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Passive Ownership and Short Selling

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Abstract

We exploit quasi-exogenous variation in passive ownership around the Russell 1000/2000 cutoff to explore the causal effects of passive ownership on the securities lending market. We find that passive ownership causes an increase in lendable supply and short interest, while lending fees remain largely unchanged. The utilization ratio—i.e., the ratio of short interest over lendable supply—goes up, implying that shorting demand increases more than lendable supply. We argue that this additional demand results from an increase in the quality of lendable supply as passive funds are less likely to recall stock loans. Finally, we document that passive ownership-induced short selling improves information efficiency around negative earnings news.

Keywords: ETFs, securities lending, short selling

JEL classification: G11, G12, G14, G15

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The past two decades have seen a tremendous growth in passive investment. In August 2019, passive investment funds overtook active funds in terms of assets under management for the first time.[1] A growing body of research tries to understand the consequences of this seismic shift in asset management (e.g., Wurgler (2010), Ramaswamy (2011), Da and Shive (2016); for a survey, see Ben-David et al. (2017)). We contribute to this literature by studying the impact of passive ownership on the securities lending market. In a way, we feel like research has jumped ahead by studying the consequences of passive ownership on diverse issues such as corporate governance, payout policy, firm value, mergers and acquisitions, corporate investment, price efficiency, activist investing etc,[2] without fully mapping out the more direct and immediate consequences of passive ownership. We argue that one such direct consequence concerns the equity lending markets, in which passive funds are known to actively participate as security lenders (Blocher and Whaley (2016)). Specifically, we conjecture that, through their role as suppliers of shares, passive lenders facilitate short selling, which can help explain—and potentially even drive—some of the aforementioned effects ascribed to passive ownership.

Short sellers need to borrow the security in the equity lending market if they want to keep open a position for more than one day. This makes equity lending key for enabling short selling, which itself is vital for the price and informational efficiency of the underlying shares in the stock market (Saffi and Sigurdson (2011), Beber and Pagano (2013), Boehmer and Wu (2013)). Because passive funds are known to actively participate as security lenders (Blocher and Whaley (2016)), we hypothesize that a sudden increase in passive ownership should first and foremost be associated with an increase in the lendable supply of securities. If this were the only effect, we would expect a decrease in the equilibrium lending fee and a resulting increase in short interest (i.e., the fraction of shares that are shorted over the number of outstanding shares) as displayed in Figure 1 Panel A. Our results, however, paint a more nuanced picture. In particular,

[1] Confer Bloomberg article by John Gittelsohn: "End of Era: Passive Equity Funds Surpass Active in Epic Shift," published September 11, 2019.

[2] See for example Crane et al. (2014), Mullins (2014), Boone and White (2015), Appel et al. (2016, 2019), Schmidt and Fahlenbrach (2017), Israeli et al. (2017), Antoniou et al. (2018), Ben-David et al. (2018), Glosten et al. (2020), Heath et al. (2020).

we find evidence of a simultaneous and pronounced shift in lending supply *and* short selling demand. Importantly, the utilization ratio (i.e., the ratio of short interest over lendable supply) and the lending fee if anything increase, as displayed in Figure 1 Panel B.

Why does passive ownership cause additional short selling demand? One possibility is that a sudden increase in passive ownership pushes up stock prices, thereby attracting short sellers who anticipate lower returns for the stock going forward. Indeed, the literature finds evidence for an *index inclusion effect* (Shleifer (1986), Chang et al. (2015))—i.e., a run-up in prices for stocks added to an index widely followed by passive investors—as well as lower future returns for added stocks (Pavlova and Sikorskaya (2022)). While this may explain part of the increase in short selling demand, we find it does not explain all of it. For example, we find that the increase in short selling demand is similar for stocks added to the index *independent* of their inclusion return. We thus entertain two additional hypotheses. First, increased short selling demand could come from arbitrage on exchange traded funds (ETFs). Indeed, when an ETF trades below its basket value, arbitrageurs want to buy the ETF in the market and short sell the stocks in the basket.[3] Second, short sellers may prefer borrowing shares from passive lenders, who are long-term and stable shareholders and thus less likely to recall equity loans. Hence, short sellers may be willing to pay more and/or demand larger quantities when borrowing shares from passive investors. Our results support the second hypothesis, suggesting that passive owners increase both the quantity and the *quality* of the supply for lendable shares.

Identifying the causal effects of passive ownership is challenging. Given ample confounding factors, the interpretation of simple correlations between ownership and short selling variables are fraught with peril. To name one example, larger stocks are more likely to be tracked by passive investors, and are also known to be less short sale constrained. Controlling for firm size is no solution as the relation between firm size,

[3] Authorized participants (APs) could deliver the shares to the ETF provider in order to receive basket stocks in return, with which they can then cover their short positions. Thus, short sales coming from APs are expected to have very short maturity. However, other arbitrageurs without AP license may also trade on the ETF mispricing by just holding the long-short arbitrage position until convergence.

passive ownership, and short sale constraints may well be non-linear. Other confounding factors are likely to be unobserved. For instance, it is plausible that investors' recognition of a stock drives both short selling and the extent with which it is held by passive index funds. To circumvent these endogeneity concerns, we employ a well-established identification strategy surrounding Russell 1000/2000 reconstitution events (Chang et al. (2015), Appel et al. (2016)). Every year in June, Russell decides which stocks from the Russell 1000 (2000) move down (up) to the Russell 2000 (1000) based on their end-of-May market capitalization. Both indexes are tracked by large passive funds with substantial assets under management (Chang et al. (2015)). Importantly, stocks at the top of the Russell 2000 have a much larger portfolio weight in their respective index compared to stocks at the bottom of the Russell 1000, and hence stocks that are demoted to the Russell 2000 experience a surge in passive ownership. Following Appel et al. (2016, 2019, 2020), we therefore use Russell 2000 index membership as an instrumental variable for passive ownership. The identification assumption is that after controlling for market capitalization, which is the key variable that determines index membership, stocks above and below the Russell 1000/2000 are similar except for their quasi-exogenous difference in passive ownership. Crucially, Appel et al. (2019) further show (and we confirm) that active ownership is not affected by the index assignment. Hence, Russell reconstitution events allow to study the causal effects of passive ownership.

We implement this identification design by carefully taking into account the latest recommendations from the literature (Ben-David et al. (2019), Appel et al. (2020), Glossner (2020), Wei and Young (2020)). We pay particular attention to sampling and to using the best available end-of-May market capitalization controls.[4] Following these recommendations, the Russell 1000/2000 setting allows us to isolate the causal effect of passive ownership without a confounding effect on total institutional ownership (Appel et al. (2020), Glossner (2020), Wei and Young (2020)). Our results obtain in the cross-section (i.e., by comparing

[4] Glossner (2020) and Wei and Young (2020) emphasize that, in order to prevent selection bias, sampling should be based on end-of-May market capitalization, which Russell uses to assign index membership. We construct our end-of-May market capitalization variable following Ben-David et al. (2019). They find that their variable strongly predicts actual index membership (and thus of the unobserved end-of-May market cap variable used by Russell). See below for further details.

firms around the Russell 1000 membership threshold), as well as when we focus on firms that change index membership—further strengthening the confidence in our findings.

Our results can be summarized as follows. In the first stage, we find that Russell 2000 membership increases passive ownership by 1.2-1.5 percentage points, which represents an increase of 11-14% relative to the mean of passive ownership in our sample. This number is in line with what has been found in prior studies (Appel et al. (2016, 2019)). In the second stage, we document a large increase in lendable supply. Indeed, the magnitude of our coefficient estimate implies that passive ownership and lendable supply go up one-for-one, essentially suggesting that new passive owners offer all their shares for lending. Concomitant to this rise in lendable supply, we find a sizable increase in short interest; i.e., the fraction of outstanding shares that are on loan. Moreover, we find that the lending fee and the utilization ratio—i.e., the ratio of shares lent to the lendable supply—if anything go up. This shows that both the supply and the demand for short selling shift up in response to increased passive ownership.

In subsequent analyses, we analyze the channels driving the increase in shorting demand, over and above what can be explained by the index inclusion effect (Pavlova and Sikorskaya (2022)). We first consider the possibility that increased short selling demand comes from ETF arbitrage. To test for this possibility, we match our sample with data on ETF mispricing and examine if there is a larger increase in short selling on days when ETFs holding the Russell 2000 stock are undervalued relative to their underlying baskets (i.e., when ETF arbitrageurs would want to short-sell the underlying stocks). While our results point in the expected direction, the effect is economically small and statistically insignificant. We conclude that the bulk of increased short selling demand comes from elsewhere.

Our second hypothesis posits that short sellers prefer borrowing from passive stockowners, so that an increase in the proportion of passive owners entices additional borrowing demand. This preference could occur for two reasons. First, passive owners are long-term shareholders with little discretion to adjust their stock positions. As such, a short seller will find it more likely that his equity loan is not recalled prematurely when borrowing from a passive fund. Second, informed short sellers may be worried that active owners opportunistically recall their shares in order to sell them when they see a rise in shorting demand (Honkanen (2020)), thereby essentially free riding on short sellers' information. We find several pieces of evidence consistent with a preference for passive lenders. First, we show that passive ownership increases the average tenure of equity loans. This means that equity loans are kept open for longer, either because lenders do not recall them or because there are more long-horizon short sellers. Second, we find that failures to deliver (henceforth FTD)—which are an indicator for short selling risk—are decreasing in passive ownership. Finally, we document that passive lenders specifically attract informed short sellers. Indeed, we find that short interest becomes a better predictor for future returns after the exogenous increase in passive ownership. Moreover, we find that short sellers become more active before earnings announcements, and we show that this accelerates the incorporation of negative earnings news into prices (as indicated by a lower price-jump ratio around earnings announcements; see Weller (2018)). Taken together, these findings are consistent with the idea that informed short sellers are concerned about active lenders free-riding on their information, and thus prefer borrowing from passive investors.

We contribute to the growing literature on passive ownership by showing that passive ownership promotes short selling not only because of an increase in supply, but also by enticing additional short selling demand. This has the potential to inform the underlying channels behind diverse findings documented in the literature. For example, consider corporate governance. Appel et al. (2016) and Mullins (2014) document that firms with passive owners improve governance by, among other things, appointing more independent directors and removing takeover defenses. In contrast, Heath et al. (2020) show that passive funds are less likely to vote against management on contentious governance issues. Our findings offer an explanation that can help reconcile this seemingly conflicting evidence: by facilitating short selling, passive owners indirectly increase the pressure on management to adopt better governance practices (Massa et al. (2015), Fang et al. (2016)). Thus, passive owners may well be worse monitors (consistent with Heath et al. (2020)) and yet their presence can lead to better governance outcomes (consistent with Appel et al. (2016)). The indirect effect of passive ownership via short selling may also play a role in explaining other findings that have commonly been attributed to passive owners directly, such as the effects on firm value (Schmidt and Fahlenbrach (2017)), payout policy (Crane et al. (2014)), mergers and acquisitions (Antoniou et al. (2018)), corporate investment (Fich et al. (2015)), activist investing (Appel et al. (2019)), price and information efficiency (Boone and White (2015), Israeli et al. (2017), Glosten et al. (2020)), and volatility (Ben-David et al. (2018)).[5] While our point may appear subtle, it is important for correctly evaluating the effectiveness of regulatory policy. Indeed, our results suggest there is a complementarity between ownership structure and the equity lending market. This implies that policies that aim to promote or curb passive ownership will have different effects depending on conditions in the equity lending market.

Our second contribution is to the literature on equity lending (e.g. Geczy et al. (2002), Cohen et al. (2007), Kolasinski et al. (2013), Kaplan et al. (2013), Thornock (2013), Aggarwal et al. (2015), Engelberg et al. (2018)). Here, the papers closest to ours are Porras Prado et al. (2016) and Palia and Sokolinski (2021). The former paper finds that lending supply is correlated with less concentrated and higher long-term institutional ownership, and with passive ownership. The latter paper shows that passive investing is correlated with both higher lending supply and lending demand and argues that short sellers may prefer borrowing from passive investors. Our contribution is in *cleanly identifying* the effect of passive ownership on equity lending markets, providing an in-depth discussion of the different channels, and exploring new data (loan recalls and investor-level lending decisions) to establish a link between passive ownership and lending supply quality. We conclude that passive owners increase lending supply and *cause* additional short-selling demand. We further show that this additional shorting demand is attracted by lower recall risk, appears to be informed, and improves the information efficiency of stock prices. Hence, passive ownership facilitates short selling and thereby improves market quality.

[5] Morck and Yeung (2011) write about identification based on IVs: "Each time an instrumental variable is shown to work in one study, that result automatically generates a latent variable problem in every other study that has used, or will use, the same instrumental variable, or another correlated with it, in a similar context." We feel that this comment aptly applies to the Russell 1000/2000 setting. Our study can be read as an attempt to provide a plausible narrative that "connects the dots" between passive ownership and firm outcomes/governance etc.

Our paper proceeds as follows. Section 1 outlines our hypotheses. Section 2 presents the data and Section 3 the empirical methodology. Section 4 documents the main results for lendable supply, short interest, lending fees, and the utilization ratio. Section 5 explores the channels behind those results. Section 6 studies the effects on the informational efficiency of the stock market. Section 7 offers robustness checks and Section 8 concludes.

1. Hypotheses

In this section, we explain the empirical hypotheses for the effects of passive ownership on the equilibrium in the securities lending market.

Existing evidence suggests that passive funds (and especially ETFs) are active lenders in the securities lending market (Blocher and Whaley (2016)). Our first prediction is therefore that passive ownership will lead to an increase in lendable supply; i.e., the fraction of outstanding shares that is available for lending to short sellers. Moreover, if the shift in supply were the only effect (i.e., if there was no simultaneous shift in demand), one would expect a decrease in the equilibrium lending fee and an increase in short interest; i.e., the fraction of shares that are actually shorted. This situation is depicted in Figure 1 Panel A. Finally, as the equilibrium demand would increase by less than the total upshift in supply, the utilization ratio—i.e., shares shorted divided by lendable shares—should not increase.

There are three reasons why an increase in passive ownership might—in addition to the upshift in lendable supply—also lead to an upshift in shorting demand. First, the additional, inelastic demand by passive investors pushes up stock prices, thereby attracting short sellers who anticipate lower returns for the stock going forward.[6] Second, many passive owners are ETFs, which are themselves trading in a secondary market. This creates room for ETF arbitrage; i.e., trades that exploit price differences between the ETF

[6] The literature is divided on whether the price effect from a surge in buying demand by passive investors should be transient (Greenwood (2005)) or permanent (Kashyap et al. (2021), Pavlova and Sikorskaya (2022)). Either way, short sellers may be attracted as they expect future returns to be either temporarily or permanently lower. In Table 12 below, we find that the increase in short interest due to passive ownership is not restricted to the months surrounding the index reconstitution.

price and the price of the underlying stock basket. Such arbitrage is common and has been found to cause excess volatility in the underlying stocks (Ben-David et al. (2018)). Authorized participants (APs) who conduct ETF arbitrage do not necessarily borrow the stocks they are shorting. Rather, at the end of the day, they can deliver ETF shares to the ETF sponsor and convert them into individual stocks to close their short position. However, some arbitrageurs who are not APs may also bet on price convergence and would have to borrow shares if they want to keep positions open overnight.

The third channel why passive ownership may cause an increase in short-selling demand has to do with the nature of passive owners as security lenders. Indeed, passive owners are long-term shareholders with little discretion to rebalance their stock positions. This feature may be appreciated by short sellers that want to hold on to their short positions for some time. Since equity loans are by design bilateral, renegotiable, and short-term agreements (Reed (2013), Engelberg et al. (2018)), such long-horizon short sellers may find it more likely that their borrowed shares are not recalled if the lender is a passive investor. Relatedly, passive lenders cannot opportunistically recall shares or free ride on the information provided by the short seller. Active lenders, in contrast, appear to be reducing their stock position after a short seller borrows some shares (Honkanen (2020)).

If one or more of these channels are at work, short sale supply and short sale *demand* increase with passive ownership. To the extent that the demand increase is on par with the supply increase, the equity lending fee may be unchanged or even go up (Figure 1 Panel B). The same is true for the utilization ratio.

To tease out which of these channels is more important for explaining a short sale demand increase, we conduct several auxiliary tests. For the first channel, we check whether the increase in short selling demand is concentrated in stocks that exhibit a larger index inclusion effect and that are thus potentially more overvalued. For the second channel, we relate short selling to ETF mispricing; i.e., the difference between the ETF price and the price of the underlying stock basket. If short selling demand is driven by ETF arbitrage, we expect it to be more pronounced on days on which the ETF is underpriced (i.e., when arbitrageurs would want to short sell the basket stocks). For the third channel, we investigate the effect of passive ownership on equity loan maturity and the probability of delivery failures (as a proxy for short selling risk). If passive owners are indeed more stable equity lenders as hypothesized, we expect loan maturity to increase and delivery failures to decrease with passive ownership.

Finally, we study whether passive ownership affects the informativeness of short sales. We are motivated by the idea that investors wanting to trade on long-lived negative information may prefer borrowing from more stable passive lenders. Honkanen (2020) finds that active funds reduce their stock holdings after lending their shares to a short seller, thereby free riding on the short seller's information. By borrowing from passive lenders, informed short sellers can avoid the risk of such information leakage. If passive ownership indeed attracts more informed short selling, then we expect (a) the correlation between short interest and future stock returns (Asquith et al. (2005)) to increase, (b) a hike in short selling prior to negative earnings announcements, and (c) in turn more information incorporation into prices prior to such negative announcements.

2. Data

2.1 Passive and active fund holdings data and Russell 1000/2000 index membership

We follow Appel et al. (2016) in how we construct the percentage of stocks held by active and passive funds. We use the s12 mutual fund holdings data from Thompson Reuters, which contains quarterly holdings of all U.S.-domiciled (open-ended) mutual funds and ETFs as reported to the SEC, and match it to CRSP mutual fund data using the MFLINKS table available on WRDS. We define a fund as passively managed if the CRSP Mutual Fund Database classifies the fund as an index fund or if its name in CRSP contains a string that suggests that it is an index fund.[7] All other funds that we can match to CRSP are classified as active funds; funds that are not matched to CRSP are left unclassified. Then we compute the

[7] We use the same set of strings to identify index funds as Appel et al. (2016): Index, Idx, Indx, Ind_ (where _ indicates a space), Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000. The comparison is case sensitive.

percentage of each stock's shares outstanding (obtained from CRSP securities data) that is owned by active, passive, and unclassified funds at the end of each quarter.

We obtain monthly data on the constituents of the Russell 1000 and Russell 2000 indexes from Mergent. In addition to index assignments and weights, the data includes Russell's float-adjusted market capitalization, which Russell uses to determine the weights in the index. We merge Russell data to our other datasets using 8-digit CUSIPs.

2.2 Market capitalization data and equity lending data

For our identification strategy, it is important to control for a stock's market capitalization, as this is the key variable that determines whether the stock is assigned to the Russell 1000 or Russell 2000 (see details below). Because we do not have access to the exact market capitalization variable used by Russell, we follow the approach proposed by Ben-David et al. (2019) in order to obtain a close substitute market capitalization measure from CRSP and Compustat data (see Appendix B for details). We construct this measure using the SAS-code provided in their paper. For robustness, we verify that our results obtain if we simply use market capitalizations computed from CRSP (see Section 7.2).

We obtain equity lending data from IHS Markit for the period July 2006 to December 2018. IHS Markit collects its equity lending data from custodians, in-house lending arms, and prime brokers that lend and borrow securities and is the leading provider of such data. In addition, we have access to the underlying raw data that includes all individual equity lending transactions in the dataset. We aggregate these data on the stock-day level and compute the following variables: *Lendable supply* is defined as the number of shares available to lend (this includes the shares that are actually lent out) divided by shares outstanding (from CRSP). *Short interest (equity loans)* is defined as shares currently on loan divided by shares outstanding.[8] *Lending fee* is defined as the value-weighted average fee that borrowers pay to equity lenders. *Tenure* is the average number of days that equity loans have been open. *Utilization* is the fraction of shares available to

[8] We call this variable *Short interest* because short selling is the main reason for borrowing equities.

lend that is actually lent out.[9] Finally, we compute monthly averages of these variables and merge the data via 8-digit CUSIPs to our other datasets.

2.3 Short interest and fails to deliver data

As mentioned above, we proxy for short selling using equity lending transactions because short selling is the main reason to borrow equities. However, there may be other reasons to borrow equities such as tax arbitrage around dividend dates (Thornock (2013)) or vote lending before annual meetings (Aggarwal et al. (2015)). Therefore, as a robustness check, we also use short interest data from Compustat. These data are provided by NASDAQ, NYSE, and American Stock Exchange and are available bi-monthly on the 15th and the last business days of the month. We average these variables to compute *Short interest (Compustat)* at the monthly level.

We also obtain data on failures to deliver (FTD) from the National Securities Clearing Corporation's settlement system, provided on the Securities and Exchange Commission (SEC)'s website.[10] Failures to deliver are closely related to shorting because short sellers (by definition) do not own the stocks they are selling. When they cannot (or strategically do not; see Boni (2006)) borrow the promised stock before the sell transaction settles, a failure to deliver is recorded. One can therefore think of fails to deliver as a proxy for short selling risk. Consistent with this view, we show in Appendix C that failures to deliver and the level of short selling are extremely closely correlated. We therefore define *Delivery Failures* as the number of shares that fail to deliver divided by open short positions as measured using the equity lending data. We compute this variable for each trading day and then average it over the month. The FTD data is available starting in February 2004. Prior to September 16, 2008, the FTD data is restricted to outstanding balances of 10,000 shares or more. We merge short interest and failure to deliver data with our other datasets using 8-digit CUSIPs.

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[9] Markit receives data from both lenders and borrowers but can only get "shares available to lend" from equity lenders. Thus, when computing utilization, we only include shares on loan where HIS Markit received the information from the lender.

[10] SEC failures to deliver data: https://www.sec.gov/data/foiadocsfailsdatahtm.

2.4 Price jump ratio

To gauge the impact of passive ownership-induced short selling on information efficiency, we rely on the *price jump ratio* developed by Weller (2018). This measure captures the fraction of the return associated with a positive or negative earnings news that occurs at the time of the earnings announcement compared to what has already been priced in during the days before. The lower this measure, the more information finds its way into prices prior to being publicly announced and hence the higher the information efficiency.

Earnings announcement dates for the construction of the price jump ratio are taken from IBES. Details on the construction of this measure are provided in Section 6.3.

2.5 Lending fraction by passive and active owners

To analyze whether stock lending comes from active or passive owners, we use data first presented in Honkanen (2020). The data are extracted from quarterly N-Q and semi-annual N-CSR filings that all mutual funds must submit to the SEC in order to report their portfolio holdings. These filings form the raw data for the widely-used Thomson Reuters Mutual Fund (s12) and CRSP mutual fund holdings databases, but here we exploit the (previously overlooked) feature that funds must identify for each portfolio position whether some of the shares of the position are currently on loan. Importantly, the filings do not report the size of the stock loans; they only identify the positions that are at least partially on loan with a footnote or an asterisk.

Honkanen (2020) hand-collects and processes the N-Q and N-CSR filings for the ten largest mutual fund families in the U.S., which account for about 60-70% of domestic equity mutual fund assets throughout our sample period. Using these data, we compute for each stock the *Lending fraction of active owners* and the *Lending fraction of passive owners* as the share of active and passive funds, respectively, that lend out the security.

2.6 Summary Statistics

Table 1 presents summary statistics. We show summary statistics separately for our two samples with bandwidths of 250 and 500 stocks around the Russell 1000/2000 cutoff. The summary statistics for both samples are quite similar. *Passive ownership* is about 11% of shares outstanding, while *Active ownership* is about 21%. With 4% owned by unclassified funds, we get a total fund ownership of about 36 percent. *Lendable supply* is 27% of shares outstanding. *Short interest* is on average 6% to 7% of shares outstanding, irrespective of the underlying data source. *Utilization* is 11% on average and *Lending fee* is 29 basis points. However, *Lending fee* has a large standard deviation of about 125 basis points, suggesting that some stocks are hard to borrow leading to very high fees. On average, equity loans are open for slightly more than two months (about 70 calendar days) and half of equity loans have a *Tenure* of more than one month. *Delivery failures* are rare at 0.5% of shorted stocks but also have a high standard deviation, suggesting that for some stocks delivery failures are more common. The median of the *Price jump ratio* in our sample is 54% when based on alpha and 46% when based on returns, similar to the 46% median reported in Weller (2018).

Our sample period spans the period from July 2006 to December 2018 and is dictated by the availability of the equity lending data. Finally, we note that all continuous variables are winsorized at the 1st and 99th percentile in order to mitigate the effect of outliers.

3. Methodology

Identifying the causal effects of passive ownership on equity lending and short selling is challenging. For example, omitted variables such as unobservable firm characteristics may drive both passive ownership and short selling at the same time. In addition, there could be reverse causality; for example, high shorting demand may increase the fee that lenders can charge and thereby make the stock more attractive to passive investors. To address these issues, we use Russell 1000 and Russell 2000 index membership as a source of exogenous variation in passive ownership. Appel et al. (2020) explain that, when implemented carefully, index membership provides a powerful instrument for passive ownership and, as such, this approach has been widely used (e.g., Chang et al. (2015), Appel et al. (2016, 2019), and Ben-David et al. (2018)). We briefly describe and motivate this identification strategy below and refer the reader to Appel et al. (2020), Glossner (2020), and Wei and Young (2020) for more detail.

The Russel 1000 index comprises the 1000 U.S. stocks with the largest market capitalization and the Russell 2000 index comprises the next largest 2000 stocks. Both indexes are tracked by a large number of index funds and ETFs. Importantly, the largest stocks in the Russell 2000 index have a much higher weight in their index than the smallest stocks in the Russell 1000 index, even though they are of roughly similar size. Thus, when a stock's market capitalization falls enough so that it moves from the Russell 1000 to the Russell 2000 index, its passive ownership increases significantly. This can be clearly seen in Figure 2 Panel A, which shows average passive ownership for the largest (smallest) firms in the Russell 2000 (1000). In contrast, and as shown in Panel B, active ownership shows no discernable change around the market capitalization cutoff that determines index membership.

The fact that Russell assigns index membership based on market capitalization (which we control for) allows us to use Russell 2000 index membership as an instrumental variable for passive ownership. Specifically, every year at the end of June, Russell reconstitutes the indexes to account for changes in firms' market capitalizations. The variable that determines index membership is the *total* (not float-adjusted) market capitalization at the end of May. The weight within the index is then determined using the *float-adjusted* market capitalization at the end of June (i.e, weights are based on market capitalizations excluding closely held shares). Until 2007, Russel simply ranked stocks by their end-of May (total) market capitalization and assigned the top 1000 stocks to the Russell 1000 index. From 2007 onwards, Russell has implemented a banding policy, according to which stocks that are close to the cut-off remain in the index they have been assigned to before. Russell has implemented this policy to reduce the number of stocks that switch indexes each year. We implement the instrumental variable strategy developed in Appel at al. (2019), which allows for identification despite the banding policy.

Specifically, we run monthly instrumental variable regressions with the following first-stage regression:

$$Passive\ Ownership_{i,t} = \alpha_t + \beta_1 * D\left(Russell\ 2000_{i,t}\right) + \sum_{n=1}^{3} \gamma_n * \left(Ln\left(Mktcap_{i,last\ May}\right)\right)^n$$

$$+\beta_2 * D(banded_{i,last\ May}) + \beta_3 * D(Russell_{i,last\ May})$$

$$+\beta_4 * D(banded_{i,last\ May}) * D(Russell\ 2000_{i,last\ May}) + \beta_5 * Ln(Float_{i,last\ June}) + \varepsilon_{i,t}$$

where α_t are time fixed effects, *D(Russell 2000)* is a dummy variable equal to one if the company is in the Russell 2000 index and equal to zero if it is in the Russell 1000 index, $Mktcap_{i,last\ May}$ is our estimate of total market capitalization at the end of last May estimated from CRSP and Compustat data using the methodology of Ben-David et al. (2019), $D(banded_{i,last\ May})$ is a dummy variable equal to one if the company was close enough to the threshold to be banded, $D(Russell\ 2000_{i,last\ May})$ is a dummy variable equal to one if the stock was in the Russell 2000 index as of last May (and thus over the course of the prior year), and $Float_{i,last\ June}$ is the float-adjusted market capitalization at the end of last June as provided by Russell. Following Appel et al. (2016, 2019), we control not only for the natural logarithm of the end-of-May market capitalization, based on which index membership for the following year is determined, but also for its second order and third order polynomial. Russell uses this measure to assign index weights for the following year. Because we control for all variables that determine Russell membership (market capitalization, banding controls, and prior index membership), the use of *D(Russell 2000)* as an instrument provides plausibly exogenous variation in passive ownership (see Appel et al. (2020), Glossner (2020)).

To determine whether a firm is banded, we compute the total market capitalization of the Russell 3000 index and sort all firms in that index by market capitalization.[11] We then compute the cumulated market capitalization percentiles for each firm (for example, if a firm has a 75th percentile, it means that firms smaller than it make up 75% of the total market capitalization of the Russell 3000 index). A firm is banded if its cumulated percentile is less than 2.5 percentage points different from the cumulated percentile of the

[11] Russell actually uses the Russell 3000E index, which includes a few additional small stocks relative to the Russell 3000. Unfortunately, our data does not contain the Russell 3000E members. However, given the fact that the additional stocks are very small, using the Russell 3000 index instead of the Russell 3000E index does not make much of a difference. Indeed, we verify in Appendix E that our approach accurately identifies banded stocks.

1000th stock. This approach follows the instructions by Russell and we show in Appendix E that it is highly predictive of actually realized index changes.

Identification will be tighter for stocks close to the cutoff between the Russell 1000 and Russell 2000 index. However, there is a trade-off as a smaller bandwidth implies fewer stocks and thus less statistical power to reject the null. We therefore show results for two samples: a larger sample of 500 stocks around the cut-off as used in Appel et al. (2019) and a smaller sample of only 250 stocks around the cut-off. Following Glossner (2020) and Wei and Young (2020), we use the total market capitalization at the end of May (constructed following Ben-David et al. (2019)) to form these samples. However, we show in Table 12 that our results are robust to sampling based on Russell's float-adjusted market capitalization at the end of the previous June (as used by Appel et al. (2019)) or the market capitalization from CRSP.

4. Lendable Supply and Short Selling

4.1 Graphical analysis

Before implementing cross-sectional IV specification as described above, we present here graphical evidence based on a simple event study analysis for stocks that switch indexes. For this event study analysis, we exploit the fact that our equity lending variables are available at the daily frequency.

In Figure 3, we plot average *Lendable supply* and *Short interest* in the 100 trading days around the date of a Russell 1000/2000 index reconstitution event. The left (right) panels display the effects for stocks that move from the Russell 1000 (2000) to the 2000 (1000) index. Panel A shows a sharp increase in lendable supply of about 2.5 percentage points after a stock moves down to the Russell 2000 index and a corresponding 2.5 percentage point decrease in lendable supply for stocks moving up to the Russell 1000 index. Such a swift change is unlikely to be driven by an underlying trend and thus strongly suggests a causal effect of index reconstitution events. Panel B displays similar results for short selling activity. Stocks moving down (up) to the Russell 2000 (1000) indices experience on average a roughly 1.5 percentage point increase (decrease) in short interest. Our results thus indicate that both lendable supply and short selling demand increase with passive ownership around index reconstitution events. These effects are not temporary; indeed, we find that these increases persist in the cross section even after excluding the months surrounding index reconstitution events from our analysis (see Section 7.2).

4.2 Lendable supply

We now turn to our instrumental variable regression to study the causal effect of passive fund ownership on lendable supply. We begin with the first stage results shown in Table 2. In Columns 1 and 2, we regress passive ownership on the Russell 2000 index inclusion dummy for the narrow band of 250 stocks (on either side of the cutoff) and the wider band of 500 stocks, respectively. As explained above, all regressions control for a third-degree polynomial of the logarithm of total market capitalization at the end of last May computed using the methodology of Ben-David et al. (2019) as well as the logarithm of float-adjusted market capitalization at the end of last June as provided by Russell. In addition, we include a dummy variable indicating whether the stock was close enough to the cutoff to be banded, a dummy for whether the stock was included in the Russell 2000 index in the previous year, as well as the interaction of these two dummy variables. We include month fixed effects (in a robustness test, we confirm that our results continue to hold when we further include stock fixed effects; see Section 7.2). Standard errors are double-clustered by stock and month.

The first stage results show that a stock's inclusion in the Russell 2000 index increases passive fund ownership by about 1.1-1.5 percentage points. The Kleibergen-Paap (2006) F-statistic comfortably exceeds the Stock-Yogo (2005) critical value of 10, confirming the instrument is not weak. In contrast, we show in Columns 3 and 4 of Table 2 that Russell 2000 membership does *not* lead to an increase in active ownership. This confirms prior literature arguing that Russell 2000 membership can serve as an instrument for passive ownership, while not affecting active ownership (e.g., Appel et al. (2016, 2019)).

In Table 3, we show the second stage results, in which we instrument passive fund ownership by the Russell 2000 index dummy. In Columns 1 and 2 of Panel A, we find that a 1 percentage point change in passive fund ownership increases lendable supply by 1.2 to 1.3 percentage points. The magnitude of the effect is large and suggests that essentially all of the shares newly held by passive investors are made available for lending. In unreported tests, we find that the coefficients are not statistically different from one; i.e., the coefficient one would obtain if passive owners of Russell 2000 stocks were to supply all their additional shares. We note, however, that part of the increase in lendable supply could also come from foreign passive investors, which our first stage results do not capture (as the s12 mutual fund data only covers U.S.-domiciled mutual funds). Thus, the economic magnitude does not necessarily imply that U.S. passive funds supply all their additional shares for lending. In any case, our results demonstrate a striking increase in lendable supply following an increase in passive ownership.

4.3 Short selling

Next, we study the effect of passive ownership on short selling activity. In Columns 3 and 4 of Table 3 Panel A, we report the second stage coefficients from the IV regression for *Short interest*, defined as the fraction of outstanding shares that are lent out. We include the same control variables as above. Depending on whether we look at the narrow (250 stocks) or wide bandwidth (500 stocks), *Short interest (equity loans)* increases 0.7 to 0.9 percentage points for every percentage point increase in passive fund ownership (Panel A, Columns 3 and 4). This effect is about 50-90% of the increase in lendable supply (see above). It thus appears that a large fraction of lendable shares newly made available by passive owners are borrowed by short sellers, despite the fact that the average stock in our sample has a large excess supply of lendable shares (as indicated by an average *Utilization* ratio of about 11%, see Table 1). Hence, short sellers seem to show a strong preference for borrowing shares from Russell 2000 index funds as opposed to borrowing shares supplied by other owners.

The preference for lendable shares supplied by passive owners is further confirmed in Panel B, Columns 1 and 2, in which we directly examine *Utilization* (i.e., the ratio of shares on loan over lendable supply) as the dependent variable. We find a statistically marginally significant increase in utilization of about 1.5 percentage points in the narrow sample and a statistically significant increase of about 1 percentage point in the wider sample. Panel B, Columns 3 and 4 focus on lending fees. In both the narrow and the wide sample, we find that lending fees increase by small and statistically insignificant 4-6 basis points. Given our earlier result of a large increase in lending supply, one might actually have expected a decrease in lending fees. We find this not to be the case.

In aggregate, we find strong evidence of a large increase in *Short interest*, which is further evidenced by an increase in *Utilization*. The *Lending Fee* is largely unchanged and, if anything, slightly increases. Interestingly, the increase in shorting is larger than what would be expected if passive ownership were to only lead to an increase in the quantity of lendable supply. Indeed, such a pure supply increase should lead to a decrease in *Utilization* and *Lending Fee*. The increase in *Utilization* thus suggests that being added to the Russell 2000 leads to a simultaneous increase in shorting demand.

5. Why does Short Selling Demand increase?

In this section, we examine possible explanations for the documented increase in shorting demand.

5.1 Index inclusion effect

Index additions trigger buying pressure by passive investors and thus cause the index inclusion effect—a run-up in prices for the added stock (e.g., Shleifer (1986), Chang et al. (2015)). This may attract short sellers who anticipate lower returns for added stocks going forward. Importantly, the index inclusion effect will be different for different stocks depending on their weights in the new and the old index, their simultaneous membership in other indexes, and the amount of assets under management tracking those indexes (Kashap et al. (2021), Pavlova and Zukuskaya (2022)). In Figure 4, we therefore split stocks that are switching between the Russell 1000 and Russell 2000 indexes by their return in the month of June; i.e., the month in which the index change is announced and the index inclusion effect is observed (Chang et al. (2015)). If the increased short selling demand were to come from short sellers betting on low returns following the index addition, the increase in short selling demand should be concentrated in stocks with high index inclusion returns. Figure 4 shows this not to be the case. Importantly, the increase in short selling demand for stocks with negative inclusion returns is almost as large as the one for stocks with positive inclusion returns.

We do not argue that trading on the index inclusion effect plays no role. The evidence suggests, however, that this is not the full story. We therefore consider two additional channels that can explain the increase in shorting demand: ETF arbitrage and passive lenders providing a higher quality of lendable supply.

5.2 ETF arbitrage

We start by examining whether the increase in shorting demand is driven by ETF arbitrage. Authorized participants can directly convert stocks into ETF shares with the ETF sponsor and thus do not have to rely on equity lending in order to exploit differences between the ETF price and the price of the underlying stock index portfolio. Other investors, however, may establish short positions in order to engage in ETF arbitrage. Hence, additional short selling demand could come from increased ETF arbitrage activity given that the inclusion in the Russell 2000 index causes additional ETF ownership. One important caveat of this potential explanation is that ETF arbitrage opportunities are usually short-lived.[12] Thus, ETF arbitrageurs can often close their short positions during the trading day, which means that they do not need to borrow the underlying stocks in the equity lending market. We nevertheless want to check whether at least part of the additional lending demand can be explained by ETF arbitrage. Importantly, such additional lending demand should only happen if the ETF is *undervalued* relative to the underlying securities (at the end of the trading day). Hence, if ETF arbitrage were responsible for the increase in shorting demand, we would expect a larger increase in *Short interest* for a given stock on days when the ETFs holding that stock are undervalued.

We examine this hypothesis in Columns 1 and 2 of Table 4. We conduct a daily analysis in which we regress *Short interest* on an interaction between *D(ETF undervalued)* and the Russell 2000 membership dummy. *D(ETF undervalued)* is a dummy variable equal to 1 if the ETFs holding the stock are on average

[12] For example, Marshall et al. (2013) find that mispricings in ETFs tracking the S&P 500 index have a median (mean) lifespan of only 2.27min (86.46min). This suggests that most ETF mispricings correct themselves within the same trading day.

undervalued.[13] We measure ETF undervaluation by computing the difference between the ETF price and its net asset value (NAV) taken from CRSP. We employ the same control variables as above and also interact them with *D(ETF undervalued)*. This setup is the reduced form version of our instrumental variable regression run at the daily level and interacted with *D(ETF undervalued)*.

The coefficient of interest is the interaction between *D(Russell 2000)* and *D(ETF undervalued)*. We would expect the coefficient of this interaction to be positive: when ETFs are undervalued, arbitrageurs will buy the ETF and short sell the underlying securities, thus giving rise to pronounced short selling. The interaction coefficient is indeed positive, but it is statistically insignificant and economically small.[14] This does not change when we restrict our analysis to dates with extreme (top or bottom quartile) ETF undervaluation (see Columns 3 and 4 of Table 4).

Importantly, the coefficient of the Russell 2000 dummy remains statistically significant and positive, suggesting that short selling is also increased on days when ETFs are overvalued. This suggests that the increase in short selling is not due to increased ETF arbitrage.[15]

5.3 The quality of lendable supply

We now turn to our second additional explanation for the increase in short selling demand: passive owners provide lendable supply of higher quality. Specifically, we hypothesize that short sellers prefer to borrow their shares from passive owners as they are stable, long-term lenders of securities. In addition, informed short sellers may be less worried about information leakage with passive lenders (Honkanen, 2020). Thus, when the supply of lendable shares provided by new passive owners increases, utilization goes up as the demand for these shares is particularly strong.

[13] In this daily regression, we account for the fact that short sellers only need to borrow the shares 2-3 days after they open the short position because equities settle at t+3 (or t+2 since September 5, 2017).

[14] Depending on the specification, the increase in short interest on days when ETFs are undervalued is only 0.7% (0.043/5.93) to 3% (0.179/5.81) relative to the average level of shorting.

[15] Note that the coefficient on the *ETF undervaluation* dummy is difficult to interpret because we also interact all control variables with this dummy variable. Thus, the coefficient on *ETF undervaluation* represents the effect for a "hypothetical" firm with all control variables equal to zero, including for example a zero market capitalization.

5.3.1 Interaction by ex-ante utilization and fee

Here we test a first implication of this idea. Specifically, we expect the increase in short-selling demand caused by passive ownership to be strongest in stocks where lending supply was most constrained ex ante. In contrast, stocks with high overall supply are likely to already have sufficiently high levels of high-quality supply and should thus see a smaller demand increase. We therefore check whether the increase in short selling demand (but not the increase in lendable supply) is particularly strong for stocks with high prior utilization ratios or lending fees—i.e., stocks for which high-quality lendable supply was more likely to be scarce.

We test this idea in Table 5 by running the reduced form regression of lendable supply and short interest on the Russell 2000 dummy interacted with a dummy equal to one for stocks whose utilization ratio (Panel A) or lending fee (Panel B) was above median at the end of the previous May (when index membership is decided). As indicated by the positive significant interaction coefficient for short interest, the increased short selling demand is indeed concentrated in stocks with high prior utilization ratios or lending fees, suggesting that short sellers are particularly eager to borrow from the new passive owners of these stocks.

5.3.2 Loan tenure

We postulate that passive owners are attractive lenders as they are stable and long-term shareholders, and therefore less likely to recall a stock loan. If this is true, we expect the average tenure of stock loans to *increase* in passive ownership. If, on the other hand, the increased short selling demand documented above were due to ETF arbitrage, the average tenure of loans should *decrease* as ETF arbitrage opportunities are short lived.

Table 6 presents the second stage IV regression on two measures of loan tenure. The dependent variable in Columns 1 and 2 is the average tenure of equity loans (measured as the natural logarithm of the monthly average of the number of days that equity loans have been open), whereas Columns 3 and 4 look at the share of loans with a tenure greater than 30 days. We find that an increase of passive ownership by one percentage point increases loan tenure by 5-6% and the share of long-tenure loans (longer than 30 days) by about 2.5-3.3 percentage points. These findings are strongly statistically significant and suggest that short sellers maintain short positions for longer when they can borrow from passive owners.

5.3.3 Delivery Failures

Because equities trades settle at t+3 (or t+2 since September 5, 2017), short sellers have three days after a sale to find a lender from whom to borrow the shares. If they are unable to do so, they cannot deliver the shares to the buyer, triggering a so-called "fail to deliver". These fails to deliver are costly to the brokers who intermediate the short sell transactions.[16] Brokers therefore typically close out fails to deliver by buying back the stock. These close-outs pose a risk for the short seller as they can lead to unmitigated losses (e.g., during a short squeeze). One can therefore think of delivery failures as *realizations* of short selling risk.[17]

If passive ownership provides more reliable supply, we expect to observe a decrease in the fraction of shorts that fail to deliver. We test this prediction in Table 7. Using *Delivery failure* (see Section 2.3 above) as the dependent variable in Columns 1 and 2, we find that a one-percentage point increase in passive ownership decreases the occurrence of delivery failures significantly by about 0.13-0.16 percentage points (about 25-30% relative to its mean).

Next, we examine if the occurrence of high levels of delivery failures also become less likely. High levels of delivery failures are indicative of stress in the equity lending market, as for example during a short squeeze.[18] Specifically, we define *D(Top quartile delivery failure)*, which is a dummy variable equal to one if the stock is in the top quartile by *Delivery failure*. We find that a one-percentage point increase in passive ownership decreases the occurrence of being in the top quartile of delivery failures by 4-5 percentage points.

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[16] Specifically, brokers are prohibited from effecting short transactions in the security without pre-borrowing (even for other clients) until the fail to deliver is closed out. For more information, see https://www.sec.gov/investor/pubs/regsho.htm.

[17] Consistent with the notion that delivery failures proxy for short selling risk, we show in Appendix D that the amount of delivery failures predict net-of-fee returns to shorting *after controlling* for short interest. As argued by Muravyev et al. (2021), this is an important hurdle to pass to be credible as a proxy for short selling risk. See also Evans et al. (2009), Reed (2013), and Engelberg et al. (2018).

[18] See for example Boni (2006), Boulton and Braga-Alves (2012), and Stratmann and Welborn (2016).

Taken together, the results support our hypothesis that passive funds are more stable lenders than active funds in the sense that their equity loans are associated with fewer delivery failures.

6. Informativeness of Short Sales

Our results indicate that passive ownership, by increasing the quantity and quality of lendable supply, attracts short selling. In this section, we test whether this additional short selling activity is informed.

6.1 Short Interest and Return Predictability

We start by investigating whether passive ownership affects the correlation between short interest and future stock returns. Past research has documented that high short interest predicts low returns (e.g., Asquith et al., 2005) and has thus concluded that short sellers, on average, are informed. We hypothesize that informed short sellers may prefer to borrow from passive owners because there is less risk of information leakage (Honkanen, 2020). Hence, as passive ownership increases, a larger fraction of short selling volume comes from informed short sellers, rendering average short interest more predictive of future returns.

We test this prediction in Table 8. Specifically, we run a reduced form regression of future stock returns on short interest interacted with the Russell 2000 dummy together with the usual market cap and banding controls.[19] For both returns over the next 5 and 10 trading days, we find that short interest is a stronger predictor for negative returns for stocks in the Russell 2000. In terms of economic significance, a one-standard deviation higher short interest for Russell 2000 stocks predicts 0.03% lower returns over the next 5 days compared to Russell 1000 stocks, which corresponds to 1.5% annualized. Hence, the additional short selling activity for Russell 2000 stocks appears to come from informed short sellers, consistent with our hypothesis.

[19] Because these controls are also interacted with short interest, the coefficient on short interest itself does not reflect the predictive power of short interest on returns. When we just run a regression of future returns on short interest together with stock and month fixed effects, we confirm the negative return predictability of short interest for our sample (unreported).

6.2 Short Selling prior to Negative Earnings Announcements

If passive owners attract informed short selling, we expect short selling activity to be more pronounced prior to negative information releases. We test this idea in the context of quarterly earnings announcements. In order to have enough earnings announcement events in our sample (which typically occur once per quarter), we focus on the wider bandwidth of 500 stocks for this analysis. We measure short interest in the 30 or 60 days prior to an earnings announcement and regress this measure in reduced form on the Russell 2000 membership dummy interacted with *D(Negative Earnings Surprise)*, a dummy variable equal to one when the cumulative 3-factor alpha or the raw return over the announcement window from t-1 to t+2 falls in the bottom tercile and zero otherwise, as well as our usual set of controls (which we also interact with the negative earnings surprise dummy).

Table 9 shows the results. Depending on the specification, we find that, for stocks in the Russell 2000 index, short interest is 0.6-0.8 percentage points higher prior to negative earnings announcements, representing an increase of about 10-13% relative to the average short interest in our sample (compare Table 1). Hence, higher passive ownership of Russell 2000 stocks attracts more informed short selling in anticipation of negative earnings announcement news.

6.3 Information Efficiency

Next, we test whether this passive ownership-induced short selling improves the information efficiency of stock prices. Our measure for information efficiency is the price jump ratio (Weller (2018)), which captures the fraction of the return associated with a large earnings surprise that is priced-in around the earnings announcement date compared to the period before. Given that we document more informed short selling prior to negative earnings surprises, we expect more information to be incorporated before as opposed to around the actual earnings announcement date. In other words, we expect the *Price jump ratio* to go down for earnings announcement events with *negative* surprises.

We construct the price jump ratio as described in Weller (2018) as

$$Price\ jump\ ratio\ (alpha) = \frac{Alpha_{t-1,t+2}}{Alpha_{t-21,t+2}},$$

where $Alpha_{t-n,t+m}$ is the cumulative 3-factor Fama French (1993) alpha from *n* days before to *m* days after the earnings announcement date. We describe the details of constructing 3-factor Fama French (1993) alphas in Appendix F. As the price jump ratio gets very large if $Alpha_{t-21,t+2}$ is close to zero, we follow Weller (2018) and only include earnings announcements if the absolute value of $Alpha_{t-21,t+2}$ is sufficiently large. Specifically, we only include observations if

$$\left|Alpha_{t-21,t+2}\right| > \sqrt{24} * \hat{\sigma}_{past\ month}\ ,$$

where $\hat{\sigma}_{past\ month}$ is the standard deviation of daily alphas over the previous month. This filter keeps about 38% of the observations (which is similar to Weller (2018)). For robustness, we also compute *Price jump ratio (return)*, where all inputs (including the volatility filter) are based on raw returns instead of alphas.

We then regress in reduced form the price jump ratio on the Russell 2000 index membership dummy, a dummy for a negative earnings reaction, and the interaction of the two, as well as our usual set of controls (which we also interact with a negative earnings reaction dummy). We set this negative earnings reaction dummy equal to one when the total market reaction over t-21 to t+2 days around the earning announcement (i.e., the denominator of the *Price jump ratio*) is in the bottom tercile and zero otherwise.

Table 10 shows the results. In Column 1 , the dependent variable is the *Price jump rati*o calculated from 3-factor alphas as in Weller (2018). Column 2 shows results for the *Price jump ratio* calculated from raw returns. In both cases, the coefficient on the interaction between the Russell 2000 dummy and the negative earnings reaction dummy—our coefficient of interest—is negative and statistically significant. It is also economically significant as the price jump ratio declines by about 10 percentage points (relative to an unconditional median of about 50 percent). Our results imply that being added to the Russell 2000 increases the share of information that is priced-in prior to the actual announcement when the earnings news is in the bottom tercile (i.e., negative), but not when it is positive. This is consistent with the idea that passive ownership improves information efficiency by facilitating short selling.

7. Robustness Checks

7.1 Changes in lending fraction by active and passive owners

As document in Section 4.2, we find that Russell 2000 index membership is associated with a large increase in lendable supply, which we attribute to the simultaneous increase in passive ownership. However, one might be concerned that this increase is driven by previous (active or passive) owners changing their lending behavior around Russell index reconstitutions.

To address this concern, we investigate hand-collected data on the equity lending decisions of the 10 largest mutual fund families in the United States (see Section 2.5 for more detail) to see if funds are more likely to lend out shares around the Russell 1000/2000 cutoff. As a first step, we check how Russell 2000 index membership affects active and passive ownership in this subsample. The results are reported in Table 11 Panel A. We find that Russell 2000 membership is associated with increased passive ownership (Columns 3 and 4), while having no effect on active ownership (Columns 1 and 2). This confirms our findings from Table 2 and thus lends credence to the representativeness of our subsample of funds for which we have detailed lending information.

In Panel B of Table 11, we then run the reduced form regression where the dependent variable is the fraction of active (or passive) owners that lent out any of their shares. As indicated by the insignificant and economically small coefficient on the Russell 2000 dummy, neither active owners (Columns 1 and 2) nor passive owners (Columns 3 and 4) behave differently in terms of equity lending depending on whether the stock is in the Russell 1000 or 2000 index. Taken together, our results suggest that the increases in lending supply and short selling demand documented in Table 3 are solely coming from a composition effect: Russell 2000 index membership increases passive ownership but does not affect the lending behavior of individual (active or passive) funds. Because passive owners are more likely to supply their shares, and because those shares are in higher demand by short sellers, both lendable supply and short selling increase for stocks with higher passive ownership.

In Appendix F, we use the disaggregated lending data for the 10 largest mutual fund families to provide additional evidence consistent with this explanation. Specifically, we show that, for a given stock and for a given quarter, passive funds holding that stock are significantly more likely to lend out shares compared to active funds holding that stock. Since a stock that is lent out has to be supplied in the first place, this result also suggests that passive funds are more likely to supply their shares for lending.

7.2 Other robustness checks

In this section, we perform a variety of robustness checks. For brevity, we focus on the second stage IV regressions at the monthly frequency with a 500-firm bandwidth for the following dependent variables: *Lendable supply*, *Short interest*, *Utilization*, *Average tenure*, and *Delivery failure*. We present the results in Table 12. All control variables are added but not reported for better readability.

In Panels A and B, we focus on the variables used for sample selection. In our main specification, we follow the recommendations by Glossner (2020) and Wei and Young (2020) and form our samples based on the end-of-May total market capitalization estimated from Compustat/CRSP data according to the Ben-David et al. (2019) methodology (i.e., the best available proxy for the unobserved market cap variable used by Russell to determine index membership). Alternatively, Appel et al. (2020) propose to use for sample construction the float-adjusted market capitalization measure provided by Russell. They argue that this approach, while potentially introducing a bias, should improve power as it accentuates the discontinuity in passive ownership around the membership cutoff (as the float-adjusted market cap determines the index weight). Confirming this intuition, we indeed obtain slightly stronger results when we implement this sampling approach in Table 12 Panel A. In Panel B, we form samples based on the simple CRSP market capitalization instead of using the market capitalization measure computed from Compustat/CRSP data following Ben-David et al. (2019) [see Appendix B]. In this case, we also base our control variables on CRSP market capitalization. Our results are again robust to this alternative sampling choice.

In Panel C, we tackle the concern that our results could partly be driven by abnormal shorting activity surrounding the months of actual index changes. Indeed, some investors may speculate on which firms change index and/or there may be abnormal trading activity after an index change becomes effective (and passive investors are forced to rebalance). To mitigate this concern, we re-run our main analyses after excluding stock-month observations surrounding actual index changes. Specifically, we exclude the months of May, June, and July whenever a stock changes the index. As shown in Panel C, our results remain largely unchanged. In similar vein, stocks are likely to change indexes after unusually positive or negative returns. Past returns have been shown to be related to future returns (see Jegadeesh and Titman (2011) for a review) and therefore short sellers may be trading on information contained in past returns. To address this concern, we control for past returns in Panel D. Our results remain very similar.

In our main analyses, we show results for samples using a 250 and 500 firm bandwidth around the cut-off. In Panel E, we show that our results remain significant if we use an even smaller bandwidth of 150 stocks. Furthermore, in our main specification, we identify our results from the cross-section (because we only include month fixed effects). In Panel F of Table 12, we show as a robustness check that our results remain statistically significant if we add firm fixed effects. Adding firm fixed effects to the specification implies that the identification now comes only from firms that have changed the index.

Finally, in Panel G, we use a different measure of short selling activity. In our main specification, we measure shorting as the fraction of shares that are on loan according to the IHS Markit data. In Panel G, we instead use a measure of short selling based on short interest data provided by the stock exchanges (as reported in Compustat). The result confirms our earlier finding and is very similar in magnitude: short selling increases by about 0.8 to 1.2 percent for every percentage point increase in passive ownership.

8. Conclusion

Exploiting Russell 1000/2000 index reconstitution events, this paper studies the causal effects of passive ownership on equity lending and short selling. We find that passive ownership leads to an increase in both the lendable supply *and* the demand for short selling. This demand increase is not fully explained by the index inclusion effect and does not come from ETF arbitrage. Instead, we argue that it is at least partly driven by a higher *quality* of lendable supply. Indeed, we find that higher passive ownership is associated with a longer maturity of equity loans, as well as with a decrease in delivery failures. Finally, we show that the additional short selling activity from Russell 2000 membership is informed as both the return predictability of short interest as well as the stock price informativeness around negative news events improve.

An important takeaway of our study is that not all lending supply is created equal. Passive owners do not only supply a larger fraction of their portfolios for equity lending, but—due to them being stable and long-term shareholders—they also lower operational risks to short sellers (e.g., by being less likely to recall loaned shares). Together, these two factors increase the propensity to short and contribute to market quality by accelerating the incorporation of negative information into prices.

We believe our results are important for understanding the channels through which passive ownership may affect diverse topics such as corporate governance, investment, innovation, mergers, and/or payout policy. Indeed, the short selling literature usually identifies short sellers as an informed group of investors with the power to influence corporate actions (e.g., through activist campaigns).[20] Hence, despite of themselves being passive and possibly less engaged shareholders, passive owners matter indirectly for corporate policy by facilitating short selling. Future research on the impact of passive investors on financial markets and corporate activity should take this indirect effect into account. Moreover, policymakers ought to be aware of the complementarity between ownership structure and the equity lending market.

[20] See, for example, Boehmer et al. (2008), Christophe et al. (2010), and Appel and Fos (2020).

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Figure 1: Illustration of Demand and Supply Shifts in the Securities Lending Market

Panel A shows the equilibrium implications that are expected when an increase in passive ownership leads only to a shift in lendable supply. As the supply curve for lendable shares shifts down, the new equilibrium in the securities lending market features a lower lending fee and an increase in lending quantity (i.e., short interest). Panel B shows the equilibrium implications that are expected when the increase in passive ownership leads to a simultaneous demand and supply shift in the securities lending market. As the supply curve for lendable shares shifts down and the demand curve shifts up, the new equilibrium in the securities lending market features an increase lending quantity, but the lending fee remains unchanged.

Panel A: Only supply shift **Panel B: Simultaneous supply and demand shift**

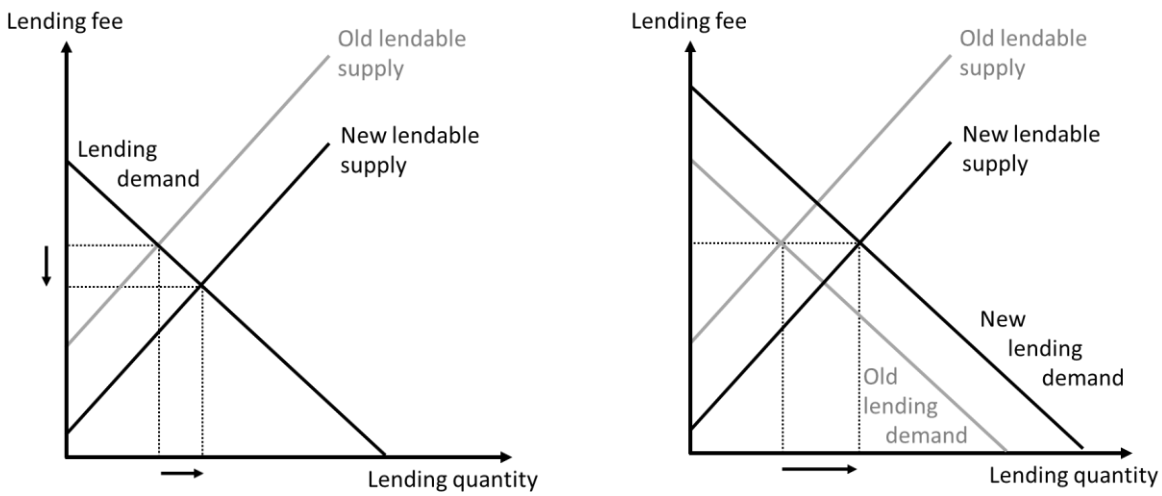
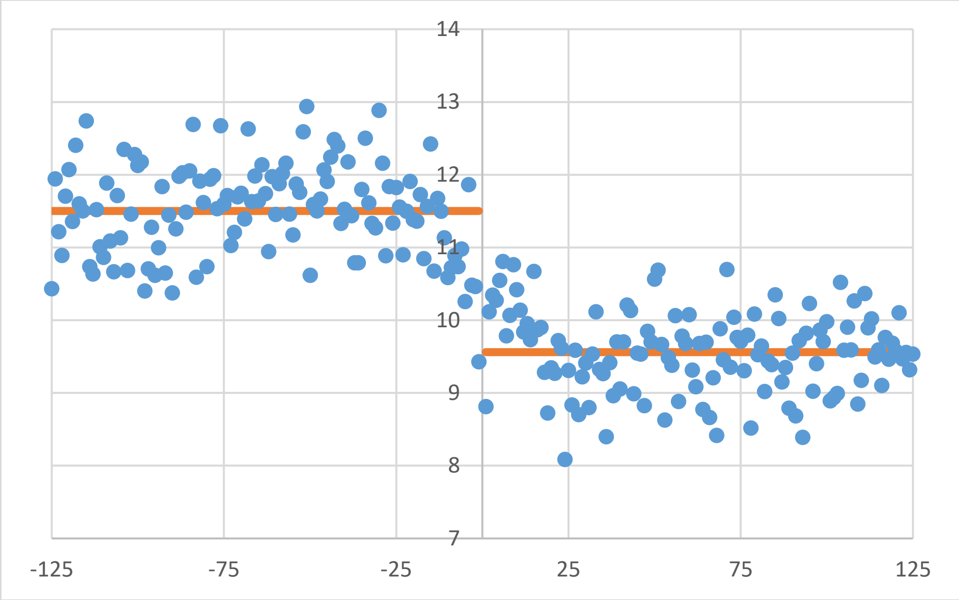


Figure 2: Passive and active ownership around the Russell 1000/2000 cutoff

This figure shows average passive (Panel A) and active (Panel B) ownership levels for the 625 largest firms in the Russell 2000 (to the left of the vertical line) and the 625 smallest firms in the Russell 1000 (to the right of the vertical line). For better visibility, firms are ranked by groups of five. Hence, each dot represents the average passive (or active) ownership level for a group of five firms (e.g., the rank -1 corresponds to the five largest firms in the Russell 2000, the rank +1 corresponds to the five smallest firms in the Russell 1000, etc.). The horizontal lines indicate the average ownership level across all ranks for firms in the Russell 2000 (to the left of the horizontal line) and in the Russell 1000 (to the right of the horizontal line).

Panel A: Passive ownership



Panel B: Active ownership

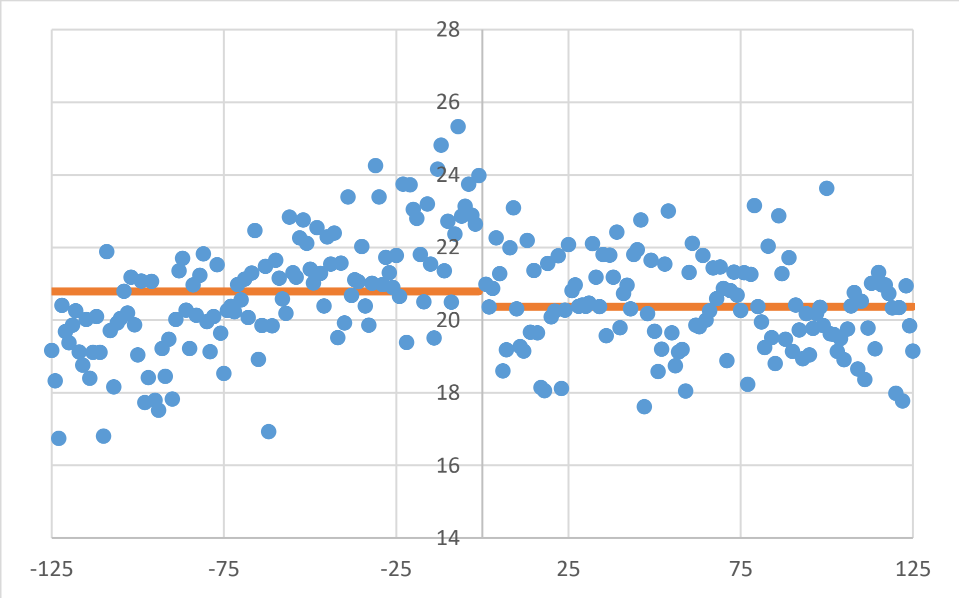
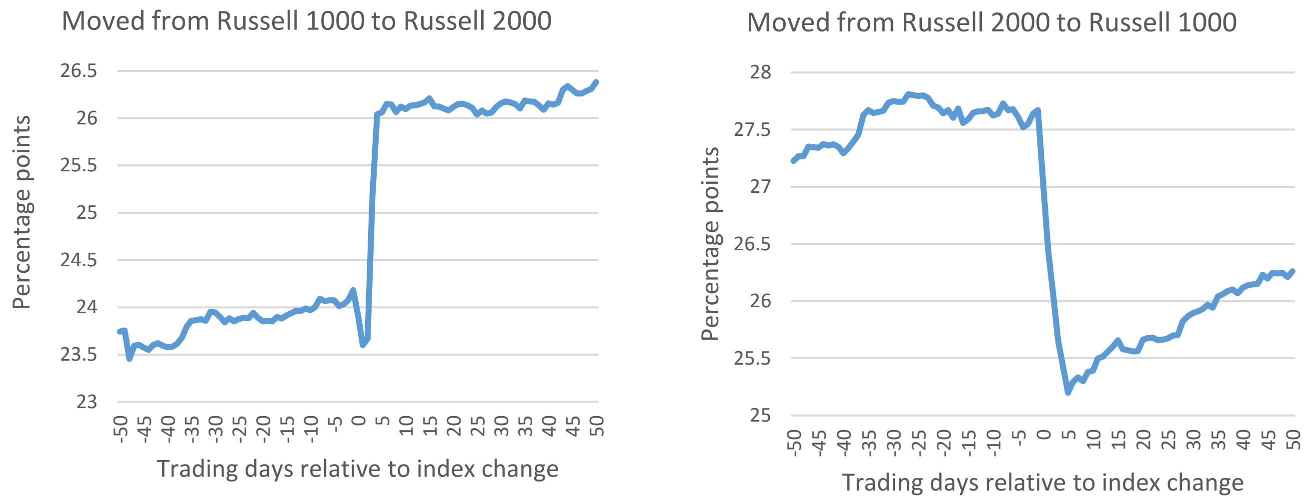


Figure 3: Changes after index switches

This figure shows changes to lendable supply and short selling after a stock switches between the Russell 1000 and Russell 2000 index. On the left, we show the average lendable supply and short interest for stocks that moved (down) from the Russell 1000 to the Russell 2000. On the right, we show the same for stocks that moved (up) from the Russell 2000 to the Russell 1000. In both cases, we display 50 trading days before and after the index change.

Panel A: Lendable supply



Panel B: Short interest (equity loans)

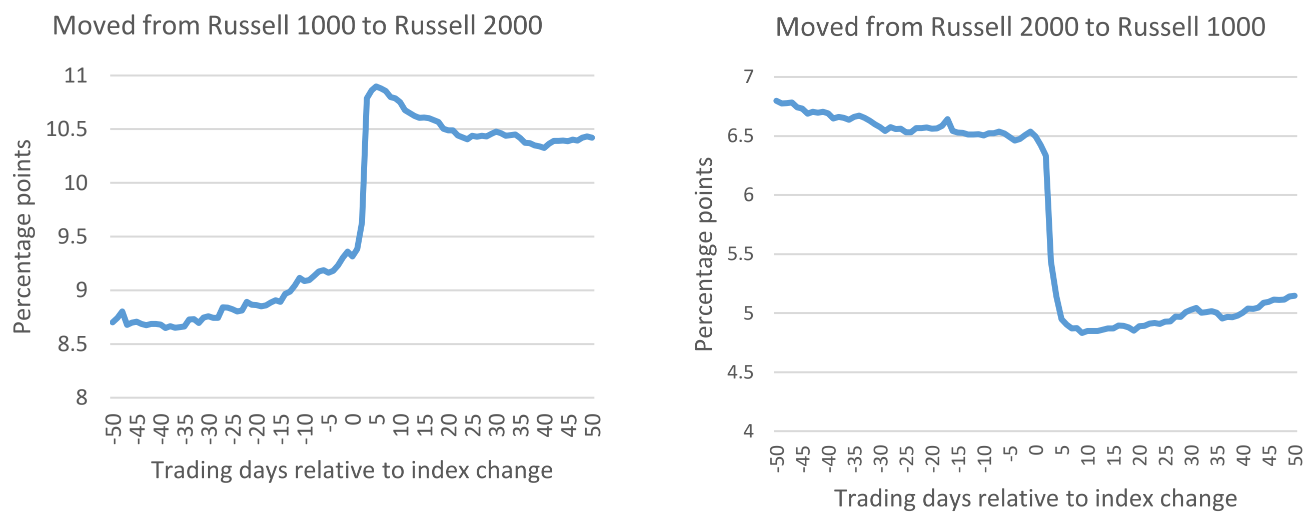
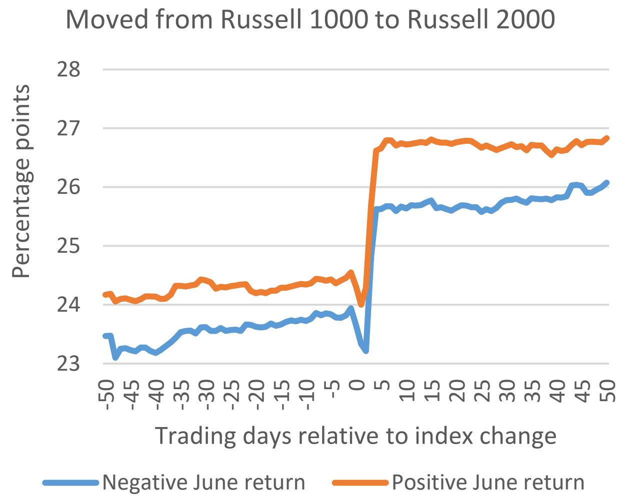
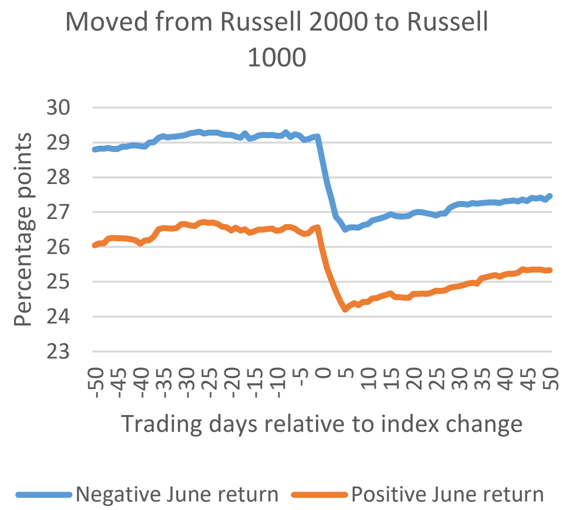


Figure 4: Changes after index switches – split by inclusion return

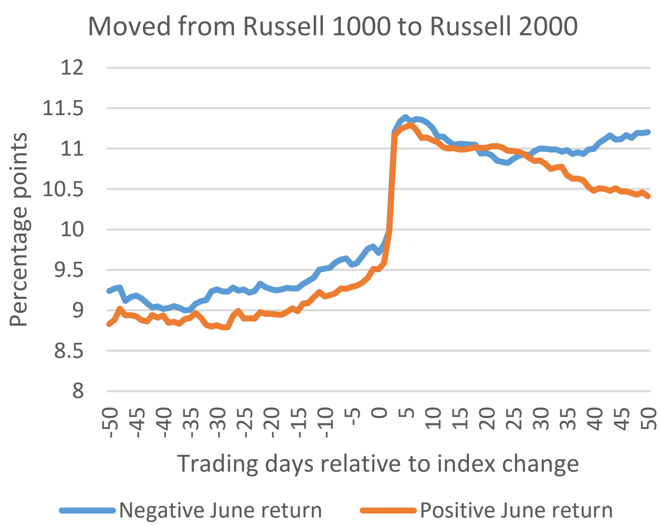
This figure shows changes to lendable supply and short selling after a stock switches between the Russell 1000 and Russell 2000 index, separately for stocks with positive (orange line) or negative (blue line) June returns (when the index inclusion effect is observed, see Chang et al. (2015)). On the left, we show the average lendable supply and short interest for stocks that moved (down) from the Russell 1000 to the Russell 2000. On the right, we show the same for stocks that moved (up) from the Russell 2000 to the Russell 1000. In both cases, we display 50 trading days before and after the index change.

Panel A: Lendable supply





Panel B: Short interest (equity loans)



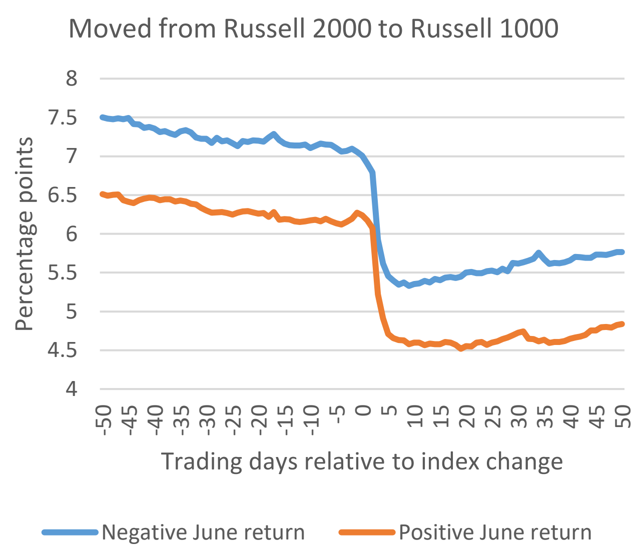


Table 1: Summary statistics

This table displays monthly summary statistics for our two samples. In Panel A, we display the summary statistics for the smaller sample of +/- 250 companies around the cut-off, while it is +/- 500 companies in Panel B. *Passive*, *Active*, and *Fund ownership* is the percent of shares outstanding held by passive, active, and all (including unclassified) funds, respectively. Lendable supply is the fraction of shares that are available to be lent out by equity lenders. *Short interest (equity loans)* is the average fraction of outstanding shares that are lent out. *Short interest (Compustat)* is the fraction of outstanding shares that are shorted based on bi-weekly short interest data. *Utilization* is the fraction of lendable supply that is lent out. *Lending fee* is the value-weighted average fee that equity borrowers pay to borrow the stock. *Average tenure* is the average number of days that an equity loan has been open. *Fraction of loans with tenure above 30 days* is the fraction of outstanding equity loan volume with a tenure above 30 days. *Delivery failure* is the number of shares that were not delivered divided by number of shares that were shorted. *Price jump ratio (alpha)* is defined as $\frac{Alpha_{t-1,t+2}}{Alpha_{t-21,t+2}}$ and *Price jump ratio (return)* is defined as $\frac{Return_{t-1,t+2}}{Return_{t-21,t+2}}$, where *t* denotes quarterly earnings announcements (see Section 6.3). Details on variable constructions can be found in Appendix A

Panel A: sample +/- 250 companies around cut-off

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Passive ownership (%)	10.5	3.50	9.89	18.5	5.67
Active ownership (%)	21.3	6.87	21.5	34.9	10.3
Fund ownership (%)	36.1	16.4	38.1	52.1	13.7
Lendable supply (%)	27.1	14.1	27.9	38.4	9.27
Short interest (equity loans) (%)	5.93	0.56	3.86	14.5	5.97
Short interest (Compustat) (%)	6.81	1.49	5.09	14.6	5.74
Utilization (%)	11.2	0.78	6.77	28.3	12.5
Lending fee (bp)	29.7	1.89	8.93	24.2	126.1
Average tenure (days)	67.9	29.1	61.2	114.4	36.2
Fraction of loans with tenure above 30 days (%)	50.8	22.3	53.5	74.1	19.4
Delivery failure (%)	0.49	0.019	0.11	1.00	1.39
Price jump ratio (alpha) (%)	54.2	-1.56	53.9	109.3	46.2
Price jump ratio (return) (%)	46.5	-5.28	46.1	99.2	43.3
Observations	72,617				

Panel B: sample +/- 500 companies around cut-off

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation
Passive ownership (%)	10.5	3.54	9.89	18.4	5.66
Active ownership (%)	20.8	6.72	20.8	34.4	10.3
Fund ownership (%)	35.7	16.3	37.5	51.7	13.6
Lendable supply (%)	27.0	14.3	27.7	38.3	9.17
Short interest (equity loans) (%)	5.81	0.55	3.70	14.4	5.97
Short interest (Compustat) (%)	6.68	1.44	4.91	14.5	5.74
Utilization (%)	11.0	0.72	6.57	27.9	12.4
Lending fee (bp)	29.3	1.59	8.90	24.5	124.8
Average tenure (days)	67.9	28.6	60.8	115.4	37.1
Fraction of loans with tenure above 30 days (%)	50.4	21.5	53.2	74.1	19.6
Delivery failure (%)	0.50	0.020	0.12	1.01	1.38
Price jump ratio (alpha) (%)	54.2	-1.10	53.9	108.9	46.2
Price jump ratio (return) (%)	46.6	-4.73	45.7	99.5	43.5
Observations	145,066				

Table 2: Russell 2000 membership as an instrument for passive ownership

This table examines how passive and active ownership depends on membership in the Russell 2000 index. In Columns 1 and 2, we regress passive ownership on an indicator whether a firm is member of the Russell 2000 index (this is the first stage of the instrumental variable specification in Tables 3, 5, 6, and 11). In Columns 3 and 4, we show results for a falsification test, in which we regress active ownership on the Russell 2000 indicator. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on monthly data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	First stage		Falsification test	
Dependent variable:	Passive ownership (%)		Active ownership (%)	
	(1)	(2)	(3)	(4)
D(Russell 2000)	1.092***	1.484***	0.000	-0.003
	(4.27)	(6.33)	(0.03)	(-0.46)
Float-adjusted market cap	5.953***	5.881***	0.087***	0.083***
	(20.85)	(24.23)	(14.70)	(18.16)
D(banded)	-0.117	-0.028	0.006	0.012***
	(-0.53)	(-0.15)	(1.04)	(2.66)
D($Russel\ 2000_{last\ May}$)	-0.104	0.104	0.029***	0.030***
	(-0.34)	(0.57)	(4.13)	(6.91)
D($Russel\ 2000_{last\ May}$)* D(banded)	0.543	0.043	-0.012	-0.009
	(1.57)	(0.17)	(-1.45)	(-1.50)
Observations	65044	129687	65044	129687
Adjusted R^2	0.513	0.511	0.134	0.129
Kleibergen-Paap F-Statistic	18.3	40.1	0.001	0.2
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 3: Passive ownership increases lendable supply and short selling

This table displays the second stage results of an instrumental variable regression where passive ownership is instrumented by membership of the Russell 2000 index. In Panel A, we focus on the effect of passive ownership on lendable supply and short selling. Specifically, in Columns 1 and 2, the dependent variable is *lendable supply* (%), the percent of shares outstanding made available to be lent out by equity lenders. In Columns 3 and 4, the dependent variable is *short interest* (%), the percent of shares outstanding that are lent out in the equity lending market (the main reason to borrow equities is to conduct short selling). In Panel B, we focus on the effect of passive ownership on utilization and lending fee. Specifically, in Columns 1 and 2, the dependent variable is *Utilization*, which measures the fraction of lendable supply that is lent out. In Columns 3 and 4, the dependent variables is the *lending fee* measured in basis points per year. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on monthly data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Effect on lendable supply and short selling

	Second stage			
Dependent variable:	Lendable supply (%)		Short interest (equity loans) (%)	
	(1)	(2)	(3)	(4)
Passive ownership (%)	1.236***	1.265***	0.916**	0.728***
	(2.95)	(4.47)	(2.43)	(3.15)
Float-adjusted market cap	7.168***	6.610***	-4.086*	-2.807**
	(2.90)	(3.98)	(-1.85)	(-2.12)
D(banded)	1.004**	1.011***	0.223	0.136
	(2.51)	(3.14)	(0.64)	(0.50)
D($Russel\ 2000_{last\ May}$)	1.171**	1.092***	0.641	-0.388
	(2.44)	(3.74)	(1.39)	(-1.32)
D($Russel\ 2000_{last\ May}$)* D(banded)	-0.648	-0.637	-1.164*	0.202
	(-0.93)	(-1.42)	(-1.75)	(0.54)
Observations	65,044	129,687	65,041	129,682
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Panel B: Effect on utilization and lending fee

	Second stage			
Dependent variable:	Utilization (%)		Lending fee (bp)	
	(1)	(2)	(3)	(4)
Passive ownership (%)	1.471*	0.980**	4.168	6.258
	(1.81)	(1.98)	(0.60)	(1.30)
Float-adjusted market cap	-13.375***	-10.171***	-82.177**	-91.133***
	(-2.80)	(-3.52)	(-1.99)	(-3.20)
D(banded)	0.288	0.301	-2.344	-5.788
	(0.44)	(0.58)	(-0.46)	(-1.20)
D($Russel\ 2000_{last\ May}$)	0.067	-1.253**	-6.288	-24.609***
	(0.08)	(-2.36)	(-0.93)	(-3.94)
D($Russel\ 2000_{last\ May}$)* D(banded)	-1.873	0.266	-1.433	13.360*
	(-1.37)	(0.36)	(-0.13)	(1.77)
Observations	65,041	129,682	65,041	129,682
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 4: ETF arbitrage

This table examines if ETF arbitrage can explain the increased shorting in stocks of the Russell 2000 index. We display daily regressions of short interest, measured using the amount of outstanding equity loans, on an interaction between *D(Russell 2000)* and *D(ETF undervalued)*. D(Russell 2000) is an indicator variable equal to one if the stock is in the Russell 2000 index. *D(ETF undervalued)* is the average of undervaluations in the ETFs that hold the specific stock. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. In addition, we interact all of these variables with *D(ETF undervalued)* (as a result, the coefficient on the *ETF undervalued* dummy is difficult to interpret; it represents the effect of a hypothetical firm with all control control variables, including market cap, equal to zero). In Regressions 1 and 2, we include all stocks within the respective bandwidth. In Regressions 3 and 4, we only include observations where the level of ETF undervaluation is in the top or bottom quartile, i.e., we compare the most overvalued with the most undervalued days. The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on daily data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	All days		Undervaluation in top or bottom quartile	
Dependent variable:	Short interest (equity loans) (%)			
	(1)	(2)	(3)	(4)
D(Russell 2000) * D(ETF undervalued)	0.043	0.179	0.094	0.094
	(0.39)	(1.37)	(0.60)	(0.69)
D(Russell 2000)	1.047***	1.033***	0.957**	1.187***
	(2.94)	(3.30)	(2.27)	(3.40)
D(ETF undervalued)	-46.118	-74.426*	-76.103	-51.174
	(-0.82)	(-1.79)	(-0.86)	(-0.88)
Observations	1,347,566	2,684,598	639,390	1,253,677
Adjusted R^2	0.110	0.072	0.129	0.140
Month fixed effects	Yes	Yes	Yes	Yes
Banding and market cap controls	Yes	Yes	Yes	Yes
Banding and market cap controls interacted with D(ETF undervalued)	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 5: Interactions by ex-ante utilization and fee

This table examines if the ex-ante level of utilization and lending fee affects the impact of passive ownership on lendable supply and short selling. We display monthly regressions of lendable supply and short interest on an interaction between *D(Russell 2000)* and either $D(Utilization_{last\ May})$ (Panel A) or $D(Lending\ fee_{last\ May})$ (Panel B). $D(Utilization_{last\ May})$ is a dummy variable equal to one if *Utilization* at the end of last May was above the median (and analogous for *Lending fee*). In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. In addition, we interact all of these variables with the ex-ante utilization or fee, respectively (as a result, the coefficient on the *ex-ante utilization* and *ex-ante fee* variables are difficult to interpret; it represents the effect of a hypothetical firm with zero market cap). The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on daily data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Interaction by ex-ante utilization

	Reduced Form Regression			
Dependent variable:	Lendable supply (%)		Short interest (equity loans) (%)	
	(1)	(2)	(3)	(4)
D(Russell 2000) * $D(Utilization_{last\ May})$	0.537	-0.106	1.617***	1.151**
	(0.61)	(-0.16)	(2.99)	(2.61)
D(Russell 2000)	1.275	2.663***	0.626*	0.746**
	(1.65)	(4.30)	(1.80)	(2.49)
D($\text{Utilization}_{\text{last May}}$)	69.860	162.302	-12.741	-179.329
	(0.21)	(0.77)	(-0.07)	(-1.51)
Observations	65105	130031	65105	130031
Adjusted R^2	0.464	0.437	0.320	0.335
Month fixed effects	Yes	Yes	Yes	Yes
Banding and market cap controls	Yes	Yes	Yes	Yes
Banding and market cap controls interacted with D($Utilization_{\text{last May}}$)	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Panel B: Interaction by ex-ante lending fee

	Reduced Form Regression			
Dependent variable:	Lendable supply (%)		Short interest (equity loans) (%)	
	(1)	(2)	(3)	(4)
D(Russell 2000) * $D(Lending\ fee_{last\ May})$	0.454	0.247	1.570**	2.702***
	(0.51)	(0.38)	(2.04)	(4.69)
D(Russell 2000)	1.366**	2.420***	1.090**	0.549
	(2.35)	(4.69)	(2.45)	(1.60)
D($\text{Lending fee}_{\text{last May}}$)	1116.748**	120.755	194.197	55.320
	(2.31)	(0.58)	(0.73)	(0.36)
Observations	65,111	130,037	65,111	130,037
Adjusted R^2	0.480	0.452	0.212	0.223
Month fixed effects	Yes	Yes	Yes	Yes
Banding and market cap controls	Yes	Yes	Yes	Yes
Banding and market cap controls interacted with D($Lending\ fee_{\text{last May}}$)	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 6: Passive ownership effect on tenure

This table displays the second stage results of an instrumental variable regression where passive ownership is instrumented by membership of the Russell 2000 index. In Columns 1 and 2, the dependent variable is the average tenure of equity loans in that stock, measured in the natural logarithm of days. In Columns 3 and 4, the dependent variable is the fraction of equity loans with a tenure above 30 days, measured in percent. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on monthly data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Second stage			
Dependent variable:	Average tenure (log)		Fraction of loans with tenure above 30 days (%)	
	(1)	(2)	(3)	(4)
Passive ownership (%)	0.059**	0.055***	3.292***	2.464***
	(2.11)	(2.82)	(3.20)	(3.83)
Float-adjusted market cap	-0.288*	-0.235**	-19.149***	-13.584***
	(-1.76)	(-2.07)	(-3.16)	(-3.64)
D(banded)	0.019	0.037	0.620	1.356*
	(0.65)	(1.58)	(0.57)	(1.73)
D($Russel\ 2000_{last\ May}$)	0.033	0.099***	1.607	2.702***
	(1.00)	(4.49)	(1.23)	(3.73)
D($Russel\ 2000_{last\ May}$)* D(banded)	0.031	-0.033	-1.034	-1.130
	(0.62)	(-1.02)	(-0.57)	(-1.07)
Observations	65,041	129,682	65,041	129,682
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 7: Passive ownership effect on delivery failures

This table displays the second stage results of an instrumental variable regression where passive ownership is instrumented by membership of the Russell 2000 index. In Regressions 1 and 2, the dependent variable is *Delivery failure*, which is the number of shares that were not delivered divided by number of shares that were shorted. In Regressions 3 and 4, the dependent variable is *D(Top quartile delivery failure)*, which is a dummy variable equal to 1 if the stock is in the top quartile by the number of delivery failures (standardized by shares shorted). In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on monthly data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Second stage			
Dependent variable:	Delivery failure (%)		D(Top quartile delivery failure) (%)	
	(1)	(2)	(3)	(4)
Passive ownership (%)	-0.163**	-0.127***	-5.085***	-3.894***
	(-2.23)	(-3.10)	(-2.76)	(-3.44)
Float-adjusted market cap	0.685	0.434*	18.800*	10.925
	(1.54)	(1.83)	(1.69)	(1.63)
D(banded)	-0.065	-0.096**	-1.189	-1.859
	(-1.11)	(-2.23)	(-0.70)	(-1.51)
D($Russel\ 2000_{last\ May}$)	-0.076	-0.120***	-1.855	-3.295***
	(-1.05)	(-2.67)	(-0.89)	(-2.94)
D($Russel\ 2000_{last\ May}$)* D(banded)	0.148	0.134**	1.607	1.552
	(1.28)	(2.21)	(0.53)	(0.89)
Observations	61,469	122,612	61,469	122,612
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 8: Short selling profitability

This table examines if short selling is more profitable in stocks of the Russell 2000 index. We display daily regressions of future returns over the next 5 or 10 trading days, on an interaction between *D(Russell 2000)* and *Short interest*. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: D(banded), an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, D($Russel\ 2000_{last\ May}$), an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. In addition, we interact all of these variables with *Short interest* (as a result, the coefficient on the *Short interest* variable is difficult to interpret; it represents the effect of a hypothetical firm with zero market cap). The sample consist of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on daily data from 2006 to 2018. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Reduced Form Regression			
Dependent variable:	$Return_{t+1,t+5}$ (%)		$Return_{t+1,t+10}$ (%)	
	(1)	(2)	(3)	(4)
D(Russell 2000) * Short interest	-0.004*	-0.005**	-0.004*	-0.005**
	(-1.97)	(-2.42)	(-1.97)	(-2.44)
Short interest	-0.252	-0.074	-0.159	-0.063
	(-0.29)	(-0.14)	(-0.19)	(-0.12)
D(Russell 2000)	-0.001	-0.006	-0.004	-0.008
	(-0.06)	(-0.48)	(-0.25)	(-0.75)
Observations	1,490,913	2,979,134	1,490,913	2,979,134
Adjusted R^2	0.337	0.336	0.326	0.324
Month fixed effects	Yes	Yes	Yes	Yes
Banding and market cap controls	Yes	Yes	Yes	Yes
Banding and market cap controls interacted with Short interest	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 9: Short selling before earnings announcements

This table examines if there is more short selling before negative earnings announcement if a stock is in the Russell 2000 (our instrument for passive ownership). We display the results of earnings announcement-level regressions, where the dependent variable is *Short interest* in the 30 or 60 days leading up to the earnings announcement and the explanatory variable of interest is the interaction between *D(Russell 2000)* and *D(Negative Earnings Surprise)*. *D(Negative Earnings Surprise)* is a dummy variable equal to one when the cumulative announcement alpha (or return) from t-1 to t+2 is in the bottom tercile and zero otherwise. In Regressions 1 and 3, we base *D(Negative Earnings Surprise)* on alphas and in Regressions 2 and 4 on returns. *D(Russell 2000)* is an indicator variable equal to one if the stock is in the Russell 2000 index. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: *D(banded)*, an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, $D(Russel\ 2000_{last\ May})$, an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. In addition, we include all these variables interacted with *D(Negative Earnings Surprise)* (as a result, the coefficient on the *Negative Earnings Surprise* dummy is difficult to interpret; it represents the effect of a hypothetical firm with zero market cap). The sample consist of all quarterly earnings announcements from 2006 to 2018 for the top 500 stocks in the Russell 2000 index and the bottom 500 stocks in the Russell 1000 index. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Reduced Form Regression			
Dependent variable:	$Short\ interest_{t-30,t-1}$		$Short\ interest_{t-60,t-1}$	
	Based on Alphas	Based on Returns	Based on Alphas	Based on Returns
	(1)	(2)	(3)	(4)
D(Russell 2000)* D(Negative Earnings Surprise)	0.694**	0.626**	0.811***	0.748**
	(2.60)	(2.28)	(2.99)	(2.52)
D(Russell 2000)	0.741**	0.763**	0.541*	0.562*
	(2.50)	(2.57)	(1.74)	(1.78)
D(Negative Earnings Surprise)	-70.481	-60.551	-57.884	-56.286
	(-0.72)	(-0.58)	(-0.60)	(-0.54)
Observations	42,995	42,995	42997	42997
Adjusted R^2	0.123	0.123	0.121	0.121
Month fixed effects	Yes	Yes	Yes	Yes
Banding and market cap controls	Yes	Yes	Yes	Yes
Banding and market cap controls interacted with D(Negative Earnings Surprise)	Yes	Yes	Yes	Yes
Number of firms around threshold	500	500	500	500

Table 10: Passive ownership effect on information efficiency

This table examines whether information efficiency is higher for negative earnings announcements if a stock is in the Russell 2000 (our instrument for passive ownership). We display the results of earnings announcement-level regressions, where the dependent variable is the *Price jump ratio* (Weller (2018)) and the explanatory variable of interest is the interaction between *D(Russell 2000)* and *D(Negative Earnings Reaction)*. In Regression 1, the price jump ratio is defined as in Weller (2018) as $\frac{Alpha_{t-1,t+2}}{Alpha_{t-21,t+2}}$, where Alpha is the 3-factor Fama French (1993) alpha in days around the earnings announcement. In Regressions 2 , the price jump ratio is based on raw returns instead. *D(Negative Earnings Reaction)* is a dummy variable equal to one when the cumulative announcement alpha or return from t-21 to t+2 is in the bottom tercile and zero otherwise. *D(Russell 2000)* is an indicator variable equal to one if the stock is in the Russell 2000 index. In both regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: *D(banded)*, an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, $D(Russel\ 2000_{last\ May})$, an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. In addition, we include all these variables interacted with *D(Negative Earnings Reaction)* (as a result, the coefficient on the *Negative Earnings Reaction* dummy is difficult to interpret; it represents the effect of a hypothetical firm with zero market cap). Following Weller (2018), we only include earnings announcements if the absolute value of the cumulative announcement alpha or return from t-21 to t+2 is larger than $\sqrt{24}$ times the variance of the daily alpha from t-50 to t-22. The sample consist of all quarterly earnings announcements from 2006 to 2018 for the top 500 stocks in the Russell 2000 index and the bottom 500 stocks in the Russell 1000 index. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

	Reduced Form Regression	
Dependent variable:	Price jump ratio (Alpha) (%)	Price jump ratio (Return) (%)
	(1)	(2)
D(Russell 2000)* D(Negative Earnings Reaction)	-9.604**	-10.389**
	(-2.37)	(-1.99)
D(Russell 2000)	2.498	3.786
	(0.95)	(1.36)
D(Negative Earnings Reaction)	-2194.652	-1289.025
	(-1.36)	(-0.86)
Observations	16602	15020
Adjusted R^2	0.027	0.065
Month fixed effects	Yes	Yes
Banding and market cap controls	Yes	Yes
Banding and market cap controls interacted with D(Negative Earnings Reaction)	Yes	Yes
Number of firms around threshold	500	500

Table 11: Changes to Lending Fraction of Active and Passive Owners

This table uses detailed lending data compiled from SEC filings for the largest 10 fund families (henceforth called SEC subsample) and examines if active and passive ownership is higher (Panel A) and if active and passive owners lend a larger fraction of their shares (Panel B) if the stock is in the Russell 2000 index. In Panel A, the dependent variable is active ownership (Columns 1 and 2) or passive ownership (Columns 3 and 4) as a fraction of shares outstanding. In Panel B, the dependent variable is the fraction of owners that lent out shares. In Columns 1 and 2, it is the share of active owners, in Columns 3 and 4 that of passive owners. The explanatory variable of interest is *D(Russell 2000)*, which is a dummy variable equal to one if the stock is in the Russell 2000 index. In all regressions, we control for a third polynomial of log-market cap measured at the end of (previous) May, the logarithm of float-adjusted market cap as of the end of June, and the following banding controls: *D(banded)*, an indicator for having an end-of-May market cap sufficiently close to the cutoff such that the firm will not switch indexes, $D(Russel\ 2000_{last\ May})$, an indicator whether the firm was in the Russell 2000 index at the end of last May (and thus over the course of the previous year), and their interaction. The sample consists of either the top 250 or 500 stocks in the Russell 2000 index and the bottom 250 or 500 stocks in the Russell 1000 index. The regressions are run on monthly data from 2006 to 2017. We include month fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Effect on active and passive ownership (SEC subsample)

	Reduced Form Regression			
Dependent variable:	Active ownership (SEC subsample)		Passive ownership (SEC subsample)	
	(1)	(2)	(3)	(4)
D(Russell 2000)	3.423	-2.327	11.058***	14.984***
	(0.55)	(-0.41)	(4.80)	(6.78)
Float-adjusted market cap	86.585***	80.117***	60.821***	59.861***
	(14.81)	(17.66)	(18.68)	(21.03)
D(banded)	4.557	11.872***	-0.616	1.236
	(0.92)	(2.93)	(-0.29)	(0.72)
$D(Russel\ 2000_{last\ May})$	27.202***	27.950***	-3.983	-0.627
	(3.85)	(6.60)	(-1.48)	(-0.38)
$D(Russel\ 2000_{last\ May})$* D(banded)	-15.457**	-10.473*	6.296**	0.152
	(-2.03)	(-1.80)	(2.03)	(0.07)
Observations	66270	132386	66270	132386
Adjusted R^2	0.177	0.163	0.654	0.618
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Panel B: Effect on average lending fraction of active and passive owners (SEC subsample)

	Reduced Form Regression			
Dependent variable:	Lending fraction of active owners (%)		Lending fraction of passive owners (%)	
	(1)	(2)	(3)	(4)
D(Russell 2000)	0.001	0.001	-0.000	-0.000
	(0.75)	(1.09)	(-0.15)	(-0.01)
Float-adjusted market cap	-0.005***	-0.004***	-0.017***	-0.016***
	(-4.73)	(-4.94)	(-4.52)	(-5.84)
D(banded)	0.000	-0.000	-0.002	-0.002
	(0.32)	(-0.73)	(-1.06)	(-1.17)
$D(Russel\ 2000_{last\ May})$	0.000	-0.002**	0.005	0.000
	(0.38)	(-2.60)	(1.65)	(0.13)
$D(Russel\ 2000_{last\ May})$* D(banded)	-0.002*	0.000	-0.005	0.001
	(-1.90)	(0.11)	(-1.28)	(0.26)
Observations	66268	132370	66261	132382
Adjusted R^2	0.096	0.087	0.113	0.117
Month fixed effects	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3
Number of firms around threshold	250	500	250	500

Table 12: Robustness checks

This table displays robustness checks to our main results. We show the second stage of instrumental variable regression where passive ownership is instrumented by membership of the Russell 2000 index. In Panel A, we form our sample based on the ranking of float-adjusted market capitalization provided by Russell rather than on our CRSP/Compustat market capitalization. In Panel B, we form our sample based on market capitalization using only information from CRSP. Similarly, all market cap control variables (and banding controls) are based only on CRSP market capitalization. In Panel C, we exclude firms in the 3 months (May to July) around the time they switch between the Russell 1000 and 2000 index. In Panel D, we include control variables for the stock return over the past 1, 3 and 6 months. In Panel E, we rerun our main specification on a smaller sample with a bandwidth of just 150 companies in each direction around the threshold. In Panel F, we add firm fixed effects to our baseline regression. Finally, in Panel G, we show a robustness check for our short selling results in which we proxy for short selling using short interest data rather than equity lending data. All regressions are run on monthly data from 2006 to 2018. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Sampling based on float-adjusted market capitalization

	Second stage				
Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	1.128***	0.921***	1.175***	0.082***	-0.142***
	(4.92)	(4.33)	(2.87)	(4.89)	(-4.01)
Observations	129,333	129,328	129,328	129,328	122,193
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	500	500	500	500	500

Panel B: Sampling and control variables only based on CRSP market cap

	Second stage				
Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	1.210***	0.542***	0.746**	0.043***	-0.115***
	(7.16)	(3.55)	(2.37)	(3.43)	(-4.18)
Observations	129,826	129,821	129,821	129,821	122,735
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	500	500	500	500	500

Panel C: Excluding firms in the 3 months around the time they switch indexes

	Second stage				
Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	1.243***	0.695***	0.912*	0.064***	-0.128***
	(4.41)	(3.05)	(1.89)	(3.26)	(-3.16)
Observations	127,385	127,380	127,380	127,380	120,408
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	500	500	500	500	500

Panel D: Adding controls for past returns

Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	Second stage				
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	1.277***	0.650***	0.826*	0.053***	-0.128***
	(4.51)	(2.95)	(1.75)	(2.75)	(-3.13)
$Return_{t-1}$	-0.259	1.600***	2.836***	-0.046*	-0.072
	(-0.61)	(3.74)	(3.45)	(-1.87)	(-1.07)
$Return_{t-3,t-1}$	-1.198	-0.864	-3.137	0.210***	-0.030
	(-1.04)	(-0.77)	(-1.33)	(3.37)	(-0.21)
$Return_{t-6,t-1}$	4.462**	-18.363***	-35.004***	-0.473***	-0.056
	(2.60)	(-7.96)	(-7.77)	(-4.76)	(-0.19)
Observations	129,687	129,682	129,682	129,682	122,612
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	500	500	500	500	500

Panel E: Smaller sample (bandwidth of 150 firms around threshold)

Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	Second stage				
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	0.965**	1.095**	3.058**	0.056*	-0.128
	(2.04)	(2.35)	(2.43)	(1.83)	(-1.31)
Observations	38,914	38,911	38,911	38,911	36,824
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	150	150	150	150	150

Panel F: Adding Firm Fixed Effects

Dependent variable	Lendable supply (%)	Short interest (equity loans) (%)	Utilization (%)	Average tenure (log)	Delivery failure (%)
	Second stage				
	(1)	(2)	(3)	(4)	(5)
Passive ownership (%)	1.074***	0.820***	0.845	0.033	-0.171***
	(3.96)	(3.17)	(1.53)	(1.51)	(-3.29)
Observations	129,687	129,682	129,682	129,682	122,612
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Banding controls	Yes	Yes	Yes	Yes	Yes
Polynomial order of market cap	3	3	3	3	3
Number of firms around threshold	500	500	500	500	500

Panel G: Short interest based on Compustat data

Dependent variable	Short interest (Compustat) (%)	
	Second stage	
	(1)	(2)
Passive ownership (%)	1.183***	0.804***
	(8.24)	(8.50)
Observations	55,436	109,900
Month fixed effects	Yes	Yes
Banding controls	Yes	Yes
Polynomial order of market cap	3	3
Number of firms around threshold	250	500

Appendix A: Variable definitions

This table displays the variable definitions for all variables used in the regressions. All continuous variables are winsorized at the 1% level on both sides.

Variable Name	Definition
D(Russell 2000)	Dummy variable equal to one if the stock is in the Russell 2000 index in the specific month and equal to zero if the stock is in the Russell 1000 index (missing if the stock is in neither index).
Passive ownership (%)	Percentage of shares outstanding held by passive investors. To determine the fraction of passive ownership, we follow Appel, Gormley, Keim (2016). Specifically, we obtain fund names by merging the Thomson Reuters data with CRSP mutual fund data using the MFLINKS table available on WRDS. We then flag a fund as passively managed if its marked as an index fund in the CRSP Mutual Fund database or if the fund name includes one of the following strings that identify it as an index fund: Index, Idx, Indx, Ind_ (where _ indicates a space), Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000. (The comparison is case sensitive).
Active ownership (%)	Percentage of shares outstanding held by active investors. Active investors are investors in the Thompson Reuters s-12 data not identified as passive.
Float-adjusted market cap	The natural logarithm of the float-adjusted market cap as of the end of last June as provided by Russell.
D(banded)	Dummy variable equal to one if a stock has an end-of-May market cap sufficiently close to the cut-off such that the firm will not switch indexes. To determine whether a firm is banded, we compute the total market capitalization of the Russell 3000 index and sort all firms in that index by market capitalization. We then compute the market capitalization percentiles for each firm (for example, if a firm has a 75 percentile, it means that firms larger than it make up 75% of the market capitalization of the Russell 3000 index). A firm is banded if its percentile is less than 2.5 percentage points different from the percentile of the 1000th stock. This approach follows the instructions by Russell and as we show in Appendix E, it is fairly predictive of actually realized index changes. Our data includes 2006, where Russell was not yet implementing banding. To be consistent, we nonetheless include the same banding controls in 2006. This should only lower the power of the test and not lead to any bias.
D(Russell $2000_{last\ May}$)	Dummy variable equal to one if the stock was in the Russell 2000 index in the previous May (and thus over the course of the previous year).
Lendable supply (%)	Monthly average of number of shares available to be lent in markit (sometimes referred to as "inventory") divided by shares outstanding from CRSP. Shares that are actually lent out are included in this measure.
Short interest (equity loans) (%)	Monthly average of number of shares lent out provided by markit (sometimes referred to as "demand") divided by shares outstanding from CRSP.
Utilization (%)	Monthly average of shares lent out divided by shares available to lent out as provided by markit. To avoid double counting, shares lent out only includes the case where markit received the data from the equity lender (rather than the borrower).
Lending fee (bp)	Monthly average of the daily value-weighted average fee for borrowing the specific security (provided by markit).
D(ETF undervalued)	For each ETF, we compute the mispricing as the difference between the ETF price (from CRSP security files) and the NAV (from CRSP mutual fund data). For each stock, we then compute the weighted average mispricing of ETFs holding the specific stock, where the weight is the number of shares that the ETF holds. D(ETF undervalued) is equal to 1 if this average mispricing is negative and 0 if it is positive.
Average tenure (log)	The natural logarithm of the monthly average of the number of days that equity loans in this stock have been open.
Fraction of loans with tenure above 30 days (%)	Monthly average of the fraction of equity loan volume that has a tenure above 30 days.
Delivery failure (%)	Number of shares that were not delivered divided by number of shares that were lent out as reported in markit. Fails to deliver (FTD) balances are obtained from the SEC website (https://www.sec.gov/data/foiadocsfailsdatahtm), and are available daily from February 2004 onwards for stocks with an outstanding balance of FTDs of 10,000 shares or more. From September 16, 2008 the balance is available for all stocks with one or more shares that have failed to deliver.
D(Top quartile delivery failure) (%)	Dummy variable equal to 1 (specifically, 100%) if the stock is in the top quartile by Delivery failure in the specific month.
D(Negative Earnings Surprise)	A dummy variable equal to one when the cumulative alpha from t-1 to t+2 around the earnings announcement is in the bottom tercile and zero otherwise.
Price jump ratio (Alpha)	$\frac{Alpha_{t-1,t+2}}{Alpha_{t-21,t+2}}$, where Alpha is the 3-factor Fama French (1993) alpha in (calendar) days around the earnings announcement. This variable is set to missing if: $\lvert Alpha_{t-21,t+2}\rvert > \sqrt{24} * \hat{\sigma}_{past\ month}$, where $\hat{\sigma}_{past\ month}$ is the standard deviation of alphas in the prior month.
Price jump ratio (Return)	$$\frac{Return_{t-1,t+2}}{Return_{t-21,t+2}}$$ This variable is set to missing if: $\lvert Return_{t-21,t+2}\rvert > \sqrt{24} * \hat{\sigma}_{past\ month}$, where $\hat{\sigma}_{past\ month}$ is the standard deviation of returns in the prior month.

D(Negative Earnings Reaction)	A dummy variable equal to one when the cumulative alpha (or return) from t-21 to t+2 around the earnings announcement is in the bottom tercile and zero otherwise.
Short interest (Compustat) (%)	Monthly average of number of shares sold short according to short interest data from Compustat divided by shares outstanding from CRSP.
D(passive fund)	A dummy variable equal to one if the CRSP Mutual Fund Database classifies the fund as an index fund or if its name in CRSP contains a string that suggests that it is an index fund.
Passive Ownership (SEC subsample)	Percentage of shares outstanding held by passive funds in a sample of the 10 largest fund families. The data is obtained from the SEC.
Active Ownership (SEC subsample)	Percentage of shares outstanding held by active funds in a sample of the 10 largest fund families. The data is obtained from the SEC.
Lending Fraction of Passive Owners (%)	The fraction of passive funds that lent out shares of the stock in a sample of the 10 largest fund families.
Lending Fraction of Active Owners (%)	The fraction of active funds that lent out shares of the stock in a sample of the 10 largest fund families.
D(lending)	Dummy variable equal to one if the fund lends out any shares in the stock.
D(passive fund)	Dummy variable equal to one if a fund is identified as passive.

Appendix B: Methodology to compute market cap

Russell assigns stocks into the Russell 1000 and 2000 indexes using the (total) market capitalization at the end of May. Unfortunately, this market capitalization is not available. Therefore, we follow Ben-David, Franzoni, and Moussawi (2019) and construct a proxy of this market capitalization from a combination of CRSP and Compustat data. We used the code that they provide in their paper. The following is an abbreviated description of the methodology copied from their paper.

CRSP and Compustat are our main sources of information. We match each Russell constituent to its CRSP PERMNO using historical CUSIP information in CRSP MSENAMES and to Compustat's GVKEY using the CRSP/Compustat Merged Database on WRDS. We rely on the CRSP database for information on reliable prices and shares outstanding for all securities traded on a major exchange (variable PERMNO), as CRSP provides reliable information on these measures for public stocks. We also use CRSP's mapping of the different issues to their company identifier (variable PERMCO), which we employ to compute our proxy for Russell's total market capitalization.

We next turn to Compustat for information on common shares of stocks that are traded over-the-counter (OTC), nonpublicly traded stocks, and securities that are not in CRSP. For companies that have one or more of their share classes listed in OTC markets, and for three companies that are not in the CRSP database,9 we use the Compustat Securities Daily database to aggregate the market capitalization of the multiple issues (variable GVKEY-IID) at the company level (variable GVKEY). For companies that have multiple shares of common stock where one or more of these share classes is closely held and not publicly traded, we use the aggregated shares outstanding variable in Compustat Quarterly for the nearest quarter (variable CSHOQ), which represents the total number of all common shares outstanding at fiscal quarter-end collected from Forms 10-Q and 10-K.

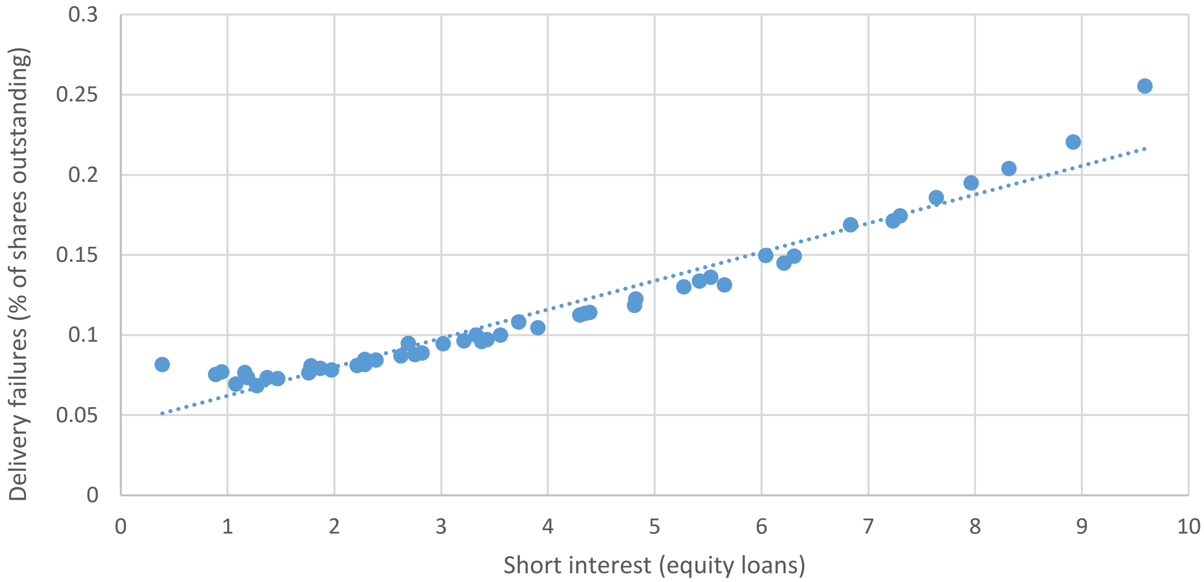
After carving out the proportion of CSHOQ attributable to nontraded share classes, we multiply it by the weighted-by-share-class-size average price of publicly traded share classes to compute the corresponding market capitalization. We then add the market capitalization of the closely held share classes to the market capitalization of the traded share classes computed using Compustat to obtain a second proxy for the total market capitalization used by Russell in ranking stocks.

In sum, we end up with two proxies for total market capitalization at the company level. We rely primarily on the CRSP-based proxy for total market capitalization. We use the Compustat-based proxy for total market capitalization only if it is higher than the CRSP-based figure.

Appendix C: Correlation of delivery failures and shorting

This figure shows a scatterplot that illustrates the correlation between failures to deliver and short selling. For each stock, we split days into 50 groups based on the amount of shorting (equity loans). Then, for each group we compute the average delivery failures, defined as the number of shares that were not delivered (as a percentage of shares outstanding), and the average of shorting, defined as shares lent out (as a percentage of shares outstanding). We then plot these averages for each of the 50 groups into the scatter plot and add a linear trend line.

Scatterplot of delivery failures and shorting



Appendix D: Delivery failures and future returns

This table examines if short selling is more profitable in stocks with high delivery failures. As argued by Muravyev et al. (2021), this is an important hurdle to pass in order to be credible as a proxy for short selling risk. The intuition is that, if short selling risk commands a risk premium, the return to shorting should be larger for stocks with larger short selling risk, after controlling for the level of short interest, which is a well-known return predictor (e.g., Boehmer, Jones, Zhang (2008), Diether, Lee, and Werner (2009), Cohen, Diether, and Malloy (2007)). We display daily regressions of future returns on the number of delivery failures divided by shares outstanding. We consider future returns over the next 5, 10, or 21 trading days. In Panel A, we use simple returns. In Panel B, we use returns net of lending fees, computed as return + lending fee (because short sellers make a profit when returns are negative). In regression 2, 4, and 6, we control for *Short interest* and *Lending fee*. We include date fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and month. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Panel A: Simple returns

Dependent variable:	$Return_{t+1,t+5}$ (%)		$Return_{t+1,t+10}$ (%)		$Return_{t+2,t+21}$ (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Delivery failures (by shares outstanding)	-0.032***	-0.018***	-0.036***	-0.021***	-0.039***	-0.023***
	(-4.98)	(-2.64)	(-6.21)	(-3.39)	(-7.22)	(-4.00)
Short interest		-0.001**		-0.001**		-0.001**
		(-2.50)		(-2.50)		(-2.44)
Lending fee		-0.000***		-0.000***		-0.000***
		(-11.50)		(-12.05)		(-12.50)
Observations	9,852,390	9,641,860	9,852,772	9,642,207	9,853,367	9,642,778
Adjusted R^2	0.152	0.155	0.151	0.154	0.140	0.146
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

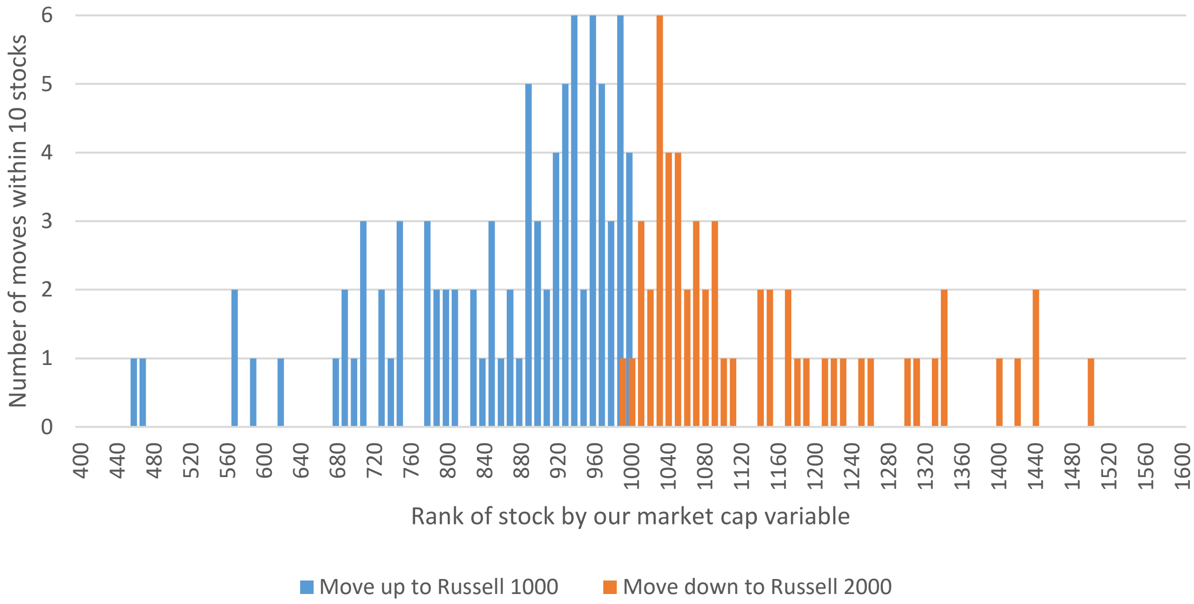
Panel B: Net-of fee returns

Dependent variable:	$Net\ of\ fee\ return_{t+1,t+5}$ (%)		$Net\ of\ fee\ return_{t+1,t+10}$ (%)		$Net\ of\ fee\ return_{t+2,t+21}$ (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Delivery failures (by shares outstanding)	-0.024***	-0.022***	-0.028***	-0.026***	-0.030***	-0.028***
	(-3.66)	(-3.21)	(-4.62)	(-4.10)	(-5.32)	(-4.66)
Short interest		-0.001**		-0.001**		-0.001**
		(-2.51)		(-2.49)		(-2.43)
Observations	9,705,519	9,606,624	9,755,466	9,621,394	9,785,475	9,619,557
Adjusted R^2	0.143	0.149	0.134	0.144	0.120	0.132
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

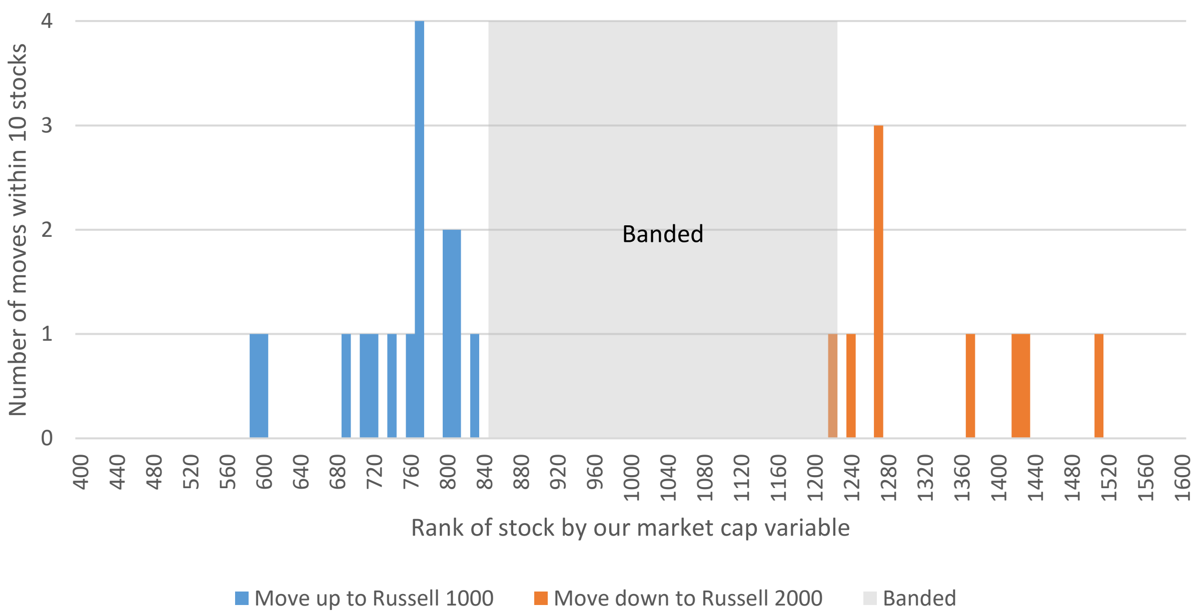
Appendix E: How well we predict the banding policy

In this figure, we display moves between the Russell 1000 and Russell 2000 indexes in 2006 (before banding) and in 2007 (with banding). For this purpose, we sort stocks by our market capitalization variable at the end of May and group them into groups of 10 stocks. We display how many stocks change indexes. In Panel A, there is a clear dividing line around rank 1000, where stocks above it move up (or stay up) and stocks below it move down (or stay down). However, up and down moves overlap a little bit, suggesting that our market capitalization variable may in a few cases be slightly different from the one used by Russell. In Panel B, we shade in grey the area for which we predict stocks to be banded. Indeed, except for one outlier at the margin, these stocks do not switch indexes, suggesting that our implementation of the banding policy is accurate. In Panel C, we tabulate the number of correctly predicted moves, the number of unpredicted (missed) moves, and the number of wrongly predicted moves by year. In the pre-banding period (2004-06), we correctly predict 98% of moves between the Russell 1000 and Russell 2000 indexes. In the post-banding period (2007-19), we still correctly predict about 94% of moves.

Panel A: Moves between Russell 1000 and Russell 2000 in 2006 (before banding)



Panel B: Moves between Russell 1000 and Russell 2000 in 2007 (with banding)



Panel C: Predicted and Unpredicted Moves between Russell 1000 and Russell 2000

Year	# correctly predicted moves	# unpredicted (missed) moves	# falsely predicted moves	% correctly predicted moves	% unpredicted (missed) moves	% falsely predicted moves
2004	445	1	5	98.7%	0.2%	1.1%
2005	375	3	4	98.2%	0.8%	1.0%
2006	378	3	4	98.2%	0.8%	1.0%
2007	240	12	1	94.9%	4.7%	0.4%
2008	356	3	2	98.6%	0.8%	0.6%
2009	362	5	3	97.8%	1.4%	0.8%
2010	277	7	3	96.5%	2.4%	1.0%
2011	226	10	5	93.8%	4.1%	2.1%
2012	253	9	5	94.8%	3.4%	1.9%
2013	203	8	5	94.0%	3.7%	2.3%
2014	200	13	6	91.3%	5.9%	2.7%
2015	196	12	8	90.7%	5.6%	3.7%
2016	260	11	4	94.5%	4.0%	1.5%
2017	247	14	13	90.1%	5.1%	4.7%
2018	248	17	12	89.5%	6.1%	4.3%
2019	223	7	15	91.0%	2.9%	6.1%
pre-banding avg	399.33	2.33	4.33	98.3%	0.6%	1.1%
post-banding avg	253.15	9.85	6.31	93.7%	3.9%	2.5%

Appendix F: Methodology to compute 3 factor Fama French (1993) alphas

We obtain the market factor, High-minus-Low Book to Market Factor (HML), and Small-minus-Big (SMB) factor, U.S. 1-month T-bill rate as the risk free rate from Kenneth French's website.

For each earnings announcement, we estimate betas by regressing daily excess returns on these factors over the past 12 months preceding the months before the earnings announcement:

$$r_{c,t} - r_{f,t} = \alpha + \beta_m * \left(r_{m,t} - r_{f,t}\right) + \beta_{HML} * HML_t + \beta_{SMB} * SMB_t$$

where $r_{c,t}$ is the daily company return, $r_{m,t}$ is the daily market return and $r_{f,t}$ is the daily risk free rate. As recommended by Levi and Welch (2016), we shrink the resulting beta estimates toward their theoretical average value:

$$\beta_{j,t}^{shrunk} = 0.7 * \beta_{j,t}$$

for $j \in \{ HML, SMB\}$ and

$$\beta_{j,t}^{shrunk} = 0.7 * \beta_{j,t} + 0.3 * 1$$

for the market factor.

Finally, we compute the three factor alpha as:

$$Alpha_{c,t} = r_{c,t} - r_{f,t} - \beta_m * \left(r_{m,t} - r_{f,t}\right) - \beta_{HML} * HML_t - \beta_{SMB} * SMB_t$$

Appendix F: Do passive funds lend more stock?

This table examines if passive funds are more likely to lend out their shares. The dependent variable is a dummy variable if the fund lends out any shares of the stock. The sample only includes funds of the largest 10 fund families. The explanatory variable of interest is *D(passive fund)*, which is a dummy variable equal to one if the CRSP Mutual Fund Database classifies the fund as an index fund or if its name in CRSP contains a string that suggests that it is an index fund. The regressions are run on quarterly data from 2006 to 2017. Depending on the specification, we include quarter, stock, and stock-quarter fixed effects. Details on variable constructions can be found in Appendix A. All standard errors are two-way clustered by stock and quarter. We report t-statistics below the coefficients in parenthesis. ***, **, * indicate significance at the 1%, 5% and 10% level.

Dependent variable:	D(lending)			
	(1)	(2)	(3)	(4)
D(passive fund)	0.0201***	0.0193***	0.0169***	0.0164***
	(12.00)	(11.50)	(11.16)	(10.89)
Observations	31,020,079	31,020,079	31,019,781	30,990,435
Quarter fixed effects	No	Yes	Yes	No
Stock fixed effects	No	No	Yes	No
Stock-Quarter fixed effect	No	No	No	Yes