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HOW TO HELP ARBITRAGEURS CORRECT UNDER-PRICING: LET THEM SHORT!

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The ability to short allows investors who purchased shares to create a portfolio that is immune to industry- and market fluctuations. In theory, this should enable investors to trade more aggressively. Utilizing the institutional feature in Hong Kong that only stocks on a special list can be shorted, we provide evidence that the emergence of shortable securities causes investors to pursue *under*-priced securities more aggressively and helps eliminate mispricing on the long side. Relatedly, *positive* earnings surprises are followed by a more immediate price reaction and a smaller post-earnings-announcement drift when it becomes easier for investors to hedge their long positions.

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1. Introduction

Over the past couple of decades, a body of empirical work has uncovered anomalous patterns in average stock returns pointing to the presence of temporary under-pricing on the long side and temporary over-pricing on the short side. In response, a growing literature has begun to examine how arbitrageurs trade on this mispricing and also what factors prevent arbitrageurs from fully eliminating mispricing (e.g., Gromb and Vayanos 2010). In this paper, we contribute to the literature by suggesting one mechanism through which we can help arbitrageurs eliminate mispricing on the *long* side and help make markets more efficient: We need to let them short.

Consider the scenario where Toyota's stock is *under*-priced. To take advantage of this mispricing, investors should purchase Toyota shares. Holding the level of under-pricing constant, the degree to which investors pursue Toyota shares will be a function of how much risk investors are willing to bear (at the portfolio level) and the volatility of the Toyota shares. Should investors have a low target volatility for their portfolios and should Toyota stock prices be highly volatile themselves, investors will only timidly pursue Toyota despite its under-pricing.

The degree to which investors pursue Toyota shares will also be a function of whether investors can short. The reason is that, by shorting, investors can immunize their portfolios against industry and market fluctuations and thereby lower portfolio risk. Shorting therefore allows investors to more aggressively pursue the under-priced Toyota shares.[2] Should hedging via "substitute securities" be difficult either due to short-sale constraints or direct short-sale bans, the risk to arbitrageurs will increase, causing them to trade more timidly. This, in turn, has the potential to slow down the market's response to good news and the elimination of underpricing on the long side.

The goal of this paper is to examine the relevance of this hedging channel and its role in determining asset prices. While the significance of this channel has been broached by the popular press

[2] See Shleifer (2000), among others, for a textbook account of industry hedging, and Michael and Kerns (1982) and Donde (2012) for practitioner accounts of the importance of industry hedging.

(e.g., Financial Times, October 28, 2008: The Short View: A Scary Squeeze), to the best of our knowledge, it has yet to be formally studied.

In this study, we focus on investors using short selling to immunize their portfolios against industry risk. To test the relevance of the industry-hedging channel, we consider three settings. Our first two tests take advantage of the institutional feature in the Hong Kong stock market that only stocks on a list of designated securities can be sold short. This short-sale list is revised (mostly) on a quarterly basis. To the extent that the addition of a stock to the list and the ability to short a new security incrementally improves long-short investors' ability to hedge and to the degree that long-short investors are informed (Cao, Liang, Lo, and Petrasek 2014), we expect the addition event to invite greater participation of informed long-short investors and to lead to positive abnormal performances among seemingly undervalued industry peers.

Our analysis shows that during our sample period, which spans 2001 to 2012, the addition of stock *s* is accompanied by strong *positive* abnormal returns among its industry peers with relatively low market-to-book ratios. No such pattern is observed among its industry peers with relatively high market-to-book ratios. This positive performance only accrues in the days after stock *s* is added to the list and not in the days leading up to the effective date. It is accompanied with significant abnormal trading activity; there is no reversal in performance.

Further inspection reveals that the positive abnormal performance is generated entirely by the subset of additions, which subsequently experience nonzero short-selling volume. Combined with the fact that the positive performance only accrues in the days after the effective date and not in the days leading up to it, this result suggests that the positive performance is directly tied to the short selling of stock *s* as opposed to an unobserved industry event, which simultaneously determines both the addition event and the strong positive performance of seemingly undervalued industry peers.

In further analyses, we detect stronger effects for additions in industries with very few shortable securities prior to the addition event. One explanation is that for industries that already have many shortable securities, the addition of one more shortable security only marginally improves arbitrageurs' ability to hedge industry risk. Our findings are thus stronger for addition events that enable long-short investors, for the first time, to hedge the risk of the corresponding industry.

Our results also strengthen when the stock being added to the short-sale list is more positively correlated with industry peers, presumably because the added stock provides a better industry hedge when its correlation with industry peers is high rather than low.

Overall, our findings are robust to research design choices. They are also economically meaningful. For instance, we observe that the emergence of a shortable security is accompanied by cumulative five-day abnormal returns of +0.516% (t-statistic = 4.79) among industry peers whose market-to-book ratios are in the bottom half. Industry peers whose market-to-book ratios are in the bottom-*quintile* experience even higher cumulative abnormal returns of +0.693% (t-statistic = 4.28). To put these numbers in perspective, around the addition event, industry peers whose market-to-book ratios are in the top half experience cumulative abnormal returns of -0.000% (t-statistic = -0.04).

If an investor had gone long on the bottom-quintile industry peers on the day of the addition event and, simultaneously, gone short on the stock added to the list, and had the investor liquidated her positions after five days and traded in the risk-free asset when there was no addition event, the investor would have generated a Sharpe Ratio of 0.14. The Sharpe Ratio of purchasing bottom-quintile industry peers without hedging the long position is only 0.11. To put these numbers in perspective, the Sharpe Ratio of the Hong Kong market is 0.07.

The reason the long-short strategy has a higher Sharpe Ratio than the long-only strategy is that the long-short strategy has a slightly higher mean (0.64% a month vs. 0.62% a month) and, more importantly in the context of this study, a significantly lower standard deviation (4.57% vs. 5.89%). The lower standard deviation illustrates why hedge funds construct long-short portfolios and aim to lower their exposure to systematic factors such as industry.

While shorting represents one channel through which investors can protect themselves from industry shocks, trading in derivative securities constitutes another. We detail our analysis regarding this point in the main body of the text. In short, we find that, for reasons that are beyond the scope of this study, derivatives securities on industry indices are non-existent and derivatives securities on single stocks are extremely rare and, if present, illiquid. Other potential mechanisms through which investors may hedge against industry shocks (e.g., ADRs or industry-specific Exchange Traded Funds) are also difficult to implement or are non-existent, leading us to believe that stocks being added to the Hong Kong short-sale list indeed incrementally improve investors' ability to protect themselves from industry shocks.

Another concern with our elimination-of-underpricing interpretation is that our analysis, up to this point, uses a firm's market-to-book ratio to infer underpricing. While a low market-to-book ratio is commonly used in the literature as an indicator for underpricing (Lakonishok, Shleifer and Vishny 1994; Haugen 1995; Ikenberry, Rankine and Stice 1996; Dechow, Hutton, Meulbroek and Sloan 2001; Baker and Wurgler 2002), it is not without shortcomings because the market-to-book ratio is related to other constructs, such as a firm's growth opportunities and cost of capital.

In our second setting, we extend our analysis to an additional proxy of underpricing. The literature on the market's response to annual earnings announcements notes the presence of a post-earnings-announcement drift (Ball and Brown 1968). This drift is commonly attributed to investor underreaction, i.e., temporary underpricing after positive earnings surprises and temporary overpricing after negative earnings surprises (DellaVigna and Pollet 2009; Hirshleifer, Lim and Teoh 2009).

As in most countries, we observe that in Hong Kong there is a positive abnormal price drift following positive earnings surprises. If the ability to short stock *s* allows arbitrageurs to more aggressively pursue temporarily underpriced stocks *i*, we expect a more immediate price reaction and a smaller post-earnings-announcement drift for stocks *i* after positive earnings surprises in less-difficult-to-short industries.

This conjecture is borne out by the data. After controlling for firm and market conditions within a regression framework, firms in less-difficult-to-short industries are 11.2% less likely to exhibit a price drift following positive earnings surprises compared to their counterparts in more-difficult-to-short industries. In other words, in less-difficult-to-short industries, a greater portion of the market's total response to positive earnings news is materialized in the initial days of the earnings surprise. This result is consistent with the notion that the presence of shortable securities puts arbitrageurs in a better position to hedge their long positions and, as such, enables them to more aggressively go after *under*-priced stocks on the long side.

In our third setting, we extend our thinking to the US. Consistent with long-short investors being informed, we provide evidence that hedging-related short selling can be used to *positively* predict peer firm's earnings announcements, earnings announcement day returns and returns in general.

Our work crosses several lines of research. The question of how the practice of short selling affects capital markets has been of great interest to the financial community and, accordingly, has motivated a significant amount of research. The focus of the literature has generally been on how the ease with which certain stocks can be shorted affects the prices of those shorted stocks themselves (e.g., Figlewski 1981; Asquith and Meulbroek 1995; Desai, Ramesh, Thiagarajan and Balachandran 2002; Rubinstein 2004; Cohen, Diether and Malloy 2007; Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2009a,b; Karpoff and Lou 2010).

However, the ability to short (or the lack thereof) need not only affect the stocks considered to be shorted. It may affect prices of a much wider set. The reason is that investors short not only to trade on over-pricing, but they also short to hedge their long positions in seemingly under-priced stocks.[3] Here, we provide evidence to this regard. Prior discussions that only consider the effect of short-sale constraints on the pricing and market quality of the stocks considered to be shorted themselves, therefore, significantly understate the true relevance of short selling to financial markets.

Our paper also adds to the literature on the limits of arbitrage (DeLong, Shleifer, Summers and Waldmann 1990; Shleifer and Vishny 1997; Shleifer 2000; Gromb and Vayanos 2010). We show that short-selling is a crucial mechanism that helps arbitrageurs not only correct mispricing on the short side, but – through the hedging channel – also helps arbitrageurs correct mispricing on the long side.

[3] Market participants also short for inventory reasons. An example is option-market makers hedging their positions by shorting stocks (Battalio and Schultz 2011; Grundy, Lim, and Verwijmeren 2013).

2. Predictions

We develop a theoretical model in Appendix A to motivate our empirical analysis. The baseline model includes an underpriced asset A and a risk-free asset. The extended model includes an underpriced asset A, a risk-free asset and an asset B that is shortable and in the same industry as asset A. In both the baseline model and the extended model, assets are sensitive to firm-specific news as well as to news about the industry.

Our focus on the industry aspect is motivated by research-design considerations. Compared to style factors such as medium-term momentum or liquidity, industries are relatively easy to quantify objectively. Moreover, our laboratory, which we describe Section 3, likely produces significant improvements in the ability to hedge industry risk but not necessarily in the ability to hedge market risk. Thus, our goal in this paper is not to reject the aforementioned channels or claim that industry exposure is more important than exposure to other factors. Rather, we focus on the industry aspect to increase the power of our analysis. To the extent that investors care about minimizing their exposure to a variety of factors, whatever effect we may find that can be tied to industry-hedging (alone) can therefore be construed as a mere prelude to the overall effect of hedging considerations in determining security prices.

In separate versions of the two models, we make assets sensitive to market-wide news (in addition to firm-specific news and industry news). The predictions that the separate versions generate are the same as the predictions generated by the simpler models presented in Appendix A; the derivation is available upon request.

In the baseline model, the investor purchases shares of asset A. Because the investor is risk-averse, the investor will not purchase an infinite amount of shares, but only enough shares to take advantage of the mispricing while ensuring that her portfolio standard deviation is below a certain threshold ("volatility limit"). The weight the investor puts in asset A is a function of the volatility limit and the standard deviation of asset A:

1. The greater the volatility limit, the more aggressively the investor pursues the underpriced asset A (i.e., the greater the weight of asset A in the investor's portfolio).

2. The lower the standard deviation of asset A, the more aggressively the investor pursues the underpriced asset A.

In the extended model, we introduce a shortable asset B that is in the same industry as asset A. Shorting "substitute security" B while purchasing shares of asset A allows the investor to construct a portfolio that is immune to industry shocks. Making a portfolio immune to industry shocks lowers risk and, as such, increases the investor's ability to pursue the underpriced asset without hitting the portfolio risk threshold. At the same time, shorting asset B introduces new idiosyncratic risk.

Our model generates the following predictions:

3. Compared to the baseline case, the introduction of asset B allows the investor to more aggressively pursue the underpriced asset A

   the higher asset A's industry exposure, i.e., the higher β_A^{in}, and the higher the volatility of the industry asset A operates, i.e., the higher σ_{in}^2.

   The reason is that when β_A^{in} and σ_{in}^2 are high, the benefits from industry hedging are high.

4. Compared to the baseline case, the introduction of asset B allows the investor to more aggressively pursue the underpriced asset A

   the greater substitute security B's industry exposure, i.e., the higher β_B^{in}, and the lower the idiosyncratic risk of the substitute security used to eliminate industry exposure, i.e., the lower $\sigma_{\epsilon,B}$.

   The reason is that when β_B^{in} is high, one only needs to short a small amount of asset B in order to make the overall portfolio industry neutral. Shorting a small amount of asset B introduces limited new idiosyncratic risk.

   Naturally, the marginal benefit from the emergence of a shortable asset *B* in industry *x* is highest when there are no other securities in industry *x* that are already shortable. The marginal benefit decreases with the emergence of additional shortable assets. However, the marginal benefit remains positive. The reason is that the investor can now pursue the underpriced asset A and short a collection of securities in industry x. A collection of substitute securities has lower idiosyncratic risk (low $\sigma_{\epsilon,B}$) than a single substitute security (high $\sigma_{\epsilon,B}$).

Under all reasonable parameter values, the portfolio weight the investor puts in asset A is greater in the extended model than that in the baseline model (simulation results are available upon request). This produces our final prediction:

5. The introduction of a shortable asset allows investors to more aggressively pursue underpriced securities and potentially help correct mispricing on the long side.

The focus of our paper is on prediction 5. We also test predictions 3 - 4.

3. Settings One and Two: The Hong Kong Short-Sale list

We begin our analysis using data from Hong Kong: we discuss the data in Section 3.1; we present our methodology and evidence from the first setting in Sections 3.2-3.4; we present our methodology and evidence from the second setting in Section 3.5; and we discuss alternative channels through which investors in Hong Kong may protect themselves from industry shocks in Section 3.6.

3.1. Data

Initially, the Hong Kong stock market did not allow short-selling. In January 1994, it introduced a pilot scheme for regulated short selling. Since then, the Hong Kong stock market has allowed short sales of securities that are included in an official short-sales list that is revised mostly on a quarterly basis.[4] As of August 2012 (the end of our sample period), the list contains 562 securities, and Hong Kong now has an active short-selling market with short selling estimated to make up around 8% of the daily trading volume (Henry and McKenzie 2007).

[4] Although the Hong Kong Stock Exchange states on its website that the list is revised on a quarterly basis, in a limited number of cases, we do observe addition events between quarterly revisions (also see Appendix A1).

The selection of stocks to the list is based on criteria set out by the Hong Kong Stock Exchange and the Securities and Futures Commission, which is the Hong Kong equivalent to the Securities and Exchange Commission in the United States.

Based on the Hong Kong Stock Exchange website, as of August 2012 (the end of our sample period), securities declared eligible for short selling are any of those that:

1) are constituent stocks of indices that are the underlying indices of equity index products traded on the exchange, or
2) are constituent stocks of indices that are the underlying indices of equity index products traded on the Hong Kong Futures Exchange Limited (HKFE) , or
3) are underlying stocks of stock options traded on the exchange, or
4) are underlying stocks of stock futures contracts traded on the HKFE, or
5) are eligible for structured product issuance pursuant to Rule 15A.35 of the Main Board Listing Rules or underlying stocks of structured products traded on the exchange, or
6) have a market capitalization of ≥ HK$3 billion and for which the following ratio is ≥ 50%: $\frac{\text{aggregate HK\$ trading volume over the preceding 12 months}}{\text{market capitalization}}$, or
7) are exchange traded funds approved by the Board of the Exchange in consultation with the Securities and Futures Commission, or
8) traded under the pilot scheme (i.e., are one of the first 17 securities that were approved for short selling in January 1994) , or
9) have been listed on the exchange for ≤ 60 trading days, with a public float capitalization of ≥ HK$10 billion for a period of 20 consecutive trading days commencing from the date of their listing on the exchange and an aggregate HK$ trading volume of ≥ HK$200 million during this period, or
10) are underlying stocks of structured products which are based on a single class of shares traded on the exchange, or
11) are applicable market making securities (other than the securities described in categories 7 and 8 above) approved by the Board of the Exchange in consultation with the Securities and Futures Commission.

Prior literature utilizes this setting to examine how the addition of stocks affects the returns of the added stocks themselves and detects significant negative cumulative abnormal returns (Chang, Cheng and

Yu 2007). Here, we analyze how the addition and the ability to short affect returns of stocks other than those being added to the short-sale list.

We detail our data collection efforts in Appendix B1. In short, we collect announcements of additions to the list of designated securities eligible for short selling directly from the website of the Hong Kong Stock Exchange: http://www.hkex.com.hk/eng/newsconsul/hkexnews/2001news.htm. This website contains Hong Kong Stock Exchange news releases starting from 2001. Our sample period, thus, spans January 2001 to August 2012. Each news release pertaining to the announcement of a security's addition to the list contains the company name, the stock code ("Ticker"), the announcement date and the effective date. We augment each observation with the corresponding International Securities Identification Number (ISIN) via historical Bloomberg data, which enables a merge with data from COMPUSTAT GLOBAL.

We also obtain annual stock-level data on the number of shares shorted and the value of short-sale transactions from the Hong Kong Stock Exchange. The annual stock-level data are available for all stocks being shorted in a given year, including those that were added to the short-sale list prior to 2001. We are thus able to identify whether a security added to the list, and subsequently shorted, is one of the first securities from its industry that is being shorted. Other data, including daily stock prices, number of shares outstanding, four-digit-GICS industry codes and accounting data come from COMPUSTAT GLOBAL.

After merging with COMPUSTAT GLOBAL and imposing various financial market and financial statement data requirements, to be described below, we arrived at our final sample of 707 common-stock additions between 2001 and 2012. These 707 addition events cover 444 distinct firms (some firms are added to the list only to be removed later and then added again).

We do not consider removals in our analysis, as even after a stock is removed from the short-sale list, existing short positions do not have to be closed out. Removals are thus unlikely to constitute a sudden negative shock to hedging ability around the effective removal date.

Appendix B2 lists the number of addition events by calendar year, and Appendix B3 presents a frequency distribution by four-digit-GICS industry code. A firm added to the list, on average, has 60 industry peers; industry peers are firms that are in the same four-digit-GICS industry code. The 707 addition events are thus associated with a total of 42,640 addition-event/industry-peer observations.

Table 1 reports descriptive statistics for the added firms as well as for the corresponding industry peers. Table 1 shows that added firms, in general, have substantially higher market capitalization and higher liquidity than their corresponding industry peers. For instance, the median market capitalization and the median daily trading volume of added firms are 1.86 billion and 2.73 million HK$, respectively. This compares to a median market capitalization of 0.40 billion and a median daily trading volume of 1.15 million HK$ among the subset of corresponding industry peers that appear undervalued (to be defined below). This difference in market capitalization and liquidity is important because it points to the possibility that arbitrageurs can aggressively purchase undervalued firms and help correct underpricing, i.e., they can have price impact. At the same time, arbitrageurs hedge their long positions by shorting the much more liquid stocks on the short-sale list. Because the shorted stocks are more liquid and/or because liquidity providers understand that the hedging-induced selling is non-information-related, the prices of the shorted stocks are not affected much. As we will show in Table 2, our results indicate exactly that.

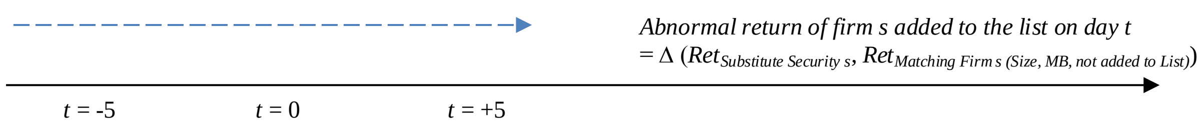
3.2. Setting One: Methodology

Our main inferences are drawn from cumulative abnormal returns of firms added to the list (hereafter referred to as "substitute securities *s*") as well as the cumulative abnormal returns of their corresponding "seemingly undervalued industry peers *i*". Seemingly undervalued industry peers *i* are defined to be stocks (1) that are in the same four-digit-GICS industry as substitute security *s*, (2) that are themselves not being added to the short-sale list at time *t*, and (3) that are in the bottom-half (quintile) of their corresponding four-digit-GICS industry based on their market-to-book ratio. For comparison, we also report results for industry peers that are in the top half.

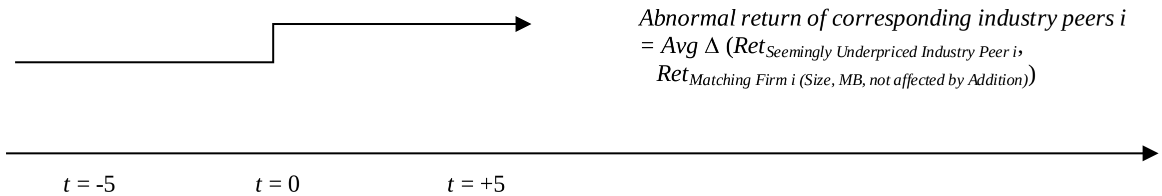
Chang, Cheng and Yu (2007) consider two measures of abnormal returns: cumulative abnormal returns based on market-adjusted returns (*MA-Ret*) and cumulative abnormal returns based on market-model-adjusted returns (*MMA-Ret*). The former represents the difference between raw returns and value-weighted market returns of stocks listed in Hong Kong. The latter is based on a market-model regression.

In untabulated analyses, we obtain marginally stronger results than those presented in this study for *MA-Ret* and *MMA-Ret*. However, given that in our analysis we separate stocks by their market-to-book ratios (*MB*) to test whether low-*MB* stocks react differentially to the emergence of a substitute security than their high-*MB* counterparts and given that value firms tend to outperform growth firms in a manner that is not captured by the market beta, we adopt a different methodology to compute abnormal returns.[5]

In particular, we follow the IPO literature (Ritter 2003) and match each substitute security *s*, which becomes shortable on the effective date *t*, with another firm that is in the same size decile as security *s*, that has the closest *MB* and that is itself not being added to the list at time *t*. The difference in returns between the substitute security and its matching firm is our measure of abnormal returns of firm *s* added to the list:



Similarly, each of the corresponding seemingly underpriced industry peers *i* is matched with another firm that is in the same size decile as industry peer *i*, that has the closest *MB* and that is "itself not being affected by the addition event at time *t*". The difference in returns between industry peer *i* and its matching firm is our measure of abnormal returns of industry peers *i*. Based on Prediction 5, we expect the average abnormal returns of seemingly underpriced industry peers to be positive:



[5] Chui and Wei (1998) provide evidence that market-to-book ratio and size are related to average returns in Hong Kong.

That the matching firm is "itself not being affected by the addition event at time *t*" is defined as follows: If, for a given event date *t*, securities *s* from industries *x* are being added to the list, we only consider firms outside of industries *x* as matching candidates for the seemingly underpriced industry peers *i*. The reason for this exclusion requirement is that we do not want to benchmark the performance of our low-*MB* firms *i* with that of other low-*MB* firms that are equally affected by the same addition event on date *t*. This exclusion requirement also ensures that we do not compare the performance of our low-*MB* firms with that of firms being added to the short-sale list. Because firms being added to the short-sale list have been shown to experience negative abnormal returns around the addition event (Chang, Cheng and Yu 2007), assigning these firms as benchmark firms would bias our measure of abnormal performance towards our findings.

In general, our matching procedure succeeds in finding counterparts that are similar in terms of firm size and *MB*: we always find a matching firm that is in the same size decile, and the mean (median) absolute difference in *MB* between substitute security *s* and its matching firm is 0.111 (0.017); the corresponding number for industry peers *i* is 0.260 (0.056).

We examine cumulative abnormal returns over t=[-5,-1] and t=[0,+5], where t=0 represents the effective date from which stock *s* can be sold short, where t=-5 represents five trading days (around one calendar week) before the effective date and where t=+5 represents five trading days after the effective date.

3.3. Setting One: Main Results

Consistent with Chang, Cheng and Yu (2007), Table 2 shows strong *negative* abnormal returns around the addition event for securities being added to the list. Most of the negative abnormal returns in our more recent sample period accrue in the days leading up to the effective date, perhaps because since the publication of Chang, Cheng and Yu (2007), investors now anticipate the price impact of short selling. Addition announcements are generally made one week prior to the effective date.

The novel evidence in Table 2 is that, in line with Prediction 5, the addition of a stock *s* also is accompanied by strong *positive* abnormal returns among its seemingly undervalued industry peers *i*. This pattern is detectable only for the subset of 601 addition events, for which the added stock *s* or any other simultaneously added stock that is in the same-four-digit-GICS industry as stock *s* subsequently experiences nonzero short-selling volume.[6]

The cumulative abnormal returns are meaningful, both statistically and economically. Equally important, the positive abnormal performance only accrues in the days *after* the emergence of the substitute security. In particular, we observe that over [-5,-1], within the subset of addition events with nonzero short-selling volume, industry peers whose *MB* are in the bottom-half experience cumulative abnormal returns of +0.076% (*t*-statistic = 0.62), and industry peers whose *MB* are in the bottom-quintile experience cumulative abnormal returns of +0.135% (*t*-statistic = 0.82). Over [0,+5], the abnormal performance of industry peers whose *MB* are in the bottom-half changes to +0.516% (*t*-statistic = 4.79), while that of industry peers whose *MB* are in the bottom-quintile changes to +0.693% (*t*-statistic = 4.28). To put these numbers in perspective, over [0,+5], the abnormal performance of industry peers whose MB are in the top-half equals -0.000% (*t*-statistic = -0.04).

The dependence of our findings on the actual emergence of a substitute security, i.e., the unreliable performance over [-5,-1] coupled with the strong positive performance over [0,+5], and the specificity of our results to actual nonzero short-selling activity in the substitute securities suggest that the positive performance of firms *i* is directly tied to the short selling of security *s*, as opposed to an unobserved industry event, which simultaneously determines both the addition event and the strong performance of industry peers with low *MB*.

The spike in abnormal performance following the addition event is accompanied by significant abnormal trading activity. The average daily turnover over [0,+5] in excess of the average daily turnover in the month prior to the effective date is 0.179% (*t*-statistic = 3.90) for industry peers whose *MB* are in

[6] The reason we consider security *s* together with other *simultaneously* added *same-industry* securities is that arbitrageurs may not need to short all of the simultaneously emerging substitute securities from industry *x* to hedge exposure to industry *x*.

the bottom-half and 0.198% (*t*-statistic = 3.64) for industry peers whose *MB* are in the bottom-quintile. In comparison, the average excess daily turnover over [0,+5] for industry peers whose *MB* are in the top-half is -0.329% (*t*-statistic = -1.59).

Figure 1 shows that the abnormal performances we observe do not revert. We plot average cumulative abnormal returns for industry peers whose *MB* are in the bottom-half and for industry peers whose *MB* are in the bottom-quintile along with the corresponding 95% confidence intervals. We do so for the following holding periods: [0,+1], [0,+5], [0,+10] and [0,+60]. We observe that for industry peers whose MB are in the bottom-half, abnormal returns grow from +0.252% after one trading day to +0.516% after roughly one calendar week to +0.710% after roughly two calendar weeks to +0.647% after roughly three calendar months. Similarly, we observe that for industry peers whose MB are in the bottom-quintile, abnormal returns grow from +0.249% after one trading day to +0.693% after roughly one calendar week to +0.895% after roughly two calendar weeks to +0.691% after roughly three calendar months.

3.4. Setting One: Additional Results

3.4.1 Trading Profitability

Table 3 summarizes how long-short investors trading around the addition event would have performed over our sample period. The "Long-Short Strategy" mirrors our main results presented in Table 2. If on trading day *t*, there is an addition event, we hedge by going short on the *Event Firm* that is being added to the short-sale list and we simultaneously go long on each corresponding *Industry Peer* that is in the bottom industry market-to-book-ratio quintile. For instance, if an *Event Firm* were associated with five seemingly undervalued *Industry Peers*, we would conduct five long-short transactions. For each of the five *Industry Peers*, we purchase shares of the *Industry Peer* and simultaneously short the *Event Firm*.

We close out positions after five trading days. The portfolio returns are value-weighted based on the *Industry Peers*' market capitalization. If, on a given trading day, there is no addition event, we invest in the risk-free asset; that is, the long-short portfolio return equals the risk-free rate.

Table 3 shows that long-short investors would have earned 0.64% a month in raw returns and 0.70% a month in abnormal returns. The Sharpe Ratio (based on monthly returns) is 0.14. In comparison, had investors only purchased shares of seemingly underpriced *Industry Peers*, their Sharpe Ratio would have been 0.10. To put these numbers in perspective, the Sharpe Ratio of the overall Hong Kong stock market based on monthly returns is 0.07.[7]

We also experiment with a "Long-Early Strategy". We purchase shares of each *Industry Peer* that is in the bottom industry market-to-book-ratio quintile, but we do so five trading days prior to the addition event. This strategy tries to take advantage of the possibility that some investors anticipate the entrance of long-short investors and their price impact on seemingly underpriced *Industry Peers* and attempt to front-run long-short investors. We find that the Sharpe Ratio of this trading strategy is, at 0.11, slightly higher yet still below that of the long-short strategy.

The reason the long-short strategy has a higher Sharpe Ratio than even the long-early strategy is that the long-short strategy has both a slightly higher mean (0.64% vs. 0.62%) and, more importantly in the context of this study, a significantly lower standard deviation (4.57% vs. 5.89%). The lower standard deviation illustrates why hedge funds construct long-short portfolios and aim to lower their exposure to systematic factors.

3.4.2 Moderating Factors: Hedging Demand and Quality of Hedging Candidate

To better understand the mechanisms at hand, we consider two moderating factors. First, we attempt to capture differences in "Hedging Demand" prior to the addition event. We separate the subset of addition events with nonzero short-selling volume into those where, prior to the addition event, the short selling of substitute securities was more-difficult-to-do versus less-difficult-to-do. If our elimination-of-underpricing hypothesis represents an accurate description of the true data generating process, then the

[7] Relatedly, $1 invested at the beginning of our sample period in 2001 in our long-short strategy would have grown to $2.18 by the end of 2012. Over the same time horizon, $1 invested in the overall Hong Kong stock market would have grown to $1.41.

emergence of a shortable security *s* in industry *x* will have a greater impact the fewer shortable securities there are in industry *x* prior to the addition event.

The forces underlying the shortability channel are twofold: (1) If industry *x* has many shortable securities already, the addition of one more shortable security only marginally improves arbitrageurs' ability to hedge industry risk. (2) In addition, any observed variation in *MB* not only reflects mispricing but is also related to differences in growth opportunities and cost of capital. If industry *x* has many shortable securities prior to the addition event, then arbitrageurs have already been in a good position to exploit mispricing in this industry by shorting the overpriced securities and aggressively longing the underpriced securities as they hedge industry risk via short positions. Firms in less-difficult-to-short industries that are in the bottom-quintile of the *MB* distribution are thus less likely to be in the bottom as a result of mispricing; rather, they are likely to face fewer growth opportunities and/or higher cost of capital. We therefore expect low *MB* firms to experience less mispricing-related abnormal performances in industries that already have many shortable securities.

Table 4 reports results for substitute securities being added to the short-sale list and the corresponding industry peers whose *MB* are in the bottom-quintile. To separate substitute securities *s* and their corresponding industry peers *i* by whether firm *s* is coming from an industry that is more-difficult-to-short versus less-difficult-to-short, we compute, for each year and for each four-digit-GICS industry, the fraction and the number of firms with nonzero short-selling volume. In columns (1) and (2), an observation is categorized as coming from a more-difficult-to-short industry if it is in the bottom decile based on the industry's *fraction* of shorted firms in the year prior to the addition event and as coming from a less-difficult-to-short industry otherwise. In columns (3) and (4), an observation is categorized as coming from a more-difficult-to-short industry if it is in the bottom decile based on the industry's *number* of shorted firms in the year prior to the addition event and as coming from a less-difficult-to-short industry otherwise.

Table 4 illustrates that the effect among industry peers *i* is substantially more positive for addition events in more-difficult-to-short industries. For instance, when assessing performances over [0,+5] and categorizing industries based on the fraction of shorted firms, we observe that for industry peers whose *MB* are in the bottom-quintile, the emergence of a shortable security in a more-difficult-to-short industry is accompanied with cumulative abnormal returns of +2.835% (*t*-statistic = 3.09). The corresponding number when the shortable security emerges in a less-difficult-to-short industry is +0.576% (*t*-statistic = 3.55). We make similar observations when categorizing an industry as more- or less-difficult-to-short based on the number of shortable firms.

The fact that our effect remains noticeable in less-difficult-to-short industries is consistent with Prediction 4. The marginal benefit from the emergence of shortable securities decreases if there already are other shortable securities in the corresponding industry. However, the marginal benefit remains positive. The reason is that the emergence of additional shortable securities in industry *x* allows investors to short a collection of securities in industry *x*. Shorting a (diversified) collection of substitute securities allows investors to immunize their portfolio against industry fluctuations while limiting the amount of (extra) firm-specific risk brought in via shorting.

Our second moderating factor captures differences in "Hedging Candidate Quality". We separate the subset of addition events with nonzero short-selling volume into those where, prior to the addition event, the *Event Firm* is more correlated with *Industry Peers* versus less correlated with *Industry Peers.* Prediction 4 states that the emergence of a shortable substitute security B allows the investor to more aggressively pursue the underpriced asset A the higher substitute security B's industry exposure, i.e., the higher β_B^{in}. The reason is that when asset B has high industry exposure, one only needs to short a small amount of asset B in order to make the overall portfolio industry neutral. Shorting a small amount of asset B limits the (extra) idiosyncratic risk brought in via shorting. In contrast, when asset B has limited industry exposure, it does not serve as a good industry hedge.

To test this prediction, we compute the industry beta of the *Event Firm* using daily stock-return data over a one-year period prior to the addition event; we exclude data from two calendar weeks prior to the addition event to avoid distortions associated with the addition event. Analogous to the previous test, an observation is categorized as being more correlated if it is in the top decile based on its industry beta

(→ better hedging candidate) and as being less correlated otherwise (→ poorer hedging candidate). The average industry beta of "better hedging candidates" is 1.94; the average industry beta of "poorer hedging candidates" is 0.75.

Table 5 shows that the results are stronger when the *Event Firm* provides a better hedge for the seemingly underpriced *Industry Peers*. When assessing performances over [0,+5], we observe that for industry peers whose *MB* are in the bottom-quintile, the emergence of a shortable security of better hedging quality is accompanied by cumulative abnormal returns of +1.379% (*t*-statistic = 4.04). The corresponding number when the shortable security is of poorer hedging quality is +0.618% (*t*-statistic = 3.18).

3.5. Setting Two: Methodology and Results

To further assess our underpricing-correction interpretation of the results, we collect data on annual earnings announcements from Bloomberg.[8] For consistency with prior analyses, our sample spans from 2001 to 2012. Each data point contains the company name, the stock ticker and the ISIN, as well as the earnings announcement date and the actual earnings announced on a per-share-basis. In a limited number of cases, Bloomberg also provides an analyst consensus forecast. Given the sparsity in analyst coverage, we assume that earnings follow a random walk, and we define *Earnings Surprise* as the actual earnings-per-share minus last year's earnings-per-share.

We match the annual earnings data with COMPUSTAT GLOBAL via the ISIN, and we compute abnormal returns as the difference in returns between the earnings-announcing firm and its matching firm. We do so from the earnings announcement day (or the ensuing trading day if earnings are announced on a non-trading day), *t*=0, to twenty trading days thereafter, *t*=+20. We restrict our analysis to twenty trading days because in our sample we do not observe a significant post-earnings-announcement drift after one calendar month. As before, matching firms are firms that are in the same size decile as the earnings-

[8] We rely on Bloomberg rather than IBES because for firms in Hong Kong, the "earnings announcement date" in IBES is not necessarily the date on which earnings are announced but the date on which the earnings information is entered into the database.

announcing firm and that have the closest *MB*. In total, our sample encompasses 2,444 annual earnings announcements made by 663 different firms.

The literature notes the presence of a post-earnings-announcement drift, with temporary underpricing (overpricing) after positive (negative) earnings surprises due to investor underreaction as one potential explanation. If the ability to short stock s allows arbitrageurs to more aggressively pursue temporarily underpriced stocks i, then we expect more of an immediate price reaction after a positive earnings surprise and, consequently, less of a post-earnings-announcement drift for stocks i in less-difficult-to-short industries.

To test our prediction, we estimate the following binary response model using the logistic function on *the subset of positive earnings surprises*:

$$Drift_{i,t} = \alpha + \beta Difficult_{i,t} + X\gamma + \varepsilon_{i,t}. \tag{1}$$

We compute abnormal returns as the difference in returns between the earnings-announcing firm and its matching firm from the earnings announcement day (or the ensuing trading day), t=0, to twenty trading days thereafter, t=+20. The cumulative abnormal return over [0,+20] is referred to as the market's total response. Our binary response model estimates the likelihood of a firm experiencing a post-earnings-announcement drift. Thus, our dependent variable in column (1) equals one if the fraction of the market's total response reached by the end of trading day t=+3 is below the median of its overall distribution, and zero otherwise. Our dependent variable in column (2) equals one if the fraction of the market's total response reached by the end of trading day t=+5 is below the median of its overall distribution, and zero otherwise.

In columns (3) and (4), we present results from an ordered logit: We sort observations into terciles based on the fraction of the market's total response reached by the end of trading day t=+3 or t=+5. The dependent variable equals three if an observation is in the bottom tercile, two if an observation is in the middle tercile and one otherwise.

Our main independent variable is $Difficult_{i,t}$ (= $Firm\ in\ Difficult\text{-}to\text{-}Short\ Industry_{i,t}$), which equals one if the earnings-announcing firm resides in an industry that is more-difficult-to-short, and zero otherwise. Control variables include: *Firm Shorted*$_{i,t}$, which equals one if the earnings-announcing firm itself experiences nonzero shorting activity in the year of the earnings announcement; *ln*(*Market/Book*$_{i,lagged}$), which is the natural logarithm of firm *i*'s market-to-book ratio as of the most recent fiscal year end; *ln(MarketCap*$_{i,lagged}$*)*, which is the natural logarithm of firm *i*'s market capitalization as of the most recent fiscal year end; *Coverage*$_{i,t}$, which is an indicator that equals one if the firm is covered by sell-side analysts, and zero otherwise; *Volatility*$_{i,lagged}$, which is firm *i*'s average daily return squared as of month *t*-1; and *Turnover*$_{i,lagged}$, which is firm *i*'s average daily number of shares traded divided by the number of shares outstanding as of month *t*-1. We also include industry averages of *Volatility*$_{i,lagged}$ and *Turnover*$_{i,lagged}$ as well as year-fixed effects. We include these variables because firms with certain firm and industry characteristics can be expected to exhibit a stronger drift. Moreover, the strength of the drift may vary through time. To facilitate interpretation of the economic significance, coefficient estimates are converted into marginal probabilities. We do not report the intercept. *Z*-statistics are reported in parentheses and are based on standard errors clustered by year.

The results presented in Panels A and B of Table 6 confirm that positive earnings surprises are associated with substantially more drift in more-difficult-to-short industries. For instance, Column (1) of Panel A reveals that being in a more-difficult-to-short industry increases the likelihood of experiencing a drift after a positive earnings surprise by 11.2% (*z*-statistic = 4.80). Columns (2)-(4) of Panel A show that similar observations apply when altering the horizon over which the delayed market response is computed and when estimating an ordered logit. Furthermore, Panel B shows that the results are very similar when excluding positive earnings surprise firms that are, for whatever reason, themselves being shorted in the year of the earnings announcement.

While we control for firm- and industry characteristics, there remains the possibility that more-difficult-to-short industries are less mature, informationally less efficient and more illiquid than their less-difficult-to-short counterparts. Informational inefficiency and illiquidity, in turn, may induce a greater post-earnings-announcement drift. To differentiate between the elimination-of-underpricing channel and the information/liquidity channel, we look to firms' reactions to negative earnings surprises. The elimination-of-underpricing channel has no prediction on the post-earnings-announcement drift after negative earnings surprises. On the other hand, if more-difficult-to-short industries are indeed informationally less efficient and more illiquid, we should observe not only a greater drift after positive earnings surprises in these industries but also after negative earnings surprises.

Panels C and D report our findings when repeating our analysis for negative earnings surprises. In short, we observe no reliable difference in the post-earnings-announcement drift between more- and less-difficult-to-short industries irrespective of the regression design. The estimate on $Difficult_{i,t}$ ranges from 0.020 (z-statistic = 0.40) to 0.062 (z-statistic = 1.10).

Together, the findings presented in Figure 3 and Table 6 are consistent with the notion that the relaxation of short-sale constraints lowers arbitrage risk, which causes arbitrageurs to trade more aggressively on perceived underpricing and thus expedites the market's response to positive earnings surprises.

3.6. Discussion

There are other vehicles through which investors can protect themselves from industry shocks. On the one hand, the presence of substitutes to the shorting channel lowers the power of our analysis and works against us making any interesting observations. On the other hand, if taken to the extreme, it raises questions about whether the relaxation of short-sale constraints could plausibly be thought of as the cause of the strong positive performance of seemingly underpriced industry peers.

The alternatives to the shorting channel are as follows: trading in derivative securities (options and futures), creating synthetic industry hedges, ADRs and shorting of industry peers traded in countries other than Hong Kong. There are no industry-specific Exchange-Traded Funds in Hong Kong.

To examine the interaction of the shorting channel with the use of derivative securities, we obtain option trading information from the *Bloomberg* database. We find no options where the underlying asset represents an entire industry. Moreover, option holders frequently require the presence of an active shorting market to hedge their positions. Perhaps not surprisingly, we therefore find that none of the stocks being added to the Hong Kong short-sale list have open interest for call and put options in the month prior to the addition event.

In general, as of May 2nd 2013, of the 1563 stocks listed on the Hong Kong Stock Exchange, only 61 had options listed on them, and many of these 61 options were associated with zero or negligible trading volume. This suggests that in Hong Kong, for reasons that are beyond the scope of this study, options are less popular for hedging purposes. Similar observations are made by Chang, Cheng and Yu (2007), who suggest that "*the options market is not so developed in Hong Kong*".

Similar observations also apply to futures. For reasons that are, again, beyond the scope of this study, Fung and Tse (2008) find that in Hong Kong, trading volume in single-stock futures is less than 0.1% of the trading volume of the underlying stock. There are no industry-specific futures.

It has also been suggested to us that when no stocks from a given industry are on the short-sale list, investors could create a synthetic industry hedge by going short on the market and going long on stocks in all industries other than the industry in question. While this is possible, we suspect that the creation of this synthetic hedge is both cumbersome and expensive, and conversations with practitioners corroborate this view.

Some Hong Kong securities have ADRs listed in the US that, in turn, can be shorted. However, the depth of this alternative channel is limited. We find that there are only 23 ADRs from Hong Kong over our sample period. The liquidity of these ADRs is low (liquidity statistics are available upon request).

Finally, investors could short industry peers in the broader Asia-Pacific region. Of the countries in this region, only Japan appears to have a deep and liquid shorting market during our sample period (Bris, Goetzmann and Zhu, 2007). The effectiveness of this channel is hampered by the fact that stocks from the same industry, yet different countries, are not subject to the same set of shocks. Moreover, by simultaneously investing in two separate markets, investors subject themselves to exchange-rate fluctuations.

4. Setting Three: The US Equity Market

The evidence from the Hong Kong stock market suggests that shorting activity need not only affect the stocks being shorted. In this section, we examine whether this finding carries over to the US equity market. The US equity market lacks a clear analogue of the institutional feature of the Hong Kong market that we exploit in the previous tests. Consequently, the results presented in this subsection are more suggestive by nature. Nevertheless, we highlight several novel features of the data, which, taken together, suggest that hedging considerations also play a role in the US.[9]

We begin by introducing the data (Section 4.1). We then present evidence that hedging-related short selling can be used to *positively* predict peer firms' earnings announcements, earnings announcement day returns and returns in general (Section 4.2).

4.1. Data

Our US sample consists of NYSE, AMEX, and NASDAQ ordinary shares with monthly short interest data over the period from 1988 to 2012; our sample covers 15,599 distinct securities. NYSE, AMEX, and NASDAQ member firms are required to report to the exchange their short positions as of settlement on the 15th of each month or on the preceding business day if the 15th is not a business day. We obtain monthly short interest data from the COMPUSTAT monthly securities database, which pools data from the NYSE, AMEX, and NASDAQ exchanges. For the period from 1988 through 2002, we augment this dataset with monthly short interest data obtained directly from the stock exchanges. We do so because we notice that, during the earlier period, many short positions reported by the stock exchanges are missing in the COMPUSTAT database; there are also a few short positions reported in COMPUSTAT that are not in the stock-exchange-provided data, but this subset is very small and economically inconsequential. We

[9] The temporary US short-sale ban of financial securities from September 18th, 2008, to October 8th, 2008 does not represent a clear analogue. Investors shorting financial securities in order to hedge industry risk did not have to close out their short positions after the temporary ban became effective. As a result, the lift of the ban on October 8th and the renewed ability to enter short positions in financial securities cannot be thought of as a clean positive shock to the ability to hedge industry risk via short-selling. Also, the US short-sale ban only represents a one-time event affecting one industry only.

measure the short interest of a stock in month *t* (SIR_t) as the ratio of the reported number of shares shorted in month *t* to the total number of shares outstanding at the end of month *t*-1.

We extract financial market data from the Center for Research in Security Prices (CRSP) and financial statement data from the COMPUSTAT annual industrial file. We obtain data on sell-side analyst earnings forecasts from the IBES unadjusted U.S. detail history file. We obtain institutional holdings data from the Thomson Financial Institutional Holdings (13F) database and option listing data from the OptionMetrics database.

Table 7 presents descriptive statistics. The average *SIR* is 2.45%. The average institutional holding is 41.46%, the average market capitalization is $2.2 billion and the average *MB* is 3.38. To put these numbers in perspective, the average firm in the full CRSP/Compustat sample from 1988 to 2012 has institutional holdings of 35.30%, a market capitalization of $1.9 billion and an *MB* of 3.27. Compared to the average CRSP/Compustat firm, our average sample firm (with monthly short interest data), therefore, has higher institutional holdings but is similar in terms of market capitalization and *MB*.

4.2. Short Selling of "Substitute" Securities and Stock Returns in the United States

If a non-negligible portion of short selling is hedging-related and if hedging investors are informed (Cao, Liang, Lo, and Petrasek 2014), then short-selling activity among substitute securities *s* should precede *positive* financial market outcomes for securities *i*. Put differently, holding stock *i*'s level of short interest constant, a high level of short interest among its peers may imply that informed long-short investors are purchasing shares of company *i* (as company *i* is currently undervalued) and they are hedging their long positions by shorting company *i*'s peers. High short interest among peers therefore predicts positive outcomes for the firm itself.

We assess our proposition with the following regression specification:

$$E_{i,t} = \alpha + \beta SIR(Substitutes)_{i,t-1} + X\gamma + \varepsilon_{i,t}, \tag{2}$$

where i indexes firms and t denotes the quarterly earnings announcement. We consider two dependent variables: *Earnings Surprise*$_{i,t}$, which is the price-scaled difference between the reported quarterly EPS and the consensus EPS forecast across analysts, and *Earnings Announcement Day Returns*$_{i,t}$, which is the cumulative abnormal return over [-1,+1], where day t=0 is the quarterly earnings announcement day or the ensuing trading day if earnings are announced on a non-trading day. Abnormal return is the difference between the raw return and the value-weighted return of a portfolio with similar size/book-to-market/past returns (Daniel, Grinblatt, Titman and Wermers 1997).

SIR(Substitutes)$_{i,t-1}$ is the average most recent short interest of firm i's substitute securities s. Substitute securities are defined to be stocks (1) that are in the same four-digit-GICS industry as firm i and (2) that are not themselves announcing earnings in the month surrounding day t=0. Other independent variables (X) include: *SIR*$_{i,t-1}$, which is the earnings-announcing firm i's most recent level of short interest; *Lagged(DependentVariable*$_{i,t-1}$*)*, which is the dependent variable from the previous earnings announcement; *ForecastDispersion*$_{i,t-1}$, which is the price-scaled standard deviation of analysts' EPS forecasts; *ln(MarketCap*$_{i,lagged}$*)*, which is the natural logarithm of the market capitalization as of the most recent fiscal year end; *ln(Market/Book*$_{i,lagged}$*)*, which is the natural logarithm of the *MB* as of the most recent fiscal year end; and *PastReturn*$_{i,t-30,t-1}$, which is the cumulative stock return over thirty calendar days prior to the earnings announcement. Again, we include year-month fixed effects and we cluster standard errors by year-month. All coefficient estimates are multiplied by 100.

Table 8 reveals that in the data, short interest among securities s positively predicts subsequent earnings surprises and earnings announcement day returns for firm i. The coefficient estimate on *SIR(Substitutes)*$_{i,t-1}$ without controlling for *SIR*$_{i,t-1}$ itself equals 0.418 (t-statistic = 1.59) for the earnings surprise regression and 4.874 (t-statistic = 2.36) for the earnings announcement day return regression. When including *SIR*$_{i,t-1}$ as an additional control variable, the estimate on *SIR(Substitutes)*$_{i,t-1}$ changes to 0.523 (t-statistic = 2.00) for the earnings surprise regression and 6.191 (t-statistic = 2.99) for the earnings announcement day return regression. The latter estimates are such that a one-standard-deviation increase in *SIR(Substitutes)*$_{i,t-1}$ translates to a 0.010% more positive earnings surprise and 0.120% more positive abnormal returns in the three days surrounding the earnings announcement. To put the earnings surprise result in perspective, an increase of 0.010% would promote the median firm (in terms of earnings surprise) to the 55th percentile.

Table 9 assesses whether our observations made around earnings announcements hold more generally and over longer horizons. The regression specification is as before:

$$Ret_{i,t+1,t+6(12)} = \alpha + \beta SIR(Substitutes)_{i,t} + X\gamma + \varepsilon_{i,t+1,t+6}, \quad (3)$$

where i indexes firms and t indexes year-months. The dependent variable is the cumulative return of firm i over the ensuing six (or twelve) calendar months. $SIR(Substitutes)_{i,t}$ is the average level of short interest across firm i's substitute securities s. X consists of: $SIR_{i,t}$, which is firm i's level of short interest; $ln(MarketCap_{i,lagged})$, which is the natural logarithm of the market capitalization as of the most recent fiscal year end; $ln(Market/Book_{i,lagged})$, which is the natural logarithm of the MB as of the most recent fiscal year end; and $PastReturn_{i,t-6,t-1}$, which is the cumulative stock return of firm i over the past six calendar months. We include year-month fixed effects and cluster standard errors by year-month. In this particular regression, we also cluster standard errors by security to account for the serial correlation induced by the overlap in cumulative returns.

As reported in Table 9, akin to the earnings announcement day results, we observe strong positive slopes on $SIR(Substitutes)_{i,t}$, suggesting that hedging-induced shorting of substitute securities s positively predicts returns for stock i. The coefficient estimate on $SIR(Substitutes)_{i,t}$ without controlling for $SIR_{i,t}$ itself equals 0.987 (t-statistic = 2.13) for the six-month horizon and 2.534 (t-statistic = 3.40) for the twelve-month horizon. When including $SIR_{i,t}$ as an additional control variable, the estimate on $SIR(Substitutes)_{i,t}$ changes to 1.215 (t-statistic = 2.64) and 2.861 (t-statistic = 3.86), respectively. The latter estimates imply that a one-standard-deviation increase in $SIR(Substitutes)_{i,t}$ leads to 1.98% more positive returns over the ensuing six months and to 5.04% more positive returns over the ensuing twelve months.

In the end, while not as direct of a test as for the Hong Kong market, the US evidence that positive outcomes for securities i can be predicted via the level of short interest among likely substitute securities *s* is at least consistent with the notion that hedging considerations also play some role in US equity markets.

5. Conclusion

That investors aggressively purchase underpriced securities and short substitute securities to hedge their industry exposure is not an idea original to this research; it is prescribed in textbooks (e.g, Shleifer 2000) and is frequently alluded to in anecdotal accounts (e.g., Michael and Kerns 1982, Donde 2012). However, to the best of our knowledge, we are the first to systematically evaluate the prevalence of hedging considerations in short selling and to assess their relevance in setting security prices. Our initial evidence is consistent with the presence of hedging-related short-selling activity, which ultimately facilitates the correction of underpricing and helps make markets more efficient. As such, our evidence should prove to be of interest to academics trying to better understand how short selling affects the degree to which prices incorporate value-relevant information and to regulators trying to assess the net impact of short selling on market quality.

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Appendix A

Setup:

Consider the presence of two risky assets, A and B, and a risk-free Asset. Without loss of generality, we determine that risky asset A's return and variance are:

$$r_A - r_f = \alpha_A + \beta_A^m r_m^e + \beta_A^{in} r_{in}^e + \epsilon_A$$
$$\sigma_A^2 = (\beta_A^m)^2 \sigma_m^2 + (\beta_A^{in})^2 \sigma_{in}^2 + \sigma_{\epsilon,A}^2.$$

Risky asset B's return and variance are:

$$r_B - r_f = \alpha_B + \beta_B^m r_m^e + \beta_B^{in} r_{in}^e + \epsilon_B$$
$$\sigma_B^2 = (\beta_B^m)^2 \sigma_m^2 + (\beta_B^{in})^2 \sigma_{in}^2 + \sigma_{\epsilon,B}^2.$$

Risky asset A is underpriced, i.e., $\alpha_A > 0$. Risky asset B is correctly priced, i.e., $\alpha_B = 0$.

The investor constructs a portfolio that takes advantage of the underpricing in risky asset A. At the same time, the investor aims to keep her portfolio risk, α_P, under a certain threshold, $\overline{\sigma_p}$ $(\sigma_p < \overline{\sigma_p})$.

Case 1: In the baseline case, asset B cannot be shorted and the investor simply constructs a portfolio based on asset A and the risk-free asset:

$$r_P = \mathrm{w} * r_A + (1 - w) * r_f.$$

The fraction of money the investor can put in asset A, $w_{A,Case1}$, is,

$$w_{A,Case1} = \frac{\sigma_p}{\sigma_A} < \frac{\overline{\sigma_p}}{\sigma_A}.$$

Predictions based on Case 1: Our equation reveals that the degree to which the investor can pursue the underpriced asset A, $w_{A,Case1}$, increases with the volatility limit, $\overline{\sigma_P}$, and decreases with the risk of asset A, σ_A.

Case 2: In the extended case, asset B can be shorted and the investor shorts asset B to make her portfolio immune to industry risk; thus, the investor will construct a portfolio based on asset A, asset B and the risk-free Asset. To sharpen our focus, we abstract away from our investor also attempting to make her portfolio market-neutral (our predictions are not materially altered when incorporating the investor's desire to make her portfolio market-neural. However, the model becomes slightly less tractable. The extended model is available upon request).

We assume that $p_{AB} > 0, \beta_A^{in} > 0 \ and \ \beta_B^{in} > 0$. The weights in asset A and B are w_A and $w_B = 1 - w_A$, respectively. To make the portfolio industry-neutral, the invest sets

$$w_A \beta_A^{in} + w_B \beta_B^{in} = 0$$

$$w_B = \frac{-\beta_A^{in}}{\beta_B^{in}} w_A$$

Intuitively, making a portfolio immune to industry shocks (by shorting the "substitute security," here, asset B) lowers risk and, as such, increases the investor's ability to pursue the underpriced asset without hitting the volatility limit, $\overline{\sigma_p}$. However, this proposition only holds if the risk brought in by the substitute security is not too high:

Let the fraction of the investors overall wealth in the risky portfolio, consisting of assets A and B, be w_{AB}. Given that $r_{AB} = w_A r_A + w_B r_B = w_A r_A - \frac{\beta_A^{in}}{\beta_B^{in}} w_A r_B$, we have:

$$r_P = w_{AB} * r_{AB} + (1 - w_{AB}) * r_f$$

$$= w_{AB} * [w_A r_A - \frac{\beta_A^{in}}{\beta_B^{in}} w_A r_B] + (1 - w_{AB}) * r_f$$

Consequently,

$$\sigma_p^2 = w_{AB}^2 [w_A^2 \sigma_A^2 + w_A^2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_B^2 - 2 w_A^2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) cov(r_A, r_B)$$

$$= w_{AB}^2 w_A^2 [\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_B^2 - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) (\beta_A^m \beta_B^m \sigma_m^2 + \beta_A^{in} \beta_B^{in} \sigma_{in}^2)]$$

$$= w_{AB}^2 w_A^2 [\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 [(\beta_B^m)^2 \sigma_m^2 + (\beta_B^{in})^2 \sigma_{in}^2 + \sigma_{\epsilon,B}^2] - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) (\beta_A^m \beta_A^m \sigma_m^2 + \beta_A^{in} \beta_B^{in} \sigma_{in}^2)]$$

$$= w_{AB}^2 w_A^2 [\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 (\beta_B^m)^2 \sigma_m^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 (\beta_B^{in})^2 \sigma_{in}^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_{\epsilon,B}^2 - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) \beta_A^m \beta_A^m \sigma_m^2 -$$

$$2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) \beta_A^{in} \beta_B^{in} \sigma_{in}^2]$$

$$= w_{AB}^2 w_A^2 [\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 (\beta_B^m)^2 \sigma_m^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_{\epsilon,B}^2 - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) \beta_A^m \beta_A^m \sigma_m^2 - (\beta_A^{in})^2 \sigma_{in}^2].$$

The fraction of wealth the investor can effectively put in underpriced asset A is

$$w_{A,Case2} = w_{AB} w_A = \frac{\sigma_p}{\sqrt{[\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 (\beta_B^m)^2 \sigma_m^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_{\epsilon,B}^2 - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) \beta_A^m \beta_A^m \sigma_m^2 - (\beta_A^{in})^2 \sigma_{in}^2]}}$$

$$< \frac{\overline{\sigma_p}}{\sqrt{[\sigma_A^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 (\beta_B^m)^2 \sigma_m^2 + \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2 \sigma_{\epsilon,B}^2 - 2 \left(\frac{\beta_A^{in}}{\beta_B^{in}}\right) \beta_A^m \beta_A^m \sigma_m^2 - (\beta_A^{in})^2 \sigma_{in}^2]}}.$$

Predictions based on case 2: The lower the denominator, the more aggressively our investor purchases the underpriced asset A.

The reduction in the denominator due to the last term, $-(\beta_A^{in})^2\sigma_{in}^2$, comes from the investor immunizing her portfolio against industry risk.

The middle terms, $\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2(\beta_B^m)^2\sigma_m^2+\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2\sigma_{\epsilon,B}^2-2\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)\beta_A^m\beta_A^m\sigma_m^2$, reflect the risk introduced by shorting asset B.

In the end, $w_{A,Case2}>w_{A,Case1}$ if and only if:

$$(\beta_B^{in})^2\sigma_{in}^2>\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2(\beta_B^m)^2\sigma_m^2+\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)^2\sigma_{\epsilon,B}^2-2\left(\frac{\beta_A^{in}}{\beta_B^{in}}\right)\beta_A^m\beta_A^m\sigma_m^2.$$

In other words, the reduction in risk due to industry immunization has to exceed the increase in risk brought in by shorting the substitute security.

Our inequality reveals that the introduction of shortable asset B allows the investor to more aggressively pursue underpriced asset A (compared to the baseline case):

1. If asset A has high industry exposure, i.e., if β_A^{in} is high;
2. If the industry asset A operates in is very volatile, i.e., if σ_{in}^2 is high;
3. If the substitute security has high industry exposure, i.e., if β_B^{in} is high; the reason is that if β_B^{in} is high, one only needs to short a small quantity of asset B in order to make the overall portfolio industry neutral,
4. If the substitute security used to eliminate industry exposure has low idiosyncratic risk, i.e., if $\sigma_{\epsilon,B}$ is low. Regarding prediction 4, asset B can be construed to be a single stock with a relative high $\sigma_{\epsilon,B}$. Alternatively, asset B can be construed to be a portfolio of shortable stocks with a relatively low $\sigma_{\epsilon,B}$. Prediction 4, thus, states that the more shortable stocks there are in the industry asset A operates in, the higher $w_{A,Case2}$ relative to $w_{A,Case1}$.

Appendix B.1

B.1.1. Background

In January 1994, the HKEX introduced a pilot program that allowed 17 securities to be shorted. Since then, the exchange has been updating the list of securities that can be shorted ("designated-securities list"), mostly at a quarterly frequency. The list includes common stocks, as well as REITs and ETFs. In our analysis, we focus on common stocks. But, initially, we also collect data on REITs and ETFs.

According to the HKEX, to be included in the designated-securities list, a security has to meet certain liquidity thresholds or be a member of an index or have derivatives traded on the exchange or be an ETF. Once any of these criteria are satisfied, it is subject to the exchange's discretion as to whether to include the security or not.

B.1.2. Initial Data Collection

The HKEX publishes the most current designated-securities list on its website. However, it does not publish historical designated-securities lists. Instead, it provides data on revisions to the list from January 2001 to August 2012 (the end of our sample period).[10] These revisions reflect securities added to the list and securities deleted from the list. Apart from regular quarterly changes to the list, the HKEX also sometimes makes irregular changes to the list.

We collect announcements of regular quarterly changes and announcements of irregular changes. For each announcement, we have the name of the company/REIT/ETF and its stock code as well as the date the news is announced and the effective date (the date from which on the stock can be shorted). Typically, the effective date is one week after the announcement date.

B.1.3. Data Cleaning

Based on the designated-securities list (as of August 2012, which is the beginning of our data collection efforts and the end of our sample period) and the historical announcements of changes made to the list, we deduct, for any given point in time, the historical designated-securities list.

When implementing this approach, we observe some anomalies: A few securities on the most current list and a few securities announced to be deleted from the list do not have a record of inclusion while others that are no longer on the most current list (but were added at some point) do not have record of deletion. We believe these anomalies to happen primarily for one of the following reasons:

[10] The HKEX also provides revisions data for 2000, but only for the first quarter of 2000.

1. A stock moves to a different trading board. The HKEX has two trading boards: Main Board and GEM (similar to pink-sheets). Once a stock moves its stock code changes.
2. Mergers and acquisitions.
3. Delisting.

We make the following changes to clean the data:

1. The Nov 21st, 2002 announcement is replaced by the Nov 28th, 2002 announcement, which constitutes a restatement of the earlier announcement.
2. 14 stocks were moved from the GEM to the Main Board. When a stock moves from the GEM to the Main Board, it typically is assigned a new trading code by the Main Board. We update the stock code accordingly.
3. 18 stocks were delisted. We use the actual delisting date as both the announcement- and effective date for the stock deleted from the list. (Despite extensive search efforts, we were unable to obtain reliable data on the date of the delisting announcement.) Historical delisting data is from WIND.
4. 3 stocks were taken over. We use the takeover-announcement date as the announcement- and effective date for the stock deleted from the list. The takeover information is from news releases.
5. We delete five addition announcements because they reflect changes in stock codes of firms already in the short list. These changes are unrelated to moves from the GEM to the Main Board.

B.1.4. Data Verification

We cross-check our data by comparing the total number of permitted stocks to be shorted (as per our deduced list) with the exchange-published number; the HKEX does publish historical information on the total number of securities on the designated-securities list.

B.1.5. Matching Short List Data with Accounting and Stock-Return Data

We obtain financial market data from COMPUSTAT GLOBAL. We cannot directly match our HKEX data with COMPUSTAT-GLOBAL data as there is no good common identifier. The identifier used by the HKEX is the company/REIT/ETF-name and stock code. COMPUTSTAT GLOBAL uses the company name, ISIN, GVKEY and CUSIP, but not the stock code. We find name matching to be unreliable and to yield poor results as HKEX and COMPUSTAT GLOBAL use different names.

Fortunately, Bloomberg data has both stock code and ISIN. We thus add ISIN to our HKEX data via Bloomberg data. This, in turn, enables a merge with COMPUSTAT GLOBAL.

For reasons detailed in the main body of the text, we focus on additions to the designated-securities list (not on deletions). Our initial data-collection- and cleaning efforts produce 1,137 addition events. Of these we are able to match 1,076 with Bloomberg data, of which we are able to match 732 to COMPUSTAT GLOBAL. The loss of addition events is due to our COMPUSTAT-GLOBAL data not covering REITs and ETFs. As our study focuses on common stocks, the effective loss in observations is minimal. Of the remaining 732 addition events, 25 lack the accounting and stock return data we need for our analysis. In the end, we arrive at our final sample of 707 common-stock additions between 2001 and 2012. These 707 addition events cover 444 distinct firms (some firms are added to the list only to be removed later and then to be added again).

Appendix B.2

This table reports the number of addition events by the calendar year of the effective date. An addition event is specified as one in which an individual stock is added to the Hong Kong short-sale list and, therefore, can be sold short from the effective date.

Year	Number of Addition Events
2001	10
2002	21
2003	33
2004	35
2005	45
2006	71
2007	135
2008	34
2009	92
2010	128
2011	100
2012	3

Appendix B.3

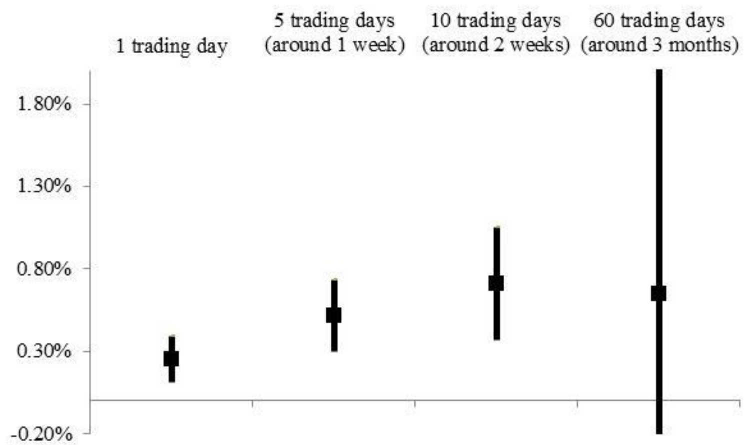
This table reports the number of addition events by four-digit-GICS industry. An addition event is specified as one in which an individual stock is added to the Hong Kong short-sale list and, therefore, can be sold short from the effective date.

GICS Industry Code	GICS Industry Name	Number of Addition Events
1010	Energy	27
1510	Materials	77
2010	Capital Goods	92
2020	Commercial & Professional Services	10
2030	Transportation	24
2510	Automobiles and Components	13
2520	Consumer Durables and Apparel	88
2530	Consumer Services	54
2540	Media	43
2550	Retailing	46
3010	Food & Staples Retailing	9
3020	Food, Beverage & Tobacco	25
3030	Household & Personal Products	11
3510	Health Care Equipment & Services	9
3520	Pharmaceuticals, Biotechnology & Life Sciences	28
4020	Diversified Financials	5
4040	Real Estate	13
4510	Software & Services	28
4520	Technology Hardware & Equipment	61
4530	Semiconductors & Semiconductor Equipment	11
5010	Telecommunication Services	10
5510	Utilities	23

Figure 1
Cumulative Abnormal Returns after Additions to the Hong Kong Short-Sale List

This figure reports cumulative abnormal returns around additions of stocks to the short-sale list in Hong Kong. Our sample starts in 2001 and ends in 2012 and encompasses a total of 707 addition events. An addition event is specified as one in which an individual stock is added to the list (=*Event Firm*) and, therefore, can be sold short from the event day, denoted as day t=0. *Industry Peers* are defined to be stocks (1) that are in the same four-digit-GICS industry as the *Event Firm*, (2) that are themselves not being added to the short-sale list on the event day. This figure focuses on the 601 addition events for which (1) the *Event Firm* or (2) any of the other same-four-digit-GICS-industry firms being added to the list on the same event day are associated with nonzero short-selling volume in the year of the addition. We plot the average cumulative abnormal returns, along with the 95% confidence interval, of the *Industry Peers* that are in the bottom industry market-to-book-ratio demile/quintile; we do so over various holding periods after the addition event: [0,1], [0,5], [0,10], [0,60]. To compute abnormal returns for *Industry Peers*, each *Industry Peer* is matched with a firm in the same size decile having the closest market-to-book ratio that is itself not being affected by the addition event.

Panel A: Bottom Market-to-Book-Ratio Demile Industry Peers



Panel B: Bottom Market-to-Book-Ratio Quintile Industry Peers

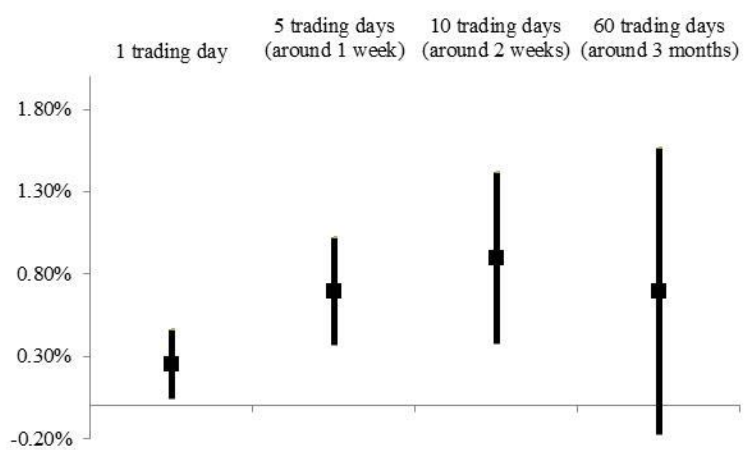


Table 1
Hong Kong Evidence: Descriptive Statistics

This table reports summary statistics for our Hong Kong sample of 707 addition events from 2001 to 2012. An addition event is specified as one in which an individual stock is added to the Hong Kong short-sale list (=*Event Firm*) and, therefore, can be sold short from the event day, denoted as day t=0. There are a total of 707 event firms and a total of 42,640 industry peers (i.e., 60.31 industry peers per event firm). *Industry Peers* are defined to be stocks (1) that are in the same four-digit-GICS industry as the *Event Firm*, (2) that are themselves not being added to the short-sale list on the event day. We separate *Industry Peers* by whether they are in the bottom industry market-to-book-ratio demile (Panel C) or bottom industry market-to-book ratio quintile (Panel D). *Market Capitalization* is the number of shares outstanding multiplied by the stock price as of t=0. *Market-to-Book Ratio* is the market capitalization as of the most recent fiscal year end divided by the book value of equity. *Daily Volatility* is the average daily return squared in the month prior to the addition event. *Daily Volume* is the average daily HK$-value of shares traded in the month prior to the addition event.

	P25	P50	P75	Mean	StDev
Panel A: Event Firms					
Market Capitalization (in HK$ millions)	1,208	1,859	3,378	3,204	6,885
Market-to-Book Ratio	0.75	1.35	2.51	2.46	3.63
Daily Volatility (*1000)	0.41	0.81	1.44	1.39	2.02
Daily Volume (in HK$ millions)	0.80	2.73	9.35	13.43	44.85
Panel B: Industry Peers (All)					
Market Capitalization (in HK$ millions)	337	897	3,062	6,208	35,299
Market-to-Book Ratio	0.53	1.01	2.08	1.97	5.77
Daily Volatility (*1000)	0.42	0.90	1.96	2.09	5.09
Daily Volume (in HK$ millions)	0.38	1.53	5.85	9.14	39.80
Panel C: Industry Peers (Bottom Half)					
Market Capitalization (in HK$ millions)	260	565	1,570	2,892	14,532
Market-to-Book Ratio	0.35	0.55	0.80	0.61	0.35
Daily Volatility (*1000)	0.43	0.95	2.12	2.20	5.05
Daily Volume (in HK$ millions)	0.29	1.13	4.78	8.57	43.01
Panel D: Industry Peers (Bottom Quintile)					
Market Capitalization (in HK$ millions)	213	404	1,044	1,892	8,828
Market-to-Book Ratio	0.24	0.32	0.44	0.35	0.16
Daily Volatility (*1000)	0.50	1.08	2.49	2.41	5.22
Daily Volume (in HK$ millions)	0.30	1.15	5.03	8.81	33.76

Table 2
Cumulative Abnormal Returns around Additions to the Hong Kong Short-Sale List

This table reports cumulative abnormal returns [%] around additions of stocks to the short-sale list in Hong Kong. Our sample starts in 2001 and ends in 2012 and is based on 707 addition events. An addition event is specified as one in which an individual stock is added to the list (=*Event Firm*) and, therefore, can be sold short from the event day, denoted as day *t*=0. *Industry Peers* are defined to be stocks (1) that are in the same four-digit-GICS industry as the *Event Firm*, (2) that are themselves not being added to the short-sale list on the event day. We separate *Industry Peers* by whether they are in the top industry market-to-book-ratio demile or bottom industry market-to-book-ratio demile/quintile. To compute abnormal returns, each *Event Firm* is matched with a firm in the same size decile having the closest market-to-book ratio that is itself not being added to the short-sale list on the event day; similarly, each *Industry Peer* is matched with a firm in the same size decile having the closest market-to-book ratio that is itself not being affected by the addition event. Panels A and B separate addition events by whether (1) the *Event Firm* or (2) any of the other same-four-digit-GICS-industry firms being added to the list on the same event day are associated with nonzero short-selling volume in the year of the addition. Out of the 707 addition events, 601 events (85%) are associated with nonzero short-selling volume. *T*-statistics are reported in parentheses. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Event Firms	Industry Peers M/B: Top Half	Industry Peers M/B: Bottom Half	Industry Peers M/B: Bottom Quintile
Panel A: Short Interest = 0				
[-5,-1]	-1.074	-0.048	**-0.602***	**-0.511**
	(-1.26)	(-0.17)	**(-1.84)**	**(-0.99)**
[0,+5]	1.342	-0.233	**0.152**	**0.123**
	(1.36)	(-0.81)	**(0.43)**	**(0.27)**
Panel B: Short Interest > 0				
[-5,-1]	-1.077**	-0.217**	**0.076**	**0.135**
	(-2.51)	(-2.10)	**(0.62)**	**(0.82)**
[0,+5]	-0.392	-0.000	**0.516*****	**0.693*****
	(-0.93)	(-0.04)	**(4.79)**	**(4.28)**

Table 3
Trading around Additions to the Hong Kong Short-Sale List

This tables reports performance statistics of a simple calendar-time trading strategy. The "*Long-Short Strategy*" is as follows: If on trading day *t*, there is an addition event, we hedge by going short the *Event Firm* that is being added to the short-sale list and we simultaneously go long each corresponding *Industry Peer* that is in the bottom industry market-to-book-ratio quintile. We close out positions after five trading days. The "*Long-Early Strategy*" is as follows: We purchase shares of each *Industry Peer* that is in the bottom industry market-to-book-ratio quintile, but we do so five trading days prior to the addition event. The portfolio returns are value-weighted based on the *Industry Peers*' market capitalization. If on a given trading day, there is no addition event, we invest in the risk-free asset. *Raw Return* is the average monthly portfolio return. *Abnormal Return* is the average abnormal monthly portfolio return, computed as the *Industry Peers*' characteristics-adjusted return minus *Event Firms*' characteristics-adjusted return for the *Long-Short Strategy* and computed as *Event Firms*' characteristics-adjusted return for the *Long-Early Strategy*. To compute characteristics-adjusted returns, we match each stock with another stock in the same size decile having the closest market-to-book ratio that is itself not being affected by the addition event and we compute the difference in performance between that stock and its matching firm. *Standard Deviation* is the monthly standard deviation of *Raw Return*. *Sharpe Ratio* is the average monthly *Raw Return*, scaled by its corresponding standard deviation.

	Long-Short Strategy	Long-Early Strategy
Raw Return	0.64%	0.62%
Abnormal Return	0.70%	0.69%
Standard Deviation	4.57%	5.89%
Sharpe Ratio	0.14	0.11

Table 4
Cumulative Abnormal Returns around Additions to the Hong Kong Short-Sale List:
Moderating Factor – Difficulty to Short prior to Addition

This table mirrors Table 2, but focuses on the 601 addition events associated with nonzero short-selling volume in the year of the addition. Panels A and B separate *Event Firms* and their corresponding *Industry Peers* by whether the *Event Firm* is coming from an industry that is more- or less-difficult-to-short prior to the addition event. Every year and for each four-digit-GICS industry, we compute the number and fraction of firms with nonzero short-selling volume. An observation is categorized as coming from a more-difficult-to-short industry if it is in the bottom decile based on the industry's number/fraction of shorted firms in the year prior to the addition event (→ more hedging demand), and as coming from a less-difficult-to-short industry otherwise (→ less hedging demand). *T*-statistics are reported in parentheses. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Difficulty-to-Short Based on **Fraction** of Firms Shortable		Difficulty-to-Short Based on **Number** of Firms Shortable	
	Event Firms	Industry Peers M/B: Bottom Quintile	Event Firms	Industry Peers M/B: Bottom Quintile
Panel A: Short Interest > 0, Industry Less-Difficult-to-Short Prior to Addition (→ Less Hedging Demand)				
[-5,-1]	-1.156***	**0.142**	-1.110**	**0.133**
	(-2.83)	**(0.85)**	(-2.49)	**(0.80)**
[0,+5]	-0.359	**0.576*** **	-0.433	**0.635*** **
	(-0.81)	**(3.55)**	(-0.96)	**(3.90)**
Panel B: Short Interest > 0, Industry More-Difficult-to-Short Prior to Addition (→ More Hedging Demand)				
[-5,-1]	0.109	**0.005**	-0.805	**0.196**
	(0.34)	**(0.01)**	(-0.49)	**(0.17)**
[0,+5]	-0.812	**2.835*** **	0.035	**2.561** **
	(-0.53)	**(3.09)**	(0.03)	**(2.40)**

Table 5
Cumulative Abnormal Returns around Additions to the Hong Kong Short-Sale List:
Moderating Factor – Industry Exposure of Hedging Candidate

This table mirrors Table 2, but focuses on the 601 addition events associated with nonzero short-selling volume in the year of the addition. Panels A and B separate *Event Firms* and their corresponding *Industry Peers* by whether the *Event Firm* is more or less correlated with *Industry Peers* prior to the addition event (and, as such, serves as a good or not-so-good industry hedge). We compute the industry beta of the *Event Firm* using daily stock-return data over a one-year period prior to the addition event, whereby we exclude data from two calendar weeks prior to the addition event. An observation is categorized as being more correlated if it is in the top decile based on its correlation (→ better hedging candidate), and as being less correlated otherwise (→ poorer hedging candidate). *T*-statistics are reported in parentheses. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Event Firms	Industry Peers M/B: Bottom Quintile
Panel A: Short Interest > 0, Event Firm Less Correlated with Industry Peers (→ Poorer Hedging Candidate)		
[-5,-1]	-0.956***	**0.135**
	(-2.33)	**(0.70)**
[0,+5]	-0.360	**0.618*** **
	(-0.88)	**(3.18)**
Panel B: Short Interest > 0, Event Firm More Correlated with Industry Peers (→ Better Hedging Candidate)		
[-5,-1]	-1.003*	**0.304**
	(-1.91)	**(0.64)**
[0,+5]	-0.254	**1.379*** **
	(-0.56)	**(4.04)**

Table 6

Post-Earnings Announcement Drift and the Role of Shortability: Hong Kong

We estimate regression equations of the degree of the post-earnings announcement drift on various firm- and industry characteristics. Our sample spans annual earnings announcements from 2001 to 2012. In Panels A and B, we analyze the subset of positive earnings surprises, where *Earnings Surprise* is the actual announced earnings minus the earnings forecast from a random-walk model; in Panels C and D, we analyze the subset of negative earnings surprises. Panel A (C) reports results for the full subset of positive (negative) earnings surprises. In Panels B and D, we exclude earnings-announcing firms with nonzero shorting activity in the year of the earnings announcement. We compute abnormal returns as the difference in returns between the earnings-announcing firm and its matching firm from the earnings announcement day (or the ensuing trading day if earnings are announced on a non-trading day), t=0, to twenty trading days thereafter, t=+20. Each earnings-announcing firm is matched with another firm in the same size decile and the closest *Market-to-Book Ratio*. The cumulative abnormal return over [0,+20] is referred to as the market's total response. Our dependent variable in columns (1) and (2) equals one if the fraction of the market's total response that is reached by the end of day t=3 and day t=5 is below the median of its overall distribution, and zero otherwise; our dependent variable in columns (3) and (4) equals one if the fraction of the market's total response that is reached by the end of day t=3 and day t=5 is in the bottom tercile of its distribution, two if it is in the middle tercile and three if it is in the top tercile. $\textit{Firm in Difficult-to-Short Industry}_{i,t}$ equals one if the earnings announcing firm is coming from an industry that is more-difficult-to-short in the year of the earnings announcement, and zero otherwise. Specifically, every year and for each four-digit-GICS industry, we compute the fraction of firms with nonzero short-selling volume. An observation is categorized as coming from a more-difficult-to-short industry if it is in the bottom decile based on the industry's fraction of shorted firms in the year of the earnings announcement, and as coming from a less-difficult-to-short industry otherwise. $\textit{Firm Shorted}_{i,t}$ equals one if the earnings announcing firm itself experiences nonzero shorting activity in the year of the earnings announcement. $ln(\textit{Market/Book}_{i,lagged})$ is the natural logarithm of firm i's market-to-book ratio as of the most recent fiscal year end. $ln(\textit{MarketCap}_{i,lagged})$ is the natural logarithm of firm i's market capitalization as of the most recent fiscal year end. $\textit{Coverage}_{i,t}$ equals one if the firm is covered by sell-side analysts, and zero otherwise. $\textit{Volatility}_{i,lagged}$ is firm i's average daily return squared as of month t-1. $\textit{Turnover}_{i,lagged}$ is firm i's average daily number of shares traded divided by the number of shares outstanding as of month t-1. $\textit{Industry Volatility}_{i,lagged}$ is the average $\textit{Volatility}_{i,lagged}$ of firms operating in the same four-digit-GICS industry as firm i as of month t-1. $\textit{Industry Turnover}_{i,lagged}$ is the average $\textit{Turnover}_{i,lagged}$ of firms operating in the same four-digit-GICS industry as firm i as of month t-1. Coefficient estimates are converted into marginal probabilities. We include year-fixed effects. We do not report the intercept. *Z*-statistics are reported in parentheses and are based on standard errors clustered by year. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 6. Continued.

	Logit		Ordered Logit	
	Drift Based on Market's Response by t=+3 (1)	Drift Based on Market's Response by t=+5 (2)	Drift Based on Market's Response by t=+3 (3)	Drift Based on Market's Response by t=+5 (4)
Panel A: All Positive Earnings-Announcing Firms				
Firm in Difficult-to-Short Industry$_{i,t}$	**0.112*****	**0.097*****	**0.086*****	**0.082*****
	(4.80)	**(2.71)**	**(8.71)**	**(3.00)**
Firm Shorted$_{i,t}$	-0.076**	-0.064	-0.055	-0.038
	(-1.97)	(-1.17)	(-1.55)	(-0.91)
ln(Market/Book$_{i,lagged}$)	0.001	0.001	0.000	0.001**
	(1.50)	(1.13)	(0.74)	(2.26)
ln(MarketCap$_{i,lagged}$)	-0.004	-0.016	-0.007	-0.013*
	(-0.22)	(-1.13)	(-0.71)	(-1.23)
Coverage$_{i,t}$	-0.027	0.005	-0.003	0.009
	(-0.37)	(0.08)	(-0.07)	(0.16)
Volatility$_{i,lagged}$	-0.121	-0.031	0.317	0.225
	(0.19)	(-0.04)	(0.93)	(0.28)
Turnover$_{i,lagged}$	1.555	1.945**	1.431*	1.102**
	(1.52)	(2.24)	(1.68)	(1.93)
Industry Volatility$_{i,lagged}$	-1.050	1.529	2.020*	2.622
	(-1.34)	(0.75)	(1.69)	(1.12)
Industry Turnover$_{i,lagged}$	-3.580*	-2.412	-6.297***	-3.226***
	(-1.68)	(-1.03)	(-2.95)	(-2.45)
# Obs.	1,104	1,104	1,104	1,104
McFadden's Pseudo R^2	0.02	0.02	0.01	0.01
Panel B: Positive Earnings-Announcing Firms with Zero Shorting Activity in Year of Earnings Announcement				
Firm in Difficult-to-Short Industry$_{i,t}$	**0.134*****	**0.101*****	**0.102*****	**0.089*****
	(6.58)	**(3.00)**	**(9.18)**	**(3.13)**
ln(Market/Book$_{i,lagged}$)	0.002*	0.001	0.000	0.002**
	(1.92)	(1.33)	(1.38)	(2.32)
ln(MarketCap$_{i,lagged}$)	0.005	-0.010	0.001	-0.011
	(0.26)	(-0.59)	(0.12)	(-0.97)
Coverage$_{i,t}$	-0.065	0.046	-0.031	0.059
	(-1.05)	(0.89)	(-0.48)	(1.01)
Volatility$_{i,lagged}$	0.259	0.068	0.427	0.340
	(0.41)	(0.10)	(1.20)	(0.41)
Turnover$_{i,lagged}$	0.763	1.317	1.062	0.620
	(0.88)	(1.58)	(1.21)	(0.90)
Industry Volatility$_{i,lagged}$	-2.072*	1.150	1.051	1.766
	(-1.74)	(0.51)	(0.80)	(0.73)
Industry Turnover$_{i,lagged}$	0.996	-1.920	-3.425	-1.508
	(0.37)	(-0.73)	(-1.14)	(-1.20)
# Obs.	941	941	941	941
McFadden's Pseudo R^2	0.02	0.02	0.01	0.01

Table 6. Continued.

	Logit		Ordered Logit	
	Drift Based on Market's Response by t=+3 (1)	Drift Based on Market's Response by t=+5 (2)	Drift Based on Market's Response by t=+3 (3)	Drift Based on Market's Response by t=+5 (4)
Panel C: All Negative Earnings-Announcing Firms				
Firm in Difficult-to-Short Industry$_{i,t}$	**0.030**	**0.055**	**0.039**	**0.020**
	(0.46)	**(1.00)**	**(1.12)**	**(0.40)**
Firm Shorted$_{i,t}$	-0.071**	-0.068***	0.034	-0.050*
	(-2.37)	(-2.49)	(0.79)	(-1.76)
ln(Market/Book$_{i,lagged}$)	0.000	0.001	0.001	0.001
	(1.26)	(0.45)	(0.94)	(0.64)
ln(MarketCap$_{i,lagged}$)	0.007	0.023**	0.010	0.024**
	(0.54)	(2.00)	(0.91)	(2.36)
Coverage$_{i,t}$	-0.019	-0.053*	0.006	-0.045
	(-0.33)	(-1.64)	(0.17)	(-1.55)
Volatility$_{i,lagged}$	-1.281	-1.544	-0.696	-0.837
	(-0.48)	(-0.62)	(-0.31)	(-0.40)
Turnover$_{i,lagged}$	-1.068	-1.676	-0.716	-0.865
	(-1.29)	(-1.23)	(-0.78)	(-0.84)
Industry Volatility$_{i,lagged}$	12.412**	3.736	5.134	2.810
	(2.19)	(0.77)	(1.61)	(1.26)
Industry Turnover$_{i,lagged}$	9.007*	8.338	3.846	6.371*
	(1.89)	(1.57)	(0.99)	(1.82)
# Obs.	1,144	1,144	1,144	1,144
McFadden's Pseudo R^2	0.02	0.02	0.01	0.01
Panel D: Negative Earnings-Announcing Firms with Zero Shorting Activity in Year of Earnings Announcement				
Firm in Difficult-to-Short Industry$_{i,t}$	**0.035**	**0.062**	**0.038**	**0.022**
	(0.51)	**(1.10)**	**(0.94)**	**(0.41)**
ln(Market/Book$_{i,lagged}$)	0.000	0.001	0.001	0.001
	(1.46)	(0.37)	(0.94)	(0.80)
ln(MarketCap$_{i,lagged}$)	0.008	0.027*	0.009	0.026**
	(0.47)	(1.94)	(0.83)	(2.32)
Coverage$_{i,t}$	-0.025	-0.020	0.005	-0.000
	(-0.51)	(-0.42)	(0.14)	(-0.01)
Volatility$_{i,lagged}$	-1.200	-1.436	-0.640	-0.812
	(-0.43)	(-0.55)	(-0.28)	(-0.37)
Turnover$_{i,lagged}$	-1.564	-2.072	-0.443	-0.603
	(-1.09)	(-1.00)	(-0.38)	(-0.49)
Industry Volatility$_{i,lagged}$	11.057**	2.507	4.452*	2.075
	(2.07)	(0.49)	(1.68)	(0.89)
Industry Turnover$_{i,lagged}$	12.606***	12.269	3.891	6.728
	(2.68)	(2.18)	(0.84)	(1.30)
# Obs.	961	961	961	961
McFadden's Pseudo R^2	0.02	0.02	0.01	0.01

Table 7
US Evidence: Descriptive Statistics

This table reports summary statistics for the sample of 1,113,586 firm-months observations from June 1988 to December 2012. *Short Interest* is defined as the number of shares shorted in month *t*, divided by the total number of shares outstanding as of month *t*-1. *Institutional Holdings* is the fraction of shares held by institutions as of month *t*-1 as reported by the Thomson Financial Institutional Holdings (13F) database. *Market Capitalization* is the number of shares outstanding multiplied by the stock price, both as of month *t*-1. *Market-to-Book Ratio* is the market capitalization as of the most recent fiscal year end divided by the book value of equity. *Daily Volatility* is the average daily return squared as of month *t*-1. *Daily Share Turnover* is the average daily number of shares traded divided by the number of shares outstanding as of month *t*-1. *Daily Volume* is the average daily $-value of number of shares traded as of month *t*-1.

	Mean	Std. Dev.	P25	Median	P75
Short Interests	2.45%	4.57%	0.07%	0.64%	2.88%
Institutional Holdings	41.46%	30.54%	13.37%	37.30%	66.96%
Market Capitalization (in $millions)	2,204	12,378	39	158	749
Market-to-Book Ratio	3.38	5.86	1.11	1.84	3.37
*Daily Volatility (*1000)*	2.25	20.01	0.33	0.81	2.02
*Daily Share Turnover (*1000)*	6.06	11.63	1.31	3.21	7.25
Daily Volume (in thousands)	548.75	4,141.25	10.23	52.76	259.06

Table 8

US Evidence: Short Interest and Earnings Surprises/Earnings-Announcement-Day Returns

We estimate regression equations of price-scaled earnings surprise/earnings announcement day returns on measures of short interest. The sample period is 1988-2012. *Earnings Surprise*$_{i,t}$, the dependent variable in Columns (1) and (2), is the price-scaled difference between reported quarterly EPS and the consensus EPS forecast across analysts. *Earnings Announcement Day Returns*$_{i,t}$, the dependent variable in Columns (3) and (4), is the cumulative abnormal return over [-1,+1], whereby day t=0 is the quarterly earnings announcement day or the ensuing trading day if earnings are announced on a non-trading day. Abnormal return is the difference between raw return and the value-weighted return of a portfolio with similar size/book-to-market/past returns (Daniel et al. 1997). *ShortInterest (Substitutes)*$_{i,t}$ is the most recent average level of short interest of the earnings announcing company's industry peers. Industry peers are defined to be stocks (1) that are in the same four-digit-GICS industry as the event firm, and (2) that are themselves not announcing earnings in the month surrounding the event day. *ShortInterest*$_{i,t}$ is the earnings announcing company's most recent level of short interest. *Lagged(DependentVariable*$_{i,t}$*)* is the dependent variable from the previous earnings announcement. *ForecastDispersion*$_{i,t}$ is the price-scaled standard deviation of analysts' EPS forecasts. *ln(MarketCap*$_{i,lagged}$*)* is the natural logarithm of the market capitalization as of the most recent fiscal year end. *ln(Market/Book*$_{i,lagged}$*)* is the natural logarithm of the book-to-market ratio as of the most recent fiscal year end. *PastReturn*$_{i,t-30,t-1}$ is the cumulative stock return over thirty calendar days prior to the earnings announcement. Coefficient estimates are multiplied by 100. We include year-month fixed effects. We do not report the intercept. *T*-statistics are reported in parentheses and are based on standard errors clustered by year-month. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

	Earnings Surprise		Earnings Announcement Day Return	
	(1)	(2)	(3)	(4)
ShortInterest (Substitutes)$_{i,t}$	**0.418**	**0.523****	**4.874****	**6.191*****
	(1.59)	**(2.00)**	**(2.36)**	**(2.99)**
ShortInterest$_{i,t}$		-0.229**		-2.856***
		(-2.55)		(-4.92)
Lagged(DependentVariable)	12.425***	12.417***	0.079	0.048
	(16.64)	(16.66)	(0.23)	(0.14)
ForecastDispersion$_{i,t}$	-19.408***	-19.239***	-18.206***	-16.102***
	(-2.82)	(-2.78)	(-3.31)	(-2.98)
ln(MarketCap$_{i,lagged}$)	0.022***	0.022***	-0.008	-0.010
	(9.86)	(9.82)	(-0.61)	(-0.82)
ln(Market/Book$_{i,lagged}$)	0.016***	0.018***	0.126***	0.102***
	(2.76)	(2.95)	(3.58)	(2.89)
PastReturn$_{i,t-30,t-1}$	0.791***	0.791***	3.048***	3.046***
	(18.26)	(18.28)	(9.85)	(9.87)
# Obs.	193,683	193,683	193,683	193,683
Adj. R^2	0.05	0.05	0.01	0.01

Table 9
US Evidence: Short Interest and Future Stock Returns

We estimate regression equations of future stock returns on measures of short interest. The sample period is 1988-2012. $FutureReturn_{i,t+1,t+6}$, the dependent variable in Columns (1) and (2), is the cumulative stock return of firm *i* over the next six calendar months. $FutureReturn_{i,t+1,t+12}$, the dependent variable in Columns (3) and (4), is the cumulative stock return of firm *i* over the next twelve calendar months. *ShortInterest (Substitutes)*$_{i,t}$ is the average level of short interest of firm *i*'s industry peers. Industry peers are defined to be stocks that are in the same four-digit-GICS industry as firm *i*. $ShortInterest_{i,t}$ is firm *i*'s level of short interest. *ln(MarketCap*$_{i,lagged}$*)* is the natural logarithm of the market capitalization as of the most recent fiscal year end. *ln*(*Market/Book*$_{i,lagged}$) is the natural logarithm of the market-to-book ratio as of the most recent fiscal year end. $PastReturn_{i,t-6,t-1}$ is the cumulative stock return of firm *i* over the past six calendar months. We include year-month fixed effects. We do not report the intercept. *T*-statistics are reported in parentheses and are based on standard errors clustered by year-month. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

	$FutureReturn_{i,t+1,t+6}$		$FutureReturn_{i,t+1,t+12}$	
	(1)	(2)	(3)	(4)
***ShortInterest (Substitutes)*$_{i,t}$**	**0.987****	**1.215*****	**2.534*****	**2.861*****
	(2.13)	**(2.64)**	**(3.40)**	**(3.86)**
$ShortInterest_{i,t}$		-0.291***		-0.412***
		(-11.74)		(-13.65)
ln(MarketCap$_{i,lagged}$*)*	-0.011***	-0.010***	-0.022***	-0.021***
	(-4.75)	(-4.21)	(-6.70)	(-6.19)
ln(Market/Book$_{i,lagged}$*)*	-0.011***	-0.009**	-0.035***	-0.033***
	(-2.63)	(-2.33)	(-6.49)	(-6.12)
$PastReturn_{i,t-6,t-1}$	0.014**	0.014**	-0.018	-0.018
	(2.34)	(2.29)	(-1.59)	(-1.63)
Amihud Illiquidity	0.001	0.001	0.001	0.001
	(1.08)	(1.08)	(0.97)	(0.96)
# Obs.	1,112,749	1,112,749	1,058,481	1,058,481
Adj. R^2	0.11	0.10	0.08	0.09