available for borrowing (expressed as percent of the total number of shares outstanding). Panel A reports the factor prices λ, and cross-sectional R^2 obtained via first-stage GMM and Fama-MacBeth (FMB) regressions. Standard errors, reported in parentheses, are based on Newey and West (1987) with Andrews (1991) optimal lag selection for GMM and Shanken (1992) adjustment for FMB. HJ is the Hansen and Jagannathan (1997) distance measure (with a simulated p-value in brackets) and χ^2 is a pricing error statistic (with Shanken (1992) p-value in brackets). Panel B reports time-series estimates with standard errors in parentheses based on Newey and West (1987) with Andrews (1991) optimal lag selection. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The test asset is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily excess returns of the European stock markets are from Ken French's data library, daily available shares for borrowing are from IHS Markit, and other data are from Bloomberg.

Panel A: Factor Prices

	Intermediary Capital Ratio				Supply of Lendable Shares			
	λ_{MKT}	λ_{ICR}	HJ	R^2 (%)	λ_{MKT}	λ_{SLS}	HJ	R^2 (%)
GMM	4.325	−0.057	0.072	3.3	5.094	−1.098	0.049	64.1
	(5.425)	(0.108)	[0.828]		(6.511)	(0.781)	[0.977]	
	λ_{MKT}	λ_{ICR}	χ^2	R^2 (%)	λ_{MKT}	λ_{SLS}	χ^2	R^2 (%)
FMB	4.325	−0.057	7.925	3.3	5.094	−1.098	1.684	64.1
	(5.764)	(0.116)	[0.094]		(6.297)	(0.716)	[0.794]	

Panel B: Factor Betas

	α	β_{MKT}	β_{ICR}	R^2 (%)	α	β_{MKT}	β_{SLS}	R^2 (%)
P_1	2.038	0.984***	24.804***	77.4	1.532	1.058***	0.645	77.0
	(3.032)	(0.033)	(5.163)		(3.059)	(0.029)	(3.854)	
P_2	−2.318	1.023***	26.149***	80.8	−2.424	1.105***	0.150	80.4
	(2.688)	(0.032)	(4.748)		(2.772)	(0.029)	(3.530)	
P_3	−1.557	0.999***	14.885***	81.0	−1.855	1.048***	0.055	81.0
	(2.442)	(0.032)	(4.765)		(2.506)	(0.030)	(2.860)	
P_4	−2.522	0.987***	18.991***	77.8	−2.486	1.049***	1.276	77.9
	(2.837)	(0.024)	(4.706)		(2.762)	(0.017)	(4.127)	
P_5	−6.104*	0.994***	21.426***	75.7	−6.500**	1.063***	5.164	75.4
	(3.277)	(0.027)	(5.282)		(3.294)	(0.021)	(3.724)	

Table 7. Short Conviction and Price Delay

This table presents panel regression estimates based on $D_{j,t} = \alpha + \beta_1 C_{j,t} + \gamma' X_{j,t} + \alpha_t + \epsilon_{j,t}$, where $D_{j,t}$ is a measure of price delay for stock j and year t, $C_{j,t}$ is the short conviction for stock j and year t, $X_{j,t}$ is a vector of controls for stock j and year t, and α_t denotes year fixed effects. We use two measures of $D_{j,t}$ constructed between July of year $t-1$ and June of year t as in Hou and Moskowitz (2005). $C_{j,t}$ and $X_{j,t}$ are measured daily and then averaged between July of year $t-1$ and June of year t. *Loan Supply* is the number of shares actively available for lending as a fraction of total shares outstanding, *Short-Selling Risk* is the variance of borrowing fees based on a one-year window, *Log Market Cap* is the market value of a company in logs, *Price-to-Book* is the market value of a company relative to its book value, *Volatility* is the exponentially weighted moving average volatility with a two-month half-life, *Bid-Ask Spread* is the volume-weighted average of intraday bid-ask spreads over a five trading day window, *Illiquidity* is the Amihud measure constructed as the absolute return divided by the dollar volume (scaled by 10^5), *Short Interest* is the number of shares on loan as a percentage of shares outstanding, *Borrowing Fee* is the cost of borrowing a share, *Inst. Ownership* is the fraction of shares outstanding owned by institutional investors (scaled by 100), *Analyst Coverage* is the number of analysts covering a stock (scaled by 100), *Leverage* is the (short- and long-term) debt of a company relative to its book value, *Profitability* is the operating income before depreciation relative to total assets, and *Skewness* is the sample skewness based on a three-month window. Standard errors, clustered by firm and year dimension, are not reported to save space. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample runs between November 2012 and December 2018 for 15 major European stock markets. Data are from Bloomberg, Caretta, and IHS Markit.

	Panel A: Price Delay D1				Panel B: Price Delay D2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Short Conviction	0.018**	0.014*	0.021**	0.019**	0.015**	0.012*	0.013	0.012
Loan Supply	−0.080	0.004	−0.033*	−0.032*	−0.041	0.015	−0.013	−0.012
Short Selling Risk		0.001**	0.002	0.002		0.001	0.001	0.001*
Log Market Cap		−0.038***	−0.017**	−0.017**		−0.028***	−0.015**	−0.015**
Price-to-Book		0.005***	0.004***	0.004**		0.004***	0.003***	0.003**
Volatility		0.272***	0.267**	0.276**		0.153**	0.154**	0.162**
Bid-Ask Spread			7.458***	7.729***			4.368**	4.574**
Illiquidity			1.781*	1.659			1.258**	1.151**
Short Interest			−0.167	−0.133			0.002	0.025
Borrowing Fees			−0.231	−0.216			−0.200	−0.184
Inst. Ownership			0.043**	0.041*			0.037***	0.035**
Analyst Coverage			−0.182**	−0.164**			−0.107*	−0.093
Leverage				−0.248				−0.221
Profitability				0.094				0.076
Skewness				0.656				0.343
Constant	0.265***	0.447***	0.273***	0.267***	0.477***	0.623***	0.509***	0.505***
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (%)	7.10	22.30	24.50	24.70	12.00	23.90	25.60	25.70
N	2,850	2,850	2,850	2,850	2,850	2,850	2,850	2,850

Table 8. Characteristics of Conviction-Sorted Portfolios

This table presents the average values of stock characteristics associated with short conviction portfolios. On each trading day, we first group stocks into five portfolios using short conviction such that P_1 (P_5) comprises stocks with low (high) short conviction as in Table 3. Within each portfolio, we then compute the average value of the corresponding firm characteristics, risk measures, liquidity measures, securities lending market variables, and investor attention variables. Finally, we present the average value these characteristics across the entire sample. *Leverage* is the (short- and long-term) debt of a company relative to its book value, *Market Cap* is the market value of a company, *Price-to-Book* is the market value of a company relative to its book value, *Profitability* is the operating income before depreciation relative to total assets, *Short-Selling Risk* is the variance of borrowing fees based on a one-year window, *Skewness* is the sample skewness based on a three-month window, *Volatility* is the exponentially weighted moving average volatility with a two-month half-life, *Amihud Illiquidity* is the absolute return divided by the dollar volume and scaled by 10^5, *Bid-Ask Spread* is the volume-weighted average of intraday bid-ask spreads over a five trading day window, *Borrowing Fee* is the cost of borrowing a share, *Loan Supply* is the number of shares actively available for lending as a fraction of total shares outstanding, *Total Short Interest* is the number of shares on loan as a percentage of shares outstanding, *Institutional Ownership* is the amount of a company's available stock owned by institutional investors, and *Analyst Coverage* is the number of analysts covering a stock. The sample runs between November 2012 and December 2018 for 15 major European stock markets. Data are from Bloomberg, Caretta, and IHS Markit.

	P_1	P_2	P_3	P_4	P_5
Panel A: Firm Characteristics					
Leverage	1.37	1.43	1.25	1.24	1.04
Market Cap ($ billions)	3.11	6.48	5.26	5.25	4.04
Price-to-Book	2.52	2.50	2.87	2.81	2.74
Profitability (%)	1.85	2.76	2.39	2.04	1.97
Panel B: Risk Measures					
Short-selling Risk	1.56	1.58	2.11	2.16	2.79
Skewness	0.11	0.06	−0.01	0.04	0.00
Volatility (%)	39.52	37.26	36.89	37.24	39.27
Panel C: Liquidity Measures					
Amihud Illiquidity	0.78	0.01	0.01	0.01	0.01
Bid-Ask Spread (%)	0.45	0.29	0.29	0.25	0.25
Panel D: Securities Lending Market Variables					
Borrowing Fee (%)	2.88	2.63	2.40	2.31	3.09
Loan Supply (%)	9.30	9.68	9.60	9.23	8.25
Total Short Interest (%)	2.88	3.63	4.38	5.45	8.69
Panel E: Investor Attention Variables					
Institutional Ownership (%)	64.49	64.40	64.36	62.72	65.65
Analyst Coverage	13.75	17.48	16.47	17.73	18.21

Table 9. Best Short and Transaction Costs

This table presents descriptive statistics and least-squares estimates, before and after transaction costs, for the excess return on the *Best Short* strategy that sells (buys) an equally-weighted portfolio of stocks with high (low) short-selling conviction. Short-selling conviction is constructed with publicly disclosed net short positions at the investor-stock level. To minimize portfolio turnover, the strategy faces rebalancing thresholds that prevent a reweighing by small amounts, i.e., the strategy is rebalanced whenever the absolute incremental portfolio weight on a single stock is at least 5% or the overall absolute change in all portfolio weights is at least 10%. Panel A reports the summary statistics whereas Panel B displays the percentage per annum α from time-series regressions that use the market excess return, size, value, profitability, investment, and momentum as traded risk factors. CAPM denotes the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), FM3 is the three-factor model of Fama and French (1993), FM4 is the four-factor model of Carhart (1997), FM5 is the five-factor model of Fama and French (2015), and FM6 is a six-factor model that includes all traded factors. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. The *Best Short* strategy is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily equity factors for European stock markets are from Ken French's data library. Other data are from Bloomberg and Caretta.

Panel A: Summary Statistics	Mean	Volatility	Skewness	Kurtosis	Sharpe Ratio
Before Transaction Costs	9.95***	7.51	0.55	6.54	1.33
Net of Bid-Ask Spreads	7.60**	7.60	0.53	6.37	1.00
Net of Bid-Ask Spreads and Borrowing Fees	6.00*	7.59	0.52	6.37	0.79

Panel B: Equity Risk Factors and α	CAPM	FM3	FM4	FM5	FM6
Before Transaction Costs	10.07**	10.40***	10.70***	10.75***	11.02***
Net of Bid-Ask Spreads	7.71**	8.04**	8.35***	8.44***	8.71***
Net of Bid-Ask Spreads and Borrowing Fees	6.11*	6.44**	6.74**	6.84**	7.11**

Table 10. Best Short and Monthly Rebalancing

This table presents descriptive statistics and least-squares estimates, before and after transaction costs, for the excess return on the monthly-rebalanced *Best Short* strategy that sells (buys) an equally-weighted portfolio of stocks with high (low) short-selling conviction. Short-selling conviction is constructed with publicly disclosed net short positions at the investor-stock level. To minimize portfolio turnover, the strategy faces rebalancing thresholds that prevent a reweighing by small amounts, i.e., the strategy is rebalanced whenever the absolute incremental portfolio weight on a single stock is at least 5% or the overall absolute change in all portfolio weights is at least 10%. Panel A reports the summary statistics whereas Panel B displays the percentage per annum α from time-series regressions that use the market excess return, size, value, profitability, investment, and momentum as traded risk factors. CAPM denotes the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), FM3 is the three-factor model of Fama and French (1993), FM4 is the four-factor model of Carhart (1997), FM5 is the five-factor model of Fama and French (2015), and FM6 is a six-factor model that includes all traded factors. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. The *Best Short* strategy is rebalanced at the end of each month but excess returns are computed daily between December 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily equity factors for European stock markets are from Ken French's data library. Other data are from Bloomberg and Caretta.

Panel A: Summary Statistics	Mean	Volatility	Skewness	Kurtosis	Sharpe Ratio
Before Transaction Costs	8.83***	7.61	−0.04	1.86	1.16
Net of Bid-Ask Spreads	7.27**	7.21	−0.04	2.25	1.01
Net of Bid-Ask Spreads and Borrowing Fees	5.75**	7.23	−0.04	2.25	0.80
Panel B: Equity Risk Factors and α	**CAPM**	**FM3**	**FM4**	**FM5**	**FM6**
Before Transaction Costs	8.93***	9.31***	9.54***	9.74***	9.97***
Net of Bid-Ask Spreads	7.42***	7.86***	7.89***	8.14***	8.18***
Net of Bid-Ask Spreads and Borrowing Fees	5.90**	6.34**	6.36**	6.62**	6.65**

Internet Appendix to

"Best Short"

(not for publication)

Abstract

We present supplementary results not included in the main body of the paper.

- Value-weighted Best Short
- Vol-adjusted Conviction
- Conviction-sorted Portfolios for Other Investors (non-hedge funds)
- Rebalancing Frequency/Time Delays
- Ad-hoc charts

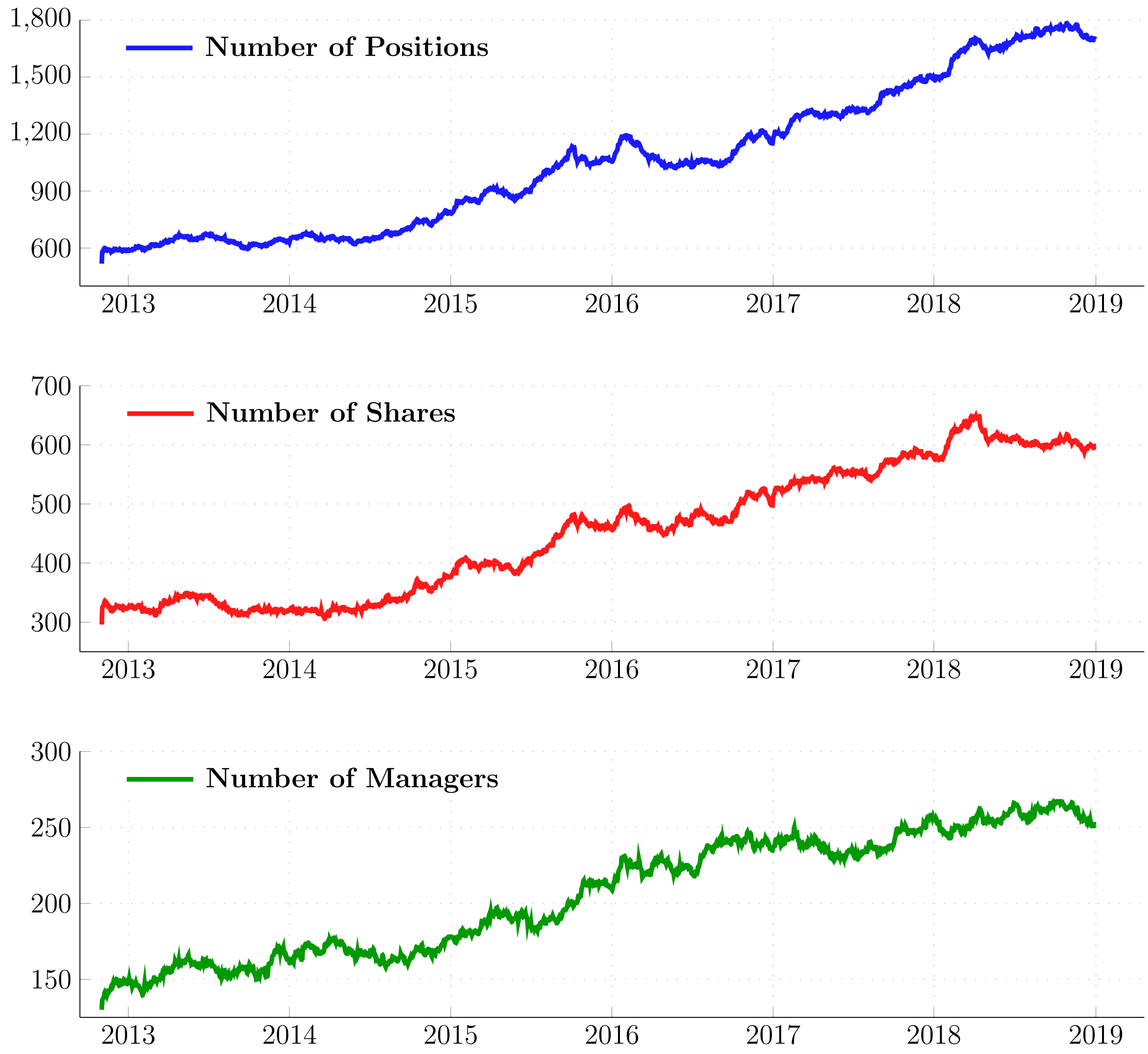

Figure A1. Publicly Disclosed Net Short Positions

This figure shows the number of net short positions, unique shares, and individual managers for our sample of publicly disclosed net short positions of European stocks. Net short positions exceeding 0.5% of the issued share capital of the reference company are publicly disclosed at the investor level under the European Union Short Selling Regulation and combine long, short, and delta-adjusted positions in derivatives on each reference stock. Publicly disclosed net short positions are obtained from Caretta. The sample runs at daily frequency between November 2012 and December 2018 for 15 major European stock markets.

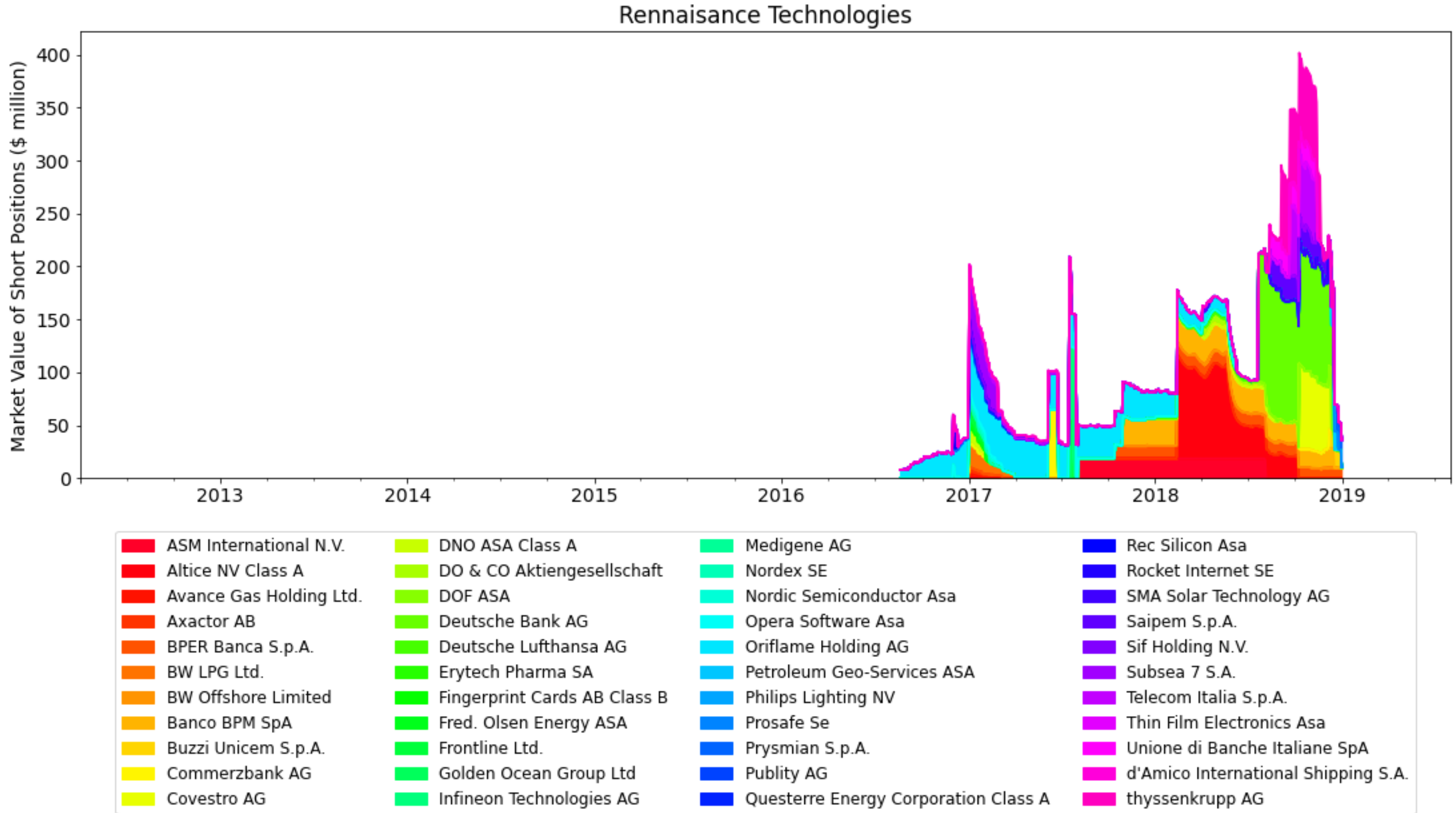

Figure A2. Example: Disclosed Short Positions by Renaissance Technologies

This figure displays the net short positions disclosed by Renaissance Technologies, an American hedge fund regarded as one of the most secretive and successful hedge funds in the world. Net short positions exceeding 0.5% of the issued share capital are publicly disclosed under the European Union Short Selling Regulation and combine long, short, and delta-adjusted positions in derivatives. Net short position are expressed in US dollars using stock market closing prices. The sample runs at daily frequency between November 1, 2012, and December 31, 2018. Data are from Bloomberg and Caretta.

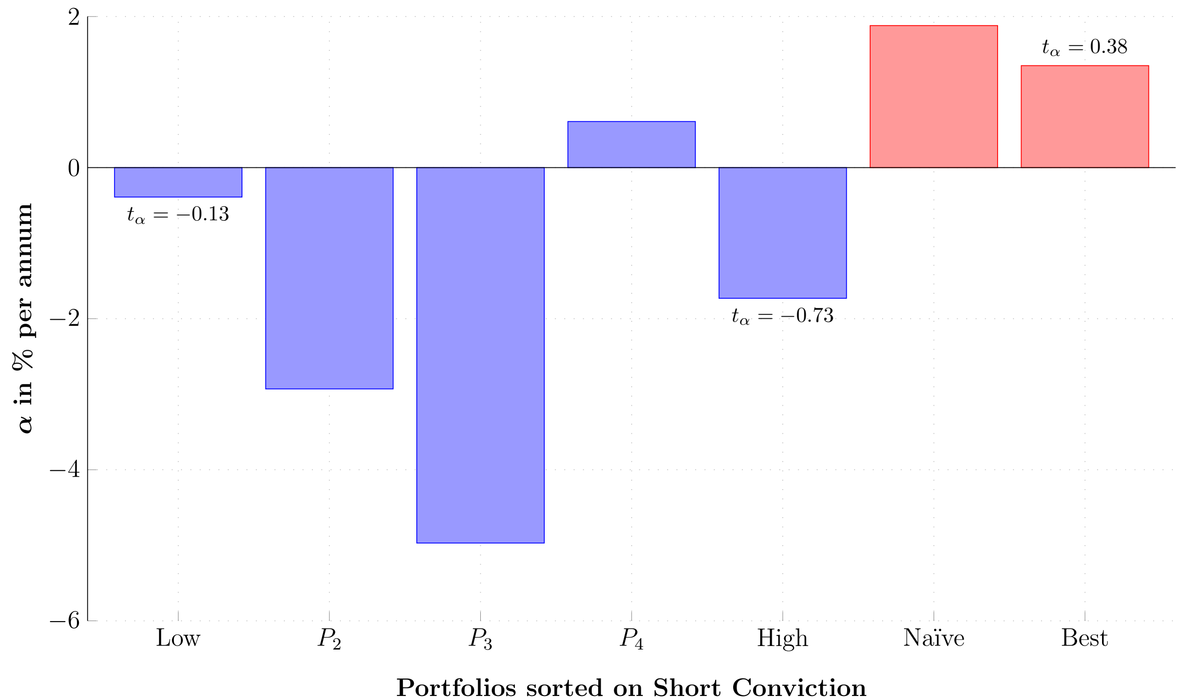

Figure A3. Short Conviction based on Other Investors

This figure displays risk-adjusted excess returns (or alpha) of equity portfolios sorted on the short conviction measured using investor-stock level net short positions disclosed by other investors (i.e., Asset Managers, Banks, Corporate Firms, Private Equity Funds, and Pension Funds). Low (High) Conviction denotes an equally-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* denotes a long-short strategy that sells the high-conviction portfolio and buys the low-conviction portfolio. Risk-adjusted excess returns are obtained using six traded factors, i.e., the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). t_α denotes the t-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. Returns are denominated in US dollars using daily spot exchange rates and expressed in percentage per annum. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta. Daily equity factors for European stock markets are from Ken French's data library.

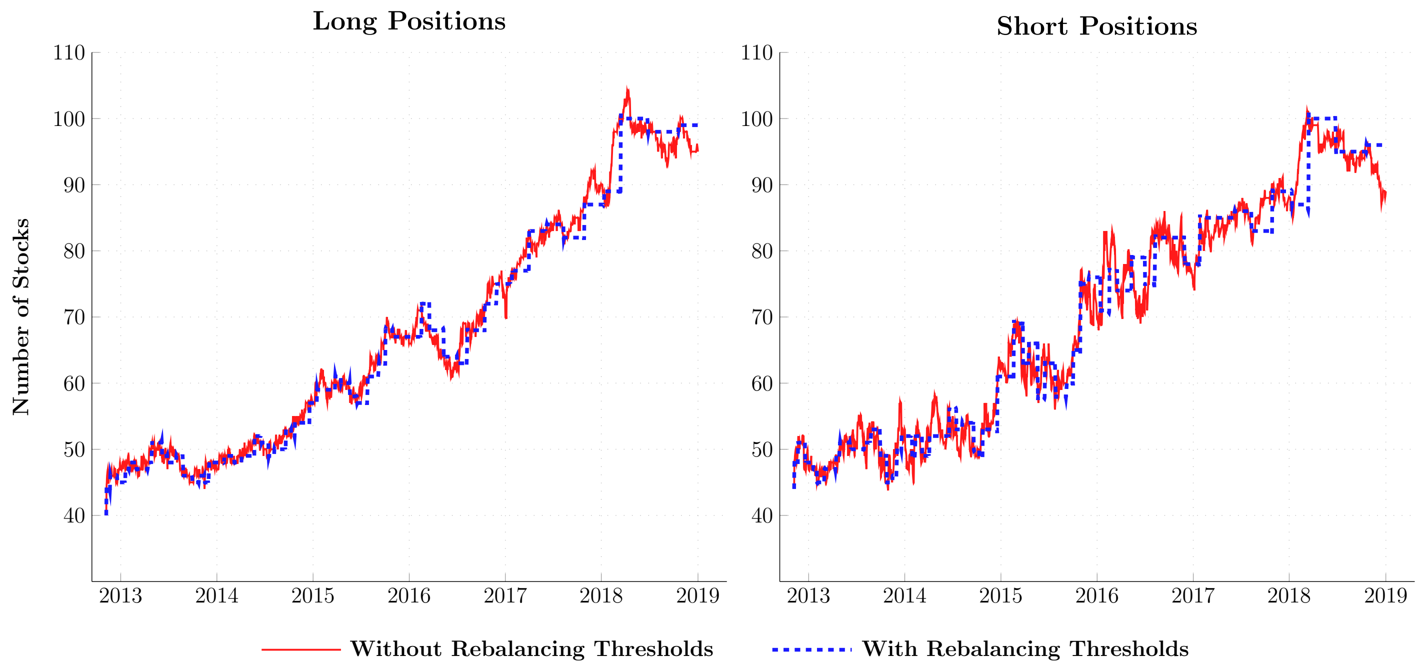

Figure A4. Number of Long and Short Positions

This figure displays the number of long and short positions before and after applying the rebalancing thresholds for the *Best Short* strategy that sells (buys) an equally-weighted portfolio of stocks with high (low) short-selling conviction. Short-selling conviction is constructed with publicly disclosed net short positions at the investor-stock level. The strategy without rebalancing thresholds is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. The strategy that faces rebalancing thresholds is rebalanced whenever the absolute incremental portfolio weight on a single stock is at least 5% or the overall absolute change in all portfolio weights is at least 10%. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are Bloomberg, Caretta, and IHS Markit.

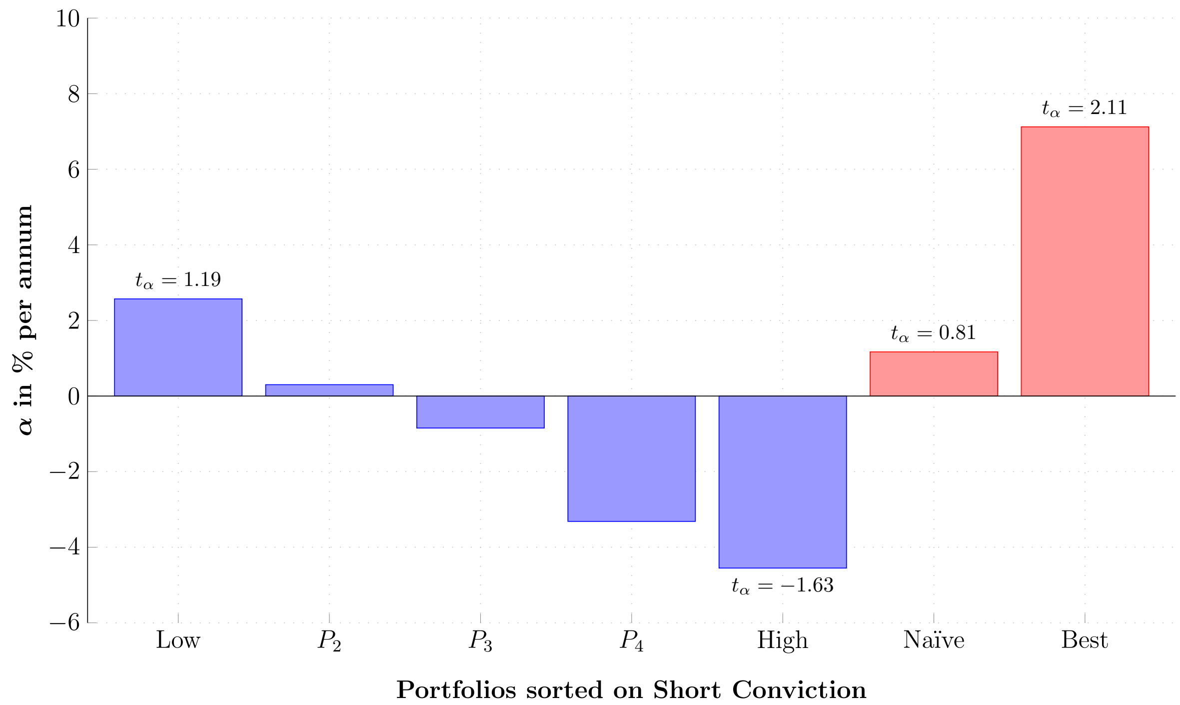

Figure A5. Value-Weighted Portfolios Sorted on Short Conviction

This figure displays risk-adjusted excess returns (or alpha) of equity portfolios sorted on short conviction constructed with publicly disclosed net short positions at the investor-stock level. Low (High) Conviction denotes a value-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* denotes a long-short strategy that sells the high-conviction portfolio and buys the low-conviction portfolio. Risk-adjusted excess returns are obtained using six traded factors, i.e., the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). t_α denotes the t-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. Returns are denominated in US dollars using daily spot exchange rates and expressed in percentage per annum. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta. Daily equity factors for European stock markets are from Ken French's data library.

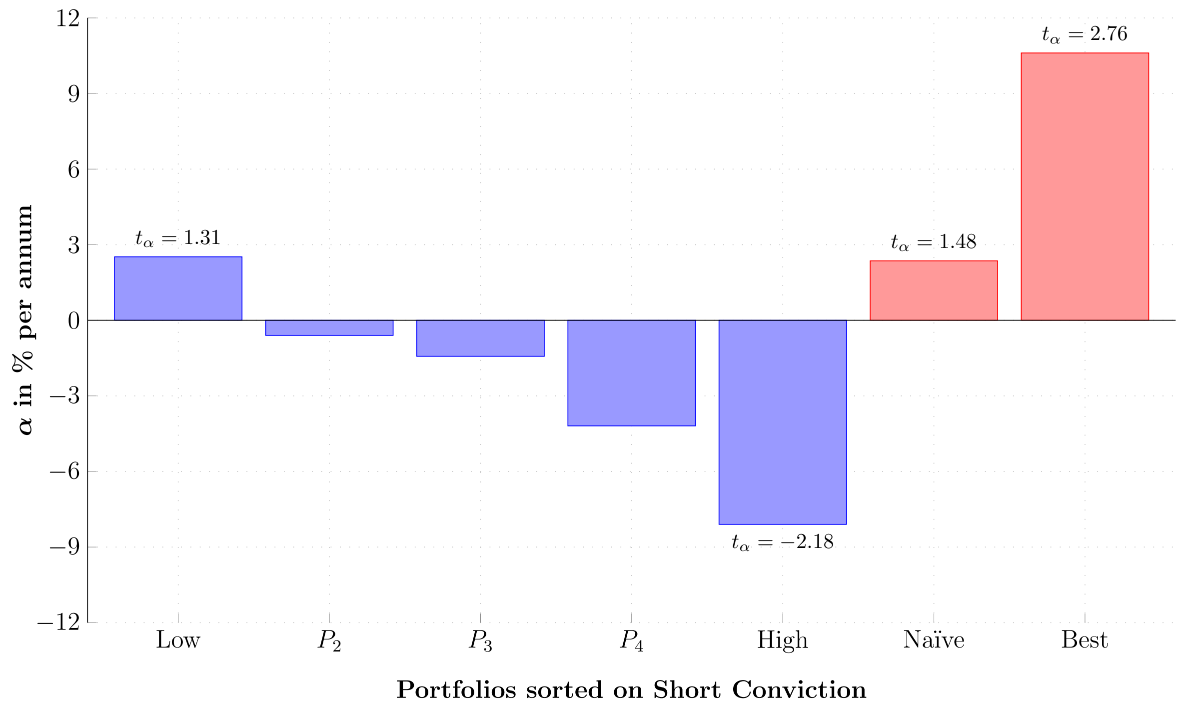

Figure A6. Portfolios Sorted on Risk-Adjusted Short Conviction

This figure displays risk-adjusted excess returns (or alpha) of equity portfolios sorted on risk-adjusted short conviction. Low (High) Conviction denotes an equally-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* denotes a long-short strategy that sells the high-conviction portfolio and buys the low-conviction portfolio. Risk-adjusted excess returns are obtained using six traded factors, i.e., the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). t_α denotes the t-statistic based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection. Returns are denominated in US dollars using daily spot exchange rates and expressed in percentage per annum. The conviction-sorted portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta. Daily equity factors for European stock markets are from Ken French's data library.

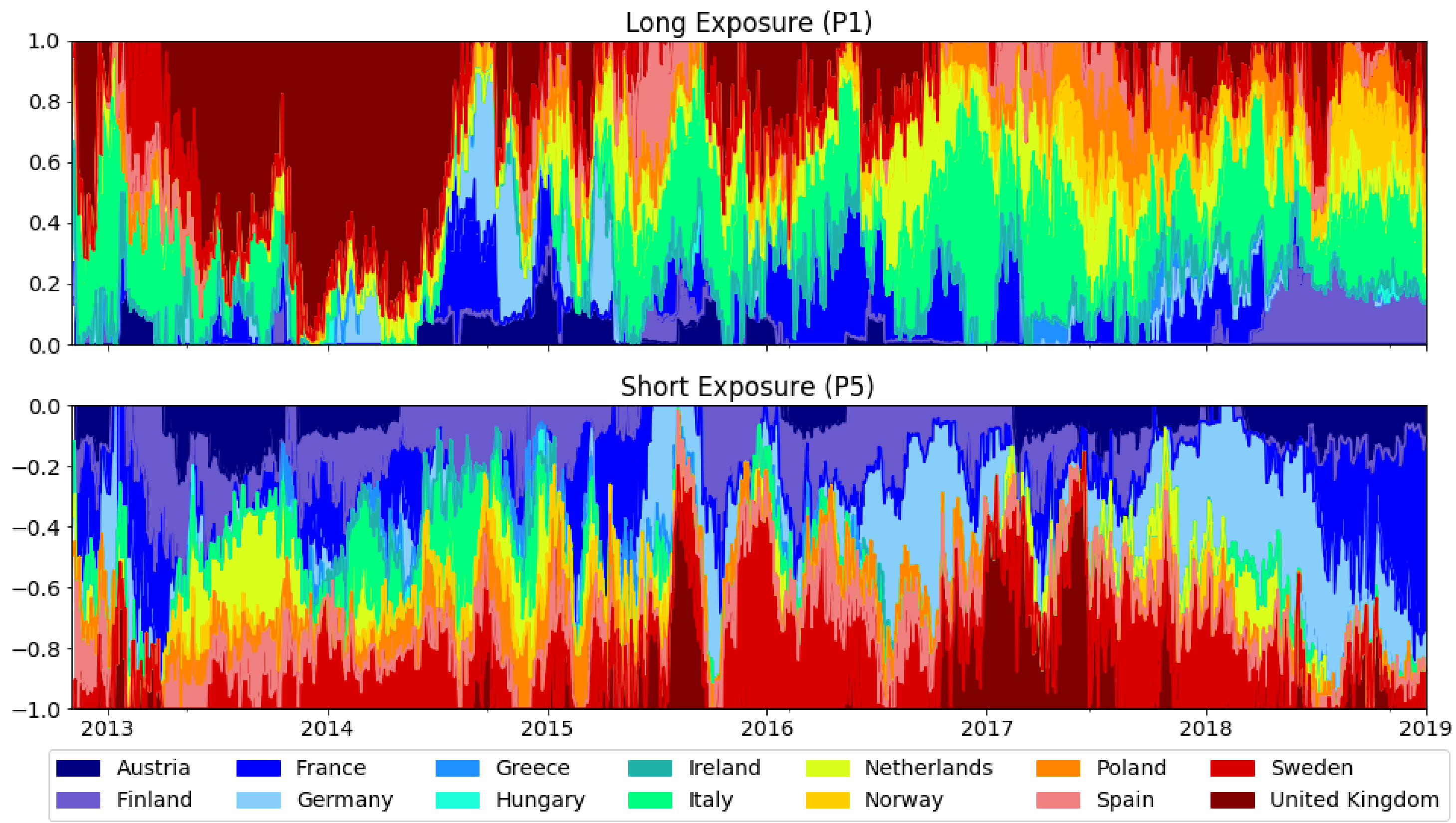

Figure A7. Country Exposure of the Best Short

This figure displays the exposure of the long and short side of the Best Short by country. Data are sourced from Caretta, and Bloomberg at daily frequency. The sample period ranges between November 2012 and December 2018.

Table A1. Value-Weighted Portfolios sorted on Short Conviction

This table reports descriptive statistics of equity portfolios sorted on short conviction measured using investor-stock level net short positions disclosed by hedge funds. P_1 (P_5) denotes the return on an value-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is the excess return on a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* is the excess return on a long-short strategy that sells P_5 (high-conviction portfolio) and buys P_1 (low-conviction portfolio). t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. AC(1) denotes the first-order serial correlation coefficient. The conviction-based portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta.

	P_1	P_2	P_3	P_4	P_5	*Naïve Short*	*Best Short*
Mean	7.66	4.03	5.30	2.51	1.76	−3.88	5.90*
	[1.06]	[0.55]	[0.81]	[0.32]	[0.24]	[−0.56]	[1.81]
Volatility	17.05	17.53	16.21	18.15	17.78	16.52	8.13
Skewness	−0.74	−1.16	−0.89	−0.88	−0.67	0.87	0.19
Kurtosis	6.52	12.11	8.26	7.35	4.73	7.72	1.77
Sharpe Ratio	0.43	0.21	0.30	0.12	0.08	−0.23	0.73
Sortino Ratio	0.56	0.26	0.40	0.15	0.10	−0.37	1.16
Max Drawdown	−30.64	−31.27	−32.78	−37.00	−40.65	−46.64	−13.65
AC(1)	0.08	0.06	0.03	0.09	0.05	0.06	0.00

Table A2. Portfolios sorted on Risk-Adjusted Short Conviction

This table reports descriptive statistics of equity portfolios sorted on risk-adjusted short conviction. P_1 (P_5) denotes the return on an equally-weighted long portfolio that buys stocks with the lowest (highest) short conviction adjusted by stock-level volatility. *Naïve Short* is the excess return on a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* is the excess return on a long-short strategy that sells P_5 (high-conviction portfolio) and buys P_1 (low-conviction portfolio). t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. AC(1) denotes the first-order serial correlation coefficient. The conviction-based portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta.

	P_1	P_2	P_3	P_4	P_5	*Naïve Short*	*Best Short*
Mean	8.55	5.54	5.14	2.90	−2.37	−3.58	10.92**
	[1.29]	[0.80]	[0.73]	[0.41]	[−0.27]	[−0.52]	[2.56]
Volatility	15.50	16.13	16.52	16.52	19.55	16.19	9.94
Skewness	−1.15	−0.87	−1.08	−0.72	−0.53	0.95	−0.11
Kurtosis	11.01	7.52	9.48	6.68	4.18	8.29	0.85
Sharpe Ratio	0.53	0.32	0.29	0.15	−0.14	−0.22	1.10
Sortino Ratio	0.67	0.42	0.37	0.20	−0.19	−0.36	1.73
Max Drawdown	−27.59	−31.52	−34.49	−35.88	−51.76	−50.14	−18.83
AC(1)	0.10	0.10	0.10	0.09	0.14	0.11	0.08

Table A3. Portfolios sorted on Short Conviction: Other Investors

This table reports descriptive statistics of equity portfolios sorted on short conviction measured using investor-stock level net short positions disclosed by other players (i.e., Asset Managers, Banks, Corporate Firms, Private Equity Funds, and Pension Funds). P_1 (P_5) denotes the return on an equally-weighted long portfolio that buys stocks with the lowest (highest) short conviction. *Naïve Short* is the excess return on a strategy that equally sells all five portfolios while investing in the riskless asset. *Best Short* is the excess return on a long-short strategy that sells P_5 (high-conviction portfolio) and buys P_1 (low-conviction portfolio). t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. AC(1) denotes the first-order serial correlation coefficient. The conviction-based portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Data are from Bloomberg and Caretta.

	P_1	P_2	P_3	P_4	P_5	*Naïve Short*	*Best Short*
Mean	6.39	3.42	0.78	7.08	5.38	−4.23	1.01
	[0.89]	[0.49]	[0.11]	[0.99]	[0.82]	[−0.63]	[0.27]
Volatility	16.17	16.09	17.46	16.94	15.54	15.49	9.44
Skewness	−0.82	−0.80	−1.18	−0.85	−0.50	0.97	−0.05
Kurtosis	7.82	6.53	11.85	7.50	3.24	8.56	1.62
Sharpe Ratio	0.37	0.19	0.02	0.40	0.32	−0.27	0.11
Sortino Ratio	0.48	0.25	0.03	0.53	0.44	−0.45	0.16
Max Drawdown	−35.57	−32.78	−44.16	−33.74	−31.60	−52.33	−15.48
AC(1)	0.14	0.12	0.12	0.13	0.10	0.14	0.01

Table A4. Portfolios sorted on Total Short Interest

This table reports descriptive statistics of equity portfolios sorted on short interest measured as the number of shares on loan as a percentage of shares outstanding at the stock level. P_1 (P_5) denotes the return on an equally-weighted long portfolio that buys stocks with the lowest (highest) short interest. AVE is the excess return on a strategy that equally sells all five portfolios while investing in the riskless asset. HML is the excess return on a long-short strategy that sells P_5 (high short-interest portfolio) and buys P_1 (low short-interest portfolio). t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. AC(1) denotes the first-order serial correlation coefficient. The portfolios are rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Data on anonymous short interest are sourced from IHS Markit.

	P_1	P_2	P_3	P_4	P_5	AVE	HML
Mean	5.58	6.48	3.94	2.43	5.62	−4.44	−0.04
	[0.81]	[0.93]	[0.54]	[0.32]	[0.70]	[−0.63]	[−0.01]
Volatility	16.30	16.42	16.61	17.64	18.32	16.42	8.98
Skewness	−1.23	−1.27	−0.71	−0.96	−0.37	0.97	−0.50
Kurtosis	10.87	12.40	5.63	8.81	3.65	8.47	2.39
Sharpe Ratio	0.34	0.39	0.24	0.14	0.31	−0.27	0.00
Sortino Ratio	0.42	0.50	0.32	0.18	0.43	−0.44	−0.01
Max Drawdown	−30.14	−30.60	−40.36	−38.10	−36.98	−52.88	−19.49
AC(1)	0.10	0.10	0.12	0.12	0.11	0.11	0.09

Table A5. Naïve Short and Canonical Risk

This table reports least-squares estimates of time-series regressions. The test asset is the excess return on the *Naïve Short* strategy that equally sells all five conviction-based portfolios while investing in the riskless asset and described in Table 3. The set of traded factors includes the market excess return (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA), and momentum (WML). CAPM denotes the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), FM3 is the three-factor model of Fama and French (1993), FM4 is the four-factor model of Carhart (1997), FM5 is the five-factor model of Fama and French (2015), and FM6 is a six-factor model that includes all traded factors. α denotes the risk-adjusted performance in percentage per annum. t-statistics based on Newey and West (1987) standard errors with Andrews (1991) optimal lag selection are reported in brackets. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The test asset is rebalanced daily between November 2012 and December 2018 for 15 major European stock markets. Returns are expressed in percentage per annum and redonominated in US dollars using daily spot exchange rates. Net short positions exceeding 0.5% of the issued share capital for stocks traded on a European Union (EU) regulated market are publicly disclosed at the investor level under the EU Short Selling Regulation. Daily equity factors for European stock markets are from Ken French's data library. Other data are from Bloomberg and Caretta.

	CAPM	FM3	FM4	FM5	FM6
MKT	−1.065***	−1.181***	−1.176***	−1.175***	−1.175***
	(0.022)	(0.024)	(0.019)	(0.023)	(0.019)
SMB		−0.543***	−0.548***	−0.539***	−0.547***
		(0.041)	(0.035)	(0.039)	(0.035)
HML		−0.195***	−0.108***	−0.223***	−0.093*
		(0.029)	(0.026)	(0.055)	(0.048)
RMW				0.035	0.044
				(0.067)	(0.061)
CMA				0.125**	0.027
				(0.061)	(0.060)
WML			0.213***		0.212***
			(0.026)		(0.026)
α	2.349	4.531***	2.478	4.310***	2.333
	(2.352)	(1.692)	(1.561)	(1.661)	(1.555)
R^2 (%)	83.60	87.12	88.09	87.16	88.08
N	1,574	1,574	1,574	1,574	1,574