Uncovering Skilled Short-sellers

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Keywords: short-selling; skill; stock-picking; market-timing; disposition effect

JEL Codes: G12; G14

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Studies on how skilled short-sellers trade typically employ aggregate shorting volume. Unfortunately, aggregate shorting volume is polluted by shorting for hedging, long-short strategies, and liquidity supplying. Using a unique data set that tracks all short-sellers in Brazil at the deal-level, we are able to uncover the skilled short-sellers and study them in isolation. This is revealing. Skilled short-sellers are actually short-term momentum investors (as opposed to contrarian as suggested by aggregate shorting volume), a significant part of their skill comes from market-timing, they are proficient at choosing when to cover their positions and, unlike unskilled short-sellers, display no disposition effect.

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1 Introduction

Skilled directional short-sellers are like reclusive celebrities: prized but elusive. They are highly regarded by practitioners and researchers because of their superior ability in predicting returns and their contribution to price efficiency.[1] Unfortunately, they are also hidden within aggregate shorting volume, which is polluted by shorting for different motives such as hedging, long-short strategies, and liquidity supplying. As a result, not much is known about the *specific* behavior of skilled short-sellers.

In this paper we rely on a unique data set that tracks *all* short-sellers and *all* equity loan contracts closed in the Brazilian stock market from 2012 to 2014. For each loan contract we have the stock traded, the loan quantity, the loan fee, the brokerage rate, the short-seller type (individual or institution), a unique identification variable for the short-seller, and the dates when the loan contract was both initiated and terminated.[2] We use this comprehensive data set in two steps. First, we discriminate the skilled short-sellers from their peers. Second, we study in detail how they trade. We find new results that contrast with the ones typically obtained from analyzing aggregate shorting. Specifically, skilled short-sellers are actually short-term momentum investors, a significant part of their skill comes from market-timing, they are also proficient at choosing when to cover their positions, and they display no disposition effect.

We define skilled short-sellers as those who consistently profit from shorting, i.e., earn a positive and statistically significant return from shorting. With our comprehensive data set, we are able to directly compute the realized performance of each short-seller. To the best of

[1] Diether, Lee, and Werner (2009), Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2012) and Rapach, Ringgenberg, and Zhou (2016) show that aggregate shorting predicts returns. Saffi and Sigurdsson (2011) find that stocks with higher short-sale constraints, characterized by low lending supply, display lower price efficiency. Engelberg, Reed, and Ringgenberg (2013) find that stocks with more short-selling risk have less price efficiency. Bris, Goetzmann, and Zhu (2007) and Boehmer and Wu (2013) relate short-selling with price discovery.

[2] Chague, De-Losso, Genaro, and Giovannetti (2017) use a less detailed data set on the Brazilian equity lending market which does not track the loan deal over time. They find that—for the same stock, on the same day—well-connected stock borrowers pay significantly lower loan fees, a result that relates search costs in the equity lending market with short-selling restrictions.

our knowledge, this is the first article to do that.

The remaining short-sellers (the ones who do not consistently profit from shorting) are not directly classified as unskilled. Indeed, shorting is used for reasons other than directional trading, such as long-short strategies (or hedging) and liquidity supplying[3], and classifying all remaining short-sellers as unskilled would be imprecise. Accordingly, we divide the short-sellers who do not consistently profit from shorting into three categories: long-short short-sellers, liquidity-suppliers, and, finally, unskilled short-sellers. Long-short short-sellers are those who do not directly profit from shorting but whose trading activity correlates with well-known long-short trading strategies; we identify them by running individual stock-day panel regressions for each short-seller. Liquidity-supplying short-sellers are those who do not directly profit from shorting but use shorting to supply liquidity to buyers, likely profiting from the bid-ask spread; we identify them as the investors who trade very frequently and buy and sell the same stock on more than 90% of the days. Finally, unskilled short-sellers are those who are not able to consistently profit from shorting and who do not follow long-short strategies nor are liquidity suppliers.

Having identified the skilled short-sellers we are then able to study their superior trading performance in detail. We find that skilled short-sellers earn 1.67% more per deal than unskilled short-sellers, which implies an annualized return of 33.4% per deal, and that 73% of this superior performance comes from correctly picking the stock ("stock-picking skill") while a significant part, the remaining 27%, comes from correctly timing market downturns ("market-timing skill"). We also find that the skilled short-sellers are actually short-term momentum investors as opposed to contrarian as suggested by aggregate shorting volume. As we show, the contrarian behavior of aggregate shorting volume actually comes from the unskilled short-sellers. We also find that skilled short-sellers are proficient at choosing when to cover their positions; 20% of their superior performance, or 0.33% per deal, can be attributed to this "cover-timing skill."

[3]Comerton-Forde, Jones, and Putniņš (2016) document the existence of short-sellers that are liquidity suppliers. They have to sell short on days with high buying pressure, when they run out of their inventory.

These results are obtained from *deal-by-deal* panel regressions with *deal-level* fixed-effects as follows. We first regress the realized return of each shorting deal closed by skilled and unskilled short-sellers on a dummy variable that identifies the deals by skilled short-sellers. It is from this benchmark regression that we estimate the 1.67% excess return per deal of skilled short-sellers mentioned above. We then control the benchmark regression for fixed-effects that capture both the entry and the exit dates of the deals, i.e., a dummy variable for each pair of dates. Since now the entry and exit dates are both fixed, it follows that market-timing skill is necessarily fixed, and hence the dummy variable that identifies skilled short-sellers now measures the portion of the excess return of skilled short-sellers solely attributable to stock-picking skill (73% of 1.67%, indicating that 27% comes from market-timing skill). Finally, we also control the benchmark regression for fixed-effects that capture both the stock sold short and the entry date of the deal, i.e., one dummy variable for each stock-entry date pair. Since in this regression the stock and entry date are both fixed, it follows that only the exit date is allowed to vary, and hence the dummy variable that identifies skilled short-sellers now measures the portion of the excess return solely attributable to cover-timing skill (20% of 1.67%).

Once we find that stock-picking, market-timing, and cover-timing skills are all important components of shorting skill, we study each one of them in further detail. We run investor-stock-day panel regressions of stock-picking on a number of stock-day variables to study stock-picking skill. The dependent variable of these regressions is a dummy variable that equals one if the short-seller picks a stock on a day and zero otherwise. The regressions include investor-day fixed-effects to focus on the cross-section of stock-picking controlling for individual characteristics and market conditions. We run the regressions on two samples, one containing deals from skilled short-sellers and the other from unskilled short-sellers. We find that skilled short-sellers tend to pick stocks that are more volatile, had negative returns over the previous 21 days, and have high book-to-market ratios. In contrast, unskilled short-sellers tend to pick stocks with low book-to-market ratios that yielded positive returns over the last 21 days. These results are consistent with skilled short-sellers being short-term momentum investors and with unskilled short-sellers being contrarian investors.

We then study market-timing skill by running the same investor-stock-day panel regressions using now different explanatory variables that capture the time-dimension: a number of market and calendar variables controlled for investor-stock fixed-effects. We find that skilled short-sellers respond more to changes in the term-spread and tend to trade when market returns are negative. In contrast, unskilled short-sellers exhibit contrarian behavior, trading when market returns are positive.

Finally, we study cover-timing skill by relating it to the so-called disposition effect. The disposition effect broadly refers to the tendency of investors to ride losses and realize gains; in this paper we define it as the tendency of short-sellers to reduce (increase) the duration of their deals after a fall (rise) in the stock price immediately after the beginning of the deal. Accordingly, using our deal-by-deal data set, we regress the duration of each shorting deal on the realized returns of the first few (three and five) days of the deal. We find that only unskilled short-sellers exhibit the disposition effect. Moreover, the higher the disposition effect of an unskilled short-seller, the lower her cover-timing skill.

In sum, by contrasting the behavior of skilled and unskilled short-sellers with respect to stock-picking, market-timing, and cover-timing, we learn that short-sellers are successful to the extent that they behave like short-term momentum investors, sell stocks that are already in distress (volatile and with high book-to-market), trade when the term spread is high and market return is low, and refrain from the disposition effect. On the other hand, we learn that short-sellers are unsuccessful to the extent that they behave like contrarian investors, sell stocks that are not in distress (stocks with low book-to-market), are less sensitive to the term spread, trade when the market return is high, and exhibit the disposition effect.

Our paper relates to a number of studies that analyze aggregate short-selling. Christophe, Ferri, and Angel (2004) find that aggregate shorting correctly anticipates negative earnings announcements. Christophe, Ferri, and Hsieh (2010) find that aggregate shorting increases three days before analysts publicly announce sell recommendations. Engelberg, Reed, and Ringgenberg (2012) find that aggregate shorting increases on days close to the disclosure of negative firm news. These articles emphasize the stock-picking ability of short-sellers. Indeed, they are consistent with our finding that most (73%) of shorting skill comes from stock-picking. However, our paper shows that a large fraction of skilled short-sellers profit (27%) comes from correctly timing the market. This is an important result to the extent that attenuates concerns about short-sellers uniquely profiting from firm-specific private information. Diether, Lee, and Werner (2009), in turn, find that *aggregate* shorting is contrarian in the US. We show that skilled short-sellers are actually momentum investors and that the contrarian behavior of aggregate shorting comes from unskilled short-sellers. Regarding the disposition effect, Beschwitz, Bastian, and Massa (2015) uses a data set on equity lending on US stocks to show that short sellers are more likely to close a position when capital gains are higher. We show that only unskilled short-sellers display disposition effect.

Other recent papers also highlight the importance of decomposing shorting volume but do not analyze skilled short-sellers in isolation. Using a data set that identifies short-sellers as institutions, individuals, proprietary, and others, Boehmer, Jones, and Zhang (2008) find that shorting from institutions are the most informative ones about future returns. Using a hand-collected data set from some disclosures of very large short positions in Europe, Jank and Smajlbegovic (2015) find that hedge funds generate risk adjusted returns 5.5% per year, outperforming other investors. Using a high-frequency data set on short-sales in the US during 2008, Comerton-Forde, Jones, and Putniņš (2016) find two distinct types of short-sales, passive short-sales (which originate from ask orders being hit by buyers) and active short-sales (which hit bid offers).

Our paper is inserted in the short-selling literature but also contributes to a larger literature that searches for skill among investors in stock market. The literature on skill typically relies on fund performance and discusses whether fund managers are truly skilled. It faces some well-known empirical difficulties. First, controlling for risk is essential and there is no consensus on which risk factors should be used (Fung and Hsieh, 2001 and Harvey, Liu, and Zhu, 2016). Second, fund capitalization changes over time, which may pollute the time series analysis (Berk and Green, 2004). Moreover, there is job rotation among fund managers, which can also render a given fund not comparable over long horizons. These difficulties are either absent or at least less of a concern in our case.

First, correcting returns for risk is unnecessary because if a short-seller is found to have positive expected return then she will necessarily have positive risk-adjusted return (the expected excess return for any stock must be positive). Second, each shorting deal is a short-term bet with a fully observed outcome (the realized profit and return). Since short-sellers typically place many of these bets, we can reliably estimate expected returns using only three years of data (as in our sample), which ensures that the basic characteristics of most investors remain unchanged. This contrasts with the funds literature, where many years of data (often more than 30) are needed to estimate a fund's expected return.

The remainder of the paper is organized as follows. In Section 2 we describe our data set and set out some basic statistics concerning short-selling in Brazil. In Section 3 we uncover the skilled short-sellers from aggregate shorting. In Section 4 we use our deal-by-deal data set to study shorting skill. Finally, Section 5 concludes.

2 Short-selling in Brazil

Short-selling is very common in Brazil. On average 25% of trading volume comes from equities being sold short. This is close to the value reported by Diether, Lee, and Werner (2009) for the US market in 2005 (24% for NYSE and 31% for Nasdaq). Figure 1 shows, on a monthly basis, the total number of shares traded, the total number of shares loaned, and the ratio between these two numbers.

[Figure 1 about here]

Stock lending is regulated by the Brazilian Securities and Exchange Commission (CVM);

all shorting loans are registered at BM&FBOVESPA, which acts as the central-counterpart in this market. Recent articles on short-selling have explored this very detailed Brazilian equity lending market data. For instance, Bonomo, Mello, and Mota (2015) test whether short-selling restrictions generate stock overpricing, and Chague, De-Losso, Genaro, and Giovannetti (2017) show that well-connected borrowers with lower search costs pay significantly lower loan fees.

2.1 Data set

Our data set contains *all* of the 4,575,324 equity loan contracts closed in Brazil from January 2012 to December 2014. For each loan contract we observe the stock ticker, the loan quantity, the loan fee, the brokerage fee, a unique identification variable for the borrower, and the dates when the loan contract was initiated and terminated. This allows us to compute the financial result of every deal of every short-seller during this period.

We apply two filters to the original data set. First, we restrict the sample to stocks that traded every day during our sample; this yields 151 stocks. Second, we exclude from the sample all loan contracts that intersect an "interest on equity" ex-date. According to Brazilian law (which was modified only in 2015), the tax treatment of interest on equity differs according to investor type: individual investors pay a tax rate of 15%, while financial institutions are exempt. As a result, on days around the ex-date of interest on equity there are many tax arbitrage trades between individuals and financial institutions in which individuals lend shares to financial institutions at a higher loan fee. These loans deals are therefore unrelated to short-selling.

After applying both filters our final sample contains 3,077,337 loan contracts. Panel A of Table 1 displays, for each year of the sample, the total number of loan contracts and the total number of distinct short-sellers who closed at least one deal by investor type. Panel B of Table 1 exhibits some statistics on the empirical distributions of two variables, the number of loan deals closed by short-sellers and the duration (measured in calendar days) of the loan contracts. Shorting deals are mostly short-term trades: the median number of days of a loan contract in our sample is 12 days for both types of investors.

[Table 1 about here]

In what follows, we regard the 3,077,337 loan contracts as 3,077,337 shorting deals. A major reason for borrowing and not short-selling would be the tax arbitrage described above, which we have already excluded from the sample.

2.2 External validity: aggregate shorting predicts returns and is contrarian

There is solid empirical evidence that *aggregate* shorting predicts lower returns. For example, Diether, Lee, and Werner (2009) find that a strategy of going long stocks with relatively low shorting and going short stocks with relatively high shorting generates a statistically significant return of 1.39% per month for NYSE stocks and 1.41% per month for NASDAQ stocks. Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2012) and Rapach, Ringgenberg, and Zhou (2016) find analogous results. Moreover, aggregate shorting is contrarian in the US; Diether, Lee, and Werner (2009) shows that aggregate shorting increases after prices have increased in the previous five days. In this section we show that, as in the US, aggregate shorting predicts lower returns and is contrarian in Brazil.

We replicate Table 5 of Diether, Lee, and Werner (2009) using our data set. We first compute their variable $relss$, the number of shorted shares divided by the number of traded shares on each day for each stock. We then sort the stocks according to $relss$ on each day. Stocks up to the 25th percentile are assigned to the "Low" portfolio, stocks between the 25th and 75th percentiles are assigned to the "Medium" portfolio,and stocks above the 75th percentile are assigned to the "High" portfolio. The "Low-High" portfolio goes long the Low portfolio and goes short the High portfolio. For each portfolio (Low, Medium, High, and

Low-High) we compute daily value-weighted risk-adjusted returns over the 2-, 5-, and 10-day ahead horizons.[4]

Consistent with the US evidence, Table 2 shows that investing in the Low-High portfolio generates statistically significant returns. For example, at the 10-day horizon, the average risk-adjusted return of the strategy is 0.604%, or 1.33% per month (1.33% = (22/10)×0.604% per month). This number is very close to the one reported by Diether, Lee, and Werner (2009), of 1.39% (1.41%) per month for NYSE (Nasdaq) stocks.

[Table 2 about here]

To show that aggregate shorting is also contrarian in Brazil, we regress aggregate shorting on past returns. Table 3 presents the results of panel regressions of $relss$ on 5-, 10-, and 21-day past returns. The coefficients in columns (1), (2), and (3) are all positive and statistically significant, implying that aggregate shorting activity is higher after prices have increased. Column (4) shows that the effect is stronger for short-term price increases.

[Table 3 about here]

2.3 Skilled short-sellers are not contrarian

In Section 3 we decompose aggregate shorting into its diverse shorting motives. In Section 4 we then focus on the skilled short-sellers to study how they trade. However, before going into these details, we anticipate in a simple and illustrative way a clear result that comes from uncovering skilled short-sellers from aggregate shorting: skilled short-sellers are not contrarian.

Figure 2 depicts the cross-deals average evolution of stock prices during the time span of the shorting deals of skilled and unskilled short-sellers. We normalize all deals to have the

[4] Risk-adjusted returns are calculated as the residuals of time-series regressions of daily stock excess returns on the 3 Fama-French risk factors calculated to Brazil, which are available at the Brazilian Center for Research in Financial Economics of the University of Sao Paulo (Nefin, www.nefin.com.br).

same length of 10 days (i.e., 14 calendar days) to compute the average evolution of prices across all deals. Prices are normalized to one on the first day of the shorting deal. Figure 2 also shows the average evolution of stock prices five days before the beginning and five days after the end of the deal.

[Figure 2 about here]

Given our definition of skilled short-sellers to be presented ahead, it is not surprising that Figure 2 shows that stock prices fall during deals from skilled investors. The bold line in Figure 2 shows that prices drop from one to around 0.983, which is consistent with the average return per deal obtained by skilled short-sellers to be presented. In contrast, the dashed line shows that unskilled investors lose on average; prices rises from one to about 1.003. These are mechanic results given our classification strategy of skilled and unskilled short-sellers.

The interesting takeaways of Figure 2 are the following. First, while prices fall continuously during skilled deals, they follow a hump-shaped pattern during unskilled deals. Moreover, prices fall prior to the beginning of skilled shorting deals, but rise prior to the beginning of unskilled deals. Finally, the evolution of prices after the end the deals shows that skilled short-sellers are proficient at covering their positions; the rate at which prices are falling clearly decreases after this point. Overall, these patterns indicate that unskilled short-sellers generally attempt to anticipate an eventual decline in prices, while skilled short-sellers expect prices to continue to fall.

3 Uncovering skilled short-sellers

In this section, we uncover the skilled short-sellers from aggregate shorting. We define skilled short-sellers as those who consistently profit from shorting, i.e., earn a positive and statistically significant return from shorting. The remaining short-sellers (the ones who do not consistently profit from shorting) are not directly classified as unskilled. Instead, we divide them into three categories: long-short short-sellers, liquidity-suppliers, and, finally, unskilled short-sellers.

We summarize our classification strategy in four steps:

- Step 1: we identify the "skilled short-sellers" as those who consistently profit from shorting;
- Step 2: among the remaining short-sellers, we identify "liquidity-suppliers" as those who frequently buy and sell the same stock on the same day;
- Step 3: among the remaining short-sellers from Steps 1 and 2, we identify "long-short investors" as those who sell short according to well-known long-short strategies;
- Step 4: all remaining short-sellers are classified as "unskilled short-sellers."

Short-sellers classified as liquidity-suppliers and long-short investors, although do not profit from shorting, may profit from their overall trading activity. Since we do not observe their overall trading activity, we cannot classify them as skilled or unskilled. Indeed, our focus in this paper is to study the investors that directly profit from shorting, identified in Step 1, and to compare them with the unskilled short-sellers, identified in Step 4.

We next describe the four steps of our classification strategy in detail.

3.1 Step 1: Identifying skilled short-sellers

Since we observe all deals of all short-sellers in the Brazilian market, we can calculate every individual performances over the whole sample period. We first compute for each deal i in our sample its realized return: $R_i = (P_{i,0} - P_{i,1})/P_{i,0}$, where $P_{i,0}$ is the price at which the short-seller sells the stock, and $P_{i,1}$ is the price at which the short-seller buys the stock back.[5]

[5] In Brazil, just as in the United States, equity transactions are settled after three trading days, while equity loans are settled on the same day. Accordingly, a short-seller does not need to borrow a stock until the morning on the third day after taking her short position. Therefore, following Geczy, Musto, and Reed (2002) and Beschwitz, Bastian, and Massa (2015), we use for $P_{i,0}$ and $P_{i,1}$ the closing prices three trading days earlier to the dates the loan contract was initiated and terminated, respectively.

We then estimate the expected return of each short-seller considering the realized returns from her deals. We say that a short-seller is "skilled" if her estimated expected return from shorting, $E(R_i)$, is positive.

Estimating investors' expected returns from ex-post returns to evaluate their skill is not new. A large literature does that for mutual and hedge funds.[6] This literature, however, faces some well-known difficulties. First, controlling for risk is essential but there is no consensus on which risk factors should be used (Fung and Hsieh, 2001; and Harvey, Liu, and Zhu, 2016). Second, fund capitalization changes over time, which may pollute the time series analysis (Berk and Green, 2004). Finally, there is job rotation among fund managers, so that the performance of a given fund may not be comparable over long horizons.

Detecting skill among short-sellers is easier. First, correcting returns for risk is not an issue: if we find that $E(R_i) > 0$ for a given short-seller, we can safely conclude that she is skilled. A long position in any stock should have positive expected return (since it is riskier, *in any sense*, than holding the risk-free asset), so a short-seller that trades randomly should on average earn negative returns. In other words, if we find that $E(R_i) > 0$ for a given short-seller, then her risk-adjusted expected return is also positive, since it must be higher than $E(R_i)$. Second, each shorting deal can be seen as a short-lived bet whose outcomes, the realized profit and return, we observe. Since a typical short-seller makes many of these bets—according to Table 1 the average institution (individual) closed 629 (18) deals in our sample—we can estimate $E(R_i)$ using our 3-year sample, which ensures that the basic characteristics of most investors remain unchanged. This contrasts with the funds literature, where many years of data (often more than 30) are needed to estimate a fund's expected return, severely shortening the sample of available funds.

We estimate the expected return of each short-seller by directly taking the sample average return across her shorting deals. Ideally, for the sample average to be a consistent estimator of $E(R_i)$, the deals should be independent, which is not always the case. For example,

[6] See for instance Carhart (1997), Kosowski, Timmermann, Wermers, and White (2006), Fama and French (2010), Kacperczyk, Nieuwerburgh, and Veldkamp (2014), and Berk and van Binsbergen (2015).

two deals on the same stock closed in the same week are likely to have correlated returns. Moreover, these deals should come from the same shorting decision, what makes the two bets intrinsically dependent. We deal with this issue in estimating $E\left(R_i\right)$ by filtering our data set to have at most one shorting deal (the largest one) per investor-stock-week.

We then say that a given short-seller is skilled, i.e., has $E\left(R_i\right) > 0$, if

$$\sqrt{N}\frac{\frac{1}{N}\sum_{i=1}^{N} R_i}{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(R_i - \frac{1}{N}\sum_{i=1}^{N} R_i\right)^2}} > t_{N-1,10\%} \tag{1}$$

where N is the number of deals made by the short-seller in the filtered data set and $t_{N-1,10\%}$ is the critical value of the t-distribution with $N-1$ degrees of freedom at the 10% level.[7]

Our sample period is particularly suitable for the detection of shorting skill since between January 2012 and December 2014 the Brazilian stock market experienced no overall trend – the cumulative market return over the period was close to zero. Considering the 151 stocks in our sample, the (equal-weighted) cumulative return between January 2012 and December 2014 was -0.5%. Such market dynamics reduces the chances of misclassifying short-sellers. During a consistently bull-market period, informed short-sellers would not have traded much and we would have tended to overestimate the proportion of uninformed short-sellers. Symmetrically, we would tend to overestimate the proportion of informed short-sellers during a consistent bearish period. Figure 3 shows that despite the absence of a negative trend in stock prices, short-sellers are still able to profit consistently over time.

[Figure 3 about here]

3.1.1 Short-selling performance is persistent

If there is indeed shorting skill in our sample then shorting performance should be persistent. To check this, we run two empirical exercises: i) we test whether past performance predicts

[7] An investor must also have a minimum total profit of US$ 1,000 considering all deals to be classified as skilled.

future performance (*persistence in time*) and ii) we check whether performance in one stock predicts performance in other stocks (*persistence across stocks*).

To evaluate persistence in time, we compute two measures of a short-seller's past performance:

- $AveRet_{past}$: the short-seller average return across all her deals between January 2012 and June 2013;
- $MedRet_{past}$: the short-seller median return across all her deals between January 2012 and June 2013.

We run deal-by-deal panel regressions on data from January 2014 and December 2014, with the deal return on the left-hand side and with $AveRet_{past}$ and $MedRet_{past}$ on the right-hand side. We exclude the last six months of 2013 to ensure that only past performance is being used to predict future performance.

To evaluate persistence across stocks, given a stock s we compute two measures of short-seller performance on stocks other than stock s:

- $AveRet_{-s}$: the short-seller average return across all her deals on stocks other than s;
- $MedRet_{-s}$: the short-seller median return across all her deals on stocks other than s.

We then run deal-by-deal panel regressions on the full sample, with the deal return on the left-hand side and with $AveRet_{-s}$ and $MedRet_{-s}$ on the right-hand side.

Columns (1) and (2) in Table 4 show favorable evidence of performance persistence in time. The average return and the median return of the short-seller between January 2012 and June 2013 are significant predictors of the returns on her deals in 2014. Columns (3) and (4) in Table 4 show favorable evidence of performance persistence across stocks. The average return and the median return of the short-seller in stocks other than stock s are significant predictors of the returns of her deals on stock s.

[Table 4 about here]

In sum, the persistence in shorting performance suggests the presence of skill in short-selling. Short-sellers that profit in the past tend to profit in the future. Short-sellers that profit trading a given stock tend to profit trading other stocks.

3.2 Step 2: identifying liquidity suppliers

Recent empirical evidence suggests that shorting may also be used by liquidity suppliers (Comerton-Forde, Jones, and Putniņš, 2016). For instance, an algo-trader who profits from bid-ask spreads by buying and selling the stock throughout the day often keeps very low inventories. Eventually, after a day with high buying pressure, the algo-trader may end up the day with a negative inventory, in which case she will have to borrow the stock in the lending market.

To identify liquidity suppliers among short-sellers that were not classified as skilled in Section 3.1, we analyze their daily buying and selling behavior in the stock market. We classify a short-seller as a liquidity supplier if on more than 90% of the days in which she sold a stock, she also bought the same stock (not necessarily in the same quantity).[8] To impose a minimum level of trading activity, we also require the liquidity supplier to have traded in more than 742 stock-days (i.e., an average of at least one stock per day in the sample).

3.3 Step 3: identifying long-short investors

To identify short-sellers who follow long-short strategies among those that were neither classified as skilled in Section 3.1 nor classified as liquidity suppliers in Section 3.2, we proceed as follows. First, we consider only short-sellers that closed more than 36 shorting deals in the sample (i.e., one deal per month) as a potential long-short investor. Second, for each one of these short-sellers, we construct a stock-week balanced panel of her shorting activity which displays the volume sold short by her in each stock-week pair. We then regress

[8] We thank the Securities and Exchange Commission of Brazil (CVM) for providing this information.

the short-sellers's shorting activity on variables that capture two common long-short trading strategies, namely, value and momentum strategies.[9]

More specifically, for each of the short-sellers who closed more than 36 shorting deals in the sample and were not classified as skilled in Section 3.1 or as liquidity suppliers in Section 3.2, we run

$$ShortVolume_{k,s,t} = \beta_0 + \beta_{Mom,k} \times Mom_{s,t} + \beta_{Value,k} \times Value_{s,t} + \epsilon_{k,s,t} \tag{2}$$

where $ShortVolume_{k,s,t}$ is the volume shorted by short-seller k on stock s in week t, $Mom_{s,t}$ is the decile of stock s in the cross-sectional distribution of the stocks weekly sorted (from winners to losers) according to the last 12-month return, and $Value_{s,t}$ is the decile of stock s in the cross-sectional distribution of the stocks weekly sorted according to their book-to-market ratio.[10]

We say that short-seller k follows long-short strategies if at least one of $\beta_{Mom,k}$ or $\beta_{Value,k}$ is significantly positive at the 5%-level.

3.4 Step 4: identifying unskilled short-sellers

The short-sellers who were not classified as skilled in Section 3.1, as liquidity suppliers in Section 3.2, or as long-short investors in Section 3.3, are classified as unskilled short-sellers.

3.5 Decomposing shorting volume

Table 5 shows the outcome of our classification strategy and exhibits the average across investors of six variables that illustrate the differences between the groups.

[Table 5 about here]

[9] The momentum strategy in particular was very profitable during the sample period, exhibiting cumulative returns of about 95%.

[10] We do not include size-related strategy since it is mechanically correlated with shorting volume as large firms exhibit higher shorting volume.

Columns 1 and 2 of Table 5 show that the group of skilled short-sellers contains 443 institutions and 1,922 individuals. They account for 34.9% and 0.4% of the total shorting volume, respectively. The group of long-short investors contains 194 institutions (which account for 25.3% of the total shorting volume) and 371 individuals (0.2%). The group of liquidity suppliers contains 28 institutions (4.9%) and 169 individuals (0.1%). Finally, the group of unskilled short-sellers contains 2,163 institutions (31.8%) and 22,120 individuals (2.3%).[11]

Column 3 of Table 5 shows that liquidity supplying institutions closed the highest number of shorting deals in our sample (4,985 on average), followed by long-short institutions (3,645) and skilled institutions (1,926). Column 4 shows that the skilled institutions as a group had the largest average volume per deal (US$ 102,145), followed by long-short institutions (US$ 95,094) and unskilled institutions (US$ 80,481). Column 5 shows that liquidity-supplying short-sellers had the shortest average duration per deal (8 calendar days for both institutions and individuals). Column 6 shows that long-short institutions trade on average the largest number of stocks (59), followed by liquidity-supplying institutions (44) and by skilled ones (38). Column 7 shows that the skilled institutions as a group exhibit the highest average profit per deal (US$ 2,390), followed by skilled individuals (US$ 790). Finally, column 8 shows that individuals pay on average higher loan fees. Unskilled individuals pay on average 23.8% higher loan fees than the average short-seller; skilled individuals pay on average 15.6% higher loan fees than the average short-seller. Among institutions, liquidity suppliers pay the lowest loan fees (6.9% below average), followed by long-short institutions (1.6% below average), skilled institutions (0.3% above average), and unskilled institutions (10.1% above average).

Overall, the numbers in Table 5 support our classification strategy. Long-short institutions typically perform their strategies by using large number of stocks and by holding large

[11] There are 1,093 institutions and 9,351 individuals who closed only one shorting deal during the entire sample. These investors account for only 0.06% of the total shorting volume. They were not classified in any of the four groups.

positions. Liquidity suppliers are likely to resort to the lending market only for short-periods of time to cover eventual declines in inventories that result from sustained trading imbalances (Comerton-Forde, Jones, and Putniņš, 2016). As such, the short duration of their deals reported in Table 5 is not surprising. Moreover, that individuals pay higher loan fees is consistent with the view that these investors are occasional short-sellers with poor connections in the equity lending market (Chague, De-Losso, Genaro, and Giovannetti, 2017).

Figure 4 shows the monthly evolution of the volume fraction by group. To better depict the fractions, we combined all shorting activity by individuals into a single time-series. As can be seen, the fractions vary substantially over time. For instance, the skilled fraction reaches a maximum of 53% in 2013 and a minimum of 30% in 2012.

[Figure 4 about here]

Finally, Table 6 exhibits a correlation matrix between the shorting activity of each group and daily stock returns and buying pressure (*Oimb*). Shorting activity is the ratio between shorted volume and traded volume for each stock-day. Oimb is the buy-order imbalance for each stock-day, given by ratio between the number of shares traded in buy-initiated deals minus the number of shares traded in sell-initiated deals and the number of shares traded in both buy- and sell-initiated deals. We identify buy-initiated deals by using tick-by-tick data and comparing the time-stamp of the buy and sell orders with the time-stamp of the deal. We say that a deal is buy-initiated if the time-stamps of the deal and of the buy-order coincide. Likewise, we say that a deal is sell-initiated if the time-stamps of the deal and the sell-order coincide. As in Diether, Lee, and Werner (2009), we truncate this variable at zero; as a result, *Oimb* takes values from zero (low buying pressure) to one (maximum buying pressure).

As expected, Table 6 shows that liquidity-supplying shorting is highly correlated with buying pressure. Liquidity supplying short-sellers step in on days with many buying-initiated deals, which is consistent with the passive short-sales described by Comerton-Forde, Jones, and Putniņš (2016). In contrast, skilled shorting activity is negatively correlated with buying pressure.

4 Shorting skill: a deal-by-deal analysis

In this section we use the classification of short-sellers from Section 3 and our deal-by-deal data set to study shorting skill. First, we find that (i) skilled short-sellers are proficient at both stock-picking and market-timing and that (ii) once they sell short, they are also proficient at choosing when to cover the position. We refer to the latter as "cover-timing" skill. Second, we analyze how stock-picking correlates with variables in the cross-section of stocks. Third, we analyze how market-timing correlates with market and calendar variables. Finally, we analyze cover-timing skill and show that it can be partially explained by the so-called disposition effect.

To show (i) and (ii), we use our deal-by-deal data set and run the following regressions:

$$R_{k,s,t,\tau,i} = \beta_0 + \beta_1 \times \mathbb{I}\left[k \in Skilled\right] + \epsilon_{k,s,t,\tau,i} \tag{3}$$

$$R_{k,s,t,\tau,i} = \beta_2 + \beta_3 \times \mathbb{I}\left[k \in Skilled\right] + \alpha_{t,\tau} + u_{k,s,t,\tau,i} \tag{4}$$

$$R_{k,s,t,\tau,i} = \beta_4 + \beta_5 \times \mathbb{I}\left[k \in Skilled\right] + \alpha_{s,t} + \eta_{k,s,t,\tau,i} \tag{5}$$

where $R_{k,s,t,\tau,i}$ is the realized return of deal i closed by short-seller k on stock s on day t and covered on day τ, calculated as in Section 3.1; $\mathbb{I}\left[k \in Skilled\right]$ is a dummy variable that equals one if short-seller k belongs to the skilled group; $\alpha_{t,\tau}$ are fixed-effects for each pair (t, τ);[12] and $\alpha_{s,t}$ are fixed-effects for each pair (s, t).

Regression (3) is our benchmark regression. Parameter β_1 is specified so that it measures the "excess return of skilled short-sellers," that is, the average return per deal that skilled

[12] For instance, all deals initiated on September 9th, 2013 and terminated on September 27th, 2013 will have the same constant; all deals initiated on September 10th, 2013 and terminated on September 25th, 2013 will have the same constant; and so on.

short-sellers earn above other short-sellers. The two regressions include additional controls to decompose shorting skill. Parameter β_3 of regression (4) measures the excess return after controlling for (t, τ) fixed-effects. Since entry and exit dates are both fixed, i.e., market-timing skill is fixed, β_3 measures the portion of the excess return solely attributable to stock-picking skills. This is the case since we are comparing deals on different stocks that were initiated and terminated on the same dates. Finally, parameter β_5 of regression (5) measures the excess return after controlling for (s, t) fixed-effects. Since stock and entry date are both fixed, β_5 measures the portion of the excess return solely attributable to exit-timing (or cover-timing) skills. This is the case since we are comparing deals on the same stock, initiated on the same date but covered on different dates.

Column (1) of Table 7 shows that the excess return of skilled short-sellers is 1.534% per deal, or 30.7% ($1.534 \times 360/18$) per year if we consider the average duration of the deals from skilled institutions (18 calendar days, according to Table 5). Column (2) shows that the excess return attributable to stock-picking skills is 1.060% per deal. From this we conclude that 69% (1.060/1.534) of the excess return of skilled short-sellers is attributable to superior stock-picking skills, whereas the remaining 31% is attributable to superior market-timing skills. Column (3) shows that the excess return attributable to cover-timing skills is 0.360% per deal, or 23% (0.360/1.534) of the excess return of skilled short-sellers.

[Table 7 about here]

Columns (1), (2), and (3) of Table 7 consider all short-sellers while columns (4), (5), and (6) consider only deals from skilled and unskilled short-sellers. We thereby compare skilled short-sellers with similar investors and not with long-short investors and liquidity suppliers. Column (4) shows that the excess return of the skilled short-sellers, now relative to the unskilled, is 1.671% per deal. Column (5) shows that the excess return attributable to stock-picking skills is 1.220% per deal. From this we conclude that 73% (1.220/1.671) of the excess return is attributable to superior stock-picking skills, with the remaining 27% is attributable to superior market-timing skills. Column (6) shows that the excess return attributable to cover-timing skills is 0.334% per deal, or 20% (0.334/1.671) of the excess return of the skilled short-sellers. These proportions are similar to those computed with the full sample.

To the best of our knowledge, we are the first to decompose shorting skill into market-timing and stock-picking skills. We find that both skills are important. Previous studies emphasize only short-sellers stock-picking skill (Christophe, Ferri, and Angel, 2004, find that aggregate shorting correctly anticipates negative earnings announcements; Christophe, Ferri, and Hsieh, 2010, find that aggregate shorting increases three days before analysts publicly announce sell recommendations; Engelberg, Reed, and Ringgenberg, 2012, find that aggregate shorting increases on days close to the disclosure of negative corporate news). The existence of cover-timing skill, in turn, is also documented by Beschwitz, Bastian, and Massa (2015), who show that aggregate covering activity predicts positive future returns.

We next show that skilled short-sellers tend to pick value stocks with low past returns and high volatility. In contrast, unskilled short-sellers act as contrarian trades, picking growth stocks with high past returns.

4.1 Stock-picking

Table 7 shows that 73% of shorting skill comes from stock-picking skill. In this section we study how skilled short-sellers pick a stock by running investor-stock-day panel regressions. To do so, we first define a variable $Pick_{k,s,t}$ that equals one if skilled short-seller k closed a shorting deal on stock s on day t, and zero otherwise. That is, $Pick_{k,s,t} = 1$ if short-seller k picked stock s on day t. We then regress $Pick_{k,s,t}$ on the following stock-day explanatory variables:

- *Lag short*: a dummy variable that equals one if short-seller k closed a shorting deal on stock s on the previous 5 days;

- *Volatility:* the standardized return volatility of stock s on day t, computed using the daily returns from the last 10 days;
- *Oimb*: the buying pressure on stock s on day t, measured as the net order imbalance truncated at zero. It takes values from zero (minimum buying pressure) to one (maximum buying pressure);
- *Return*: the stock return of stock s on day t;
- *21-day return*: the cumulative stock returns of stock s over the last 21 days;
- *Book*: the standardized book-to-market ratio of stock s on day t;
- *Size*: the standardized log market-capitalization of stock s on day t;
- *Volume*: the standardized log trading volume of stock s on day t;
- *Bid-ask spread*: the standardized daily average bid-ask spread of stock s on day t;

Since in this section we are interested in stock-picking, the regressions include investor-day fixed-effects. That is, within each pair (k, t), we evaluate which stocks investor k chooses to sell short on day t.

Table 8 displays the results. Columns (1) and (2) consider the 443 institutions that were classified as skilled in Section 3.1. Columns (3) and (4) consider 443 randomly chosen unskilled institutions.[13]

[Table 8 about here]

[13]We consider only 443 unskilled institutions as opposed to all 2,163 for computational reasons. Since these regressions use balanced panels, they contain $N \times T \times S$ observations, where N is the number of investors, T is the number of days (742), and S is the number of stocks (151). With $N = 443$, we then have 49,634,606 observations, and with $N = 2,163$ we would have 242,346,846 observations.

Column (1) of Table 8 shows the results of regressing skilled stock-picking on *Volatility*, *Oimb*, *Return*, and *21-day return*; column (2) shows the results using all explanatory variables. Since the results are qualitatively the same, we describe the results in Column (2) only. Column (2) shows that a stock with a one-standard deviation higher volatility has a 7.0 higher probability of being picked by a skilled short-seller (7.0% = 0.059/0.848).[14] Stocks with higher buying pressure are less likely to be picked by skilled short-sellers, which indicates that skilled short-sellers do not provide liquidity to buyers. Stocks with 0.5 higher *Oimb* are 21.5% less likely to be picked ($-0.5 \times 0.365/0.848$). Stocks with low 21-day returns are more likely to be picked by skilled short-sellers; for instance, stocks with a negative return of 20% during the last 21 days are 4.7% more likely to be picked ($-20 \times 0.002/0.848$). One-standard deviation increases in *Book*, *Size*, and *Volume* result in increases in the skilled stock-picking probability of 3.3% (0.028/0.848), 3.8% (0.032/0.848), and 11.8% (0.100/0.848) respectively. Finally, a one-standard deviation increase in the bid-ask spread reduces the stock-picking probability by 9.6% ($-0.081/0.848$). Cross variations in daily returns do not explain differences in skilled stock-picking after controlling for *Book*, *Size*, *Volume*, and *Bid-ask spread* in Column (2).

We now turn to unskilled stock-picking. Column (4) shows that stocks with higher buying pressure are also less likely to be picked by unskilled short-sellers; stocks with 0.5 higher *Oimb* are 10.2% less likely to be picked ($-0.5 \times 0.026/0.128$).[15] In contrast to skilled short-sellers, stocks with positive contemporaneous and 21-day returns are more likely to be picked by unskilled short-sellers. Stocks with positive contemporaneous returns, for instance 2%, are 3.1% more likely to be picked by unskilled short-sellers ($2 \times 0.002/0.128$). Similarly, stocks with positive 21-day return, for instance by 20%, are 2.4% more likely to be picked ($20 \times 0.00015/0.128$). In contrast to skilled short-sellers, a one-standard deviation increase in *Book*

[14] 0.848 is the unconditional probability in percentage points of a stock being picked by a skilled short-seller.

[15] 0.128 is the unconditional probability in percentage points of a stock being picked by a unskilled short-seller.

results in a 1.6% ($-0.002/0.128$) decrease in the probability of unskilled stock-picking. One-standard deviation increases in *Size* and *Volume* result in increases in the unskilled stock-picking probability of 10.2% ($0.013/0.128$) and 19.5% ($0.025/0.128$) respectively. Finally, a one-standard deviation increase in the bid-ask spread also reduces the unskilled stock-picking probability by 9.4% ($-0.012/0.128$). Cross-sectional variation in volatility does not explain differences in unskilled stock-picking after controlling for *Book*, *Size*, *Volume*, and *Bid-ask spread* in Column (4).

The main conclusion that emerges from Table 8 is that skilled short-sellers tend to pick stocks that are more volatile, had negative returns in the last 21 days, and that have high book-to-market ratio. In contrast, unskilled short-sellers tend to pick stocks with low book-to-market ratio that yielded positive returns in the last 21 days. These results are consistent with skilled short-sellers being short-term momentum investors who sell stocks that are already in distress, and with unskilled short-sellers being contrarian investors who try to anticipate periods of distress.

4.2 Market-timing

In this section we study *when* short-sellers decide to trade. We run the same investor-stock-day panel regressions of Section 4.1, but now using market and calendar variables as regressors and controlling for investor-stock fixed-effects instead of for investor-day fixed effects. Specifically, we regress $Pick_{k,s,t}$, defined in the previous section, on the following regressors:

- *Lag short*: a dummy variable that equals one if short-seller k closed a shorting deal on stock s on the previous 5 days;
- *Term spread:* the slope of the Brazilian bond yield curve computed on day t (one-year maturity minus one-month maturity). It reflects the maturity risk-premium associated with the yield curve;

- *Dividend yield*: the total amount of dividend paid by firms in the Brazilian stock market over the last 12 months divided by their market capitalization on day t. It reflects the risk-premium associated with the stock market;
- *Market Volatility*: the market return volatility computed using daily returns from the last 10 days;
- *Market*: the market return on day t;
- *Monday, Tuesday, Thursday, and Friday*: dummy variables that indicate the day of the week.

Since in this section we are interested in market-timing, the regressions include investor-stock fixed-effects. That is, within each pair (k, s), we evaluate when investor k chooses to sell short. Table 9 shows the results. As in the previous section, columns (1) and (2) consider the 443 institutions that were classified as skilled in Section 3.1, while columns (3) and (4) consider the same set of randomly selected unskilled institutions as in Section 4.1.

[Table 9 about here]

Columns (1) and (2) of Table 9 show that skilled short-sellers tend to short when the term spread is higher, the market volatility is lower, and market returns are lower. On days when the term spread is one percentage point higher there is an increase of 15.1% in the shorting activity by skilled short-sellers ($15.1\% = 1 \times 0.178/0.848$). On days when the market volatility and the market return are one percentage point higher there are decreases of 12.7% ($-1 \times 0.108/0.848$) and 0.6% ($-1 \times 0.005/0.848$), respectively, in the shorting activity by skilled short-sellers. Column (2) shows that there is day-of-the-week seasonality in skilled shorting; skilled shorting is 1.8% higher on Friday and 1.9% lower on Monday. This suggests that skilled short-sellers are actually exploring the Monday effect[16] to their advantage.

[16] The so-called Monday-effect is a long documented calendar anomaly that can be traced back to at least

Columns (3) and (4) of Table 9 show that unskilled short-sellers also tend to short when the market volatility is lower and when the term spread is higher, although the effects are smaller. On days when the term spread is one percentage point higher there is an increase of 1.5% in the shorting activity by unskilled short-sellers ($1.5\% = 1 \times 0.002/0.128$). On days when the market volatility is one percentage point higher there is a decrease of 11.7% ($-1 \times 0.015/0.128$) in unskilled shorting. Unskilled shorting, unlike skilled shorting, co-moves with the market return. On days when the market return is one percentage point higher, unskilled shorting is 0.8% higher ($1 \times 0.001/0.128$). Finally, unskilled short-sellers do not take advantage of the Monday effect. Their shorting activity is lower both on Friday (0,3%) and on Monday (0,4%). These results may be consistent with Chen and Singal (2003), who show that some short-sellers decrease their activity on Friday to avoid being exposed to weekend news.

In sum, skilled short-sellers respond more to changes in the term spread and tend to trade when market returns are negative. In contrast, unskilled short-sellers exhibit contrarian behavior in that they tend to trade when market returns are positive.

4.3 Cover-timing

Table 7 shows that skilled short-sellers have cover-timing skill, which accounts for about one fifth of the skilled short-sellers' superior performance. In this section we discuss a possible explanation for cover-timing skill based on the disposition effect. We first show that only unskilled short-sellers are susceptible to the disposition effect. We then show that, among unskilled short-sellers, the higher the disposition effect, the worse the cover-timing skill.

The disposition effect refers to the tendency of investors to ride losses and realize gains. This asymmetric behavior across gains and losses is consistent with investors having loss-averse type of preferences (see for instance Tversky and Kahneman, 1991, and Barberis and Xiong, 2009). At least since Shefrin and Statman (1985), many papers have documented

Cross (1973) (see also French, 1980; and Keim and Stambaugh, 1984). According to it, returns tend to be lower on Mondays and higher on Fridays.

the disposition effect in financial markets. Using proprietary data from a large discount brokerage house, Odean (1998) finds that individual investors are strongly affected by the disposition effect. Using an extensive data set from Finnish households, Grinblatt and Keloharju (2001) also document the disposition effect among individual investors. Using data from the Treasury Bond futures contract at the Chicago Board of Trade, Coval and Shumway (2005) finds that professional investors are also subject to the disposition effect and that are highly loss-averse. Locke and Mann (2005) show that futures traders tend to ride losses, although the authors argue this behavior does not affect their overall trading performance.

Regarding short-sellers, Beschwitz, Bastian, and Massa (2015) uses a data set on equity lending on US stocks to show that short sellers are more likely to close a position when capital gains are higher. As we show now, disposition effect is only present among unskilled short-sellers.

We use our deal-by-deal data set to test the presence of disposition effect among skilled and unskilled short-sellers in a very direct way. We say that short-sellers display the disposition effect if they reduce (increase) the duration of their deals after initial favorable (unfavorable) returns—i.e., if they ride losses and realize gains. More precisely, we say that short-sellers display the disposition effect if $\beta > 0$ in the following regressions:

$$Days_{k,s,t,i} = \beta \times Ret_{s,t+1 \to t+h} + \alpha_{k,t} + \epsilon_{k,s,t,i} \tag{6}$$

where $Days_{k,s,t,i}$ is the duration of deal i closed by short-seller k on stock s on day t; $Ret_{s,t+1 \to t+h}$ is the cumulative return of stock s from days $t+1$ to $t+h$; and $\alpha_{k,t}$ are fixed-effects for each pair (k,t). By considering investor-day fixed-effects, we estimate the effect of $Ret_{s,t+1 \to t+h}$ on $Days_{k,s,t,i}$ within the deals that investor k closed on day t. This is important because by fixing k and t we are able to compare the relative performance across all deals initiated on day t by investor k.[17]

[17]Disposition effect is about relative performance. Indeed, according to Barberis and Xiong (2009), on a

Columns (1) and (2) of Table 10 show that skilled short-sellers do not exhibit the disposition effect; the estimated β is not statistically different from zero. In contrast, columns (3) and (4) show that unskilled short-sellers do exhibit the disposition effect. For instance, column (4) shows that if the stock price increases (decreases) by 10% during the first 3 days of the deal, then unskilled short-sellers increase (decrease) by 3.3% the duration of the deal ($0.033 = 10 \times 0.059/18$).

[Table 10 about here]

We next assess to which extent cover-timing skill and the disposition effect are related. To do so we first quantify the cover-timing skill of each short-seller by computing her average return on the days immediately after the covering of the short position. That is, we say a short-seller has good covering-skills if stock prices increase after her short positions are closed. This approach to measuring covering-skill is similar to the one implemented by Beschwitz, Bastian, and Massa (2015); they conclude that short-sellers have covering-skills after showing that (aggregate) covering predicts future positive returns. We consider two measures of cover-skill: $Ret_{k,\tau+1,\tau+3}$, the average return over the next three days, and $Ret_{k,\tau+1,\tau+5}$, the average return of the next five days, where τ indicates the day the short position was covered and k indicates that the average return considers all deals by short-seller k. Second, we quantify the disposition effect for each short-seller by running the regression in equation (6) and keeping the estimated coefficient, $\widehat{\beta}_k$. We say a short-seller is highly susceptible to the disposition effect if she has a high $\widehat{\beta}_k$.

Table 11 shows the regressions of disposition effects on covering skills of skilled and unskilled short-sellers. The estimated coefficients in columns (1) and (2) show that there

long investment perspective, an investor shows disposition effect if when she sells a stock in her portfolio, she has a greater propensity to sell a stock that has gone up in value since purchase than one that has gone down.

is no relation between disposition effect and covering skill among skilled short-sellers. This was expected, since we have previously shown that the disposition effect had no role in shorting deals by the skilled investors. In contrast, columns (3) and (4) show that there is a direct relation between disposition effect and covering skill among unskilled short-sellers. The negative coefficients estimated in columns (3) and (3) suggest that the more susceptible to the disposition effect the short-seller is, the worse are her covering skills.

[Table 11 about here]

5 Conclusion

Short-sellers are usually seen as a somewhat homogeneous group of investors who bring relevant information to stock prices. Using a unique data set, we show that skilled short-sellers are a special group and should be studied in isolation. By doing so, we find new results that contrast with the ones typically obtained from analyzing aggregate shorting. Specifically, skilled short-sellers are actually short-term momentum investors, a significant part of their skill comes from market-timing, they are also proficient at choosing when to cover their positions and display no disposition effect.

The Brazilian stock market, such as other "modern but not so big" stock markets, offers a good laboratory for empirical studies in Finance. Importantly, ensuring external validity of our results, standard empirical facts for the equity lending market and short-selling documented for the US and Europe also hold in Brazil—see Section 2.2 of this paper and Chague, De-Losso, Genaro, and Giovannetti (2017). Additionally, the size of our data set turns out to be appropriate for empirical analysis: it allows us to run deal-by-deal regressions without having to resort to any aggregation. For instance, regressions at the deal-level were essential to directly decompose skill into stock-picking and market-timing in Section 4 by using deal-level fixed effects. A similar empirical analysis for the US, in case analogous data were available, would likely be computationally unfeasible, requiring the econometrician to work with billions of observations.

A potential line of future research is to investigate the extent to which different short-selling groups contribute to market efficiency. While skilled short-sellers directly contribute to the price discovery process, other groups of short-sellers are likely to play important roles in improving pricing efficiency. For instance, liquidity-supplying short-sellers may improve market liquidity conditions by helping informed buyers to incorporate positive news into stock prices.

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A Tables and Graphs

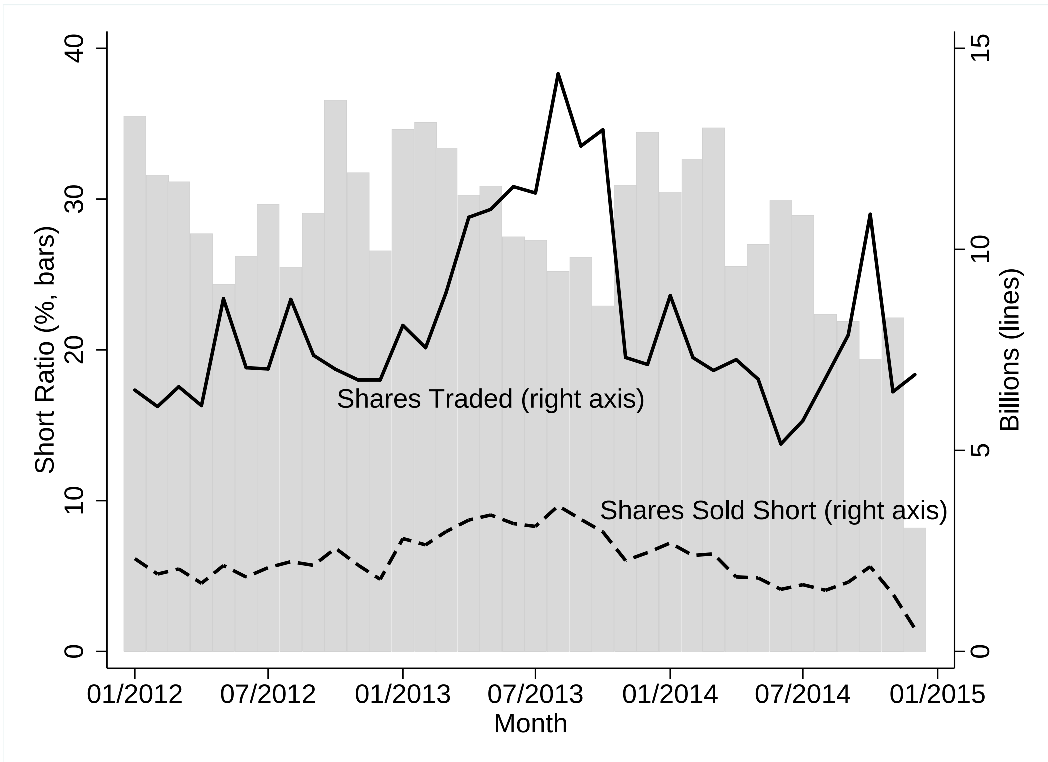

Figure 1: Short-selling as a fraction of total trades. This figure shows, month-by-month, the total number of shares traded (bold line), the total number of shares sold short (dashed line), and the ratio between these two series (gray bars).

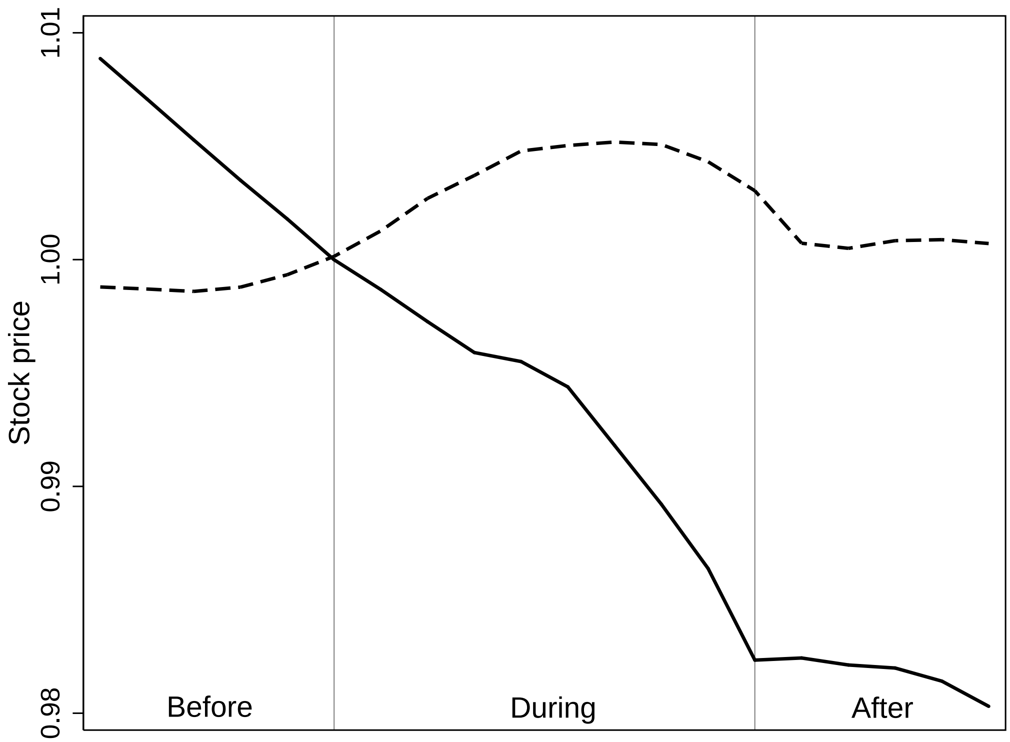

Figure 2: Skilled and unskilled deals. This figure depicts the average evolution of stock prices during skilled (bold line) and unskilled (dashed line) shorting deals. Because different deals have different durations, all deals were normalized to have the same length of 10 trading days. Within each (normalized) trading day we then take the average of the stock prices across all deals. Stocks prices are normalized within deals to equal one on the first day of the deal. The figure also shows the average evolution of stock prices five days before (Before) the beginning and five days after the end of the shorting deal (After). We use only deals that lasted between 10 and 30 calendar days.

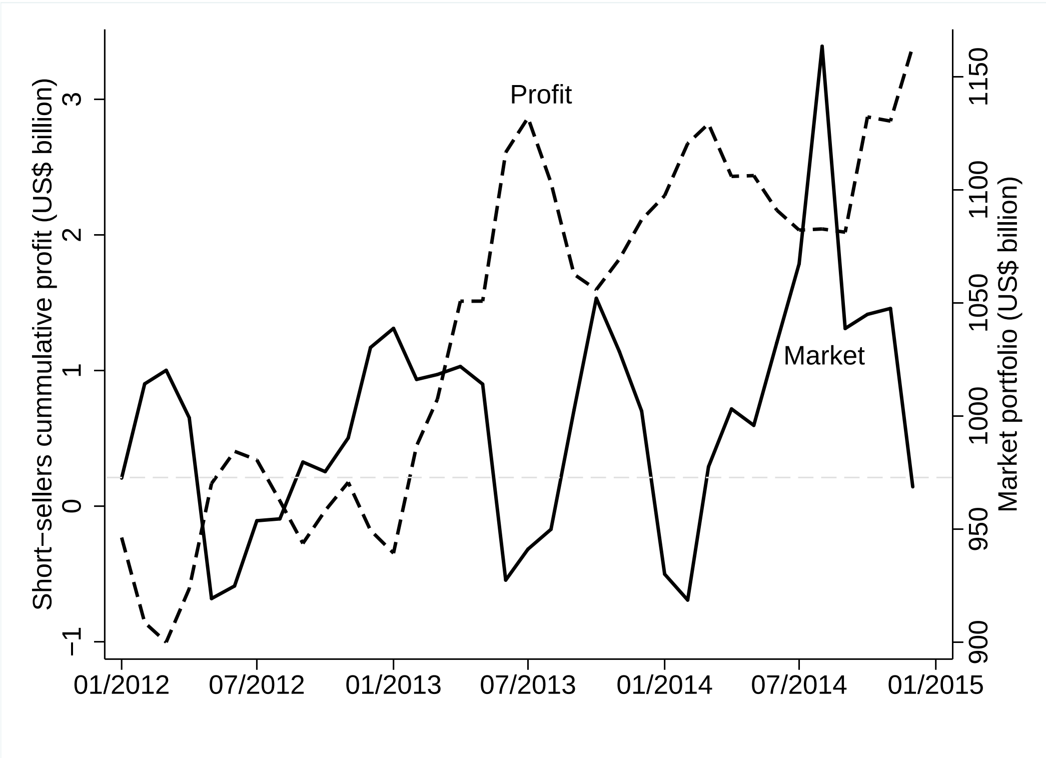

Figure 3: Short-sellers aggregate profit. This Figure shows the equal-weighted cumulative market returns (bold line) on the 152 stocks used in our main sample and the cumulative profit (dashed line) in US$ billion obtained by all short-sellers from all deals. The profit on a short-selling deal i (in US$) is computed as $\pi_i = (P_{i,0} - P_{i,1}) \times q_i - C_i$, where $P_{i,0}$ is the price at which the short-seller sell the stock, $P_{i,1}$ is the price at which the short-seller buys the stock back, q_i is the number of shares sold short and C_i is the cost of the equity loan (loan and brokerage fees paid by the short-seller).

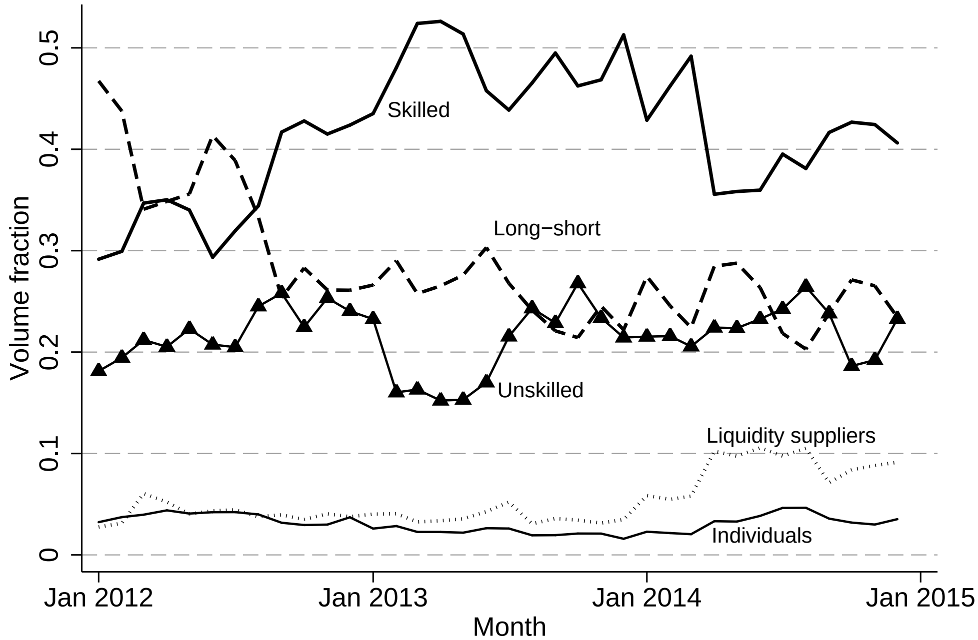

Figure 4: Decomposing shorting volume over time. This figure shows how the total shorting volume of the Brazilian stock market from 2012 to 2014 can be decomposed into skilled, long-short, liquidity-supplying, unskilled, and individual shorting volumes.

Table 1: Descriptive statistics

This table shows descriptive statistics of our equity lending data set. Panel A exhibits for each year the total number of loan contracts and the total number of distinct short-sellers that closed at least one deal (by investor type). Panel B exhibits the average and the corresponding 5%, 25%, 50%, 75%, and 99% quantiles of the empirical distribution of two variables at the short-seller level: the number of loan deals closed by each short-seller and the average duration (in calendar days) of the loan contracts of each short-seller.

Panel A

	N. of deals			N. of investors		
Year	All	Individuals	Institutions	All	Individuals	Institutions
2012	884,472	212,876	671,596	22,071	19,538	2,533
2013	1,153,609	204,106	949,503	18,756	16,571	2,185
2014	1,039,256	194,539	844,717	14,981	13,108	1,873
Full Sample	3,077,337	611,521	2,465,816	37,913	33,990	3,923

Panel B

	N. of deals		Avg. duration (in days)	
Percentile	Individuals	Institutions	Individuals	Institutions
5%	1	1	2	2
25%	2	2	6	4
50%	5	12	12	12
75%	15	79	20	21
95%	69	2,611	29	29
99%	203	11,861	39	36
Average	18.0	629.2	14.1	13.5

Table 2: Return predictability of aggregate short-selling in Brazil

This table shows the returns of portfolios formed according to *relss*, the number of shorted shares divided by the number of traded shares on each day for each stock. We sort the stocks according to *relss* on each day. Stocks up to the 25th percentile are assigned to the "Low" portfolio. Stocks between the 25th and the 75th percentiles are assigned to the "Medium" portfolio. Stocks above the 75th percentile are assigned to the "High" portfolio. The "Low-High" portfolio goes long the Low portfolio and short the High portfolio. For each portfolio (Low, Medium, High, and Low-High) we compute daily value-weighted risk-adjusted returns over the 2-, 5-, and 10-day ahead horizons. Standard deviations are shown in parentheses.

Lowest 25	25-75	Highest 25	Low-High
Holding period = [t+1, t+2]			
0.073*	-0.051***	-0.050**	0.123**
(0.039)	(0.019)	(0.024)	(0.048)
Holding period = [t+1, t+5]			
0.151*	-0.115***	-0.155***	0.306***
(0.079)	(0.040)	(0.049)	(0.095)
Holding period = [t+1, t+10]			
0.257*	-0.196***	-0.348***	0.604***
(0.144)	(0.068)	(0.092)	(0.169)

Table 3: Aggregate shorting is contrarian

This table shows the stock-day regressions of $relss$ on 5-, 10-, and 21-day past returns. $relss$ is the number of shorted shares divided by the number of traded shares on each day for each stock. All regressions include stock and day fixed effects. Standard errors are shown in parentheses and clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: $relss$			
	(1)	(2)	(3)	(4)
Ret_{-5}	0.020***			0.014***
	(0.004)			(0.003)
Ret_{-10}		0.013**		0.007**
		(0.004)		(0.003)
Ret_{-21}			0.006**	-0.001
			(0.003)	(0.003)
Stock F.E.	Yes	Yes	Yes	Yes
Day F.E.	Yes	Yes	Yes	Yes
N	112,042	112,042	112,042	112,042
R2-adj	0.40	0.40	0.40	0.40

Table 4: Performance persistence

This table shows the estimates of deal-by-deal panel regressions with the return on a shorting deal as the dependent variable. The regressions in columns (1) and (2) use data from January 2014 and December 2014, and have as explanatory variables $AveRet_{past}$, the short-seller average return across all her deals between January 2012 and June 2013, and $MedRet_{past}$, the short-seller median return across all her deals between January 2012 and June 2013. We exclude the last six months of 2013 to ensure that only past performance is being used to predict future performance. The regressions in Columns (3) and (4) use data from the whole sample period, and have as explanatory variables $AveRet_{-s}$, the short-seller average return across all her deals on stocks other than s, and $MedRet_{-s}$, the short-seller median return across all her deals on stocks other than s. All regressions include stock and day fixed effects. Standard errors are shown in parentheses and clustered by stock. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: deal return			
	Persistence in time		Persistence across stocks	
	(1)	(2)	(3)	(4)
$AveRet_{past}$	0.066***			
	(0.010)			
$MedRet_{past}$		0.070***		
		(0.010)		
$AveRet_{-s}$			0.102***	
			(0.010)	
$MedRet_{-s}$				0.110***
				(0.012)
Stock F.E.	Yes	Yes	Yes	Yes
Day F.E.	Yes	Yes	Yes	Yes
N	846,800	846,800	3,031,971	3,031,971
R2-adj	0.25	0.25	0.19	0.19

Table 5: Descriptive statistics by short-selling group

This table displays descriptive statistics for the following variables at the short-seller level: i) number of deals, ii) average volume per deal in US$, iii) average duration per deal in calendar days, iv) number of different stocks traded, v) average profit per deal in US$, and vi) average loan fee. To compute the average loan fee, we divide the loan fee of the deal by the average loan fee for the respective stock. By doing this, loan fees paid by short-sellers that trade different stocks become comparable and hence the number exhibited in the table reflects the difference in percentage points that the short-seller pays above or below the average. The descriptive statistics are shown by groups of short-sellers. All individuals and institutions that closed at least two shorting deals during 2012 and 2014 are classified as either a "skilled short-seller," a "long-short investor," a "liquidity-supplier," or an "unskilled short-seller." This classification involves four steps. In step 1, we identify the "skilled short-sellers" as those who consistently profit from shorting by looking at their realized performance over the deals. In Step 2, from among the short-sellers that are not classified as skilled in Step 1, we identify the "liquidity-suppliers" as those who frequently buy and sell the same stock on the same day. In Step, 3 from among the short-sellers that are not classified as skilled in Step 1 or as liquidity-suppliers in Step 2, we identify the "long-short investors" as those who sell short according to well-known long-short strategies. Finally, in Step 4 the remaining short-sellers are classified as "unskilled short-sellers." "N" refers to the number of short-sellers in each group. "Volume fraction" refers to the share of each group in the total shorting volume over the whole sample period.

Short-sellers groups	N	Volume fraction	Number of deals	Average volume	Average duration	Number of stocks	Average profit	Average loan fee spread
Panel A: Institutions								
Skilled short-sellers	443	34.9%	1,926	102,145	18	38	2,390	0.3%
Long-short investors	194	25.3%	3,645	95,094	19	59	-307	-1.6%
Liquidity suppliers	28	4.9%	4,985	25,348	8	44	-213	-6.9%
Unskilled short-sellers	2,163	31.8%	352	80,481	16	14	-341	10.1%
Panel B: Individuals								
Skilled short-sellers	1,922	0.4%	41	20,971	15	12	790	15.6%
Long-short investors	371	0.2%	120	17,832	16	29	-27	20.6%
Liquidity suppliers	169	0.1%	68	19,651	8	10	-117	17.7%
Unskilled short-sellers	22,120	2.3%	21	15,930	16	6	-83	23.8%

Table 6: Correlation matrix

This table shows the correlation matrix of the daily shorting activity by skilled institutions (*Skilled*), long-short institutions (*Long-short*), liquidity supplying institutions (*Liq-sup*), unskilled institutions (*Unskilled*), individuals short-sellers (*Individuals*), daily stock returns (*Return*), and *Oimb*. *Oimb* is the stock-day buying pressure measured as the net order imbalance truncated at zero. To limit the size of the correlation matrix, we combine all groups of individuals into the *Individuals* groups. Shorting activity of each group of short-sellers is the stock-day sum of the volume sold short by the group divided by the stock traded volume. Our classification of short-sellers into groups is described in Table 5. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Skilled	*Long-short*	*Liq-sup*	*Unskilled*	*Individuals*	*Return*	*Oimb*
Skilled	1						
Long-short	0.0050	1					
Liq-sup	0.1684***	0.0011	1				
Unskilled	0.0041	0.0029	-0.0005	1			
Individuals	0.0129***	0.0006	0.0222***	0.0619***	1		
Return	-0.0028	-0.0001	0.0004	-0.0003	-0.0015	1	
Oimb	-0.0055*	-0.0097***	0.0147***	-0.0156***	-0.0108***	0.2607***	1

Table 7: Shorting skills: stock-picking, market-timing and cover-timing

This table shows deal-by-deal regressions of $R_{k,s,t,\tau,i}$ on a dummy variable $\mathbb{I}[k \in Skilled]$ that equals one if short-seller k is a skilled short-seller. Our classification of short-sellers into groups is described in Table 5. $R_{k,s,t,\tau,i}$ is the realized return of shorting deal i closed by short-seller k on stock s on day t which was covered on day τ. Regressions in columns (2) and (5) include entry/exit fixed-effects, i.e., fixed-effects for each (t,τ)-pair. Regressions in columns (3) and (6) include stock/entry fixed-effects, i.e., fixed-effects for each (s,t)-pair. Standard errors are shown in parentheses and clustered by stock-day. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	All short-sellers			Skilled & unskilled		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}[k \in Skilled]$	1.534***	1.060***	0.360***	1.671***	1.220***	0.334***
	(0.059)	(0.040)	(0.023)	(0.070)	(0.049)	(0.022)
Constant	-0.196***	-0.053	0.159***	-0.333***	-0.138***	0.244***
	(0.045)	(0.038)	(0.007)	(0.041)	(0.034)	(0.009)
Fixed-effects	None	Entry/exit	Stock/entry	None	Entry/exit	Stock/entry
R2	0.01	0.28	0.68	0.01	0.29	0.68
N	3,077,337	3,077,337	3,077,337	2,158,677	2,158,677	2,158,677

Table 8: Stock-picking

This table shows the estimates of investor-stock-day panel regressions with $Pick_{k,s,t}$ as the dependent variable. Columns (1) and (2) consider only the 443 skilled institutions, and columns (3) and (4) consider only 443 unskilled institutions randomly chosen among the 2,163 total unskilled institutions. Table 5 describes how short-sellers are classified as skilled and unskilled. $Pick_{k,s,t}$ equals one if skilled short-seller k closed a shorting deal on stock s on day t, and zero otherwise. That is, $Pick_{k,s,t} = 1$ if short-seller k picked stock s on day t. The explanatory variables are: i) *Lag short*: a dummy variable that equals one if short-seller k closed a shorting deal on stock s on the previous 5 days; ii) *Volatility:* the standardized return volatility of stock s on day t computed using daily returns from the last 10 days; iii) *Oimb*: the buying pressure on stock s on day t, measured as the net order imbalance truncated at zero; iv) *21-day return*: the cumulative stock returns of stock s over the last 21 days; v) *Book*: the standardized book-to-market ratio of stock s on day t; v) *Size*: the standardized log market-capitalization of stock s on day t; vi) *Volume*: the standardized log trading volume of stock s on day t; and vii) *Bid-ask spread*: the standardized daily average bid-ask spread of stock s on day t. All regressions include investor-day fixed-effects. Standard errors are shown in parentheses and clustered at the stock-day level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Skilled		Unskilled	
	(1)	(2)	(3)	(4)
Lag short	20.01***	19.93***	16.89***	16.86***
	(0.056)	(0.056)	(0.091)	(0.091)
Volatility	0.040***	0.059***	-0.003***	0.000
	(0.003)	(0.003)	(0.001)	(0.001)
Oimb	-0.365***	-0.189***	-0.064***	-0.026***
	(0.008)	(0.009)	(0.002)	(0.002)
Return	0.002**	0.000	0.003***	0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
21-day Return	-0.002***	-0.002***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Book		0.028***		-0.002***
		(0.003)		(0.000)
Size		0.032***		0.013***
		(0.004)		(0.001)
Volume		0.100***		0.025***
		(0.005)		(0.002)
Bid-ask spread		-0.081***		-0.012***
		(0.002)		(0.000)
Constant	0.373***	0.359***	0.063***	0.060***
	(0.002)	(0.002)	(0.001)	(0.000)
Fixed-effects	Investor/day	Investor/day	Investor/day	Investor/day
R2	0.19	0.19	0.12	0.12
N	49,634,606	49,634,606	49,634,606	49,634,606

Table 9: Market-timing

This table shows the estimates of investor-stock-day panel regressions $Pick_{k,s,t}$ as the dependent variable. Columns (1) and (2) consider only the 443 skilled institutions, and columns (3) and (4) consider only 443 unskilled institutions randomly chosen out of the 2,163 total unskilled institutions. Table 5 describes how short-sellers are classified as skilled and unskilled. $Pick_{k,s,t}$ equals one if skilled short-seller k closed a shorting deal on stock s on day t, and zero otherwise. That is, $Pick_{k,s,t} = 1$ if short-seller k picked stock s on day t. The explanatory variables are: i) *Lag short*: a dummy variable that equals one if short-seller k closed a shorting deal on stock s on the previous 5 days; ii) *Term spread:* the slope of the Brazilian bond yield curve computed on day t (one year minus one month); iii) *Dividend yield*: is the total amount of dividend paid by firms in the Brazilian stock market over the last 12 months divided by their market capitalization on day t; iv) *Market Volatility*: the market return volatility computed using daily returns from the last 10 days; v) *Market*: the market return on day t; vi) *Volume*: the standardized log trading volume of stock s on day t; and vii) *Bid-ask spread*: the standardized daily average bid-ask spread of stock s on day t. All regressions include investor-stock fixed-effects. Standard errors are shown in parentheses and clustered by stock-day. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Skilled		Unskilled	
	(1)	(2)	(3)	(4)
Lag short	16.68***	16.68***	13.91***	13.91***
	(0.053)	(0.053)	(0.087)	(0.087)
Term spread	0.178***	0.178***	0.002**	0.002**
	(0.003)	(0.003)	(0.001)	(0.001)
Dividend yield	0.011	0.010	-0.001	-0.001
	(0.008)	(0.008)	(0.002)	(0.002)
Volatility	-0.108***	-0.108***	-0.015***	-0.015***
	(0.006)	(0.006)	(0.001)	(0.001)
Market	-0.005***	-0.005***	0.001**	0.001**
	(0.002)	(0.002)	(0.001)	(0.001)
Monday		-0.019***		-0.004**
		(0.006)		(0.002)
Tuesday		-0.002		0.001
		(0.006)		(0.002)
Thursday		0.000		-0.001
		(0.006)		(0.002)
Friday		0.018***		-0.003*
		(0.006)		(0.002)
Constant	0.435***	0.436***	0.435***	0.436***
	(0.021)	(0.021)	(0.021)	(0.021)
Fixed-effects	Investor/stock	Investor/stock	Investor/stock	Investor/stock
R2	0.17	0.17	0.17	0.17
N	48,634,606	48,634,606	48,634,606	48,634,606

Table 10: Disposition effect

This table shows the estimates of investor-stock-day panel regressions of the duration of the shorting deals (*Days*) on the stock returns on the first days of the deal (*Ret*). $Days_{k,s,t,i}$ is the duration, in calendar days, of deal i closed by short-seller k on stock s on day t. $Ret_{s,t+1 \rightarrow t+h}$ is the cumulative return of stock s from days $t+1$ to $t+h$, with $h = 3$ and 5 . All regressions include investor-day fixed-effects, i.e., fixed-effects for each (k,t)-pair. Standard errors are shown in parentheses and clustered by stock-day. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Skilled		Unskilled	
	(1)	(2)	(3)	(4)
$Ret_{t+1,t+3}$	0.012		0.039***	
	(0.010)		(0.012)	
$Ret_{t+1,t+5}$		0.007		0.059***
		(0.008)		(0.008)
Constant	20.9***	20.9***	17.4***	17.4***
	(0.029)	(0.029)	(0.017)	(0.016)
Fixed-effect	Investor/day	Investor/day	Investor/day	Investor/day
R2	0.65	0.65	0.71	0.71
N	932,960	932,960	1,225,717	1,225,717

Table 11: Cover-timing and the disposition effect

This table shows investor-level regressions of cover-timing skill on the disposition effect. We measure cover-timing skill as $Ret_{k,\tau+1,\tau+h}$, the average across all deals from short-seller k of the stock return over the next h days after the shorting deals was covered, where τ indicates the day the short position was covered, and h can equal three or five. *Disposition effect* is the β coefficient in the regression in Table 10 estimated using only deals from short-seller k. Columns (1) and (2) consider only skilled short-sellers, while columns (3) and (4) consider only unskilled short-sellers. Because *Disposition effect* has to be estimated for each short-seller, we consider only investors that closed at least 30 deals or more. Robust standard errors are presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Skilled		Unskilled	
	$Ret_{k,\tau+1,\tau+3}$	$Ret_{k,\tau+1,\tau+5}$	$Ret_{k,\tau+1,\tau+3}$	$Ret_{k,\tau+1,\tau+5}$
	(1)	(2)	(3)	(4)
Disposition effect	-0.284	-0.026	-0.201***	-0.163***
	(0.231)	(0.025)	(0.066)	(0.049)
Constant	0.005	0.001	0.016	0.013
	(0.055)	(0.055)	(0.034)	(0.034)
R2	0.01	0.01	0.01	0.01
N	339	339	851	851