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PRICE EFFICIENCY AND SHORT SELLING

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Price Efficiency and Short Selling *

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ABSTRACT

This paper investigates the effect of short-sale constraints on price efficiency. We use a unique global dataset on equity lending collected from several custodians from January 2004 to June 2006. This information is available weekly for 17,015 stocks from 26 countries. Our main findings are as follows. Stocks with limited lending supply and high borrowing fees respond more slowly to market shocks. Second, short-sale constraints have a small impact on the distribution of weekly stock returns. Limited lending supply is associated with higher skewness, but not with fewer extreme negative returns. Third, stocks with limited lending supply and higher borrowing fees are associated with lower R^2s on average.

JEL classification: G14, G15, G12.

Keywords: Short-sales constraints, market efficiency, equity lending.

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Introduction

Price efficiency is defined as the degree to which stock prices reflect all available information, both timely and accurately. This paper uses data on equity lending studies whether short-sale constraints affect the efficiency of stock prices around the world. This information is collected from several custodians, containing over 85.7 million lending supply postings and 46.4 million lending transactions from January 2004 to June 2006. The data cover 17,015 individual stocks in 26 markets and contain lending supply and lending transactions for more than 90% of global stocks in terms of market capitalization, making it, to the best of our knowledge, the most comprehensive international data on stock lending.

For each of these stocks and for each week in our sample, we compute two measures of short-sale constraints: the supply of shares available for short-selling and the borrowing fee. Our main findings are as follows. First, short-sale constraints are associated with lower price efficiency. In general, stocks with limited lending supply and high borrowing fees respond more slowly to market shocks. Second, short-sale constraints affect the distribution of weekly stock returns. A limited lending supply is associated with higher skewness, but not with kurtosis or less frequent extreme negative returns. The observed relationship with skewness seems to come from changes in the frequency of large positive returns rather than in the frequency of large negative returns. This mitigates regulatory concerns that removing short-sale constraints increases the frequency of crashes at the stock level. Third, stocks with limited lending supply and higher borrowing fees are associated with lower R^2s. This finding challenges the view that low R^2s are associated with higher price efficiency, contrary to results by Morck, Yeung, and Yu (2000) at the country-level.

The impact of short-selling on price efficiency still remains an open question. Fears that it was one of the factors behind the crash of 1929 prompted the SEC to adopt short-sale restrictions under the Securities Exchange Act of 1934. Since then, the SEC and the US Congress have regularly released reports on short-sales and their impact on stock prices. In 2004, the SEC proposed changes in regulation to relax short-sale constraints, launching a pilot program to evaluate their effects. The Pilot Program began on May 2nd, 2005 and was scheduled to end on April 28th, 2006 but the SEC decided to extended it until August 6th, 2007.

"The Pilot will enable us to obtain empirical data to help assess whether short sale regulation should be removed, in part or in whole, for actively-traded securities, or if retained, should be applied to additional securities. (...) We will examine, among other things, the impact of price tests on market quality (including volatility and liquidity), whether any price changes are caused by short selling, costs imposed by a price test, and the use of alternative means to establish short positions." Securities Exchange Act Release No. 50104 (July 28th, 2004)

An interesting example on how short sale constraints can affect how efficiently prices respond to information is provided by Northern Rock Plc, a UK mortgage lender that was severely hit by the turbulence in credit markets seen in 2007. [1] In September 17th, 2007, the bank was given an emergency loan by the Bank of England and a British government guarantee on its deposits, following an investors' run on its deposits because of difficulties faced by the bank in raising funds to finance its operations. After a period of uncertainty the company began to search for a buyer for its operations. Bidders were expected to submit their offers by Friday, November 16th, when its share price closed at 132.6 pence, valuing the bank at $1.2 billion. Before the opening of the stock market on Monday November 19th, news broke out at 7:30am that the company released a statement saying that *"the range of values for the existing equity implied by the proposals is materially below the market price at the close of business on Friday, 16th November 2007"*.

As can be seen in Figure 1, prices did not exhibit a quick fall when the market opened, taking almost an hour to stabilize. An explanation for this slow response to the news could come from the lending market of Northern Rock's shares. Since October 17th, borrowing Northern Rock shares for has been very difficult, with utilization (the fraction of lending supply already loaned out) above 80% and annualized borrowing fees around 1000 basis points (bps). This is in sharp contrast to how the lending market on Northern Rock shares appeared before the company's troubles begun, when average utilization was around 20% and annualized borrowing fees were only around 10 bps. Furthermore, it compares to an average utilization for the UK stock market as whole equal to 9.9% and an average annualized (value-weighted) borrowing fee equal to 67 bps. As stock lenders begun to sell their holdings

[1] We are grateful to Will Duff Gordon for highlighting this example.

in the aftermath of the bank run, it became increasingly difficult for investors to borrow shares to sell Northern Rock short, which might explain the sluggish response to news reported during the weekend that bidders valued the firm much less than implied by the closing market price on November 16th.

[Figure 1 about here]

The example above highlights the importance of empirical work studying the impact of the stock lending market on price efficiency. We begin our analysis by constructing two measures of short-sale constraints: the supply of shares available for lending and the borrowing fee. Whenever an investor wishes to short a particular firm, she first needs to locate shares of the firm to borrow. Thus, a low lending supply indicates that short-sales constraints are binding more tightly, as the investor needs to bear higher searching costs to locate the shares [Duffie, Garleanu, and Pedersen (2002)]. Furthermore, even if the investor finds them, she would still need to compensate the lender by paying a borrowing fee. The higher is this fee, the tighter short-sales constraints faced by the investor will also be. However, an increase in the fee (i.e. the price of shorting) could be do to either (1) an increase in the demand for shares, related to private information or (2) a decrease in the supply available for lending. Thus, higher borrowing fees accompanied by a larger lending supply of shares do not necessarily imply that short-sale constraints are tighter. As shown by Cohen, Diether, and Malloy (2007), borrowing fees are not a sufficient statistic and it is important to differentiate between shorting demand and shorting supply whenever testing for the impact of short-sales constraints.

The availability of stock-level information on short-sale constraints enables us to control for any effects on price efficiency that come from differences across countries due to different the regulatory environments, levels of financial development and levels of income. We show that the lending supply contains information above and beyond that contained in borrowing fees and that lower levels of price efficiency are associated with low lending supply and high borrowing fees. Our paper also contributes to the literature by providing a comprehensive overview of international stock lending markets and the determinants of lending supply and borrowing fees. To the best of our knowledge, this paper is the first to test the impact of short-sales constraints on price efficiency at the stock level for such a wide range of firms and countries.

Our analysis proceeds as follows. We estimate panel regressions to explain cross-sectional differences in price efficiency using both stock lending measures as proxies for short-sale constraints. Our dependent variables comprise various proxies of price efficiency previously used in the literature. First, we use the correlation between contemporaneous stock returns and lagged market returns [Bris, Goetzmann, and Zhu (2007)]. Ranking stocks by lending supply, we find that the lowest decile of firms has a 45% expected difference between the highest and lowest decile of firms due to differences in lending supply and borrowing fee.

Then, we consider the three measures of stock price delay used by Hou and Moskowitz (2005). We estimate a regression of weekly stock returns on the contemporaneous returns of a world index, a domestic index and four lags of the domestic index. We then re-estimate this equation imposing the constraint that coefficients of lagged domestic returns are zero. The first delay measure (D1) compares the difference in R^2s from these two regressions, with higher values of D1 implying that a stock has higher delay in responding to new market information. Other variations of the delay measure yield the same result: lower lending supply and higher borrowing fees are associated with smaller efficiency of stock prices.

A third measure of efficiency is the R^2 of a market model regression. This measure has gained support in recent years as a proxy for efficiency, with *low* R^2s levels generally being associated with better levels of governance and financial developement [e.g. Morck, Yeung, and Yu (2000), Durnev, Morck, and Yeung (2004), Li, Morck, Yang, and Yeung (2004)]. Our results, however, show that stocks in the upper decile of lending supply have R^2s which are more than 60% *larger* than those of stocks in the lower decile, consistent with results found by Kelly (2005), Hou, Peng, and Xiong (2006) and Teoh, Yang, and Zhang (2006).

Our evidence on the relationship between short-sales constraints and R^2 levels is opposite to the evidence found by Morck, Yeung, and Yu (2000) and Bris, Goetzmann, and Zhu (2007) at the country-level. However, Bris, Goetzmann, and Zhu (2007) cleverly advocate using the difference from the co-movement between a firm's returns and the market depending on the sign of the market return (i.e. Down R^2s minus Up R^2). Regardless of whether short-sales constraints are associated with higher or smaller levels of idiosyncratic risk, their insight is that the difference in R^2s should decrease with fewer constraints, with prices on bad market-news days becoming relatively more efficient than those in good market-news ones. Using this measure, our proxies of short-sales constraints produce the same conclusions.

Our contribution to this debate is to show that great care should be taken when using firms' R^2s as a measure of efficiency. At the security-level, the data support the view that price efficiency is associated with higher R^2s, not less. It seems that the changes due to fewer short-sale constraints affect R^2s in the opposite direction to that caused by increases in the efficiency of corporate investment [Durnev, Morck, and Yeung (2004) and Chen, Goldstein, and Jiang (2007)] or transparency [Jin and Myers (2006)]. Even in countries where regulators allow short-selling to take place, price efficiency is still affected by how easily a particular firm can be located and borrowed on its lending markets.

We also compute various characteristics of the distribution of stock returns to test whether short-sale constraints increase the likelihood of crashes: skewness of weekly stock returns, kurtosis, the frequency of large negative returns, and the frequency of large positive returns. Similar to Bris, Goetzmann, and Zhu (2007), the frequency of large negative returns is computed as the proportion of returns that are two standard deviations below the previous year's average. Ranking stocks by lending supply, the difference in raw skewness explained by lending supply between firms in the bottom and the top decile is 98%, with the actual value for firms in the bottom decile equal to 0.34 and in the top decile equal to 0.02. However, we cannot find significant differences in the frequency of large negative returns based on our two proxies.

All these effects are economically large and allow us to conclude that short-sale constraints hinder price efficiency, but do not affect the frequency of stock price crashes. These findings can be used to mitigate regulatory concerns that removing short-sale constraints makes prices more efficient at the expense of increasing the frequency and severity of stock crashes. The conclusions hold for US and non-US firms, for different time-periods and are robust to controls for firm size, leverage, liquidity and whether a firm has American Depositary Receipts (ADRs) or Global Depositary Receipts (GDRs) issued, respectively, in the US or the UK. The results are also robust to possible measurement errors in our proxies short-sale constraints and to alternative specifications of lending supply an borrowing fee. Furthermore, results remain the same when we constrain the sample to US firms and add as additional control variables turnover, ILLIQ (Amihud (2002)'s proxy for liquidity) and a dummy for whether options are available.

The rest of the paper proceeds as follows. Section I contains a review of the literature. Section II describes our hypotheses and the measures of price efficiency. Section III describes the data and our measures of short-sale constraints. Section IV reports our empirical results. Finally, section V concludes.

I. Literature Review

It is generally accepted that short-sale constraints affect the efficiency of security prices [e.g. Miller (1977), Diamond and Verrecchia (1987), Duffie, Garleanu, and Pedersen (2002) and Bai, Chang, and Wang (2006)]. The main conclusion is that prices may no longer incorporate all available information, whenever agents have heterogeneous beliefs but are prevented from fully reflecting their beliefs on prices. Miller (1977) argues that short-sale constraints keep pessimistic investors out of the market, causing prices to be biased upwards because they only reflect the valuations of the more optimistic investors who trade. Diamond and Verrecchia (1987) develop a model in which short-sale constraints eliminate some informative trades. Prices are not biased upwards, but become less efficient when restrictions are in place, as they reduce the speed of adjustment to private information. Duffie, Garleanu, and Pedersen (2002) develop a model in which search costs and bargaining over borrowing fees generate endogenous short-selling constraints and affect asset prices. In our case, the lending supply of shares could be interpreted as a proxy for the cost of searching. In a recent paper, Bai, Chang, and Wang (2006) show that short-sale constraints can actually lower asset prices and make them more volatile. This happens because the loss in the informativeness of prices due to fewer informed investors increases the amount of risk borne by uninformed investors, who require lower prices as compensation to bear extra risk. Thus, regardless of whether short-sale constraints have positive or negative impact on prices, these papers imply that these constraints reduce the informational efficiency of prices, i.e. they no longer reflect all available information.

Empirical evidence of the impact of short-sale constraints on price efficiency is mostly concentrated on US stocks. High short interest (i.e., high number of stocks sold short as a fraction of total shares outstanding) is generally interpreted as evidence of short-sale constraints and many papers show that stocks with high short interest exhibit lower subsequent returns.[2] D'Avolio (2002) describes the market for borrowing and shows that the cost of short-selling a stock is high exactly at times when investor disagreement is also high, indicating that prices will not fully reflect negative information. Similarly, Reed (2003) studies rebate rates in the equity lending market as a proxy for short-sale constraints and shows that stock prices are slower to incorporate information when borrowing fees are high. However, most of these papers rely on indirect measures of short-sale constraints or a very restricted sample of lending data. An important benefit of our measures is that they can avoid these shortcomings. For instance, high short interest might be due to increased borrowing demand reflecting investors' negative views about the stock that are unrelated to short-sale constraints, or be due to a fall in the supply of shares available for lending resulting in short-sale constraints. We estimate short-sales constraints by using the supply of shares available for lending and the borrowing fee. Furthermore, previous studies which use borrowing fees are all based on data from a single custodian. Custodians provide various services to prime brokers and have different pricing strategies. Thus, data from a single custodian may not be representative of the average lending price.[3] Our data contains information from more than 10 custodians and therefore allows us to compute representative estimates of the average borrowing fee.

International evidence on the relationship between short-sale constraints and price efficiency is rare due to the difficulty in obtaining good proxies for short-sale constraints, especially at the security level. One exception is Bris, Goetzmann, and Zhu (2007), who use regulatory information on whether short-selling is prohibited or practiced in 46 different countries. They conclude that stock prices in countries with constraints in place are less efficient than those where investors are allowed to short stocks. Our proxies for short-sales constraints are of a different nature and contain information about how individual firms, rather than countries, are affected. Chang, Cheng, and Yu (2006) focus on regulatory restrictions to short-sell individual stocks in Hong Kong and find that constraints tend to cause overvaluation and this effect is more dramatic for stocks with wide dispersion of investor opinions. We contribute to the literature on price efficiency in international markets by showing (i) that the negative relationship

[2]Figlewski and Webb (1993), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2004), Diether, Lee, and Werner (2005), Boehmer, Jones, and Zhang (2006), Boehmne, Danielsen, and Sorescu (2006) and Cohen, Diether, and Malloy (2007)

[3]The average coefficient of variation of the borrowing fee for a given stock at a given point in time is about 0.5.

between short-sale constraints and price efficiency is pervasive across the world and (ii) that firms' lending market characteristics are also important to explain observed differences in price efficiency.

Our paper is also related to the literature about the R^2 of a market-model regression and its use as a measure of efficiency [e.g. Roll (1988)]. Morck, Yeung, and Yu (2000) document how stock markets in poor countries have higher R^2s relative to rich ones and show it can be explained by the fact that there are better property rights in richer countries. Jin and Myers (2006) advocate that these higher R^2s are caused by a lack of transparency in poorer countries. When cash flows are better than what is expected by outside investors, firm insiders can capture a higher proportion of cash flows. If cash-flows are below outsiders' expectations, they are forced to reduce this capture to keep running the firm. This increases the proportion of idiosyncratic risk borne by insiders, leaving outside investors subject to relatively more systematic risk. This would imply that firms with more short-sale constraints should have higher R^2s.

Our findings contradict this conjecture, as we find a negative relationship between short-sale constraints and R^2s. More specifically, a higher supply of shares and low borrowing fees are associated with high R^2s. Our results are in fact consistent with theoretical work by West (1988), who shows that the volatility of stock returns decreases as information about future cash-flows is incorporated more quickly into prices. News affecting these future cash-flows are factored into prices relatively earlier, leading investors to update their beliefs sooner. This earlier updating makes the affected cash-flows to be divided by a larger discount factor, reducing idiosyncratic volatility as a consequence.

Our empirical results for R^2s are similar to US-based evidence found by Kelly (2005) using the breadth of ownership [Chen, Hong, and Stein (2002)] as a proxy for short-sale constraints. In a recent paper Teoh, Yang, and Zhang (2006) show that financial anomalies (e.g., accruals and post-earnings announcement drift) are more pronounced for firms with low R^2s. Hou, Peng, and Xiong (2006) also provides evidence that R^2s are negatively related to price momentum. The conflicting evidence from these papers casts doubt on whether a lower proportion of idiosyncratic risk relative to total risk is indicative of price efficiency in all cases.

II. Hypotheses and Measures of Price Efficiency

Our main hypothesis is that short-sale constraints decrease the information content in stock prices, based on the theoretical work by Miller (1977), Diamond and Verrecchia (1987), Duffie, Garleanu, and Pedersen (2002) and Bai, Chang, and Wang (2006). In order to test it we construct novel measures of short-sale constraints and use them to explain various proxies for efficiency that have been proposed by the literature.

The first measure of price efficiency is the cross-correlation between current stock returns and lagged domestic market returns [Bris, Goetzmann, and Zhu (2007)]. In a given year, we compute $Corr(r_{i,t}, r_{m,t-1})$, the correlation between weekly stock returns at time t and domestic value-weighted market returns at time $t-1$. However, this measure does not capture any correlation that $r_{i,t}$ and $r_{m,t-1}$ might have with other omitted variables.

The second set of price efficiency measures addresses this concern and are based on Hou and Moskowitz (2005). The idea behind these measures is that if investors cannot fully incorporate information in today's stock prices, they will defer their actions such that this information is only gradually reflected in prices. The price response delay is measured from a market model regression extended with lagged returns of a domestic market index. The larger is the explanatory power of these lags, the higher is the delay in responding to information. Based on this idea, Hou and Moskowitz (2005) propose three different measures of price delay and apply them to evaluate frictions in the US stock market. For each stock in a given year, we estimate a regression of the stock return in week t on the value-weighted domestic index returns and its lagged values up to four weeks ago plus the world index return:

$$r_{i,t} = \alpha_i + \beta_i * r_{m,t} + \sum_{n=1}^{4} \delta_i(-n) * r_{m,t-n} + \gamma_i * r_{W,t} + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ represents returns of stock i in week t, $r_{m,t-n}$ the corresponding value-weighted domestic market return in week t and $r_{W,t}$ represents the returns of the value-weighted world index in week t. All returns are expressed in terms of the domestic currency. We focus on the impact of domestic market news and only use lags of the domestic index.

The first delay measure, D1 compares the fraction of variability in stock returns that is due to lagged market returns, by comparing the R^2 from the regression above with the one when coefficients on lagged market returns, $\delta_i(-n)$, are constrained to zero.

$$D1_i = 1 - \frac{R^2_{\delta_i^{(-n)}=0, \forall n \in [1,4]}}{R^2}. \tag{2}$$

The larger is this measure, the greater is the variation in stock returns captured by lagged market returns, implying a higher price delay to market information. However, D1 does not take into account the precision or magnitude of lagged market returns coefficients and therefore we also compute two additional delay measures:

$$D2_i = \frac{\sum_{n=1}^{4} |\delta_i(-n)|}{|\beta_i| + \sum_{n=1}^{4} |\delta_i(-n)|} \tag{3}$$

$$D3_i = \frac{\sum_{n=1}^{4} |\delta_i(-n)|/se\left(\delta_i(-n)\right)}{|\beta_i|/se\left(\beta_i\right) + \sum_{n=1}^{4} |\delta_i(-n)|/se\left(\delta_i(-n)\right)}, \tag{4}$$

where $se(.)$ denotes the standard error of the estimated coefficient. These measures capture the magnitude of the lagged coefficients relative to the magnitude of all coefficients. We use the absolute values of each coefficient, since price efficiency is reduced when they are different from zero regardless of their estimated signs. Hou and Moskowitz (2005) report that most coefficients estimated in their sample are either zero or positive for the portfolios they construct. They also state that results are the same when they use the absolute value of coefficients instead. In our case, it is crucial that absolute values are used to compute the delay measures.

A third type of price efficiency measure, which has gained support in recent years, is the R^2 of a market model regression. Morck, Yeung, and Yu (2000) document that stocks in poorer economies have less idiosyncratic risk (i.e., higher R^2) than stocks in rich countries and show how measures of property rights can explain this difference, conjecturing that stronger property rights result in relatively more firm-specific variation in stock prices. Jin and Myers (2006) suggest that country differences in R^2s are caused by lack of transparency, which limits the ability of outside investors to monitor firm insiders. Their interpretation is that more opaqueness shifts firm-specific risk from outsiders to insiders, increasing R^2s. The results that lower R^2s are associated with better governance and higher transparency is also seen Bris, Goetzmann, and Zhu (2007)'s hypothesis. They construct a dummy variable, based on market regulatory information and interviews with government officials, indicating whether short-selling is allowed and practiced in a given country in a given year. They show that countries where short sales are allowed and practiced have lower R^2 levels and a smaller difference in R^2s between bad-news and good-news weeks that those in which short-selling is forbidden or not practiced. Contradictory evidence to their result can be found in Kelly (2005). He shows that US firms with low R^2s tend to have tighter short-sale constraints, measured by changes in the breadth of institutional ownership proposed by Chen, Hong, and Stein (2002). Another finding is that firms with higher bid-ask spreads, sensitivity to past market returns and liquidity also have lower R^2s. Given this evidence that associates low R^2s with stocks generally seem to be less rather than more efficient, it is still an open question whether high or low R^2s indicate price efficiency.

Given the debate on the correct direction of the relationship between short-sales constraints and R^2 levels, Bris, Goetzmann, and Zhu (2007) also propose using the difference from the co-movement between a firm's returns and the market depending on the sign of the market return, i.e. compute separate R^2s of market-model regressions using only bad market-return weeks (Down R^2) and, similarly, the R^2 for good market-return weeks (Up R^2) and then take the difference. Regardless of whether short-sales constraints are associated with higher or smaller levels of idiosyncratic risk, their insight is that the difference in R^2s should decrease with fewer constraints, and prices during bad market-news days become relatively more efficient than those in good market-news ones.

Although most researchers would agree that relaxing short-sale constraints increases the speed upon which prices reflect information, it is still relevant from a policy perspective to test whether relaxing them makes extreme negative price fluctuations more likely. Regulators might not be willing to relax short-sales constraints if that is the case. We use three measures to investigate these claims: skewness, kurtosis, and frequency of extreme returns.

Negative skewness means that the left tail of the return distribution becomes fatter. Diamond and Verrecchia (1987) hypothesize that short-sale constraints should make returns less negatively skewed.

Hong and Stein (2003) argue that short-sale constraints are positively related to skewness through the following mechanism: if constraints are relaxed, more pessimistic investors re-enter markets to trade on their beliefs. The return of these investors increases the likelihood of negative returns. Our hypothesis is that whenever short-selling is easier, prices reflect bad news more quickly, increasing the likelihood of observing large negative returns. We compute skewness using two different return measures. First, we take weekly returns and compute their skewness for each firm-year in the sample. Second, we estimate a market-model equation with the domestic and the world index returns as factors and compute the skewness of the residuals generated by this regression.

Short-selling has been blamed as a contributing factor to many crashes in the past, from the 1929 market crash to the Black Monday in 1987 [for further analysis refer to Lamont (2003)] to the 1997 Asian crises. Thus, research on whether the frequency of extreme negative returns decreases with short-selling constraints is very important to regulators. To further investigate how these constraints affect the distribution of returns, we compute kurtosis and the frequency of weekly returns that are two standard deviations below (and also above) the average for the previous year. Combining the results from skewness, kurtosis, the frequency of extreme negative returns and the frequency of extreme positive returns allow us to disentangle which part of the distribution of returns (i.e., extreme negative or extreme positive), if any, is being affected by short-sale constraints.

A concern that must be addressed is the causality of the relationship. Our main hypothesis is that inefficiency is caused by more stringent short-sales constraints. However, it is not possible rule out the reverse order of causality, i.e., it could be the case that inefficient stocks drive investors away from the lending market, reducing lending supply and increasing borrowing fees. We attempt to mitigate these fears by performing robustness tests using lending supply and borrowing fees lagged by one year. Our findings are unaltered and reinforce our claim that price efficiency is reduced when investors face more short-sale constraints.

III. Data Description

This section describes the data used to test our hypotheses. We start by describing our stock lending data and our measures of short-sale constraints, followed by the returns data collected to estimate the price efficiency measures and the variables used to control for other factors which might affect the results.

A. *Stock lending data*

The stock lending data come from Data Explorers Limited, which collects this information from a significant number of the largest custodians in the securities lending industry.[4] The data comprise weekly security-level information on the value of shares available for lending and actual lending transactions for equities from all over the world. It begins in January 2004 and ends in June 2006, with coverage growing rapidly during the sample period. In 2004 it contains information from 11 custodians, increasing to 15 in 2006. Overall, the data set has a total of 85.7 million lending supply postings and 46.4 million lending transactions.

Figure 2 shows that the total value of supply in the dataset has grown from USD 1 trillion in January 2004 to about USD 5 trillion in June 2006.[5]

[Figure 2 about here]

A.1. Lending Supply

Stock lending supply reported by custodians equals the value of shares available for lending at a given point in time. Since the dataset has grown extensively since the beginning of our sample, lending supply has an upward drift for almost all securities. In order to control for this growth, we define lending supply for security i as the fraction of lending supply relative to market capitalization and then divide it by aggregate supply of shares available for lending in a given week:

$$\text{Supply}_{i,t} = \frac{\left(\frac{\text{Supply}_{i,t}}{\text{Market Capitalization}_t}\right)}{\text{Aggregate Supply}_t}, \tag{5}$$

[4]This includes ABN Amro, Mellon, and State Street among others, which we cannot name due to a confidentiality agreement with Dataexplorer Ltd.

[5]The dataset is on monthly frequency until July 2004 and becomes weekly thereafter.

where i denotes stock and t stands for week. In the robustness section, we also show that results still hold if we use the residuals from a regression of supply on market capitalization. For ease of interpretation, Figure 3 shows the distribution of supply as a fraction of market cap for the week ending on June 28, 2006. We can observe great variation in lending supply across firms, although they stocks do not have any regulatory constraints on being sold short. This highlights the usefulness of our measures to pin down how short-sale constraints affect price efficiency on an individual stock level.

[Figure 3 about here]

Because our regressions are based on price efficiency measures computed at the yearly frequency, we use averages of weekly measures for borrowing fees and supply within a year. Finally, we take the natural logarithm of supply and winsorize the borrowing fee at 0.5% to limit the effect of outliers on our results.

The data provide a direct estimate of the number of shares available for lending, regardless of whether they are loaned out or not. In Cohen, Diether, and Malloy (2007), they use short interest (i.e. the percentage of total shares on loan) coupled with borrowing fees to detect shocks on supply and demand.

A.2. Borrowing Fee

Each stock lending transaction comes with information on the borrowing fee and the currency used. Fees can be divided into two parts depending on the type of collateral used. If borrowers use cash as a collateral - the dominant form in the US - them the borrowing fee is defined as the difference between the risk free interest rate and the rate paid for the collateral. If instead the collateral is non-cash then the fee is negotiated between the borrower and the lender and defined directly in basis points per year. This can be expressed by the following equation:

$$\text{Borrowing Fee}_{n,i,t} = \begin{cases} \text{Fee}_{n,i,t} & \text{if non-cash collateral} \\ \text{Riskfree rate}_t - \text{Rebate rate}_{n,i,t} & \text{if cash collateral} \end{cases}, \tag{6}$$

where n denotes transaction, i stands for security and t denotes the week in which the transaction appears in the dataset. Loans can further be divided into two categories: open-term and fixed-term.

Open-term loans are renegotiated every day, but fixed-term ones have predefined clauses and maturities. The overnight risk-free rate for the collateral currency is used for open-term loans. The Fed Open rate is used for loans with cash collateral denominated in US dollars and the Euro Overnight Index average (EONIA) is used for the ones denominated in Euros. The risk-free rate proxy for other currencies is the overnight rate at London Interbank market (LIBOR) and local money market rates for smaller currencies. Linear interpolation of LIBOR rates is used for fixed-term loans in accordance with conventions in the securities lending industry.[6]

The borrowing fee is weighted by loan amount using the following equation:

$$\text{Borrowing Fee}_{i,t} = \sum_{n=1}^{N_{i,t}} \left[\frac{\text{Loan amount}_{n,i,t}}{\sum_{n=1}^{N_{i,t}} \text{Loan amount}_{n,i,t}} \cdot \text{Implied Fee}_{n,i,t} \right], \tag{7}$$

where n denotes transaction, i stands for security, t denotes the week in which the transaction appears in the dataset and $N_{i,t}$ is the total number of outstanding transactions for security i in week t. Value weighting is used to limit the influence of small and expensive transactions on the average borrowing fee estimate[7].

Figure 4 plots the distribution of yearly value-weighted borrowing fees. The figure shows that fee levels vary considerably between stocks, with close to 60% being below 60 bps per year. These stocks are often referred by practitioners as “general collateral”. However, in 30% of the cases the fee is above 100 bps, which are referred to as “specials”. Furthermore, in 5% of the cases the borrowing fee reaches levels above 400 bps. Thus, short-selling stocks can be constrained due to high borrowing fees even though stocks are registered in countries that allow short sales.

[Figure 4 about here]

We also need to be careful in controlling for a widespread practice in the securities lending industry. The transfer of stock ownership during dividend-payment periods to investors with favorable dividend

[6] In unreported regressions we find that our results are even stronger if we use the reported reinvestment rate instead of the risk-free rate

[7] Unreported results show a negative relationship between borrowing fee and transaction size.

tax legislation is a very common reason for stock lending [e.g. McDonald (2001), Rydqvist and Dai (2005) and Christoffersen, Geczy, and Musto (2006)]. This is generally referred to as “tax-arbitrage” and the gains from this type of transactions are shared through an increase in borrowing fees. Thus, fees during these periods are not representative of a general lending price for a given security. Figure 5 shows both the increased borrowing fees and lending volume during dividend-payment periods for all the dividend-paying stocks in our sample. The average increase in fee is around 40% and the average increase in utilization (amount on loan divided by supply) is about 20%. We control for this tax-arbitrage by excluding all transactions that are less than three weeks away from the week dividends are paid from our borrowing fee estimates.

Another practice is vote trading, i.e., borrowing shares to use their voting rights during corporate votes. Although our data aggregates lending to enable short-selling and lending used for vote trading, the evidence that the average price charged for these votes is zero [Christoffersen, Geczy, Musto, and Reed (2007)] makes us believe that our results are unaffected, especially in light of the yearly frequencies used.

[Figure 5 about here]

A.3. Determinants of Lending Supply, Borrowing Fees and Utilization

Table I contains descriptive statistics for the stock lending database. The number of stocks covered by the dataset is representative of the world market both as a percentage of market capitalization and as a percentage of the number of stocks. For example, the supply data covers more than 92% (93%) of the market capitalization of the US (UK) stock market. More than 70% of the total number of firms listed on Datastream are covered in our sample, with a bias towards large firms. When we examine the statistics of firms with lending transactions, there is a negligible decrease in coverage as measured by market capitalization (it falls from 93% to 91%) and a moderate one measured by the number of firms (falling from 64% to 57%). The average proportion of shares lent out in the US is about 3% of market capitalization, but with a high standard deviation of 4.46%. The average (value-weighted) borrowing fee charged to borrow US shares is close to 35 basis points per year, but this fee is very volatile in the cross-section, having a 200 basis points standard deviation. US stocks in our sample have a larger lending supply and are more expensive to borrow than those used by D'Avolio (2002), who uses data by a single custodian from April, 2000 to September, 2001.

[Table I about here]

In order to shed more light on how our main explanatory variables are related to firm and country characteristics we show a multivariate analysis in Table II with country fixed-effects. Firms that cross-list abroad, have high book to market ratios, and lower leverage tend to have higher supply and smaller lending fees. Lending supply is also related to market capitalization, with larger firms exhibiting higher supply than smaller ones. We control for this effect by using market capitalization as a control variable in all of our regressions. Furthermore, liquid stocks are easier to locate and less expensive to borrow compared to illiquid ones.

[Table II about here]

We also included data on ownership from Datastream to further investigate how our proxies for short-sales constraints are related to stock ownership. Each measure shows the proportion of the firm owned by a different class of shareholders. First, we find that employee/family ownership has a negative effect on supply.[8] For example Vanco, a UK based technology company, is largely owned by its employees and has only 6.1% of market capitalization available for lending compared to 13.5% for the UK market in general. Employees keep their stock holdings in private accounts that are generally not big enough to be included in securities lending programs by custodians. We also find that government ownership reduces the lending supply. An example is The Mass Transit Railway Corporation (MTRC) listed in Hong Kong. This company was privatized in 2000, but the government still owns 76% of the shares. Only 0.17% of its shares is available for lending, compared to the market average in Hong Kong of 3.7%. Governments dislike losing their voting rights in exchange for gaining a few extra basis points in return, not to mention the bad signal sent to markets in case the shorting demand increases.

Long-term holdings of investment companies is associated with higher supply and lower borrowing fees. This is logical, since investment companies often have the infrastructure to lend out securities and

[8]Datastream aggregates holdings by family owners and firm employees under the same variable (NOSHEM).

generally try to earn extra basis points by doing so. This category includes many investors who are unable or unwilling to short-sell (e.g. passive index funds or long-only mutual funds) and that generate extra gains by lending stocks in their portfolios. This makes them large suppliers of shares for lending [D'Avolio (2002)]. Surprisingly, pension fund ownership is unrelated to lending supply or borrowing fees. However, these results are probably due to the fact that many institutional investors invest their money through investment companies. Another potential explanation is that companies' pension funds are often not big enough to participate in lending programs and are turned down by custodians unless their portfolios are sufficiently large.

Finally, cross-holdings are negatively related to supply. This is often due to subsidiary companies, which are almost solely owned by the parent company with very little free float and shares available for lending. For example, 96.5% of the shares in SAP System Integration AG are held by their parent companies (SAP Deutschland AG & Co. KG and SAP AG) and only 0.02% of market capitalization is available for lending.

B. Other Variables

We obtain weekly stock returns, market capitalization, currency and interest rates from Datastream. Leverage and book-to-market ratios are computed by matching accounting data extracted from Compustat Global. Accounting data are only available for a subset of firms and thus, we perform the analysis on samples with and without accounting-based controls. We construct dummy variables to control for cross-listing from various sources. Information on American Depositary Receipts (ADRs) comes from the Bank of New York and JP Morgan's websites and from CRSP tapes. Information on Global Depositary Receipts (GDRs) is taken from the London Stock Exchange Website.

In Table III, we present summary statistics for the measures of price efficiency and other variables of interest for our analyses. Panel A shows data for firms with accounting information available from Compustat Global, while Panel B repeats the calculations using all available shares. The average yearly R^2 in our larger sample equals 18.94% a year, which is similar to the values documented by Campbell, Lettau, Malkiel, and Xu (2001) for US-based stocks. The average correlation between contemporaneous weekly returns and lagged market returns is 2.80%. Stock returns are highly skewed to the right, with mean skewness equal to 0.096, similar to Bris, Goetzmann, and Zhu (2007). The percentage of weekly returns two standard deviations below (above) the previous year's average is around 2.63% (2.85%). This is slightly bigger than the 2.28% expected from a normal distribution and reflects the fatter tails observed in empirical data. Overall, our summary statistics match the patterns documented in the literature.

[Table III about here]

Table IV shows the characteristics of stocks sorted by lending supply. Firms with higher supply tend to have smaller and less volatile fees. The only noticeable difference from the number of weeks with supply information across deciles (shown under Column $\#_{Sup}$) is that firms with higher supply do have a higher number of weeks with lending transactions. When we look at utilization, i.e., shares lent out divided by the total number of shares available for lending, firms with higher supply tend to have much lower utilization rates than those with low supply. They also tend to be larger firms and are more likely to have shares cross-listed outside their home countries. Finally, firms in the lowest decile of lending supply have lower average annualized returns (12.74%) than those in the top decile (15.23%) and display much higher standard deviations of returns (8.62% vs. 4.62%). This observation is consistent with the literature on the negative relationship between short-interest and stock returns.

[Table IV about here]

IV. Empirical Results

We start by examining whether our proxies for short-sale constraints are related to the different measures of price efficiency. We estimate GLS regressions using yearly data with random firm-effects and corrected for heteroscedasticity using robust standard errors. We include country-year fixed effects to control for country and year-specific variation, such as those related to differences in corporate governance regimes [Morck, Yeung, and Yu (2000)] and opaqueness [Jin and Myers (2006)]. We also add a dummy variable to control for securities that have ADRs or GDRs traded outside the domestic market, based on evidence that cross-listing makes prices more efficient [Doidge, Karolyi, Lins, Miller, and Stulz (2005)].[9] All regressions control for market capitalization and we also estimate regressions controlling for leverage and book-to-market ratios whenever accounting data from Compustat Global are available. Liquidity effects are controlled via the proportion of zero-return weeks in a given year, similar to Bekaert, Harvey, and Lundblad (2005). After describing our base specification, we also perform different tests to evaluate the robustness of our conclusions to different time periods, measurement errors, differences between US and non-US stocks, using lagged values of the short-sales constraints proxies and alternative definitions of our supply measure.

We analyze the economic significance of short-sale constraints by looking at how price efficiency measures vary with lending supply and borrowing fees. For each dependent variable, we compare the estimated expected differences between stocks in the lowest and highest deciles of firms ranked by lending supply that are due to our proxies for short-sale constraints.

A. *Cross-correlation*

To measure price efficiency, we first employ the cross-correlation of stock returns proposed by Bris, Goetzmann, and Zhu (2007). The cross-correlation is defined as the correlation between contemporaneous stock returns and lagged market returns. Because correlation is bounded between -1 and 1, we apply the following transformation: $\ln[(\rho+1)/(1-\rho)]$ and use it as a proxy for efficiency. We find results that are largely consistent with Bris, Goetzmann, and Zhu (2007), that is, firms with larger supply and lower borrowing fees have smaller cross-correlation. The regression results in Table V imply that the expected change in correlation due to differences in lending supply between bottom and top decile is -32%. The actual values are 0.06 for firms in the bottom decile and 0.04 for firms in the top decile. Leverage and book-to-market ratios are not statistically significant, but firms with higher size or liquidity tend to be more efficient. The impact of cross-listing is only marginally significant and we don't find support for the claim that it improves efficiency using cross-correlation.

[Table V about here]

[9] The dummy variable is dynamic such that it only takes a value of one after the security is cross-listed.

However, the cross-correlation might be a biased measure of efficiency since it does not control for the correlation of contemporaneous stock returns or lagged domestic index returns with omitted variables. We address this concern by looking at measures of efficiency that accounts for possible correlation with omitted variables.

B. Delay Measures

We also test the hypothesis that short-sale constrained stocks are less efficient by estimating regressions of delay measures on our measures of short-sale constraints. These measures compare the usefulness of domestic market index lagged returns to explain stock returns. Using the price delay measures D1, D2 and D3 as dependent variables, we run panel-data regressions using supply available for lending and the borrowing fee as explanatory variables.

As predicted, the results in Table VI show that all three measures of price delay decrease with the supply available for lending and increase with borrowing fees. For example, consider the -0.01 coefficient for Ln(Supply) when D1 is the dependent variable. The expected difference in D1 due to differences in supply between stocks in the bottom decile and those in the top decile is -18.88%.[10] Since lending supply and borrowing fees are strongly negatively correlated (the correlation coefficient is -0.44), ranking firms by lending supply also produces an uniform sort on borrowing fees, as seen in Table IV. The expected value for D1 caused by the differences in borrowing fees is 3.85% lower than for firms in the bottom decile relative to the top decile of firms ranked by lending supply. Hence, lending supply and borrowing fee are not only statistically significant, but also have a large economic impact on the price delay measures. Stock prices for firms with high book-to-market, market capitalization and liquidity, and low leverage ratios are also more efficient. We expect smaller price delays associated with cross-listing if firms that cross-list their shares internationally benefit locally from the better disclosure and transparency environments. This is exactly what we find, which is consistent with Doidge, Karolyi, Lins, Miller, and Stulz (2005) and Foucault and Gehrig (2006).

[Table VI about here]

[10]We obtain this value first from multiplying the estimated coefficient by the difference in Ln(Supply) between the top and bottom deciles shown in Table IV. Then we divide it by the bottom decile value for D1.

C. *R^2*

We now repeat the analysis looking at how the proportion of idiosyncratic risk relative to total risk is related to short-sale constraints. Again, we transform the dependent variable using ln[R^2/(1-R^2)] to avoid any statistical complications caused by R^2s being bounded between 0 and 1. Results in Table VII suggest that stocks with higher supply and lower borrowing fees have higher R^2s. The average R^2 in the sample is 0.13 for firms in the bottom decile and 0.18 for firms in the top decile of firms ranked by lending supply. The coefficient on log supply reported under "Overall R^2" equals 0.06 and implies that the expected difference in R^2s for stocks in the bottom decile relative to those in the top decile is 25.8%. Furthermore, the estimated impact from the observed decrease in borrowing fees between the lowest and the top decile of firms (also ranked by lending supply) increases R^2s by 6.9%. This means that even in countries where short-selling is allowed, there are large cross-sectional differences in R^2s due to short-sale constraints. Additionally, firms with higher liquidity (i.e. those with fewer weeks of zero returns) and market capitalization or lower leverage have smaller idiosyncratic risk relative to total risk. In line with Foucault and Gehrig (2006), who argue that cross-listing makes prices more efficient because of the larger number of informed investors trading the stock, we find that firms that cross-list have higher R^2s.

[Table VII about here]

All these results point to *high* R^2s as a proxy of price efficiency, but they are at odds with results found at the country level by Bris, Goetzmann, and Zhu (2007). They show that R^2 levels are higher in countries where short-selling is prohibited or not practiced, but smaller in those with more liquid securities or where more firms have cross-listed.[11]

These results might be caused by an unknown omitted-variable at the country level that correlates with their dummy variable - that also proxies for short-sale constraints - while the measures we use are robust to country-year fixed effects. Our data additionally indicate that stocks are still put up for

[11]In Column (I) of Table IV in their paper, Bris, Goetzmann, and Zhu (2007) report positive estimates for ADR0 and ADR1, their dummy variables employed to capture cross-listing effects when R^2s are used as the dependent variable. However, these dummies are only significant for cross-listings from countries where short-sales are allowed and practiced and only in the regression with controls for country and industry characteristics.

lending by custodians and used for short-selling in the over-the-counter market in 6 out of the 46 countries classified by Bris, Goetzmann, and Zhu (2007) as places in which short-sales are prohibited and/or not practiced.[12] This makes their dummy variable a potentially imperfect measure of short-sale constraints. The proxies for short-sale constraints we use are a more direct measure of constraints for individual securities, since they capture within-country variability in shorting supply and borrowing fees that cannot be investigated using a country-level dummy. Moreover, our findings are similar to those of Kelly (2005), who shows that US firms with low R^2s are associated with higher transaction costs, sensitivity to past market returns and liquidity. He also uses the change in breadth of institutional ownership [Chen, Hong, and Stein (2002)] as a proxy for short-sale constraints and find that firms with more binding constraints have lower R^2s. Our findings are also consistent with Hou, Peng, and Xiong (2006) and Teoh, Yang, and Zhang (2006), who find that financial anomalies are more pronounced in firms with lower R^2s.

We also present results using the alternative measures proposed by Bris, Goetzmann, and Zhu (2007), who compute separate R^2s of market-model regressions using only bad market-return weeks (Down R^2) and, similarly, the R^2 for good market-return weeks (Up R^2) and then take the difference. With these alternative dependent variables, we find that our proxies are not statistically significant for the Down R^2s. When we use the Up R^2s as the dependent variable, both variables are statistically significant, with the coefficients being equal to 0.036 for lending supply and -0.025 for the borrowing fee. The lack of statistical power for the Down R^2 estimates can be explained by the smaller number of negative market-return weeks. Most stock markets around the world had very high returns in 2004 and 2005, with a much larger proportion of positive market-return weeks than negative ones. On average, Down R^2s are computed from just 18.9 weekly observations, while Up R^2s are based on 33.7 observations. We follow the discussion by looking at the difference between Down R^2s and Up R^2s. Our firm-level conclusions are identical to Bris, Goetzmann, and Zhu (2007) at the country-level: fewer short-sales constraints reduce the difference between R^2s, following the intuition that returns on weeks of negative market returns will be more similar to positive ones when investors can more easily short-sell securities, hence the difference in R^2 should decrease with fewer short-sale constraints. Regardless

[12]The countries in which the Bris, Goetzmann, and Zhu (2007) definition is not appropriate are China, Finland, Israel, New Zealand, South Africa and Spain.

of the debate on how R^2 *levels* should be affected by short-sales constraints, it is hard to dispute that fewer constraints should lead to a smaller difference between Down R^2 and Up R^2.

More generally, the discussion on the usefulness of R^2s is related to how cross-sectional differences are explained by country or security-level variables. Morck, Yeung, and Yu (2000) document how stock markets in poor countries have higher R^2s relative to rich ones and show that this difference can be explained by stronger property rights in rich countries. Jin and Myers (2006) advocate that the higher R^2s observed in less developed countries are also related to a lack of transparency, which allows firm insiders to willingly soak up more idiosyncratic risk and leave outside investors exposed to more systematic risk. If a firm is more opaque, insiders can grab a higher fraction of cash-flows following above-expectations earnings while they need absorb a higher proportion of losses following bad news, causing a decrease in the amount of firm-specific risk borne by outsiders. On the other hand, West (1988) shows that the volatility of stock returns decreases as information about future cash-flows is more easily incorporated into prices. News affecting these future cash-flows are factored into prices relatively earlier at higher discount rates. This heavier discounting reduces idiosyncratic volatility. If relaxing constraints increases the amount of and speed by which information is incorporated into prices, we would expect less idiosyncratic risk, i.e., higher R^2s, the larger the shorting supply of shares and the smaller the borrowing fee. The opposing directions implied by these papers indicate that R^2s might be poor predictors of price efficiency. It is important to understand theoretically if there are differential impacts on idiosyncratic risk coming from increases in transparency and less constrained short-selling. A recent paper by Brown and Kapadia (2006) corroborates our results and shows that the decrease in idiosyncratic risk observed for the US in recent years [Campbell, Lettau, Malkiel, and Xu (2001)] are due to a riskier set of firms choosing to become publicly traded. Once they control for this group of firms, the results that relate lower R^2s to higher efficiency no longer hold.

D. Skewness, Frequency of Extreme Returns and Regulatory Concerns

Regulators are generally concerned that relaxing short-sale constraints may increase the probability of crashes. The widespread use of short-selling by hedge-funds and their huge impact on daily trading volume has generated questions about the fairness and legality of this type of trade [see for example the article at Forbes.com (2006)]. We test forthis concern by looking at how our proxies for short-selling constraints affect four characteristics of distribution of returns: skewness, kurtosis, and the frequency of extreme negative and extreme positive returns at the stock level.

Stocks in our sample on average have positive skewness. The coefficient on lending supply is equal to -0.07 in Table VIII and is statistically significant at the 1% level. Ranking firms by lending supply, the estimated difference in skewness between the bottom and top deciles due to lending supply is 86%. The actual difference equals 94%, with the average skewness equal to 0.34 in the bottom decile and 0.02 in the top decile of firms. However, we do not find significant results for the borrowing fee measure. Our results imply that lending supply is associated with lower skewness, similar to results found by Bris, Goetzmann, and Zhu (2007) for international market indices and Chang, Cheng, and Yu (2006) in Hong Kong's stock market. Skewness also decreases with liquidity and market capitalization. These results are the same regardless of whether we compute the skewness of raw returns or from residuals generated by a market-model equation, to remove the impact of systematic market fluctuations. Using our proxies allow us to show that the link between skewness and short-sale constraints also exists at the stock level across different countries. This is another example of the usefulness of our lending supply measure as a proxy for short-sale constraints.

[Table VIII about here]

We can also examine how kurtosis is affected to test whether short-sales constraints are associated with "thicker" tails of the distribution of returns, meaning a higher frequency of extreme returns. In Table IX we estimate the relationship between short sale constraints and kurtosis using as dependent variables both raw stock returns and residuals from a market-model regression. We find weak support for the hypothesis that smaller lending supply increases kurtosis, but strong support for the impact of higher borrowing fees. Low liquidity and low market capitalization also increase the kurtosis. However, the change in kurtosis could be related to thicker tails either on the positive or negative side of the return distribution.

[Table IX about here]

Although the results for skewness are consistent with the idea that short-sales constraints might affect the frequency of crashes, they are not conclusive. The correlation found between lending supply and skewness might be due to an increase in the relative proportion of modest negative returns relative to positive returns or, instead, from an increase in the frequency of extreme negative ones relative to low returns near the average. We disentangle this by examining the proportion of weekly returns in a given year that are two standard deviations below the previous year average, showing results in Table X. The first two columns show the results using the frequency of extreme negative returns as the dependent variable. We don't find any explanatory power for lending supply or borrowing fee. We only find evidence that crashes are less likely for stocks that cross-list abroad, have higher liquidity, market capitalization, or book-to-market ratios. Overall, there is no support for the argument that short-sale constraints are related to the frequency of stock crashes.

[Table X about here]

Because most countries had large and increasing average stock returns in the 2004-2006 period, our lack of explanatory power might be due to the absence of major international crises during this period. In columns 3 and 4, we estimate our regressions using the frequency of large *positive* returns and we only find weak evidence that higher lending supply decreases extreme positive returns. The coefficient estimated for lending supply in Table X equals to -0.001 but it is no longer significant once we control for leverage and B/M. Firms that cross-list abroad and are larger in terms of market capitalization also exhibit a smaller frequency or large gains.

Overall, our results show that relaxing short-sale constraints is associated with lower skewness. This result is similar to evidence found at the country level by Charoenrook and Daouk (2005) and Bris, Goetzmann, and Zhu (2007) but, contrary to the former, we also find support for the hypothesis that relaxing short-sales constraints decreases skewness at the security level. However, combining these results with those found for the frequency of extreme returns, it seems that the impact on skewness, if any, comes from changes in the frequency of extreme positive returns rather than in extreme negative returns.

E. Regressions for US Firms with Additional Controls

One of the drawbacks of using international data is the reduced availability of various control variables commonly available for US firms, such as turnover and whether tradable options are available.[13] In an effort to reduce the biases caused by the omitted-variables problem, we now present regressions for a subset of the data that only includes US firms. Within this smaller sample, we construct three additional control variables. Using CRSP data, we compute average daily turnover and ILLIQ [Amihud (2002)] in a given year. It is possible that the explanatory power of lending supply and borrowing fees is in fact capturing the effects due to turnover and liquidity. Firms with higher turnover and liquidity have been shown to be more efficient than those with lower turnover and liquidity [Kelly (2005)].

Although our global database has a dummy variable for firms that cross-list, an important variable missing from our base regressions is whether firms have options being traded on their shares. Using quarterly data on options' trading volume, we construct a dummy variable to capture whether a firm has options being traded in a particular year.[14,15]

The constrained data has 6,061 observations for 3,770 different US firms. Most firms in our panel (about 70%) do not have options traded on US exchanges. The previous results found in the global data still hold when we control for turnover, ILLIQ and "optionability" in Table XI: lending supply is associated with higher price efficiency across most measures, while higher borrowing fees are usually associated with smaller efficiency. In most regressions, the impact of Amihud (2002)'s ILLIQ measure is statistically significant, with less efficient firms also having lower liquidity.

[Table XI about here]

The last four columns of Table XI use characteristics of the distribution of stock returns as dependent variables. The results found in the US are different than those found for the global data once we control for turnover, ILLIQ and "optionability". Lending supply only has explanatory power using

[13] Option trading will most likely be reflected in the lending market since option sellers will have to hedge their exposure. Therefore options trading was not completely ignored in previous regressions.

[14] We kindly thank Robert Battalio for giving us the option data.

[15] We also obtain similar results using a variable that ranks firms by option trading volume and a variable with the frequency of quarters in a year for which options were traded.

skewness as the dependent variable. In the global data, it also had shown modest explanatory power to explain the frequency of extreme positive returns.

For US firms, higher borrowing fees are associated with fewer extreme returns, regardless of whether they are positive or negative. However, given these results, we would also expect a negative and significant coefficient when kurtosis is the dependent variable. Stock turnover is strongly associated with higher kurtosis and the frequency of extreme positive and negative returns, but is not associated with skewness.

Overall, higher lending supply and lower borrowing fees are related to lower price efficiency. However, the results found for their impact on skewness and kurtosis are mixed and should not be taken as evidence in support or against the impact of short-sale variables on the likelihood and frequency of crashes.

F. Additional Tests

This section describes the various robustness tests we conduct to evaluate the sensitivity of our conclusions to different assumptions. Given the large growth in the scope and coverage of the database, we create a balanced panel and divide the sample into two different periods of relative stability in stock coverage. Based on Figure 2, we define Period 1 as the week beginning on March 24th, 2004 and ending on March 23th, 2005, while Period 2 as the period between July 6th, 2005 and June 28th, 2006. Results in Table XII show that the significance of the results with respect to lending supply are weaker in Period 1, regardless of the dependent variable we consider. When we examine the estimates for the borrowing fee, results are broadly consistent with our conclusions in Period 1, but the statistical significance is smaller in Period 2. These results can be due to the reduction in the number of data points from using just one cross-section of data or a smaller predictive power of borrowing fees to explain variation within a cross-section rather than between cross-sections.

[Table XII about here]

In table XIII, we test whether our results are sensitive to the variability of short-sale constraints proxies within a year. It might be the case that yearly averages have lower explanatory power for firms that exhibit higher variability within a year. We split our data into three groups according to the coefficient of variation in weekly lending supply or borrowing fee in a given year. Firms in the Low group are those with smaller variations of the short-sales constraints proxies. We estimate a single regression with different coefficients according to which group stocks belong to. The results are similar regardless of the group to which they belong. [16]

[Table XIII about here]

Our sample includes both US and non-US stocks and given the size of the US market, comprising almost 40% of stocks in our sample, it is important to know whether there are large differences in estimated parameters between US and non-US stocks. In Table XIV we split stocks in two groups depending on whether they are traded in the US or not. The sensitivities of price efficiency measures to lending supply and borrowing fees are similar inside and outside US markets and remain highly significant. When we look at the impact on skewness and the frequency of extreme returns we get the same qualitative results as found in Table VIII and Table X, revealing that short-sale constraints reduce skewness, but do not seem to affect the frequency of large negative returns.

[Table XIV about here]

Another concern that must be addressed is the causality of the relationship. Our hypothesis is that inefficiency is caused by more stringent short-sales constraints. However, we cannot fully reject the reverse order of causality. This would mean that inefficient stocks drive investors away from the lending market, reducing lending supply and increasing borrowing fees. In Table XV we re-estimate regressions using lending supply and borrowing fees lagged by one year. The estimated parameters keep being statistically significant and reinforce our claim that price efficiency is reduced when investors face more short-sale constraints.

[Table XV about here]

[16] Unreported robustness checks also compute the borrowing fee using the actual reinvestment rate that is feasible for lenders, rather than the risk-free rate in each country. Our results for the borrowing fee variable are even stronger than those presented in the text.

We also use two alternative lending supply measures for robustness. First, we compute Residual Supply as residuals from regressing stock lending supply scaled by aggregate supply on firm size. Second, we compute Utilization by dividing the total amount lent by the total supply of shares available. In Table XVI and Table XVII we repeat our regressions replacing lending supply with these alternatives. Looking at the parameters estimated for Residual Supply, we can see that our effects are above and beyond any influence that firm size might have. All our conclusions are similar when we use this measure. In Column (ii) we see that the explanatory power of Utilization is very low for each different dependent variable. Although statistically significant at the 5% for cross-correlation and D2, utilization is not robust across the other price efficiency measures, skewness and the frequency of extreme negative and positive returns. These results can be explained by the fact that stocks with high utilization aren't necessarily short-sale constrained, but are in high demand from investors, similar to the econometric problems that arise when short interest is used as a proxy for short-sale constraints.

[Table XVI about here]

[Table XVII about here]

Lastly, the country fixed-effects we use as controls in our main regressions do not account for different slopes across countries. We test this possibility by adding interactions of lending supply, borrowing fees and market capitalization with a dummy variable that controls for OECD membership which proxy for the level of financial development. Out of the twenty-six countries, eight are not members of the OECD (China, Hong Kong, Israel, Mexico, Singapore, South Africa and South Korea), however these countries comprise only about 5% of the observations. Looking first at efficiency measures as the dependent variables, in Table XVIII we can see that the impact of lending supply comes mainly from OECD countries. The only significant difference between slope coefficients is found when the cross-correlation between contemporaneous stock returns and lagged stock market returns is used as the dependent variable. We also find that OECD-members are less affected by changes in lending supply (estimated impact$= -0.007$) than non-OECD members (estimated impact$= -0.034$). Furthermore, we can also reject the joint hypothesis that the both parameters are equal to zero for all efficiency measures. The lack of significance of borrowing fee parameters is most likely due to multicolinearity, as the joint hypothesis test that both parameters are equal to zero is rejected for all efficiency measures. As for market capitalization, there does not seem to be any difference between OECD and non-OECD countries.

[Table XVIII about here]

The impact of these interactions on characteristics of the distribution of stock returns yield the same (mixed) results found before. Borrowing fees are not significant to explain any of the measures, but changes in lending supply of OECD members are found to have a smaller impact than non-OECD members for kurtosis and the frequency of extreme positive returns. At least in 2004 and 2005, our proxies for short-sale constraints do not seem to have a major impact on the distribution of returns.

V. Conclusion

Using a unique dataset with weekly stock lending transactions across 26 countries, this paper estimates the impact of short-sale constraints on measures of price efficiency. We find strong evidence to support the hypotheses implied by Diamond and Verrecchia (1987), Duffie, Garleanu, and Pedersen (2002) and Bai, Chang, and Wang (2006) that short-sale constraints are associated with less price efficiency.

We use two measures of short-sale constraints: the supply of shares available for lending and the borrowing fee. The availability of stock-level information on short-sale constraints enables us to control for any effects on price efficiency that come from country differences such as differences in the regulatory environment, stages of financial development or income levels. We also provide a comprehensive overview of stock lending markets across the world and show how lending supply and borrowing fees are related to firm characteristics. To the best of our knowledge, these have not been done before in the literature for such a wide range of securities and countries.

We estimate panel regressions to explain cross-sectional differences in price efficiency. Stocks with limited lending supply and high borrowing fees have longer delays in responding to market-wide shocks. Relaxing shorting restrictions is associated with an increase in the speed by which information is incorporated into prices. Large and more liquid firms also tend to have more efficient prices, while those with higher leverage or low book-to-market ratios tend to be less efficient.

We look at changes in the distribution of stock returns based on four measures: the skewness and kurtosis of weekly stock returns, and the frequency of large negative and large positive returns. We find that short-sales constraints are associated with smaller skewness and higher kurtosis, but they also show that short-sale constraints do not affect the frequency of large negative returns, with the change in kurtosis and skewness being due to changes in the frequency of large positive ones. These findings reduce concerns expressed by regulators that removing short-sale constraints could increase the frequency of crashes at the stock level. When we restrict the analysis to US firms, we are not able to replicate these effects and it seems hard to claim any strong relationship between the frequency and magnitude of crashes with lending supply and borrowing fees.

We also provide evidence against the usefulness of using low R^2s of market model regressions to proxy for price efficiency [Morck, Yeung, and Yu (2000), Jin and Myers (2006)]. Our proxies imply a negative relationship between R^2 levels and short-sale constraints at the firm-level, opposite to the evidence found at the country-level by Bris, Goetzmann, and Zhu (2007). They use a dummy variable for countries in which shorting is allowed and practiced based on market regulatory information and interviews with government officials, while we have access to firm-level characteristics on how easy it is to short-sell a particular stock. Our variables allow us to control for country fixed-effects and for firm characteristics such as leverage, size and book-to-market ratios and our findings reinforce their suggestion that using the difference in R^2s obtained in regressions conditional on the sign of market returns is a better measure of efficiency: these differences should decrease as short-sales constraints are relaxed, regardless of the impact on R^2 levels.

The results presented above are relevant to market participants and regulators alike, displaying the gains in efficiency associated with a higher supply of shares available for lending. The negative impact that short-sales constraints have on price efficiency measures is economically large, but these constraints do not seem to affect the frequency of stock price crashes. The conclusions are the same for US and non-US firms, they hold across time-periods and are robust to controls for firm size, leverage, liquidity and to whether a firm has ADRs or GDRs issued abroad. Furthermore, results are also similar when we focus on US firms, adding turnover, liquidity [Amihud (2002)] and a dummy for whether options are available as additional variables.

Notes

[1]We are grateful to Will Duff Gordon for highlighting this example.

[2]Figlewski and Webb (1993), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2004), Diether, Lee, and Werner (2005), Boehmer, Jones, and Zhang (2006), Boehmne, Danielsen, and Sorescu (2006) and Cohen, Diether, and Malloy (2007)

[3]The average coefficient of variation of the borrowing fee for a given stock at a given point in time is about 0.5.

[4]This includes ABN Amro, Mellon, and State Street among others, which we cannot name due to a confidentiality agreement with Dataexplorer Ltd.

[5]The dataset is on monthly frequency until July 2004 and becomes weekly thereafter.

[6]In unreported regressions we find that our results are even stronger if we use the reported reinvestment rate instead of the risk-free rate

[7]Unreported results show a negative relationship between borrowing fee and transaction size.

[8]Datastream aggregates holdings by family owners and firm employees under the same variable (NOSHEM).

[9]The dummy variable is dynamic such that it only takes a value of one after the security is cross-listed.

[10]We obtain this value first from multiplying the estimated coefficient by the difference in Ln(Supply) between the top and bottom deciles shown in Table IV. Then we divide it by the bottom decile value for D1.

[11]In Column (I) of Table IV in their paper, Bris, Goetzmann, and Zhu (2007) report positive estimates for ADR0 and ADR1, their dummy variables employed to capture cross-listing effects when R^2s are used as the dependent variable. However, these dummies are only significant for cross-listings from countries where short-sales are allowed and practiced and only in the regression with controls for country and industry characteristics.

[12]The countries in which the Bris, Goetzmann, and Zhu (2007) definition is not appropriate are China, Finland, Israel, New Zealand, South Africa and Spain.

[13]Option trading will most likely be reflected in the lending market since option sellers will have to hedge their exposure. Therefore options trading was not completely ignored in previous regressions.

[14]We kindly thank Robert Battalio for giving us the option data.

[15]We also obtain similar results using a variable that ranks firms by option trading volume and a variable with the frequency of quarters in a year for which options were traded.

[16]Unreported robustness checks also compute the borrowing fee using the actual reinvestment rate that is feasible for lenders, rather than the risk-free rate in each country. Our results for the borrowing fee variable are even stronger than those presented in the text.

Table I: Stock lending markets around the world

This table shows summary statistics for each country with lending data available on June 28th, 2006. Market cap is the sum of market capitalization in USD billions and Stocks reports the number of stocks covered seem in the database. In the “Stocks with lending supply” panel, MC(%) shows the fraction of firms with lending supply data in terms of market capitalization of the domestic market, while Stocks(%) reports the fraction of stocks with lending data. Avg. supply and St. dev. denote, respectively, the average supply of shares relative to total shares outstanding and its standard deviation in a given year. The “Stocks with lending transactions” panel contains summary statistics for firms with recorded lending transactions. We report annual means and standard deviations for the amount of shares lent (as % of market capitalization) and the size-weighted borrowing fee. Markets that are classified as “Short sales not allowed and/or not practiced” by Bris, Goetzmann, and Zhu (2007) are marked with a *.

	Market		Stocks with lending supply				Stocks with lending transactions					
Country	Market cap	Stocks	MC(%)	Stocks(%)	Avg. supply	St.dev.	MC(%)	Stocks(%)	On loan(%)	St.dev.	Avg. Fee (bps)	St.dev.
AUSTRALIA	910	798	95	43	5.69	5.00	93	37	1.25	1.51	40	138
AUSTRIA	157	64	97	73	4.92	4.92	96	67	1.14	1.55	46	25
BELGIUM	256	132	100	56	3.62	3.77	99	52	0.61	0.84	40	181
CANADA	1,186	720	91	56	10.92	8.90	91	52	1.68	2.49	32	174
*CHINA	101	127	88	41	8.06	4.92	88	39	1.92	1.60	86	146
DENMARK	171	133	94	59	3.70	6.24	92	53	1.07	2.10	41	326
*FINLAND	208	122	97	63	5.07	7.55	95	57	0.74	1.10	23	603
FRANCE	1,596	527	98	60	3.52	9.35	97	53	1.06	4.11	92	177
GERMANY	1,125	378	99	79	5.79	14.99	98	71	1.56	3.60	62	162
HONG KONG	965	621	94	33	3.68	3.45	92	29	0.64	0.85	43	139
*ISRAEL	99	135	23	26	5.98	5.37	15	19	1.58	2.47	89	186
ITALY	779	275	96	79	3.01	4.78	96	68	1.04	2.31	154	129
JAPAN	4,558	2,508	95	73	3.51	4.57	92	63	0.73	1.08	58	174
MEXICO	1,102	51	99	76	2.53	3.10	99	69	0.14	0.24	200	101
NETHERLANDS	748	133	76	65	8.21	6.54	76	62	1.49	1.91	35	160
*NEW ZEALAND	31	62	71	29	5.07	4.44	68	27	0.73	1.92	41	118
NORWAY	240	141	97	68	4.87	5.72	96	60	1.28	1.83	76	126
PORTUGAL	74	40	93	60	1.85	1.96	90	50	0.43	0.78	37	233
SINGAPORE	230	296	90	39	4.20	4.07	84	31	0.58	0.81	44	140
SOUTH AFRICA	322	151	80	38	3.11	2.40	78	32	0.23	0.44	52	88
*SOUTH KOREA	627	410	84	36	2.84	2.40	83	33	0.40	0.48	123	135
*SPAIN	722	122	96	84	4.37	5.17	95	81	1.64	2.49	81	119
SWEDEN	379	251	97	68	4.41	5.75	94	58	0.81	1.24	46	161
SWITZERLAND	1,041	267	98	76	9.78	9.30	97	68	1.27	2.03	31	34
THAILAND	165	134	54	33	2.43	1.88	48	25	0.27	0.27	77	124
UNITED KINGDOM	2,926	1,372	93	62	13.52	9.93	92	53	1.40	1.96	12	115
UNITED STATES	16,800	7,045	92	70	12.24	34.09	91	64	3.03	4.46	35	200
WORLD	37,516	17,015	93	64	8.87	23.90	91	57	1.97	3.51	50	188

Table II
Determinants of Lending Supply and Borrowing Fees

The table estimates lending supply and borrowing fees as a function of firm characteristics in 2004 and 2006. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. Ln(Supply) is the yearly average of stock lending supply as a fraction of market capitalization and then scaled by aggregate supply. “ADR or GDR” is a dummy variable equal to one if the firm has ADRs or GDRs issued abroad. Zero-return weeks is the proportion of zero-return weeks in a given year. Ownership variables and price data are obtained from Datastream. The panel regressions are estimated using fixed country-year effects with robust (Huber/White/sandwich) standard errors clustered at the firm level. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Ln(Supply)		Borrowing Fee	
			(i)	(ii)	(i)	(ii)
ADR or GDR	0.06	0.24	0.049	0.076	-0.179	-0.276
			(1.32)	(1.59)	(4.37)***	(5.05)***
Ln(Book to market)	-0.15	0.73		0.056		-0.152
				(2.60)***		(4.17)***
Leverage	0.16	0.18		-0.211		0.247
				(3.04)***		(3.07)***
Ln(Market Cap)	-0.12	1.47	0.307	0.282	-0.261	-0.275
			(41.32)***	(28.69)***	(29.88)***	(21.48)***
Zero-return weeks	0.03	0.03	-4.660	-4.476	2.936	2.913
			(13.85)***	(9.74)***	(7.15)***	(4.89)***
Ownership (%)						
Employees / Family	6.16	13.65	-0.010	-0.010	0.004	0.002
			(12.59)***	(9.08)***	(4.12)***	(2.03)**
Government	0.30	3.80	-0.015	-0.016	0.002	0.004
			(8.26)***	(6.98)***	(1.15)	(1.53)
Cross-holdings	8.71	16.89	-0.014	-0.013	0.003	0.004
			(16.11)***	(11.29)***	(4.05)***	(3.55)***
Investment companies (LT)	18.59	21.95	0.015	0.013	-0.006	-0.005
			(17.63)***	(12.39)***	(8.88)***	(4.32)***
Pension funds	1.04	2.34	-0.002	0.000	0.010	0.011
			(0.25)	(0.01)	(2.49)**	(1.54)
Mean(Dependent)			0.11	0.28	0.92	0.85
StDev(Dependent)			1.29	1.21	1.34	1.27
Observations			13,873	7,471	13,873	7,471
No. of companies			8,570	4,405	8,570	4,405
R^2			0.48	0.54	0.31	0.34
Country-year FE			Yes	Yes	Yes	Yes

Table III

Stock market characteristics around the world

The table shows summary statistics based on yearly values for 2004 and 2005. Each firm must have at least 50 weekly return observations, less than 10 zero-return observations and at least 6 lending observations in a given year. Furthermore, each country must have at least 16 firms in a given year. Panel A contains firms for which accounting data from Compustat Global is available, while Panel B relaxes this requirement and uses all available data. Fee is winsorized at 0.5%. R^2 comes from a regression of weekly stock returns on the domestic index and a world index. Cross-correlation is the correlation between contemporaneous weekly stock returns and lagged domestic market returns. D1, D2 and D3 are proxies for price delay proposed by Hou and Moskowitz (2005)

	Obs.	Mean	Median	St.dev.	Min.	Max
PANEL A: Small sample (firms with accounting data)						
R^2 (x100)	7,501	19.52	17.37	13.54	0	77
Cross-correlation (x100)	7,501	2.80	2.70	14.39	-45	52
D1	7,501	0.33	0.26	0.24	0.00	1.00
D2	7,501	0.55	0.53	0.19	0.07	1.00
D3	7,501	0.60	0.60	0.18	0.10	1.00
Skewness of raw returns (x100)	7,501	9.56	9.84	91.49	-713	697
Skewness of abnormal returns (x100)	7,501	15.67	18.26	95.74	-712	601
Kurtosis of raw returns	7,501	2.10	1.05	3.74	-1	51
Kurtosis of abnormal returns	7,501	2.31	1.20	3.77	-1	51
Freq. extreme negative returns (x100)	7,501	2.36	1.89	3.33	0	51
Freq. extreme positive returns (x100)	7,501	2.57	1.89	4.43	0	100
Ln(supply)	7,501	0.28	0.50	1.21	-7	4
Fee (% p.a.)	7,501	0.85	0.25	1.27	0	9
ADR or GDR dummy	7,501	0.06	0.00	0.24	0	1
Ln(Book to market)	7,501	-0.15	-0.10	0.73	-4	5
Leverage (x100)	7,501	16.15	11.95	18.14	0	339
Market cap (USD billions)	7,501	3.20	0.78	11.04	0	342
Zero-return weeks (% per year)	7,501	2.50	1.89	3.35	0	17
Number of stocks per country-year	7,501	3,889	2,493	2,723	11	6,941
PANEL B: Large sample (firms without accounting data)						
R^2 (x100)	14,055	18.94	16.06	14.25	0	96
Cross-correlation (x100)	14,055	2.63	2.58	14.55	-47	54
D1	14,055	0.35	0.28	0.25	0	1
D2	14,055	0.56	0.54	0.19	0	1
D3	14,055	0.61	0.60	0.18	0	1
Skewness of raw returns (x100)	14,055	9.42	10.45	93.44	-713	697
Skewness of abnormal returns (x100)	14,055	14.71	17.27	95.50	-712	636
Kurtosis of raw returns	14,055	2.14	1.01	3.95	-1	51
Kurtosis of abnormal returns	14,055	2.27	1.12	3.86	-1	51
Freq. extreme negative returns (x100)	14,055	2.63	1.89	3.82	0	60
Freq. extreme positive returns (x100)	14,055	2.85	1.92	5.24	0	100
Ln(supply)	14,055	0.10	0.31	1.30	-8	4
Fee (% p.a.)	14,055	0.93	0.29	1.34	0	9
ADR or GDR dummy	14,055	0.08	0.00	0.27	0	1
Market cap (USD billions)	14,055	3.24	0.67	12.25	0	538
Zero-return weeks (% per year)	14,055	2.77	1.89	3.59	0	17
Number of stocks per country-year	14,055	3,769	2,493	2,876	11	6,941

Table IV: Descriptive Statics - Stocks sorted on Lending Supply

The table shows characteristics of portfolios formed by ranking stocks according to lending supply deciles based on yearly values for 2004 and 2005. Each firm must have at least 50 weekly return observations, less than 10 zero return observations and at least 6 lending observations in a given year to be included. Furthermore, each country must have at least 16 firms in a given year. Obs. gives the number of firm-year observations included in each portfolio. μ_{Supply} reports the mean logarithm of weekly lending supply scaled by total lending supply. μ_{Fee} reports average borrowing fee winsorized at 0.5%, while σ_{Fee} the standard deviation for each decile. Columns $\#_{Sup}$ and $\#_{Loans}$ show, respectively, the average number of weeks with lending supply and lending transactions. Util. reports average dollar value of lending transactions scaled by available supply. μ_{ret} and σ_{ret} report annualized mean weekly returns and standard deviations. Size(bi) shows the average market capitalization in billions of US dollars. D_{Cross} shows the proportion of stocks cross-listing their shares outside their parent country in each decile.

Decile	Obs.	μ_{Supply}	μ_{Fee}	σ_{Fee}	$\#_{Sup}$	$\#_{Loans}$	Util.	μ_{ret}	σ_{ret}	Size (bi)	D_{Cross}
1	1,404	-2.53	2.02	1.98	38	20	0.40	12.74	8.62	1.59	0.04
2	1,406	-1.22	1.67	1.68	41	24	0.30	19.10	6.90	0.88	0.04
3	1,406	-0.65	1.34	1.54	41	25	0.25	16.65	6.06	1.00	0.05
4	1,405	-0.21	1.04	1.28	41	27	0.22	16.94	6.02	1.36	0.06
5	1,406	0.15	0.80	1.15	42	28	0.20	15.20	6.19	2.07	0.07
6	1,406	0.47	0.65	1.03	42	29	0.18	14.01	5.94	3.05	0.08
7	1,405	0.75	0.48	0.81	42	29	0.16	12.74	5.30	4.76	0.07
8	1,406	1.02	0.42	0.76	42	30	0.14	13.64	4.98	6.62	0.09
9	1,407	1.32	0.40	0.62	42	31	0.15	12.91	4.56	5.18	0.11
10	1,404	1.99	0.47	0.61	42	32	0.12	15.23	4.62	5.92	0.16
Overall	14,055	0.11	0.93	1.34	41	28	0.21	14.92	6.03	3.24	0.08

Table V
Cross-correlation

The table shows results of regressing cross-correlation as a function of lending supply, borrowing fees and firm controls. The dependent variable is the cross-correlation (ρ) between contemporaneous weekly stock returns and lagged domestic market returns, transformed using Cross-correlation=ln[(ρ+1)/(1-ρ)]. The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Cross-correlation	
			(i)	(ii)
Ln(Supply)	0.28	1.21	-0.008	-0.008
			(1.96)*	(3.39)***
Fee (% p.a.)	0.85	1.27	0.015	0.009
			(4.37)***	(4.15)***
ADR or GDR	0.06	0.24	0.029	0.021
			(1.87)*	(2.01)**
Ln(Book to market)	-0.15	0.73	0.000	
			(0.08)	
Leverage	0.16	0.18	0.011	
			(0.62)	
Ln(Market cap)	-0.12	1.47	-0.020	-0.019
			(6.84)***	(9.50)***
Zero-return weeks	0.03	0.03	0.366	0.304
			(3.22)***	(3.85)***
Mean(Dependent)			0.06	0.05
StDev(Dependent)			0.29	0.30
Observations			7,501	14,055
No. of companies			4,423	8,709
R^2 within			0.19	0.17
R^2 overall			0.15	0.14
R^2 between			0.12	0.11
Country-year FE			Yes	Yes

Table VI
Delay Measures

The table shows results of regressing proxies for price delay D1, D2 and D3 as a function of lending supply, borrowing fees and firm controls. The dependent variables are proxies for price delay similar to Hou and Moskowitz (2005). The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	D1		D2		D3	
			(i)	(ii)	(i)	(ii)	(i)	(ii)
Ln(Supply)	0.28	1.21	-0.010	-0.019	-0.009	-0.015	-0.008	-0.014
			(2.98)***	(8.37)***	(3.75)***	(9.29)***	(3.67)***	(8.91)***
Fee (% p.a.)	0.85	1.27	0.018	0.011	0.013	0.008	0.013	0.008
			(6.02)***	(5.54)***	(6.39)***	(5.76)***	(6.54)***	(6.08)***
ADR or GDR	0.06	0.24	-0.050	-0.030	-0.048	-0.034	-0.048	-0.035
			(4.15)***	(3.62)***	(5.39)***	(5.38)***	(5.46)***	(5.77)***
Ln(Book to market)	-0.15	0.73	-0.038		-0.029		-0.029	
			(8.82)***		(9.23)***		(9.68)***	
Leverage	0.16	0.18	0.043		0.022		0.020	
			(2.72)***		(1.85)*		(1.76)*	
Ln(Market cap)	-0.12	1.47	-0.038	-0.043	-0.023	-0.027	-0.023	-0.027
			(15.72)***	(24.54)***	(12.20)***	(20.61)***	(13.20)***	(21.40)***
Zero-return weeks	0.03	0.03	0.576	0.538	0.381	0.349	0.336	0.310
			(5.68)***	(7.77)***	(5.27)***	(7.09)***	(4.91)***	(6.68)***
Mean(Dependent)			0.33	0.35	0.55	0.56	0.60	0.61
StDev(Dependent)			0.24	0.25	0.19	0.19	0.18	0.18
Observations			7,501	14,055	7,501	14,055	7,501	14,055
No. of companies			4,423	8,709	4,423	8,709	4,423	8,709
R^2 within			0.05	0.05	0.05	0.05	0.07	0.09
R^2 overall			0.21	0.22	0.17	0.20	0.18	0.22
R^2 between			0.27	0.28	0.24	0.26	0.23	0.28
Country-year FE			Yes	Yes	Yes	Yes	Yes	Yes

Table VII: R^2

The table shows results of regressing R^2s as a function of lending supply, borrowing fees and firm controls. The dependent variables are computed by regressing all weekly stock returns in a given year as a function of a domestic market index and a world market index and transformed using $\ln[R^2/(1-R^2)]$. Overall R^2 uses all available returns in a given year, Down R^2 computes R^2s only based on negative local-market return weeks, Up R^2 from positive local-market return weeks and Diff R^2 is computed as Down R^2 minus Up R^2. The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Overall R^2	Down R^2	Up R^2	Diff R^2	Overall R^2	Down R^2	Up	Diff R^2
Ln(Supply)	0.28	1.21	0.060	-0.004	0.036	-0.039	0.047	-0.018	0.039	-0.056
			(5.38)***	(0.40)	(3.11)***	(2.58)***	(2.83)***	(1.02)	(2.29)**	(2.36)**
Fee (% p.a.)	0.854	1.268	-0.050	0.010	-0.025	0.036	-0.106	0.013	-0.069	0.083
			(5.19)***	(1.03)	(2.43)**	(2.66)***	(7.08)***	(0.92)	(4.42)***	(4.09)***
ADR or GDR	0.06	0.24	0.213	0.173	0.201	-0.030	0.156	0.185	0.147	0.038
			(4.95)***	(3.73)***	(4.16)***	(0.49)	(2.68)***	(2.73)***	(2.13)**	(0.43)
Ln(Book to market)	-0.147	0.73					0.164	0.065	0.143	-0.078
							(7.49)***	(2.89)***	(5.91)***	(2.46)**
Leverage	0.16	0.18					-0.243	-0.385	-0.071	-0.311
							(2.96)***	(4.35)***	(0.78)	(2.49)**
Ln(Market cap)	-0.12	1.47	0.280	0.115	0.183	-0.067	0.231	0.099	0.146	-0.048
			(31.71)***	(13.09)***	(20.62)***	(5.77)***	(19.43)***	(7.37)***	(11.41)***	(2.70)***
Zero-return weeks	0.03	0.03	-3.352	-0.589	-1.032	0.481	-3.868	-0.516	-1.368	0.922
			(9.98)***	(1.65)*	(2.90)***	(0.99)	(7.76)***	(0.97)	(2.60)***	(1.27)
Mean(Dependent)			-1.86	-1.88	-2.49	0.61	-1.77	-1.83	-2.48	0.65
StDev(Dependent)			1.31	1.36	1.36	1.82	1.23	1.35	1.33	1.81
Observations			14,055	14,055	14,055	14,055	7,501	7,501	7,501	7,501
No. of Companies			8,709	8,709	8,709	8,709	4,423	4,423	4,423	4,423
R^2 within			0.09	0.03	0.13	0.03	0.31	0.05	0.13	0.04
R^2 overall			0.26	0.06	0.10	0.04	0.25	0.04	0.09	0.04
R^2 between			0.31	0.07	0.13	0.03	0.31	0.05	0.13	0.04
Country-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VIII
Skewness

The table shows results of regressing kurtosis as a function of lending supply, borrowing fees and firm controls. Raw skewness is based on weekly stock returns, while abnormal skewness uses the residuals of a market-model equation. The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Skewness abnormal		Skewness raw	
			(i)	(ii)	(i)	(ii)
Ln(Supply)	0.28	1.21	-0.069	-0.072	-0.064	-0.073
			(5.31)***	(7.92)***	(4.90)***	(7.33)***
Fee (% p.a.)	0.85	1.27	0.007	0.008	0.001	0.007
			(0.64)	(1.00)	(0.10)	(0.83)
ADR or GDR	0.06	0.24	-0.013	-0.040	-0.010	-0.029
			(0.29)	(1.26)	(0.21)	(0.84)
Ln(Book to market)	-0.15	0.73	-0.051		-0.049	
			(2.86)***		(2.69)***	
Leverage	0.16	0.18	-0.075		-0.034	
			(1.08)		(0.50)	
Ln(Market cap)	-0.12	1.47	-0.009	-0.007	-0.020	-0.014
			(0.93)	(1.09)	(2.15)**	(2.04)**
Zero-return weeks	0.03	0.03	0.940	0.973	0.986	1.065
			(2.15)**	(3.26)***	(2.22)**	(3.43)***
Mean(Dependent)			0.16	0.15	0.10	0.09
StDev(Dependent)			0.96	0.96	0.91	0.93
Observations			7,501	14,055	7,501	14,055
No. of companies			4,423	8,709	4,423	8,709
R^2 within			0.01	0.01	0.01	0.01
R^2 overall			0.07	0.07	0.07	0.07
R^2 between			0.10	0.09	0.09	0.08
Country-year FE			Yes	Yes	Yes	Yes

Table IX
Kurtosis

The table shows results of regressing kurtosis as a function of lending supply, borrowing fees and firm controls. Raw kurtosis is based on weekly stock returns, while abnormal kurtosis uses the residuals of a market-model equation. The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Kurtosis abnormal		Kurtosis raw	
			(i)	(ii)	(i)	(ii)
Ln(Supply)	0.28	1.21	-0.018	-0.043	-0.058	-0.111
			(0.32)	(1.13)	(1.02)	(2.44)**
Fee (% p.a.)	0.85	1.27	0.135	0.118	0.168	0.133
			(2.95)***	(3.42)***	(3.56)***	(3.63)***
ADR or GDR	0.06	0.24	0.235	0.259	0.214	0.328
			(1.16)	(1.75)*	(1.02)	(1.93)*
Ln(Book to market)	-0.15	0.73	0.124		0.098	
			(1.72)*		(1.29)	
Leverage	0.16	0.18	0.166		0.266	
			(0.57)		(0.92)	
Ln(Market cap)	-0.12	1.47	-0.215	-0.186	-0.248	-0.253
			(5.17)***	(6.53)***	(5.92)***	(8.40)***
Zero-return weeks	0.03	0.03	6.319	6.750	7.486	7.771
			(3.08)***	(4.94)***	(3.52)***	(5.37)***
Mean(Dependent)			2.31	2.27	2.10	2.14
StDev(Dependent)			3.77	3.86	3.74	3.95
Observations			7,501	14,055	7,501	14,055
No. of companies			4,423	8,709	4,423	8,709
R^2 within			0.01	0.01	0.01	0.01
R^2 overall			0.03	0.03	0.03	0.04
R^2 between			0.03	0.03	0.04	0.05
Country-year FE			Yes	Yes	Yes	Yes

Table X
Frequency of Extreme Events

The table shows results of regressing extreme return measures as a function of lending supply, borrowing fees and firm controls. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion that are two standard deviations above the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Zero-return weeks is the proportion of zero-return weeks in a given year. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St.dev.	Extreme Down		Extreme Up	
			(i)	(ii)	(i)	(ii)
Ln(Supply)	0.34	1.17	-0.010	0.040	-0.070	-0.090
			(0.30)	(1.06)	(1.35)	(2.73)***
Fee (% p.a.)	0.80	1.20	0.050	0.010	-0.050	-0.040
			(1.27)	(0.48)	(1.26)	(1.35)
ADR or GDR	0.06	0.24	-0.250	-0.350	-0.110	-0.290
			(1.79)*	(3.46)***	(0.63)	(2.44)**
Ln(Book to market)	-0.16	0.71	0.270		0.010	
			(4.11)***		(0.20)	
Leverage	0.16	0.18	0.170		0.000	
			(0.69)		(0.02)	
Ln(Market cap)	-0.05	1.45	-0.050	-0.080	-0.140	-0.150
			(1.63)	(3.21)***	(4.09)***	(6.35)***
Zero-return weeks	0.02	0.03	-3.520	-3.740	-0.360	-1.580
			(2.06)**	(3.42)***	(0.18)	(1.30)
Mean(Dependent)			0.02	0.02	0.02	0.03
StDev(Dependent)			0.023	0.025	0.024	0.025
Observations			7,057	12,516	7,057	12,516
No. of companies			4,186	7,651	4,186	7,651
R^2 within			0.08	0.08	0.10	0.09
R^2 overall			0.08	0.08	0.07	0.08
R^2 between			0.07	0.07	0.04	0.07
Country-year FE			Yes	Yes	Yes	Yes

Table XI: Robustness Check – Additional control variables for US data

The tables shows regressions of US firms' price efficiency proxies as a function of lending supply, borrowing fees and firm controls, added by Optionability (fraction of quarters in a year with options being traded), Amihud (2002)'s ILLIQ measure and annualized stock turnover. The regressions include the same control variables as the base specification (ii) in tables V-X. Other coefficients estimates are not included to preserve space. The R^2 coefficients are transformed using $\ln[R^2/(1-R^2)]$. Correlations are transformed using Cross-correlation=$\ln[(\rho+1)/(1-\rho)]$. D1 and D2 are the price efficiency measures proposed by Hou and Moskowitz (2005). Skewness and kurtosis are based on raw returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion that are two standard deviations above the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St. dev	Cross-Corr	D1	D2	R^2	Skewness	Kurtosis	Extreme Down	Extreme Up
Ln(Supply)	0.18	1.15	-0.016	-0.023	-0.024	0.121	-0.063	0.030	0.000	-0.001
			(3.65)***	(6.50)***	(9.07)***	(6.82)***	(4.61)***	(0.53)	(0.52)	(1.55)
Implied fee (% p.a.)	0.43	0.97	0.009	0.012	0.005	-0.085	0.021	0.038	-0.002	-0.001
			(2.18)**	(3.13)***	(1.71)*	(4.38)***	(1.29)	(0.59)	(3.00)***	(2.04)**
Ln(Market Cap)	-0.27	1.60	-0.015	-0.046	-0.027	0.273	-0.001	-0.353	-0.001	-0.001
			(5.15)***	(18.19)***	(13.77)***	(20.93)***	(0.06)	(8.00)***	(1.16)	(2.43)**
Optionability	0.37	0.48	0.010	-0.002	0.017	0.018	-0.043	0.250	-0.003	-0.003
			(1.23)	(0.30)	(3.03)***	(0.58)	(1.68)*	(2.19)**	(2.62)***	(1.56)
ILLIQ	0.21	1.92	0.001	0.006	0.003	-0.030	0.006	-0.003	0.000	0.000
			(1.03)	(2.10)**	(2.00)**	(1.78)*	(0.89)	(0.17)	(0.79)	(0.06)
Turnover (%)	0.83	1.16	0.000	0.003	0.011	0.003	0.001	0.249	0.003	0.002
			(0.01)	(1.04)	(3.68)***	(0.28)	(0.06)	(2.96)***	(4.00)***	(3.34)***
Mean(Dependent)			0.02	0.32	0.54	-1.75	-0.07	2.16	0.03	0.03
StDev(Dependent)			0.28	0.24	0.19	1.20	0.92	3.96	0.04	0.05
Observations			6,061	6,061	6,061	6,061	6,061	6,061	6,061	6,061
No. of companies			3,770	3,770	3,770	3,770	3,770	3,770	3,770	3,770
R^2 within			0.08	0.02	0.01	0.03	0.00	0.01	0.03	0.00
R^2 overall			0.04	0.19	0.13	0.23	0.01	0.03	0.01	0.01
R^2 between			0.02	0.27	0.20	0.31	0.02	0.03	0.00	0.01
Year fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table XII

Robustness with respect to time period

This table report coefficients of Ln(supply) and Fee in a balanced panel of two different periods. Period 1 goes from March 24, 2004 to March 23, 2005 and Period 2 from July 13, 2005 to June 28, 2006. The regressions include the same control variables as the base specification (ii) in Tables V-X. Other coefficients are not included to preserve space. The R^2 coefficients are transformed using $\ln[R^2/(1-R^2)]$. Correlations are transformed using Cross-correlation=$\ln[(\rho+1)/(1-\rho)]$. D1, D2 and D3 are the price efficiency measures proposed by Hou and Moskowitz (2005). Skewness and kurtosis are based on raw returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Ln(supply)		Fee	
Dep. Variable	Period 1	Period 2	Period 1	Period 2
R^2	0.026	0.075	-0.109	-0.044
	(1.65)*	(4.15)***	(6.91)***	(3.13)***
Corr	-0.008	-0.010	0.024	0.011
	(2.18)**	(2.15)**	(6.18)***	(3.16)***
D1	-0.001	-0.020	0.021	0.001
	(0.34)	(5.59)***	(6.94)***	(0.19)
D2	0.002	0.001	0.015	0.001
	(0.83)	(0.26)	(5.71)***	(0.22)
D3	0.002	0.001	0.013	0.000
	(0.91)	(0.36)	(6.17)***	(0.09)
Skewness abnormal	-0.069	-0.091	0.015	-0.009
	(4.95)***	(5.55)***	(1.23)	(0.63)
Kurtosis raw	-0.056	-0.020	0.175	0.108
	(0.80)	(0.24)	(2.97)***	(1.52)
Extreme Down	-0.001	0.003	0.001	0.000
	(1.58)	(5.15)***	(1.96)**	(0.11)

Table XIII
Robustness with respect to measurement error

The table presents regression coefficients by splitting the firms into three groups. Each year the sample is split into three groups (“Low”, “Medium”, “High”) based on the coefficients of variation of, respectively, Ln(Supply) or Fee in a given year. The coefficients for each variable are then estimated separately for each group in a single regression. The regressions include the same control variables as the base specification (ii) in tables V-X. Other coefficient estimates are not included to preserve space. The R^2 coefficients are transformed using ln[R^2/(1-R^2)]. Correlations are transformed using Cross-correlation=ln[(ρ+1)/(1-ρ)]. D1 and D2 are the price efficiency measures proposed by Hou and Moskowitz (2005). Skewness and kurtosis are computed from weekly returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year’s average. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year’s average. Extreme Up is the proportion of weekly returns in a given year that are two standard deviations above the previous year’s average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Ln(Supply)			Fee		
Dep. Variable	Low	Med.	High	Low	Med.	High
R^2	0.070	0.109	0.121	-0.066	-0.070	-0.065
	(4.10)***	(6.51)***	(8.36)***	(5.85)***	(4.25)***	(4.23)***
Corr	0.005	-0.012	-0.012	0.010	0.011	0.004
	(1.23)	(3.30)***	(3.67)***	(3.79)***	(2.82)***	(1.25)
D1	-0.011	-0.020	-0.022	0.010	0.012	0.012
	(3.21)***	(5.88)***	(7.42)***	(4.68)***	(3.37)***	(3.60)***
D2	-0.006	-0.019	-0.017	0.007	0.008	0.010
	(2.51)**	(7.67)***	(8.05)***	(4.69)***	(3.36)***	(4.04)***
D3	-0.006	-0.018	-0.015	0.007	0.008	0.010
	(2.36)**	(7.39)***	(7.71)***	(4.99)***	(3.45)***	(4.17)***
Skewness abnormal	-0.041	-0.078	-0.079	0.017	-0.033	0.014
	(3.00)***	(5.43)***	(6.29)***	(1.87)*	(2.24)**	(1.08)
Skewness raw	-0.035	-0.075	-0.086	0.017	-0.038	0.010
	(2.51)**	(5.00)***	(6.14)***	(1.86)*	(2.49)**	(0.71)
Kurtosis abnormal	-0.093	-0.024	-0.032	0.130	0.127	0.078
	(1.58)	(0.44)	(0.57)	(3.35)***	(1.99)**	(1.66)*
Kurtosis raw	-0.143	-0.081	-0.116	0.137	0.152	0.106
	(2.37)**	(1.41)	(1.65)*	(3.39)***	(2.23)**	(2.11)**
Extreme Down	-0.002	0.001	0.001	0.000	0.001	0.001
	(3.31)***	(2.05)**	(1.58)	(1.01)	(2.32)**	(1.77)*
Extreme Up	-0.002	-0.002	0.000	-0.001	0.000	0.000
	(3.39)***	(4.00)***	(0.40)	(1.81)*	(0.18)	(0.47)

Table XIV
Robustness with respect to geographic region

This table split the sample between US and non-US firms. The coefficients on Ln(supply) and Fee are estimated separately depending on which country the observation belongs to. The regressions include the same control variables as the base specification (ii) in tables V-X. Other coefficient estimates are not included to preserve space. The R^2 coefficients are transformed using $\ln[R^2/(1\text{-}R^2)]$. Correlations are transformed using Cross-correlation=$\ln[(\rho+1)/(1\text{-}\rho)]$. D1, D2 and D3 are the price efficiency measures proposed by Hou and Moskowitz (2005). Skewness and kurtosis are computed from weekly returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion of weekly returns in a given year that are two standard deviations above the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Ln(supply)		Fee	
	US	Non US	US	Non US
R^2	0.148	0.052	-0.075	-0.073
	(10.29)***	(3.37)***	(4.46)***	(6.00)***
Corr	-0.010	-0.007	0.004	0.012
	(3.01)***	(2.00)**	(1.10)	(4.37)***
D1	-0.027	-0.009	0.011	0.013
	(9.10)***	(2.99)***	(3.42)***	(5.14)***
D2	-0.021	-0.008	0.007	0.010
	(9.60)***	(3.89)***	(3.06)***	(5.72)***
D3	-0.019	-0.008	0.006	0.010
	(9.17)***	(3.98)***	(3.08)***	(5.87)***
Skewness abnormal	-0.052	-0.094	0.010	0.003
	(4.14)***	(8.25)***	(0.65)	(0.28)
Skewness raw	-0.057	-0.091	0.014	0.000
	(3.98)***	(7.76)***	(0.84)	(0.01)
Kurtosis abnormal	0.133	-0.252	0.146	0.062
	(2.48)**	(5.06)***	(2.29)**	(1.55)
Kurtosis raw	-0.006	-0.238	0.178	0.085
	(0.08)	(4.57)***	(2.60)***	(2.00)**
Extreme Down	0.001	0.000	0.000	0.000
	(1.38)	0.00	(0.60)	(0.90)
Extreme Up	0.000	-0.002	-0.001	-0.001
	(0.13)	(3.53)***	(1.29)	(1.25)

Table XV: Robustness to Supply measures – Lagged Variables

This table reports regression results using lending supply and borrowing fee lagged by one year. The regressions include the same control variables as the base specification (ii) in tables V-X. Other coefficient estimates are not included to preserve space. The R^2 coefficients are transformed using $\ln[R^2/(1-R^2)]$. Correlations are transformed using Cross-correlation=$\ln[(\rho+1)/(1-\rho)]$. D1 is the price efficiency measure proposed by Hou and Moskowitz (2005). Skewness and kurtosis are computed from weekly returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion of weekly returns in a given year that are two standard deviations above the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

	Mean	St. dev	R^2	Cross-corr	D1	Skewness	Kurtosis	Extreme Down	Extreme Up
Ln(Lag[Supply])	-0.04	1.56	0.061	-0.008	-0.012	-0.034	-0.094	0.000	-0.001
			(5.66)***	(3.26)***	(5.77)***	(4.07)***	(2.61)***	(0.96)	(2.60)***
Lag(Fee) (% p.a.)	1.06	1.52	-0.066	0.008	0.012	0.002	0.126	0.001	0.000
			(6.56)***	(3.60)***	(5.88)***	(0.16)	(3.02)***	(1.61)	(0.57)
ADR or GDR	0.08	0.27	0.196	0.013	-0.032	0.010	0.351	-0.003	-0.003
			(4.02)***	(1.06)	(3.43)***	(0.25)	(1.79)*	(2.47)**	(2.04)**
Ln(Market cap)	-0.30	1.68	0.267	-0.019	-0.044	-0.052	-0.248	-0.001	-0.002
			(26.43)***	(8.86)***	(22.17)***	(7.12)***	(7.46)***	(2.17)**	(6.07)***
Zero-return weeks	0.03	0.04	-3.298	0.134	0.573	1.317	5.341	-0.058	-0.028
			(8.07)***	(1.47)	(7.02)***	(4.02)***	(3.49)***	(5.49)***	(2.23)**
Mean(Dependent)			-1.89	0.07	0.35	0.15	2.38	0.02	0.03
StDev(Dependent)			1.36	0.30	0.25	1.03	4.90	0.03	0.03
Observations			9,789	9,789	9,789	9,789	9,789	8,414	8,414
No. of companies			7,552	7,552	7,552	7,552	7,552	6,380	6,380
R^2 within			0.09	0.14	0.04	0.02	0.01	0.10	0.12
R^2 overall			0.32	0.14	0.25	0.08	0.06	0.08	0.07
R^2 between			0.32	0.14	0.25	0.08	0.06	0.08	0.07
Country-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table XVI: Robustness to Supply measures – Price Efficiency Measures

This table reports regression results using alternatives measures of lending supply. Residual Supply is the residuals of lending supply scaled by aggregate supply, after controlling for firm market capitalization. Utilization is number of shares lent out divided by shares outstanding. The R^2 coefficients are transformed using $\ln[R^2/(1-R^2)]$. Correlations are transformed using Cross-correlation=$\ln[(\rho+1)/(1-\rho)]$. D1 is a price efficiency measure proposed by Hou and Moskowitz (2005). The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

			R^2		Cross-correlation		D1		D2	
	Mean	St. dev	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Ln(Residual)	0.00	1.14	0.101		-0.009		-0.018		-0.015	
			(8.44)***		(3.34)***		(7.59)***		(8.69)***	
Utilization	0.21	0.22		-0.008		0.066		0.005		0.017
				(0.14)		(5.08)***		(0.49)		(2.13)**
Fee (% p.a.)	0.93	1.34	-0.070	-0.091	0.009	0.008	0.012	0.015	0.008	0.011
			(7.04)***	(8.79)***	(4.16)***	(3.45)***	(5.79)***	(7.18)***	(6.03)***	(7.13)***
ADR or GDR	0.08	0.27	0.178	0.180	0.021	0.017	-0.031	-0.032	-0.034	-0.036
			(4.09)***	(4.08)***	(1.97)**	(1.64)	(3.73)***	(3.76)***	(5.49)***	(5.60)***
Ln(Market cap)	-0.26	1.58	0.285	0.284	-0.021	-0.020	-0.048	-0.047	-0.031	-0.031
			(33.81)***	(32.65)***	(11.30)***	(10.53)***	(28.72)***	(27.79)***	(24.85)***	(23.78)***
Zero-return weeks	0.03	0.04	-2.896	-3.250	0.305	0.349	0.550	0.612	0.357	0.415
			(8.33)***	(9.39)***	(3.86)***	(4.47)***	(7.92)***	(8.88)***	(7.24)***	(8.45)***
Mean(Dependent)			-1.86	-1.86	0.05	0.05	0.35	0.35	0.56	0.56
StDev(Dependent)			1.31	1.31	0.30	0.30	0.25	0.25	0.19	0.19
Observations			14,055	14,031	14,055	14,031	14,055	14,031	14,055	14,031
No. of companies			8,709	8,689	8,709	8,689	8,709	8,689	8,709	8,689
R^2 within			0.11	0.11	0.17	0.17	0.05	0.05	0.05	0.05
R^2 overall			0.30	0.29	0.14	0.14	0.22	0.22	0.20	0.20
R^2 between			0.35	0.34	0.11	0.11	0.28	0.27	0.26	0.25
Country-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table XVII: Robustness to Supply measures – Characteristics of the Distribution of Stock Returns

This table reports results using alternatives measures of lending supply. Residual Supply is the residuals of lending supply scaled by aggregate supply, after controlling for firm market capitalization. Utilization is number of shares lent out divided by shares outstanding. Skewness and Kurtosis are compute from weekly returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion that are two standard deviations above the previous year's average. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

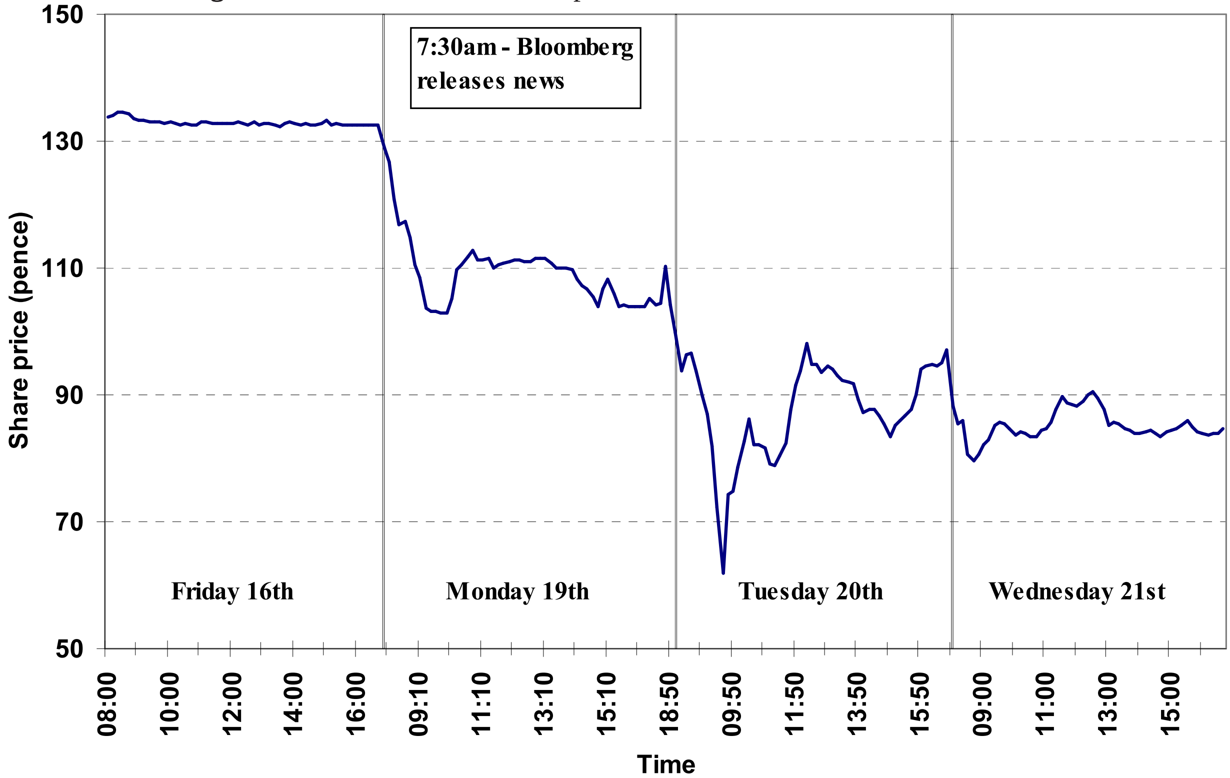
			Skewness		Kurtosis		Extreme Down		Extreme Up	
	Mean	St. dev	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Residual Supply	0.00	1.14	-0.078		-0.010		0.000		-0.001	
			(8.56)***		(0.26)		(1.14)		(2.80)***	
Utilization	0.21	0.22		0.002		1.203		0.003		-0.002
				(0.05)		(6.06)***		(1.48)		(1.26)
Fee (% p.a.)	0.93	1.34	0.008	0.026	0.126	0.053	0.000	0.000	0.000	0.000
			(0.99)	(2.95)***	(3.63)***	(1.50)	(0.50)	(0.25)	(1.38)	(0.12)
ADR or GDR	0.08	0.27	-0.044	-0.044	0.256	0.198	-0.004	-0.004	-0.003	-0.003
			(1.37)	(1.37)	(1.74)*	(1.35)	(3.45)***	(3.50)***	(2.46)**	(2.25)**
Ln(Market cap)	-0.26	1.58	-0.027	-0.025	-0.196	-0.181	-0.001	-0.001	-0.002	-0.002
			(4.32)***	(3.93)***	(7.29)***	(6.75)***	(2.84)***	(2.83)***	(7.74)***	(7.87)***
Zero-return weeks	0.03	0.04	0.979	1.301	6.895	6.917	-0.037	-0.039	-0.016	-0.015
			(3.28)***	(4.41)***	(5.04)***	(5.13)***	(3.41)***	(3.65)***	(1.31)	(1.24)
Mean(Dependent)			0.15	0.15	2.27	2.26	0.02	0.02	0.03	0.03
StDev(Dependent)			0.96	0.95	3.86	3.86	0.03	0.03	0.03	0.03
Observations			14,055	14,031	14,055	14,031	12,516	12,496	12,516	12,496
No. of companies			8,709	8,689	8,709	8,689	7,651	7,633	7,651	7,633
R^2 within			0.01	0.00	0.01	0.01	0.08	0.08	0.09	0.09
R^2 overall			0.07	0.06	0.03	0.03	0.08	0.08	0.08	0.08
R^2 between			0.09	0.08	0.03	0.04	0.07	0.07	0.07	0.07
Country-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table XVIII: Robustness Check – Differential impact between OECD and non-OECD countries

The regressions include the same control variables as in Column (ii) from Tables V, D_{OECD} equals 1 if a country belongs to the OECD. Correlations are transformed using Cross-correlation=ln[(ρ+1)/(1-ρ)]. D1, D2 and D3 are the price efficiency measures proposed by Hou and Moskowitz (2005). The R^2 coefficients are transformed using ln[R^2/(1-R^2)]. Skewness and kurtosis are based on raw returns. Extreme Down is the proportion of weekly returns in a given year that are two standard deviations below the previous year's average. Extreme Up is the proportion that are two standard deviations above the previous year's average. We also report p-values of tests of equality between coefficients and their respective products with the OECD dummy and joint tests of significance of OECD and non-OECD parameters. The lending data are from 2004 and 2005 and cover 26 different countries. Each firm-year must have at least 50 weekly return observations and less than 10 weeks with zero returns and countries must have at least 16 companies to be included in the sample. The panel regressions are estimated using GLS random firm-effects with robust (Huber/White/sandwich) standard errors. T-statistics are reported in parentheses and significance levels are indicated as follows: *=statistical significance at the 10% level; **=significant at the 5% percent level; ***=significant at the 1% level.

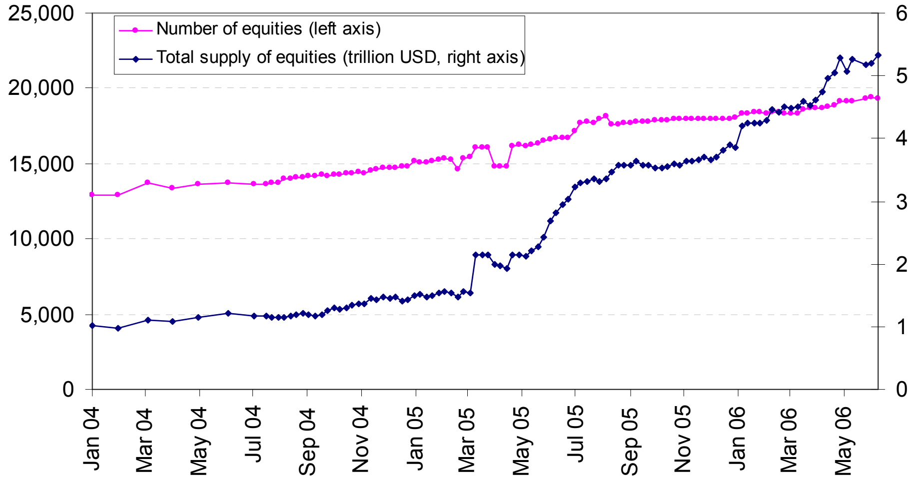
	Cross-Correlation	D1	D2	D3	R^2	Skewness	Kurtosis	Extreme Down	Extreme Up
D_{OECD}	0.247	-0.109	-0.089	-0.090	-0.098	-0.402	-6.586	-0.066	-0.044
	(1.89)*	(1.15)	(1.03)	(1.04)	(0.13)	(0.53)	(1.31)	(1.77)*	(1.69)*
Ln(Supply)	-0.034	0.002	0.001	0.001	0.008	-0.037	-0.440	-0.003	-0.006
	(3.56)***	(0.17)	(0.15)	(0.07)	(0.19)	(0.94)	(2.26)**	(1.43)	(3.27)***
D_{OECD}*Ln(Supply)	0.027	-0.021	-0.017	-0.015	0.102	-0.038	0.343	0.003	0.006
	(2.74)***	(2.31)**	(2.38)**	(2.11)**	(2.27)**	(0.92)	(1.73)*	(1.55)	(2.70)***
Fee (% p.a.)	-0.013	0.006	0.005	0.005	-0.020	0.018	-0.122	-0.002	-0.001
	(1.61)	(0.91)	(0.89)	(0.86)	(0.57)	(0.60)	(1.01)	(1.19)	(1.05)
D_{OECD}*Fee	0.024	0.006	0.003	0.003	-0.051	-0.011	0.271	0.001	0.001
	(2.84)***	(0.80)	(0.54)	(0.58)	(1.38)	(0.35)	(2.13)**	(1.04)	(0.47)
ADR or GDR	0.023	-0.032	-0.034	-0.036	0.169	-0.034	0.317	-0.004	-0.004
	(2.19)**	(3.76)***	(5.41)***	(5.77)***	(3.88)***	(0.99)	(1.85)*	(3.55)***	(1.98)**
Zero-return weeks	-0.030	-0.040	-0.029	-0.029	0.304	0.008	-0.218	-0.002	-0.002
	(3.54)***	(6.10)***	(5.52)***	(5.57)***	(8.72)***	(0.34)	(2.12)**	(1.97)**	(1.54)
Ln(Market cap)	0.306	0.536	0.347	0.308	-2.827	1.061	7.761	-0.045	-0.011
	(3.87)***	(7.73)***	(7.04)***	(6.63)***	(8.15)***	(3.42)***	(5.37)***	(4.02)***	(0.69)
D_{OECD}*Ln(Market cap)	0.011	-0.002	0.002	0.002	-0.050	-0.023	-0.037	0.001	-0.001
	(1.30)	(0.33)	(0.33)	(0.44)	(1.41)	(0.94)	(0.35)	(0.92)	(0.54)
R^2	0.14	0.23	0.20	0.22	0.30	0.07	0.04	0.07	0.03
F test: Ln(Supply) params=0	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.27	0.00
F test: Fee params=0	0.00	0.00	0.00	0.00	0.00	0.63	0.00	0.44	0.14
F test: Mkt. Cap. params=0	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.01

Figure 1. Northern Rock's share price - November 2007 - 10min intervals



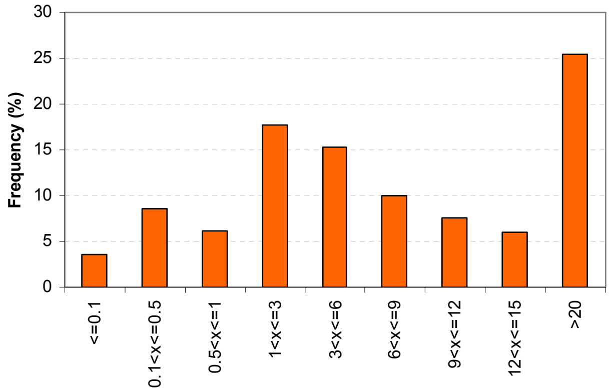
This figure plots Northern Rock Plc's share price in 10 minute intervals between November 16th and November 21st, 2007. Intraday price data come from Reuters. Each observation represents the average trading price of all transactions within a particular 10 minute interval.

Figure 2. Total Supply of Equities



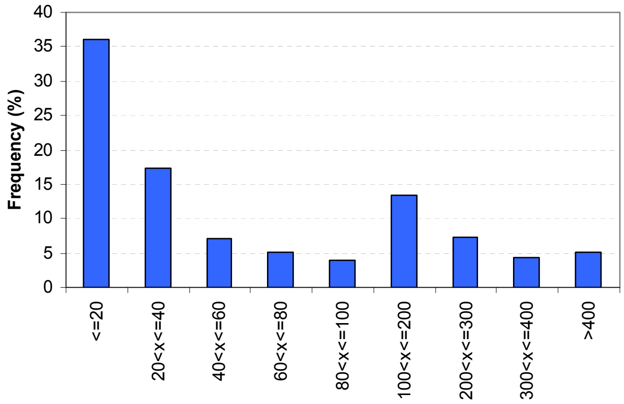
The figure shows the total supply of equities available in the database from January 2004 to June 2006. The left axis display the number of different stocks and the right axis the aggregate value of lending supply expressed in trillions of US dollars.

Figure 3. Distribution of supply (% of firm size)



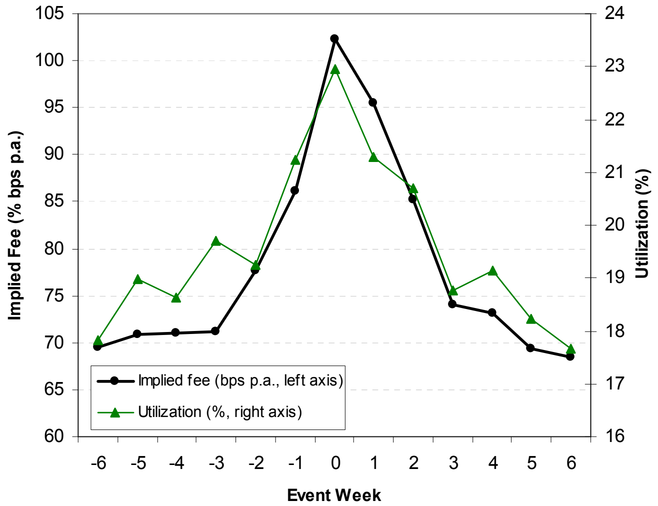
The figure contains the distribution of supply as a percentage of firm size on June 28th, 2006. The vertical axis contains the frequency of firms with yearly average lending supply in each interval reported in the horizontal axis.

Figure 4. Distribution of yearly VW borrowing fee averages



This figure contains the distribution of yearly average borrowing fees in basis points per year. The vertical axis contains the frequency of firms with borrowing fees in each interval reported in the horizontal axis.

Figure 5. Fees and Utilization around dividend payments



This figure shows borrowing fees and lending volume around dividend payments. For each firm in the period between January 2004 and June 2006, we compute the average borrowing fee and lending supply on a six-week period around ex-dividend dates. Ex-dividend dates are taken from Datastream.

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