5-2022

Can shorts predict returns? A global perspective

Ekkehart BOEHMER
Singapore Management University, EBOEHMER@smu.edu.sg

Zsuzsa R. HUSZAR

Yanchu WANG

Xiaoyan ZHANG

Xinran ZHANG

Can Shorts Predict Returns? A Global Perspective

Ekkehart Boehmer

Zsuzsa R. Huszár

Yanchu Wang

Xiaoyan Zhang

Xinran Zhang*

February 2021

Abstract

Using multiple short sale measures, we examine the predictive power of short sales for future stock returns in 38 countries from July 2006 to December 2014. We find that the days-to-cover ratio and the utilization ratio measures have the most robust predictive power for future stock returns in the global capital market. Our results display significant cross-country and cross-firm differences in the predictive power of alternative short sale measures. The predictive power of shorts is stronger in countries with non-prohibitive short sale regulations and for stocks with relatively low liquidity, high shorting fees, and low price efficiency.

Keywords: stock price efficiency, liquidity, market development, short sale regulation, short selling.
JEL classification: G14, G12.

---

* Boehmer (eboehmer@smu.edu.sg) is from the LKC School of Business, Singapore Management University, Huszár (bizzrh@nus.edu.sg) is affiliated with the Finance Department at the National University of Singapore (NUS), the Central European University (CEU) and the LKC School of Business, Singapore Management University. Wang (wang.yanchu@mail.shufe.edu.cn) is from the Shanghai University of Finance and Economics. Zhang (zhangxiaoyan@pbcsf.tsinghua.edu.cn) and Zhang (zhangxr.15@pbcsf.tsinghua.edu.cn) are from the PBC School of Finance, Tsinghua University. The authors thank Data Explorer (now part of IHS Markit) and MSCI for providing data and assistance. The authors thank Sumit Agarwal, Tarun Chordia, Andrew Karolyi, B. C. Kho, Pedro Saffi, Wenlan Qian, Ingrid Werner (discussant), Bohui Zhang (discussant), Dexin Zhou (discussant), two anonymous referees, and conference participants at the Fourth Symposium on Emerging Markets: China and Beyond; the 3rd Asian Bureau of Finance and Economic Research (ABFER) conference, Singapore; the 2015 China International Conference in Finance (CICF), Shenzhen, China; and the 2015 Summer Institute of Finance Sixth Annual Conference, Beijing, China. Huszár acknowledges the financial support for the project from the National University of Singapore Business School from start-up grant (R-315-000-087-133) and research grant (R-315-000-110-112). Xiaoyan Zhang acknowledges financial support from the National Natural Science Foundation of China [Grant 71790605]. The authors have no conflicts of interest to disclose.

Can Shorts Predict Returns?

A Global Perspective

February 2021

Abstract

Using multiple short sale measures, we examine the predictive power of short sales for future stock returns in 38 countries from July 2006 to December 2014. We find that the days-to-cover ratio and the utilization ratio measures have the most robust predictive power for future stock returns in the global capital market. Our results display significant cross-country and cross-firm differences in the predictive power of alternative short sale measures. The predictive power of shorts is stronger in countries with non-prohibitive short sale regulations and for stocks with relatively low liquidity, high shorting fees, and low price efficiency.

Keywords: stock price efficiency, liquidity, market development, short sale regulation, short selling.
JEL classification: G14, G12.

1. Introduction

Short sellers play an important role in preventing overpricing and the formation of price bubbles in financial markets. Theoretical work by Diamond and Verrecchia (1987, the DV model hereafter) argues that the high costs of short selling and the resulting absence of liquidity-motivated short selling make short sellers more informed than average traders. Empirically, Boehmer, Jones, and Zhang (2008) show that the high trading activity of short sellers can predict low future stock returns. Engelberg, Reed, and Ringgenberg (2012) report that the information advantage of short sellers arises partly from their superior public information-processing skills. Both empirical articles, among many others, show that informed short selling is prevalent by documenting that high volume of short selling predicts future negative returns.[1]

These empirical studies are based on U.S. data, which are relatively easy to obtain. In the well-developed U.S. stock markets, short sellers are generally active institutional traders, who are known to contribute to a significant fraction of total trading volume and to promote pricing efficiency (Boehmer and Wu, 2013). Unfortunately, these U.S.-based results may not be easily generalizable internationally. In many countries, short sales are prohibited; stock borrowing and lending may be illegal, restricted, or undesirable; and short sellers may face high transaction costs. These factors make trading costly, and potentially lower the profits from short sales to the point that these trades become unattractive, even for informed short sellers. In some extreme cases, prohibitive shorting costs could eliminate shorting activities entirely, even if short sellers possess valuable private information. Meanwhile, short sellers may find it difficult to obtain private information in these markets and, therefore, some foreign markets may not experience the benefits of short selling. This suggests that the relevant trading and regulatory environments can play an

[1] Additional empirical evidence is provided by Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), and Boehmer, Huszár, and Jordan (2010).

important role for short sellers. Moreover, this cross-country variation raises the important question of what factors would affect the costs and benefits of short selling, and thus the predictive power of short selling for future returns, or the informativeness of short selling.

To address this question, we conduct a comprehensive analysis of short selling informativeness across 38 countries from 2006 to 2014. Our unique international setting allows country-level variations in relevant regulations and market development, as well as firm-level variations in short sale constraints, market liquidity, and pricing efficiency. As the channels that capture information from short sellers may differ across countries and firms, we examine eight alternative short sale information measures from previous literature, including the short interest ratio (shares on loan scaled by shares outstanding), the days-to-cover ratio (shares on loan scaled by trading volumes), loan supply (shares available for loans scaled by shares outstanding), utilization ratio (shares on loan scaled by shares available for loans) in the stock lending market, and four measures of demand and supply shocks in the stock lending market.

Our empirical study has two parts. First, we examine the return predictability of eight alternative shorting measures in our pooled sample of 38 countries. We find that most of the shorting measures can predict returns over horizons ranging from five to 60 days, with the days-to-cover ratio and the utilization ratio having the most robust predictive power. These results suggest that the short sellers in our sample countries are, on average, informed about future stock returns. We also document that the predictive power of the various short selling measures displays large variation across countries.

In the second part of our study, we focus on the cross-country and cross-firm differences in the predictive power of short sales. Our hypothesis is that the informativeness of short sales, or the predictive power of short sales for future stock returns, depends on the costs and benefits of short selling. These costs and benefits depend on the state of short sale regulations (including uptick rules, short sale bans, and the presence of effective security lending markets), overall market development (such as country-level openness or GDP per capita), short selling fees, liquidity, and pricing efficiency.

We ask how the abovementioned factors influence short sales' predictive power for future returns. The DV model provide an intuitive theoretical discussion on how short sale constraints affect the informativeness of short selling in three different settings. When short selling is prohibited, or equivalently, when shorting costs are infinitely high, there would be zero short selling, and thus no information flow from short sellers to the market. In this case, short selling cannot improve the informational efficiency of prices. At the other extreme, when short selling costs are close to zero, uninformed short sellers might crowd into the market. Their trades would make overall short selling, and the market as a whole, noisier. At best, their trades would leave the information content of prices unaffected. For the case in between infinite and close-to-zero shorting costs, the informed short sellers would become more active and begin trading on their private information. These trades would improve informational efficiency (see Boehmer and Wu, 2013) and lead to a potential predictive relation between short selling trades and future stock returns. [2]

Parallel reasoning can be made towards market regulation, market development, liquidity, and market efficiency, as they can all affect the costs and benefits of shorting and thus affect the informativeness of short sales. Other than the shorting constraint angle taken in the DV model,

[2] It is challenging to test the theory of the DV model in an empirical setting, because it might be subjective to identify countries/firms with "sufficiently high" and "sufficiently low" shorting cost/efficiency/liquidity/development. For the main empirical results, we use the sample median to separate high and low groups. For the robustness check in Section 5.2, we use two cutoff points on the high end and the and low end to further accommodate potential nonlinearities in the data. Results using different cutoff points are qualitatively similar.

similar arguments can also be made through the efficiency perspective. For instance, if the market were highly efficient and prices reflected all information instantaneously, it would be hard to find that short selling predicts future returns because the material information would already be incorporated into stock prices. In extremely inefficient markets, where the incorporation of new information takes a very long time, short sellers might choose not to trade and reveal their information because, owing to the long trading window, the costs are too high for them to make a profit. Short sales would have predictive power for future stock returns only in cases between sufficiently high and sufficiently low degrees of efficiency.

With a sample of 38 countries, we observe substantial cross-sectional variation in regulations, short sale constraints, market development, liquidity, and efficiency. These empirical results provide rich implications about the cross-country and cross-firm differences in various dimensions of shorting activity. We examine how different factors affect shorts' predictive power using panel regressions with interactions between short selling and market regulation, market development, short sale constraints, liquidity, and efficiency measures. For the sake of brevity, in summarizing our results, we focus on the cross-country and cross-firm differences using the days-to-cover ratio and the utilization ratio, the two short sale measures with the strongest and most robust predictive power for returns globally.

Among the regulations, the uptick rule and the naked short sale ban both increase the cost of shorting, reduce information efficiency, and increase the potential benefits of shorting. Therefore, these regulations improve the predictive power of short selling most significantly. This result is consistent with the DV model, as it shows that uninformed short sellers are likely to abstain from short selling when there is a sufficient shorting cost (created by the regulation), while informed short-sellers are more willing to enter the market when higher profits are possible owing to the lower information efficiency. Overall, these regulations improve the informativeness of short selling. On the other hand, the existence of a centralized stock lending market reduces the direct and indirect costs of shorting and increases market efficiency. In this latter case, the overall predictive power of short selling is expected to decline because it might attract more uninformed than informed short sellers to the market.

We obtain similar results for the other factors. For instance, short selling's predictive power for future returns is slightly stronger in less-developed countries (proxied by GDP per capita) and for firms with higher shorting fees, lower liquidity, and lower pricing efficiency. For less-developed countries or firms with higher fees and lower liquidity and efficiency, the direct or indirect cost of shorting is likely to be higher, reducing the proportion of uninformed short sellers. Alternatively, for these countries or firms, the potential benefits of shorting could be greater owing to the possibility of more mispricing and lower price efficiency, which would attract more informed short sellers. Either way, short selling is more informative overall for these markets or firms. This finding is also consistent with Easley, O'Hara, and Yang (2014)'s work, which shows that informed traders want to protect their trade secrets, and that market transparency can discourage them from trading.

Previous studies, such as Bris, Goetzmann, and Zhu (2007) and Saffi and Sigurdsson (2011), find that binding short sale restrictions or stock lending market underdevelopment may delay the incorporation of private information, and that shorting activity in general improves efficiency globally. The more recent, burgeoning literature on short sale bans (e.g., Beber and Pagano, 2013; Boehmer, Jones, and Zhang, 2013) shows that outright short sale bans are associated with significant declines in market quality and large welfare losses. The above results are largely consistent with the prohibitive cost of shorting case in the DV model, and the view that the absence of short selling reduces pricing efficiency. The recommendation for regulators would be to lower the prohibitive cost of shorting and to allow short selling, which would improve price efficiency.

Our study makes two unique contributions to this literature. Unlike global studies focusing on efficiency measures (e.g., Bris, Goetzmann, and Zhu, 2007; Saffi and Sigurdsson, 2011) and US-focused studies (e.g., Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012), we examine a comprehensive set of short sale measures for 38 countries. We are the first to document that most shorting measures predict returns in the global capital market, especially the days-to-cover-ratio and the utilization ratio. We further document a large variation in return predictability across countries and across firms.

Moreover, we contribute by investigating this variation directly and finding that the predictive power of short selling is higher for countries and firms with relatively high costs of short selling, tighter regulation, lower development, higher shorting fees, less liquidity, and lower market efficiency. Our findings are more consistent with the close-to-zero shorting cost scenario of The DV model, in the sense that low shorting costs are likely to attract uninformed short sellers, whose trading may be too noisy to improve market efficiency, while informed short sellers might stay away because the benefit of shorting is limited. The findings in our international setting send clear message to all policy makers: there is no one-size-fits-all policy prescription, and any policy change needs to consider the market environment, investor sophistication, and degree of information efficiency. Combining with previous literature, we make the following recommendations for policy makers: lowering shorting cost generally improves price efficiency, but regulators need to be aware that close to zero shorting cost might encourage large-scale uninformed short selling and might reduce overall price efficiency.

The rest of this paper is organized as follows. We introduce the data in Section 2. In Section 3, we discuss the overall return predictability of short selling in the global capital market. Section 4 investigates the factors that might contribute to cross-country and cross-firm differences in short selling's predictive power. We provide further discussion in Section 5. Section 6 concludes.

2. Data

2.1 Data Sources and Coverage

We obtain stock-level data from 38 countries, including 23 developed markets and 15 emerging markets. Our daily sample starts on July 3, 2006, and ends on December 31, 2014. The short sale data, including a comprehensive set of stock lending market and shorting measures, are obtained from IHS Markit.[3] The U.S. stock-level trading and accounting data are collected from the Center for Research in Security Prices (CRSP) and Compustat. We collect data on non-U.S. countries from Datastream. We match the data from Datastream, CRSP, Compustat, and Markit using either the International Securities Identification Number (ISIN), the Stock Exchange Daily Official List identifier (SEDOL), or the Committee on Uniform Security Identification Procedures identifier (CUSIP). We are able to match 51.30% of the data in Markit to other datasets.[4] We follow the standard data cleaning procedures, and impose the filters proposed by Griffin, Kelly, and Nardari (2010) and Lee (2011). Details on the data-cleaning process are provided in Appendix A, and details on data-coverage statistics are reported in Appendix Table 1 Panel A.

[3] Following Saffi and Sigurdsson (2011), we extract all firm-day observations from IHS Markit's securities finance data with record type = 1, which combines different contracts with different dividend-sharing agreements. This method allows us to consider all outstanding stock-lending contracts for each stock, regardless of the type of collateral used or the loan terms.
[4] The match between DataStream/CRSP and Markit is significantly below 100%, because we only include common equity data from DataStream/CRSP, while Markit includes many non-common equity data.

Across the 38 sample countries, our final sample covers more than 91% of the Datastream universe on average.[5] To ensure that our global sample has adequate data coverage, we compare our data coverage with that of Saffi and Sigurdsson (2011), who use Markit data from January 2005 to December 2008. Our sample covers 13 more countries (Ireland, Brazil, Chile, China, Greece, Hungary, Indonesia, Malaysia, the Philippines, Poland, Russia, Taiwan, and Turkey) and six more years (2009 to 2014). For 2008, for example, Saffi and Sigurdsson (2011) report a total market capitalization of about $27 trillion for their sample firms, while the total market capitalization of the same set of countries in our sample is about $35 trillion. Overall, our sample reflects a comprehensive coverage and adequate representation of global stock markets.

2.2 Shorting Measures

Markit provides the following raw data items: the number of shares out on loan (or borrowed), the number of shares available for lending, the utilization ratio (percentage of shares out on loan over the shares available for borrowing), the value-weighted average lending fee, and the most recent value-weighted lending fee on recently opened contracts. To predict future returns, we compute eight shorting measures based on this information and two fee measures to proxy for the cost of shorting. Given the potential noisiness in the daily data, we calculate the short sale measures based on all stock borrowing contracts over the previous five days. Finally, we require that each country has valid daily data points for at least 10 firms to be included in the sample.

The first two short sale measures are the short interest ratio (*SIR*) and days-to-cover ratio (*DTCR*). Since short selling is the primary reason for stock borrowing, we consider the number of shares borrowed as a proxy for short selling. We calculate *SIR* as the ratio of the total number of

[5] Our sample includes all the countries for which Markit provides at least one year of coverage for at least one firm at a given time in some dimension, be it lending supply, borrowing demand, or lending costs. Effectively, we include all the countries for which Markit has at least some data coverage for common equities.

shares on loan divided by the total number of shares outstanding each day, and then average it over the previous five days. This procedure is consistent with the literature, such as Dechow et al. (2001), Desai et al. (2002), Asquith et al. (2005), and Boehmer et al. (2010).

The second shorting measure, *DTCR*, is computed as the total number of shares on loan scaled by the daily trading volume, averaged over the previous five days. Different from *SIR*, *DTCR* is scaled by daily volume rather than shares outstanding, and hence is a more dynamic measure, reflecting the number of days required (under normal circumstances) to cover the outstanding short positions. The *DTCR* measure is a standard measure for short selling activity, according to "Short Interest Highlights" in the *Wall Street Journal*.[6] According to Hong et al. (2016), *DTCR* dominates *SIR* as a short sale measure, because it also incorporates liquidity information.[7] The predictions for these two trade-based measures are similar: stocks with high *SIR* or high *DTCR* are expected to earn negative future returns, if short sellers can identify overvalued stocks.

Following Saffi and Sigurdsson (2011) and Aggarwal, Saffi, and Sturgess (2015), we define our third short selling measure, *SUPPLY*, as the daily percentage of shares available for borrowing (i.e., the shares available for borrowing relative to the total number of shares outstanding, averaged over the previous five days). Sufficient lending supply is necessary to facilitate short selling and price discovery, as discussed in Boehmer and Wu (2013), while high lending supply might indicate the absence of negative signals from the lending institutions. On the other hand, if the lending supply is low or concentrated, search costs would be high and the

[6] WSJ: "Short Interest: NYSE Highlights," http://www.wsj.com/mdc/public/page/2_3062-nyseshort-highlites.html.
[7] Notice that our *DTCR* measure is different from the *RelSS* measure used in Boehmer et al. (2008), which measures shares shorted over one day divided by daily trading volumes. Their measure reflects the proportion of trading volume related to short selling. The difference between the two measures is the numerator: While their measure's numerator is shares shorted over a specific day, our measure's numerator, total shares on loan, includes the shares shorted on that day as well as any other outstanding shares shorted before that day and not yet covered.

information discovery process would be slow, as discussed in Porras-Prado, Saffi, and Sturgess (2016). In this case, low supply might also imply that there is negative news about the firm, and it would be more profitable for informed investors to sell short. To summarize, between firms with relatively high and low (non-zero) short supply, stocks with lower shorting supply are likely to have lower future returns, if short sellers can identify overvalued stocks.

Our fourth short selling measure is the utilization ratio (*UTI*), computed as the daily percentage of shares on loan over shares available for borrowing, averaged over the previous five days, as in Saffi and Sigurdsson (2011). High *UTI* is generally associated with high shorting demand, and we expect it to be associated with low future returns.

Finally, we adopt four stock lending market shock measures from Cohen et al. (2007) to capture supply and demand dynamics in the securities lending market. For each stock, each day, we identify whether the stock experiences inward or outward shifts in supply or demand in the stock lending market. We first compute the stock-level average lending fees and the average loan amounts of all lending contracts from the previous five days, and then compare them with the previous non-overlapping five-day window to compute the changes.[8] Stocks with demand inward shifts (*DIN* = 1) experience a decrease in both average lending fees and loan amounts. Stocks with demand outward shifts (*DOUT* = 1) experience an increase in both lending fees and loan amounts. For supply shocks, stocks are identified as having supply inward shifts (*SIN* = 1) if the lending fees increase and the loan quantities decrease. Stocks are identified as having supply outward shifts (*SOUT* = 1) if the lending fees decrease and the loan quantities increase. Cohen et al. (2007) argue that, in capturing the private negative information from shorting, the increase in demand in

[8] For instance, to compute changes in lending supply on day *t* for stock *i*, we compare the average lending supply for the stock over day *t*-5 to *t*-1 and compare it with the average lending supply for the same stock over day *t*-10 to *t*-6.

interaction with reduced supply is the most informative signal; they also show that stocks with *DOUT* = 1 are on average associated with about 3% lower monthly returns.

In Table 1, we report the summary statistics for all shorting variables. We present the time-series average of the cross-sectional daily *medians* for each country for the first four shorting variables. For the four shock variables, we report the time-series average of the cross-sectional *means* within each country, because the shock variables are dummy variables and the medians would be either 0 or 1, which would not provide much information.

Because we have one of the most comprehensive global datasets of shorting measures, we discuss the summary statistics in detail. The average *SIR* is 1.84% for the United States, which is comparable to the results of earlier studies in the U.S. setting, such as Boehmer et al. (2010). The second and third highest average *SIR*, 0.78% and 0.35%, are reported for the Netherlands and Spain, respectively. The high shorting activity in Spain is possibly driven by the Euro debt crisis. Shorting is concentrated in a few stocks in many small (e.g., New Zealand) and less-developed markets (e.g., China, Indonesia, and Malaysia), either because only a few stocks are actively traded, or because regulatory restrictions limit shorting to a few stocks. As a result, the time series average of the daily median *SIR* is zero or close to zero in several countries. The cross-country pattern is slightly different for the *DTCR* measure, because low trading volumes can magnify the relative shorting measures, as observed in Switzerland, Austria, and the Netherlands. The average *DTCR* is the second highest in the United States at 3.30, while the highest *DTCR* value is in Austria, at 4.44, likely driven by low trading volume.

Only five countries have more than a 5% average loan supply: Canada, the Netherlands, Switzerland, the United Kingdom, and the United States. Unsurprisingly, the highest loan supply (17.04%) is reported for the U.S. market, where high institutional ownership and active institutional trading support a large loan supply in the OTC market. All Asian countries have limited stock loan supplies, possibly because of the relative underdevelopment of their stock lending markets or because of their low institutional ownership penetration.

The utilization measure, capturing the intersection of demand and loan supply, is the percentage of the stock loan that is lent out. The three highest utilization ratios are reported for Spain, the United States, and Portugal, at about 12.04%, 9.53%, and 7.51%, respectively. The high utilization ratios in Spain and Portugal are possibly driven by the debt crisis in these countries, whereas for the United States, the high utilization ratio might be driven by the financial crisis or by the active trading of institutional investors. The utilization ratios for most of the other countries are below 5%.

The four stock-lending market-shock measures, *DIN* (demand inward shift), *DOUT* (demand outward shift), *SIN* (supply inward shift), and *SOUT* (supply outward shift) all have averages about 0.18. This finding suggests that there is significant activity in the stock lending market for about 18% of the observations, in either the demand or supply side of the contracts. As the U.S. market is one of the most active shorting markets, we find that the frequency of these shocks is significantly higher than the sample average. In the U.S. sample, the time series average of the mean percentage of firms with a demand inward shift (*DIN*), a demand outward shift (*DOUT*), a supply inward shift (*SIN*), or a supply outward shift (*SOUT*) are 0.28, 0.27, 0.22, and 0.21, respectively. The summary statistics for the shock variables are missing for Chile and China, because we require that each country to have valid daily data points for at least 10 firms to be included in the sample, while these two countries do not have enough valid data points for lending fees.[9]

2.3 Returns and Control Variables

To examine the future return predictability of short selling over different horizons, we compute raw returns over 5-, 20-, 40-, and 60-day windows. Risk adjustment might not be important for shorter horizons such as the 5-day window, but is essential for investment horizons longer than 20 days. For the risk-adjustment calculations, we adopt the factor model in Hou, Karolyi, and Kho (2011; HKK, hereafter), which includes both global and country-specific market factors (*MKT*), momentum factors (*MOM*)[10], and cash-flow-to-price factors (*CP*). The advantage of the HKK factor model is that it incorporates information from both local and global markets, and it includes other important pricing factors in addition to the market factor. To be specific, for firm *i* at time *t*, the HKK model assumes that expected returns are determined as follows:

$$E(R_{it}) - r_f = b_{i,MKT}^{global} E\left(MKT_t^{global}\right) + b_{i,MKT}^{local} E\left(MKT_t^{local}\right) + b_{i,MOM}^{global} E\left(MOM_t^{global}\right)$$
$$+ b_{i,MOM}^{local} E\left(MOM_t^{local}\right) + b_{i,CP}^{global} E(CP_t^{global}) + b_{i,CP}^{local} E(CP_t^{local}). \qquad (1)$$

The superscripts *global* and *local* indicate whether the factors are constructed in the global or local market. We first construct pricing factors as in HKK (see Appendix A for details on the factor construction). Next, we compute betas for each firm each month, using the previous three months of daily data, requiring at least 36 non-missing daily observations to estimate the historical betas. The risk-adjusted returns are calculated as the difference between the raw returns and the model-

---

[9] Appendix Table 1 Panel B reports the correlation coefficients among the eight shorting variables, computed over all firms and all days. All coefficients are highly significant with p-values lower than 1%. The two shorting activity measures, *SIR* and *DTCR*, are correlated at 0.12. The *SIR* is highly correlated with *SUPPLY* and *UTI*, with correlation coefficients at 0.57 and 0.56, respectively. Demand and supply shocks are significantly negatively correlated, because they sum up to one each day for each firm.
[10] The momentum factor is calculated following Jegadeesh and Titman's (1993) 6/1/6 strategy.

implied returns for the corresponding period, which are products of the betas estimated from the previous three months and the current factor values.[11] We also consider alternative asset pricing models, and the results are similar to those using the HKK model.[12]

As control variables for the prediction of future returns, we include the log market capitalization from the previous month (*MV*), the book-to-market ratio from the last fiscal year-end (*BM*), the average daily turnover from the previous month (*Turnover*), the percentage of zero return days from the previous month (*PctZero*), the idiosyncratic volatility calculated using the HKK model using data from the previous quarter (*IdioVOL*), the past one-month returns (*LagRet1m*), and the past six-month cumulative returns (*LagRet6m*) with one month skipped. We use these variables to control for known stock return patterns related to size, value, momentum, idiosyncratic volatility, and liquidity. We report summary statistics on the control variables in Panel D of Appendix Table 1. The magnitudes and patterns are consistent with those in the literature.

3. Do Short Sellers Predict Future Returns in the Global Capital Markets?

In this section, we examine whether short selling can predict future returns in the global capital market. We start with a cross-country pooled panel regression in Section 3.1, to test whether short selling on average has return predictability in the global market. In Section 3.2, we estimate

[11] We present summary statistics of the raw returns and the HKK adjusted returns in Appendix Table 1 Panel C. From the time-series mean of the cross-sectional median, the returns are mostly negative with reasonable magnitude. The negative signs are mostly driven by large negative returns during the global financial crisis.

[12] We thank one of the referees for this suggestion. To be specific, we first consider a seven-factor asset pricing model following Hou, Karolyi, and Kho (2011) and Fama and French (1998) that includes three global factors (global market, global momentum, and global cash-flow-to-price factors) and four local factors (local market, local size, local value, and local momentum factors). The Appendix Table 2 Panel B shows that the results found using the seven-factor model are economically and statistically consistent with the results found using the HKK model. We also examine the robustness of our results using the Fama and French global-local factor model as specified in Bekaert, Hodrick, and Zhang (2010) and find similar results (available on request).

the panel regression within each country, and investigate the cross-country differences in short selling's predictive power for future returns.

3.1 Pooled Panel Regression Across Countries

We adopt a panel regression approach across all countries to determine whether shorts are globally informed and can thus predict future stock returns. We specify the following pooled panel regression across countries and days:

$$r_{i,t+1,t+n} = a + b \times SHORT_{i,t-5,t-1} + c' \; Control_{i,t-1} + \varepsilon_{i,t+1,t+n}, \qquad (2)$$

where the dependent variable, $r_{i,t+1,t+n}$, is the cumulative raw return or the risk-adjusted return on stock *i* over the window *t*+1 to *t*+*n*, with *n* taking the value of 5, 20, 40, or 60 to capture future 5-, 20- , 40- , or 60-day returns. The independent variable $SHORT_{i,t-5,t-1}$ represents one of the eight short sale measures from day *t*-5 to *t*-1 for stock *i*. Note that one day, day *t*, is skipped between the short selling measures and future stock returns. We also include an array of firm-level control variables computed from the previous month and thus observable on day *t*-1, which are discussed in Section 2.3. With the exception of the securities lending market shift measures (*DIN*, *DOUT*, *SIN*, and *SOUT*), we normalize all variables to a mean of zero and a standard deviation of one within each country-year pair to facilitate the interpretation of the findings across countries. To account for potential return differences at the country and year levels, we include both country and year fixed effects. Finally, we compute standard errors using double clustering by firm and year.[13]

Table 2 reports the panel regression results for predicting future risk-adjusted returns using the HKK model from Hou, Karolyi, and Kho (2011).[14] The eight shorting variables are listed in

[13] Alternatively, we find similar results when we compute Newey-West adjusted standard errors. Results are available on request.

[14] We present raw return results and results using alternative risk adjustment model in Appendix Table 2. Results using raw returns have larger and more significant coefficients, as well as higher explanatory power. It is possible that the predictive information contained in some of the shorting variables for raw returns could be related to information

the first column with their expected sign in the second column. The return measures are multiplied by 10,000 and are presented in basis points. Given that all continuous shorting variables are normalized to with zero means and unit volatilities, the coefficient represents the magnitude of changes in future returns in basis points in response to a one standard deviation increase in the respective shorting measures.

Table 2 presents the results for predicting returns over the next five, 20, 40, and 60 days. To be consistent with previous literature, we first focus on the results at the 20-day horizon, which is approximately a calendar month. A one standard deviation increase in *SIR* is associated with a 1.30 bps decrease in the future 20-day risk-adjusted returns, with an insignificant *t*-statistic of -1.33. Alternatively, a one standard deviation increase in *DTCR* predicts a 13.74 bps drop in the future 20-day risk-adjusted returns with a large *t*-statistic of -16.21. The utilization ratio is also associated with negative return predictability. A one standard deviation higher *UTI* predicts 9.48 bps lower 20-day future returns with *t*-statistics of -8.71. All negative signs are consistent with the expectation that higher shorting activity conveys new negative stock information from short sellers. Regarding the stock lending supply, a greater lendable supply indicates less negative news expectations from the lending institutions, because otherwise the institutions would not be willing to lend their shares. Thus, a higher *SUPPLY* is expected to predict positive returns, which is what we find in Table 2. A one standard deviation higher *SUPPLY* predicts 1.88 bps higher 20-day future returns with a *t*-statistic of 1.86.

For the four shock variables, with demand shifts inwards (*DIN* = 1) and supply shifts inwards (*SIN* = 1), the expected signs for future returns are positive. The coefficients on *DIN* and

in the risk factors and/or loadings on these factors, and thus, when we use risk-adjusted returns, the predictive power of these shorting measures decreases. Results using the alternative risk model, which combines the Fama–French and HKK risk factors, are qualitatively similar to those using HKK risk adjustment.

SIN are 2.77 bps, and 1.38 bps, respectively, consistent with Cohen et al.'s (2007) findings based on U.S. data. For the demand outward shift (*DOUT* = 1) and supply outward shifts (*SOUT* = 1), we expect lower future returns. The coefficient of *DOUT* is -3.68 bps, with a statistically significant *t*-statistic of -3.40, while the coefficient on *SOUT* is positive and insignificant.

Our discussion so far has been based on 20-day investment horizons, which are close to a calendar month. Could the differences in the predictive powers of the alternative measures be related to the investment horizon? Some information might be incorporated into prices quickly, while other information might take longer time to be reflected in share prices. Thus, we next examine the predictive regression results over 5, 40, and 60 days.

As Table 2 shows, *DTCR, UTI, DIN* and *DOUT* predict future returns significantly across the four horizons with the expected signs, whereas the rest of the variables have mixed signs and sometimes become insignificant. The R^2s across regressions is mostly around 0.20% at the 5-day return regression and increases up to 0.40% with the 60-day horizon, which is quite reasonable given the large dimension of the panel.

The results in Table 2 prompt three key observations. First, more than half of the eight variables predict future returns with the expected signs over the four investment horizons, indicating that most of the shorting variables are informative about future returns globally. Second, in many cases, the coefficients become larger and more precise with longer investment horizons, perhaps indicating that short sellers have relevant information about longer-term values, such as firm fundamentals, or that the market is relatively inefficient and information incorporation takes longer than a few days. Third, among the eight shorting variables, *DTCR* and *UTI* are economically and statistically the most informative about future returns. Therefore, we focus our later discussions on these two variables.[15]

3.2 Short Selling's Predictive Power by Country

In Section 3.1, we establish the overall predictive power of shorting variables in the global capital market by requiring that all the coefficients in equation (2) to be the same across the countries. In this section, we re-estimate equation (2) for each country to examine whether there are significant cross-country differences in short selling's predictive power for future returns. To estimate the country-level panel regressions, we require that, for each day, there are at least 10 firms with valid observations in the country.

The results are reported in Table 3. We use *DTCR* and *UTI* to predict 20- and 60-day HKK risk-adjusted returns. As shown in the upper section of Table 3, *DTCR* predicts future 20-day returns with the expected negative sign in 35 countries, of which 20 coefficients are significant at the 5% level. We observe substantial cross-country variation. For instance, for 20-day returns, the estimates for *DTCR* range from -33.20 bps (Australia) to 155.26 bps (China). Thus, for a one standard deviation increase in *DTCR*, the future HKK 20-day risk-adjusted return decreases by 33.20 bps in Australia and increases by 155.26 bps in China. The large magnitude of the coefficient in China is driven mainly by the data, because there are only a few non-zero *DTCR* observations for China, and the *DTCR* values tend to be small owing to the heavy regulation on short selling in China and the potentially limited coverage by IHS Markit. The *UTI* has the expected negative sign in 27 countries, and nine are significant at the 5% level.[16] The weaker statistical significance of

[15] As the United States has the largest market weight in both the global capital market and in our sample, U.S. firms could dominate our results. Thus, we re-estimate our analysis in Table 2 with a sample that excludes U.S. firms to test the robustness of our results. The results are similar to those obtained using all countries are available on request.
[16] The *UTI* coefficient estimates are not available for Chile and China because all *UTI* observations are zero or missing, and the coefficients cannot be estimated.

UTI might be owing to the fact that stock lending market development and data coverage vary greatly globally, introducing noise into the scaling variable, the loan supply. For the HKK adjusted 60-day returns in the right-hand panel, the results are qualitatively similar to those found with a 20-day horizon.[17]

In summary, the results in Sections 3.1 and 3.2 show that most of the shorting variables can predict future stock returns with the expected signs and that many of them are statistically significant. We consistently find that the predictive power of *DTCR* and *UTI* are the most robust across horizons, countries, and risk-adjustment methods. However, the predictive power of the shorting measures displays substantial cross-country variation. In Section 4, we provide further insights into these cross-country variations and examine the factors driving these differences.

4. Examining Cross-country and Cross-firm Variation in Short Sales' Return Predictability

In previous sections, we document large cross-country variations in short selling's predictive power for future returns. In this section, we investigate various factors that may affect the cross-country variation in the ability of short sale measures to predict returns. We first examine market-level influences, such as country-level short sale regulations and market development in Section 4.1. Next, we examine firm-level influences on short selling, such as shorting costs, liquidity, and price efficiency in Section 4.2. The country level and firm level variables all provide insights for our discussion on the costs and benefits of short sales, and help us to understand when and where short sellers are willing and able to contribute to price discovery.

4.1 Cross-Country Variations in Short Sale Regulations and Country Developments

[17] As an alternative approach, we construct long-short portfolios within each country using the shorting measures to show their predictive power in the cross-section setting in Appendix Table 3. The standard errors for alphas are adjusted using the Newey-West (1987). The portfolios formed with higher *DTCR* and *UTI* earn negative and significant returns in the future, and show a substantial cross-country variation.

Prior studies show that country-level shorting regulations affect shorting constraints, which are directly linked to the informativeness of short selling. At the market level, Bris et al. (2007) find that stock markets that restrict short selling are less efficient. On the other hand, at the firm level, Kolasinski, Reed, and Thornock (2013) show that newly imposed regulatory constraints on shorting in the aftermath of the global financial crisis enhance the informativeness of short selling. Both seemingly contradictory findings are consistent with the DV model, which considers the informational role of short selling in conjunction with trading costs. On the one extreme, consistent with Bris et al. (2007), when short sale costs are prohibitively high, informed short sellers may abstain from trading, which delays information discovery process and thus reduces market efficiency. On the other extreme, consistent with Kolasinski et al. (2013)'s U.S. based findings, when short sale costs are negligible, uninformed investors would likely crowd in, resulting in less informative or uninformative aggregate shorting based on the mixture of informed and uninformed shorting. In the intermediate state, some uninformed investors are likely to abstain from shorting, and shorting is likely to convey material negative information from informed short seller. This outcome is consistent with Kolasinski (2013) et al., who show that short sale regulation following the global financial crisis results increased shorting costs but enhanced the informativeness of the shorts.

In examining cross-country short sale regulatory differences, we focus on three types of regulations: the uptick rules (or, more generally, price tests), the naked short sale bans, and the presence of a centralized stock lending market. Price test rules, preventing shorting below a benchmark price (aka uptick rule), usually represented by the current midpoint quote, the last trade, or current bid price, tend to increase shorting costs by forcing short sellers to provide liquidity to the market. However, the common uptick rule is not considered overly restrictive because it imposes only moderate costs on short sellers. Studies such as Diether, Lee, and Werner (2009) find that the removal of the uptick rule in 2005 for pilot stocks had no material impact on returns or volatilities. We define an uptick dummy that takes the value of one for trading days in a country when some form of price test is in effect and zero otherwise.[18] Ten countries have an uptick rule in place throughout the sample period, and three have an uptick rule for some portion of the sample period.

Our second regulatory measure captures naked short sale bans, which were broadly adopted during the 2008 financial crisis, requiring short sellers to borrow (or at least locate) shares in advance, thereby introducing additional direct costs for short sellers and complicating the timing of short transactions. Our naked short sale ban dummy takes the value of one for days when a naked short sale ban is in effect in that specific country and zero otherwise.[19] Most countries implemented naked bans for at least part of the sample period.

Centralized stock lending markets can take two forms. In one form, exchange regulators directly or indirectly manage a regulated stock lending market (e.g., Japan, Taiwan, and Singapore), generally through a central counterpart (CCP). In the other form, a private company manages a centralized lending market, for example previously SecFinex in Europe. By providing structured lending channels or a trustworthy counterparty, CCPs can alleviate short sale constraints by reducing counterparty risk and search costs. However, the increased transparency or regulatory

[18] To save space, we present summary statistics for the regulation variables in Appendix Table 4. We collect information from exchanges or regulatory agencies to complement the results in Gruenewald, Wagner, and Weber (2010) and Beber and Pagano (2013). For instance, the United States lifted the uptick rule in 2007 and re-introduced a new form of uptick rule in combination with daily circuit breakers in 2010.

[19] In addition to naked short-sale bans, several countries have implemented outright bans on financial stocks, key industrial stocks, or all stocks during and after the global financial crisis. Previous studies, such as Beber and Pagano (2013) show that outright shorting bans adversely affect market quality worldwide. Boehmer et al. (2013) find similar results for the United States. The naked short-sale ban is a less restrictive regulation than outright bans. The empirical results with outright bans are quite similar to those reported with naked short bans, because most outright bans apply only to a subset of stocks. These results are available on request.

oversight may dissuade some informed short sellers from participating, as documented in Easley et al. (2014). Half of the sample countries have some form of centralized lending market during our sample period. While we are aware that some of the centralized markets are not through CCPs, for simplicity we use a CCP dummy, which takes on the value of one for the years when there is an active centralized stock lending market operating in the specific country and zero otherwise.

We examine how short sale regulations affect the ability of short sellers to predict future returns, using a panel regression with interactions:

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 DREG_{C,t}\right) SHORT_{i,t-5,t-1} + c' \ Control_{i,t-1} + \varepsilon_{i,t+1,t+n}. \quad (3)$$

The variable $DREG_{C,t}$ is a specific short sale regulation dummy for country *C* on day *t*, representing the presence of an uptick rule, naked short sale ban, or a centralized lending market. The coefficient b_0 represents the overall predictive power of shorts for future returns, and the coefficient b_1 measures the additional predictive power of short selling when the regulatory dummy has a value of one. Thus, $b_0 + b_1$ would be the total predictive power of shorts when the regulation is in place.

Table 4 Panel A presents the regression results for Equation (3). The left-hand panel uses future 20-day HKK risk-adjusted returns, and the right-hand panel uses future 60-day HKK risk-adjusted returns. Our discussion focuses on the two most robust shorting measures: the *DTCR* and the *UTI*. All coefficients are displayed in basis points.

We start with the uptick rule. For *DTCR*, when the uptick rule is not in place, a one standard deviation increase in *DTCR* is associated with a significant 13.64 bps decrease in the 20-day risk-adjusted returns. In comparison, when the uptick rule is in place, a one standard deviation increase in *DTCR* is associated with a 13.72 bps decrease in return, or 0.08 bps lower HKK risk-adjusted returns over the 20-day horizon. For *UTI*, without the uptick rule, a one standard deviation increase in *UTI* is associated with a 4.52 bps decrease in the 20-day risk-adjusted returns. With an uptick rule in place, a one standard deviation increase in *UTI* is associated with a 13.15 bps decrease in the 20-day HKK risk-adjusted returns. Thus, the uptick rule increases the return predictability of both *DTCR* and *UTI*. Next, we examine how the naked short sale ban influences the return predictability of short selling. Without the naked ban, the two key short sale measures predict future 20-day risk-adjusted returns significantly with the expected signs. Similar to our findings with the uptick rule, the predictive power of *DTCR* and *UTI* increases when the naked ban is in place. Finally, in the case of CCP, the predictive powers of both *DTCR* and *UTI* decrease with the existence of a centralized stock lending market, but the difference is not statistically significant. While without a CCP, a one standard deviation increase in *DTCR* is associated with a significant 14.48 bps decrease in the 20-day risk-adjusted returns; with a CCP, a one standard deviation increase in *DTCR* is associated with a 12.72 bps decrease in return or 1.76 bps higher HKK risk-adjusted returns over the 20-day horizon. By reducing entry barriers and the difficulty of locating shares and executing short sales, CCPs may attract less-informed traders to participate, dilute the private information of informed traders, and reduce the predictive power of short selling.[20]

Therefore, in terms of regulations, the uptick rule and naked short sale ban enhance the predictive power of *DTCR* and *UTI* in our sample, while the existence of a centralized stock lending market seemly reduces the predictive power of short selling measures in most cases, but the coefficients are not statistically significant.

Other than regulations, countries differ greatly from each other in terms of their development levels. An open empirical question remains: Does market development affect the informativeness of shorting measures? In poorly developed countries, shorting costs may be

[20] It is difficult to precisely measure the relevance or importance of CCP because we do not know how much of the short-sale trading activity is going through centralized and decentralized platforms and how much of that is captured by IHS Markit. Detailed discussion of this issue is provided in Huszar and Porras-Prado (2019).

relatively high, while efficiency can be low and abundant mispricing can increase the reward for informed shorting. On the other hand, high efficiency, high transparency, and low opacity in highly developed countries reduce the cost of shorting but may also discourage informed short sellers who want to protect their trade secrets (Easley et al., 2014). Thus, it is an empirical question whether shorts can predict returns in countries with low and high market development levels. The answer clearly depends on the interactions of the costs and benefits of short selling and on which one dominates.

To answer this question, we construct four development measures. Bailey, Karolyi, and Salva (2006) suggest that market development is positively related to degrees of informed trading and market efficiency. Following their methods, we first use the annual GDP per capita in USD (*GDPPC*) and the stock market capitalization relative to the country's total GDP (*Stock/GDP*) as proxies for market development, with data from the World Bank. The World Bank World Development Indicators provide additional information on market development, such as market capacity, operation efficiency, foreign accessibility, corporate opacity, legal protection, and political stability. Karolyi (2015) constructs six indices to measure market development from the above perspectives, and we compute the averages of the six individual indices and use them as an overall market development measure.[21] A lower average indicates lower market development and vice versa. Finally, an interesting information quality measure is the corporate opacity index, which combines information on analyst coverage, accounting standards, information disclosure, and blockholder control. To better understand this measure's impact on short's predictive power, we directly examine the corporate opacity index. Here we use an empirical specification similar to that in equation (3) and estimate a panel regression with interaction terms:

---

[21] We are grateful to Andrew Karolyi for generously sharing his market development measures with us. The annual measures of Karolyi (2015) are from 2006 to 2014.

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 HIGH_{C,t}^{DEV}\right) SHORT_{i,t-5,t-1} + c' \; Control_{i,t-1} + \varepsilon_{i,t+1,t+n}. \quad (4)$$

Here, we measure the day *t* value of the development dummy, $HIGH_{C,t}^{DEV}$, using information from the previous year, and the subscript *t* indicates that the variable's value is part of day *t*'s information set. To be more specific, for each year, we compute the average of the individual market development measures across all countries. The dummy variable $HIGH_{C,t}^{DEV}$ takes a value of one if the country's last-year annual average development measure is higher than the last-year annual cross-country median and zero otherwise.[22] [23]

We present the estimation results for equation (4) in Table 4 Panel B. First, all coefficients of *DTCR* and *UTI* are always significant and negative in both poorly and highly developed countries, indicating that the two measures have robust predictive power for future returns. However, of the 16 cases, the coefficients on b_1, which measures the difference between high and low market development, are statistically significant in only two, yet with have mixed signs. This indicates that differences in market development probably do not affect the predictive power of *DTCR* or *UTI* for future returns in a systematic way in our sample.

4.2 Cross-Firm Variations in Shorting Fees, Liquidity, and Efficiency Measures

Whether short sellers actively collect information and trade on it depends on the costs and benefits of such trades, and these costs and benefits can vary substantially across firms. In this section, we focus on how fees, liquidity and efficiency measures affect the costs and benefits of shorts, and thus influence short's predictive power for future returns. We first provide predictions from previous studies and introduce the measures, and then we present the empirical results.

---

[22] In addition to using the median to separate the countries/firms into two groups, we also consider an alternative by using the 10th and 90th percentiles as cutoffs, and separate the countries/firms into three groups. The results using the three groups (low, middle, high) are mostly consistent with the results found using the two groups. We provide a detailed discussion in Section 4.6.3. We thank one of our referees for this suggestion.

[23] Appendix Table 5 Panel A presents the time-series mean for the country development dummy variables. As one might expect, developed markets have high market development measures, and emerging markets have low ones.

High fees are driven by either high shorting demand in the presence of high frictions or by high demand with low supply. Thus, higher fees are expected, ex ante, to capture higher borrowing demand, more negative information from informed short sellers, and to predict more negative returns. High fees can be used as a proxy for more binding shorting constraint, and low fees can be used as a proxy for less binding shorting constraint. However, connected borrowers might overcome search costs and negotiate lower fees on the borrowing contracts than average borrowers pay (Chague et al., 2017; Duffie et al., 2002), which might render the lending fee an imperfect measure for shorting constraint. According to The DV model, prohibitively high and zero shorting costs both reduce market efficiency. We expect that both very high and very low fees reduce the predictive power of short selling, while moderate (non-binding) fees enhance the predictive power of short selling by discouraging uninformed short sellers from participating.

Liquidity directly affects transaction costs for all market participants. High (low) liquidity is normally associated with low (high) trading costs and high (low) market efficiency. In the case of short selling, lower trading costs might make it easier to short sell in general and for uninformed short sellers to crowd in; at the same time, with high liquidity and potentially high efficiency, the benefits of short selling might decrease and discourage informed short-sellers from participation. Combined together, high liquidity is likely to reduce the predictive power of short selling.

Price efficiency can also affect the costs and benefits of short selling. As mentioned in the introduction, prices reflect information instantaneously in the case of high efficiency. It would be hard for short sellers to produce new information because, in a highly efficient market, most information is already impounded into prices. In the case of very low efficiency, it might take a very long time for stock prices to fully incorporate new information, and this lengthy investment horizon can discourage even informed short sellers from participating, because the high costs could deplete their profits. Thus, only in markets with some finite degree of inefficiency can we expect short selling to predict future stock returns, and thus contribute to the price discovery process.[24]

We obtain shorting fee data from Markit. Following Saffi and Sigurdsson (2011), we use two value-weighted fee measures for each stock for each day. The first measure is the daily value-weighted average fee for stock *i* on day *t* based on all outstanding contracts, $ALLFEE_{i,t}$, which includes all outstanding contracts, and thus combines information from old and new contracts.[25] For each stock on each day, we average the *ALLFEE* measure over the previous five days. To create a more dynamic measure that captures the lending fees in the most recent contracts, we the second measure current fee, $CURRFEE_{i,t}$, which is the value-weighted fee on only the new contracts opened during the previous five days. In general, the *ALLFEE* and *CURRFEE* measures are highly correlated.

For firm-level liquidity measures, we use the standard measures, such as average daily stock turnover (trading volume over shares outstanding), average daily relative bid-ask spread (bid-ask spread scaled by price), and the number of zero-return days from the previous month.

Previous literature provides many approaches for computing efficiency measures. For brevity, we follow Saffi and Sigurdsson (2011) to compute four firm-level efficiency measures, and we also follow Hou et al.'s (2012) to compute two accounting efficiency measures. Here we mainly focus on the intuition of each measure. The first efficiency measure is the cross-correlation between firm returns and the lagged local market return, with high cross-correlation coefficients indicating that market-level information takes longer to be incorporated into prices, thus indicating low efficiency. The second measure is a variance ratio measure introduced in Lo and MacKinlay

[24] We thank our referees for suggesting this argument.
[25] To save space, details on the fee measures and efficiency measures are provided in Appendix A. Summary statistics on fees, liquidity measures and efficiency measures are reported in Appendix Table 5 Panel B to E.

(1988), computed as the variance of monthly returns over the variance of weekly returns multiplied by four. As in Boehmer and Wu (2013), we deduct one from the raw variance ratio and compute the absolute value. If the market is efficient and behaves like a random walk, the variance ratio should be close to zero. The third and fourth efficiency variables, introduced in Hou and Moskowitz (2005), measure how lagged market information affects stock returns. The third efficiency measure, *Delay_R2*, is a delay measure based on variances, in the sense that the more lagged market information can account for current stock returns variances, the less efficient the firm is. The fourth efficiency measure, *Delay_beta*, is a delay measure based on loadings on lagged market returns. Larger coefficients of the lagged market information, compared to those of current market information, indicate that prices are less efficient. Each of the four measures is calculated for each firm each year. Finally, we construct two efficiency measures based on earnings response coefficients (ERC), as in Hou et al.'s (2012). The first ERC measure, the *Announcement ERC*, is computed by regressing annual announcement event returns on firm-specific unexpected earnings. A high ERC coefficient indicates that announcement event returns respond quickly to the news in the earnings and indicates high efficiency. The second ERC measure, the *Annual ERC*, is also estimated by regressing the buy and hold returns over the year on the unexpected earnings over the same horizon. In this case, a higher ERC coefficient indicates that annual returns respond more to the news in the earnings, and again indicates higher efficiency.

After we obtain the firm level measures on fee, liquidity and efficiency, we estimate the following panel regressions with interactions:

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 LOW_{i,t}^{FEE}\right) SHORT_{i,t-5,t-1} + c' \, Control_{i,t-1} + \varepsilon_{i,t+1,t+n}; \quad (5)$$

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 HIGH_{i,t}^{LIQ}\right) SHORT_{i,t-5,t-1} + c' \, Control_{i,t-1} + \varepsilon_{i,t+1,t+n}; \quad (6)$$

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 HIGH_{i,t}^{EFF}\right) SHORT_{i,t-5,t-1} + c' \, Control_{i,t-1} + \varepsilon_{i,t+1,t+n}. \quad (7)$$

In equation (5), the dummy variable $LOW_{i,t}^{FEE}$ takes a value of one, if the firm's fee is below the median of all sample firms' fee measures for that day and zero otherwise. Similarly, in equation (6), the dummy variable $HIGH_{i,t}^{LIQ}$ takes on the value of one, if the firm is more liquid than the median firm in the whole sample for the same day, and zero otherwise. For the four firm-level efficiency variables, we first compute each efficiency variable for each firm each year, as well as medians across all sample firms for each year. The dummy variable for high efficiency, $HIGH_{i,t}^{EFF}$ takes on the value of one if the firm is more efficient than the sample median in the corresponding year, and zero otherwise. For the ERC measures, $HIGH_{i,t}^{EFF}$ takes on the value of one if the specific country ERC measure is higher than the cross-country median in the corresponding year, and zero otherwise.

We present the empirical results for the interaction between lending fees and short sellers' ability to predict returns in Table 5 Panel A. For *DTCR*, the coefficients are significant and negative for both low- and high-fee firms at the 20- and 60-day horizons. The difference between high- and low-fee firms is not significantly different from zero, except for the 60-day horizon, using *CURRFEE*. Thus, the difference in shorting fees mostly does not affect the predictive power of *DTCR* in a significant way. For the *UTI* measure with the 20-day horizon, the coefficient for high-fee firms is -14.86 basis points, and is highly significant. For low-fee firms, the coefficient turns slightly positive at 1.58 basis points and is insignificant. The difference of 16.44 basis points is highly significant. Similar patterns are observed with the 60-day investment horizon. That is to say, the predictive power of *UTI* is significantly lower when the fees are low, consistent with the DV model's hypothesis that low fees allow uninformed short sellers to participate in the market, so that the overall predictive power of short selling declines.

The estimation results for equation (6) are reported in Table 5 Panel B. When we use turnover as the liquidity proxy, the *DTCR* coefficient is -16.63 basis points for the low liquidity firms. For high liquidity firms, the coefficient becomes -16.63 + 9.14 = -7.49 basis points. Both coefficients are highly significant, indicating that *DTCR* has predictive power for future returns for firms with high and low liquidity. The difference of 9.14 basis points is also highly significant. The same pattern persists for the alternative liquidity measures, such as bid-ask spread or percentage of zero returns, an alternative shorting measure, and a longer investment horizon of 60-day. These findings indicate that the predictive power of short selling is prevalent for all firms, but is stronger for firms with lower liquidity. Low liquidity normally means high costs of trading or short selling, which may discourage relatively uninformed short sellers from participating, and thereby enhance the informativeness of short selling and facilitate the price discovery process.

Table 5 Panel C reports results for efficiency measures. Taking the cross correlation measure as an example, for *DTCR* over 20 days, the coefficient for low efficiency firms is -18.12 basis points, the difference in coefficients between high- and low-efficiency firms is 8.28 basis points, and the coefficient for high efficiency firms is -18.12 + 8.28 = -9.84 basis points. All three coefficients are highly significant. Thus, the *DTCR* can significantly predict returns for firms with high or low efficiencies and more so for firms with lower efficiency. Similar patterns can be observed for *DTCR* at the 60-day horizon, with alternative pricing efficiency measures and with the alternative shorting measure, *UTI*. That is to say, the predictive power of short sale measures is generally higher for firms with lower efficiency. As mentioned at the beginning of this subsection, in highly efficient markets, where information is incorporated into prices quickly, the predictive power of short selling is expected to be weaker or insignificant.[26]

To summarize this section, the predictive power of shorts is stronger in countries with non-prohibitive short sale regulations and for stocks with relatively high shorting fees, low liquidity, and low price efficiency.

5. Further Discussion

5.1 Exogenous Shocks on Fees and Efficiencies and Implications on Short Selling

Since fees and efficiency measures are naturally related to shorting activities, one might be concerned that our results for the fee and efficiency measures are driven by their connections with shorting activities. Even though the purpose of our study is not to establish causality among fees, efficiency, and shorting activities, it is still informative to investigate how an exogenous shock to fees and efficiency affects shorts' predictive power for future returns.

Raddatz, Schmukler, and Williams (2017) show that inclusions and exclusions of stocks in benchmark equity indexes are important events for component stocks, significantly impacting the capital flows and returns on these stocks. According to Cremers, Ferreira, Matos, and Starks (2016), the MSCI indices are the most followed equity indices by mutual funds around the world. For instance, the MSCI All-Capital World Index (ACWI) contains the largest firms and covers about 85% of the free float adjusted market capitalization in each of the 23 developed markets and 26 emerging markets included in the world index sample. The MSCI makes quarterly decisions about the inclusions and exclusions of the index components. These decisions mostly depend on the firm's market capitalizations and trading volumes, and are not related to short activities per se.

[26] In Appendix Table 6, we include both LOW^{FEE} and $HIGH^{EFF}$, and examine how they jointly affect short's predictive power for returns. The results show that both stay significant in more than half of the cases, indicating that both cost- and benefit-based channels for return predictability through shorts are economically important.

Therefore, in this subsection we assume that the MSCI ACWI index inclusions and exclusions are exogenous shocks to the firms' shorting fees and efficiencies, and examine how these shocks affect shorts' predictive power for future returns.[27] From MSCI Inc., we obtain 25 quarterly snapshots of MSCI ACWI stock components from 2008 Q4 to 2014 Q4. After merging with our sample, we obtain 748 inclusions and 613 exclusions with valid trading and shorting data.

To capture the impact of the inclusions and exclusions on fees and efficiency measures, we present the means of the fees and the efficiency measures, before and after the events, in Table 6 Panel A. With the event day being day 0, we choose the before-event window as from day -250 to day -1, and the after-event window as from day 0 to day 250. The one-year horizon of the window length allows us to fees and efficiency measures with more precision.

To save space, we use *ALLFEE* as a proxy for shorting fee, and *Delay_R2* as a proxy for efficiency measure. In the top half panel, we focus on the index inclusions, and in the bottom half panel, we examine the index exclusions. To better understand cross-country differences, we present summary statistics for all markets, developed markets and emerging markets. Table 6 in Panel A reports an average fee of 1.57% before inclusion and 1.23% after inclusion for the pooled all-market sample, where the drop of 0.35% is significant with a *t*-statistic of 5.05.

Firms in both developed and emerging markets experience significant drops in shorting fees after index inclusions, but with possibly different implications. Here, the average market fees differ significantly initially. For instance, before inclusions, average *ALLFEE* for firms from developed markets is 0.89%, while for firms from emerging markets, it is 3.14%. After index

[27] We check whether there are other regulations/events that can work as exogenous shocks to fees and efficiency measures. Short-sale specific regulations, other than those in Section 4.1, are mostly country-specific, and cannot be used in the global setting. In Appendix Table 7, we also single out nine firm level events that we consider as potential candidates for exogenous shocks. These events are included based on previous studies in Gagnon (2018), Gagnon and Wittmer (2014), Choi et al. (2010), Henry and Koski (2010), Corwin (2003) and Huszar and Porras Prado (2019). Unfortunately, we have concerns for each of these events as exogenous shocks, and we list them in the same table. We thank the editor for suggesting MSCI ACWI inclusions and exclusions as shocks.

inclusions, the low shorting fees for firms from developed markets become even lower to 0.54%, while the high shorting fees for firms from emerging markets decline to 2.79%, still substantially higher than in developed markets. These differences in fee patterns become important when we examine short's predictive power in Table 6 Panel B. For the efficiency measures, *Delay_R2* significantly decreases after the inclusion, indicating the markets are more efficient after the index inclusion event. The cross-market differences for efficiency measures are not as large as for the fees. For the exclusion events in the bottom half panel, the patterns are opposite to those of inclusions. The differences between before-event and after-event are statistically significant for all markets, developed markets and emerging markets, indicating that exclusions increase fees for shorting, and market efficiency deteriorates after exclusions.

To measure how the inclusions and exclusions affect the shorts' predictive power for returns, we estimate the following panel regression:

$$\begin{gathered} \mathrm{r}_{\mathrm{i,t+1,t+n}} = a_0 + a_1 AFTER_{it} + (b_0 + b_1 AFTER_{it}) SHORT_{i,t-5,t-1} \\ +c' Controls_{i,t-1} + \varepsilon_{i,t+1,t+n}. \end{gathered} \tag{8}$$

Here, the variable $AFTER_{i,t}$ takes on the value of one for firm *i* after the inclusion/exclusion event, which happens for firm *i* on day *t*, and zero otherwise. That is, the coefficient a_1 captures changes in returns after the event, and coefficient b_1 measures the change in shorts' predictive power for return for the event firm after the event. Previous studies, such as Raddatz et al. (2017), show that the institutional flows change significantly after the index inclusions and exclusions, and these flows can affect both returns and shorting costs. Therefore, we include institutional flow as one of the control variables. We obtain the institutional holdings (IO) data from Factset/Lionshare and compute IOflow as the quarterly changes of IO holding divided by market capitalization. Other control variables are the same as in equation (2). Finally, we compute standard errors using double clustering by firm and year.

In Table 6 Panel B, we present the estimates of equation (8) for HKK-adjusted 20-day returns for index inclusions, for all markets, developed markets and emerging markets. There are four interesting findings. First, the coefficients on the after-event dummy are always positive and significant, indicating that index inclusions on average are associated with higher future returns. Second, the coefficients on institutional flow are also always positive and significant, showing that higher institutional flows are associated with higher returns. Third, the coefficients on shorts are always negative and mostly significant, across measures and across markets, indicating negative return predicting power. Finally, our focus of this specification is the coefficients on the interactions between shorts and the after-event dummy, which are mostly negative, but only significant for half of the cases.

The most significant cases are for the emerging markets, in the right columns of Table 6 Panel B, the coefficients on the interaction of shorting measures and event dummy are -35.35 for *DTCR* and -36.77 for *UTI*, respectively, and both are highly significant. This is consistent with the intuition of the DV model for the case of prohibitively high shorting cost. That is, firms from emerging market normally have high shorting cost, and index inclusions effectively lower the cost of shorting, which attracts informed short sellers to participate and improves short's predictive power for future returns. For firms from developed markets, the interaction terms between short and after are not significantly different from zero. Possibly the costs of shorting are already quite low in these markets, and index inclusions, which further lower the shorting cost, don't significantly affect the predictive power of shorting. The coefficients for all markets are in the middle of those for "developed markets" and "emerging markets." These results, especially those for emerging markets, are in general consistent with our earlier finding in Table 5, where short's predictive power is higher for firms with higher fees.

We report the estimates for index exclusions in Table 6 Panel C. The coefficients on the after-event dummy are all negative, meaning that returns decrease after index exclusions. The institutional flows still positively and significantly affect stock returns in all cases. The coefficients on shorting are all negative and mostly significant, supporting the shorts predict returns negatively in general. Finally, the coefficients on the interactions between shorting and after-event dummy are all positive. In the case of emerging markets, the interaction coefficients are both statistically significant, while in the case of developed markets, they are both statistically insignificant. This result is parallel and consistent with what we find in Panel B. That is, for firms from emerging markets, index exclusions increase the shorting fees from relatively high level to an even higher level, and informed short sellers might abstain from shorting, which reduces short's predictive power. For firms from developed markets, index exclusions also increase shorting fees, but from a very low level to a less low level. This increase in shorting fees does not significantly affect short's predictive power for future returns.

Overall, the exercise on exogenous shocks on fees and efficiency measures, using MSCI ACWI index inclusion and exclusion events, provide further support for our findings in Section 4.2. That is, shorts' return predictability is stronger for firms in emerging markets, which tend to have high shorting costs and low market efficiencies in general, in the event of index inclusions and exclusions.

5.2 Examining Nonlinearity in Short Sales Return Predictability

In earlier sections, we separate countries and firms into two groups based on the cross-country/cross-firm medians. The seminal theoretical work of The DV model proposes the notions of "prohibitively high" shorting costs and "close to zero" shorting costs. However, what accounts for prohibitively high and close-to-zero shorting costs is a subjective matter. In this section, we re-examine the earlier results on market development, fees, liquidity, and efficiency by dividing firms into three groups using cross-country/cross-firm 10th and 90th percentiles. Take market development as an example. We have low-, middle-, and high-development countries, with low-development countries being those below the 10th percentile for the development measure, high-development countries being those above the 90th percentile, and the middle group including all the rest. This three-group setup can also help us to separate the tail firms and to identify nonlinear patterns in the data. We estimate the following specification:

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 XHIGH_{i,t} + b_2 XLOW_{i,t}\right) SHORT_{i,t-5,t-1}$$
$$+ c' Controls_{i,t-1} + \varepsilon_{i,t+1,t+n}. \qquad (9)$$

Here variable $XHIGH_{i,t}$ takes value of one, if the firm belongs to a country with top 10% development measures, and zero otherwise. Variable $XLOW_{i,t}$ takes value of one, if the firm belongs to a country with bottom 10% development measures, and zero otherwise. We can define similar three-group setup for fees, liquidity and efficiency measures.

These relevant nonlinearity results are reported in Table 7. For market development measures in Panel A, the sign for high development is mixed, but we observe more positive and significant coefficients than negative and significant ones, indicating that shorts' predictive power is weaker in high-development countries, which supports the results in Section 4.1. For the fee measures in Table 7 Panel B, all coefficients on high fees are negative and significant, while all coefficients on low fees are positive, with half of them being significant. There is a clear pattern that high fees increase shorts' predictive power, while low fees reduce it, which is consistent with our finding in Section 4.2. In Table 7 Panel C, when we separate firms by liquidity, it is interesting to find that majority of the coefficients on both high and low liquidity are positive, and more than half of these coefficients are significant. The implication is that both very high and very low liquidity would hurt the predictive power of shorts for future returns. This finding generally supports the results in Section 4.2, when we separate firms by liquidity median, but don't separate out the tail firms. In case of low liquidity stocks, short selling may become too risky due to potential short squeezes or inability to exit at the most suitable time; and thus, short sellers may abstain trading these stocks. This leads to weaker predictive power of shorts for returns. Finally, for the efficiency measures in Panel D, we have more mixed signs. In most cases, high efficiency weakens the predictive power of shorts, while low efficiency improves it, which is in line with results in Section 4.2.

6. Conclusion

We provide a global perspective on short sales' predictive power for future returns by adopting multiple short sale measures and examining whether these variables can predict returns in 38 countries between July 2006 and December 2014. While most of our shorting variables can predict future returns with the expected signs across countries, the days-to-cover ratio and the utilization ratio are the most robust return predictors globally.

Our empirical results reveal significant cross-country and cross-firm variation in the predictive power of the short selling variables. To better understand informed short sellers' cost-benefit assessment and price discovery role, we investigate how short-sale regulations, market development, short sale costs, liquidity, and efficiency significantly influence these traders and their trades. Short sale regulations such as uptick rules and naked bans generally strengthen the return predictability of short selling measures. Shorting cost, liquidity, and efficiency also affect the predictive power of short selling, consistent with the DV model's shorting constraint theory, as well as alternatives through efficiency perspective. The information-discovery role of short sellers is most prevalent in less-developed countries and for firms with lower liquidity and pricing efficiency. Overall, our results suggest that regulators should take a measured approach to short selling and, more generally, should consider shorting not only in insulation but in conjunction with other determinants of price discovery in security markets.

References

Aggarwal, R., Saffi, P. A. C., and Sturgess, J., 2015. The role of institutional investors in voting: Evidence from the securities lending market. *Journal of Finance*, 70 (5), 2309-2346.

Asquith, P., Pathak, P. A., and Ritter, J. R., 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics,* 78, 243-276.

Bailey, W., Karolyi, A. G., and Salva, C., 2006. The economic consequences of increased disclosure: Evidence from international cross-listings. *Journal of Financial Economics,* 81, 175-213.

Beber, A., and Pagano M., 2013. Short selling bans around the world: Evidence from the 2007–09 Crisis. *Journal of Finance,* 68 (1), 343–381.

Bekaert, G., Hodrick, R. J., and Zhang, X., 2009. International stock return comovements. *Journal of Finance*, 64, 2591–2626.

Boehmer, E., Huszár, Z. R., and Jordan, B. D., 2010. The good news in short interest. *Journal of Financial Economics*, 96 (1), 80-97.

Boehmer, E., Jones, C. M., and Zhang, X., 2008. Which shorts are informed. *Journal of Finance,* 63, 491-527.

Boehmer, E., Jones, C. M., and Zhang, X., 2013. Shackling short sellers: The 2008 shorting ban. *Review of Financial Studies,* 26 (6), 1363-1400.

Boehmer E. and Wu, J., 2013. Short selling and the price discovery process. *Review of Financial Studies*, 26, 287-322.

Bris, A., Goetzmann, W. N., and Zhu, N., 2007. Efficiency and the bear: Short sales and markets around the world. *Journal of Finance,* 62 (3), 1029-1079.

Chague, F., De-Losso, R. De Genaro, A. and Giovannetti, B. 2017. Well-connected short sellers pay lower loan fees: A market-wide analysis. *Journal of Financial Economics,* 123(3), 646-670.

Choi, D., Getmansky, M., Henderson, B., and Tookes, H., 2010. Convertible bond arbitrageurs as suppliers of capital. *The Review of Financial Studies*, 23 (6), 2492-2522.

Cohen, L., Diether, K., and Malloy, C., 2007. Supply and demand shifts in the shorting market. *Journal of Finance,* 62, 2061-2096.

Corwin, S., 2003. The determinants of underpricing of seasoned equity offers. *Journal of Finance* 58 (5), 2249-2279.

Cremers, M., Ferreira, M. A., Matos, P., and Starks, L., 2016. Indexing and active fund management: International evidence. *Journal of Financial Economics*, 120(3), 539-560.

Dechow, P., Hutton, A., Meulbroek, L., and Sloan, R., 2001. Short sellers, fundamental analysis, and stock returns. *Journal of Financial Economics,* 61, 77–106.

Desai, H., Ramesh, K., Thiagarajan, S.R., and Balachandran, B.V., 2002. An investigation of the informational role of short interest in the NASDAQ market. *Journal of Finance,* 57, 2263–2287.

Diamond, D. and Verrecchia, R., 1987. Constraints on short selling and asset price adjustment to private information. *Journal of Financial Economics,* 18, 277–311.

Diether, K. B., Lee, K-H., and Werner, I. M., 2009. It's SHO time! Short sale price tests and market quality. *Journal of Finance,* 64 (1), 37-73.

Duffie, D., Gârleanu, N., and Pedersen, L., 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics,* 66, 307–339.

Easley, D., O'Hara, M., and Yang, L. 2014. Opaque Trading, Disclosure, and Asset Prices: Implications for Hedge Fund Regulation. *Review of Financials Studies*, 27 (4), 1190-1237.

Engelberg, J. E., Reed, A.V., and Ringgenberg, M. C., 2012. How are shorts informed? Short sellers, news and information processing. *Journal of Financial Economics*, 105 (2), 260-278.

Fama, E. F. and French, K. R., 1998. Value versus growth: The international evidence. *The Journal of Finance*, *53*(6), 1975-1999.

Gagnon, L., 2018. Short Sale constraints and single stock futures introductions. *Financial Review*, 53(1), 5-50.

Gagnon, L., and Witmer, J., 2014. Distribution of ownership, short sale constraints, and market efficiency: Evidence from Cross-Listed Stocks. *Financial Management*, 43 (3), 631-670.

Griffin, J. M., Kelly, P. J., Nardari, F., 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. *Review of Financial Studies*, 23 (8), 3225-3277.

Grunewald, S. N., Wagner, A. F., and Weber, R. H., 2010. Short selling regulation after the financial crisis–First principles revisited. *International Journal of Disclosure and Governance*, 7(2), 108-135.

Henry, T. R. and Koski, J. L., 2010. Short selling around seasoned equity offerings. *The Review of Financial Studies*, 23 (12), 389-4418.

Hong, H. Li, W., Xi Ni, Sheinkman, J., and Yan P., 2016. Days to cover and stock returns. Working paper.

Hou, K., Karolyi, A. G., and Kho, B. C., 2011. What factors drive global stock returns? *Review of Financial Studies*, 24, 2527-2574.

Hou, K. and Moskowitz, T. J., 2005. Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies*, *18*(3), 981-1020.

Hou, K., Van Dijk, M. A., and Zhang, Y., 2012. The implied cost of capital: A new approach. *Journal of Accounting and Economics*, *53*(3), 504-526.

Huszar, Z. R. and M. Porras Prado, M. 2019. An analysis of over-the-counter and centralized stock lending markets, *Journal of Financial Markets* 43, 31-53.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48 (1), 65-91.

Karolyi, G. A., 2015. Cracking the emerging markets enigma. *Oxford University Press*.

Kolasinski, A. C., Reed, A., Thornock, J. R., 2013. Can short restrictions actually increase informed short selling? *Financial Management*, 42 (1), 155-181.

Lee, K. H., 2011. The world price of liquidity risk. *Journal of Financial Economics*, 99(1), 136-161.

Lo, A. W., MacKinlay, A. C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41-66.

Newey, W. and West, K. 1987. A Simple, Positive Semi-definite, Heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55 (3), 703-08.

Porras Prado, M., Saffi, P. A. C., and Sturgess, J. 2016. Ownership structure, limits to arbitrage and stock returns: Evidence from equity lending markets, *Review of Financial Studies*, 29 (12), 3211-3244.

Raddatz, C., Schmukler, S. L., and Williams, T., 2017. International asset allocations and capital flows: The benchmark effect. *Journal of International Economics*, 108, 413-430.

Saffi, P. A. C. and Sigurdsson, K., 2011. Price efficiency and short selling. *Review of Financial Studies*, 24 (3), 821-852.

Table 1. Summary Statistics

This table provides the summary statistics of the shorting variables. Our data sample period is from July 3, 2006, to December 31, 2014. We report the time-series averages of the daily within-country cross-sectional medians of the first four shorting variables. For the four shock variables, we report the time-series averages of the daily within-country cross-sectional means. Variable SIR is the daily percentage of the total number of shares on loan divided by the total number of shares outstanding, averaged over the previous five days. Variable DTCR is the total number of shares on loan relative to the daily trading volume, averaged over the previous five days. Variable SUPPLY is the daily percentage of shares available for borrowing relative to the total number of shares outstanding, averaged over the previous five days. The utilization ratio UTI is the daily percentage of shares on loan relative to the shares available for borrowing, averaged over the previous five days. We construct four demand-supply shock variables, DIN, DOUT, SIN, and SOUT, based on the change in the lending fees and the change in the loan quantities from the average of the previous five days. The demand inward shift dummy, DIN, takes a value of one for stocks that experience decreases in both lending fees and loan amounts. The demand outward shift dummy variable, DOUT, takes a value of one for stocks that experience increases in both lending fees and loan amounts. The supply inwards shift dummy, SIN, takes a value of one for stocks that experience declines in loan amounts and increases in loan fees. The supply outward shift dummy, SOUT, takes a value of one for stocks that experience declines in lending fees and increases in loan amounts.

Country	SIR (%)	DTCR	Supply (%)	UTI (%)	DIN	DOUT	SIN	SOUT
Australia	0.10	1.26	2.92	1.45	0.22	0.20	0.20	0.19
Austria	0.29	4.44	2.63	4.59	0.27	0.24	0.19	0.18
Belgium	0.09	1.82	2.49	2.22	0.23	0.21	0.19	0.18
Brazil	0.02	0.07	0.58	0.12	0.20	0.16	0.16	0.20
Canada	0.30	2.42	6.52	2.74	0.25	0.24	0.19	0.20
Chile	0.00	0.00	0.24	0.00	-	-	-	-
China	0.00	0.00	0.02	0.00	-	-	-	-
Denmark	0.04	0.83	1.76	1.41	0.23	0.20	0.19	0.17
Finland	0.15	1.96	3.82	3.36	0.26	0.24	0.19	0.17
France	0.10	1.62	1.35	2.78	0.23	0.21	0.18	0.16
Germany	0.07	1.40	2.34	1.80	0.23	0.21	0.18	0.16
Greece	0.00	0.00	0.36	0.00	0.12	0.12	0.12	0.11
Hong Kong	0.01	0.28	1.36	0.27	0.25	0.21	0.18	0.17
Hungary	0.02	0.51	1.55	1.11	0.10	0.10	0.07	0.06
Indonesia	0.00	0.00	0.22	0.00	0.07	0.06	0.05	0.04
Ireland	0.05	1.02	3.04	0.77	0.20	0.18	0.18	0.17
Israel	0.01	0.08	0.36	1.05	0.22	0.19	0.17	0.16
Italy	0.22	1.70	1.99	3.42	0.25	0.22	0.17	0.16
Japan	0.29	1.47	2.41	3.29	0.24	0.21	0.19	0.18
Korea	0.09	0.16	0.71	0.37	0.14	0.13	0.09	0.11
Malaysia	0.00	0.00	0.27	0.00	0.06	0.07	0.04	0.07
Mexico	0.09	1.25	2.20	2.81	0.26	0.22	0.20	0.21

Netherlands	0.78	2.85	7.15	5.89	0.27	0.24	0.21	0.19
New Zealand	0.01	0.59	0.97	0.46	0.19	0.18	0.16	0.16
Norway	0.11	1.72	1.74	4.23	0.24	0.23	0.19	0.17
Philippines	0.00	0.00	0.44	0.00	0.05	0.07	0.03	0.01
Poland	0.00	0.00	0.61	0.00	0.21	0.19	0.15	0.15
Portugal	0.20	1.91	1.70	7.51	0.27	0.23	0.19	0.18
Russia	0.00	0.00	0.08	0.00	0.12	0.10	0.09	0.08
Singapore	0.00	0.30	1.01	0.13	0.23	0.19	0.18	0.16
South Africa	0.07	0.64	2.72	0.11	0.23	0.21	0.18	0.17
Spain	0.35	2.12	2.66	12.04	0.26	0.22	0.19	0.17
Sweden	0.08	1.09	2.83	3.21	0.24	0.23	0.18	0.17
Switzerland	0.23	3.22	5.91	2.70	0.23	0.22	0.19	0.19
Taiwan	0.14	0.45	0.88	5.90	0.12	0.12	0.10	0.12
Turkey	0.03	0.06	0.87	1.61	0.21	0.20	0.15	0.16
United Kingdom	0.21	2.10	9.19	1.53	0.23	0.21	0.21	0.19
United States	1.84	3.30	17.04	9.53	0.28	0.27	0.22	0.21

Table 2. Pooled Panel Regression Using Alternative Short Sale Measures to Predict Future Risk-Adjusted Returns Over Different Horizons

This table provides panel regression results of using alternative shorting measures to predict future 5- , 20- , 40- , and 60-day risk-adjusted returns (see Hou, Karolyi, and Kho, 2011), as specified in equation (2). The independent variables include various shorting measures and various firm controls. Variable SIR is the daily percentage of the total number of shares on loan divided by the total number of shares outstanding, averaged over the previous five days. Variable DTCR is the total number of shares on loan relative to the daily trading volume, averaged over the previous five days. Variable SUPPLY is the daily percentage of the shares available for borrowing relative to the total number of shares outstanding, averaged over the previous five days. The utilization ratio, UTI, is daily percentage of shares on loan relative to the shares available for borrowing, averaged over the previous five days. We construct four demand-supply shock variables, DIN, DOUT, SIN, and SOUT, based on the change in the lending fees and the change in the loan quantities for the previous five days. The demand inward shift dummy, DIN, takes a value of one for stocks that experience decreases in both lending fees and loan amounts. The demand outward shift dummy variable, DOUT, takes a value of one for stocks that experience increases in both lending fees and loan amounts. The supply inwards shift dummy, SIN, takes a value of one for stocks that experience declines in loan amounts and increases in loan fees. The supply outward shift dummy, SOUT, takes a value of one for stocks that experience declines in lending fees and increases in loan amounts. The firm controls include the natural logarithm of the market capitalization value (MV; in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The first four shorting variables are standardized to have a mean of zero and a volatility of one, within each country–year pair. In the regression analysis, we include country and year fixed effects, and cluster standard errors by firm and year. All coefficient estimates in this table are presented in basis point units. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Expected		Predict 5-day Return		Predict 20-day Return		Predict 40-day Return		Predict 60-day Return	
SHORT	Sign	Coefficient	Shorts	R2	Shorts	R2	Shorts	R2	Shorts	R2
SIR	-	Estimate	-0.53	0.20%	-1.30	0.44%	-4.06	0.57%	-9.53	0.69%
		[t-stats]	[-2.07]		[-1.33]		[-2.08]		[-3.23]	
DTCR	-	Estimate	-4.25	0.19%	-13.74	0.41%	-23.90	0.52%	-33.86	0.62%
		[t-stats]	[-18.09]		[-16.21]		[-14.65]		[-13.89]	
SUPPLY	+	Estimate	0.91	0.20%	1.88	0.43%	1.71	0.56%	-1.64	0.67%
		[t-stats]	[3.44]		[1.86]		[0.85]		[-0.55]	
UTI	-	Estimate	-3.56	0.21%	-9.48	0.45%	-15.57	0.58%	-22.38	0.70%
		[t-stats]	[-12.33]		[-8.71]		[-7.12]		[-6.72]	
DIN	+	Estimate	1.85	0.17%	2.77	0.32%	6.00	0.37%	5.66	0.43%
		[t-stats]	[4.35]		[2.63]		[3.59]		[2.54]	
DOUT	-	Estimate	-1.49	0.17%	-3.68	0.32%	-9.05	0.38%	-7.24	0.43%
		[t-stats]	[-3.41]		[-3.40]		[-5.29]		[-3.15]	
SIN	+	Estimate	1.12	0.17%	1.38	0.32%	2.81	0.37%	2.40	0.43%
		[t-stats]	[2.50]		[1.27]		[1.61]		[1.01]	
SOUT	-	Estimate	-0.41	0.17%	0.12	0.32%	2.70	0.37%	4.27	0.43%
		[t-stats]	[-0.91]		[0.11]		[1.53]		[1.79]	

Table 3. Predicting Future Risk Adjusted 20-Day and 60-day Returns: Panel Regression within Each Country

This table provides the panel regression results of using two alternative shorting measures to predict future 20-day and 60-day risk-adjusted returns (see Hou, Karolyi, and Kho, 2011) as specified in equation (2) within each country. The independent variables include various shorting measures and firm controls. The two shorting measures are DTCR, the total number of shares on loan relative to the daily trading volume, averaged over the previous five days, and UTI, the utilization ratio as the percentage of the total number of shares on loan relative to the number of shares available for borrowing, averaged over the previous five days. The firm controls include the natural logarithm of the market capitalization value (MV) (in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The two shorting variables are standardized to have a mean of zero and a volatility of one within each country-year pair. In the regression analysis, we include year fixed effects, and cluster standard errors by firm and year. All coefficient estimates in this table are presented in basis point unit. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Short Sale Measure	Predicting Future 20-day Returns DTCR	UTI	Predicting Future 60-day Returns DTCR	UTI
Expected Sign	-	-	-	-
# Negative	35	27	34	27
# Negative significant at 5%	20	11	16	12
# Positive	3	9	4	9
# Positive significant at 5%	1	0	1	0
Australia	-33.20***	-4.71	-66.30***	-19.87
Austria	-29.69**	-8.77	-38.81	-18.74
Belgium	-21.12***	-15.11*	-43.97**	-33.74
Brazil	-25.93***	9.80	-41.80*	47.89
Canada	-12.36***	-5.21	-28.26**	-13.71
Chile	-3.76		-34.52***	
China	155.26***		238.96**	
Denmark	-18.82**	-0.38	-61.78**	-51.12
Finland	-27.87***	-29.21***	-56.78**	-73.69***
France	-13.67***	-13.30***	-35.81***	-38.93***
Germany	-27.32***	-13.47**	-63.73***	-57.71***
Greece	-0.78	12.85	31.94	42.67
Hong Kong	-15.92***	-3.83	-33.03**	-9.56
Hungary	-13.38	22.11	4.97	42.91
Indonesia	18.89	-2.16	49.46	7.75
Ireland	-23.74	19.45	-102.46	114.21
Israel	-11.45	4.02	-36.93	25.88
Italy	-12.11**	-1.37	-16.61	-14.13
Japan	-10.54***	-9.99***	-28.08***	-15.47***
Korea	-17.83***	-13.39**	-46.07***	-52.05***
Malaysia	-23.18***	2.05	-77.67***	5.06
Mexico	-12.85	-16.02	-27.83	-9.97
Netherlands	-1.67	-3.38	-3.18	-13.62
New Zealand	-11.48	-11.78	-27.49	-6.09
Norway	-5.50	-7.57	-42.92	-26.21
Philippines	1.82	22.74	-23.89	43.21
Poland	-12.26	3.36	-40.94	-12.57
Portugal	-24.02	-15.70	-40.32	-23.86
Russia	-2.45	-16.26*	-1.79	-48.41**
Singapore	-25.12***	-24.88***	-39.48**	-80.41***
South Africa	-15.28**	-7.06	-34.98*	-25.26
Spain	-2.34	-10.52	-0.72	-7.99
Sweden	-21.01***	-23.29***	-41.52**	-91.99***
Switzerland	-14.09***	-12.23**	-23.25	-42.55**
Taiwan	-17.69***	-0.24	-36.59***	-16.97
Turkey	-11.45*	-3.80	-26.86	-16.61
United Kingdom	-2.53	7.76	-8.65	1.74
United States	-11.54***	-18.78***	-30.35***	-23.53***

Table 4. Short Regulations, Market Development Measures and Their Impacts on Short's Predictive Power

This table reports the pooled panel regression results using country level variables. Dependent variables are either 20-day or 60-day risk-adjusted returns We include two shorting measures as independent variables: DTCR (the total number of shares on loan relative to the daily trading volume averaged over the previous five days), UTI (the daily percentage of total number of shares on loan over the total number of shares available for borrowing averaged over the previous five days). In Panel A, we report the pooled panel regression results specified in Equation (3). The regulation dummy (DREG) takes on the value of one when uptick rule, or naked short ban, or CCP is in place. In Panel B, we report the pooled panel regression results specified in Equation (4). We report parameter estimates on the shorting variables for different values of the market development variable, based on GDP per capita (GDDPC), or relative stock market capitalization (Stock/GDP), or opacity and market development indices from the World Bank. The high development dummy $HIGH^{DEV}$ takes on the value of one when the country's development measure is higher than cross-country median and zero otherwise. The firm controls are as follows: the natural logarithm of the market capitalization value (MV; in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The shorting variables are standardized within each country-year. The pooled stock level regression using the country measures include year fixed effect, and standard errors are clustered by firm and year. All coefficient estimates in this table are presented in basis point units. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Short Sale Regulations' Impacts on Short's Predictive Power

			20-day Risk-adjusted Returns		60-day Risk-adjusted Returns	
Short Sale Measure			DTCR	UTI	DTCR	UTI
Uptick	DREG=0	b_0	-13.64***	-4.52***	-27.56***	-14.45***
	Diff	b_1	-0.08	-8.63***	-10.77**	-12.03*
	DREG=1	b_0+b_1	-13.72***	-13.15***	-38.33***	-26.49***
Naked Ban	DREG=0	b_0	-11.49***	-5.46***	-28.18***	-2.12
	Diff	b_1	-4.51***	-7.00***	-10.53**	-33.62***
	DREG=1	b_0+b_1	-16.00***	-12.47***	-38.71***	-35.74***
CCP	DREG=0	b_0	-14.48***	-9.39***	-36.26***	-17.75***
	Diff	b_1	1.76	0.68	5.81	-6.06
	DREG=1	b_0+b_1	-12.72***	-8.71***	-30.45***	-23.81***

Panel B. Market Development Measures' Impact on Short's Predictive Power

			20-day Risk-adjusted Returns		60-day Risk-adjusted Returns	
Short Sale Measures			DTCR	UTI	DTCR	UTI
GDPPC	$HIGH^{DEV} = 0$	b_0	-14.34***	-8.53***	-33.02***	-33.37***
	Diff	b_1	0.85	-0.72	-0.69	17.20**
	$HIGH^{DEV} = 1$	b_0+b_1	-13.49***	-9.25***	-33.71***	-16.17***
Stock/GDP	$HIGH^{DEV} = 0$	b_0	-14.06***	-7.36***	-31.62***	-23.71***
	Diff	b_1	0.43	-2.00	-2.23	3.71
	$HIGH^{DEV} = 1$	b_0+b_1	-13.63***	-9.36***	-33.84***	-19.99***
Corporate opacity	$HIGH^{DEV} = 0$	b_0	-12.97***	-8.25***	-31.08***	-21.46***
	Diff	b_1	-1.11	-1.29	-3.90	1.41
	$HIGH^{DEV} = 1$	b_0+b_1	-14.09***	-9.54***	-34.98***	-20.05***
Market development	$HIGH^{DEV} = 0$	b_0	-15.18***	-5.25**	-32.75***	-27.52***
	Diff	b_1	1.80	-4.69*	-0.96	8.64
	$HIGH^{DEV} = 1$	b_0+b_1	-13.38***	-9.94***	-33.71***	-18.88***

Table 5. Short Selling Fee Measures, Liquidity Measures and Efficiency Measures and Their Impacts on Short's Predictive Power

This table reports the market development measures, short selling fee measures, liquidity measures and efficiency measures and their impacts on short's predictive power for future return. Panel A reports the pooled panel regression results specified in Equation (5). We report the parameter estimates on the shorting variables, for different values of the low fee dummy variable, LOW^{FEE}, which is based on the ALLFEE measure and the CURRFEE measures. It takes a value of one if the firm's fee measure is below the median of all sample firms' fee measures for the same day and zero otherwise. Panel B reports the pooled panel regression results specified in Equation (6). We report the parameter estimates on the shorting variables, for different values of the high liquidity dummy variable, $HIGH^{LIQ}$, which is based on the value of firm-level turnover, relative bid-ask spread, and percentage zero measures from previous month. It takes on the value of one when the firm is more liquid than the median across all firms for the same day and zero otherwise. Panel C reports the pooled panel regression results specified in Equation (7). We report the parameter estimates on the shorting variables, for different values of the high efficiency dummy variable, $HIGH^{EFF}$, which is based on the value of firm-level cross-correlation, variance ratio, delay_R2, delay_beta, and country-level efficiency measures, such as announcement ERC and annual ERC. It takes on the value of one when the firm is more efficient than the median across all firms for the same day and zero otherwise. The definitions and constructions of these efficiency variables are discussed in Internet Appendix A. For the panel regression, the dependent variables are 20-day or 60-day risk-adjusted returns. We include two shorting measures as independent variables: DTCR (the total number of shares on loan relative to the daily trading volume averaged over the previous five days) and UTI (the daily percentage of the total number of shares on loan over the total number of shares available for borrowing averaged over the previous five days). Firm controls include: the natural logarithm of the market capitalization value (MV; in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with one month skipping (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The shorting variables are standardized within each country-year. The pooled stock level regressions using the country measures include year fixed effects with standard errors double clustered by firm and year. All coefficient estimates in this table are presented in basis point units. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Short Selling Fee Measures' Impacts on Short's Predictive Power

			20-day Risk-adjusted Returns		60-day Risk-adjusted Returns	
Short Sale Measures			DTCR	UTI	DTCR	UTI
ALLFEE	$LOW^{FEE} = 0$	b_0	-13.73***	-14.86***	-30.13***	-33.72***
	Diff	b_1	1.33	16.44***	-3.34	36.30***
	$LOW^{FEE} = 1$	b_0+b_1	-12.40***	1.58	-33.47***	2.58
CURRFEE	$LOW^{FEE} = 0$	b_0	-11.65***	-14.75***	-27.37***	-34.03***
	Diff	b_1	-2.01	13.95***	-9.18**	35.14***
	$LOW^{FEE} = 1$	b_0+b_1	-13.65***	-0.79	-36.55***	1.11

Panel B. Liquidity Measures' Impacts on Short's Predictive Power

			20-day Risk-adjusted Returns		60-day Risk-adjusted Returns	
Short Sale Measures			DTCR	UTI	DTCR	UTI
Turnover	$HIGH^{LIQ} = 0$	b_0	-16.63***	-11.15***	-38.29***	-24.66***
	Diff	b_1	9.14***	3.56*	15.23***	7.31
	$HIGH^{LIQ} = 1$	b_0+b_1	-7.49***	-7.59***	-23.06***	-17.35***
Bid-ask spread	$HIGH^{LIQ} = 0$	b_0	-19.78***	-18.71***	-38.6***	-35.73***
	Diff	b_1	10.09***	18.65***	6.96	25.75***
	$HIGH^{LIQ} = 1$	b_0+b_1	-9.69***	-0.06	-31.64***	-9.99**
PctZero	$HIGH^{LIQ} = 0$	b_0	-13.71***	-13.08***	-28.25***	-29.23***
	Diff	b_1	0.05	7.39***	-9.99***	15.79***
	$HIGH^{LIQ} = 1$	b_0+b_1	-13.66***	-5.69***	-38.25***	-13.44***

Panel C. Efficiency Measures' Impacts on Short's Predictive Power

Short Sale Measure			20-day Risk-adjusted Returns DTCR	UTI	60-day Risk-adjusted Returns DTCR	UTI
Cross-correlation	$HIGH^{EFF} = 0$	b_0	-18.12***	-12.65***	-39.65***	-26.90***
	Diff	b_1	8.28***	6.77***	11.32**	11.89*
	$HIGH^{EFF} = 1$	b_0+b_1	-9.84***	-5.87***	-28.33***	-15.01***
Variance ratio	$HIGH^{EFF} = 0$	b_0	-13.08***	-8.04***	-30.42***	-17.73***
	Diff	b_1	-1.25	-1.91	-6.05	-5.30
	$HIGH^{EFF} = 1$	b_0+b_1	-14.33***	-9.95***	-36.48***	-23.02***
Delay_R2	$HIGH^{EFF} = 0$	b_0	-18.10***	-15.06***	-38.14***	-26.09***
	Diff	b_1	7.15***	10.20***	7.09	8.86
	$HIGH^{EFF} = 1$	b_0+b_1	-10.95***	-4.86***	-31.05***	-17.24***
Delay_beta	$HIGH^{EFF} = 0$	b_0	-16.88***	-13.23***	-36.91***	-27.49***
	Diff	b_1	5.39***	7.64***	5.44	12.05*
	$HIGH^{EFF} = 1$	b_0+b_1	-11.49***	-5.58***	-31.47***	-15.44***
Announcement ERC	$HIGH^{EFF} = 0$	b_0	-16.14***	-10.93***	-38.81***	-31.22***
	Diff	b_1	4.17**	3.16	8.94*	18.12***
	$HIGH^{EFF} = 1$	b_0+b_1	-11.97***	-7.77***	-29.87***	-13.10***
Annual ERC	$HIGH^{EFF} = 0$	b_0	-20.56***	-17.30***	-46.54***	-40.53***
	Diff	b_1	12.78***	14.98***	23.96***	35.60***
	$HIGH^{EFF} = 1$	b_0+b_1	-7.78***	-2.32	-22.58***	-4.93

Table 6. Exogenous Shocks on Fees and Efficiency Measures

This table reports the impact of MSCI index inclusions and exclusions on shorting fees, stock efficiencies and short's predictive power, using the panel regression specification from equation (8). The sample period is from January 2009 to December 2014. Panel A reports the changes in fees and delay measures as efficiency proxies for included and excluded firms, using a 250-day window before and after the event. Panel B presents the regression estimates for inclusion events with risk-adjusted returns over 20-day horizons returns. We require each country to have at least 10 inclusion/exclusion events during the sample period. We report three specifications: All Markets, Developed Markets and Emerging Markets. We use two shorting measures as independent variables: DTCR (the total number of shares on loan relative to the daily trading volume averaged over the previous five days) and UTI (the daily percentage of the total number of shares on loan over the total number of shares available for borrowing averaged over the previous five days). We also include a variable, Institutional Flow, measuring the changes of quarterly institutional holding divided by stock market capitalization as additional control. Other firm controls are the same as those in Table 2 and throughout the paper. The two shorting variables are standardized to have a mean of zero and a volatility of one within each country-year pair. In the regression analysis, we include year fixed effects, and cluster standard errors by firm and year. All coefficient estimates in this table are presented in basis points. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Panel C repeat the above exercises for firms excluded from the MSCI ACWI, as specified in equation (8).

Panel A. Shorting Fee and Efficiency Measures Before and After the Events

		All Markets				Developed Markets				Emerging Markets			
		Before [-250,-1]	After [0,250]	Diff	t-stat	Before [-250,-1]	After [0,250]	Diff	t-stat	Before [-250,-1]	After [0,250]	Diff	t-stat
Inclusions	ALLFEE	1.57	1.23	-0.35	-5.05	0.89	0.54	-0.35	-4.56	3.14	2.79	-0.34	-2.39
	Delay_R2	0.12	0.09	-0.03	-2.73	0.12	0.10	-0.02	-1.70	0.11	0.07	-0.03	-2.33
Exclusions	ALLFEE	1.54	1.96	0.42	4.06	0.91	1.24	0.33	3.16	3.60	4.29	0.69	2.56
	Delay_R2	0.08	0.12	0.04	4.01	0.07	0.11	0.04	3.45	0.09	0.13	0.04	2.04

Panel B. The Impact of Inclusions on Short's Predictive Power for Risk-adjusted 20-day Returns

	All Markets		Developed Markets		Emerging Markets	
	DTCR	UTI	DTCR	UTI	DTCR	UTI
After	58.38***	58.21***	54.69***	52.91***	69.08***	70.47***
Institutional Flow	220.13***	220.21***	237.92***	238.01***	154.04***	154.16***
Short	-12.97***	-8.18***	-12.63***	-10.94***	-12.50***	-0.40
Short*After	-13.53**	-2.58	-4.18	7.76	-35.35***	-36.77***

Panel C. The Impact of Exclusions on Short's Predictive Power for Risk-adjusted 20-day Returns

	All Markets		Developed Markets		Emerging Markets	
	DTCR	UTI	DTCR	UTI	DTCR	UTI
After	-8.44	-9.65	-9.14	-10.46	-10.33	-7.49
Institutional Flow	221.94***	222.03***	234.57***	234.67***	156.22***	156.38***
Short	-13.53***	-8.39***	-12.35***	-10.21***	-20.41***	-2.93
Short*After	12.55*	13.49**	7.40	11.30	26.17*	16.04**

Table 7. Market Development Measures, Short Selling Fee Measures, Liquidity Measures and Efficiency Measures and Their Impacts on Short's Predictive Power with Two Tail Cutoffs

This table reports the pooled panel regression results specified in equation (9). We report the parameter estimates on the shorting variables and interactions. The high dummy variable, XHIGH, takes a value of one when the country's (firm's) measure is higher than the cross-country (cross-firm) 90th percentile and zero otherwise. The low dummy variable, XLOW, takes a value of one when the country's (or firm's) measure is lower than the cross-country (or cross-firm) 10th percentile and zero otherwise. In Panel A, we examine country level development measures, proxied by GDPPC, or Stock/GDP or Corporate opacity, or market development as defined in Table 4. In Panel B to D, we investigate firm level fee, liquidity, and efficiency measures, respectively. For the panel regression, the dependent variables are 20-day or 60-day risk-adjusted returns. We include two shorting measures as independent variables: DTCR (the total number of shares on loan relative to the daily trading volume averaged over the previous five days) and UTI (the daily percentage of total number of shares on loan over the total number of shares available for borrowing averaged over the previous five days. Firm controls include: the natural logarithm of the market capitalization value (MV; in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over previous month (LagRet1m), idiosyncratic volatility estimated using the model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The shorting variables are standardized within each country-year. The pooled stock-level regressions using the country measures include year fixed effects with standard errors, double clustered by firm and year. All coefficient estimates in this table are presented in basis points. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Market Development Measures' Impact on Short's Predictive Power with Two Tail Cutoffs

		20-day Risk-adjusted Returns		60-day Risk adjusted Returns	
Short Sale measure		DTCR	UTI	DTCR	UTI
GDPPC	b_0(Short)	-14.06***	-9.26***	-34.40***	-20.10***
	b_1(Short*$XHIGH^{DEV}$)	6.99	1.90	19.56	-9.48
	b_2(Short*$XLOW^{DEV}$)	6.38	6.89	1.41	3.57
Stock/GDP	b_0(Short)	-13.21***	-8.50***	-33.63***	-18.14***
	b_1(Short*$XHIGH^{DEV}$)	-6.10*	-8.71**	-2.35	-35.71***
	b_2(Short*$XLOW^{DEV}$)	-0.26	16.36**	22.94	75.00***
Corporate opacity	b_0(Short)	-13.19***	-10.62***	-33.55***	-17.27***
	b_1(Short*$XHIGH^{DEV}$)	-0.19	9.81***	3.52	2.73
	b_2(Short*$XLOW^{DEV}$)	-4.62	-0.09	-4.93	-33.92***
Market development	b_0(Short)	-16.14***	-13.18***	-39.67***	-29.04***
	b_1(Short*$XHIGH^{DEV}$)	19.32***	31.97***	50.10***	70.13***
	b_2(Short*$XLOW^{DEV}$)	9.76**	7.49	21.23	4.66

Panel B. Short Selling Fee Measures' Impacts on Short's Predictive Power with Two Tail Cutoffs

		20-day Risk-adjusted Returns		60-day Risk-adjusted Returns	
Short Sale Measure		DTCR	UTI	DTCR	UTI
ALLFEE	b_0(Short)	-13.81***	-6.18***	-33.6***	-19.14***
	b_1(Short*$XLOW^{FEE}$)	9.35***	25.48***	14.49**	57.30***
	b_2(Short*$XHIGH^{FEE}$)	-4.04	-19.31***	-9.25	-22.51***
CURRFEE	b_0(Short)	-13.77***	-5.30***	-34.01***	-17.94***
	b_1(Short*$XLOW^{FEE}$)	7.11***	19.81***	11.88*	55.99***
	b_2(Short*$XHIGH^{FEE}$)	-2.30	-21.08***	-2.04	-25.89***

Panel C. Liquidity Measures' Impacts on Short's Predictive Power with Two Tail Cutoffs

Short Sale Measure		20-day Risk-adjusted Returns DTCR	20-day Risk-adjusted Returns UTI	60-day Risk-adjusted Returns DTCR	60-day Risk-adjusted Returns UTI
Turnover	b_0(Short)	-15.36***	-10.18***	-36.76***	-24.91***
	b_1(Short*$XHIGH^{LIQ}$)	17.17***	2.65	45.81***	15.68
	b_2(Short*$XLOW^{LIQ}$)	5.47***	11.44***	9.55*	37.62***
Bid-ask spread	b_0(Short)	-15.65***	-12.24***	-36.66***	-26.40***
	b_1(Short*$XHIGH^{LIQ}$)	21.52***	35.17***	31.82***	57.42***
	b_2(Short*$XLOW^{LIQ}$)	16.70***	23.85***	33.68**	58.75***
PctZero	b_0(Short)	-14.39***	-14.05***	-30.76***	-30.05***
	b_1(Short*$XHIGH^{LIQ}$)	1.90	10.77***	-7.41**	20.09***
	b_2(Short*$XLOW^{LIQ}$)	-2.26	12.42**	7.32	27.17*

Panel D. Efficiency Measures' Impacts on Short's Predictive Power with Two Tail Cutoffs

Short Sale Measure		20-day Risk-adjusted Returns DTCR	20-day Risk-adjusted Returns UTI	60-day Risk-adjusted Returns DTCR	60-day Risk-adjusted Returns UTI
Cross-correlation	b_0(Short)	-13.36***	-9.30***	-33.62***	-20.93***
	b_1(Short*$XHIGH^{EFF}$)	10.56***	13.32***	25.34***	24.48**
	b_2(Short*$XLOW^{EFF}$)	-18.15***	-15.35***	-33.07***	-29.15**
Variance ratio	b_0(Short)	-12.63***	-8.47***	-31.94***	-18.80***
	b_1(Short*$XHIGH^{EFF}$)	-4.47	-2.63	-10.92	-9.05
	b_2(Short*$XLOW^{EFF}$)	-8.44**	-4.53	-6.76	-11.68
Delay_R2	b_0(Short)	-13.60***	-9.72***	-33.57***	-21.54***
	b_1(Short*$XHIGH^{EFF}$)	2.48	6.06**	-0.34	0.21
	b_2(Short*$XLOW^{EFF}$)	-8.87*	-1.56	2.09	24.90
Delay_beta	b_0(Short)	-13.37***	-9.69***	-32.28***	-21.47***
	b_1(Short*$XHIGH^{EFF}$)	1.54	7.33**	-3.15	5.99
	b_2(Short*$XLOW^{EFF}$)	-7.02*	-2.33	-13.72	2.56
Announcement ERC	b_0(Short)	-16.5**	6.75	-64.36***	-30.96
	b_1(Short*$XHIGH^{EFF}$)	-3.91	-10.80*	-6.04	-23.47
	b_2(Short*$XLOW^{EFF}$)	6.73	-5.45	37.20**	33.68*
Annual ERC	b_0(Short)	-25.89***	-13.36	-62.08***	-51.83**
	b_1(Short*$XHIGH^{EFF}$)	-7.31*	-2.44	-8.73	6.32
	b_2(Short*$XLOW^{EFF}$)	19.73***	6.81	37.82**	25.74

Internet Appendix for

"Can Shorts Predict Returns? A Global Perspective"

Appendix A. Data Construction

Data Filters

Our sample includes active and delisted common stocks from 38 countries from July 3, 2006, to December 31, 2014. Following Hou, Karolyi, and Kho (2011) and Lee (2011),[1] we apply the following filters to the data:

1. We exclude cross-listed stocks and non-common equities (e.g., duplicates, depository receipts, preferred stocks, warrants, debt securities, unit trusts, and expired securities). To screen out non-common stocks, we exclude securities with names like "REIT," "REAL EST," "GDR," "PF," "PREF," or "PRF," as these terms are likely to represent real estate investment trusts, global depository receipts, or preferred stocks. In addition, in Belgium, AFV and VVPR shares are dropped because they have preferential dividend or tax incentives. In Canada, stocks with names like "INC.FD." are excluded, as these securities are income trusts, not common equity shares. In Mexico, ACP and BCP share types are removed because they have the special feature of being convertible into series A and B shares, respectively, after one year. In France, ADP and CIP share types are dropped because they carry no voting rights but carry preferential dividend rights. In Germany, GSH share types are excluded because they offer fixed dividends and carry non-voting rights. Similarly, in Italy, RSP share types are dropped because they have no voting provisions.
2. Our sample is restricted to stocks from major exchanges and stocks identified as major security with a primary quote by Datastream.
3. To filter out common data errors and outliers in the international data, we treat as missing all monthly returns above 300% that are reversed within one month. In addition, if the monthly return R_t or R_{t+1} is greater than 300% and $(1 + \mathrm{R}_t) \times (1 + \mathrm{R}_{t+1}) - 1 < 50\%$, then both R_t and R_{t+1} are considered missing. In addition, to exclude remaining outliers in returns that cannot be identified as stock splits or mergers, we treat as missing all monthly returns that fall outside the 0.1% and 99.9% range in a country in each year. For daily returns, we consider as missing all daily returns above 100% that are reversed the following day. Specifically, the daily returns for both days t and t-1 are considered missing if $(1 + \mathrm{R}_t) \times (1 + \mathrm{R}_{t+1}) - 1 < 50\%$, and at least one of the two returns is 100% or greater. We also treat as missing the daily returns that fall outside the 1% and 99% range in a country in each year. In addition, any daily return is considered missing if either the total return index from Datastream for the previous or current day is less than 0.01 because calculating daily returns based on these extremely small index values could exaggerate the proportion of zero return days, as the return index is rounded to the nearest tenth by Datastream.
4. We delete non-trading days by defining them as days on which 90% or more of the stocks in that country have zero return, and we exclude a stock if the number of zero-return days is more than 80% in a given month.

In addition, Markit includes "zero" value observations as well as missing values. The zero values are kept as is in the Markit - DS matching sample, because they have economic meanings. If the

[1] We thank a referee for suggesting the references.

observation value is missing in Markit, the value stays missing (not set to zero) in the Markit - DS matched sample.

Below is a brief summary of the number of observations after each cleaning step.

Data	Cleaning Step	N (observations)
Datastream data	1. Original daily return data	97,225,227
	2. Merge with monthly information and exclude observations after dead date	56,371,392
	3. After filter 1, 2, and 3	52,648,520
Markit data	4. Original daily short selling data	67,422,111
Panel data	5. Merge Datastream and Markit dataset by ISIN/Sedol/CUSIP	30,092,777
	6. After filter 4	29,389,233

Risk Factor Construction

We first calculate country-level factors, including the market factor, momentum factor, and cash-flow-to-price sensitivity factor. The market factor is computed as the country-level market portfolio return in excess of the risk-free rate. The momentum factor is calculated following Jegadeesh and Titman's (1993) 6/1/6 strategy. For every month, we sort firms within each country into quintile portfolios based on past six-month returns. Then we skip a month, and long stocks from the top quintile and short stocks from the bottom quintile for the next six months. The momentum factor is the return on this long-short strategy with equal-weighting and monthly balancing. To construct the cash-flow-to-price sensitivity factor, we first form quintile portfolios based on the cash-flow-to-price ratio within the country at the end of June of each year *t*. The portfolios are held from July of year *t* to June of year *t*+1. The cash-flow-to-price factor is the value-weighted profits from the long-short strategy, where the long position contains stocks from the top quintile with the highest cash-flow-to-price ratios, and the short position contains firms from the lowest cash-flow-to-price ratios quintile.

The global market factor is the global market portfolio return in excess of the risk-free rate. The global momentum and cash-flow-to-price factors are constructed similarly to country-level momentum and cash-flow-to-price factors, except that the quintile portfolios are formed by sorting all stocks in the global market.

Fee Measures

The first measure is the daily value-weighted average fee for stock *i* on day *t* based on all outstanding contracts:

$$ALLFEE_{i,t} = \sum_{n=1}^{N_{i,t}} \left(\frac{BorrowedAmount_{n,i,t}}{\sum_{n=1}^{N_{i,t}} BorrowedAmount_{n,i,t}} ContractFee_{n,i,t} \right). \quad \text{(A1)}$$

Here the market capitalization of the *n*-th contract size, $BorrowedAmount_{n,i,t}$, is used for the weighting to reduce the influence of small (and presumably expensive) transactions, and the $ContractFee_{n,i,t}$ is the fee on the *n*-th borrowing contract in stock *i* at time *t*, considered as either the fee for non-cash contracts or the general collateral rate minus the rebate rate. The *ALLFEE* measure includes all outstanding contracts, and thus combines information from old and new contracts. For each stock on each day, we average the *ALLFEE* measure over the previous five days.

Although overnight contracts are common in the United States and Europe, lenders also use term loans in other countries. To create a more dynamic measure that captures the lending fees in the most recent contracts, we compute the current fee as follows:

$$CURRFEE_{i,t} = \sum_{m=1}^{M_{i,t}} \left(\frac{BorrowedAmount_{m,i,t}}{\sum_{m=1}^{M_{i,t}} BorrowedAmount_{m,i,t}} ContractFee_{m,i,t} \right). \tag{A2}$$

The current fee is the value-weighted fee on the *M* new contracts opened during the previous five days. In general, the *ALLFEE* and *CURRFEE* measures are highly correlated because fees are revised overnight unless the term lending contracts are used for securities lending.

Efficiency Measures

We follow Saffi and Sigurdsson (2011) to construct four firm-level return-based efficiency measures, and we follow Hou et al. (2012) to construct two country-level earnings-based efficiency measures.

The first price efficiency measure is the cross-correlation between the current stock weekly returns and the lagged local-market weekly returns. We define weekly return as the compounding daily returns from Wednesday to the following Wednesday. For a given year *T*, we compute $\rho_{ijT}^{Cross} = \mathrm{Corr}(\mathrm{r}_{ijT}, \mathrm{r}_{mjt-1}$; i.e., the correlation between firm i's returns at week *t* and the local value-weighted market returns at week *t-1*). As correlations are bounded by -1 and 1, we apply the transformation $\ln[\frac{1+\rho}{1-\rho}]$, and adopt the result as a proxy for efficiency.

Our second efficiency measure is based on variance ratios. Lo and MacKinlay (1988) show that, if prices are efficient and follow a random walk, then the absence of autocorrelations makes the variance of stock returns a linear function of the frequency with which they are calculated. For a given year *T*, we estimate the variance of monthly returns, and then divide it by four times the variance of weekly returns. We transform the variance ratio by subtracting one and computing the absolute value. The resulting variance ratio measure should be equal to zero under the null hypothesis that prices follow a random walk.

The third and fourth efficiency measures are proposed by Hou and Moskowitz (2005). If investors cannot fully incorporate current information into current stock prices, they defer their actions, and information is incorporated into prices gradually. We estimate the price-response delay using a market-model regression that is extended using the lagged returns of a local market return and the contemporaneous global returns. For each stock *i* during year *T*, we estimate the following specification:

$$\mathrm{r}_{i,t} = \alpha_i + \beta_i \times r_{m,t} + \sum_{n=1}^{4} \beta_i(-n) \times r_{m,t-n} + \gamma_i \times r_{W,t} + \varepsilon_{i,t}, \tag{A3}$$

where $r_{i,t}$ represents the returns for stock *i* in week *t*; $r_{m,t-n}$ is the corresponding value-weighted local market return in week *t-n*; and $r_{W,t}$ represents the returns of the value-weighted global market return in week *t*. We focus on the impact of the local market news and use only lags of the local market.

The delay measure, Delay_R2, is based on the fraction of variability in stock returns that is attributable to lagged local market returns. We first estimate equation (A3) and obtain the R^2. We then estimate a constrained version of (A3), where coefficients on the lagged local market returns are restricted to be zero. The resulting R2 is referred to as $R^2_{\beta_i^{(-n)}=0,\forall n\in[1,4]}$. The third efficiency measure is defined as

$$\text{Delay\_R2}_i = 1 - \frac{R^2_{\beta_i^{(-n)}=0,\forall n\in[1,4]}}{R^2}. \quad \text{(A4)}$$

The larger this measure is, the greater the variation in stock returns captured by lagged local market returns, which implies a longer price delay in responding to market information and lower price efficiency. Since Delay_R2 does not take into account the magnitude of the coefficients of lagged market returns, we compute the fourth efficiency measure, Delay_beta, based on the coefficients, as follows:

$$\text{Delay\_beta}_i = \frac{\sum_{n=1}^{4}|\beta_i(-n)|}{|\beta_i|+\sum_{n=1}^{4}|\beta_i(-n)|}. \quad \text{(A5)}$$

This measure captures the magnitude of the lagged coefficients relative to the magnitude of all local market-return coefficients. We use the absolute values of each coefficient regardless of its estimated signs because price efficiency declines as these measures deviate from zero.

The earnings response coefficient (ERC) captures the reaction of stock prices to the unexpected earnings news. We obtain the earnings and analysts data from IBES. Since global stocks tend to have better coverage for annual earnings announcements than for quarterly announcements, we use annual earnings and forecast information to construct our measures. We calculate these measures only for stocks with valid analyst forecast EPS, actual EPS, and Price information, when the information is available in the same currency. Unlike for the above four efficiency measures, which are estimated at the firm level, the ERC measures are estimated at the country level owing to the short sample period and small number of observations for each firm.

We compute two ERC measures at the country level, following Hou et al. (2012). We first calculate unexpected earnings as actual earnings minus the mean of analyst forecasts divided by the stock price from last period. For the *Announcement ERC*, we estimate a cross-sectional regression for each country each year by regressing annual announcement returns, which covers day -1 to +1 and is adjusted by local market return, on the firm's unexpected earnings. A high ERC coefficient indicates that announcement event returns respond quickly to the news in the earnings, which indicates high efficiency.

For the *Annual ERC*, we also estimate an annual cross-sectional regression for each country by regressing the annual buy and hold returns over the year on the unexpected earnings over the same year. In this case, a higher ERC coefficient indicates that annual returns respond more to the news in the earnings, again indicating higher efficiency.

Appendix Table 1. Summary Statistics

This table provides an overview of the data coverage of our final sample by country in Panel A, correlations of the shorting variables in Panel B, summary statistics of holding period returns by country in Panel C, and summary statistics of stock characteristics by country in Panel D. Our data sample period is from July 3, 2006, to December 31, 2014. Panel A reports the time-series averages of our final sample's daily aggregate market capitalization, the percentage of market coverage for the DataStream sample, the average number of firms and the total number of trading days for each country. Panel B reports the correlation coefficients for the eight shorting measures, computed over a pooled sample across all firms and all days. Variable SIR is the daily percentage of the total number of shares on loan divided by the total number of shares outstanding, averaged over the previous five days. Variable DTCR is the total number of shares on loan relative to the daily trading volume, averaged over the previous five days. Variable SUPPLY is the daily percentage of shares available for borrowing relative to the total number of shares outstanding, averaged over the previous five days. The utilization ratio UTI is the daily percentage of shares on loan relative to the shares available for borrowing, averaged over the previous five days. We construct four demand-supply shock variables, DIN, DOUT, SIN, and SOUT, based on the change in the lending fees and the change in the loan quantities from the average of the previous five days. The demand inward shift dummy, DIN, takes a value of one for stocks that experience decreases in both lending fees and loan amounts. The demand outward shift dummy variable, DOUT, takes a value of one for stocks that experience increases in both lending fees and loan amounts. The supply inwards shift dummy, SIN, takes a value of one for stocks that experience declines in loan amounts and increases in loan fees. The supply outward shift dummy, SOUT, takes a value of one for stocks that experience declines in lending fees and increases in loan amounts. Panel C reports the time-series means of the daily cross-sectional medians of raw and risk-adjusted returns (see Hou, Karolyi and Kho, 2011) for 1-, 5-, 20-, and 60-day investment horizons, by country. Panel D reports the time series average of the daily within-country cross-sectional medians for the following firm characteristics: market capitalization (MV), book-to-market (BM), past 6-month return with 1 month skipped (LagRet6m), previous-month return (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous month (Turnover), percentage of zero return days within a month (PctZero), and relative bid-ask spread (bid-ask spread scaled by price).

Panel A. Average Data Coverage in Each Country

Country	Aggregate Market Cap ($ billion)	Our Sample's Coverage of Datastream Data	N (Firms)	N (days)
Australia	1,099	90.84%	643	2,098
Austria	123	97.40%	58	2,054
Belgium	258	89.74%	97	2,120
Brazil	413	66.01%	89	2,049
Canada	1,259	91.34%	618	2,095
Chile	160	70.59%	35	2,059
China	1,490	47.29%	419	1,396
Denmark	138	67.97%	94	2,072
Finland	202	99.34%	99	2,081
France	1,902	97.56%	413	2,120
Germany	1,302	89.83%	399	2,108
Greece	68	66.93%	73	2,068
Hong Kong	1,559	89.54%	616	2,046
Hungary	23	85.86%	11	2,061
Indonesia	189	64.87%	81	2,017
Ireland	74	90.77%	33	2,103
Israel	134	86.16%	97	2,140
Italy	543	85.78%	209	2,100
Japan	3,888	99.43%	2,340	2,017
Korea	896	94.49%	791	2,047
Malaysia	308	87.25%	204	2,039
Mexico	288	81.23%	70	2,080
Netherlands	553	92.06%	78	2,120
New Zealand	38	81.32%	58	2,086
Norway	267	96.77%	138	2,083
Philippines	106	76.08%	47	2,019
Poland	139	85.69%	105	2,072
Portugal	80	96.58%	33	2,120
Russia	710	83.80%	77	2,045
Singapore	471	95.60%	307	2,085
South Africa	381	90.33%	136	2,071
Spain	610	88.15%	112	2,113
Sweden	410	86.17%	225	2,081
Switzerland	1,108	90.09%	221	2,084
Taiwan	642	95.03%	536	2,033
Turkey	204	87.11%	119	2,069
United Kingdom	2,445	81.59%	894	2,103
United States	15,381	99.56%	3,979	2,140

Panel B. Correlation Analysis of Shorting Measures

	SIR	DTCR	SUPPLY	UTI	DIN	DOUT	SIN
DTCR	0.12						
p-value	*<.0001*						
SUPPLY	0.57	0.05					
p-value	*<.0001*	*<.0001*					
UTI	0.56	0.13	0.11				
p-value	*<.0001*	*<.0001*	*<.0001*				
DIN	0.03	0.01	0.06	0.02			
p-value	*<.0001*	*<.0001*	*<.0001*	*<.0001*			
DOUT	0.09	0.01	0.08	0.10	-0.31		
p-value	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*		
SIN	0.02	0.00	0.06	0.00	-0.27	-0.26	
p-value	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	
SOUT	0.04	0.01	0.06	0.03	-0.27	-0.26	-0.23
p-value	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*

Panel C. Summary Statistics of Holding Period Returns in Each Country

	Raw Returns				Risk-Adjusted Returns			
Country	1-day	5-day	20-day	60-day	1-day	5-day	20-day	60-day
Australia	-0.08%	-0.24%	-0.26%	1.12%	-0.08%	-0.29%	-0.61%	-0.44%
Austria	-0.04%	-0.08%	0.10%	1.72%	-0.04%	-0.10%	-0.12%	0.35%
Belgium	-0.04%	-0.07%	0.22%	1.54%	-0.04%	-0.17%	-0.33%	-0.23%
Brazil	-0.03%	0.02%	0.80%	3.57%	-0.05%	-0.12%	0.07%	1.13%
Canada	-0.08%	-0.17%	0.01%	1.60%	-0.09%	-0.28%	-0.51%	-0.33%
Chile	-0.02%	0.03%	0.50%	2.11%	-0.03%	-0.10%	-0.22%	-0.65%
China	-0.05%	0.07%	0.49%	0.76%	-0.08%	-0.15%	-0.67%	-2.53%
Denmark	-0.08%	-0.33%	-0.72%	-0.57%	-0.09%	-0.39%	-1.14%	-2.57%
Finland	-0.05%	-0.10%	0.03%	0.79%	-0.06%	-0.23%	-0.60%	-1.27%
France	-0.08%	-0.17%	-0.04%	0.85%	-0.07%	-0.20%	-0.35%	-0.18%
Germany	-0.07%	-0.17%	-0.06%	0.95%	-0.07%	-0.19%	-0.29%	0.05%
Greece	-0.13%	-0.43%	-0.75%	-0.46%	-0.09%	-0.27%	-0.54%	-0.45%
Hong Kong	-0.13%	-0.27%	-0.28%	0.91%	-0.11%	-0.30%	-0.62%	-0.72%
Hungary	-0.06%	-0.16%	-0.15%	0.28%	-0.04%	-0.13%	-0.22%	-0.71%
Indonesia	-0.01%	-0.12%	0.54%	3.36%	-0.02%	-0.08%	-0.17%	-1.19%
Ireland	-0.05%	-0.19%	0.10%	1.60%	-0.06%	-0.25%	-0.39%	0.18%
Israel	-0.06%	-0.10%	0.39%	2.56%	-0.07%	-0.23%	-0.38%	-0.46%
Italy	-0.11%	-0.30%	-0.56%	-0.36%	-0.10%	-0.29%	-0.64%	-0.59%
Japan	-0.06%	-0.18%	-0.24%	-0.02%	-0.05%	-0.16%	-0.33%	-0.46%
Korea	-0.11%	-0.22%	0.02%	0.91%	-0.08%	-0.20%	-0.39%	-0.58%
Malaysia	-0.04%	-0.02%	0.40%	2.06%	-0.09%	-0.26%	-0.70%	-1.50%
Mexico	-0.02%	0.04%	0.75%	3.12%	-0.06%	-0.19%	-0.39%	-0.64%
Netherlands	-0.04%	-0.05%	0.27%	1.60%	-0.06%	-0.15%	-0.22%	0.02%
New Zealand	0.01%	0.11%	0.79%	3.15%	-0.02%	-0.06%	-0.03%	0.38%
Norway	-0.10%	-0.25%	-0.20%	1.10%	-0.09%	-0.32%	-0.74%	-1.11%
Philippines	-0.01%	0.21%	1.51%	5.37%	-0.06%	-0.13%	-0.07%	0.03%
Poland	-0.07%	-0.11%	0.21%	1.92%	-0.06%	-0.19%	-0.28%	-0.14%
Portugal	-0.09%	-0.26%	-0.38%	-0.33%	-0.05%	-0.13%	-0.25%	-0.08%
Russia	-0.15%	-0.47%	-0.76%	0.60%	-0.10%	-0.35%	-0.77%	-0.40%
Singapore	-0.05%	-0.06%	0.36%	2.09%	-0.07%	-0.19%	-0.28%	-0.16%
South Africa	-0.02%	0.08%	0.69%	2.76%	-0.04%	-0.09%	-0.10%	0.26%
Spain	-0.10%	-0.26%	-0.34%	0.37%	-0.08%	-0.25%	-0.47%	-0.31%
Sweden	-0.07%	-0.14%	0.07%	1.50%	-0.08%	-0.26%	-0.51%	-0.48%
Switzerland	-0.02%	0.01%	0.43%	2.08%	-0.03%	-0.09%	-0.04%	0.44%
Taiwan	-0.12%	-0.14%	0.10%	1.20%	-0.12%	-0.25%	-0.50%	-0.72%
Turkey	-0.12%	-0.12%	0.26%	2.08%	-0.12%	-0.24%	-0.43%	-0.35%
United Kingdom	-0.07%	-0.21%	-0.02%	1.60%	-0.07%	-0.28%	-0.50%	-0.16%
United States	-0.04%	-0.03%	0.37%	1.98%	-0.06%	-0.19%	-0.36%	-0.36%

Panel D. Summary Statistics of Stock Characteristics in Each Country

Country	LagRet6m	LagRet1m	MV	BM	IdioVOL (*100)	Turnover (*1000)	PctZero (*100)	Relative BA
Australia	4.24%	-0.14%	181	0.61	2.71	1.66	11.31	0.02
Austria	3.55%	0.00%	970	0.78	1.62	1.03	3.88	0.01
Belgium	3.87%	0.13%	443	0.83	1.45	0.73	4.87	0.01
Brazil	9.39%	0.71%	1,661	0.55	1.88	2.80	3.01	0.01
Canada	3.18%	-0.09%	258	0.63	2.37	1.73	6.38	0.02
Chile	5.25%	0.47%	2,681	0.56	1.14	0.68	3.34	0.01
China	10.04%	0.86%	1,742	0.49	1.73	10.72	2.43	0.00
Denmark	0.17%	-0.82%	218	0.86	1.82	1.13	13.78	0.01
Finland	3.02%	-0.01%	371	0.63	1.61	1.31	7.86	0.01
France	3.17%	-0.07%	368	0.73	1.61	1.00	5.53	0.01
Germany	2.83%	-0.14%	204	0.66	2.17	1.39	3.24	0.02
Greece	1.33%	-0.87%	334	1.22	2.14	0.98	8.74	0.01
Hong Kong	4.21%	-0.05%	370	1.00	2.21	1.31	12.93	0.01
Hungary	2.35%	-0.09%	319	0.89	1.51	0.93	8.39	0.02
Indonesia	9.42%	0.28%	1,401	0.42	2.39	1.47	17.19	0.01
Ireland	3.02%	-0.11%	353	0.73	2.30	1.20	9.79	0.02
Israel	6.61%	0.38%	385	0.72	1.58	1.24	0.29	0.01
Italy	0.40%	-0.60%	369	0.84	1.63	1.71	3.66	0.02
Japan	-0.50%	-0.36%	256	1.13	1.72	1.86	4.94	0.00
Korea	2.85%	-0.17%	189	1.00	2.63	5.30	5.19	0.00
Malaysia	7.80%	0.55%	389	0.96	1.57	0.97	19.10	0.01
Mexico	8.14%	0.84%	1,546	0.54	1.45	1.03	0.00	0.01
Netherlands	3.77%	0.16%	1,125	0.68	1.46	2.51	0.94	0.00
New Zealand	6.72%	0.78%	281	0.65	1.36	0.67	24.34	0.01
Norway	3.77%	-0.48%	360	0.74	2.13	1.30	11.83	0.01
Philippines	13.85%	1.41%	1,271	0.70	1.74	0.86	18.01	0.01
Poland	6.29%	0.28%	416	0.73	1.93	1.01	7.31	0.01
Portugal	2.28%	-0.32%	682	0.86	1.47	1.38	7.48	0.01
Russia	4.36%	-0.60%	1,973	1.03	1.88	0.31	1.16	0.01
Singapore	7.13%	0.42%	252	0.99	1.91	1.07	23.38	0.02
South Africa	5.07%	0.73%	893	0.54	1.59	1.56	7.82	0.01
Spain	0.72%	-0.56%	1,033	0.68	1.61	1.92	4.67	0.01
Sweden	4.88%	0.02%	179	0.57	1.93	1.61	10.72	0.01
Switzerland	4.51%	0.33%	621	0.64	1.42	1.00	8.77	0.01
Taiwan	4.98%	0.13%	330	0.80	1.64	4.96	7.21	0.00
Turkey	5.22%	0.24%	478	0.83	1.63	6.00	11.58	0.01
United Kingdom	3.86%	-0.08%	281	0.57	1.85	1.92	8.36	0.02
United States	1.97%	0.11%	424	0.57	2.02	5.66	0.00	0.00

Appendix Table 2. Pooled Panel Regressions Using Alternative Short Sale Measures to Predict Future Raw Returns and Seven Factor Risk-Adjusted Returns Over Different Horizons

This table provides panel regression results of using alternative shorting measures to predict future 5- , 20- , 40- , and 60-day raw return in Panel A and seven factor risk-adjusted returns in Panel B as specified in equation (2). The seven-factor model includes three global factors (global market, global momentum, and global cash-flow-to-price factors) and four local factors (local market, local size, local value, and local momentum factors). The independent variables include various shorting measures and firm controls. Variable SIR is the daily percentage of the total number of shares on loan divided by the total number of shares outstanding, averaged over the previous five days. Variable DTCR is the total number of shares on loan relative to the daily trading volume averaged over the previous five days. Variable SUPPLY is the daily percentage of the shares available for borrowing relative to the total number of shares outstanding averaged over the previous five days. The utilization ratio, UTI, is the daily percentage of shares on loan relative to the shares available for borrowing averaged over the previous five days. We construct four demand-supply shock variables, DIN, DOUT, SIN, and SOUT, based on the change in the lending fees and the change in the loan quantities over the previous five days. The demand inward shift dummy, DIN, takes a value of one for stocks that experience decreases in both lending fees and loan amounts. The demand outward shift dummy variable, DOUT, takes a value of one for stocks that experience increases in both lending fees and loan amounts. The supply inwards shift dummy, SIN, takes as value of one for stocks that experience declines in loan amounts and increases in loan fees. The supply outward shift dummy, SOUT, takes a value of one for stocks that experience declines in lending fees and increases in loan amounts. The firm controls include the natural logarithm of the market capitalization value (MV) (in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The first four shorting variables are standardized to have a mean of zero and a volatility of one, within each country–year pair. In the regression analysis, we include country and year fixed effects, and cluster standard errors by firm and year. All coefficient estimates in this table are presented in basis point unit. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Pooled Panel Regression Using Individual Shorting Measures to Predict Future Raw Returns

	Expected		Predict 5-day Return		Predict 20-day Return		Predict 40-day Return		Predict 60-day Return	
SHORT	Sign	Coefficient	Shorts	R2	Shorts	R2	Shorts	R2	Shorts	R2
SIR	-	Estimate	-1.57	0.92%	-4.81	3.40%	-8.34	6.48%	-11.75	9.41%
		[t-stats]	[-5.73]		[-4.67]		[-4.04]		[-3.80]	
DTCR	-	Estimate	-4.98	0.89%	-18.10	3.27%	-29.57	6.23%	-39.23	9.09%
		[t-stats]	[-19.52]		[-19.78]		[-16.94]		[-15.18]	
SUPPLY	+	Estimate	2.95	0.92%	8.04	3.43%	16.72	6.56%	23.06	9.54%
		[t-stats]	[10.37]		[7.44]		[7.84]		[7.22]	
UTI	-	Estimate	-5.41	0.92%	-15.33	3.41%	-23.98	6.49%	-29.47	9.42%
		[t-stats]	[-17.65]		[-13.23]		[-10.38]		[-8.40]	
DIN	+	Estimate	-1.66	0.80%	-0.56	2.98%	5.16	5.87%	2.58	8.74%
		[t-stats]	[-3.47]		[-0.47]		[2.80]		[1.07]	
DOUT	-	Estimate	1.52	0.80%	0.88	2.98%	-5.58	5.87%	-4.21	8.74%
		[t-stats]	[3.10]		[0.73]		[-2.97]		[-1.70]	
SIN	+	Estimate	-3.23	0.80%	-14.46	2.98%	-17.72	5.87%	-10.30	8.74%
		[t-stats]	[-6.44]		[-11.98]		[-9.23]		[-4.02]	
SOUT	-	Estimate	2.99	0.80%	11.74	2.98%	18.64	5.88%	14.55	8.74%
		[t-stats]	[5.95]		[9.64]		[9.65]		[5.64]	

Panel B. Pooled Panel Regression Using Individual Shorting Measures to Predict Future Seven Factor Risk-Adjusted Returns

	Expected		Predict 5-day Return		Predict 20-day Return		Predict 40-day Return		Predict 60-day Return	
SHORT	Sign	Coefficient	Shorts	R2	Shorts	R2	Shorts	R2	Shorts	R2
SIR	-	Estimate	-0.71	0.12%	-1.17	0.49%	-2.25	0.97%	-5.08	1.42%
		[t-stats]	[-2.69]		[-1.17]		[-1.12]		[-1.67]	
DTCR	-	Estimate	-3.65	0.12%	-11.31	0.49%	-19.37	0.98%	-26.11	1.44%
		[t-stats]	[-15.35]		[-13.01]		[-11.51]		[-10.41]	
Supply	+	Estimate	1.01	0.11%	2.66	0.46%	4.26	0.91%	4.14	1.35%
		[t-stats]	[3.70]		[2.55]		[2.06]		[1.32]	
UTI	-	Estimate	-3.39	0.12%	-8.86	0.49%	-13.32	0.97%	-17.89	1.43%
		[t-stats]	[-11.54]		[-7.96]		[-5.88]		[-5.15]	
DIN	+	Estimate	1.56	0.11%	2.76	0.44%	6.14	0.87%	4.58	1.29%
		[t-stats]	[3.64]		[2.57]		[3.57]		[1.98]	
DOUT	-	Estimate	-1.46	0.11%	-3.34	0.44%	-7.22	0.87%	-3.94	1.29%
		[t-stats]	[-3.31]		[-3.04]		[-4.11]		[-1.66]	
SIN	+	Estimate	1.07	0.11%	2.45	0.44%	0.57	0.87%	-0.91	1.29%
		[t-stats]	[2.35]		[2.20]		[0.32]		[-0.37]	
SOUT	-	Estimate	-0.13	0.11%	-1.70	0.44%	-0.95	0.87%	-0.17	1.29%
		[t-stats]	[-0.29]		[-1.51]		[-0.53]		[-0.07]	

Appendix Table 3. Country Long-Short Portfolios Risk Adjusted Alphas over 20-day

This table reports the risk-adjusted alphas for long-short country portfolios with 20-day investment horizon. For each day, we sort all the firms within a country into portfolios based on either DTCR or UTI. In the long portfolio, we include stocks with the highest shorting variable values and short stocks with the lowest shorting variable values. In countries with more than 100 firms in the cross-section, we form decile portfolios; in countries with fewer than 100 firms, we form quintile portfolios. We compute value-weighted risk-adjusted portfolio returns (alphas) on these long-short portfolios by regressing portfolio returns on global and local risk factors in the Hou, Karolyi, and Kho (2011) model. The days-to-cover-ratio, DTCR, is computed as the total number of shares on loan relative to the daily trading volume averaged over the previous five days. The utilization ratio, UTI, is computed as the percentage of the total number of shares on loan relative to the number of shares available for borrowing averaged over the previous five days. All coefficient estimates in this table are presented in percentage unit. Given the overlapping nature of the data, the standard errors for alphas are adjusted using the Newey-West (1987) with 20 lags. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Short Sale Measure	DTCR	UTI
Expected Sign	-	-
# Negative	32	27
# Negative significant at 5%	16	12
# Positive	4	9
# Positive significant at 5%	1	2
Global	-0.47***	-0.45***
Global without US	-0.43***	-0.33***
Australia	-0.61***	-0.63***
Austria	-0.28	0.05
Belgium	-0.63**	-0.01
Brazil	-0.59	0.29
Canada	-0.24	-0.13
Denmark	-0.32	-0.50
Finland	-1.04***	-0.52***
France	-0.34*	-0.53**
Germany	-0.94***	-0.81***
Greece	-0.41	-1.87**
Hong Kong	-0.49	-0.28
Hungary	-0.28	3.24**
Indonesia	-4.56***	-2.85*
Ireland	-0.11	0.09
Israel	-1.26***	0.27
Italy	0.05	-0.37*
Japan	-0.31*	-0.15
Korea	-0.62*	-1.01**
Malaysia	-0.60*	-0.55
Mexico	-0.53***	0.42*
Netherlands	-0.61**	-0.58*
New Zealand	-0.41	-0.11
Norway	-1.11***	-0.07
Philippines	-4.77***	1.42*
Poland	-1.28***	0.24
Portugal	0.70***	-0.70**
Russia	1.09*	-0.97*
Singapore	-0.86***	-0.97***
South Africa	-0.68***	-0.28
Spain	-0.18	-0.38
Sweden	-0.14	-0.84**
Switzerland	-0.88***	-0.28
Taiwan	0.65	-0.78***
Turkey	-1.05***	-0.42
United Kingdom	-0.06	0.37**
United States	-0.54***	-0.65***

Appendix Table 4. Short Sale Regulations in Each Country

This table reports the summary of short sale regulations of each country during our sample period. In Panel A, the column Uptick reports whether some form of price test was in place in a given country during our sample period (with YES or NO). If the price tests are not in place for the full sample period, we report the specific period when the restrictions are in place. The columns NakedBan (prohibiting naked shorting) and CCP (centralized clearing for stock lending) are defined similarly. Panel B provides the websites with documentation on short sale regulations. We collected information from exchanges or the relevant national or EU regulatory agencies to complement the two well-known published papers on short sale bans by Gruenewald, Wagner, and Weber (2010) and Beber and Pagano (2013).

Panel A. Country Short Sale Regulations

Country	Uptick	NakedBan	CCP
Australia	No	After 2001	No
Austria	No	2008-2010	Yes
Belgium	No	2008-2009, 2011-present	Yes
Brazil	No	Yes	Yes
Canada	Before 2012	After 2012	Yes
Chile	Yes	Yes	No
China	No	No	No
Denmark	No	After 2012	No
Finland	No	After 2012	No
France	No	After 2008	Yes
Germany	No	After 2008	Yes
Greece	Before 2007, 2009–present	Yes	No
Hong Kong	Yes	Yes	No
Hungary	No	After 2012	No
Indonesia	No	No	No
Ireland	No	After 2012	No
Israel	No	Yes	No
Italy	No	2008-2008, 2008-2009,2012-present	No
Japan	Yes	After 2008	Yes
Korea	Yes	After 2006	No
Malaysia	Yes	Yes	After 2007
Mexico	Yes	Yes	Yes
Netherlands	No	2008-2009, 2012-present	Yes
New Zealand	No	No	No
Norway	No	After 2008	No
Philippines	Yes	Yes	No
Poland	No	No	No
Portugal	No	After 2008	Yes
Russia	Yes	No	No
Singapore	No	Yes	Yes
South Africa	No	Yes	No
Spain	No	Yes	No
Sweden	No	After 2012	No
Switzerland	No	2008-2009	Yes
Taiwan	Yes	No	Yes
Turkey	Yes	No	No
United Kingdom	No	After 2012	Yes
United States	Before 2007, 2010–present	2008	No

Panel B. Country Short Sale Regulation Website Links

Country	Reference websites
Australia	https://www.asx.com.au/documents/media/mr_021008_asx_position_shortselling_securities.pdf
Austria	https://www.fma.gv.at/en/capital-markets/short-selling/
Belgium	http://www.fsma.be/en/OtherNews/Article/press/div/2011-08-11_shortselling.aspx; http://www.srz.com/021612_EU_Short_Selling_Update/
Brazil	http://www.b3.com.br/en_us/products-and-services/securities-lending/information.htm
Canada	https://www.osc.gov.on.ca/en/SecuritiesLaw_csa_20120302_23-312_rfc-trans-short-selling.htm
Chile	http://inter.bolsadesantiago.com/sitios/en/Regulations/StockTrading Manual.pdf
China	http://www.csrc.gov.cn/pub/csrc_en/newsfacts/release/200812/t20081229_69251.html http://english.sse.com.cn/overseasinvestors/start/trading/ http://english.sse.com.cn/aboutsse/news/newsrelease/c/3984744.shtml
Denmark	https://www.finanstilsynet.dk/en/Nyhedscenter/Sektornyt/2012/EU-forordning-erstatter-dansk-shortselling-forbud.aspx
Finland	http://www.fin-fsa.fi/en/Publications/supervision_releases/2012/Pages/63_2012.aspx
France	http://www.amf-france.org/en_US/Acteurs-et-produits/Marches-financiers-et-infrastructures/Ventes-a-decouvert/Presentation.html
Germany	http://www.bafin.de/cln_179/nn_720486/SharedDocs/Artikel/EN/Service/Meldungen/meldung__100727__anzeigepflicht__leerverkauf__en.html?__nnn=true
Greece	http://www.srz.com/082511_france_spain_italy_belgium_greece_extend_short_sale_bans/
Hong Kong	https://www.sfc.hk/web/doc/EN/research/research/RS%20Paper%2042.pdfhttps://www.hkex.com.hk/Services/Trading/Securities/Overview/Regulated-Short-Selling?sc_lang=en
Hungary	http://www.esma.europa.eu/system/files/2013-159.pdf
Indonesia	https://www.idx.co.id/en-us/regulation/trading-regulation/
Ireland	https://www.centralbank.ie/regulation/securities-markets/shortselling/Pages/Introduction.aspx
Israel	http://www.tase.co.il/Resources/PDF/RulesandRegulations/English/Trading/NR_Trading_Eng_2_161871.pdf
Italy	http://www.consob.it/mainen/press_release/comunicato_20120111.htm
Japan	https://www.jpx.co.jp/english/equities/trading/regulations/02.html/
Korea	http://www.bloomberg.com/news/articles/2013-11-13/south-korea-to-lift-short-sale-ban-on-financial-stocks-tomorrow
Malaysia	http://www.bursamalaysia.com/market/products-services/securities-borrowing-lending-sbl/sbl-circulars/
Mexico	https://www.bmv.com.mx/docs-pub/STC_MANUAL_REGLAMENTO/MANUAL_OPERATIVOu0swy170673vnc5g08o6u8t0w63dcw.PDF
Netherlands	http://essay.utwente.nl/66633/1/Klamer_MA_MB.pdf
New Zealand	https://www.nzx.com/regulation/nzx-rules-guidance/archive/participant-and-derivatives-guidance
Norway	http://www.finanstilsynet.no/en/Document-repository/News/2012/Q4/Norwegian-status-on-implementation-of-Short-Selling-Regulation-No-2362012/
Philippines	https://www.sec.gov.ph/wp-content/uploads/2015/11/Draft2-SRC-IRR.2011.pdf
Poland	https://www.knf.gov.pl/en/MARKET/Short_selling_reporting https://www.gpw.pl/short-selling
Portugal	https://www.cmvm.pt/en/Comunicados/Comunicados/Pages/20121031m.aspx https://www.cmvm.pt/en/Comunicados/Comunicados/Pages/20110816a.aspx
Russia	https://www.nationalclearingcentre.ru/catalog/021002
Singapore	https://www.mas.gov.sg/-/media/MAS/News-and-Publications/Consultation-Papers/Review-of-Securities-Market-Structure-and-Practices.pdf

South Africa	https://www.daytradetheworld.com/wiki/johannesburgstockexchange/
Spain	http://www.srz.com/021612_EU_Short_Selling_Update/
Sweden	http://fi.se/Folder-EN/Startpage/Reporting/Short-Selling/Listan/New-short-selling-regulations-as-of-November/
Switzerland	https://www.ropesgray.com/files/Publication/4d99e032-15d2-4a26-934f-17e1d321d517/Presentation/PublicationAttachment/2d2e412b-60d1-4a9e-a5e1-1b3c3a38b531/20121023_HF_IM_Alert.pdf
Taiwan	https://www.twse.com.tw/en/page/products/sbl/faq.html
Turkey	https://www.tspb.org.tr/wp-content/uploads/2015/07/Short_Selling20151.pdf
United Kingdom	http://www.fca.org.uk/firms/markets/international-markets/eu/short-selling-regulations
United States	http://www.sec.gov/news/press/2010/2010-26.htm

Appendix Table 5. Market Development, Lending Fee, Liquidity and Efficiency Dummy Variables

This table reports the dummy variables representing market development, lending fee, liquidity, and efficiency measures as used in Table 4 and Table 5. Panel A reports the summary statistics of four market development proxies: the annual GDP per capita in USD (GDPPC), the stock market capitalization relative to the country's total GDP (Stock/GDP), a corporate opacity measure, and the market development index from World Bank. The development dummy ($HIGH^{DEV}$) takes on the value of one when the country's development measure is higher than the cross-country median and zero otherwise. We report the time-series averages of the four dummy variables for each country. Panel B reports the summary statistics for the ALLFEE and CURRFEE measures as defined in equations (A1) and (A2). The low-fee dummy (LOW^{FEE}) takes on a value of one if the firm's specific fee measure is below the median of all sample firms' fee measures on the same day and zero otherwise. We report the time-series average of the daily cross-sectional median within each country for the two fee measures and the two dummy variables. Panel C reports summary statistics of high-liquidity dummy ($HIGH^{LIQ}$) variables based on three alternative firm liquidity measures: turnover, relative bid-ask spread, and the frequency of percentage zero returns from previous month. $HIGH^{LIQ}$ takes on a value of one for firms with a liquidity measure greater than the median across all firms for the same day and zero otherwise. We report the times-series average of the daily cross-sectional median by country. Panel D reports the summary statistics of the six efficiency measures. Details on the construction of the efficiency measures are provided in Internet Appendix A. The first four firm-level efficiency measures are constructed following Saffi and Sigurdsson (2011). The first measure is the cross-correlation between firm return and lagged local market return. The second measure is a variance ratio measure, as in Lo and MacKinlay (1988), which should be close to zero for high-efficiency firms. The third efficiency measure is a delay measure based on variances (in terms of R2), in the sense that the more lagged information can account for current stock returns variances, the less efficient the firm is. The fourth efficiency measure is a delay measure based on loadings on lagged and current market returns; if the coefficients of the lagged market information are large relative to those of current market information, the firm is less efficient. The last two efficiency measures are country-level earnings response coefficients, constructed following Hou et al. (2012). The fifth efficiency measure, the announcement ERC, is computed with annual cross-sectional regressions within each country, by regressing annual announcement event returns on the firm-specific unexpected earnings. The sixth efficiency measure, the annual ERC, is also estimated with annual cross-sectional regressions within each country by regressing the buy-and-hold returns over the year on the unexpected earnings over the same horizon. We report the time-series average of the daily cross-sectional median within each country for six efficiency measures. Panel E reports the time-series average of the daily median within each country for the high-efficiency dummy ($HIGH^{EFF}$), which takes a value of one when the firm's (country's) efficiency measure is higher than the cross-firm (country) median and zero otherwise.

Panel A. Market Development Dummy Variables

Country	HIGH^{DEV} using GDPPC	HIGH^{DEV} using Stock/GDP	HIGH^{DEV} using Corporate opacity	HIGH^{DEV} using Market development
Australia	1.00	1.00	1.00	1.00
Austria	1.00	0.00	0.00	0.78
Belgium	1.00	0.11	0.00	1.00
Brazil	0.00	0.00	0.00	0.00
Canada	1.00	1.00	1.00	1.00
Chile	0.00	1.00	0.00	0.00
China	0.00	0.33	0.00	0.00
Denmark	1.00	0.33	0.00	1.00
Finland	1.00	1.00	1.00	1.00
France	1.00	1.00	1.00	1.00
Germany	1.00	0.00	1.00	1.00
Greece	0.00	0.00	0.00	0.00
Hong Kong	0.33	1.00	1.00	1.00
Hungary	0.00	0.00	0.00	0.00
Indonesia	0.00	0.00	0.00	0.00
Ireland	1.00	0.00	1.00	1.00
Israel	0.11	0.56	0.00	0.44
Italy	0.67	0.00	0.00	0.67
Japan	0.89	1.00	0.00	0.89
Korea	0.00	0.89	0.00	0.00
Malaysia	0.00	1.00	1.00	0.00
Mexico	0.00	0.00	1.00	0.00
Netherlands	1.00	0.78	1.00	1.00
New Zealand	0.56	0.00	1.00	1.00
Norway	1.00	0.11	1.00	1.00
Philippines	0.00	0.56	0.00	0.00
Poland	0.00	0.00	0.00	0.00
Portugal	0.00	0.00	0.00	0.67
Russia	0.00	0.33	0.00	0.00
Singapore	1.00	1.00	1.00	1.00
South Africa	0.00	1.00	1.00	1.00
Spain	0.44	0.00	1.00	1.00
Sweden	1.00	1.00	1.00	1.00
Switzerland	1.00	1.00	1.00	1.00
Taiwan	0.00	1.00	0.00	0.00
Turkey	0.00	0.00	0.00	0.00
United Kingdom	1.00	1.00	1.00	1.00
United States	1.00	1.00	1.00	1.00

Panel B. Lending Fee Measures and Dummy Variables[2]

Country	ALLFEE	LOW^{FEE} using ALLFEE	CURRFEE	LOW^{FEE} using CURRFEE
Australia	1.05	0.01	0.77	0.12
Austria	0.50	0.49	0.66	0.16
Belgium	0.76	0.12	0.79	0.12
Brazil	3.55	0.00	3.52	0.00
Canada	0.45	0.48	0.57	0.24
Denmark	1.38	0.01	1.38	0.01
Finland	1.06	0.10	1.19	0.07
France	0.78	0.19	0.77	0.10
Germany	0.66	0.39	0.82	0.15
Greece	4.15	0.00	4.17	0.03
Hong Kong	1.35	0.00	1.30	0.00
Hungary	1.80	0.00		
Indonesia	2.39	0.07	3.12	0.00
Ireland	1.26	0.16	1.53	0.08
Israel	3.68	0.00	3.49	0.01
Italy	1.59	0.00	1.69	0.00
Japan	0.70	0.47	0.77	0.30
Korea	3.06	0.00	2.89	0.00
Malaysia	5.01	0.00	4.82	0.00
Mexico	1.69	0.12	1.83	0.12
Netherlands	0.37	0.69	0.50	0.29
New Zealand	1.77	0.00	1.86	0.00
Norway	1.66	0.00	1.72	0.00
Philippines	2.78	0.00		
Poland	3.37	0.01	3.67	0.00
Portugal	1.26	0.02	1.32	0.03
Russia	2.32	0.06	2.49	0.09
Singapore	1.83	0.00	1.47	0.00
South Africa	0.44	0.45	0.47	0.37
Spain	2.03	0.00	1.94	0.00
Sweden	1.33	0.00	1.41	0.03
Switzerland	0.48	0.40	0.59	0.29
Taiwan	2.71	0.03	2.62	0.04
Turkey	3.98	0.00	4.10	0.00
United Kingdom	0.51	0.34	0.90	0.02
United States	0.11	1.00	0.13	1.00

[2] China and Chile are missing from the table because they had insufficient data on lending fees in IHS Markit database.

Panel C. Liquidity Dummy Variables

Country	$HIGH^{LIQ}$ using Turnover	$HIGH^{LIQ}$ using BASpread	$HIGH^{LIQ}$ using PctZero
Australia	0.00	0.00	0.00
Austria	0.00	0.70	0.54
Belgium	0.00	0.00	0.68
Brazil	0.70	0.35	0.61
Canada	0.01	0.00	0.25
Chile	0.00	0.04	0.61
China	0.92	0.99	0.75
Denmark	0.00	0.00	0.00
Finland	0.00	0.01	0.09
France	0.00	0.01	0.59
Germany	0.00	0.00	0.72
Greece	0.00	0.03	0.13
Hong Kong	0.00	0.00	0.00
Hungary	0.01	0.00	0.19
Indonesia	0.01	0.00	0.00
Ireland	0.01	0.00	0.38
Israel	0.00	0.86	0.95
Italy	0.06	0.28	0.83
Japan	0.07	1.00	0.18
Korea	1.00	0.99	0.33
Malaysia	0.00	0.00	0.00
Mexico	0.00	0.26	1.00
Netherlands	0.44	1.00	0.97
New Zealand	0.00	0.00	0.00
Norway	0.09	0.00	0.00
Philippines	0.00	0.36	0.05
Poland	0.00	0.14	0.21
Portugal	0.04	0.58	0.42
Russia	0.00	0.79	0.88
Singapore	0.00	0.00	0.00
South Africa	0.00	0.12	0.19
Spain	0.24	0.45	0.71
Sweden	0.02	0.00	0.02
Switzerland	0.00	0.10	0.01
Taiwan	0.95	1.00	0.13
Turkey	0.98	0.60	0.00
United Kingdom	0.04	0.00	0.09
United States	1.00	1.00	1.00

Panel D. Efficiency Measures

Country	Cross correlation	Variance ratio	Delay_R2	Delay_beta	Announcement ERC	Annual ERC
Australia	0.05	0.33	0.29	0.52	0.21	0.04
Austria	-0.01	0.35	0.22	0.50	0.04	0.07
Belgium	-0.01	0.31	0.23	0.54	0.40	0.04
Brazil	0.01	0.29	0.14	0.41	0.27	0.03
Canada	0.00	0.30	0.23	0.50	0.15	0.03
Chile	-0.04	0.28	0.12	0.39	0.21	-0.01
China	-0.05	0.27	0.12	0.38	0.05	0.00
Denmark	0.03	0.30	0.23	0.54	0.14	0.04
Finland	-0.01	0.29	0.17	0.48	0.22	0.02
France	0.05	0.31	0.25	0.50	0.15	0.04
Germany	-0.02	0.31	0.30	0.53	0.15	0.07
Greece	0.08	0.33	0.20	0.46	0.20	0.09
Hong Kong	0.04	0.33	0.32	0.54	0.29	0.02
Hungary	0.00	0.25	0.13	0.42	1.25	0.12
Indonesia	-0.05	0.34	0.27	0.53	0.24	0.03
Ireland	0.09	0.32	0.35	0.68	0.35	0.08
Israel	0.01	0.29	0.19	0.48	-0.04	-0.01
Italy	0.02	0.30	0.16	0.45	0.33	0.08
Japan	-0.06	0.33	0.23	0.48	0.19	0.03
Korea	-0.02	0.33	0.25	0.50	0.14	0.04
Malaysia	0.11	0.32	0.15	0.43	0.44	0.04
Mexico	-0.01	0.30	0.16	0.46	0.28	0.04
Netherlands	-0.05	0.31	0.14	0.45	0.24	0.02
New Zealand	-0.03	0.30	0.14	0.42	-0.16	0.04
Norway	-0.09	0.31	0.20	0.50	0.49	0.07
Philippines	-0.02	0.33	0.18	0.44	0.20	0.02
Poland	0.02	0.29	0.15	0.42	0.25	0.03
Portugal	0.05	0.31	0.17	0.43	0.09	0.02
Russia	-0.06	0.35	0.21	0.46	-0.06	0.16
Singapore	0.17	0.32	0.26	0.50	0.18	0.02
South Africa	-0.09	0.30	0.13	0.40	0.10	0.04
Spain	0.00	0.32	0.16	0.47	0.57	0.10
Sweden	-0.12	0.29	0.17	0.45	0.12	0.05
Switzerland	0.05	0.31	0.22	0.48	0.08	0.01
Taiwan	0.07	0.31	0.17	0.43	0.09	0.01
Turkey	-0.04	0.27	0.09	0.36	0.06	0.04
United Kingdom	0.02	0.34	0.39	0.53	0.25	0.05
United States	-0.07	0.30	0.24	0.50	0.21	0.03

Panel E. Efficiency Dummy Variables

	$HIGH^{EFF}$ using Cross correlation	$HIGH^{EFF}$ using Variance ratio	$HIGH^{EFF}$ using Delay_R2	$HIGH^{EFF}$ using Delay_beta	$HIGH^{EFF}$ using Announcement ERC	$HIGH^{EFF}$ using Annual ERC
Australia	0.42	0.48	0.42	0.43	0.56	0.56
Austria	0.48	0.45	0.51	0.48	0.22	0.44
Belgium	0.48	0.51	0.52	0.40	0.56	0.44
Brazil	0.47	0.54	0.71	0.65	0.67	0.22
Canada	0.48	0.51	0.50	0.48	0.44	0.67
Chile	0.48	0.55	0.70	0.70	0.44	0.33
China	0.56	0.57	0.75	0.75	0.11	0.11
Denmark	0.44	0.52	0.50	0.42	0.33	0.56
Finland	0.50	0.53	0.64	0.50	0.33	0.44
France	0.42	0.51	0.47	0.47	0.44	0.67
Germany	0.51	0.50	0.40	0.43	0.56	0.89
Greece	0.40	0.49	0.56	0.57	0.56	0.67
Hong Kong	0.44	0.48	0.37	0.40	0.67	0.22
Hungary	0.45	0.55	0.70	0.64	0.67	0.67
Indonesia	0.56	0.46	0.45	0.41	0.56	0.44
Ireland	0.38	0.50	0.32	0.22	0.56	0.22
Israel	0.47	0.52	0.57	0.53	0.44	0.33
Italy	0.45	0.51	0.65	0.57	0.67	0.89
Japan	0.56	0.48	0.50	0.50	0.56	0.56
Korea	0.51	0.47	0.47	0.47	0.44	0.78
Malaysia	0.35	0.49	0.66	0.62	0.78	0.78
Mexico	0.51	0.51	0.63	0.56	0.44	0.44
Netherlands	0.55	0.51	0.67	0.56	0.67	0.44
New Zealand	0.49	0.53	0.64	0.59	0.22	0.22
Norway	0.58	0.50	0.54	0.46	0.78	0.89
Philippines	0.50	0.48	0.58	0.57	0.44	0.22
Poland	0.45	0.53	0.70	0.64	0.44	0.44
Portugal	0.41	0.49	0.63	0.61	0.33	0.44
Russia	0.55	0.46	0.56	0.55	0.33	0.67
Singapore	0.28	0.49	0.46	0.49	0.56	0.44
South Africa	0.60	0.52	0.71	0.66	0.56	0.44
Spain	0.46	0.48	0.61	0.53	0.56	0.67
Sweden	0.64	0.54	0.60	0.56	0.56	0.89
Switzerland	0.43	0.51	0.51	0.51	0.22	0.11
Taiwan	0.39	0.51	0.64	0.65	0.22	0.00
Turkey	0.54	0.56	0.85	0.80	0.56	0.44
United Kingdom	0.46	0.46	0.33	0.43	0.89	0.78
United States	0.57	0.51	0.47	0.47	0.67	0.56

Appendix Table 6. Fee and Efficiency Measures' Joint Impacts on Short's Predictive Power

This table reports the impact of fee and efficiency measures on short's predictive power, as specified in the following equation.

$$r_{i,t+1,t+n} = a + \left(b_0 + b_1 LOW_{i,t}^{FEE} + b_2 HIGH_{i,t}^{EFF}\right) SHORT_{i,t-5,t-1} + c'Control_{i,t-1} + \varepsilon_{i,t+1,t+n}.$$

We report the parameter estimates on the shorting variable and interactions with the LOW^{FEE} and $HIGH^{EFF}$ dummy variables. The low-fee dummy (LOW^{FEE}) is based on the ALLFEE measure and the CURRFEE measure. It takes a value of one if the firm's fee measure is below the median of all sample firms' fee measures for the same day and zero otherwise. The high-efficiency ($HIGH^{EFF}$) dummy is based on the value of firm-level cross-correlation, variance ratio, delay_R2, delay_beta, and country-level efficiency measures, such as announcement ERC and annual ERC. It takes on the value of one when the firm is more efficient than the median across all firms for the same day and zero otherwise. To save space and given the high correlation between ALLFEE and CURRFEE, we present only LOW^{FEE}, constructed from ALLFEE. For the panel regression, the dependent variables are either 20-day or 60-day risk-adjusted returns (see Hou, Karolyi, and Kho, 2011). We include two shorting measures as independent variables: DTCR (the total number of shares on loan relative to the daily trading volume averaged over the previous five days) and UTI (the daily percentage of the total number of shares on loan over the total number of shares available for borrowing averaged over the previous five days). Firm controls include: the natural logarithm of the market capitalization value (MV in millions of USD), book-to-market ratio (BM) from the fiscal year-end, previous 6-month cumulative returns with 1 month skipped (LagRet6m), cumulative returns over the previous month (LagRet1m), idiosyncratic volatility estimated using the HKK model (IdioVOL), average daily turnover from the previous calendar month (Turnover), and the percentage of zero return days (PctZeros) based on the previous calendar month. The shorting variables are standardized within each country-year. For the pooled regressions using the first four firm-level efficiency measures, we include both country and year fixed effects. For the pooled regressions using the last two country-level efficiency measures, we include year fixed effects. The standard errors are double clustered by firm and year. All coefficient estimates in this table are presented in basis point units. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

			20-day Risk adjusted Returns		60-day Risk adjusted Returns	
Cost	Efficiency	Parameter	DTCR	UTI	DTCR	UTI
ALLFEE	Cross-correlation	b_0(Short)	-17.85***	-17.23***	-35.22***	-35.56***
		b_1(Short*LOW^{FEE})	0.80	16.23***	-3.97	36.19***
		b_2(Short*$HIGH^{EFF}$)	8.08***	4.52**	9.90**	3.44
ALLFEE	Variance ratio	b_0(Short)	-13.14***	-14.33***	-27.49***	-32.18***
		b_1(Short*LOW^{FEE})	1.38	16.60***	-3.24	36.49***
		b_2(Short*$HIGH^{EFF}$)	-1.26	-1.11	-5.22	-3.02
ALLFEE	Delay_R2	b_0(Short)	-18.07***	-20.59***	-32.96***	-35.93***
		b_1(Short*LOW^{FEE})	1.12	15.80***	-3.35	36.26***
		b_2(Short*$HIGH^{EFF}$)	7.18***	9.97***	4.34	3.50
ALLFEE	Delay_beta	b_0(Short)	-17.12***	-19.69***	-33.06***	-41.15***
		b_1(Short*LOW^{FEE})	1.26	16.11***	-3.31	35.97***
		b_2(Short*$HIGH^{EFF}$)	5.80***	8.94***	4.72	12.97*
ALLFEE	Announcement ERC	b_0(Short)	-17.47***	-18.01***	-39.16***	-48.87***
		b_1(Short*LOW^{FEE})	1.08	15.97***	-3.93	33.99***
		b_2(Short*$HIGH^{EFF}$)	6.50***	5.53**	15.7***	26.67***
ALLFEE	Annual ERC	b_0(Short)	-19.62***	-20.18***	-41.71***	-48.32***
		b_1(Short*LOW^{FEE})	1.51	16.02***	-2.74	35.54***
		b_2(Short*$HIGH^{EFF}$)	10.79***	9.93***	20.82***	26.55***

Appendix Table 7. List of Eleven Policies and Regulations Related to Short selling at Firm Level

#	Policies and Regulations	Limitations
1	**Implementation or introduction of short selling:** Less developed or developing countries, such as Vietnam, Malaysia and China recently allowed short selling on their exchanges. The reason for the market liberalization was that regulators after careful consideration regarded the stock market sufficiently developed, where at least a group of hand-selected stocks deemed to be resilient to price manipulation. Since the opening and relaxing short sale restrictions can hardly be seen as exogenous policy decision, empirical studies on the 2010 Chinese pilot project, allowing margin long and margin shorts, provide conflicting insights on short sale benefits. Recent papers document that the "benefits" of short selling were hard to measure as the shortable stocks were/are different from the non-shortable stocks, because shortable stocks are those with greater trading volume and large market capitalization. Even in the more established HKex, regulators control the shortable stocks and regularly review the list, to ensure that stocks on the list are not susceptible to manipulation. Not only there is the issue that only few countries implemented short selling for the first time during our sample period, the data coverage is extremely limited from IHS Markit securities lending database for those countries. More importantly, in the absence of shorting before the introduction, we cannot meaningfully compare the short sellers' information before and after.	Data limitation does not allow meaningful examination
2	**Introduction of Futures/Options:** Short sale restrictions could be alleviated by the introduction of individual stock futures and options which could be an exogenous shock if the exchange is would not be financially invested in it these instruments. Exchanges choose to make market for option and futures when there is sufficient demand for the derivatives and the underlying security. Singapore has attempted the introduction of individual stock options for major stocks several times. The projects were cancelled because of the lack of demand. In these smaller markets, financial institutions' ad-hoc warrant programs support speculative or leveraged trading, or online contract for difference programs. In a recent paper Gagnon (2018) shows that the individual stock future listing in financial stocks surged during and after the 2008 crisis, showing clear market response to demand. While the data from OneChicago used by Gagnon (2018) could be considered to examine the effect of a shock to short sale constraints, again the setting is limited to the USA and does not allow us to showcase our international data. Our extensive research on margin rules, derivatives, bid-ask spread etc. could not reveal any systematic shift with available data that would be suitable exogenous shock across a number of countries during our sample period.	Derivative listing is endogenous with stock performance
3	**Cross listings:** Cross listings may be considered as an external shock to short sale constraints. Gagnon and Wittmer (2014) show that cross-listed stocks with unevenly distributed ownership have more binding short-sale constraints. The authors find that stocks trade at a premium in the market where long sellers are relatively scarcer, which reduces the speed at which prices adjust to bad news. The authors used tick level data around the financial crisis. This investigation would require large number of cross listings outside the USA with good quality institutional data to control for IO trading and ownership across the countries.	Data availability is limited
4	**Convertible bonds:** The issuance of convertible bonds is an interesting corporate event, where so-called arbitrage shorting demand is expected to increase, potentially diluting the information shorts. This events could be exogenous demand shocks, but the sample would be restricted again primarily US firms because of data availability. Choi et al. (2010) report that there is also some endogeneity issue with stock returns as they find that the capital providers, buyers of the convertible bonds, shy away in adverse market conditions.	Data is limited and the shocks are endogenous

5	**Seasoned Equity Offering (SEO):**[3] SEOs could be considered as a negative shock on short selling, with a ban on using new shares in SEO for covering outstanding shorts, restricts speculative short selling. Very likely the reason for this prohibition was that manipulated short sales a push down price below fundamentals which is consistent with Henry and Koski's (2010) findings. There was a dramatic increase in the size of seasoned equity offering (SEO) discounts during the 1990s. For example, Corwin (2003) reports an average discount of 1.15% for seasoned equity offers from 1980 to 1989 and an average discount of 2.92% from 1990 to 1998.	The events are endogenous, CEOs often time secondary equity issuance..
6	**Margin regulations on short selling:** There have been a number of changes in regulations related to margin financing. While the Chinese regulatory changes are well known, the margin requirements also changed in some countries, most of these changes were generic and thus, we could not document effectively changes in margin requirements to support a cross-country empirical study.	Data availability is limited
7	**Stock splits:** These corporate events have no effect on short sale constraints.	Not suitable
8	**Stock delisting:** After SOX and in recent years more and more stocks delist to reduce regulatory burden. The move to OTC presents a clear shock to short selling but again, there is issue with data availability. After delisting, we do not have return data and unable to compare the return predictability of short sellers before and after delisting.	No Data
9	**Securities lending market change, Shift in Supply:** There have been several efforts to introduce centralized securities lending market in both developed and developing countries (SecFinex in Europe and US, for example as a private company). While we made every attempt to collect information on the existence of centralized securities lending markets, the information on the usage or activity of these centralized or regulated securities lending programs is extremely limited which was motivation for Huszar and Porras Prado (2019)'s Japanese study. The authors argued that by examining the coexistence of OTC and centralized securities lending market in Japan, we can gain useful inference for other markets where we do not have much information about the securities lending market activities at the stock level.	Data availability is limited

[3] Short Selling in Connection with a Public Offering: Amendments to Rule 105 of Regulation M, https://www.sec.gov/divisions/marketreg/tmcompliance/regmrule105-secg.htm