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Can Shorts Predict Returns? A Global Perspective

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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 nonprohibitive short sale regulations and for stocks with relatively low liquidity, high shorting fees, and low price efficiency. (*JEL* G14, G12)

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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 resultant 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 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 the 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

[1] Desai et al. (2002), Asquith, Pathak, and Ritter (2005), and Boehmer, Huszár, and Jordan (2010) provide additional evidence.

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 5 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 gross domestic product [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 provides 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 applied toward 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, similar arguments also can be made through the efficiency perspective. For instance, if the market were

[2] It is challenging to test the theory of the DV model in an empirical setting, because the identification of countries and/or firms with "sufficiently high" and "sufficiently low" shorting cost, efficiency, liquidity, and/or development may be subjective. 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.

highly efficient and prices reflected all information instantaneously, it would be difficult 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 the predictive power of shorts 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, the predictive power of short selling 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), have found 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 U.S.-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 a 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 the degree of information efficiency. Combining with previous literature, we make the following recommendation for policy makers: lowering the shorting cost generally improves price efficiency, but regulators need to be aware that a close-to-zero shorting cost might encourage large-scale uninformed short selling and might reduce overall price efficiency.

1. Data

1.1 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 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 data sets.[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 Internet Appendix A, and details on data coverage statistics are reported in Internet Appendix Table 1, panel A.

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 6 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.

1.2 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

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[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.

[5] Our sample includes all the countries for which Markit provides at least 1 year of coverage for at least one firm at a given time along 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.

over the previous 5 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 shares on loan divided by the total number of shares outstanding each day, and then average it over the previous 5 days. This procedure is consistent with those outlined in the literature, such as by 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 5 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 5 days). Sufficient lending supply is necessary to facilitate short selling and price discovery, as discussed in Boehmer and Wu (2013), while a 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 information discovery process would be slow, as discussed in Porras Prado, Saffi, and Sturgess (2016). In this case, low supply might also imply negative news about the firm, and it would be more profitable for informed investors to sell short. In summary, between firms with relatively high and low (nonzero) short supply, stocks with lower shorting supply are likely to have lower future returns, if short sellers can identify overvalued stocks.

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). Their measure gauges shares shorted over one day divided by daily trading volumes and 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.

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 5 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 5 days, and then compare them with the previous non-overlapping 5-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 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.

Table 1 reports 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 data sets 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

[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 days t-5 to t-1 and compare it with the average lending supply for the same stock over days t-10 to t-6.

Table 1
Summary statistics

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

Summary statistics This table provides summary statistics for 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 5 days. Variable DTCR is the total number of shares on loan relative to the daily trading volume, averaged over the previous 5 days. Variable SUPPLY is the daily percentage of shares available for borrowing relative to the total number of shares outstanding, averaged over the previous 5 days. The utilization ratio UTI is the daily percentage of shares on loan relative to the shares available for borrowing, averaged over the previous 5 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 5 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.

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 over-the-counter (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]

1.3 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 used in Hou, Karolyi, and Kho (2011, HKK, hereafter). It includes both global and country-specific

[9] Internet 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 to one each day for each firm.

market factors (*MKT*), momentum factors (*MOM*),[10] and cash-flow-to-price factors (*CP*). The advantages of the HKK factor model is its incorporation of information from both local and global markets and its inclusion of 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:

$$\begin{aligned}E(R_{it})-r_f=&b^{global}_{i,MKT}E\left(MKT^{global}_t\right)+b^{local}_{i,MKT}E\left(MKT^{local}_t\right)\\&+b^{global}_{i,MOM}E\left(MOM^{global}_t\right)\\&+b^{local}_{i,MOM}E\left(MOM^{local}_t\right)+b^{global}_{i,CP}E(CP^{global}_t)+b^{local}_{i,CP}E(CP^{local}_t).\end{aligned} \tag{1}$$

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 Internet Appendix A for details on the factor construction). Next, we compute betas for each firm each month, using the previous 3 months of daily data, requiring at least 36 nonmissing daily observations to estimate the historical betas. The risk-adjusted returns are calculated as the difference between the raw returns and the model-implied returns for the corresponding period, which are products of the betas estimated from the previous 3 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 1-month returns (*LagRet1m*), and the past 6-month cumulative returns (*LagRet6m*) with 1 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 Internet Appendix Table 1. The magnitudes and patterns are consistent with those in the literature.

10 The momentum factor is calculated following Jegadeesh and Titman's (1993) 6-1-6 strategy.

11 We present the summary statistics of the raw returns and the HKK-adjusted returns in Internet 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 Internet 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).

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

2.1 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 days $t-5$ 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 **??**. 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 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.

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 Internet Appendix Table 2. Results using raw returns have larger and more significant coefficients, as well as higher explanatory power. The predictive information contained in some of the shorting variables for raw returns could be related to information 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 the HKK risk adjustment.

Table 2
Pooled panel regression using alternative short-sale measures to predict future risk-adjusted returns over different horizons

SHORT	Expected sign	Coefficient	Predict 5-day return Shorts	R^2	Predict 20-day return Shorts	R^2	Predict 40-day return Shorts	R^2	Predict 60-day return Shorts	R^2
SIR	-	Estimate	−0.53	0.20%	−1.30	0.44%	−4.06	0.57%	−9.53	0.69%
		[t-stat]	[−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-stat]	[−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-stat]	[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-stat]	[−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-stat]	[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−stat]	[−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-stat]	[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-stat]	[−0.91]		[0.11]		[1.53]		[1.79]	

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-level 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 5 days. Variable DTCR is the total number of shares on loan relative to the daily trading volume, averaged over the previous 5 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 5 days. The utilization ratio, UTI, is daily percentage of shares on loan relative to the shares available for borrowing, averaged over the previous 5 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 5 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 points.

Table 2 presents the results for predicting returns over the next 5, 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-basis-point (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; otherwise, the institutions would not be willing to lend their shares. Thus, a higher *SUPPLY* is expected to predict positive returns, and this 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 inward (*DIN*=1) and supply shifts inward (*SIN*=1), the expected signs for future returns are positive. The coefficients for *DIN* and *SIN* are 2.77 and 1.38 bps, respectively, consistent with Cohen, Diether, and Malloy'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 for *DOUT* is −3.68 bps, with a statistically significant t-statistic of −3.40, while the coefficient for *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^2's 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.

Three key observations can be extracted from the results in Table 2. 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]

2.2 The predictive power of short selling by country

In Section 3.1, we establish the overall predictive power of short selling variables in the global capital market by requiring that all the coefficients in

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[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 reestimate 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 and are available on request.

Equation (2) to be the same across the countries. In this section, we reestimate Equation (2) for each country to examine whether there are significant cross-country differences in the predictive power of short selling 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.

Table 3 reports the results. 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 (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 mainly driven by the data, because there are only a few nonzero *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 *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-side 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.

3. Examining Cross-Country and Cross-Firm Variation in the Return Predictability of Short Sales

In previous sections, we document large cross-country variations in the predictive power of short selling for future returns. In this section, we investigate

[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.

[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 Internet Appendix Table 3. The standard errors for alphas are adjusted using the Newey and 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.

Table 3
Predicting future risk-adjusted 20- and 60-day returns: Panel regression within each country

	Predicting future 20-day returns		Predicting future 60-day returns	
Short-sale measure	DTCR	UTI	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***

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 5 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 5 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 points. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

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- 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.

3.1 Cross-country variations in short-sale regulations and country developments

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 et al. (2013), who show that short-sale regulations following the global financial crisis 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 the 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. Some 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 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:

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

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.

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18 To save space, we present summary statistics for the regulation variables in Internet Appendix Table 4. We collect information from exchanges or regulatory agencies to complement the results in Grunewald, Wagner, and Weber (2010) and Beber and Pagano (2013). For instance, the United States lifted the uptick rule in 2007 and reintroduced 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), have shown 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 to a subset of stocks only. These results are available on request.

Table 4
Short regulations, market development measures, and their impacts on the predictive power of shorts

A. The impact of short sale regulations on the predictive power of shorts

			20-day risk-adjusted returns		60-day risk-adjusted returns	
Short-sale measures			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***

B. The impact of market development measures on the predictive power of shorts

			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***

This table reports the pooled panel regression results using country-level variables. Dependent variables are either 20- 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 5 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 5 days). Panel A reports 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. Panel B reports 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), relative stock market capitalization (Stock/GDP), or opacity and market development indexes 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 a year fixed effect, and standard errors are clustered by firm and year. All coefficient estimates in this table are presented in basis points. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

Table 4, panel A, presents the regression results for Equation (3). The left-hand-side 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 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

[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. Huszar and Porras Prado (2019) provide a detailed discussion of this issue.

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 indexes to measure market development from the above perspectives, and we compute the averages of the six individual indexes 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 the predictive power of shorts, 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:

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

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 for *DTCR* and *UTI* are always significant and negative in both poorly and highly developed countries, indicating that the two measures

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.

22 In addition to using the median to separate the countries and/or firms into two groups, we also consider an alternative approach by using the 10th and 90th percentiles as cutoffs and separate the countries and/or firms into three groups. The results using the three groups (low, middle, and 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 Internet 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.

have robust predictive power for future returns. However, of the 16 cases, the coefficients for 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.

3.2 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 the predictive power of shorts for future returns. We first provide predictions from previous studies and introduce the measures, and then we present the empirical results.

High fees are driven by either high shorting demand in the presence of high frictions or 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, Gârleanu, and Pedersen 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 (nonbinding) 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, 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 difficult 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 5 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 5 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 (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. The larger coefficients for the lagged market information, compared to those of

24 We thank our referees for suggesting this argument.

25 To save space, we provide details on the fee measures and efficiency measures in Internet Appendix A. Summary statistics on fees, liquidity measures, and efficiency measures are reported in Internet Appendix Table 5, panels B to E.

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 for fees, liquidity, and efficiency, we estimate the following panel regressions with these interactions:

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

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

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

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 bps, and is highly

Table 5
Short-selling fee measures, liquidity measures, and efficiency measures and their impacts on the predictive power of shorts

A. The impact of short sale regulations on the predictive power of shorts

			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

B. The impact of market development measures on the predictive power of shorts

			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***

(*Continued*)

significant. For low-fee firms, the coefficient turns slightly positive at 1.58 bps and is insignificant. The difference of 16.44 bps 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.

Table 5, panel B, reports the estimation results for Equation (6). When we use turnover as the liquidity proxy, the *DTCR* coefficient is −16.63 bps for the low-liquidity firms. For high-liquidity firms, the coefficient becomes $-16.63+9.14=-7.49$ bps. 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 bps 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 days. 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
Continued

C. The impact of efficiency measures on the predictive power of shorts

			20-day risk-adjusted returns		60-day risk-adjusted returns	
Short-sale measures			DTCR	UTI	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_R^2	$HIGH^{EFF}=0$	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

This table reports the market development measures, short-selling fee measures, liquidity measures and efficiency measures and their impacts on the predictive power of shorts 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_R^2, 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- 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 5 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 5 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 a year fixed effects with standard errors double clustered by the firm and year. All coefficient estimates in this table are presented in basis points. $*p<.1$; $**p<.05$; $***p<.01$.

Table 5, panel C, reports results for efficiency measures. Taking the cross-correlation measure as an example, for *DTCR* over 20 days, we find that the coefficient for low efficiency firms is −18.12 bps, the difference in coefficients between high- and low-efficiency firms is 8.28 bps, and the coefficient for high efficiency firms is −18.12+8.28=−9.84 bps. 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 nonprohibitive short-sale regulations and for stocks with relatively high shorting fees, low liquidity, and low price efficiency.

4. Further Discussion

4.1 Exogenous shocks on fees and efficiencies and implications for 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 the predictive power of shorts 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 affecting the capital flows and returns on these stocks. According to Cremers, Ferreira, Matos, and Starks (2016), the MSCI indexes are the most followed equity indexes 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. 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 the predictive power of shorts for future returns.[27] From MSCI Inc., we obtain 25 quarterly snapshots

[26] In Internet Appendix Table 6, we include both LOW^{FEE} and HIGH^{EFF} and examine how they jointly affect the predictive power of shorts 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.

[27] We check for other regulations and/or events that could 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 Internet 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 the previous studies in

Table 6
Exogenous shocks on fees and efficiency measures

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_R^2	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_R^2	0.08	0.12	0.04	4.01	0.07	0.11	0.04	3.45	0.09	0.13	0.04	2.04

B. The impact of inclusions on the predictive power of shorts 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***

C. The impact of exclusions on the predictive power of shorts 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**

This table reports the impact of MSCI index inclusions and exclusions on shorting fees, stock efficiencies and the predictive power of shorts, 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 5 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 5 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. Panel C repeats the above exercises for firms excluded from the MSCI ACWI, as specified in Equation (8). $*p<.1$; $**p<.05$; $***p<.01$.

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

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Gagnon (2018), Gagnon and Witmer (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.

choose the before event window to be from day −250 to day −1, and the after event window to be from day 0 to day 250. The 1-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, 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 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 the predictive power of shorts 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 predictive power of shorts for returns, we estimate the following panel regression:

$$r_{i,t+1,t+n} = a_0 + a_1 AFTER_{it} + (b_0 + b_1 AFTER_{it}) SHORT_{i,t-5,t-1} + c' Controls_{i,t-1} + \varepsilon_{i,t+1,t+n} \tag{8}$$

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 the predictive power of shorts for returns for the event firm after the event. Previous studies, such as Raddatz, Schmukler, and Williams (2017), have shown 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.

Table 6, panel B, presents the estimates of Equation (8) for HKK-adjusted 20-day returns for index inclusions, for all markets, developed markets and emerging markets. We highlight four interesting findings. First, the coefficients for the after-event dummy are always positive and significant, indicating that index inclusions on average are associated with higher future returns. Second, the coefficients for institutional flow are also always positive and significant, showing that higher institutional flows are associated with higher returns. Third, the coefficients for 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 for 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 for 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 markets normally have high shorting cost, and index inclusions effectively lower the cost of shorting, which attracts informed short sellers to participate and improves the predictive power of shorts 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 shorts. 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 the predictive power of shorts is higher for firms with higher fees.

We report the estimates for index exclusions in Table 6, panel C. The coefficients for 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 for shorting are all negative and mostly significant, supporting the shorts predict returns negatively in general. Finally, the coefficients for 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 to 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 the predictive power of shorts. 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 the predictive power of shorts 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, the return predictability for shorting 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.

4.2 Examining nonlinearity in the return predictability of short sales

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 reexamine 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:

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

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 fee, liquidity, and efficiency measures.

Table 7 reports these relevant nonlinearity results. 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 the predictive power for shorting 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 for high fees are negative and significant, while all coefficients for low fees are positive, with half of them being significant. A clear pattern is revealed: high fees increase the predictive power of shorts, while low fees reduce it, a finding that 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

Table 7
Market development measures, short-selling fee measures, liquidity measures, and efficiency measures and their impacts on the predictive power of shorts with two tail cutoffs

A. The impact of market development measures on the predictive power of shorts 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

B. The impact of short-selling fee measures on the predictive power of shorts 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***

C. The impact of liquidity measures on the predictive power of shorts with two tail cutoffs

		20-day risk-adjusted returns		60-day risk-adjusted returns	
Short-sale measure		DTCR	UTI	DTCR	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*

(*Continued*)

that majority of the coefficients for 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; thus, short sellers may abstain from trading these stocks. This leads to weaker predictive power of shorts for returns. Finally, for the efficiency measures in panel D, we obtain

Table 7
Continued

D. The impacts of efficiency measures on the predictive power of shorts with two tail cutoffs

		20-day risk-adjusted returns		60-day risk-adjusted returns	
Short-sale measure		DTCR	UTI	DTCR	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_R^2	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

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 panels B to D, we investigate firm-level fee, liquidity, and efficiency measures, respectively. For the panel regression, the dependent variables are 20- 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 5 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 5 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. *$p<.1$; **$p<.05$; ***$p<.01$.

several mixed signs. In most cases, high efficiency weakens the predictive power of shorts, while low efficiency improves it, which is in line with the results in Section 4.2.

5. 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 also in conjunction with other determinants of price discovery in security markets.

References

Aggarwal, R., P. A. C. Saffi, and J. Sturgess. 2015. The role of institutional investors in voting: Evidence from the securities lending market. *Journal of Finance* 70:2309–46.

Asquith, P., P. A. Pathak, and J. R. Ritter. 2005. Short interest, institutional ownership, and stock returns. *Journal of Financial Economics* 78:243–76.

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

Beber, A., and M. Pagano. 2013. Short selling bans around the world: Evidence from the 2007–09 crisis. Journal of Finance 68:343–81.

Bekaert, G., R. J. Hodrick, and X. Zhang. 2009. International stock return comovements. *Journal of Finance* 64:2591–626.

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

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

———. 2013. Shackling short sellers: The 2008 shorting ban. *Review of Financial Studies* 26:1363–400.

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

Bris, A., W. N. Goetzmann, and N. Zhu. 2007. Efficiency and the bear: Short sales and markets around the world. *Journal of Finance* 62:1029–79.

Chague, F., R. De-Losso, A. De Genaro, and B. Giovannetti. 2017. Well-connected short sellers pay lower loan fees: A market-wide analysis. *Journal of Financial Economics* 123:646–70.

Choi, D., M. Getmansky, B. Henderson, and H. Tookes. 2010. Convertible bond arbitrageurs as suppliers of capital. *Review of Financial Studies* 23:2492–522.

Cohen, L., K. Diether, and C. Malloy. 2007. Supply and demand shifts in the shorting market. *Journal of Finance* 62:2061–96.

Corwin, S. 2003. The determinants of underpricing of seasoned equity offers. *Journal of Finance* 58:2249–79.

Cremers, M., M. A. Ferreira, P. Matos, and L. Starks. 2016. Indexing and active fund management: International evidence. *Journal of Financial Economics* 120:539–60.

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

Desai, H., K. Ramesh, S. R. Thiagarajan, and B. V. Balachandran. 2002. An investigation of the informational role of short interest in the NASDAQ market. *Journal of Finance* 57:2263–87.

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

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

Duffie, D., N. Gârleanu, and L. Pedersen. 2002. Securities lending, shorting, and pricing. *Journal of Financial Economics* 66:307–39.

Easley, D., M. O'Hara, and L. Yang. 2014. Opaque trading, disclosure, and asset prices: Implications for hedge fund regulation. *Review of Financials Studies* 27:1190–237.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2012. How are shorts informed? Short sellers, news and information processing. *Journal of Financial Economics* 105:260–78.

Fama, E. F., and K. R. French. 1998. Value versus growth: The international evidence. *Journal of Finance* 53:1975–99.

Gagnon, L. 2018. Short Sale constraints and single stock futures introductions. *Financial Review* 53:5–50.

Gagnon, L., and J. Witmer. 2014. Distribution of ownership, short sale constraints, and market efficiency: Evidence from Cross-Listed Stocks. *Financial Management* 43:631–70.

Griffin, J. M., P. J. Kelly, and F. Nardari. 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. *Review of Financial Studies* 23:3225–77.

Grunewald, S. N., A. F. Wagner, and R. H. Weber. 2010. Short selling regulation after the financial crisis–First principles revisited. *International Journal of Disclosure and Governance* 7:108–35.

Henry, T. R., and J. L. Koski. 2010. Short selling around seasoned equity offerings. *Review of Financial Studies* 23:4389–418.

Hong, H. G., F. W. Li, S. X. Ni, J. Sheinkman, and P. Yan. 2016. Days to cover and stock returns. Working Paper, Columbia University.

Hou, K., A. G. Karolyi, and B. C. Kho. 2011. What factors drive global stock returns? *Review of Financial Studies* 24:2527–74.

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

Hou, K., M. A. Van Dijk, and Y. Zhang. 2012. The implied cost of capital: A new approach. *Journal of Accounting and Economics* 53:504–26.

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

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

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

Kolasinski, A. C., A. Reed, and J. R. Thornock. 2013. Can short restrictions actually increase informed short selling? *Financial Management* 42:155–81.

Lee, KH. 2011. The world price of liquidity risk. *Journal of Financial Economics* 99:136–61.

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

Newey, W., and K. West. 1987. A Simple, Positive Semi-definite, Heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

Porras Prado, M., P. A. C. Saffi, and J. Sturgess. 2016. Ownership structure, limits to arbitrage and stock returns: Evidence from equity lending markets. *Review of Financial Studies* 29:3211–44.

Raddatz, C., S. L. Schmukler, and T. Williams. 2017. International asset allocations and capital flows: The benchmark effect. *Journal of International Economics* 108:413–30.

Saffi, P. A. C., and K. Sigurdsson. 2011. Price efficiency and short selling. *Review of Financial Studies* 24:821–52.