Title

Essays on Capital Market Implication of Stock Indexing: Price Discovery and Mandatory Reporting Quality

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Essays on Capital Market Implication of Stock Indexing:
Price Discovery and Mandatory Reporting Quality

by

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Abstract

In the first chapter titled "Identifying the Effect of Stock Indexing: Impetus or Impediment to Arbitrage and Price Discovery?", with Panos N. Patatoukas, we validate Russell reconstitution as a quasi-natural experimental setting and explore securities lending market dynamics and price discovery process at both the upper and lower cutoffs.

The rise of stock indexing has raised concerns that index investing impedes arbitrage and degrades price discovery. This paper uses Russell's reconstitution to identify the causal effect of index investing on information arbitrage and price discovery. While index investing has no discernible effect on the ability of arbitrageurs to trade and impound news into the prices of large- and mid-cap stocks, we find that index investing increases the speed of price adjustment to news for micro-cap stocks. Our causal evidence identifies the relaxation of arbitrage constraints as a mechanism through which indexing facilitates informed trading for more arbitrage-constrained micro-cap stocks.

In the second chapter titled "Does Index Membership Affect the Quality of Mandatory Financial Report? Evidence from Index Deletions", I examine the effect of stock indexing on mandatory disclosure quality.

This paper examines whether stock indexing affects the quality of mandatory financial reports. Using a fuzzy regression discontinuity design at the lower cutoff of the Russell 2000 Index, I find that small-cap firms moving out of the Russell 2000 exhibit more errors in annual and quarterly financial statement numbers, reduce the amount of textual disclosure, and increase the ambiguous tone in 10-K filings. On the contrary, mandatory reporting quality does not change following the addition to the Russell 2000. The evidence suggests that index deletion poses a higher informational risk to investors and highlights the positive effect of index membership in ensuring disclosure quality for small-cap firms in a limited information environment.

Dedicated to my parents for their love and support.

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CHAPTER 1:

Identifying the Effect of Stock Indexing: Impetus or Impediment to Arbitrage and Price Discovery?

(with Panos N. Patatoukas)

I. Introduction

What is the effect of stock indexing on information arbitrage and the efficacy of the price discovery process? Forty-three years after John C. Bogle, the Vanguard Group founder, launched the world's first index mutual fund on Aug. 31, 1976, and over twenty-six years after the debut of the first index ETF on Jan. 22, 1993, index investing continues to grow. According to the Investment Company Institute (ICI), the share of index funds in the fund market has more than doubled from 18% in 2009 to 38% in 2019 (e.g., ICI (2020)). At year-end 2019, total net assets in index funds reached $8.4 trillion with a 50-50 split between index mutual funds and index ETFs (ICI Fact Book (2020)).

The rise of stock indexing has reshaped the investment landscape by democratizing access to low-cost passive strategies. Yet, it has also raised concerns that the ascent of index investing distorts stock prices.[1] The conventional argument is that indexing is akin to free-riding on other people's research since index investors rely on prices without contributing to price discovery. The substitution of active investors with index investors, the argument goes, impedes price discovery, and reduces price efficiency. Another related argument is that basket trading, i.e., the mass buying or selling of index constituents, leads to excess comovement (e.g., Sullivan and Xiong (2012) and Da and Shive (2018)), amplifies return volatility (e.g., Krause, Ehsani, and Lien (2014) and Ben-David, Franzoni, and Moussawi (2018)), and decreases stock liquidity due to higher adverse selection costs (e.g., Hamm (2014) and Israeli, Lee, and Sridharan (2017)). This argument implies that index investing increases the cost and risk of information arbitrage, thereby, reducing price efficiency.

Whereas the critics often argue that indexing hinders informational efficiency, indexing can facilitate information arbitrage and promote price discovery. First, there is evidence that higher index ownership leads to enhanced public information production by analysts and managers (e.g., Boone and White (2015)). Second, index products provide efficient means to risk transferring and hedging. In fact, arbitrageurs routinely use index products as building blocks of active strategies that allow them to bet more aggressively on firm-specific information while hedging out systematic exposure (e.g., Easley, Michayluk, O'Hara, and Putniņš (2020), Huang, O'Hara, and Zhong (2020), and Li and Zhu (2019)). In

[1] The fear of indexing may be overblown. Beyond active funds, there are several other active investors in financial markets, including hedge funds, pension funds, life insurance companies, and individuals. Despite the significant growth of index investing over the past decade, index funds remain relatively small investors in the U.S. stock markets. At year-end 2019, index funds held 15% of the value of U.S. stocks, active funds held another 15%, while other investors held the remaining 70% (ICI Fact Book (2020)).

addition, indexing can improve arbitrageurs' ability to take short positions and exploit inefficiencies. This is because index funds control a large portion of the inventory of lendable stock and typically participate in securities lending programs (e.g., D'Avolio (2002) and Nagel (2005)). Indeed, low-cost index funds actively use stock loan fees generated from such programs to enhance fund performance and offset fees for index investors (e.g., Blocher and Whaley (2015) and Prado, Saffi, and Sturgess (2016)).[2]

The premise that price efficiency decreases with the cost of information arbitrage dates back to Grossman and Stiglitz (1980). Within the context of their noisy rational expectations model, a decrease in the cost of information arbitrage increases price informativeness. With respect to the effect of short-sales constraints on price efficiency, Diamond and Verrecchia (1987) propose a rational expectations model whereby the dominant effect of short-sales constraints is to eliminate more informative trades and reduce the speed of price adjustment to news. A prediction of their model is that relaxing short-sales constraints improves stock liquidity due to lower adverse selection costs and increases the speed of price adjustment to news. The ideal experimental setting for testing Diamond and Verrecchia's (1987) prediction would identify an exogenous source of variation in the severity of short-sales constraints and examine changes in stock liquidity and the speed of price adjustment to news before and after the change.

This paper aims to identify the causal effect of indexing on arbitrage conditions and price discovery. Sorting out causation from association is an important issue in the ongoing debate surrounding the rise of index investing. Building on Chang, Hong, and Liskovich's (2015) regression discontinuity approach, we use FTSE Russell's index reconstitution as a source of exogenous variation in index investing. This quasi-natural experimental setting tackles head-on the endogeneity issue in the relation of index investing with informational efficiency. Simply put, the issue is that stocks with different levels of index fund ownership may differ along dimensions that are endogenously related to stock liquidity, the severity of short-sales constraints, and the overall efficacy of the price discovery process. The endogeneity issue confounds association studies on the effect of changes in index investing on outcome variables of interest. An association study would rely on observables to control for forces that simultaneously determine index investing and outcome variables, but without being able to rule out the role of correlated omitted variables and reverse causality.[3]

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[2] For example, Vanguard has an active approach to stock lending dubbed "value lending" that is designed to capture a scarcity premium found in hard-to-borrow stocks (Vanguard Group (2018)). Across index fund managers there is variation in the structure of securities lending programs and fee-split arrangements with investors. While Vanguard returns all stock lending proceeds to the Vanguard funds, Blackrock retains 20% to 28.5% for itself depending on the fund (e.g., "ETFs' Hidden Source of Return—Securities Lending" by L. Braham, *Barron's*, Apr. 7, 2018).

[3] A longstanding literature examines the stock price effects of S&P 500 index inclusions (e.g., Shleifer (1986), Harris and Gurel (1986), Vijh (1994), and Barberis, Shleifer, and Wurgler (2005)). Different from the Russell indices which are rules-based, the S&P 500 constituents are selected by a committee of members of the S&P Dow Jones Indices' staff. According to the S&P's methodology, the S&P 500 index does not simply contain the 500 largest stocks but rather it covers leading companies from leading industries. The black-box nature of the S&P 500 selection does not allow for a quasi-experimental design similar to that in the Russell setting.

The Russell reconstitution process follows a set of rules based on market-cap breakpoints and a transparent timeline. Each year on the May rank day, FTSE Russell sorts in descending order all eligible stocks based on market cap. The largest 4,000 eligible stocks constitute the Russell 3000E index. Stocks ranked #1 to #1,000 constitute the Russell 1000 and stocks ranked #1,001 to #3,000 constitute the Russell 2000. The #1,000 breakpoint separates large- and mid-cap Russell 1000 stocks from small-cap Russell 2000 stocks (upper cutoff). The #3,000 breakpoint separates Russell 3000E micro-cap stocks from Russell 2000 small-cap stocks (lower cutoff). Since companies cannot precisely manipulate their May-rank-day market cap to place themselves on either side of the cutoff, the reconstitution creates exogenous variation in end-of-June index membership, when the reconstituted Russell indexes go into effect.

With respect to indexing, Chang et al. (2015) point out that the Russell 2000 is a relatively more popular benchmark among index institutions than either the Russell 1000 or the Russell 3000E. With more money tracking Russell 2000 stocks relative to otherwise similar stocks at the reconstitution cutoffs, small and random differences in their May-rank-day market cap cause discontinuous changes in index ownership due to forced buying and selling of stock additions and deletions around the reconstitution cutoffs. Stocks added to the Russell 2000, either by dropping below the #1,000 breakpoint or by rising above the #3,000 breakpoint, will experience a discontinuous increase in index ownership due to forced buying by tracking institutions. Stocks deleted from the Russell 2000, either by rising above the #1,000 breakpoint or by dropping below the #3,000 breakpoint, will experience a discontinuous decrease in index ownership due to forced selling by tracking institutions.

To estimate the effect of stock indexing, we implement a regression discontinuity design (RDD) and zero in on changes in outcomes before and after the Russell reconstitution. The RDD builds on the idea that stocks near the reconstitution cutoff are similar except with respect to their index membership and takes advantage of the fact that small and random differences in May-rank-day market cap cause large and discontinuous changes in index investing at the end-of-June. First, we validate that the Russell reconstitution leads to discontinuous changes in the fraction of shares held by index institutions. Then, we identify the treatment effects for stock additions and deletions relative to counterfactual stocks that could have been added to or deleted from the Russell 2000 if their May-rank-day market cap were only slightly different.

The RDD reveals stark differences at the #3,000 breakpoint vis-a-vis the #1,000 breakpoint. While our estimates imply that exogenous variation in index investing has no discernible effects at the upper cutoff separating large- and mid-cap stocks from small-cap stocks, we find significant treatment effects at the lower cutoff separating small- from micro-cap stocks. Micro-cap stock additions to the Russell 2000 experience a discontinuous relaxation of securities lending constraints, an improvement in liquidity, an increase in synchronicity, as well as an increase in the speed of price adjustment to market, industry, and firm news. On the flip side, micro-cap stock deletions from the Russell 2000 experience a discontinuous tightening of securities lending constraints, a deterioration in liquidity, a decrease in synchronicity, as well as a decrease in the speed of price adjustment to news.

The lack of discernible effects at the upper cutoff together with evidence of significant effects for micro-cap stock additions and deletions at the lower cutoff of the Russell 2000 offer a new perspective on the effect of indexing. In cross-sectional tests, we further explore variation in the addition effects at the lower cutoff with pre-reconstitution characteristics, including the intensity of arbitrage constraints and a stock's information environment. The evidence shows that an exogenous increase in index investing facilitates the timelier incorporation of news especially for stocks that are that are harder-to-borrow and harder-to-trade prior to their reconstitution into the Russell 2000. This finding highlights the relaxation of arbitrage constraints as a mechanism through which an exogenous increase in index investing enables more informed trading and improves price discovery.

Overall, the evidence is consistent with the premise that indexing can facilitate information arbitrage and increase price efficiency for more arbitrage-constrained micro-cap stocks. Prior research often interprets evidence of higher price synchronicity as de facto evidence of a deteriorating information environment and more noise in prices (e.g., Hamm (2014) and Israeli et al. (2017)). In contrast, our evidence from micro-cap stock additions at the lower cutoff of the Russell 2000 shows that higher price synchronicity due to an exogenous increase in index investing reflects the earlier resolution of uncertainty through the timelier incorporation of news rather than a decrease in price informativeness.

We acknowledge that causality does not automatically translate into generalizability. The RDD estimates may not be representative of treatment effects that would occur further away from the cutoffs (e.g., Cattaneo, Idrobo, and Titiunik (2017)). Nevertheless, our sensitivity analyses show that RDD estimates are robust to alternative bandwidths around the Russell reconstitution cutoffs. While our paper is silent with respect to the welfare implications of indexing, Chabakauri and Rytchkov (2020) analytically demonstrate that investors are better off in an economy with indexing than in a pre-indexing economy.

Our paper is related to prior association studies providing mixed results on the effect of passive ownership changes. Israeli et al. (2017) find that increases in ETF ownership are associated with a weaker relation between stock returns and future earnings, which they interpret as evidence of a deterioration in long-run informational efficiency due to lower stock liquidity and less informed trading. Glosten, Nallareddy, and Zou (2020) find that increases in ETF ownership are associated with a stronger relation between stock returns and contemporaneous earnings, which they interpret as an improvement in short-run informational efficiency due to stronger responsiveness to common information across stocks. Bhojraj, Mohanram, and Zhang (2020) provide evidence that sector-ETF membership is associated with stronger earnings-return relation due to stronger responsiveness to industry and idiosyncratic information, while broad-ETF membership is associated with weaker earnings-return relation due to weaker responsiveness to market information. Different from prior association studies, our paper provides new evidence on the causal effect of index investing on arbitrage conditions, price synchronicity, and the speed of price adjustment to market, industry, and firm news.

Our paper is also related to Coles, Heath, and Ringgenberg (2020). Like our paper, they use the Russell reconstitution to identify the effect of exogenous variation in index investing. Unlike our paper, they focus exclusively on the upper cutoff of the Russell 2000.

Whereas Coles et al. (2020) conclude that index investing does not affect price efficiency, our paper yields a much more nuanced understanding of the effect of indexing on the price discovery process and presents novel evidence regarding which stocks are and are not affected, and, most importantly, why. At the upper cutoff, we find that index investing has no discernible effect on the ability of arbitrageurs to trade and impound news into the prices of large- and mid-cap stocks. At the lower cutoff, however, we find strong evidence that index investing facilitates informed trading and increases the speed of price adjustment to news for micro-cap stocks, particularly those that are more arbitrage-constrained (i.e., stocks that are more illiquid and harder to borrow). Our evidence shows that exogenous variation in index investing is impactful at the lower cutoff of the Russell 2000 since micro- and small-cap stocks are significantly more arbitrage-constrained relative to mid- and large-cap stocks at the upper cutoff of the Russell 2000.

Our paper demonstrates how researchers can use the Russell reconstitution as a source of exogenous variation in index investing not only at the upper cutoff, separating large- and mid-cap stocks from small-cap stocks, but also at the lower cutoff, separating small- from micro-cap stocks. In this regard, our application is related to Cao, Gustafson, and Velthuis's (2019) study of the effect of index membership on small firm financing. Our evidence further highlights the economic significance of the lower cutoff as an important experimental setting. An overarching implication for future research is that unless there is strong motivation to focus exclusively on either the upper or the lower cutoff, researchers need to consider the effect of variation in index investing at both reconstitution cutoffs.

II. Research Design

A. The annual Russell reconstitution

FTSE Russell's U.S. equity indexes are designed to represent the investable opportunity set in the U.S. market, and the annual reconstitution process is key to maintaining an accurate representation of the investable stocks. The Russell reconstitution follows a set of rules based on market-cap breakpoints and a transparent timeline.

Table 1 reports the timeline of the annual Russell reconstitution between 2007 and 2016. The reconstitution event dates are available from FTSE Russell's Client Service. May is the ranking month. On the May rank day, FTSE Russell sorts in descending order all eligible stocks based on their total market cap at the close and determines the breakpoints between large- and mid-cap stocks as well as small- and micro-cap stocks. During our sample period, the rank day consistently falls on the last trading day at the end-of-May. The largest 4,000 eligible stocks become the Russell 3000E index. If there are fewer than 4,000 eligible stocks, then the Russell 3000E includes all eligible stocks.[4]

Prior to the 2007 reconstitution, stocks ranked #1 to #1,000 were included in the Russell 1000 and stocks ranked #1,001 to #3,000 were included in the Russell 2000. Starting with the 2007 reconstitution, FTSE Russell uses a banding policy for existing index members that mitigates index turnover around the #1,000 breakpoint. The banding policy works as follows. Stocks that were previously in the Russell 2000 (1000) are moved to the Russell 1000 (2000) only if their market cap is sufficiently larger (smaller) than that of stock #1,000 (#1,001). If a constituent falls within a $+/-2.5\%$ band around the percentile rank corresponding to the #1,000 breakpoint, the stock maintains its prior index assignment. The banding policy shifts the cutoff for prior Russell 2000 (1000) members crossing to Russell 1000 (2000) to the left (right) of the #1,000 breakpoint. Over our sample period, prior Russell 1000 (2000) members would typically need to cross just below (above) stock #1,226 (#833) to be added to (deleted from) Russell 2000. The banding policy does not affect the assignment of newly eligible index members since it only applies to prior index constituents. In addition, the banding policy does not affect index assignments at the #3,000 breakpoint since it only applies to the #1000 breakpoint. Due to banding, index turnover is significantly higher at the lower cutoff relative to upper cutoff of the Russell 2000.

June is the transition month. During this month, FTSE Russell communicates to the marketplace the preliminary and updated lists of projected additions and deletions for its indexes. The newly reconstituted indexes go into effect after market close on the last Friday in June. The annual Russell reconstitution day is a highly anticipated market event and the last Friday in June is one of the busiest trading days of the year because of stock index rebalancing.[5] While FTSE Russell ranks stocks based on their May-rank-day market cap to determine index memberships, the reconstituted Russell indexes weight stocks by their end-

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[4] Only common stocks listed on eligible U.S. exchanges that pass FTSE Russell's investability rules (e.g., total market cap $>$ \$30 million, rank day closing stock price >\$1, float>5% of shares outstanding) are considered for inclusion in the U.S. indexes; see "Russell U.S. Equity Indexes: Construction and Methodology."

[5] See, e.g., "Russell Rebalancing Brings Frenzy to a Summer Friday: Surge in Trading Expected as Stocks Added to and Dropped from U.S. Benchmarks" by A. Loder, *The Wall Street Journal*, Jun. 27, 2019.

of-June float-adjusted market cap. The float-adjusted index weights shift less (more) liquid stocks toward the bottom (top) of each index with the objective to minimize tracking costs for index funds. FTSE Russell determines the float-adjusted market cap using only the free-floating shares available to the public, which excludes shares that are not part of the investable set (e.g., shares not listed on an exchange, shares held by insiders, etc.).

B. Sample construction

We obtain Russell 3000E index constituent data for each annual reconstitution between 2007 and 2016 from FTSE Russell's Client Service. Our sample starts with the 2007 reconstitution because this is the first year with comprehensive coverage of securities lending market data from Markit. The post-2007 period overlaps with FTSE Russell's post-banding period and ensures consistency in the reconstitution process around the upper cutoff of the Russell 2000. In addition, the analysis of index turnover at the lower cutoff of the Russell 2000 is only possible post-2006. This is because the Russell 3000E index, which includes the largest 4,000 stocks and allows us to identify index turnover around the #3,000 breakpoint, is not available until June 2005.[6] The RDD focuses on changes in outcome variables from the year before to the year after each annual reconstitution. Therefore, our dataset effectively covers the period between the end-of-June of 2006 and the end-of-May of 2017. Appendix A provides the variable definitions.

Table 2, Panel A, reports the end-of-May market-cap breakpoints between 2007 and 2016. Starting with the Russell 1000, the average market cap of the smallest Russell 1000 stock without banding is \$2.35BN, which corresponds to the #1,000 breakpoint. Newly eligible index members with end-of-May market cap at or above this cutoff will be included in the Russell 1000 at the end-of-June. The average market cap of the smallest Russell 1000 stock with banding is \$1.67BN, which corresponds to the lower band of the #1,000 breakpoint. Prior Russell 1000 index members with end-of-May market cap just below this cutoff will be added to Russell 2000 at the end-of-June.

Turning to the Russell 2000, the average market cap of the largest Russell 2000 stock with banding is \$3.1BN, which corresponds to the upper band of the #1,000 breakpoint. Prior Russell 2000 stocks with end-of-May market cap above this cutoff will be deleted from Russell 2000 and will be added to Russell 1000 at the end-of-June. The average market cap of the largest Russell 2000 stock without banding is \$2.35BN, which corresponds to the #1,001 breakpoint. Newly eligible index members with end-of-May market cap at or just below this cutoff will be included in the Russell 2000 at the end-of-June. The average market cap of the smallest Russell 2000 stock is \$145.7MN, which corresponds to the #3,000 breakpoint. Recall that the banding policy applies only at the #1,000 breakpoint and, therefore, at the #3,000 breakpoint there is only a single cutoff value. Newly eligible or prior index members with end-of-May market cap at or just above this cutoff value will be included in both the Russell 2000 and the Russell 3000E and those that were just below will be included in only the Russell 3000E.

Table 2, Panel B, reports the counts of stock additions and deletions at the reconstitution cutoffs of the Russell 2000 between 2007 and 2016. We note that the counts

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[6] Chang et al. (2015) make a similar observation in their Internet Appendix.

are conditioned on prior index membership, thereby, excluding additions of newly eligible stocks such as IPOs. On average, index turnover is 3.5 times higher at the lower cutoff relative to the upper cutoff. This asymmetry is driven by Russell's post-2007 banding policy, which is designed to moderate index turnover at the upper cutoff but not at the lower cutoff. Due to the asymmetry in index turnover, the aggregate significance of stock additions at the lower cutoff is disproportionately large relative to the size of individual stocks.

C. Instrument for index assignment variable

The Russell reconstitution process creates index membership discontinuities. With respect to the #3,000 breakpoint, the reconstitution process creates a single discontinuity. With respect to the #1,000 breakpoint, the banding policy creates two discontinuities at the lower and upper bands of the #1,000 breakpoint. The true index assignment variable, i.e., FTSE Russell's end-of-May market cap ranking, should perfectly predict end-of-June index membership. FTSE Russell, however, uses a proprietary measure of total market capitalization and does not provide the end-of-May market cap rankings.

To construct an instrument for the unobservable index assignment variable, we start with the reconstituted Russell 3000E list available from FTSE Russell's Client Service at the end-of-June. For each constituent, we measure end-of-May market cap by multiplying the closing price on the rank day by the number of shares outstanding at the company level. Following Chang et al. (2015), we obtain the number of shares as of the most recent earnings report date prior to the rank day from Compustat and multiply this number by the CRSP factor to adjust shares for any corporate distribution after the fiscal quarter ends and before the rank day. We also obtain shares from CRSP as of the rank day and calculate total market cap using the larger of Compustat and CRSP shares.

We sort all Russell 3000E constituents in descending order from largest to smallest based on their end-of-May total market cap. Then, we generate market cap rankings relative to the Russell 1000/2000 market-cap breakpoints. We center the market cap rankings at each cutoff (zero ranking). Positive (negative) rankings identify stocks ranked below (above) the cutoff. We note that the historical market-cap breakpoints available online from FTSE Russell's website are rounded. This rounding is a source of error in the relative market cap rankings, especially for stocks close to the index breakpoints. To improve the strength of our instrument for the index assignment variable, we obtain the raw (i.e., before rounding) values of the market-cap breakpoints directly from FTSE Russell's Client Service. Table 2, Panel A, reports the market cap ranges between 2007 and 2016.

Our instrument is an indicator variable (τ) for Russell 3000E constituents predicted to be included in the Russell 2000 at the end-of-June. We make predictions about end-of-June index assignments using prior index membership and end-of-May market cap rankings. At the lower cutoff, we predict that prior Russell 2000 members ranked at or just above the #3,000 breakpoint will remain in Russell 2000, whereas those ranked below will be deleted from Russell 2000 and will be included in Russell 3000E. We also predict that prior Russell 3000E members ranked at or just above the #3,000 cutoff will be added to Russell 2000, and those ranked below will remain in Russell 3000E. At the upper band of the #1,000 cutoff, we predict that prior Russell 2000 members ranked just below the upper band will remain in Russell 2000, while those ranked above will be deleted from Russell 2000 and will be included in Russell 1000. With respect to the lower band of the #1,000 breakpoint, we predict that prior Russell 1000 members ranked just below the lower band will be added to Russell 2000, and those ranked above will remain in Russell 1000.

By definition, the true assignment variable; that is, FTSE Russell's end-of-May market cap ranking, will perfectly predict end-of-June index membership. Our instrument is unlikely to perfectly match the true index assignment variable and any differences will lead to imperfect compliance. Some stocks assigned to the treatment groups may fail to receive the treatment and some stocks may receive the treatment despite being assigned to the control groups. Our application of a fuzzy RDD accounts for imperfect compliance under the assumption that the predicted treatment status is a very strong instrument for the actual treatment status (strong IV assumption).

D. Discontinuities in predicted index membership

If our instrument for the index assignment variable is strong, we should observe that the predicted Russell 2000 index membership is discontinuous at the cutoffs. Figure 1 provides graphical evidence that our instrument for the index assignment variable is a very strong predictor of stock additions and deletions at the Russell reconstitution cutoffs. We consider the $+/-200$ bandwidth centered at each cutoff (zero ranking). Positive (negative) rankings identify stocks ranked below (above) the reconstitution cutoff based on their end-of-May total market cap. We organize stocks in ten equal-spaced bins on either side of the reconstitution cutoff. Each dot represents the average Russell 2000 index assignment probability within a bin over the midpoint rank of the bin.

Starting with the lower cutoff of the Russell 2000, Figure 1, Panel A, plots the predicted Russell 2000 index membership for prior Russell 3000E members at the #3,000 breakpoint. We predict that stocks ranked above the cutoff at the end-of-May will be added to the Russell 2000 at the end-of-June. The evidence shows a discontinuous jump in the probability of addition to the Russell 2000 for prior Russell 3000E members ranked above the #3,000 breakpoint. Figure 1, Panel B, plots the predicted Russell 2000 index membership for prior Russell 2000 members at the #3,000 breakpoint. We predict that Russell 2000 stocks ranked below the cutoff at the end-of-May will be deleted from the Russell 2000 and be reconstituted in the Russell 3000E at the end-of-June. The evidence shows a large discontinuous jump in the probability of deletion from the Russell 2000 for prior Russell 2000 members ranked below the #3,000 breakpoint at the end-of-May.

Turning to the upper cutoff of the Russell 2000, Figure 1, Panel C, plots the predicted Russell 2000 index membership for prior Russell 1000 members at the lower band of the #1,000 cutoff (zero ranking). We predict that Russell 1000 stocks ranked below the cutoff at the end-of-May will be added to the Russell 2000 at the end-of-June. While some stocks remain in the Russell 1000 despite being ranked below the cutoff, there is a discontinuous jump in the probability of addition to the Russell 2000 for prior Russell 1000 members ranked below the lower band of the #1,000 breakpoint.

Similarly, Figure 1, Panel D, plots the predicted Russell 2000 index membership for prior Russell 2000 members at the upper band of the #1,000 cutoff (zero ranking). We predict that Russell 2000 stocks ranked above the cutoff at the end-of-May will be deleted from the Russell 2000 at the end-of-June. While some stocks remain in the Russell 2000 despite being ranked above the cutoff, there is a discontinuous jump in the probability of deletion from the Russell 2000 for prior Russell 2000 members ranked above the upper band of the #1,000 breakpoint at the end-of-May.

Since the Russell indexes are value weighted, the discontinuities in end-of-June index assignments imply that there should be discontinuous changes in the end-of-June index weights. Stock additions to (deletions from) the Russell 2000 will be more (less) heavily weighted relative to counterfactual stocks that could have been added (deleted) if their end-of-May market cap were only slightly different. To confirm this implication, we measure the change in the end-of-June Russell index weights relative to the pre-reconstitution values. Figure 2 provides graphical evidence consistent with this implication.

At the lower cutoff, Figure 2, Panel A, shows that end-of-June index weights jump discontinuously for prior Russell 3000E members ranked above the #3,000 breakpoint at the end-of-May. Symmetrically, Figure 2, Panel B, shows that end-of-June index weights drop discontinuously for prior Russell 2000 members ranked below the cutoff at the end-of-May. The Russell 2000 index is a subset of the Russell 3000E index. Relative to the Russell 2000 index weights, the Russell 3000E index weights are skewed by the market cap weights of the largest stocks included in the Russell 1000. The evidence at the lower cutoff is consistent with the fact that prior Russell 3000E members will be weighted more heavily when added to the Russell 2000. The evidence is also consistent with the fact that prior Russell 2000 members will be weighted less heavily when reconstituted in the Russell 3000E.

At the upper cutoff, Figure 2, Panel C, shows that end-of-June index weights jump discontinuously for prior Russell 1000 members ranked just below the lower band of the #1,000 breakpoint at the end-of-May. Figure 2, Panel D, shows that end-of-June index weights drop discontinuously for prior Russell 2000 stocks ranked just above the upper band of the #1,000 breakpoint at the end-of-May. The evidence at the upper cutoff is consistent with the fact that prior Russell 2000 (1000) members will be weighted less (more) heavily when reconstituted in the Russell 1000 (2000).

Viewed together, the plots provide graphical evidence that our instrument for the index assignment variable is a very strong predictor of end-of-June Russell 2000 index assignment. We provide formal tests of discontinuity in the predicted index assignment probabilities when discussing the first-stage results of the fuzzy RDD (see Table 3).

E. Fuzzy regression discontinuity design (RDD)

1. Two-equation system

The fuzzy RDD examines how outcome variables of interest behave around the reconstitution cutoffs for treatment stocks relative to counterfactual stocks that could have been added to or deleted from the Russell 2000 if their May-rank-day market cap were only slightly different. We specify the fuzzy RDD as a two-stage least squares (2SLS) system:

$$\begin{cases} d_{it} = \alpha_0 + \alpha_1 \tau_{it} + \alpha_2 r_{it} + \alpha_3 \tau_{it} \times r_{it} + u_{it} \\ \\ y_{it} = \beta_0 + \beta_1 d_{it} + \beta_2 r_{it} + \beta_3 d_{it} \times r_{it} + \varepsilon_{it}, \end{cases}$$

where d is the indicator variable for actual Russell 2000 index membership at the end-of-June, r is the end-of-May total market cap ranking centered at the reconstitution cutoff (zero ranking) so that positive (negative) values represent stocks ranked below (above) the cutoff, τ is the indicator variable for predicted Russell 2000 index membership, and y is the outcome variable. The linear rank control functions in the two-equation system mitigate the influence of stocks ranked away from either side of the cutoff so that stocks ranked closest to the cutoff contribute more to the estimated discontinuity.

The first stage estimates a regression of the actual Russell 2000 index membership on the predicted index membership. The α_1 coefficient on τ measures the change in the probability of Russell 2000 index membership for stock additions and deletions near the reconstitution cutoff. If our instrument for the index assignment variable is a perfect predictor of actual index membership, the probability of Russell 2000 index membership would change exactly from 0% to 100% at the reconstitution cutoff and the coefficient estimate on τ would be exactly equal to one; that is $\alpha_1 = 1$. The second stage estimates a regression for each outcome variable on the predicted index assignment from the first stage. The β_1 coefficient on d estimates the treatment effect for stock additions and deletions near the reconstitution cutoff. More generally, the β_1 coefficient is defined as the ratio of the difference in expected outcomes at the cutoff divided by the change in the probability of treatment near the cutoff (e.g., Lee and Lemieux (2010); Roberts and Whited (2013)).

We implement the fuzzy RDD using Calonico, Cattaneo, and Titiunik's (2015) rdrobust software in R. Statistical inferences are based on Calonico et al.'s (2014) heteroskedasticity-robust nearest-neighbor variance estimator. The rdrobust software does not report R^2 statistics. The reason for this omission is that R^2 statistics in the fuzzy RDD setting do not have a meaningful interpretation (see, e.g., Wooldridge's (2012) discussion of IV estimation in Chapter 15). Consistent with Chang et al. (2015), we estimate the two-equation system of the fuzzy RDD conditioning on prior index membership around each reconstitution cutoff.

2. First-stage fuzzy RDD results

Table 3 reports the first-stage fuzzy RDD results. Consistent with the strong IV assumption, we find large discontinuities in the predicted index membership at the Russell reconstitution cutoffs. At the lower cutoff, the results show that the probability of addition to the Russell 2000 increases by 97% for prior Russell 3000E members ranked just above the cutoff, and the probability of deletion increases by 96% for prior Russell 2000 members ranked below the cutoff. At the upper cutoff, the results show that the probability of addition to the Russell 2000 increases by 88% for prior Russell 1000 members ranked just below the lower band of the #1,000 breakpoint and the probability of deletion from the Russell 2000 increases by 84% for prior Russell 2000 members ranked above the upper band. Even though compliance is not perfect, the first-stage results show that our instrument for the index assignment variable is a very strong predictor of actual index assignment.[7]

3. Local randomization at the reconstitution cutoff

A prerequisite for the validity of the Russell setting as a quasi-natural experimental setting is that companies near the reconstitution cutoff cannot precisely manipulate their May-rank-day market cap to place themselves on either side of the cutoff. If companies have only limited control over the index assignment variable, observations that end up near but on either side of the cutoff should be similar in terms of their May-rank-day market cap. In contrast, a discontinuity in the sorting variable at the cutoff would imply that companies can systematically game the index assignment rule, thereby, invalidating the RDD (e.g., Bakke and Whited (2012) and Roberts and Whited (2013)). The evidence is consistent with local randomization such that companies near the reconstitution cutoff cannot precisely manipulate their May-rank-day market cap to place themselves on either side of the cutoff.

Figure 3 plots end-of-May market cap values against end-of-May market cap rankings around the Russell reconstitution cutoffs across equally-spaced bins within a $+/-200$ bandwidth. Figure 3, Panel A, shows that end-of-May market cap values decline smoothly with no discontinuous changes near the #3,000 breakpoint. Figure 3, Panel B, repeats the analysis separately for the upper band and the lower band of the #1,000 breakpoint. The plot shows that end-of-May market cap values decline smoothly with no discontinuous jumps or drops near the cutoffs. In untabulated analysis, we fail to reject the null that the density of the end-of-May total market cap is continuous at the reconstitution cutoffs using McCrary's (2008) test. Table 4 reports the estimated pre-assignment effects for end-of-May total market cap. The RDD results confirm that there are no discontinuous breaks in the end-of-May total market cap of stocks that were added to or deleted from the Russell 2000 relative to the counterfactual stocks.

Table 4 also reports RDD results for the pre-reconstitution change in log total market cap between the end-of-June in the prior year and the end-of-May in the current year. We skip the window between the end-of-May and the end-of-June as the transition month in prior year's reconstitution. The estimated effects for the pre-reconstitution change in log market cap are indistinguishable from zero. We find the same result for the pre-reconstitution change in the rank transformation of total market cap. The null results imply that there are no systematic differences in the pre-ranking trajectories of stocks reconstituted in and out of the Russell 2000 relative to counterfactual stocks that could have been added to or deleted from the index if their end-of-May market cap were only slightly different. These null results address Appel, Gormley, and Keim's (2020) concern that index switching would not be an exogenous event if the index assignment instrument in the fuzzy

[7] Pei and Shen (2017) examine the validity of the fuzzy RDD in the presence of measurement error in the assignment variable. Their focus, however, is the case where the noise in the assignment variable induces extreme attenuation bias to the point that the first-stage discontinuity becomes smooth, thereby, eliminating the source of identification. Pei and Shen (2017) point out that if a significant first-stage discontinuity exists, a fuzzy RDD can still be applied to identify causal treatment effects despite measurement error in the assignment variable (see also Battistin, Brugiavini, Rettore, and Weber (2009)). Clearly, our first-stage results provide strong evidence of first-stage discontinuity at both the upper and lower cutoffs of the Russell 2000.

RDD is related to pre-reconstitution movements in total market cap. Next, we search for pre-assignment effects on institutional ownership (IO) at the end-of-March; that is, the most recent quarter prior to Russell's reconstitution at the end-of-June.

We measure the index component of institutional ownership (index IO) as the fraction of shares held by index institutions that report their quarterly holdings in SEC Form 13F and N-30Ds. We separate index from non-index institutions using FactSet's Global Ownership Database. Appendix B provides details on the measurement of index IO. Table 4 shows that stock additions and deletions are like the counterfactual stocks in terms of the pre-reconstitution level of index ownership. The estimated pre-assignment effects for index IO are indistinguishable from zero. These null results further help reassure that evidence of post-reconstitution treatment effects does not reflect discontinuities in unobservable characteristics (e.g., Roberts and Whited (2013)).[8]

[8] Prior studies often use end-of-June Russell index weights instead of end-of-May total market cap values to instrument the index assignment variable (see, e.g., Wei and Young (2020) review). Chang et al. (2015) warn against this choice as one that would invalidate the RDD for two reasons. First, FTSE Russell ranks stocks based on their end-of-May total market cap to determine index memberships. Since end-of-June index weights are based on end-of-June rather than end-of-May closing prices, stocks are reshuffled due to the June returns. Second, end-of-June weights are based on float-adjusted market cap, which only includes free-floating shares. The float-adjusted index weights shift less (more) liquid stocks toward the bottom (top) of each index so that higher (lower) ranked stocks in terms of end-of-May total market cap will end up with lower (higher) end-of-June float-adjusted weights. In additional analysis, we find significant discontinuities in pre-reconstitution characteristics when we use end-of-June Russell index weights to instrument the index assignment variable, which violates the assumption of local randomization and invalidates the RDD.

III. Identifying the Effect of Stock Indexing

This section presents evidence on the causal effect of stock indexing on arbitrage conditions and price discovery. We first confirm evidence of forced buying and selling by tracking institutions near the Russell reconstitution cutoffs. We then examine the effect of exogenous variation in index investing on securities lending market conditions, liquidity conditions, return synchronicity, and the speed of price adjustment to news.

A. Pre-reconstitution characteristics

Table 5 reports average pre-reconstitution characteristics for counterfactual stocks within the $+/-200$ bandwidth around the Russell reconstitution cutoffs. We identify four groups of counterfactual stocks. At the upper (lower) band of the #1,000 breakpoint, we identify static Russell 2000 (static Russell 1000) stocks that would have been reconstituted in the Russell 1000 (Russell 2000) if their end-of-May market cap were slightly higher (lower). On the left (right) of the #3,000 breakpoint, we identify static Russell 2000 (static Russell 3000E) stocks that would have reconstituted in the Russell 3000E (Russell 2000) if their end-of-May market cap were slightly lower (higher). Throughout, we quantify the magnitude of the estimated addition and deletion effects relative to pre-reconstitution average values of static stock characteristics.

The comparison of pre-reconstitution characteristics highlights that micro- and small-cap stocks at the lower cutoff of the Russell 2000 are significantly more arbitrage-constrained relative to mid- and large-cap stocks at the upper cutoff of the Russell 2000. Indeed, static micro-cap stocks have a combination of low index IO, low lendable quantity, high inventory concentration, together with high stock loan fees, high short selling risk, wider bid-ask spread, and higher stock illiquidity ratios. One key insight from this comparison is that exogenous variation in index investing is more likely to be impactful for stock additions and deletions at the lower cutoff of the Russell 2000.

B. The effect of stock indexing on index and non-index ownership

A key feature of the Russell setting is that small and random differences in market cap at the end-of-May can move stocks between indexes and cause discontinuous changes in index investing at the end-of-June. Table 6 presents the fuzzy RDD estimates of the treatment effects on institutional ownership (IO). Our estimation zeroes in on the change in the quarterly values of total IO and its components from March, i.e., the last value available prior to the reconstitution, to September, i.e., the first value available after the reconstitution.

Table 6, Panel A, reports the estimated addition and deletion effects at the lower cutoff of the Russell 2000. Starting with stock additions, we find a discontinuous jump in total IO, which is consistent with forced buying by tracking institutions. Breaking down total IO, the estimated addition effects show a 3.87 percentage point increase in index IO, which corresponds to a 132% increase relative to the pre-reconstitution average value of static Russell 3000E stocks, while the change in non-index IO is indistinguishable from zero. Turning to stock deletions, we find a discontinuous drop in total IO, which is consistent with forced selling by tracking institutions. Separating index from non-index IO holdings, the estimated deletion effects show a -4.31 percentage point decrease in index IO, which corresponds to a -50% decrease relative to the pre-reconstitution average value of static Russell 2000 stocks, and an indistinguishable from zero change in non-index IO.

Table 6, Panel B, reports the estimated addition and deletion effects at the upper reconstitution cutoff of the Russell 2000. Again, consistent with forced buying and selling activity by tracking institutions, we find significant addition and deletion effects at the upper cutoff. The treatment effects show a 3.35 percentage point increase in index IO for stock additions at the lower band of the #1,000 breakpoint, which corresponds to a 25% increase relative to the pre-reconstitution average value of static Russell 1000 stocks, and a -2.91 percentage point decrease in index IO for stock deletions at the upper band of the #1,000 breakpoint, which corresponds to a 19% decrease relative to the pre-reconstitution average value of static Russell 2000 stocks. Again, the estimated treatment effects on the non-index component of IO are indistinguishable from zero.

To graphically illustrate the treatment effects on index holdings, Figure 4 plots the mean portfolio values of index IO changes across equally spaced bins to the left and right of the reconstitution cutoffs within a $+/-200$ bandwidth. Figure 4, Panel A, presents the addition and deletion effects within the $+/-200$ bandwidth at the #3,000 breakpoint; that is, the lower cutoff of the Russell 2000. Starting with stock additions, the hollow green dots to the right of the cutoff show that index IO remains unchanged for the counterfactual group of static micro-cap stocks. The solid green dots to the left of the cutoff, however, show that the treated group of prior Russell 3000E stocks that are predicted to be added to the Russell 2000 experience a large and discontinuous jump in index IO. Turning to stock deletions, the hollow red dots to the left of the cutoff show that the counterfactual group of static Russell 2000 stocks does not experience a change in index IO. The solid red dots to the right of the cutoff show that the treated group of prior Russell 2000 members that are predicted to be deleted from the Russell 2000 experience a large and discontinuous drop in index IO.

Figure 4, Panel B, presents the addition and deletion effects within the $+/-200$ bandwidth at the lower and the upper bands of the #1,000 breakpoint. Starting with stock additions at the lower band of the #1,000 breakpoint, the hollow green dots on the left of the cutoff show that the counterfactual group of static Russell 1000 stocks does not experience a change in index IO. The solid green dots show that the treated group of prior Russell 1000 stocks that are predicted to be added to the Russell 2000 experience a discontinuous increase in index IO. With respect to stock deletions at the upper band of the #1,000 breakpoint, the hollow red dots on the right of the cutoff show that the counterfactual group of static Russell 2000 stocks does not experience a change in index IO. The solid red dots show that the treated group of prior Russell 2000 stocks that are predicted to be deleted from the Russell 2000 experience a discontinuous drop in index IO.

In summary, we find that small and random differences in end-of-May market cap cause large and discontinuous changes in index IO for stock additions and deletions relative to counterfactual stocks at the Russell reconstitution cutoffs. While consistent with prior evidence of forced buying and selling by passive institutions tracking the Russell indexes (e.g., Appel et al. (2016), (2019), Ben-David et al. (2018), (2019), and Glossner (2020)), our evidence highlights the relevance of the annual Russell reconstitution as a source of exogenous variation in index IO at both the upper and lower cutoffs of the Russell 2000. Our evidence further highlights the importance of using a thorough measure of index IO when evaluating the overall IO effect of forced buying and selling by tracking institutions. [9]

C. The effect of stock indexing on securities lending conditions

Next, we provide evidence on the effect of stock indexing on securities lending market conditions. Table 7 presents the estimated treatment effects of stock indexing on securities lending market conditions. Our estimates zero in on changes from the year before to the year after Russell's reconstitution at the end-of-June. The pre-reconstitution window is from the first Wednesday after last year's reconstitution day to the last Tuesday before this year's end-of-May ranking day. The post-reconstitution window is from the first Wednesday after this year's reconstitution day to the last Tuesday before next year's end-of-May ranking day. The window skips June as the transition month in the index reconstitution process.

We obtain daily securities lending data from Markit. Markit aggregates survey information from institutional lenders that collectively account for most of the U.S. securities lending market. Our dataset includes the quantity of stock inventory that is available to lend (Lendable Quantity) and the quantity of stock on loan (Quantity on Loan) both expressed as a percentage of the shares outstanding. Our dataset also includes information about stock inventory concentration. Markit's inventory concentration score ranges from 0 to 100; a small score indicates many lenders with low inventory and a top score indicates a single lender with all the inventory. To investigate the effect of stock indexing on the borrow cost, we use Markit's indicative rate of the standard borrow cost, which is expressed as a percentage of the stock price. Following Engelberg, Reed, and Ringgenberg (2018), we use the standard deviation of daily stock loan fees to measure short-selling risk in the year before and year after Russell's reconstitution.

Starting with stock additions at the lower reconstitution cutoff, Table 7, Panel A, provides evidence that exogenous increases in indexing lead to significant relaxation of securities lending constraints. The estimated treatment effects show a 3.22 percentage point increase in lendable quantity, which corresponds to a 38% increase relative to the pre-reconstitution average value of static Russell 3000E stocks, accompanied by a significant decrease in inventory concentration across stock lenders and an increase in the lendable quantity on loan. The evidence also shows a −0.87 percentage point decrease in stock loan fees and a −0.62 percentage point decrease in short-selling risk, as indicated by the discontinuous drop in the variability of stock loan fees. Turning to stock deletions at the lower cutoff, we find evidence that exogenous decreases in indexing lead to significant tightening of securities lending constraints. The estimated treatment effects show a −4.18 percentage point decrease in lendable quantity, which corresponds to a −27% decrease relative to the pre-reconstitution average value of static Russell 2000 stocks, accompanied by a significant increase in inventory concentration, a decrease in the lendable quantity on loan, and a 1.54 percentage point increase in stock loan fees.

[9] In additional analysis, we find weaker evidence of addition and deletion effects using Bushee's (1998) factor-based classification of quasi-indexer institutions (QIX). When compared to FactSet's measure of index IO, QIX is a less direct measure of the fraction of shares held by index institutions.

With respect to the upper reconstitution cutoff, Table 7, Panel B, shows that stock additions at the lower band of the #1,000 breakpoint experience a 2.83 percentage point increase in lendable quantity, which corresponds to a 11% increase relative to the pre-reconstitution average value of static Russell 1000 stocks. On the flip side, stock deletions at the upper band of the #1,000 breakpoint experience a −1.86 percentage point decrease in lendable quantity, which corresponds to a −7% decrease relative to the pre-reconstitution average value of static Russell 2000 stocks. In contrast to evidence of significant effects at the lower cutoff, the estimated effects on inventory concentration, stock loan fee, and short selling risk are indistinguishable from zero at the upper cutoff. These null findings are consistent with the fact that pre-reconstitution stock lending conditions are significantly more relaxed at the upper cutoff relative to the lower cutoff. Indeed, the pre-reconstitution level of lendable quantity, as a percentage of shares outstanding, is 8.42% for micro-cap stocks at the #3,000 breakpoint and 24.85%, nearly three times higher, for mid-cap stocks at the lower band of the #1,000 breakpoint (see Table 5).

Figure 5 provides insights into the stock lending inventory dynamics from the year before to the year after Russell's reconstitution at the end-of-June (day zero). The figure plots the cumulative change in Markit's inventory concentration score for additions and deletions at the lower and upper cutoffs of the Russell 2000. The green (red) solid line presents the cumulative addition (deletion) effect on inventory concentration for stock additions (deletions) at the lower cutoff of the Russell 2000 relative to the counterfactual static stocks on the right (left) of the #3,000 breakpoint. The green (red) dashed line presents the cumulative addition (deletion) effect on inventory concentration for stock additions (deletions) at the upper cutoff of the Russell 2000 relative to the counterfactual static stocks on the left (right) of the lower (upper) band of the #1,000 breakpoint.

With respect to the lower reconstitution cutoff, Figure 5 shows a discontinuous decrease (increase) in inventory concentration for additions (deletions) to the Russell 2000 in the days following the annual Russell reconstitution. The post-reconstitution changes are mostly complete within the first trading week after day zero and persist in the subsequent year. In addition, there is only limited evidence of pre-reconstitution changes in inventory concentration. Consistent with the RDD estimates, the figure also shows that there are no discernible pre- and post-reconstitution effects on stock lending inventory concentration for stock additions and deletions at the upper reconstitution cutoff.

In summary, we find evidence of large and discontinuous changes in securities lending conditions due to stock indexing. The treatment effects are especially pronounced for stock additions and deletions at the lower cutoff of the Russell 2000 since the pre-reconstitution stock lending supply constraints are more binding for micro-cap stocks. The evidence establishes that at the lower cutoff the Russell reconstitution is an exogenous source of variation in the severity of shorts-sales constraints. The relaxation of stock lending supply conditions is a mechanism through which indexing can improve stock liquidity and accelerate the speed of price adjustment to news. Next, we provide evidence on the effect of stock indexing on liquidity conditions.

D. The effect of stock indexing on liquidity

Table 8 presents the estimated treatment effects of stock indexing on liquidity. Our estimates zero in on changes in liquidity from the year before to the year after Russell's reconstitution at the end-of-June. Again, the pre-reconstitution window is from the first Wednesday after last year's reconstitution day to the last Tuesday before this year's end-of-May ranking day and the post-reconstitution window is from the first Wednesday after this year's reconstitution day to the last Tuesday before next year's end-of-May ranking day. We skip June as the transition month in the reconstitution process. Therefore, our results are not skewed by the spike in share turnover due to rebalancing on the reconstitution day.

We obtain daily information on closing asks and bids from CRSP and measure the bid-ask spread as the daily spread of the closing ask minus the closing bid divided by the midpoint. We explore two complementary stock illiquidity ratios. First, we use Amihud's (2002) illiquidity ratio of the absolute value of the daily stock return divided by the daily dollar trading volume multiplied by 10^8. Second, we use Gao and Ritter's (2010) inelasticity ratio of the absolute value of the daily stock return divided by the daily share turnover.

With respect to the lower reconstitution cutoff, Table 8, Panel A, provides evidence that stock indexing has a significant effect on all three measures of liquidity. Stock additions at the #3,000 breakpoint experience a −0.47 percentage point decrease in the bid-ask spread, which corresponds to a −39% decrease relative to the pre-reconstitution average spread of static Russell 3000E stocks, accompanied by a significant drop in illiquidity ratios. On the flip side, stock deletions at the #3,000 breakpoint experience a 0.26 percentage point increase in the bid-ask spread, which corresponds to a 57% increase relative to the pre-reconstitution average spread of static Russell 2000 stocks, accompanied by a significant jump in illiquidity ratios.

Turning to the upper reconstitution cutoff, Table 8, Panel B, reports that the estimated treatment effects on liquidity are indistinguishable from zero. The lack of evidence of treatment effects at the upper cutoff is consistent with the fact that liquidity is significantly higher for large- and mid- cap stocks relative to micro-cap stocks in the pre-reconstitution year. To illustrate, the average pre-reconstitution bid-ask spread, as a percentage of the midpoint, is 0.12% for mid-cap stocks at the lower band of the #1,000 breakpoint and 1.20%, ten times wider, for micro-cap stocks at the #3,000 breakpoint and (see Table 5).

Figure 6 provides insights into the stock liquidity dynamics from the year before to the year after Russell's reconstitution at the end-of-June (day zero). The figure plots the cumulative change in the bid-ask spread for additions and deletions at the lower and upper cutoffs of the Russell 2000 relative to counterfactual stocks. With respect to the lower reconstitution cutoff, the figure shows a discontinuous decrease (increase) in the bid-ask spread for additions (deletions) to the Russell 2000 in the days following the annual Russell reconstitution that persists in the subsequent year. In addition, there is no evidence of pre-reconstitution changes in the bid-ask spread. Consistent with the RDD estimates, the figure also shows that there are no discernible pre- and post-reconstitution effects on bid-ask spread for stock additions and deletions at the upper reconstitution cutoff.

We hasten to note that our evidence on the effect of exogenous variation in index investing on stock liquidity differs from the association evidence of Israeli et al. (2017). While their study finds that increases in ETF ownership are associated with lower stock liquidity, we provide causal evidence that an exogenous increase in index investing (a) does not hurt liquidity for stock additions at the upper cutoff and (b) improves liquidity for stock additions at the lower cutoff of the Russell 2000 index.

E. The effect of stock indexing on price synchronicity and volatility components

Next, we provide evidence on the effect of stock indexing on stock price synchronicity and volatility. We measure price synchronicity for each firm in the year before and after the index reconstitution as the R^2 from the following regression of weekly firm returns ($r_{i,w,t}$) on the contemporaneous market returns ($r_{m,w,t}$) and industry returns ($r_{j,w,t}$):

$$r_{i,w,t} = \alpha_{it} + \beta_{it} r_{m,w,t} + \gamma_{it} r_{j,w,t} + \varepsilon_{i,w,t}.$$

We compute weekly returns from Wednesday to Tuesday. The pre-reconstitution window is from the first Wednesday after last year's reconstitution day to the last Tuesday before this year's end-of-May ranking day and the post-reconstitution window is from the first Wednesday after this year's reconstitution day to the last Tuesday before next year's end-of-May ranking day. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios.

Following prior research, we use a logit transformation of the regression model R^2; that is $log\left(\frac{R^2}{1-R^2}\right)$. This logit transformation mitigates skewness and circumvents the bounded nature of the regression model R^2within the [0, 1] interval (e.g., Morck, Yeung, and Yu (2000) and Durnev, Morck, and Yeung (2004)). We note that (a) the R^2 is equal to the variance of the systematic component of returns divided by the variance of total returns, and (b) the variance of total returns is equal to the variance of systematic returns plus the variance of idiosyncratic returns. It follows from (a) and (b) that the logit transformation of R^2 is equal to the log variance of systematic returns (Systematic Volatility) minus the log variance of idiosyncratic returns (Idiosyncratic Volatility). It follows that the treatment effect for Δ(Price Synchronicity) is equal to the effect for Δ(Systematic Volatility) minus the effect for Δ(Idiosyncratic Volatility).

Table 9 presents the estimated treatment effects of stock indexing on price synchronicity and volatility components. The fuzzy RDD estimates focus on changes from the year before to the year after Russell's reconstitution. With respect to the upper reconstitution cutoff, the estimated treatment effects of stock additions and deletions on price synchronicity and volatility components are all indistinguishable from zero. Focusing on the lower reconstitution cutoff, we find that stock indexing has a significant effect on price synchronicity. Micro-cap stock additions to the Russell 2000 experience a discontinuous jump in price synchronicity. On the flip side, stock deletions from the Russell 2000 experience a discontinuous drop in price synchronicity. Breaking down price synchronicity into changes in systematic and idiosyncratic volatility, we find that the change in systematic volatility is the dominant force at play. More specifically, micro-cap stock additions to the

Russell 2000 experience a discontinuous jump in systematic volatility while the estimated treatment effect on idiosyncratic volatility is indistinguishable from zero. On the flip side, stock deletions from the Russell 2000 experience a discontinuous drop in systematic volatility accompanied by a smaller but significant drop in idiosyncratic volatility, which partially offsets the overall effect on price synchronicity.

Some prior studies interpret an increase in price synchronicity as indicative of a deteriorating information environment whereby less firm-specific information is incorporated in prices (e.g., Durnev et al. (2004) and Chan and Hameed (2006)). Other studies, however, take the opposite view and interpret higher price synchronicity as indicative of a lower level of uncertainty that remains unresolved (e.g., Ali, Hwang, and Trombley (2003) and Zhang (2006)). Within the context of our study, the question is whether the increase in price synchronicity for stock additions at the lower cutoff reflects the earlier resolution of uncertainty through the timelier incorporation of news rather than a decrease in stock price informativeness. To address this question, we next provide evidence on the effect of stock indexing on the speed of price adjustment to news.

F. The effect of stock indexing on the speed of price adjustment to news

To investigate the effect of indexing on the speed of price adjustment to news, we compute different variants of Hou and Moskowitz's (2005) market delay measure for each firm in the year before and after the index reconstitution. We compute $Market\ Delay$ as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of market returns. Intuitively, the $Market\ Delay$ measure captures the fraction of variation in weekly firm returns explained by lagged market returns. The higher the value of the measure, the stronger is the delay in response to market news.

Along the lines of Hou and Moskowitz's (2005) market delay measure, we compute $Industry\ Delay$ as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of industry returns. The $Industry\ Delay$ measure captures the fraction of variation in weekly firm returns explained by lagged industry returns; the higher its value the stronger is the delay in response to industry news. We compute $Firm\ Delay$ as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of firm returns. The $Firm\ Delay$ measure captures the fraction of variation in weekly firm returns explained by lagged firm returns; the higher its value the stronger is the delay in response to firm news.

We also introduce a higher frequency measure of the speed of price adjustment to firm news that focuses on quarterly earnings announcements. We compute $Earnings\ Delay$ as one minus the ratio of the R^2 from the regression of daily firm returns on contemporaneous market and industry returns over the R^2 from the regression of the daily firm returns on contemporaneous market and industry returns and four lags of firm returns. Our estimation zeroes in on the 20-day trading window commencing two days after each announcement.[10] We estimate earnings announcement delay for each firm in the year before and after the reconstitution. The $Earnings\ Delay$ measure captures the fraction of variation in daily firm returns post-earnings announcement; the higher its value the stronger is the delay in response to earnings news.

To measure the speed of price adjustment to negative news, we compute $Negative\ Delay$ as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of negative values of market, industry, and firm returns. We set positive values of lagged market, industry, and firm returns to zero. By construction, the $Negative\ Delay$ measure captures the fraction of variation in weekly firm returns explained by lagged values of negative returns; the higher its value the stronger is the delay in response to negative news.

Table 10 presents the estimated treatment effects of the speed of price adjustment to news. To mitigate skewness, we use logit transformations of the price delay measures; that is $log\left(\frac{Delay}{1-Delay}\right)$. Our estimates zero in on changes from the year before to the year after Russell's reconstitution. Starting with the lower cutoff, we find that stock indexing has a significant effect on the speed of price adjustment to news. Stock additions (deletions) at the #3,000 breakpoint experience a discontinuous drop (jump) in price delay with respect to market, industry, and firm news, as well as with respect to overall negative news. In contrast, the estimated effects at the upper cutoff imply that there are no discernible addition or deletion effects on the speed of price adjustment to news.

Prior association studies often interpret evidence of higher price synchronicity as de facto evidence of a deteriorating information environment and more noise in prices (e.g., Hamm (2014) and Israeli et al. (2017)). Different form prior research, our evidence from the lower cutoff of the Russell 2000 implies that higher price synchronicity due to an exogenous increase in index investing reflects the earlier resolution of uncertainty through the timelier incorporation of news rather than a decrease in stock price informativeness.[11]

G. Variation with pre-reconstitution characteristics

Focusing on the lower reconstitution cutoff, we group micro-cap stock additions into more and less arbitrage-constrained partitions based on pre-reconstitution characteristics. We define as harder-to-borrow stocks those with below average lendable quantity or above average stock inventory concentration, stock loan fees, or short-selling risk. We define as harder-to-trade stocks those with above average bid-ask spread or above average illiquidity ratios. We then classify as more arbitrage-constrained stocks that are harder-to-borrow and harder-to-trade. We classify the rest of the stocks as less arbitrage-constrained. This classification generates two balanced portfolios of stock additions at the lower cutoff of the

[10] We combine information from Compustat and IBES to identify day zero of the earnings announcements. When the announcement dates differ between Compustat and IBES, we use the earlier of the two. We shift the earnings announcement by one trading day when the time stamp of the announcement is after trading hours.

[11] In additional analysis, we confirm that the vast majority of additions (deletions) at the lower cutoff that experience an increase (a decrease) in synchronicity also experience a decrease (an increase) in price delay.

Russell 2000. We estimate the conditional addition effects relative to the counterfactual group of static Russell 3000E micro-cap stocks on the right of the #3,000 breakpoint.[12]

Table 11 presents the estimated treatment effects on price synchronicity and delay separately for more and less arbitrage-constrained stock additions at the lower cutoff of the Russell 2000. The evidence shows that the discontinuous jump in price synchronicity at the lower reconstitution cutoff is nearly twice as large for more constrained relative to less constrained stock additions. Breaking down the drivers of price synchronicity, we confirm that for both addition groups the jump in synchronicity is due to a corresponding jump in systematic volatility rather than a change in idiosyncratic volatility. We also find that the discontinuous drop in price delay is nearly two to three times as large for more constrained relative to less constrained micro-cap additions. The last two columns confirm that the differences in the conditional addition effects are significantly different from zero.

Next, we search for variation across partitions of stock additions at the lower reconstitution cutoff based on pre-reconstitution management earnings guidance and sell-side analysts' coverage—two salient characteristics of a stock's information environment. We separate stocks with below median analyst coverage and no management guidance (stocks with less coverage) from stocks with above median analyst coverage and management guidance (stocks with more coverage). This classification generates two balanced portfolios of stock additions at the lower cutoff. Table 12 presents the conditional addition effects on price synchronicity and delay separately for micro-cap stocks with less and more coverage. While the conditional addition effects are significant for both micro-cap partitions, we fail to detect significant differences. The last two columns show that the differences in the conditional addition effects are indistinguishable from zero. This null result further highlights the relaxation of arbitrage constraints as a mechanism through which an exogenous increase in index investing facilitates informed trading and promotes price discovery for more arbitrage-constrained micro-cap stocks.

In summary, our evidence shows that an exogenous increase in index investing leads to timelier incorporation of systematic and firm news especially for stocks that are more arbitrage-constrained prior to their reconstitution into the Russell 2000. Viewed as whole, the evidence is consistent with Diamond and Verrecchia's (1987) prediction that an exogenous source of relaxation in the severity of short-sales constraints improves stock liquidity and increases the speed of price adjustment to news.

H. Sensitivity checks

So far, we report results using a +/-200 bandwidth, linear rank controls, and a uniform kernel function, which equal weights observations within the bandwidth around the cutoff. Appendix C reports result using alternative choices for the bandwidth, the kernel function, and the rank control polynomial order (Tables A1-A4). With respect to the bandwidth choice, we note that the +/−200 bandwidth is sufficiently wide to capture 60%

[12] In additional analysis, we split the counterfactual group of static micro-cap stocks based on the pre-reconstitution intensity of arbitrage constraints. We find that splitting the counterfactual group does not affect our estimates of the conditional addition effects since the static micro-cap stocks are unaffected by the Russell reconstitution regardless of their pre-reconstitution characteristics.

of index turnover. Appendix C reports consistent estimates using a +/−100 bandwidth, which captures 36% of index turnover. Appendix C also reports consistent results using Imbens and Kalyanaraman's (2012) mean squared error (MSE) bandwidth selection criterion. As we explain in Section II.D.1, the linear rank control functions in the fuzzy RDD mitigate the influence of stocks ranked away from either side of the cutoff so that stocks ranked closest to the cutoff contribute more to the estimated discontinuity.[13] Appendix C reports consistent results using cubic rank control functions. Appendix C also reports consistent estimates using a triangular kernel function, which places more weight on observations near the cutoff. The evidence also shows that the estimates are not sensitive to the inclusion of year fixed effects.

Throughout, we estimate the fuzzy RDD system conditioning on prior index membership around the reconstitution cutoff. Our estimation follows Chang's et al. (2015) implementation and compares stocks reconstituted in and out of the Russell 2000 relative to counterfactual stocks near the reconstitution cutoff. Appel et al. (2020) express concern that conditioning on prior index membership could introduce bias and, similar to Ben-David et al. (2019), they recommend estimating the fuzzy RDD system on the full sample of stocks near the reconstitution cutoff without conditioning on prior index assignment. Our inferences are not sensitive to this alternative estimation. Appendix C reports the results for the full sample of stocks within the +/-200 bandwidth around the upper and lower reconstitution cutoffs without conditioning on prior index membership (Table A5).

[13] Cattaneo et al. (2017) recommend the use of local linear functions and caution that the use of higher-order polynomial rank control functions tends to produce overfitting and yields unreliable results near boundary points (see also Gelman and Imbens (2019)).

IV. Conclusion

We use the annual Russell reconstitution to identify the causal effect of stock indexing on information arbitrage and price discovery. While our evidence shows that exogenous variation in index investing has no discernible effects at the upper cutoff separating large- and mid-cap stocks from small-cap stocks, we find significant addition and deletion effects at the lower cutoff separating small- from micro-cap stocks. Micro-cap stock additions to the Russell 2000 experience a relaxation of stock lending constraints, an improvement in liquidity, and an increase in the speed of price adjustment to market, industry, and firm news. On the flip side, micro-cap stock deletions from the Russell 2000 experience a tightening of stock lending constraints, a deterioration in liquidity, and a decrease in the speed of price adjustment to news. The evidence shows that the addition and deletion effects are especially pronounced at the lower cutoff of the Russell 2000 since the pre-reconstitution arbitrage constraints are more binding for micro-cap stocks.

Overall, our paper provides new evidence on the causal effect of stock indexing on arbitrage conditions and price discovery. The critics of stock indexing often argue that index investing leads to excess comovement and reduces price informativeness. In contrast, our causal evidence shows that index investing facilitates informed trading and increases the speed of price adjustment to news for more arbitrage-constrained micro-cap stocks. To be clear, we do not argue that there is only a bright side to stock indexing. Moving forward, a growing concern with respect to stock indexing is the concentration of ownership and voting power among the "Big 3" index fund managers: Vanguard, BlackRock, and State Street.

The Big 3 dominate the field with a collective 81% share of index fund assets. Mr. Bogle, the founder of Vanguard himself, sounded a warning on index funds and argued that more competition in the indexing field would be a solution to the rising concentration. Mr. Bogle also acknowledged, however, that the high barriers to entry prevent new competitors from entering the indexing field.[14] The rise of concentration among the Big 3 is the subject of an ongoing debate regarding the future of corporate governance.[15] While it might be too early to resolve this debate, the issue deserves the attention of policy makers (e.g., Bebchuk and Hirst (2019)). At the same time, policy makers may need to resist a hasty regulatory response before index fund stewardship is more fully understood (e.g., Fisch, Hamdani, and Davidoff Solomon (2019)).

[14] See "Bogle Sounds a Warning on Index Funds" by J. C. Bogle, *The Wall Street Journal*, Jun. 27, 2019.

[15] Heath, Macciocchi, Michaely, and Ringgenberg (2020) argue that indexing weakens corporate governance because index funds are more likely to cede power to firm management on contentious issues. Schmidt and Fahlenbrach (2017) propose that index-tracking institutions are less attentive to managerial actions that are more difficult and costly to monitor, such as M&A activity and changes in CEO power. Appel et al. (2016) provide evidence that passive mutual funds use their large voting blocs to exert influence over essential corporate governance structures, including board independence, removal of poison pills, and equal voting rights for shareholders. In a follow-up study, Appel et al. (2019) also provide evidence that passive institutional ownership facilitates shareholder activism by mitigating free-rider problems.

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TABLE 1: Annual Russell reconstitution timeline

This table reports the timeline of the annual Russell reconstitution between 2007 and 2016. The reconstitution event dates are available from FTSE Russell's Client Service.

Year	Ranking Day	Reconstitution Day	Effective Date
2007	May 31, Thu	Jun 22, Fri	Jun 25, Mon
2008	May 30, Fri	Jun 27, Fri	Jun 30, Mon
2009	May 29, Fri	Jun 26, Fri	Jun 29, Mon
2010	May 28, Fri	Jun 25, Fri	Jun 28, Mon
2011	May 31, Tue	Jun 24, Fri	Jun 27, Mon
2012	May 31, Thu	Jun 22, Fri	Jun 25, Mon
2013	May 31, Fri	Jun 28, Fri	Jul 01, Mon
2014	May 30, Fri	Jun 27, Fri	Jun 30, Mon
2015	May 29, Fri	Jun 26, Fri	Jun 29, Mon
2016	May 27, Fri	Jun 24, Fri	Jun 27, Mon

TABLE 2: Russell 1000/2000 market-cap breakpoints

Panel A of this table reports the end-of-May total market-cap breakpoints ($MN) for the Russell 1000/2000 indexes between 2007 and 2016. We obtain the actual market-cap breakpoints before rounding directly from FTSE Russell's Client Service. Panel B of this table reports the counts and aggregate end-of-May market cap ($MN) of additions and deletions at the #3,000 and #1,000 breakpoints of the Russell 2000 index.

Panel A: End-of-May total market-cap breakpoints ($MN).

	Russell 1000 Index			Russell 2000 Index		
Year	Largest	Smallest	Smallest w/ Band	Largest w/ Band	Largest	Smallest
2007	$468,519.1	$2,484.5	$1,798.4	$3,152.2	$2,477.1	$261.8
2008	$468,980.7	$2,008.0	$1,363.2	$2,750.8	$2,000.1	$166.7
2009	$338,407.9	$1,237.7	$829.2	$1,687.7	$1,235.9	$78.3
2010	$283,061.3	$1,742.9	$1,256.1	$2,273.5	$1,733.8	$111.9
2011	$411,180.4	$2,224.0	$1,624.4	$2,971.5	$2,224.0	$130.3
2012	$540,213.4	$1,956.0	$1,354.5	$2,607.5	$1,950.6	$100.7
2013	$422,091.7	$2,551.8	$1,822.3	$3,298.1	$2,551.8	$128.9
2014	$545,254.2	$3,087.2	$2,199.9	$4,053.5	$3,080.0	$168.7
2015	$750,547.0	$3,385.2	$2,426.8	$4,307.4	$3,384.0	$176.7
2016	$549,659.6	$2,853.4	$1,977.7	$3,860.1	$2,851.7	$132.9
Mean	$477,791.5	$2,353.1	$1,665.2	$3,096.2	$2,348.9	$145.7

Panel B: Index turnover.

	#1,000 Breakpoint				#3,000 Breakpoint			
	Additions		Deletions		Additions		Deletions	
Year	Obs.	Mkt Cap ($MN)	Obs.	Mkt Cap ($MN)	Obs.	Mkt Cap ($MN)	Obs.	Mkt Cap ($MN)
2007	9	$14,026.7	17	$64,060.5	114	$42,525.1	167	$34,203.9
2008	40	$35,670.5	45	$172,525.4	211	$53,602.8	141	$17,366.5
2009	43	$24,015.2	45	$95,292.3	224	$26,916.4	94	$5,494.3
2010	16	$14,963.5	26	$70,697.8	112	$21,018.0	139	$11,651.1
2011	25	$32,528.8	36	$133,030.1	104	$23,558.8	87	$8,307.2
2012	30	$28,804.6	40	$117,213.0	127	$19,976.7	82	$5,787.9
2013	27	$36,857.1	30	$122,696.7	68	$16,992.5	86	$8,081.4
2014	29	$52,787.6	29	$147,113.4	58	$14,772.0	124	$15,710.3
2015	49	$84,252.1	28	$150,248.0	75	$22,384.3	135	$16,785.6
2016	52	$69,624.4	35	$156,388.5	133	$24,894.3	89	$8,386.5
Mean	32	$39,353.0	33.1	$122,926.6	122.6	$26,664.1	114.4	$13,177.5

TABLE 3: First-stage fuzzy RDD

This table reports first-stage fuzzy RDD results. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. The t-statistics are based on heteroskedasticity-robust standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint

	#3,000 Breakpoint	
	Additions	Deletions
τ	0.97^{***}	0.96^{***}
t-stat	146.09	106.54
Adj. R^2	98.0%	95.7%
Obs.	1,733	1,956

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint	
	Additions | Lower Band	Deletions | Upper Band
τ	0.88^{***}	0.84^{***}
t-stat	48.27	55.85
Adj. R^2	92.5%	92.4%
Obs.	761	1,147

TABLE 4: Local randomization at the Russell reconstitution cutoffs

This table reports second-stage fuzzy RDD results for pre-reconstitution characteristics, including the end-of-May total market cap, the pre-reconstitution change in total market cap between the end-of-June in the prior year and the end-of-May in the current year, as well as the end-of-March index institutional ownership and its components. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: Pre-assignment effects at the #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
End-of-May Market Cap ($BN)	0.01	1.40	0.00	-0.33
Δ(Log Market Cap) June-to-May	0.04	0.89	0.00	0.11
Δ(Rank Market Cap) June-to-May	0.00	0.04	-0.01	-0.96
End-of-March Index IO (%)	-0.07	-0.27	0.09	0.24
End-of-March Non-Index IO (%)	-1.08	-0.50	1.14	0.54
End-of-March Total IO (%)	-1.14	-0.51	1.23	0.53

Panel B: Pre-assignment effects at the #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
End-of-May Market Cap ($BN)	0.03	0.31	-0.04	-0.36
Δ(Log Market Cap) June-to-May	-0.04	-0.55	-0.01	-0.20
Δ(Rank Market Cap) June-to-May	0.00	-0.15	0.00	0.14
End-of-March Index IO (%)	-0.06	-0.06	0.32	0.36
End-of-March Non-Index IO (%)	1.78	0.48	4.83	1.52
End-of-March Total IO (%)	1.73	0.43	5.15	1.47

TABLE 5: Pre-reconstitution characteristics

This table reports the pre-reconstitution mean values of characteristics for counterfactual stocks within a +/-200 bandwidth around the Russell reconstitution cutoffs. The sample period is between 2007 and 2016.

	#1,000 Breakpoint		#3,000 Breakpoint	
Static Stocks:	Russell 2000 (Upper Band)	Russell 1000 (Lower Band)	Russell 2000	Russell 3000E
End-of-May Market Cap ($BN)	2.77	1.96	0.16	0.13
Index Weight (Basis Points)	17.65	1.04	0.92	0.06
End-of-March Index IO (%)	15.20	13.34	8.61	2.93
End-of-March Non-Index IO (%)	70.89	70.48	42.88	35.24
End-of-March Total IO (%)	86.10	83.82	51.49	38.17
Pre-Recon Lendable Quantity (%)	27.42	24.85	15.43	8.42
Pre-Recon Inventory Concentration (%)	16.52	17.59	23.97	37.63
Pre-Recon Quantity on Loan (%)	6.78	6.54	4.13	1.03
Pre-Recon Stock Loan Fee (%)	0.71	0.98	2.21	2.32
Pre-Recon Short Selling Risk (%)	0.30	0.52	0.98	1.25
Pre-Recon Bid-Ask Spread (%)	0.10	0.12	0.45	1.20
Pre-Recon Illiquidity Ratio (%)	0.14	0.18	7.92	30.55
Pre-Recon Inelasticity Ratio (%)	2.52	2.42	10.23	23.41
Pre-Recon Price Synchronicity (logit)	-0.68	-0.79	-1.51	-2.47
Pre-Recon Systematic Volatility (log)	-7.27	-7.19	-7.24	-8.32
Pre-Recon Idiosyncratic Volatility (log)	-6.59	-6.40	-5.73	-5.85
Pre-Recon Market Delay (logit)	-1.84	-1.76	-1.05	-0.08
Pre-Recon Industry Delay (logit)	-1.84	-1.79	-1.06	-0.06
Pre-Recon Firm Delay (logit)	-1.94	-1.86	-1.11	-0.11
Pre-Recon Earnings Delay (logit)	-2.58	-2.22	-1.33	0.49
Pre-Recon Negative Delay (logit)	-0.61	-0.51	0.19	1.17

TABLE 6: The effect of stock indexing on index and non-index ownership

This table reports second-stage fuzzy RDD results for changes in institutional ownership from March (i.e., the last quarterly value available prior to Russell's reconstitution) to September (i.e., the first quarterly value available after Russell's reconstitution). Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
Δ(Index IO)	3.87***	27.16	-4.31***	-23.60
Δ(Non-Index IO)	0.29	0.40	0.82	0.86
Δ(Total IO)	4.16***	5.43	-3.49***	-3.48
Obs.	1,707		1,940	

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
Δ(Index IO)	3.35***	10.61	-2.91***	-8.98
Δ(Non-Index IO)	-0.31	-0.19	-0.14	-0.09
Δ(Total IO)	3.04*	1.78	-3.04*	-1.87
Obs.	759		1,131	

TABLE 7: The effect of stock indexing on securities lending conditions

This table reports second-stage fuzzy RDD results for changes in securities lending market conditions from the year before to the year after the annual Russell reconstitution. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
Δ(Lendable Quantity)	3.22***	9.98	-4.18***	-10.37
Δ(Inventory Concentration)	-8.52***	-6.11	6.13***	7.61
Δ(Quantity on Loan)	1.70***	6.82	-1.71***	-5.30
Δ(Stock Loan Fee)	-0.87**	-2.13	1.54***	2.80
Δ(Short Selling Risk)	-0.62**	-2.32	0.34	1.23
Obs.	1,590		1,820	

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
Δ(Lendable Quantity)	2.83***	3.39	-1.86***	-2.79
Δ(Inventory Concentration)	-0.13	-0.23	0.60	1.38
Δ(Quantity on Loan)	1.43*	1.67	-0.02	-0.03
Δ(Stock Loan Fee)	-0.11	-0.25	-0.03	-0.09
Δ(Short Selling Risk)	0.20	0.81	0.11	0.43
Obs.	720		1,096	

TABLE 8: The effect of stock indexing on liquidity conditions

This table reports second-stage fuzzy RDD results for changes in liquidity from the year before to the year after the annual Russell reconstitution. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
Δ(Bid-Ask Spread)	-0.47***	-7.60	0.26***	8.25
Δ(Illiquidity Ratio)	-13.28***	-5.08	3.34**	2.51
Δ(Inelasticity Ratio)	-8.33***	-5.61	2.56***	2.99
Obs.	1,696		1,933	

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
Δ(Bid-Ask Spread)	0.00	0.20	0.00	0.32
Δ(Illiquidity Ratio)	0.01	0.09	-0.03	-0.81
Δ(Inelasticity Ratio)	-0.19	-0.49	-0.20	-0.63
Obs.	756		1,127	

TABLE 9: The effect of stock indexing on price synchronicity and volatility

This table reports second-stage fuzzy RDD results for changes in price synchronicity and stock return volatility components from the year before to the year after the annual Russell reconstitution. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
Δ(Price Synchronicity)	1.07***	6.18	-0.64***	-4.64
Δ(Systematic Volatility)	1.15***	5.54	-0.86***	-5.36
Δ(Idiosyncratic Volatility)	0.09	0.80	-0.23**	-2.43
Obs.	1,591		1,779	

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
Δ(Price Synchronicity)	0.23	0.97	-0.24	-1.23
Δ(Systematic Volatility)	0.39	1.42	-0.27	-1.22
Δ(Idiosyncratic Volatility)	0.16	0.89	-0.04	-0.26
Obs.	716		1,079	

TABLE 10: The effect of stock indexing on the speed of price adjustment to news

This table reports second-stage fuzzy RDD results for changes in price delay from the year before to the year after the annual Russell reconstitution. Panel A reports results for additions and deletions at the #3,000 breakpoint. Panel B reports results for additions at the lower band of the #1,000 and deletions at the upper band of the #1,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

Panel A: #3,000 breakpoint.

	#3,000 Breakpoint			
	Additions		Deletions	
	Treatment	z-stat	Treatment	z-stat
Δ(Market Delay)	-1.01***	-4.96	0.58***	3.30
Δ(Industry Delay)	-1.00***	-4.97	0.66***	3.78
Δ(Firm Delay)	-0.92***	-4.44	0.71***	3.98
Δ(Earnings Delay)	-1.80***	-8.73	1.03***	5.99
Δ(Negative Delay)	-0.95***	-5.38	0.70***	4.71
Obs.	1,591		1,779	

Panel B: #1,000 breakpoint.

	#1,000 Breakpoint			
	Additions | Lower Band		Deletions | Upper Band	
	Treatment	z-stat	Treatment	z-stat
Δ(Market Delay)	-0.32	-1.02	0.15	0.59
Δ(Industry Delay)	-0.39	-1.22	0.03	0.12
Δ(Firm Delay)	-0.50	-1.59	0.02	0.10
Δ(Earnings Delay)	-0.29	-0.84	0.35	1.23
Δ(Negative Delay)	-0.42	-1.59	0.09	0.42
Obs.	716		1,079	

TABLE 11: Variation with pre-reconstitution arbitrage constraints

This table reports second-stage fuzzy RDD results for changes in price synchronicity, return volatility, and price delay from the year before to the year after the annual Russell reconstitution for micro-cap stock additions at the lower cutoff of the Russell 2000. We partition micro-cap stock additions at the lower cutoff of the Russell 2000 into (a) more arbitrage-constrained and (b) less arbitrage-constrained based on pre-reconstitution characteristics. We define as harder-to-borrow stocks those with below average lendable quantity or above average stock inventory concentration, stock loan fees, or short-selling risk. We define as harder-to-trade stocks those with above average bid-ask spread or above average illiquidity ratios. We then classify as more arbitrage-constrained stocks that are harder-to-borrow and harder-to-trade. We classify the rest of the stocks as less arbitrage-constrained. This classification generates two balanced portfolios of micro-cap stock additions at the lower cutoff. We estimate the conditional addition effects relative to the counterfactual group of static Russell 3000E micro-cap constituents on the right of the #3,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

	#3,000 Breakpoint | Additions					
	Less Constrained (a)		More Constrained (b)		$(b)-(a)$	
	Treatment	z-stat	Treatment	z-stat	Difference	z-stat
Δ(Price Synchronicity)	0.74***	3.66	1.35***	6.30	0.61**	2.41
Δ(Systematic Volatility)	0.71***	3.02	1.53***	5.79	0.82***	2.69
Δ(Idiosyncratic Volatility)	-0.03	-0.22	0.18	1.31	0.21	1.35
Δ(Market Delay)	-0.69***	-2.81	-1.29***	-5.14	-0.60**	-2.01
Δ(Industry Delay)	-0.65***	-2.72	-1.31***	-5.36	-0.66**	-2.27
Δ(Firm Delay)	-0.46*	-1.87	-1.31***	-5.45	-0.85***	-2.91
Δ(Earnings Delay)	-1.28***	-5.43	-2.26***	-9.12	-0.98***	-3.45
Δ(Negative Delay)	-0.64***	-3.00	-1.23***	-5.75	-0.59**	-2.30
Obs.	1,279		1,306		1,591	

TABLE 12: Variation with pre-reconstitution information environment

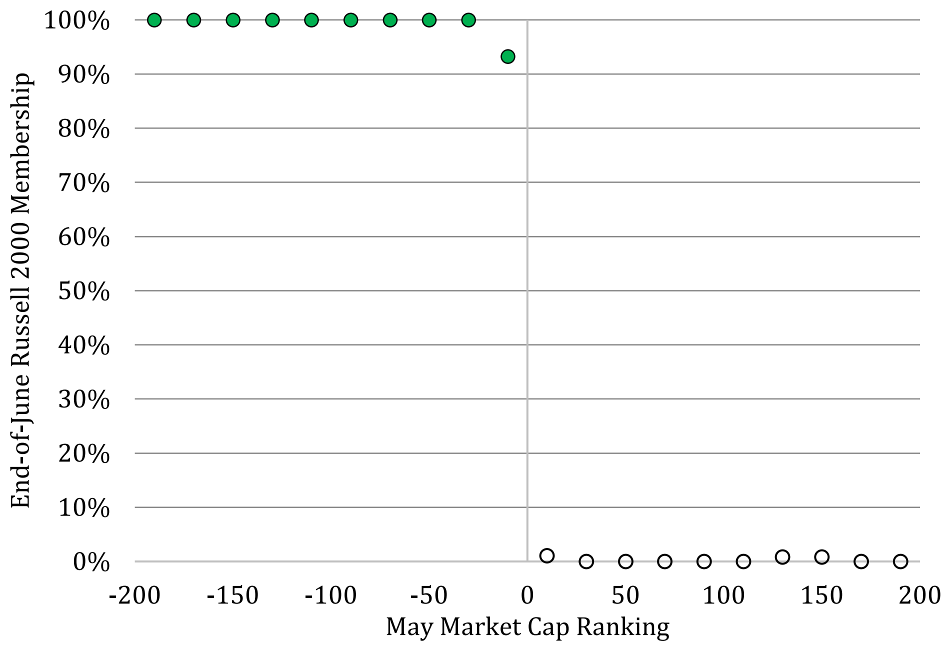
This table reports second-stage fuzzy RDD results for changes in price synchronicity, return volatility, and price delay from the year before to the year after the annual Russell reconstitution for micro-cap stock additions at the lower cutoff of the Russell 2000. We partition micro-cap stock additions at the lower cutoff of the Russell 2000 into (a) stocks with less coverage and (b) stocks with more coverage based on pre-reconstitution management earnings guidance and sell-side analysts' coverage. Specifically, we separate stocks with below median analyst coverage and no management guidance (stocks with less coverage) from stocks with above median analyst coverage and management guidance (stocks with more coverage). This classification generates two balanced portfolios of micro-cap stock additions at the lower cutoff. We estimate the conditional addition effects relative to the counterfactual group of static Russell 3000E micro-cap constituents on the right of the #3,000 breakpoint. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016.

	#3,000 Breakpoint | Additions					
	Less Coverage (a)		More Coverage (b)		$(b)-(a)$	
	Treatment	z-stat	Treatment	z-stat	Difference	z-stat
Δ(Price Synchronicity)	1.11***	4.48	1.01***	5.36	-0.09	-0.36
Δ(Systematic Volatility)	1.26***	4.41	1.04***	4.52	-0.22	-0.71
Δ(Idiosyncratic Volatility)	0.15	1.16	0.02	0.18	-0.13	-0.82
Δ(Market Delay)	-1.14***	-4.12	-0.89***	-3.89	0.24	0.80
Δ(Industry Delay)	-1.08***	-3.93	-0.92***	-4.16	0.16	0.53
Δ(Firm Delay)	-0.94***	-3.42	-0.88***	-3.77	0.07	0.22
Δ(Earnings Delay)	-1.99***	-8.27	-1.63***	-6.24	0.36	1.25
Δ(Negative Delay)	-1.04***	-4.18	-0.87***	-4.42	0.17	0.65
Obs.	1,268		1,317		1,591	

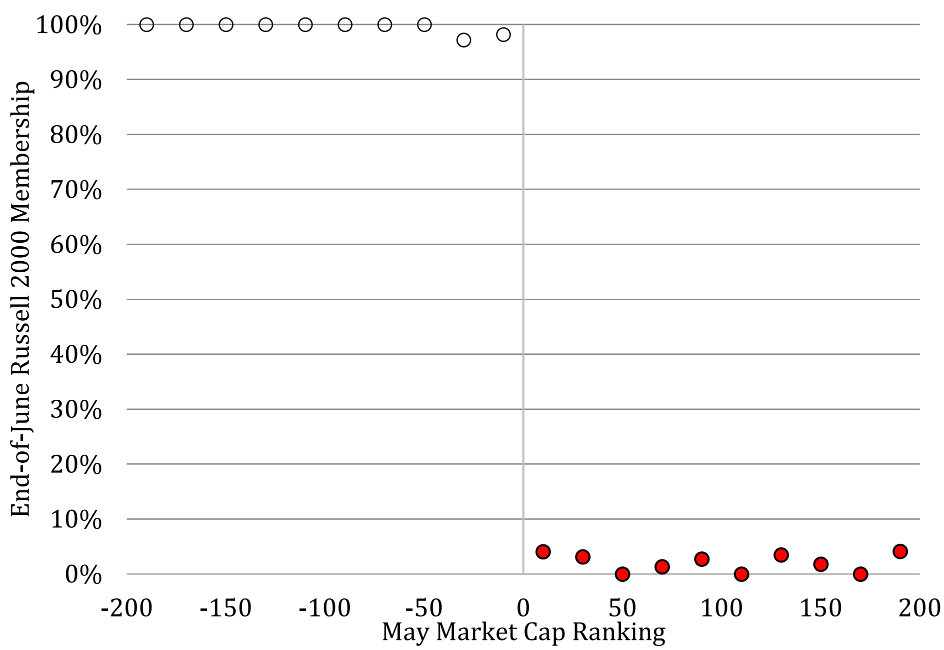
FIGURE 1: Discontinuity in predicted index membership

This figure presents evidence of discontinuities in the predicted Russell 2000 index membership at the reconstitution cutoffs conditioning on prior index membership. Panels A and B plot the average Russell 2000 index assignment probability at the #3,000 breakpoint. Panels C and D plot the average Russell 2000 index assignment probability at the lower and upper bands of the #1,000 breakpoint. The sample period is between 2007 and 2016.

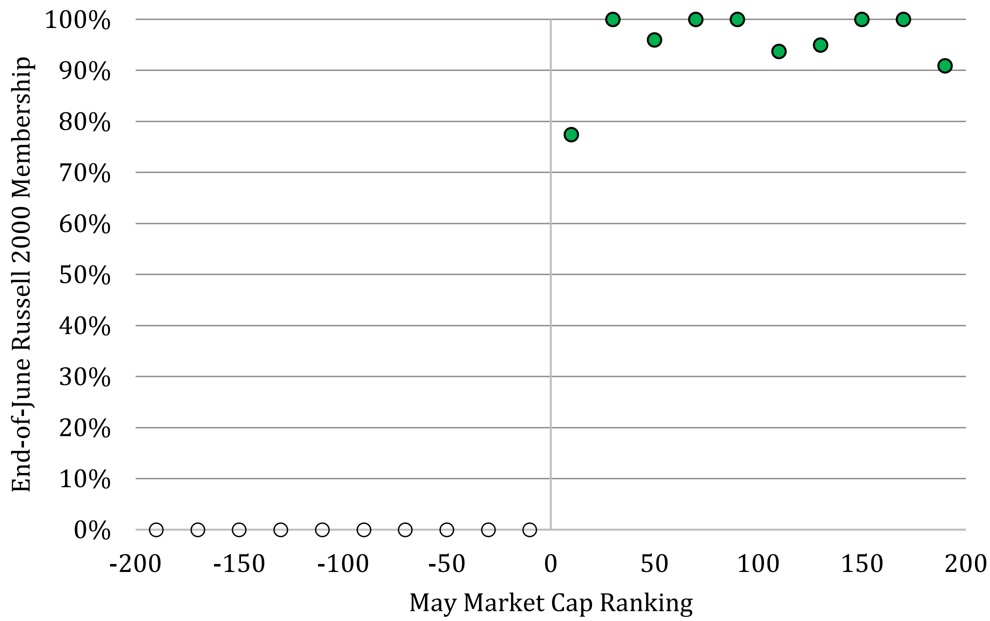
Panel A: #3000 breakpoint | prior Russell 3000E members.



Panel B: #3000 breakpoint | prior Russell 2000 members.



Panel C: Lower band #1,000 breakpoint | prior Russell 1000 members.



Panel D: Upper band #1,000 breakpoint | prior Russell 2000 members.

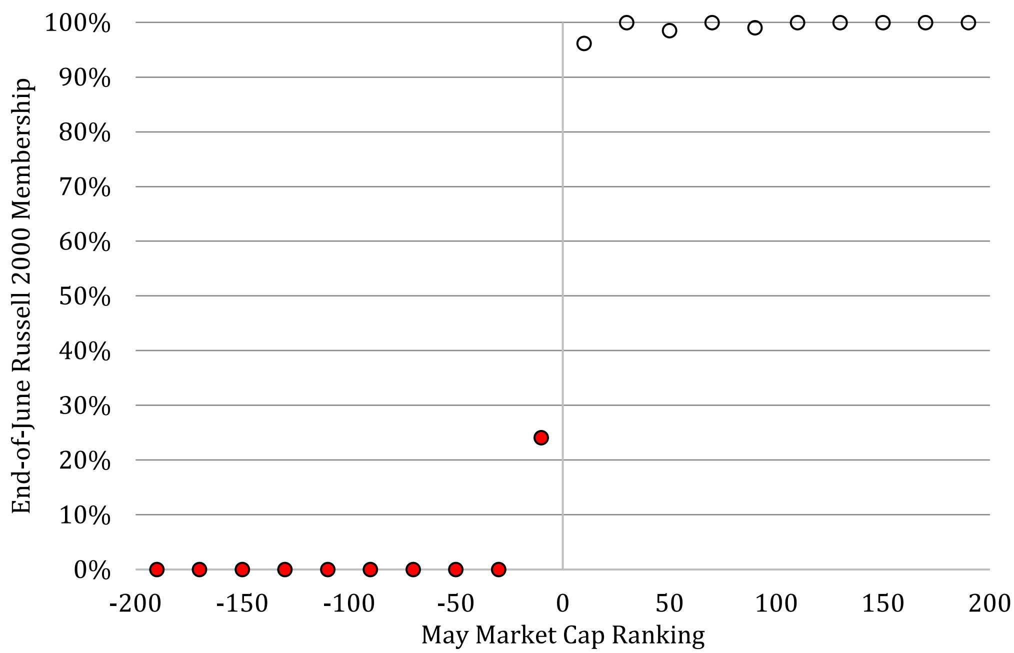
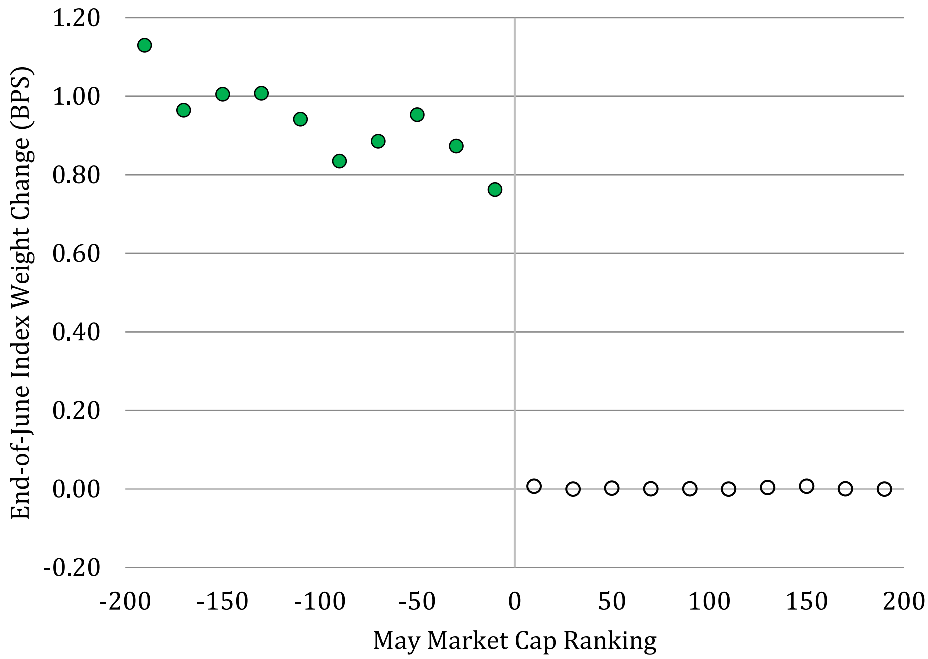


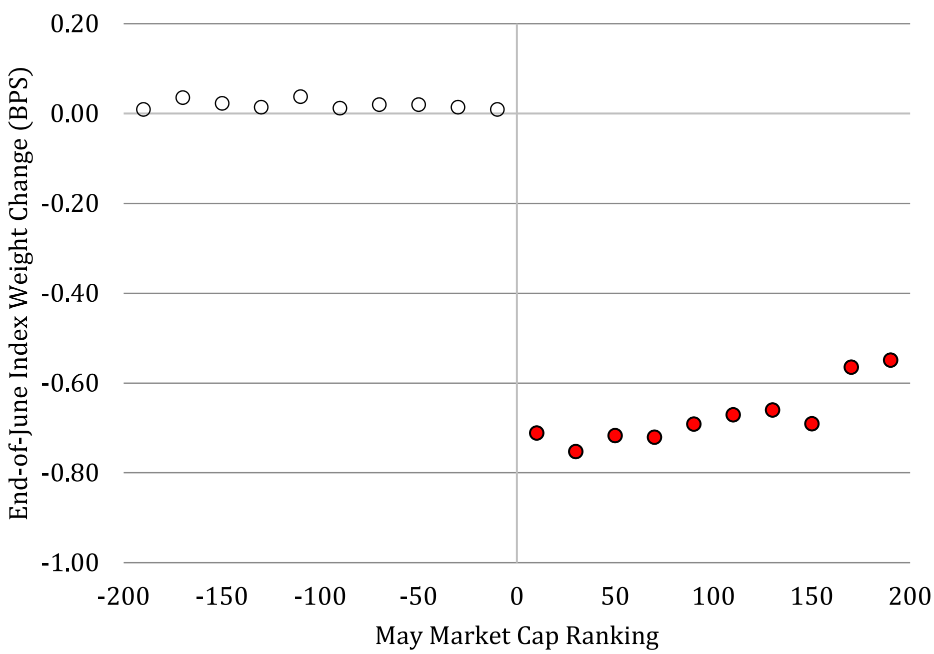
FIGURE 2: Discontinuity in end-of-June index weights

This figure presents evidence of discontinuities in end-of-June index weight changes at the Russell 2000 reconstitution cutoffs conditioning on prior index membership. Panels A and B plot the average end-of-June index weight change at the #3,000 cutoff. Panels C and D plot the average end-of-June index weight change at the lower and upper bands of the #1,000 cutoff. The sample period is between 2007 and 2016.

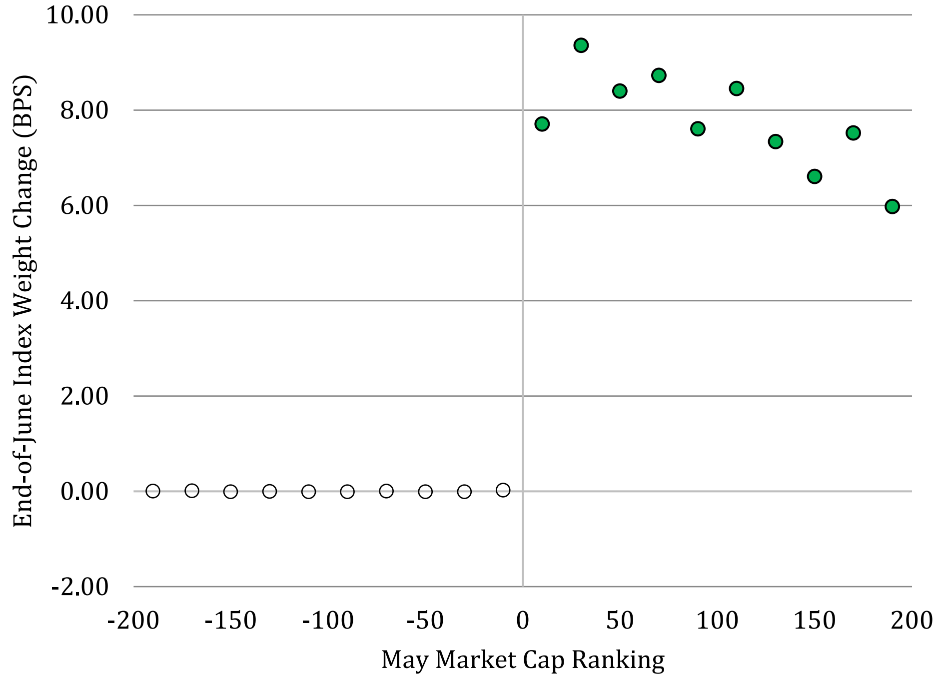
Panel A: #3000 breakpoint | prior Russell 3000E members.



Panel B: #3000 breakpoint | prior Russell 2000 members.



Panel C: Lower band #1,000 breakpoint | prior Russell 1000 members.



Panel D: Upper band #1,000 breakpoint | prior Russell 2000 members.

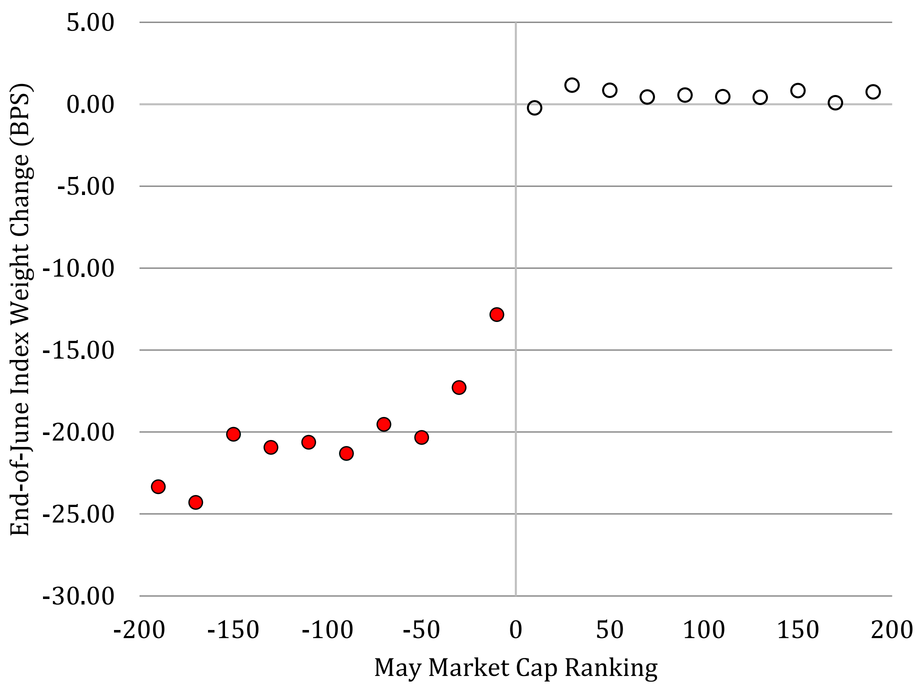
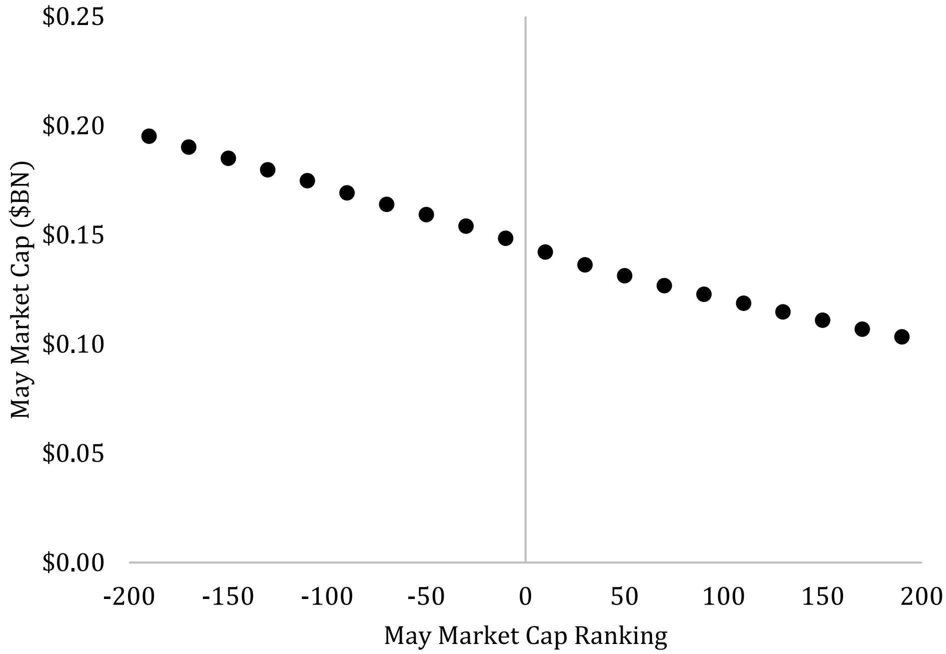


FIGURE 3: Continuity in end-of-May market cap

This figure presents evidence of continuity in the end-of-May total market cap around the Russell 2000 index reconstitution cutoffs. Panel A plots end-of-May market cap values against end-of-May market cap rankings at the #3,000 breakpoint. Panel B plots end-of-May market cap values against end-of-May market cap rankings at the lower and upper bands of the #1,000 breakpoint. The sample period is between 2007 and 2016.

Panel A: Lower cutoff of Russell 2000 index.



Panel B: Upper cutoff of Russell 2000 index.

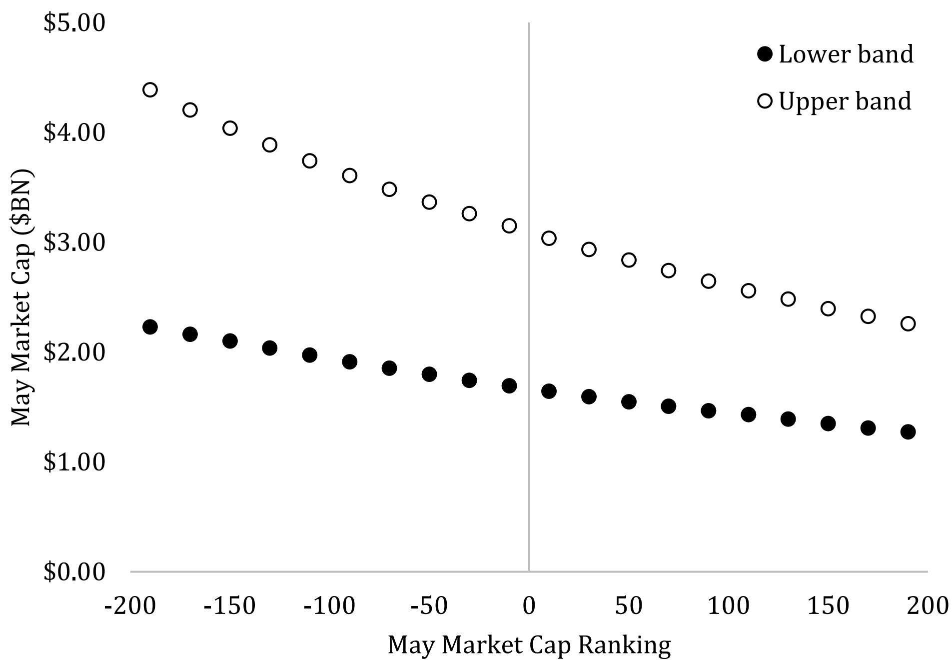
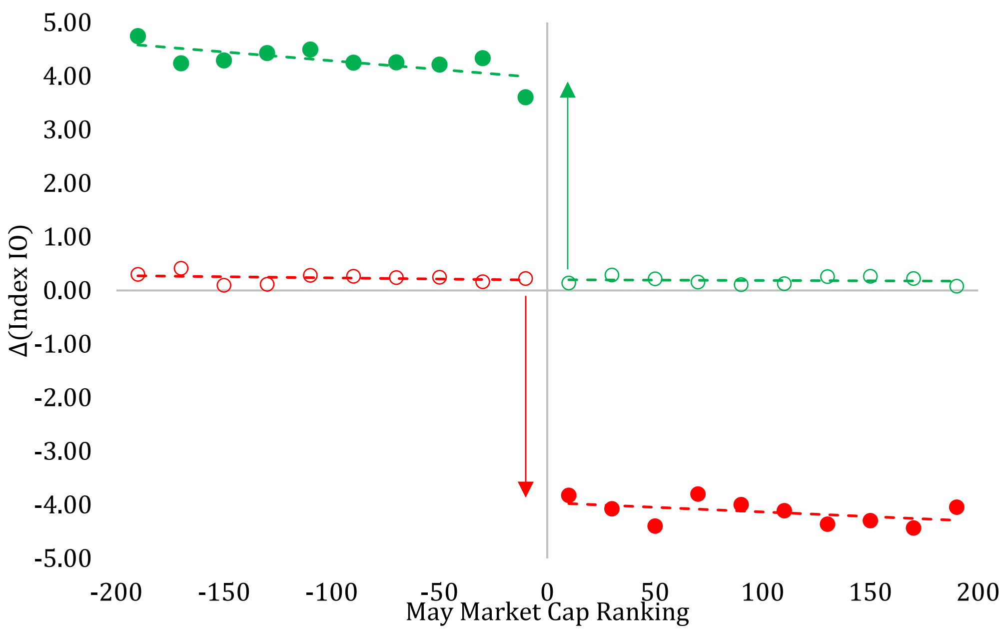


FIGURE 4: Post-reconstitution index ownership changes

This figure plots the average change in the % of shares held by index institutions (index IO) from March to September across equal-spaced portfolio bins within a +/-200 bandwidth around the index reconstitution cutoff for stock additions (solid green dots) and deletions (solid red dots) relative to the counterfactual groups of stocks (hollow dots). Panel A presents evidence of addition and deletion effects at the #3,000 breakpoint. Panel B presents evidence of addition (deletion) effects at the lower (upper) band of the #1,000 breakpoint. The sample period is between 2007 and 2016.

Panel A: Lower cutoff of Russell 2000 index.



Panel B: Upper cutoff of Russell 2000 index.

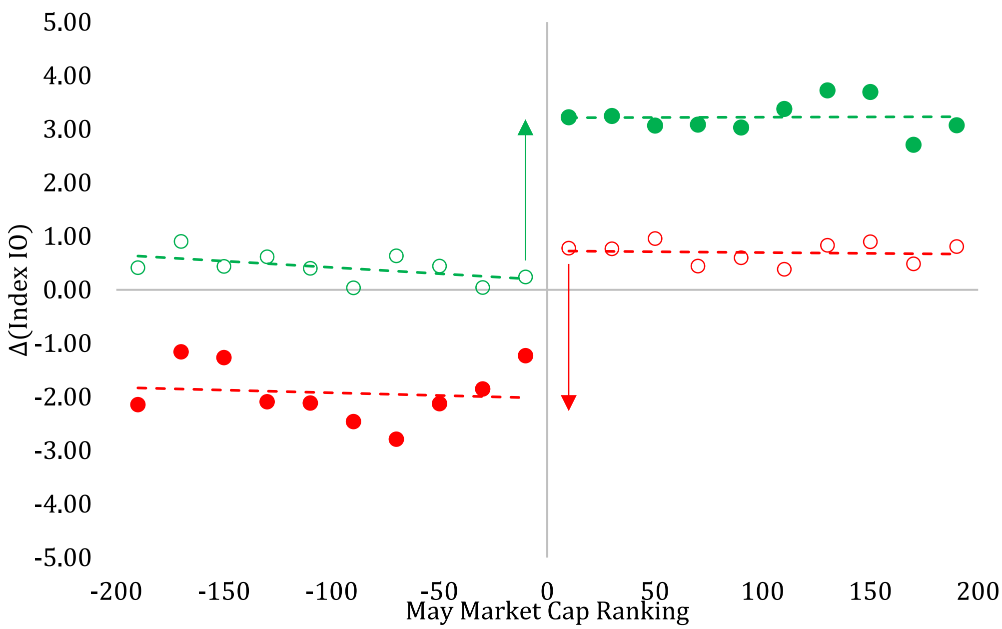


FIGURE 5: Pre- and post-reconstitution stock lending inventory dynamics
Additions and deletions at the upper and lower Russell reconstitution cutoffs

This figure plots the cumulative change in stock lending inventory concentration for additions and deletions at the lower and upper cutoffs of the Russell 2000 index. The cumulation window is between trading days -250 and +250 relative to the day of the annual Russell reconstitution at the end-of-June (day zero). Markit's measure of inventory concentration ranges from zero to 100. A low score indicates many lenders with low inventory and a top score indicates a single lender with all the inventory. The green (red) solid line presents the cumulative addition (deletion) effect on inventory concentration for stock additions (deletions) at the lower cutoff of the Russell 2000 relative to the counterfactual static stocks on the right (left) of the #3,000 breakpoint. The green (red) dashed line presents the cumulative addition (deletion) effect on inventory concentration for stock additions (deletions) at the upper cutoff of the Russell 2000 relative to the counterfactual static stocks on the left (right) of the lower (upper) band of the #1,000 breakpoint.

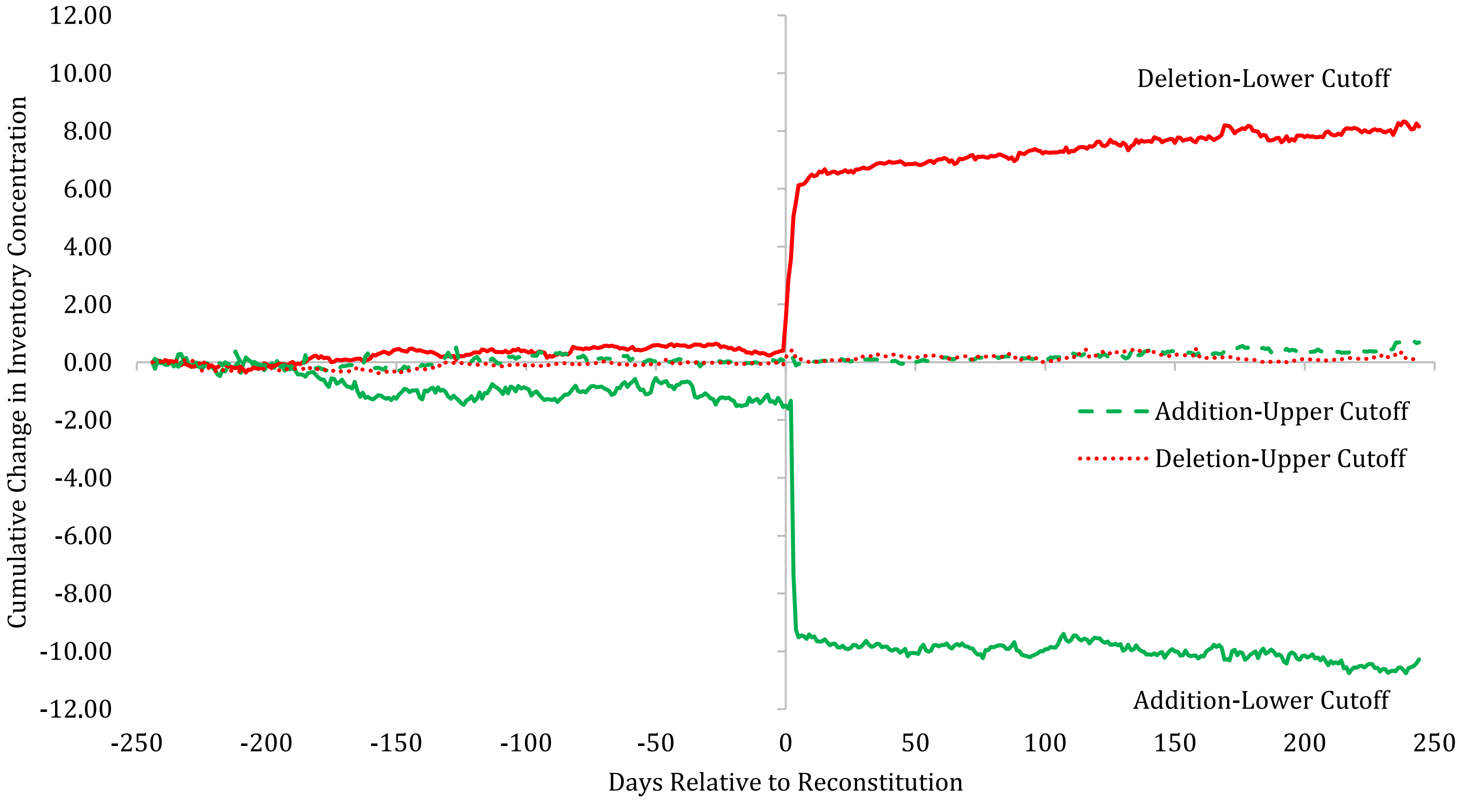
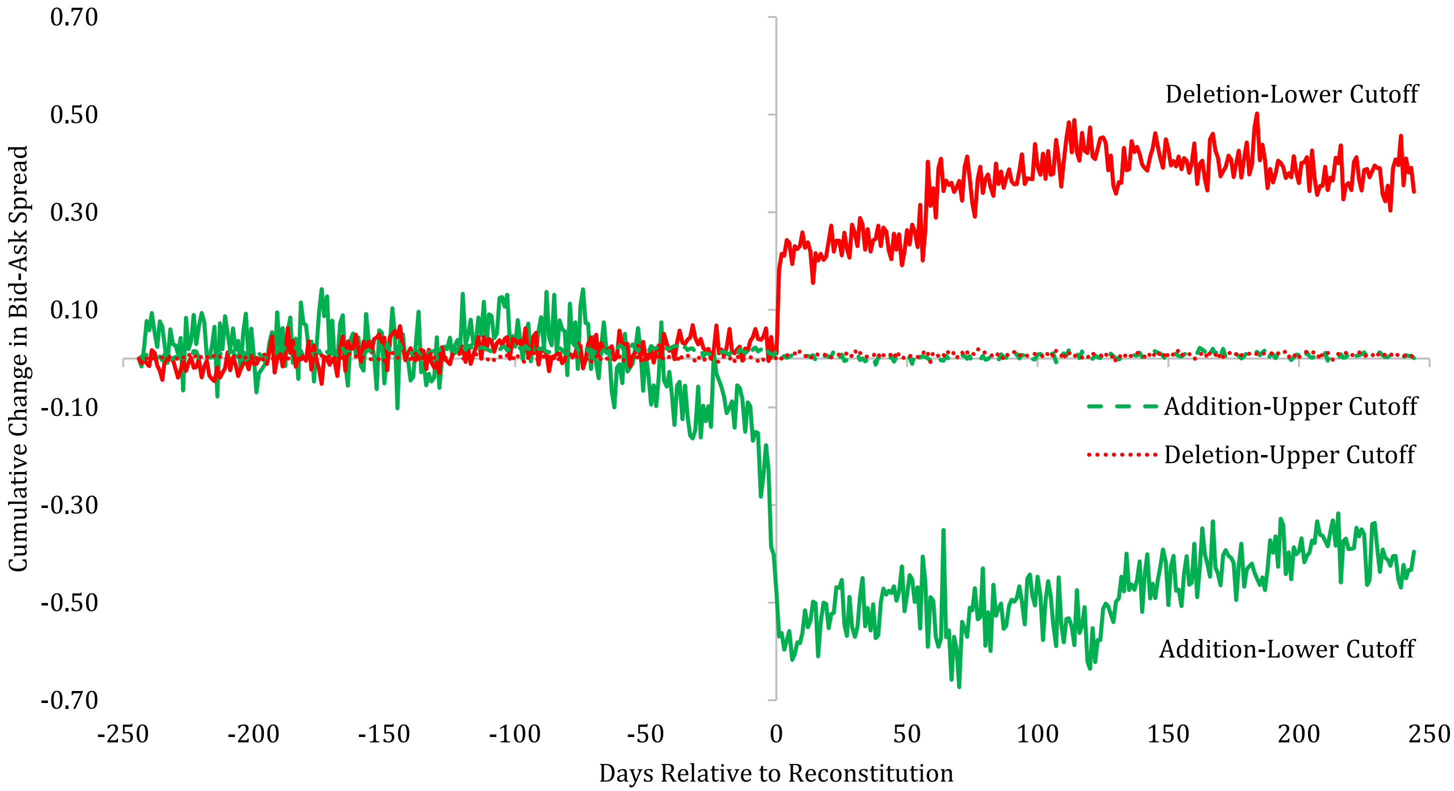


FIGURE 6: Pre- and post-reconstitution stock liquidity dynamics
Additions and deletions at the upper and lower Russell reconstitution cutoffs

This figure plots the cumulative change in the bid-ask spread for additions and deletions at the lower and upper cutoffs of the Russell 2000 index. The cumulation window is between trading days -250 and +250 relative to the day of the annual Russell reconstitution at the end-of-June (day zero). The green (red) solid line presents the cumulative addition (deletion) effect on bid-ask spread for stock additions (deletions) at the lower cutoff of the Russell 2000 relative to the counterfactual static stocks on the right (left) of the #3,000 breakpoint. The green (red) dashed line presents the cumulative addition (deletion) effect on bid-ask spread for stock additions (deletions) at the upper cutoff of the Russell 2000 relative to the counterfactual static stocks on the left (right) of the lower (upper) band of the #1,000 breakpoint.



APPENDIX A
Variable definitions

Institutional Ownership (IO)	
Total IO	Percentage of shares outstanding held by institutions that manage over $100 million and report their quarterly holdings in SEC Form 13F and N-30Ds. We obtain institutional ownership (IO) data from the FactSet Global Ownership Database.
Index IO	Percentage of shares outstanding held by index institutions. FactSet analysts separate index from non-index institutions using information from various sources, including fund managers, prospectuses, factsheets, audited reports, and fund accounts. We obtain index IO data from the FactSet Global Ownership Database.
Non-Index IO	Percentage of shares outstanding held by institutions minus the percentage of shares outstanding held by index institutions.

Securities Lending Conditions	
Lendable Quantity	Markit's quantity of stock inventory available to lend as a percentage of the number of shares outstanding in the company.
Inventory Concentration	Markit's standardized measure of the distribution of stock inventory. The measure ranges from zero to 100. A low score indicates many lenders with low inventory and a top score indicates a single lender with all the inventory.
Quantity on Loan	Markit's quantity of stock on loan as a percentage of the number of shares outstanding in the company.
Stock Loan Fee	Markit's indicative rate of the standard borrow cost on a given day expressed as a percentage of the stock price This is a derived rate using Markit's proprietary analytics and data set. The calculation uses borrow costs between agent lenders and prime brokers as well as rates from hedge funds to produce an indication of the current market rate.
Short Selling Risk	Standard deviation of Markit's daily stock loan fee in the year before and year after Russell's reconstitution.

Stock Liquidity Conditions	
Bid-Ask Spread	The daily CRSP spread of closing ask minus closing bid divided by the midpoint available from CRSP.
Illiquidity Ratio	Amihud's (2002) ratio of the absolute daily stock return divided by the daily dollar trading volume multiplied by 10^8.
Inelasticity Ratio	Gao and Ritter's (2010) ratio of the absolute daily stock return divided by the daily share turnover. We measure daily share turnover as the number of shares traded over the number of shares outstanding in the company.

Price Synchronicity and Volatility	
Price Synchronicity	R^2 from a regression of weekly firm returns on the contemporaneous weekly market and industry returns. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.
Systematic (Idiosyncratic) Volatility	The log variance of the systematic (idiosyncratic) portion of weekly firm returns. We measure the systematic (idiosyncratic) portion of returns as the fitted (residual) values from a regression of weekly firm returns on contemporaneous market and industry returns. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios.

Price Delay	
Market Delay	Fraction of variation in weekly firm returns explained by lagged market returns measured as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of market returns. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.
Industry Delay	Fraction of variation in weekly firm returns explained by lagged industry returns measured as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of industry returns. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.

Price Delay	
Firm Delay	Fraction of variation in weekly firm returns explained by lagged firm returns measured as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of firm returns. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.
Earnings Delay	Fraction of variation in daily firm returns post-earnings announcement measured as one minus the ratio of the R^2 from the regression of daily firm returns on contemporaneous market and industry returns over the R^2 from the regression of the daily firm returns on contemporaneous market and industry returns and four lags of firm returns. The post-earnings announcement period covers the 20-day trading window commencing two days after the quarterly earnings announcement. We combine information from Compustat and IBES to identify day zero of the quarterly earnings announcements. When the earnings announcement dates differ between Compustat and IBES, we use the earlier of the two. We shift the earnings announcement by one trading day when the time stamp of the announcement is after trading hours. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.
Negative Delay	Fraction of variation in weekly firm returns explained by lagged negative returns measured as one minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and four lags of negative market, industry, and firm returns. We set positive values of lagged market, industry, and firm returns to zero. We compute weekly returns from Wednesday to Tuesday. We measure market returns using Fama and French's value-weighted market portfolio. We measure industry returns using Fama and French's twelve value-weighted industry portfolios. We use a logit transformation to mitigate skewness.

APPENDIX B
FactSet Institutional Ownership Database

We measure the index component of institutional ownership (index IO) as the fraction of shares held by index institutions that report their quarterly holdings in SEC Form 13F and N-30Ds. We separate index from non-index institutions using FactSet's Global Ownership Database. The Research Staff at FactSet manually attribute the index style for an institutional portfolio based on information they receive directly from fund managers or from the prospectus, factsheets or auditor reports and accounts for each fund. Specifically, we extract the institutional ownership data via FactSet's "Percent Ownership-Grouped Analysis" function (OS_GRP_HLDR_PCTOS). We then specify the holder type parameter as institutions and group the percentage of holdings by index and non-index investor type. As of December 2020, FactSet identifies 84 unique index institutions around the globe.

We note that FactSet analysts identify index holdings at the fund family/institution level. The aggregation of index holdings at the fund family/institution level rather than at the fund level introduces noise in the measurement of index IO. This is because institutions classified as index can also be large fund managers who have many different fund styles to cater to all types of investors. To illustrate, Vanguard is classified in the FactSet database as an index institution, and some of the funds in the Vanguard fund family are not classified as index funds (e.g., Vanguard Growth & Income, Vanguard Tax Managed Balanced, Vanguard Alternative Strategies, Vanguard Wellington).

APPENDIX C

In the manuscript, we report fuzzy RDD results using a $+/-200$ bandwidth with linear rank control functions and a uniform kernel function, which equal weights observations within the bandwidth around the Russell reconstitution cutoff. Throughout, we estimate the two-equation system of the fuzzy RDD conditioning on prior index membership around each reconstitution cutoff.

Appendix C reports results using alternative choices for the bandwidth, the kernel function, as well as the rank control polynomial order. With respect to the bandwidth choice, Appendix C reports consistent estimates using a $+/-100$ bandwidth, which captures 36% of all Russell index turnover. We also find consistent estimates using Imbens and Kalyanaraman's (2012) mean squared error (MSE) bandwidth selection criterion, which attempts to optimally balance bias and variance. The MSE bandwidth selection criterion is fully data-driven and does not require a fixed bandwidth choice across specifications. Across alternative bandwidths, Appendix C reports consistent estimates using a triangular kernel function, which places more weight on observations near the cutoff, and cubic (i.e., third-order polynomial) rank control functions. Local randomization implies that the assignment to treatment is independent of baseline covariates (e.g., Lee and Lemieux 2010). Consistent with local randomization, we report similar estimates after the inclusion of year fixed effects as baseline covariates.

Tables C1-C4 report fuzzy RDD estimates of addition and deletion effects at the Russell reconstitution cutoffs for each outcome variable of interest conditioning on prior index membership. Table C5 reports fuzzy RDD estimates for the full sample of stocks within the $+/-200$ bandwidth around each reconstitution cutoff without conditioning on prior index membership. All estimates zero in on the change from the year before to the year after the annual Russell reconstitution. [a], [b], and [c] indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. The variables are listed in the order of appearance in the manuscript. Appendix A provides all variable definitions.

TABLE C1: # 3,000 Breakpoint | Additions

	Triangular Kernel Function			Year Fixed Effects			Cubic Rank Controls		
	200	100	MSE	200	100	MSE	200	100	MSE
Δ(Index IO)	3.87[a]	3.85[a]	3.87[a]	3.89[a]	3.85[a]	3.96[a]	3.70[a]	3.89[a]	3.79[a]
Δ(Non-index IO)	-0.12	0.57	-0.05	0.28	-0.37	-0.48	1.02	1.16	-0.22
Δ(Total IO)	3.75[a]	4.41[a]	3.80[a]	4.17[a]	3.48[a]	3.84[a]	4.72[b]	5.06	3.68[a]
Δ(Lendable Quantity)	3.15[a]	3.05[a]	3.15[a]	3.15[a]	3.06[a]	3.04[a]	3.05[a]	3.54[a]	2.99[a]
Δ(Inventory Concentration)	-7.79[a]	-5.40[b]	-8.44[a]	-8.22[a]	-6.55[a]	-8.41[a]	-3.55	-3.98	-6.74[a]
Δ(Quantity on Loan)	1.80[a]	1.70[a]	1.65[a]	1.66[a]	1.69[a]	1.84[a]	1.43[a]	1.48[c]	1.94[a]
Δ(Stock Loan Fee)	-0.99[b]	-1.20[c]	-0.69[c]	-0.88[b]	-1.25[b]	-1.07[b]	-1.70[c]	-3.09[b]	-1.48[b]
Δ(Short Selling Risk)	-0.63[b]	-0.47	-0.63[b]	-0.64[b]	-0.69[c]	-0.69[b]	-0.43	-0.05	-0.77[c]
Δ(Bid-Ask Spread)	-0.47[a]	-0.49[a]	-0.47[a]	-0.49[a]	-0.50[a]	-0.50[a]	-0.46[a]	-0.55[a]	-0.47[a]
Δ(Illiquidity Ratio)	-14.00[a]	-16.34[a]	-13.88[a]	-14.23[a]	-16.35[a]	-14.69[a]	-15.36[a]	-14.08[c]	-14.56[a]
Δ(Inelasticity Ratio)	-8.50[a]	-9.54[a]	-8.50[a]	-8.83[a]	-9.85[a]	-8.88[a]	-8.84[a]	-8.80[b]	-8.18[a]
Δ(Price Synchronicity)	1.08[a]	1.37[a]	1.09[a]	1.04[a]	1.06[a]	1.09[a]	1.61[a]	2.11[a]	1.20[a]
Δ(Systematic Volatility)	1.20[a]	1.47[a]	1.19[a]	1.06[a]	1.10[a]	1.02[a]	1.70[a]	2.24[a]	1.33[a]
Δ(Idiosyncratic Volatility)	0.12	0.11	0.10	0.02	0.04	0.07	0.09	0.13	0.06
Δ(Market Delay)	-0.99[a]	-1.33[a]	-1.02[a]	-1.01[a]	-0.99[a]	-1.07[a]	-1.60[a]	-2.06[a]	-1.15[a]
Δ(Industry Delay)	-1.05[a]	-1.53[a]	-1.04[a]	-0.99[a]	-1.11[a]	-1.03[a]	-1.90[a]	-2.24[a]	-1.20[a]
Δ(Firm Delay)	-0.93[a]	-1.21[a]	-0.95[a]	-0.89[a]	-0.92[a]	-1.00[a]	-1.42[a]	-1.93[a]	-1.16[a]
Δ(Earnings Delay)	-1.68[a]	-1.62[a]	-1.70[a]	-1.81[a]	-1.53[a]	-1.75[a]	-1.59[a]	-1.80[a]	-1.66[a]
Δ(Negative Delay)	-0.97[a]	-1.29[a]	-0.97[a]	-0.93[a]	-0.98[a]	-1.03[a]	-1.56[a]	-2.04[a]	-1.06[a]

TABLE C2: # 3,000 Breakpoint | Deletions

	Triangular Kernel Function			Year Fixed Effects			Cubic Rank Controls		
	200	100	MSE	200	100	MSE	200	100	MSE
Δ(Index IO)	-4.34[a]	-4.35[a]	-4.36[a]	-4.28[a]	-4.35[a]	-4.36[a]	-4.38[a]	-3.89[a]	-4.47[a]
Δ(Non-index IO)	0.34	-0.66	0.00	0.71	-0.10	0.61	-0.99	1.12	-1.51
Δ(Total IO)	-4.01[a]	-5.01[a]	-4.35[a]	-3.57[a]	-4.45[a]	-3.71[a]	-5.37[a]	-2.77	-5.41[a]
Δ(Lendable Quantity)	-4.22[a]	-4.55[a]	-4.23[a]	-4.17[a]	-4.58[a]	-4.07[a]	-4.76[a]	-5.54[a]	-4.76[a]
Δ(Inventory Concentration)	6.44[a]	6.58[a]	6.42[a]	6.11[a]	7.16[a]	6.46[a]	6.62[a]	3.51[c]	7.09[a]
Δ(Quantity on Loan)	-1.66[a]	-1.85[a]	-1.66[a]	-1.71[a]	-1.82[a]	-1.81[a]	-2.01[a]	-2.22[a]	-1.82[a]
Δ(Stock Loan Fee)	1.18[b]	0.95	1.10[b]	1.54[a]	1.08	1.10[c]	0.89	1.13	0.73
Δ(Short Selling Risk)	0.25	0.42	0.25	0.33	0.52	0.26	0.72	1.20[b]	0.20
Δ(Bid-Ask Spread)	0.27[a]	0.28[a]	0.26[a]	0.27[a]	0.28[a]	0.27[a]	0.33[a]	0.43[a]	0.31[a]
Δ(Illiquidity Ratio)	3.75[b]	5.22[b]	3.91[b]	3.59[a]	4.62[a]	3.44[a]	7.57[b]	11.11[b]	6.18[b]
Δ(Inelasticity Ratio)	2.71[a]	3.66[b]	2.65[a]	2.66[a]	3.18[a]	2.42[a]	5.33[a]	6.63[b]	3.98[b]
Δ(Price Synchronicity)	-0.63[a]	-0.70[a]	-0.63[a]	-0.63[a]	-0.64[a]	-0.56[a]	-0.83[a]	-1.06[a]	-0.74[a]
Δ(Systematic Volatility)	-0.87[a]	-0.90[a]	-0.87[a]	-0.85[a]	-0.90[a]	-0.88[a]	-0.92[a]	-0.88[b]	-1.00[a]
Δ(Idiosyncratic Volatility)	-0.24[b]	-0.19	-0.24[b]	-0.22[a]	-0.26[b]	-0.24[a]	-0.09	0.18	-0.18
Δ(Market Delay)	0.54[a]	0.63[b]	0.53[a]	0.57[a]	0.53[b]	0.52[a]	0.82[b]	1.05[b]	0.63[b]
Δ(Industry Delay)	0.64[a]	0.71[a]	0.62[a]	0.66[a]	0.64[a]	0.64[a]	0.87[a]	1.02[b]	0.72[a]
Δ(Firm Delay)	0.60[a]	0.71[b]	0.62[a]	0.72[a]	0.47[b]	0.65[a]	0.96[a]	1.77[a]	0.68[a]
Δ(Earnings Delay)	0.89[a]	0.82[a]	0.85[a]	1.02[a]	0.89[a]	0.97[a]	0.94[a]	0.81[c]	0.80[a]
Δ(Negative Delay)	0.65[a]	0.77[a]	0.65[a]	0.70[a]	0.63[a]	0.70[a]	0.96[a]	1.33[a]	0.77[a]

TABLE C3: # 1,000 Breakpoint, Lower Band | Additions

	Triangular Kernel Function			Year Fixed Effects			Cubic Rank Controls		
	200	100	*MSE*	200	100	*MSE*	200	100	*MSE*
Δ(Index IO)	3.48[a]	4.00[a]	3.44[a]	3.26[a]	3.46[a]	3.26[a]	4.16[a]	3.47[c]	3.80[a]
Δ(Non-index IO)	-0.35	0.30	-0.49	-0.34	-0.73	-1.01	0.32	7.33	-0.39
Δ(Total IO)	3.13	4.30	3.00	2.92[c]	2.73	2.88[c]	4.48	10.79	4.22
Δ(Lendable Quantity)	3.18[a]	4.38[a]	2.62[a]	2.68[a]	2.93[b]	2.64[a]	5.07[b]	11.94[b]	3.81[a]
Δ(Inventory Concentration)	-0.85	-2.59[a]	-0.51	-0.11	-2.65[a]	-0.34	-3.93[a]	-0.54	-1.08
Δ(Quantity on Loan)	2.18[b]	3.64[b]	1.70[b]	1.42[c]	2.96[b]	1.15	5.04[b]	10.70[b]	2.51[c]
Δ(Stock Loan Fee)	0.16	0.57	-0.08	-0.15	0.58	-0.04	1.23	3.15	0.95
Δ(Short Selling Risk)	0.41	0.57	0.21	0.20	0.64[c]	0.63[c]	0.83	2.59[c]	1.17[c]
Δ(Bid-Ask Spread)	0.01	0.02	0.01	0.00	-0.01	-0.01	0.05	0.15[c]	0.03
Δ(Illiquidity Ratio)	-0.06	-0.19	-0.09	-0.01	-0.13	-0.16	-0.16	-0.07	-0.10
Δ(Inelasticity Ratio)	-0.42	-1.07	-0.40	-0.24	-0.57	-0.25	-0.96	0.11	-0.58
Δ(Price Synchronicity)	0.15	0.09	0.15	0.25	0.01	0.20	0.16	0.69	0.28
Δ(Systematic Volatility)	0.31	0.19	0.28	0.36[c]	0.04	0.20	0.33	1.28	0.44
Δ(Idiosyncratic Volatility)	0.16	0.11	0.09	0.11	0.03	0.11	0.17	0.59	0.17
Δ(Market Delay)	-0.27	-0.31	-0.17	-0.35	-0.08	-0.19	-0.30	-2.07	-0.19
Δ(Industry Delay)	-0.30	-0.22	-0.30	-0.42	-0.14	-0.29	-0.08	-0.83	-0.26
Δ(Firm Delay)	-0.42	-0.31	-0.39	-0.52[c]	-0.31	-0.41	-0.26	-0.61	-0.35
Δ(Earnings Delay)	-0.06	0.43	-0.21	-0.26	0.11	-0.24	0.84	0.92	-0.36
Δ(Negative Delay)	-0.33	-0.23	-0.19	-0.43[c]	-0.13	-0.35	-0.33	-0.81	-0.40

TABLE C4: # 1,000 Breakpoint, Upper Band | Deletions

	Triangular Kernel Function			Year Fixed Effects			Cubic Rank Controls		
	200	100	MSE	200	100	MSE	200	100	MSE
Δ(Index IO)	-2.84[a]	-2.70[a]	-2.65[a]	-2.86[a]	-2.57[a]	-2.10[a]	-2.43[b]	-3.22	-2.89[a]
Δ(Non-index IO)	0.59	3.26	1.71	-0.07	1.62	2.24	3.83	0.18	5.26
Δ(Total IO)	-2.24	0.56	-1.09	-2.94[c]	-0.95	1.18	1.40	-3.04	2.43
Δ(Lendable Quantity)	-2.08[a]	-2.55[b]	-2.30[b]	-1.83[a]	-2.03[b]	-1.72[c]	-2.73	-2.94	-3.52
Δ(Inventory Concentration)	0.79	0.94	0.84	0.59	0.28	0.35	1.04	3.03	0.42
Δ(Quantity on Loan)	-0.21	-0.18	-0.34	-0.03	-0.40	-0.43	0.25	2.11	1.46
Δ(Stock Loan Fee)	-0.16	-0.36	-0.19	-0.01	-0.31	-0.55	-0.16	-0.19	-0.94
Δ(Short Selling Risk)	-0.03	-0.30	-0.09	0.14	-0.17	-0.17	-0.13	-0.27	-0.63
Δ(Bid-Ask Spread)	0.00	0.00	0.00	0.00	0.01	0.01	0.00	-0.04	0.00
Δ(Illiquidity Ratio)	-0.02	-0.03	-0.03	-0.02	0.02	-0.03	0.01	-0.03	0.02
Δ(Inelasticity Ratio)	-0.11	0.06	0.05	-0.10	0.10	-0.16	0.46	2.17	0.43
Δ(Price Synchronicity)	-0.11	0.20	0.06	-0.10	0.17	0.11	0.29	1.38	0.38
Δ(Systematic Volatility)	-0.26	-0.19	-0.32	-0.06	0.00	0.01	-0.31	0.35	-0.33
Δ(Idiosyncratic Volatility)	-0.15	-0.39	-0.23	0.04	-0.16	-0.20	-0.60	-1.03	-0.65
Δ(Market Delay)	-0.06	-0.81	-1.45[c]	0.03	-0.50	-0.51	-1.49[c]	-4.90[b]	-2.74[b]
Δ(Industry Delay)	-0.15	-0.82	-1.26[c]	-0.10	-0.58	-0.41	-1.51[c]	-4.57[c]	-2.40[b]
Δ(Firm Delay)	-0.03	-0.30	-0.06	-0.12	-0.33	-0.27	-0.53	-2.72	-1.34
Δ(Earnings Delay)	0.18	-0.27	-0.28	0.21	-0.17	-0.16	-0.60	-1.14	-0.54
Δ(Negative Delay)	-0.03	-0.42	-0.14	-0.05	-0.37	-0.38	-0.60	-1.89	-1.40

TABLE C5: Full sample within $+/-200$ bandwidth around each reconstitution cutoff

	#3,000 Breakpoint			#1,000 Breakpoint| Lower Band			#1,000 Breakpoint| Upper Band		
	Treatment	z-stat	Obs.	Treatment	z-stat	Obs.	Treatment	z-stat	Obs.
Δ(Index IO)	4.06[a]	23.96	3,941	3.40[a]	3.13	3,952	-2.59[a]	-4.39	3,960
Δ(Non-index IO)	-0.08	-0.13	3,941	0.99	0.23	3,952	0.07	0.03	3,960
Δ(Total IO)	3.99[a]	6.20	3,941	4.39	0.94	3,952	-2.52	-0.98	3,960
Δ(Lendable Quantity)	3.76[a]	12.81	3,613	2.41	1.02	3,788	-1.04	-0.90	3,808
Δ(Inventory Concentration)	-7.56[a]	-8.80	3,613	2.41	1.23	3,788	1.15	1.17	3,808
Δ(Quantity on Loan)	1.75[a]	8.58	3,613	1.56	0.67	3,788	0.96	0.97	3,808
Δ(Stock Loan Fee)	-1.22[a]	-3.45	3,613	-0.98	-0.77	3,788	0.22	0.49	3,808
Δ(Short Selling Risk)	-0.57[a]	-2.85	3,613	1.29	1.28	3,788	0.49	1.21	3,808
Δ(Bid-Ask Spread)	-0.36[a]	-9.92	3,885	-0.04	-0.92	3,921	0.00	-0.20	3,936
Δ(Illiquidity Ratio)	-7.77[a]	-5.40	3,885	0.16	0.29	3,921	-0.21	-1.57	3,936
Δ(Inelasticity Ratio)	-5.25[a]	-6.34	3,885	-1.01	-0.98	3,921	-0.7	-1.21	3,936
Δ(Price Synchronicity)	0.78[a]	7.13	3,546	0.68	1.23	3,732	-0.25	-0.80	3,751
Δ(Systematic Volatility)	0.91[a]	7.22	3,546	0.93	1.41	3,732	-0.1	-0.27	3,751
Δ(Idiosyncratic Volatility)	0.13[c]	1.91	3,546	0.25	0.62	3,732	0.15	0.66	3,751
Δ(Market Delay)	-0.72[a]	-5.52	3,546	-1.07	-1.43	3,732	0.14	0.32	3,751
Δ(Industry Delay)	-0.78[a]	-5.96	3,546	-0.86	-1.14	3,732	-0.01	-0.03	3,751
Δ(Firm Delay)	-0.76[a]	-5.61	3,545	-0.48	-0.63	3,730	0.41	0.99	3,749
Δ(Earnings Delay)	-1.38[a]	-9.80	3,510	0.23	0.29	3,714	0.38	0.90	3,722
Δ(Negative Delay)	-0.76[a]	-6.66	3,546	-0.48	-0.79	3,732	0.10	0.28	3,751

CHAPTER 2:

Does Index Membership Affect the Quality of Mandatory Financial Report? Evidence from Index Deletions

I. Introduction

The explosive growth of stock indexing marks one of the most significant changes in investment trends over the last decade. Stock indexing, a buy-and-hold strategy that tracks a prespecified basket of securities at minimal cost, offers investors easy access to designated asset classes, and index funds serve as investment and hedging instruments for capital market participants. By the end of 2019, total net assets in index funds had grown to $8.5 trillion, representing 39 percent of assets in long-term funds, up from 18 percent at year-end 2008 (ICI Factbook (2020)).

To accurately represent a designated asset class in a constantly changing market, index providers, such as S&P, MSCI, and FTSE Russell, periodically reconstitute their indices. The index turnover is an economically significant event associated with massive trading and pricing impact (Shleifer (1986), Chen, Noronha, and Singal (2004), and Chang, Hong, and Liskovich (2015)), and it draws significant media attention, increasing investor awareness.[16] Furthermore, stock additions to and deletions from an index experience significant changes in investor base and information environment, all of which are determinants of financial reporting quality (see, e.g., Dechow, Ge, and Schrand (2010) for a review). Consequently, the effect of index membership on the quality of mandatory reports is ex-ante unclear, and the importance of high-quality disclosure in well-functioning capital markets warrants further empirical investigation.

The primary purpose of mandatory disclosure is to protect investors, maintain fair, orderly, and efficient markets, and facilitate capital formation. By providing equal access to material information on time, mandatory disclosure reduces information asymmetries across different capital market participants and levels the playing field. In particular, understanding the link between stock indexing and the quality of mandatory reports is particularly relevant for small-cap firms that are often neglected by institutional investors, equity analysts, and financial journalists due to lack of visibility and high volatilities and trading costs (O'Brien and Bhushan (1990), Keim and Madhavan (1997), and Gompers and Metrick (2001)).[17] Relative to large-cap firms in a rich information environment, high-

[16] Media outlets such as the Wall Street Journal disseminate Russell index reconstitution schedules and the change in index constituents. See, e.g., "Russell Rebalancing Brings Frenzy to a Summer Friday: Surge in Trading Expected as Stocks Added to and Dropped from U.S. Benchmarks" by A. Loder, The Wall Street Journal, Jun. 27, 2019.

[17] Despite small market capitalization at the firm level, the small-cap universe as a whole is an important asset class. More than $1.6 trillion assets managed by both index and non-index funds track the Russell 2000 Small-Cap Index in 2018. See, e.g., "Are you following the wrong small-cap index?" by N. Bullock, Financial Times, Jun. 8, 2018.

quality mandatory disclosures face higher demand in the informationally constrained small-cap universe. If the quality of mandatory filing is systematically affected by index membership, it violates the intended purposes of mandatory disclosure and raises concern for the welfare and protection of investors.

How stationary is mandatory reporting quality? Unlike voluntary disclosure, the degree of freedom in mandatory filings such as 10-K and 10-Q is restrictive due to mandates stipulating the scope, item, and timing of disclosure. On top of regulation, managers often adhere to generic boilerplates to mitigate risks associated with the judicial and regulatory review (Lang and Stice-Lawrence (2015) and Cazier, McMullin, and Treu (2020)), and professional gatekeepers, including auditors and audit committees, ensure higher-quality financial statements (Roychowdhury and Srinivasan (2019)).

At the other end of the spectrum, capital market participants pay little attention to annual and quarterly mandatory filings, as reflected in the surprisingly low daily EDGAR download count of 10-K filings by retail investors (Loughran and McDonald (2017)) and under-reaction to filings (You and Zhang (2009)). Furthermore, material information is available through a timelier source such that lengthy and complex mandatory reports often serve a confirmatory purpose rather than a primary source of information (Gigler and Hemmer (1998)). When both supplier and demander perceive mandatory disclosure as a formality, the link between stock indexing and disclosure quality may be tenuous, and mandatory disclosure quality may remain unaffected around index turnover.

On the contrary, stock indexing could affect the quality of mandatory reports because managers exert substantial discretion in the informativeness and the amount of detail provided in mandatory filings. For example, managers have flexibility over the scope and aggregation of segments (Lang and Lundholm (1996)) and the numerical formats in financial statements and footnotes, affecting investor risk judgments (Nelson and Rupar (2015)). Indeed, Cohen, Malloy, and Nguyen (2020) document that period-over-period changes to the language and construction of mandatory financial reports contain value-relevant information and predict future performance, but investors are inattentive to these changes. Recent literature also documents that managers cater to institutional investor demand for higher quality disclosure by increasing the frequency and contents of 8-K filings (Boone and White (2015) and Bird and Karolyi (2016)).

To examine the effect of stock indexing on mandatory reporting quality of small-cap stocks, I utilize FTSE Russell's annual index reconstitution as a quasi-natural experimental setting and exploit a local random index assignment to draw causal inferences. Specifically, I employ a fuzzy regression discontinuity design (RDD) that estimates the post-reconstitution difference in financial reporting quality separately for stock additions to and deletions from the Russell 2000 Index.

The Russell US indices are leading performance benchmarks with more than \$9 trillion assets tracking their performance. To accurately represent the designated market performance, FTSE Russell rebalances its indices annually based on a mechanical set of rules. At the end of each May, FTSE Russell ranks the largest 4,000 eligible stocks to constitute the Russell 3000E Index, the broadest US equity index in FTSE Russell, and stocks ranked 1-1000 and 1001-3000 constitute the Russell 1000 and 2000 Index, respectively.[18] On the end-of-May rank day, small-cap stocks near the #3,000 cutoff are similar in observable characteristics, but small and random differences in their end-of-May total market cap affect the firm's ranking and cause discontinuous changes in the probability of Russell 2000 index membership.

I document the asymmetric effect of stock indexing on the quality of mandatory filings, as proxied by the level of error in financial statement data and textual properties. Whereas mandatory disclosure quality remains unchanged for micro-cap stock additions to the Russell 2000, small-cap stock deletions from the index experience exogenous deterioration in quality.

Specifically, the distribution of a firm's financial statement numbers diverges further from a theoretical distribution posited by Benford's Law following index deletion. Relative to the control firms, the mean absolute deviation and the maximum deviation from Benford's distribution increase by 9.4% and 19.4%, respectively. Whereas 81% of counterfactual stocks at the bottom of the Russell 2000 conform to Benford's Law, only 71% of stock deletions conform to Benford's Law following index assignment, highlighting a deterioration in the informational quality of reported financial results. Moreover, I document that stock indexing does not affect disaggregation quality, as proxied by the number of non-missing financial statement items. The null finding indicates that greater divergence from Benford's Law is not caused by a systematic change in the number of financial statement items.

Focusing on small-cap stock deletions from the Russell 2000, I delve into the source of error in financial statements. I find that the level of error in the balance sheet and income statement items increases, but the quality of the statement of cash flow items remains intact. Consistent with prior literature, accrual items are more susceptible to errors than cash flow items (Amiram, Bozanic, and Rouen (2015)). Next, I examine the effect of stock indexing on the quality of quarterly financial statement numbers and find greater divergence from Benford's Law. As with the findings on annual financial statements, small-cap index deletions exhibit a higher level of errors in the quarterly balance sheet and income statement items relative to counterfactual stocks. Furthermore, the increase in the level of error is not solely attributed to the fourth quarter but pervasive over interim quarters.

The index membership affects not only the quality of financial statement data but also 10-K textual disclosures. I find significant deletion effects on the amount of textual disclosure and tone ambiguity in 10-K filings, but no treatment effect on the readability. Relative to 10-K filings of counterfactuals, small-cap stock deletions use 9.5% fewer words (e.g., 4,620 words) and result in smaller net file size. Simultaneously, the tone of 10-K filings becomes more ambiguous due to a higher proportion of uncertain terms (e.g., approximate,

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[18] Starting with the 2007 reconstitution, FTSE Russell implements a banding policy to mitigate large-cap stocks' turnover near the #1,000 cutoff. The banding policy does not affect index assignments at the #3,000 cutoff.

contingency, uncertain, and indefinite) and weak modal words (e.g., might, possible, approximate, and contingent). Overall, a shorter and more ambiguous annual report could increase the informational risk and hinder investors' ability to process information. In extension, I examine the effect of index membership on textual disclosure in 10-Q filings. Because quarterly reports are less exhaustive in scope with fewer details and discussions, I fail to find a significant index membership effect on the firm's quarterly amount of textual disclosure and tone ambiguity.

While the RDD mitigates concerns for omitted correlated variables and reverse causality, the local treatment effect may lack external validity and fail to generalize to firms positioned further away from the reconstitution cutoff (e.g., Cattaneo, Idrobo, and Titiunik (2017)). Nonetheless, I find that RDD estimates around the #3,000 cutoff of the Russell 2000 are robust to alternative bandwidths and specifications.

What are the potential mechanisms behind the deterioration of mandatory reporting quality following index deletion? First, index deletion forces passive institutions to exit from their equity positions. If passive institutional investors demand higher-quality disclosure and effectively engage in widespread, low-cost monitoring of disclosure practice (Black (1992, 1998) and Appel, Gormley, and Keim (2016)), the reduction of passive institutional investors' monitoring efforts may increase managerial discretion and lead to quality deterioration. Second, index deletion may negatively affect the information environment, resulting in fewer analyst following and media coverage of micro-cap firms. Because both media and analysts play a governance role in aligning managers' and shareholders' interests (Jensen and Meckling (1976) and Dyck and Zingales (2002)), mandatory reporting quality may deteriorate following index deletion. Third, index deletion may trigger turnover in internal and external preparer of mandatory reports, such as accounting and financial officers and auditors. Disruption in the reporting process could result in lower quality mandatory filings. Lastly, a genuine improvement in reporting quality requires investment in the reporting process, such as hiring skilled management and Big-N auditor, but quality deterioration does not necessarily depend on additional investment.

I contribute to the accounting literature with new causal evidence of index membership on mandatory reporting quality. Financial reporting quality is a multifaceted concept with various empirical proxies capturing different quality dimensions, including the completeness, the confirmatory and predictive value, and the neutrality and freedom from error dimensions (see, e.g., Gaynor, Kelton, Mercer, and Yohn (2016) for a review). Recent papers examine the effect of an exogenous increase in passive institutional ownership on earnings attributes, including accruals and earnings quality, earnings management, and earnings comparability (Fang (2018) and Francis, Maharjan, and Teng (2018)). Different from papers that explicitly focus on summary statistics, I examine the neutrality and freedom from error dimensions of reporting quality with the distributional properties of financial statement numbers and complement the literature with the index deletion effect.

Next, I extend recent research on the determinants of textual disclosure, which have received less attention relative to the determinants of quantitative accounting data or the consequence of textual disclosure (Li (2008), Cazier and Pfeiffer (2016), and Dyer, Lang, and

Stice-Lawrence (2017)). Furthermore, I contribute to the growing literature on tone sentiment, with an emphasis on ambiguous tone in 10-K filings. While positive and negative tone received much attention (Huang, Teoh, and Zhang (2014) and Davis, Matsumoto, and Zhang (2015)), the literature on the causes and consequences of ambiguous text is nascent (Ertugrul, Lei, Qiu, and Wan (2017) and Jiang, Pittman, and Saffar (2019)).

Lastly, I fill the gap in prior accounting research using the Russell reconstitution setting by examining the treatment effects on small-cap stocks near the #3,000 reconstitution cutoff with the post-2006 sample. Prior accounting studies estimate the effect of an exogenous increase in passive institutional ownership on various outcomes, including tax avoidance and planning (e.g., Khan, Srinivasan, and Tan (2017) and Chen, Miao, and Shevlin (2019)), voluntary corporate disclosures (e.g., Lin, Mao, and Wang (2018)), 8-K filings (e.g., Bird and Karolyi (2016)), earnings attributes (e.g., Fang (2018) and Francis et al. (2018)), and reporting conservatism (e.g., Hillegeist, Penalva, and Weng (2019)). These studies utilize large-cap additions to the Russell 2000 near the #1,000 cutoff and end their sample in 2006 due to the banding policy that invalidates RDD. My study is the first accounting paper to examine the post-2006 sample, which covers the rapid growth in stock indexing. It also highlights the relevance of the #3,000 cutoff and the need for more research on the effect of index membership on small public firms.

The paper proceeds as follows. Section II describes the research design. Section III reports the empirical results. Section IV examines the robustness and potential channels of results. Section V concludes.

II. Research Design

A. Institutional background

FTSE Russell rebalances its family of US Russell indices annually to accurately track the designated market performance and reflect market changes in the preceding year. Russell's annual reconstitution is a highly anticipated event that follows a transparent timeline and mechanical rules in redefining the market-cap breakpoints separating the large-and small-cap universes.

On the rank day in each May, the largest 4,000 eligible stocks constitute the Russell 3000E Index, which is the broadest U.S. equity index in FTSE Russell, and a subset of stocks ranked 1-1000 and 1001-3000 constitute the Russell 1000 and 2000 Index, respectively.[19] Starting with the 2007 reconstitution, FTSE Russell implemented a banding policy at the #1,000 cutoff separating the Russell 1000 and 2000 Index to mitigate index turnover.[20] The banding policy does not affect index assignments at the #3,000 cutoff, which separates Russell 2000 constituents from stocks ranked 3001-4000 in the Russell 3000E Index.

The newly reconstituted Russell indices take effect after the market close on the last Friday in June. While end-of-May total market capitalization determines index membership, stocks' end-of-June, free-float market capitalization determines the initial index weights within Russell indices. Unlike the total shares outstanding, free-float shares exclude locked-in shares held by insiders, promoters, and governments.

B. Sample construction

The sample consists of the newly reconstituted Russell 3000E constituents between 2007 and 2016. While the annual constituent list is publicly available, Russell does not provide the actual index assignment variable (end-of-May market cap rankings) such that I replicate the end-of-May rankings with publicly available market cap data and predict index membership.[21]

Following Chang et al. (2015), I compute the end-of-May market cap with the closing price on the rank day and the number of total shares outstanding at the company level. For each constituent, I obtain Compustat shares outstanding data on the most recent earnings

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[19] Eligible securities include common stocks listed on eligible U.S. exchanges with a total market cap larger than $30 mil, rank day closing stock price at or above $1, and float over 5% of shares. See detailed information regarding the reconstitution methodology, timeline, and size breakpoints on FTSE Russell's website.

[20] The Russell methodology provides detailed information on the banding policy. The index assignment for stocks near the #1,000 cutoff is determined by a function of prior Russell 1000/2000 membership and the market cap ranking on the rank day. Also, see the research design of Chang et al. (2015) and Coles et al. (2020) for analyses at the #1,000 cutoff in the post-banding period.

[21] Because the actual index assignment variable (Russell's proprietary measure of end-of-May total market capitalization) is not available, prior studies often rank stocks using end-of-June Russell index weights. The usage of end-of-June weights violates the assumption of local random assignment and invalidates the RDD (see Chang et al. (2015) and Wei and Young (2020)).

report date before the rank day and adjust shares with CRSP factors to account for any corporate distribution between the fiscal quarter ends and the rank day. I also obtain CRSP shares outstanding on the rank day and choose the larger of Compustat and CRSP shares.

After sorting Russell 3000E constituents in descending order of their end-of-May market caps, I generate rankings relative to the official #3,000 breakpoint obtained from FTSE Russell's Client Service. The breakpoint value is the end-of-May total market cap of the smallest Russell 2000 stock and corresponds to zero rankings. Positive (negative) rankings identify stocks ranked below (above) the cutoff. Next, I predict Russell index turnover using prior index membership and relative market cap rankings.[22] Prior Russell 2000 members ranked at or above the #3,000 cutoff will remain in Russell 2000, whereas those ranked below will be deleted from Russell 2000 and move down to Russell 3000E. Similarly, prior Russell 3000E members ranked at or above the #3,000 cutoff will be added to Russell 2000, and those ranked below will remain in Russell 3000E.

C. Fuzzy regression discontinuity design

To estimate the causal effect of Russell 2000 membership, I exploit a random index assignment near the reconstitution cutoff as a quasi-experimental setting and implement a fuzzy regression discontinuity design (RDD) to compare the post-reconstitution difference in outcome variables between treated and counterfactuals. Next, I validate the RDD's local continuity assumption with lagged outcome variables measured prior to the reconstitution. Therefore, the sample period effectively ranges from July 2006 to June 2017. Appendix A provides the variable definitions.

Following Chang et al. (2015), I employ fuzzy RDD in the Russell reconstitution setting to account for incompliance with the treatment arising from the predicted index membership.[23] I specify the fuzzy RDD as a two-stage least squares system (Hahn et al. (2001)). The first stage examines the validity of an instrument by regressing the actual Russell 2000 index membership on the predicted index membership:

$$d_{it} = \alpha_0 + \alpha_1 \tau_{it} + \alpha_2 r_{it} + \alpha_3 (\tau_{it} \times r_{it}) + u_{it}$$

where d is the indicator for actual Russell 2000 index membership at the end-of-June, τ is the indicator for predicted Russell 2000 index membership, r is the end-of-May total market cap ranking centered at the index reconstitution cutoff (zero ranking) so that positive (negative) values represent stocks ranked below (above) the cutoff.

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[22] Identification at the #3,000 cutoff of the Russell 2000 hinges on the random assignment of small-cap stocks to the Russell 2000 and the Russell 3000E. Therefore, analysis at the #3,000 cutoff is feasible after the introduction of the Russell 3000E Index in 2005 (Chang et al. (2015) make a similar observation in their Internet Appendix). However, Cao, Gustafson, and Velthuis (2019) utilize a backtested list of index constituents and extend the small-cap sample prior to 2005.

[23] The canonical RD (sharp RD) assumes perfect compliance with the treatment and estimates the treatment effect as the difference in expected outcomes at the cutoff (e.g., Hahn, Todd, and Van der Klaauw (2001)). The fuzzy RD accounts for imperfect compliance by dividing the difference in expected outcomes by the change in the probability of treatment near the cutoff (e.g., Lee and Lemieux (2010) and Roberts and Whited (2013)).

$$y_{it} = \beta_0 + \beta_1 d_{it} + \beta_2 r_{it} + \beta_3 (d_{it} \times r_{it}) + \varepsilon_{it}$$

The second stage regresses each outcome variable, y, on the predicted index assignment, d, from the first stage, and the β_1 coefficient estimates the treatment effect separately for stock additions and deletions near the reconstitution cutoff.

I implement the fuzzy RDD using Calonico, Cattaneo, and Titiunik's (2015) rdrobust package and draw statistical inferences based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. The local polynomial estimation requires the choice of the kernel function, the order of the polynomial, and the bandwidth. The baseline specification is a local linear polynomial with a triangular kernel function, which places more weight on observations near the cutoff.

Cattaneo et al. (2017) and Gelman and Imbens (2019) caution that the use of higher-order polynomial rank control functions tends to produce overfitting of the data and yields unreliable results near boundary points. Therefore, employing a low-order polynomial is substantially more robust and less sensitive to boundary-related problems.

The bandwidth selection involves a trade-off between power and bias. A tighter bandwidth captures fewer observations near the cutoff and reduces power, while a wider bandwidth captures observations far from the cutoff and induces bias. I employ a fixed 200 bandwidth capturing 60% of index turnover and the mean squared error (MSE) optimal bandwidth in Imbens and Kalyanaraman (2012). The MSE-optimal bandwidth selection criterion optimally balances bias and variance and does not require a fixed bandwidth choice. Nevertheless, I examine the sensitivity of the results to alternative specifications in the robustness test and find consistent results.

D. Benford's Law

1. Background

First discovered by astronomer Simon Newcomb in 1881 and tested in various samples by physicist Frank Benford in 1938, Benford's Law posits the distribution of the first digits of naturally-occurring numbers converges to the base ten logarithms of first digits:

$$Benford's\ Distribution_d = log_{10}\left(1 + \frac{1}{d}\right),$$

where d refers to the leading digits from one to nine.

Formally, the distribution of the first digits of a collection of random samples drawn from a random distribution of numbers will converge to Benford's distribution (Hill (1995)).

Benford's Law is used in various disciplines such as mathematics, statistics, and economics to detect errors in a large dataset (see, e.g., Varian (1972) and Michalski and Stoltz (2013)). In accounting, researchers and practitioners apply Benford's Law to the internal account detail and transactional data to detect fraud and examine audit quality and tax compliance (Nigrini (1996, 2012), Durtschi, Hillison, and Pacini (2004), Nigrini and Miller (2009)).

Amiram et al. (2015) provide empirical evidence that Benford's Law statistics capture financial statement data quality. They find that financial statement data with greater divergence from Benford's distribution is positively associated with accrual-based earnings management proxies, is negatively associated with earnings persistence, and predicts material misstatements and restatements.

Benford's Law statistics offer several advantages over existing measures of accounting quality. Theoretically, firm characteristics or business models do not affect the distribution of digits in financial statements and cause greater divergence from Benford's distribution. The correlation between firm characteristics and existing quality measures is a significant limitation of the accruals-based models (Dechow et al. (2010) and Owens, Wu, and Zimmerman (2016)).[24] Moreover, the test statistics are free from traditional prediction models and do not require time-series, cross-sectional, forward-looking, or return data to estimate, allowing maximum coverage in the small-cap universe.

2. Measuring Test Statistics

I employ four firm-year test statistics to examine financial statement data conformity to Benford's Law. Each test statistic utilizes all line items in the balance sheet, income statement, and statement of cash flows. Eligible firm-year financial data comes from Compustat and requires non-missing and non-zero values. For variables quoted in decimal values, I take the first non-zero digit of the absolute value.

The Mean Absolute Deviation (MAD) statistic is the mean absolute difference between the empirical distribution of the leading digits in a firm's annual financial statements and the theoretical distribution in Benford's Law. It assesses the overall shift in the empirical distribution of leading digits in financial statement data where the higher value indicates greater divergence from the law. Following is the calculation of MAD for firm i in time t:

$$MAD_{i,t} = \left(\sum_{d=1}^{9} \left|AD_{i,t,d} - ED_{i,t,d}\right|\right) / 9$$

where d refers to the leading digits from one to nine, AD (actual distribution) is the empirical proportion of the leading digits, and ED (expected distribution) is the theoretical proportion of the leading digits in Benford's Law.

While the scale invariance of the MAD statistic enables comparability across firms and through time, a smaller sample size could mechanically inflate deviation in the proportion of the leading digits (the small denominator problem). In order to account for potential

[24] Despite its theoretical appeal, Benford's Law statistic may be spuriously correlated with firm profitability because unprofitable firms may be more likely to manipulate their financial statements (Amiram et al. (2015)). In untablulated analyses, I test differences in profitability between treated and counterfactual firms before and after the reconstitution. Across various profitability measures, including Gross Margin, ROA, ROE, and Book-to-Market, the estimated fuzzy RD treatment effects are indistinguishable from zero and robust to alternative specifications. The null findings reassure that the treatment effects on Benford's Law statistics do not reflect sampling bias.

continuity frictions in smaller samples, the Standardized Mean Absolute Deviation (SMAD) statistic incorporates the total number of digits used in the MAD calculation (Barney and Schulzke (2015) and Bowler (2016)). For each number of digits used in the sample, I compute 10,000 benchmark MAD statistics by drawing the leading digits based on the theoretical Benford distribution. The standardization subtracts the average benchmark MAD statistic from the actual firm-year MAD statistic, then scales the difference by the standard deviation of the benchmark MAD statistics. The higher value of SMAD still indicates greater divergence from Benford's Law, allowing comparison across firm-year statistics measured with the different number of the leading digits. Following is the calculation of SMAD for firm i in time t:

$$SMAD_{i,t} = \frac{\left(MAD_{i,t} - Mean\left(Benchmark\ MAD_p\right)\right)}{SD\left(Benchmark\ MAD_p\right)}$$

where p refers to the total number of digits used to calculate $MAD_{i,t}$, and the underlying $Benchmark\ MAD_p$ is drawn 10,000 times based on Benford's distribution for the number of leading digits used in actual firm-year samples.

The Kolmogorov–Smirnov (KS) statistic captures the maximum deviation of the cumulative difference between the empirical and the theoretical distribution of the leading digits in financial statements. Following is the calculation of KS for firm i in time t:

$$KS_{i,t} = Max\begin{pmatrix} \left|\sum_{d=1}^{1} AD_{i,t,d} - \sum_{d=1}^{1} ED_{i,t,d}\right|, \\ \left|\sum_{d=1}^{2} AD_{i,t,d} - \sum_{d=1}^{2} ED_{i,t,d}\right|, \\ \dots, \\ \left|\sum_{d=1}^{9} AD_{i,t,d} - \sum_{d=1}^{9} ED_{i,t,d}\right| \end{pmatrix}$$

Contrary to the MAD and the SMAD statistic, the KS statistic offers a critical value to test the firm-level conformity to Benford's distribution. Following Amiram et al. (2015), I examine the distributional conformity with the critical value at the 5% level, which is defined as 1.36 divided by the square root of the total number of digits used.

III. Empirical Results

Section III presents evidence on the causal effect of index membership on the quality of mandatory disclosure. First, I provide descriptive statistics for stocks near the #3,000 reconstitution cutoff and document the asymmetric effect of stock indexing on mandatory disclosure quality. Whereas mandatory disclosure quality remains unchanged for stock additions to the Russell 2000, the quality deteriorates for stock deletions from the index. Next, focusing on the deletion effect, I identify the source of annual financial statement error and explore the treatment effect on the length and tone of textual disclosure in annual 10-K filings. Lastly, I extend the analyses to quarterly statements (10-Q filings).

A. Descriptive statistics

Table 1 reports the average values of pre-reconstitution characteristics for stocks within a fixed 200 bandwidth around the #3,000 reconstitution cutoff. The average market capitalization is approximately $150 million, and the aggregate market cap of small-cap index turnover amounts to $40 billion due to the high turnover rate at the #3,000 cutoff.

On average, institutional investors hold 43.6% shares with a split between 5.6% and 38% shares held by passive indexers (Index IO) and active institutions (Non-Index IO). The percentage of shares held by exchange-traded funds, a subset of passive indexers, accounts for 1.3% of the total equity stakes.

Regarding the level of error in annual financial statement data, the average mean absolute deviation (MAD) statistic is 3.26, with a standard deviation of 1.13, and 74% firm-years conform to Benford's Law at the 5 % level. The average size of textual disclosure in 10-K filings is 0.35 megabytes with 47,000 words, and the average percentage of ambiguous words is 2.06%. Consistent with prior literature, the Fog Index displays limited variability with a mean value of 20 and a standard deviation of 1.

The limited media and analyst coverage highlights how small-cap stocks near the #3,000 cutoff are informationally constrained. 80% of sample firms have analyst coverage, but only 53% of firms are followed by more than two equity analysts. On average, 3.3 equity analysts provide 29 EPS forecasts during the index membership year, highlighting the limited analyst interest in the small-cap universe. Similarly, media coverage is limited, with five daily news articles addressing the small-cap stocks on average. Lastly, the frequency of Big-4 and 6 auditor is 52% and 64%, respectively.

B. The effect of stock indexing on annual financial statement data quality

Table 2 presents the estimated index membership effects on the post-reconstitution quality of annual financial statement data. The post-reconstitution window includes 10-K filings with a fiscal month between July and next June. I evaluate mandatory disclosure quality by examining the distributional conformity of financial statement data to Benford's Law. For brevity, I discuss the estimates under the main RD specification based on a fixed 200 bandwidth, triangle kernel, and linear-polynomial function.

I find the asymmetric effect of Russell 2000 membership on the quality of financial statement data around stock additions and deletions. Whereas financial statement quality remains unchanged for stock additions to the Russell 2000, the quality deteriorates for stock deletions from the index. The estimated treatment effects show a 0.28 (0.36) higher level or 9.4% (19.4%) increase in the MAD (SMAD) statistic for deletions relative to counterfactuals. Similarly, the level of the KS statistic is 1.37 higher (increases by 15.8%) for deletions, resulting in a 10% lower number of firm-year that conform to Benford's distribution at the 5% level. Specifically, 81% of counterfactual firms conform to Benford's distribution, but only 71% of deletions conform after the reconstitution.[25]

In addition to Benford's Law, I examine the number of non-missing financial items reported in firms' annual financial statements. Chen, Miao, and Shevlin (2015) construct a new measure of disclosure quality, disaggregation quality, by counting the number of non-missing Compustat items. Because greater disaggregation leads to finer information available to investors, an increase in the number of items indicates higher disclosure quality. On top of directly measuring the level of disaggregation, the measure highlights a link between the number of available items and the deviation from Benford's Law, complementing the SMAD statistic. I find no treatment effect on the number of non-missing Compustat items for both stock additions and deletions. The null findings indicate that disaggregation quality remains the same, and greater divergence from Benford's Law is not attributed to a systematic change in the number of non-missing items.

Figure 1 visualizes the discontinuity in the divergence of annual financial statement data from Benford's Law for small-cap deletions from the Russell 2000. Stocks within a fixed 200 bandwidth centered at the lower cutoff (zero ranking) are placed into ten equal-spaced bins on either side of the reconstitution cutoff, and each dot represents the mean values of Benford's Law test statistics. The solid red dots to the right of the cutoff represent the predicted deletions from the Russell 2000, and the hollow dots to the left of the cutoff represent the counterfactuals. Consistent with the RDD estimates, the post-reconstitution level of the MAD statistic in Panel A and the KS statistic in Panel B is discontinuously higher for deletions.

The estimated treatment effects are robust to alternative RDD specifications. In Table 6, I re-estimate the treatment effect using a uniform weight that equal weights observations within the bandwidth, including year fixed effects, and employing a second-order polynomial. Table 6, Panel A and B report consistent results for small-cap stock additions and deletions.

To rule out the pre-existing discontinuity in the level of error in financial statement data driving the index membership effect, I conduct the balance test with lagged dependent variables measured prior to the annual reconstitution. In Appendix B, Panel A, the estimated pre-reconstitution effects on Benford's Law test statistics and the number of non-missing Compustat items are economically small and statistically insignificant. The null results

[25] Amiram et al. (2015) report that 86% of their sample firms conform to Benford's distribution at the 5% level, which is in line with the frequency of small-cap counterfactuals used in the sample.

corroborate that both treated and counterfactual firms exhibit a similar pre-reconstitution level of financial statement data quality and eliminate selection bias concerns.

C. The index deletion effect on the quality of financial statement partitions

Having shown that index deletion causes an exogenous deterioration in financial statement data quality, I delve into the source of higher error by partitioning financial statements into accrual and cash flow components. I measure Benford's Law test statistics and the number of non-missing Compustat items separately for the balance sheet and income statement and the statement of cash flows, using 10-K filings whose fiscal month falls between July and next June.

The first two columns in Table 3 present the index deletion effect on the level of error in the balance sheet and income statement items. Under a fixed 200 bandwidth, the estimated effects show a 0.33 (0.38) higher level or 10.1% (20.4%) increase in the MAD (SMAD) statistic for deletions relative to counterfactuals. Similarly, the level of KS statistic is 1.46 higher (increases by 15.2%) for deletions, resulting in a 9% lower number of firm-year that conform to Benford's distribution at the 5% level. Specifically, 80% of counterfactual firms conform to Benford's distribution, but only 71% of deletions conform after the reconstitution.

Contrary to the higher level of error in the balance sheet and income statement, the level of error in the statement of cash flows remains unaffected for deletions following the annual reconstitution. The RDD estimates in the last two columns of Table 3 are indistinguishable from zero, except for the KS statistic that is marginally significant at the 10% level. The finding is in line with Amiram et al. (2015), who identify that the statement of cash flows is least susceptible to errors, with 97% of sample firms conforming to Benford's distribution at the 5% level.[26]

Figure 2 visualizes the discontinuity in the level of error in the partitions of annual financial statement data for small-cap deletions from the Russell 2000. Panel A plots the mean absolute deviation (MAD) statistics for the balance sheet and income statement items, and Penal B plots the results for cash flow items. Consistent with the RDD estimates, the post-reconstitution level of the MAD statistic increases discontinuously for the balance sheet and income statement data while remains similar for cash flow data.

The estimated treatment effects are robust to alternative RDD specifications, and I find no index deletion effect on the number of non-missing items in financial statement partitions. The null results indicate that the quality of disaggregation remains the same, and greater divergence from Benford's Law in the balance sheet and income statement is independent of the number of non-missing items.

[26] Consistent with Amiram et al. (2015), I find that the statement of cash flow is least susceptible to errors with 96% sample firm-year conformity and 73% sample firm-year conformity in the pool of balance sheet and income statement data. Decomposing accrual items into the balance sheet and the income statement, 83% and 64% of sample firm-year conform to Benford's Law, respectively.

In Appendix B, Panel B, the estimated pre-reconstitution effects on Benford's Law test statistics and the number of non-missing Compustat items are economically small and statistically insignificant. The null results corroborate that both treated and counterfactual firms exhibit a similar pre-reconstitution level of financial statement data quality and eliminate selection bias concerns.

D. The index deletion effect on quarterly financial statement data quality

I examine whether the index deletion effect on annual financial statement data quality extends to quarterly statements. Because annual financial statement data incorporates interim quarter performance, I expect the distribution of quarterly financial data to deviate further from Benford's distribution for stock deletions relative to counterfactuals that remain in the Russell 2000. Moreover, quarterly data quality may deteriorate since quarterly financial statements are not audited but only reviewed.

Table 4 presents the estimated index deletion effects on the level of quarterly financial statement data errors. The post-reconstitution window includes 10-Q filings with a fiscal quarter between July and next June. First, I measure conformity to Benford's Law for each firm-quarter using all eligible items in Quarterly Compustat for the overall financial statement and its partitions.[27] Next, I average each firm-quarter test statistic within the post-reconstitution window, excluding the fourth fiscal quarter, and estimate the quarterly average of financial statement data quality.[28]

Consistent with the deletion effects on annual financial statement data, the distribution of the leading digits in quarterly data deviates further from Benford's theoretical distribution due to error in the balance sheet and income statement items, not the cash flow items. The number of non-missing Quarterly Compustat items remains unaffected after the reconstitution.

Under a fixed 200 bandwidth, the treatment effect on the quality of the overall quarterly statement items shows a 0.20 (0.29) higher level or 5.6% (8.8%) increase in the MAD (SMAD) statistic for deletions relative to counterfactuals. Similarly, the KS statistic is 0.7 higher (increases by 6.8%) for deletions, but the frequency of sample firms conforming to Benford's distribution at the 5% level remains the same between deletions and counterfactuals. Within financial statement partitions, the estimated treatment effect on the balance sheet and income statement partitions shows a 0.24 (0.32) higher level or 6.1% (9.2%) increase in the MAD (SMAD) statistic for deletions. The KS statistic is 0.92 higher (increases by 8.2%) for deletions.

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[27] Compustat provides annual financial statement items by partitions but provides quarterly items in aggregate. To classify quarterly items to the balance sheet, income statement, and statement of cash flows, I utilize both annual item names and CRSP's list of year-to-date income statement items.

[28] In untabluated analysis, I incorporate the fourth fiscal quarter financial statement and find a consistent RD treatment effect. The findings highlight that the deterioration in annual data is not sorely attributed to the fourth-quarter results.

Overall, the treatment effects on quarterly financial statement data quality are robust to alternative RDD specifications and unlikely driven by the pre-existing difference in quality. Appendix B, Panel C, presents the lack of pre-existing discontinuities in Benford's Law test statistics measured using the overall and partitions of quarterly statements.

E. The index deletion effect on textual disclosure

This section examines whether index membership affects textual disclosure in 10-K and 10-Q filings. Prior literature finds that a manager caters to the demand for higher quality disclosure by increasing the frequency and the contents of 8-K filings following an exogenous increase in institutional ownership (Bird and Karolyi (2016)). However, evidence on the effect of index membership on textual disclosure in annual and quarterly filings is limited. To fill this gap, I focus on the length, readability, and sentiment dimensions of textual disclosure (Miller (2010), Lang and Stice-Lawrence (2015), Loughran and McDonald (2016), and Jiang et al. (2019)).

Length, often measured by the file size or word count, captures the amount of textual disclosure. The net file size is the natural logarithm of 10-K/Q document size in megabytes, excluding non-textual components such as tables, exhibits, HTML, and encoded images. The word count is the natural logarithm of the word count from 10-K/Q filings, based on words appearing in the Loughran–McDonald Master Dictionary. Next, I access reading difficulty with the Fog and the Smog Index.[29] Lastly, the frequency of words appearing in the sentiment categories of Loughran-McDonald Master Dictionary gauges the tone of 10-K/Q filings (Loughran and McDonald (2011)). In particular, I focus on tone ambiguity, a combined frequency of uncertain terms (e.g., approximate, contingency, uncertain, and indefinite) and weak modal words (e.g., might, possible, approximate, and contingent) in 10-K/Q filings, to proxy for additional informational risk in processing the report.

Table 5 presents the index deletion effects on textual disclosure in 10-K and 10-Q filings following the annual reconstitution. The post-reconstitution window includes mandatory filings with a fiscal month between July and next June. Consistent with financial statement data quality, I find an asymmetric effect on textual properties and focus the discussion on the index deletion effects.

Under a fixed 200 bandwidth, the estimated treatment effects in Table 5 show a -0.10 (-0.10) lower level or 9.9% (0.93%) decrease in the natural logarithm of the net file size (the word count) for small-cap deletions relative to counterfactuals remaining in the Russell 2000 Index. Despite a significant reduction in the amount of textual disclosure, the coefficient estimates on the Fog and the Smog Index are indistinguishable from zero. The null

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[29] The Fog Index is defined as 0.4 times the sum of the average number of words per sentence and percent of polysyllables in each sentence. The Smog index is defined as 1.043 * square root (number of polysyllables * 30/number of sentences) + 3.129. In addition to the Fog and the Smog Index, WRDS SEC Analytics Suite provides additional readability measures, ranging from the Flesch readability formula to the LIX Readability Index. For brevity, I report the Fog and the Smog Index, but find consistent treatment effects across all readability measures in untabulated analyses.

findings in readability highlight the distinction between length and readability, indicating a shorter report is not necessarily easier to read. Regarding the post-reconstitution tone of 10-K filings, the percentage of ambiguous words, including uncertain terms and weak modal words, increases significantly for deletions. On the contrary, the word frequency in other sentiment categories, including negative, positive, litigious, strong modal, and constraining, remains similar between deletions and counterfactuals.

Figure 3 visualizes the treatment effects on the amount of textual disclosure and the frequency of ambiguous words in 10-K filings. As before, the graph plots mean values across equally-spaced bins within a fixed 200 bandwidth of the cutoff, and solid red dots (the hollow dots) represent the predicted deletions (counterfactuals). In Panel A, the amount of textual disclosure, as captured by the natural log of word count, is discontinuously lower for deletions. In Panel B, the usage of ambiguous words is discontinuously higher for deletions. Sharp discontinuities in both RDD estimates and visual evidence suggest that a shorter and more ambiguous annual report could increase informational risk and hinder investors' ability to process information.

In contrast to significant index deletion effects on 10-K textual disclosure, I find no treatment effects on the length, tone, and readability dimensions of 10-Q textual disclosure. The null findings are not surprising since quarterly reports are less exhaustive in scope with fewer details and discussions. On average, 10-Q (10-K) filings contain 10 (18) items, and the average word count in 10-Q (10-K) filings is 18,277 (46,972) words with the standard deviation of 12,675 (25,599) for small firms near the reconstitution cutoff. Furthermore, more frequent quarterly filings exhibit lower cross-sectional and over-time variation in textual disclosure (e.g., Cohen et al. (2020)).

Overall, the treatment effects on textual disclosure are robust to alternative RDD specifications and unlikely driven by the pre-existing difference in quality. Table 6, Panel B, presents consistent RD estimates under alternative specifications, and Appendix B, Panel D, confirms insignificant pre-reconstitution treatment effects on textual disclosure.

In summary, the evidence shows that index deletion reduces the amount of textual disclosure and simultaneously increases the frequency of ambiguous words in 10-K filings. Sharp discontinuities in both RDD estimates and visual evidence, combined with insignificant pre-reconstitution treatment effects on textual disclosure, reassure the index deletion effects on textual disclosure. All else equal, shorter and more ambiguous annual reports will be less informative to investors and increase informational risk, indicating a deterioration in textual disclosure quality.

IV. Robustness and Additional Analyses

A. Alternative specifications

In the manuscript, I estimate the discontinuity in outcome variables in a local linear regression with a triangular kernel function that places more weight on observations near the cutoff. As a robustness check, I estimate the local average treatment effects with a uniform kernel function that equally weights sample firms near the cutoff and include year fixed effects as baseline covariates. Lee and Lemieux (2010) note that RDD identification does not require other baseline covariates, including fixed effects. Under the valid RD design, the use of other baseline covariates reduces sampling variability and increases efficiency. Next, I relax the linearity assumption with a quadratic polynomial function.[30]

Table 6 provides evidence that the estimated index membership effects on financial statement data quality and textual disclosure are consistent and robust to alternative specification and bandwidth choices. Table 6, Panel A, presents the index membership effects on stock additions to the Russell 2000. Across all measures of the quality of quantitative and qualitative information in mandatory filings, the addition effect is small and insignificant. On the flip side, Table 6, Panel B, confirms the significant index deletion effect on the level of financial statement errors and the length and tone ambiguity of 10-K filings.

B. Potential channels

In this section, I explore potential channels through which index membership affects mandatory reporting quality. To explain the deterioration in mandatory disclosure quality following index deletion, I examine post-reconstitution discontinuities in the level of passive institutional ownership, information environment, including news coverage and analyst following, management turnover, and the firm's choice of Big-N auditor.

1. Passive institutions

The first channel is the presence of passive institutional investors engaging in widespread, low-cost monitoring of disclosure practice.[31] To the extent that "the integrity of the numbers in the financial reporting system is directly related to the long-term interests of a corporation" (Levitt (1998)), passive institutions with long investment horizons could benefit from high-quality financial reports as they increase the value of assets under management (Del Guercio and Hawkins (1999)) and reduce transaction costs. Consistent with this notion, recent literature documents that passive institutional investors wield considerable power over their holdings by engaging in the active governance and monitoring role (see, e.g., Bebchuk and Hirst (2019) for a review). As passive institutions exit from

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[30] Following the recommendation of Cattaneo et al. (2017) and Gelman and Imbens (2019), I do not examine third, fourth, or higher-degree polynomials that lead to noisy and overfitted estimates.

[31] BlackRock, one of the indexing giants, claims in its investment stewardship that it recognizes the critical importance of financial statements, believes that shareholders have a right to timely and detailed information on the financial performance, and takes particular note of cases involving significant financial restatements or ad hoc notifications of material financial weakness.

equity positions following index deletion, the reduction in monitoring effort may increase managerial discretion and lead to deterioration in disclosure quality.

I obtain the September level of institutional ownership, the first available quarterly value after the reconstitution, from the Factset Global Ownership Database. Table 7 presents the index deletion effect on the breakdown of institutional ownership based on Factset's classification. The treatment effect shows a -4.22% (-1.57%) lower level of the index (ETF) institutional ownership for stock deletions from the Russell 2000 relative to counterfactuals, indicating a significant reduction in monitoring effort of passive institutions. On the contrary, the ownership of non-index institutions remains comparable between treated and counterfactuals.

2. Information environment

The second channel is a change in the information environment following index deletion. Prior literature documents that both media and analysts could play a governance role in aligning managers' and shareholders' interests (Jensen and Meckling (1976) and Dyck and Zingales (2002)), which in turn could affect financial reporting quality. However, equity analysts and financial journalists often neglect small-cap index deletions due to small size and lack of visibility. If index deletion permanently reduces a firm's visibility, as proxied by lower news and analyst coverage, the quality of mandatory filings may deteriorate.

I obtain daily news coverage data from RavenPack News Analytics and measure the average and the total number of daily news articles during the year of index membership. Similarly, I obtain equity analyst data from IBES detailed EPS file and measure the number of unique analysts and annual and quarterly EPS forecasts during the year of index membership. In Table 7, the estimated index deletion effects on the news coverage, analyst following, and the number of EPS forecasts are indistinguishable from zero and robust to alternative RDD specification.[32] The lack of exogenous discontinuity in media and analyst coverage suggests that the information environment is an unlikely channel.

3. Internal and external preparers

The third channel is a change in inside preparers and external auditors who are directly involved in the preparation of financial reports. If index membership causes a discontinuous change in the management or auditor, disruption in the reporting process could affect financial reporting quality (see, e.g., Healy and Palepu (2001), Dechow et al. (2010), and DeFond and Zhang (2014)).

I obtain management turnover data from the Director and Officer Changes database of Audit Analytics, which collects a director or officer change in Item 5.02 of an 8-K or 8-K/A filings and identifies the management position based on the annual title. To identify turnover in inside preparers of mandatory reports, I create indicators for the turnover of financial persons, including CEO, CFO, audit committee, and accounting and finance officers, during

[32] Cao et al. (2019) also examine the number of analyst following and EPS forecasts near the #3,000 cutoff and report no changes for small-cap stock deletions.

the year of index membership. Lastly, I examine the choice of Big-4(6) auditor using the audit fee database of Audit Analytics.

Table 7 presents the index deletion effect on the insider turnover and the choice of Big-4(6) auditor. The coefficient estimates are indistinguishable from zero and robust to alternative RD specifications. Furthermore, I do not detect pre-existing discontinuities in lagged outcome variables, indicating that treated stocks and counterfactuals were similar prior to the index reconstitution.

In summary, null results in the information environment and financial report preparer channel suggest the presence of index institutions as a potential mechanism in ensuring mandatory reporting quality for small public firms.

V. Conclusion

This paper examines the causal effect of index membership on the quality of mandatory financial reports for small public firms, which various capital market participants neglect due to lack of visibility and high volatilities. By exploiting quasi-random assignment to the Russell 2000 Index near the lower reconstitution cutoff, I find the asymmetric index membership effects on mandatory reporting quality. Whereas addition to the Russell 2000 does not affect reporting quality, deletion from the Russell 2000 introduces more error to annual and quarterly financial statement numbers, reduces annual textual disclosure, and increases tone ambiguity in 10-K filings. In summary, index deletion causes a higher informational risk to investors in the small-and micro-cap universes where high-quality mandatory reports are needed the most.

I explore potential channels through which index deletion deteriorates the quality of mandatory reports. While index deletion from the Russell 2000 causes an exogenous reduction in passive institutional ownership, the effects on alternative governance mechanisms, such as media coverage and analyst following, and shocks to internal and external preparers of the report remain unchanged. The evidence suggests a reduction in passive institutional investors' monitoring effort as a potential mechanism.

The popularity of stock indexing and the growing power of indexing giants fuel the debate on the pros and cons of stock indexing. While not all sides are bright with indexing, my findings suggest the positive role of index membership and passive institutional investors in ensuring mandatory reporting quality for public firms in the informationally constrained universe. Lastly, the consequence of stock indexing to small firms deserves more research as prior indexing literature exclusively focuses on large-cap additions before 2007. While prior studies are well executed, it remains an open question whether results generalize from large-cap to small-cap stocks and from the pre-2006 period to the post-2006 period.

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TABLE 1: Pre-reconstitution firm characteristics

This table reports the pre-reconstitution mean values of characteristics for stocks within a fixed 200 bandwidth around the #3,000 reconstitution cutoff. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions. Institutional ownership (IO) is the percentage of shares held by institutional investors. Holdings are grouped by Factset's index, non-index, and ETF holdings classification. The MAD, the SMAD, and the KS statistic measure the deviation from Benford's Law. I(KS conformity) tests whether the KS statistic is not significantly different from zero at the 5 % level. Ln(# items) counts the number of Compustat line items with non-missing values. Ln(NetFileSize) and Ln(Words) are the natural log of the character size in megabytes and word counts in 10-K filings. Fin-Ambiguity is the proportion of uncertainty terms and weak modal words in 10-K filings. The Fog and the Smog Index access reading difficulty. I(Analyst Coverage), I(# Analysts>=3), and Ln(# Analysts) are based on the number of unique analysts issuing EPS forecasts, using analyst data from IBES detailed EPS file. Ln(# Analyst Forecasts) measure the total number of annual and quarterly EPS forecasts issued by analysts during the prior index membership. The average and the total number of daily news articles are measured during the prior index membership, using news coverage data from RavenPack News Analytics. I(Big 4 Auditor) and I(Big 6 Auditor) capture the frequency of Big 4 and 6 Auditor, using Audit Analytics data.

	+/- 200 bandwidth		
	Mean	Median	Stdev
End-of-May Market Cap ($MN)	$146.80	$138.36	$57.72
Index IO (%)	5.60	4.77	4.42
Non-Index IO (%)	38.04	35.76	22.46
ETF IO (%)	1.30	0.62	1.62
Total IO (%)	43.64	41.06	24.70
MAD (%)	3.26	3.10	1.13
SMAD	2.16	2.01	1.68
KS (%)	9.68	8.90	4.56
I(KS Conformity)	0.74	1.00	0.44
Ln(# Items)	5.47	5.55	0.19
Words	46,972	41,363	25,599
Ln(Words)	10.66	10.63	0.43
NetFileSize(MB)	0.35	0.32	0.18
Ln(NetFileSize)	-1.13	-1.15	0.41
Fin-Ambiguity (%)	2.06	2.03	0.46
Fog Index	20.24	20.17	0.98
Smog Index	17.56	17.51	0.68
I(Analyst Coverage)	0.80	1.00	0.40
I(#Analysts >=3)	0.53	1.00	0.50
Ln(# Analysts)	1.20	1.39	0.77
Ln(# Analyst Forecasts)	2.55	3.00	1.55
Ln(Avg Daily News)	1.71	1.62	0.47
Ln(Total Daily News)	5.01	4.98	0.85
I(Big 4 Auditor)	0.52	1.00	0.51
I(Big 6 Auditor)	0.64	1.00	0.51

TABLE 2: The effect of stock indexing on conformity to Benford's Law

This table reports second-stage fuzzy RDD results for conformity of 10-K financial statement data to Benford's Law after the annual Russell reconstitution. The test statistics utilize all financial statement variables in the balance sheet, income statement, and statement of cash flow. The MAD and the Standardized MAD (SMAD) statistics access the mean absolute deviation from Benford's distribution of leading digits. The KS statistic accesses the maximum deviation from Benford's distribution, and I(KS conformity) reports the frequency of the KS statistic that is not significantly different from zero at the 5 % level. Ln(# Items) counts the number of Compustat line items with non-missing data. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Additions compare firms added to the bottom of the Russell 2000 against firms that remain just outside the index. Conversely, deletions compare firms that move out of the Russell 2000 against firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

		Additions		Deletions	
Dept. Variables	bws.	200	OPT	200	OPT
MAD	coef	0.06	0.06	0.28**	0.22**
	z-stat	0.54	0.51	2.43	2.33
	obs.	1,614	1,870	1,842	2,662
SMAD	coef	0.12	0.12	0.36**	0.28*
	z-stat	0.67	0.71	2.02	1.89
	obs.	1,614	1,882	1,842	2,662
KS	coef	-0.27	-0.30	1.37***	1.30***
	z-stat	-0.56	-0.64	2.87	2.88
	obs.	1,614	1,790	1,842	2,065
I(KS Conformity)	coef	-0.03	-0.02	-0.10**	-0.09**
	z-stat	-0.59	-0.40	-2.13	-2.25
	obs.	1,614	1,984	1,842	2,529
Ln(# Items)	coef	0.01	0.00	-0.01	-0.01
	z-stat	0.53	0.16	-0.36	-0.31
	obs.	1,614	2,416	1,842	2,029

TABLE 3: The index deletion effect on conformity to Benford's Law by partitions

This table reports second-stage fuzzy RDD results for conformity of 10-K financial statement data to Benford's Law after the annual Russell reconstitution. The test statistics utilize all financial statement variables in the balance sheet and income statement, and the statement of cash flow. The MAD and the Standardized MAD (SMAD) statistics access the mean absolute deviation from Benford's distribution of leading digits. The KS statistic accesses the maximum deviation from Benford's distribution, and I(KS conformity) reports the frequency of the KS statistic that is not significantly different from zero at the 5 % level. Ln(# Items) counts the number of Compustat line items with non-missing data. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Focusing on deletions, the sample includes firms that move out of the Russell 2000 and firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

		BS & IS		CFS	
Dept. Variables	bws.	200	OPT	200	OPT
MAD	coef	0.33**	0.26**	0.27	0.27
	z-stat	2.57	2.46	1.45	1.44
	obs.	1,842	2,618	1,837	1,851
SMAD	coef	0.38**	0.28*	0.17	0.16
	z-stat	2.16	1.96	1.42	1.36
	obs.	1,842	2,792	1,837	1,994
KS	coef	1.46***	1.21***	1.40*	1.47*
	z-stat	2.85	2.66	1.80	1.72
	obs.	1,842	2,360	1,837	1,564
I(KS Conformity)	coef	-0.09**	-0.08**	0.00	0.00
	z-stat	-1.97	-1.98	-0.06	-0.08
	obs.	1,842	2,253	1,837	1,920
Ln(# Items)	coef	-0.01	-0.01	0.00	0.00
	z-stat	-0.35	-0.30	-0.35	-0.27
	obs.	1,842	2,022	1,837	2,128

TABLE 4: The index deletion effect on conformity to Benford's Law in 10-Q filings

This table reports second-stage fuzzy RDD results for the average conformity of 10-Q financial statement data to Benford's Law after the annual Russell reconstitution. Variables of interest are measured for each quarter then averaged across the post-reconstitution window. The test statistics utilize all financial statement variables in the balance sheet and income statement, and the statement of cash flow. The MAD and the Standardized MAD (SMAD) statistics access the mean absolute deviation from Benford's distribution of leading digits. The KS statistic accesses the maximum deviation from Benford's distribution, and I(KS conformity) reports the frequency of the KS statistic that is not significantly different from zero at the 5 % level. Ln(# Items) counts the number of Compustat line items with non-missing data. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Focusing on deletions, the sample includes firms that move out of the Russell 2000 and firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

		All		BS & IS		CFS	
Dept. Variables	bws.	200	OPT	200	OPT	200	OPT
MAD	coef	0.20**	0.21**	0.24**	0.24**	0.07	0.08
	z-stat	2.11	2.24	2.31	2.45	0.58	0.69
	obs.	1,901	2,072	1,901	2,158	1,899	2,254
SMAD	coef	0.29*	0.29**	0.32**	0.28**	0.04	0.04
	z-stat	1.91	2.15	2.07	2.27	0.54	0.58
	obs.	1,901	2,513	1,901	3,010	1,899	2,034
KS	coef	0.70**	0.71**	0.92**	0.91***	0.68	0.72
	z-stat	1.97	2.15	2.38	2.59	1.42	1.43
	obs.	1,901	2,202	1,901	2,299	1,899	1,779
I(KS Conformity)	coef	-0.02	-0.02	-0.03	-0.03	0.00	0.00
	z-stat	-0.54	-0.53	-0.82	-1.00	0.15	0.20
	obs.	1,901	1,890	1,901	2,153	1,899	1,788
Ln(# Items)	coef	0.00	0.00	-0.01	-0.01	0.01	0.02
	z-stat	-0.24	-0.29	-0.30	-0.32	1.23	1.50
	obs.	1,901	2,093	1,901	2,037	1,899	1,380

TABLE 5: The index deletion effect on textual disclosure

This table reports second-stage fuzzy RDD results for textual disclosure of 10-K and 10-Qs filed after the annual Russell reconstitution. 10-Q variables of interest are measured for each quarter then averaged across the post-reconstitution window. Ln(Words) and Ln(NetFileSize) are the natural log of the word counts and the character size in megabytes. Fin-Ambiguity is the proportional weights of uncertain terms and weak modal words relative to the total number of words in a firm's mandatory report. The Fog and the Smog Index access readability, where the higher value indicates lower readability. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Focusing on deletions, the sample includes firms that move out of the Russell 2000 and firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

		10-K		10-Q	
Dept. Variables	bws.	200	OPT	200	OPT
Ln(Words)	coef	-0.10**	-0.11**	-0.03	-0.03
	z-stat	-2.35	-2.27	-0.58	-0.69
	obs.	1,778	1,461	1,846	1,673
Ln(NetFileSize)	coef	-0.10**	-0.11**	-0.03	-0.03
	z-stat	-2.35	-2.26	-0.60	-0.69
	obs.	1,778	1,471	1,846	1,684
Fin-Ambiguity	coef	0.08*	0.08*	0.02	-0.03
	z-stat	1.75	1.66	0.29	-0.44
	obs.	1,778	1,718	1,846	1,426
Fog Index	coef	-0.15	-0.16	-0.14	-0.16
	z-stat	-1.45	-1.49	-0.49	-0.66
	obs.	1,763	1,669	1,846	2,319
Smog Index	coef	-0.10	-0.10	-0.06	-0.06
	z-stat	-1.39	-1.40	-0.45	-0.50
	obs.	1,763	1,753	1,846	2,292

TABLE 6: Specification Robustness

This table reports second-stage fuzzy RDD results for the main variables of interest measured after the annual Russell reconstitution. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Additions compare firms added to the bottom of the Russell 2000 against firms that remain just outside the index. Conversely, deletions compare firms that move out of the Russell 2000 against firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

Panel A: Additions to the Russell 2000

	Uniform Kernel		Year Fixed Effects		Quadratic Polynomial	
Dept. Variables	200	OPT	200	OPT	200	OPT
MAD	0.08	0.10	0.06	0.06	0.04	0.08
SMAD	0.15	0.19	0.11	0.12	0.08	0.12
KS	-0.33	-0.12	-0.29	-0.32	-0.20	-0.16
I(KS Conformity)	-0.01	-0.03	-0.03	-0.02	-0.06	-0.03
Ln(# Items)	0.00	0.00	0.01	0.00	0.03	0.02
Ln(Words)	0.01	0.01	-0.02	0.00	-0.03	0.02
Ln(NetFileSize)	0.01	0.02	-0.02	0.00	-0.03	0.01
Fin-Ambiguity	0.07	0.07	0.09	0.08	0.14*	0.10
Fog Index	0.12	0.09	0.09	0.09	0.07	0.09
Smog Index	0.08	0.06	0.06	0.06	0.04	0.07

Panel B: Deletions from the Russell 2000

	Uniform Kernel		Year Fixed Effects		Quadratic Polynomial	
Dept. Variables	200	OPT	200	OPT	200	OPT
MAD	0.26**	0.26**	0.27**	0.22**	0.31*	0.33**
SMAD	0.33**	0.31**	0.36**	0.26*	0.41*	0.45**
KS	1.21***	1.18***	1.35***	1.27***	1.61**	1.33**
I(KS Conformity)	-0.08*	-0.07*	-0.10**	-0.09**	-0.13**	-0.10*
Ln(# Items)	0.00	-0.01	-0.01	0.00	-0.01	0.00
Ln(Words)	-0.08*	-0.09*	-0.10**	-0.10**	-0.14**	-0.15***
Ln(NetFileSize)	-0.08*	-0.08*	-0.10**	-0.10**	-0.14**	-0.14**
Fin-Ambiguity	0.09**	0.09*	0.07	0.07	0.05	0.12**
Fog Index	-0.08	-0.05	-0.13	-0.14	-0.26*	-0.23
Smog Index	-0.05	-0.05	-0.09	-0.09	-0.18*	-0.17*

TABLE 7: Potential Channels

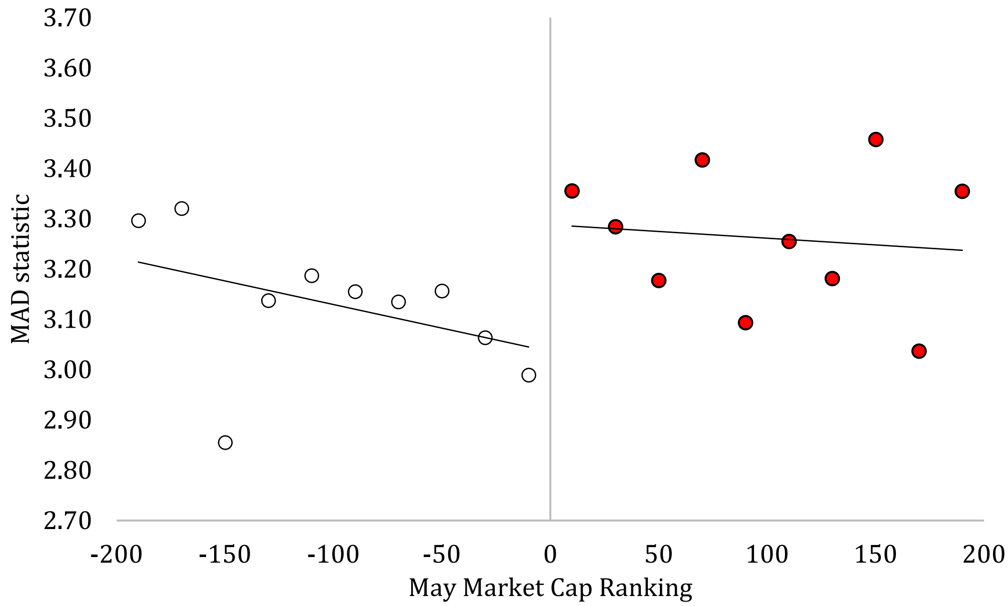
This table reports second-stage fuzzy RDD results for the main variables of interest measured after the annual Russell reconstitution. Eligible sample firms are defined with a fixed bandwidth of 200 firms and optimal mean squared error bandwidth in Imbens and Kalyanaraman (2012). Index deletions compare firms that move out of the Russell 2000 against firms that remain just inside the index. Statistical inferences are based on Calonico's et al. (2014) heteroskedasticity-robust nearest-neighbor variance estimator. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is between 2007 and 2016. Appendix A contains detailed variable definitions.

	Triangular Kernel		Uniform Kernel		Year Fixed Effects		Quadratic Polynomial	
Dept. Variables	200	OPT	200	OPT	200	OPT	200	OPT
Index IO (%)	-4.25***	-4.22***	-4.22***	-4.23***	-4.24***	-4.25***	-4.32***	-4.23***
Non-Index IO (%)	1.52	1.85	1.96	2.40	1.47	1.81	-1.10	-0.37
ETF IO (%)	-1.64***	-1.62***	-1.57***	-1.60***	-1.65***	-1.62***	-1.72***	-1.62***
Total IO (%)	-2.73	-2.37	-2.26	-1.80	-2.76	-2.41	-5.41	-4.62
I(Analyst Coverage)	-0.01	-0.03	0.04	0.00	-0.01	-0.03	-0.07	-0.02
I(#Analysts >=3)	-0.06	-0.06	-0.03	-0.06	-0.06	-0.06	-0.10	-0.06
Ln(# Analysts)	-0.01	0.00	0.05	0.00	-0.01	0.00	-0.10	0.00
Ln(# Analyst Forecasts)	-0.03	0.00	0.09	0.01	-0.03	0.00	-0.23	0.02
Ln(Avg Daily News)	0.01	0.01	0.04	0.01	0.01	0.01	-0.04	0.01
Ln(Total Daily News)	-0.01	0.01	0.09	0.01	-0.02	0.01	-0.16	-0.04
I(Big 4 Auditor)	-0.02	-0.01	0.00	0.00	-0.02	-0.01	-0.07	-0.05
I(Big 6 Auditor)	-0.02	0.00	0.02	0.03	-0.01	0.01	-0.13*	-0.11
I(Δ Fin. Person)	0.01	0.00	-0.01	0.00	0.01	0.00	0.08	0.02
I(Δ CEO)	0.04	0.05	0.03	0.04	0.04	0.05	0.07	0.06
I(Δ CFO)	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.02
I(Δ Audit Committee)	-0.01	0.00	0.00	-0.01	-0.01	0.01	-0.01	-0.01

FIGURE 1: Post-reconstitution Benford's Law test statistics

This figure plots the average level of Benford's Law statistics across equal-spaced portfolio bins within a fixed 200 bandwidth around the lower (#3,000) reconstitution cutoff. Solid red dots represent deletions from the Russell 2000 Index, and hollow dots represent the counterfactuals that remained in the Russell 2000. Panel A presents the discontinuity in the mean absolute deviation (MAD), and Panel B presents the Kolmogorov–Smirnov (KS) statistic. The sample period is between 2007 and 2016.

Panel A: MAD statistic | prior Russell 2000 members



Panel B: KS statistic | prior Russell 2000 members

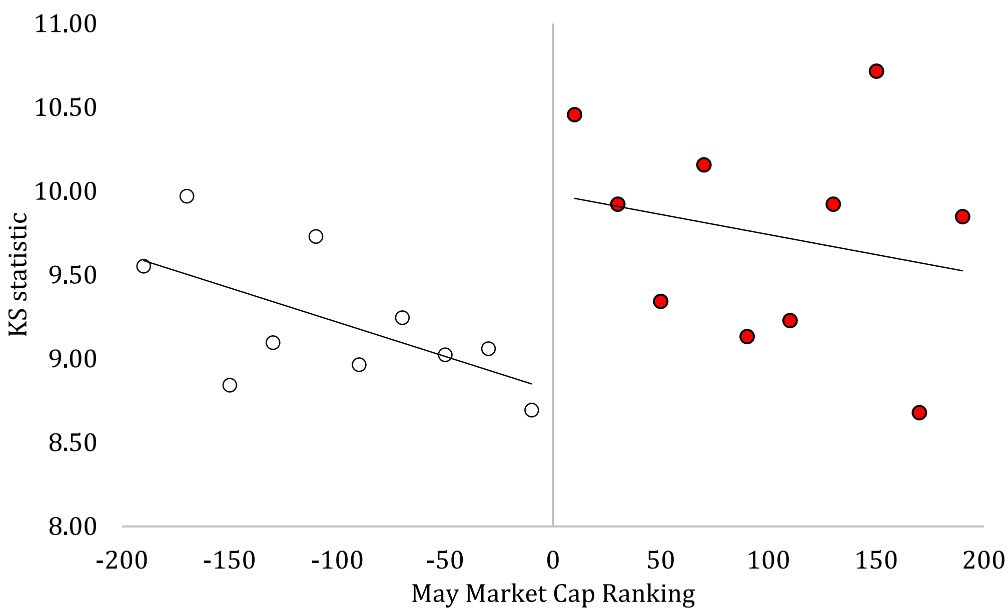
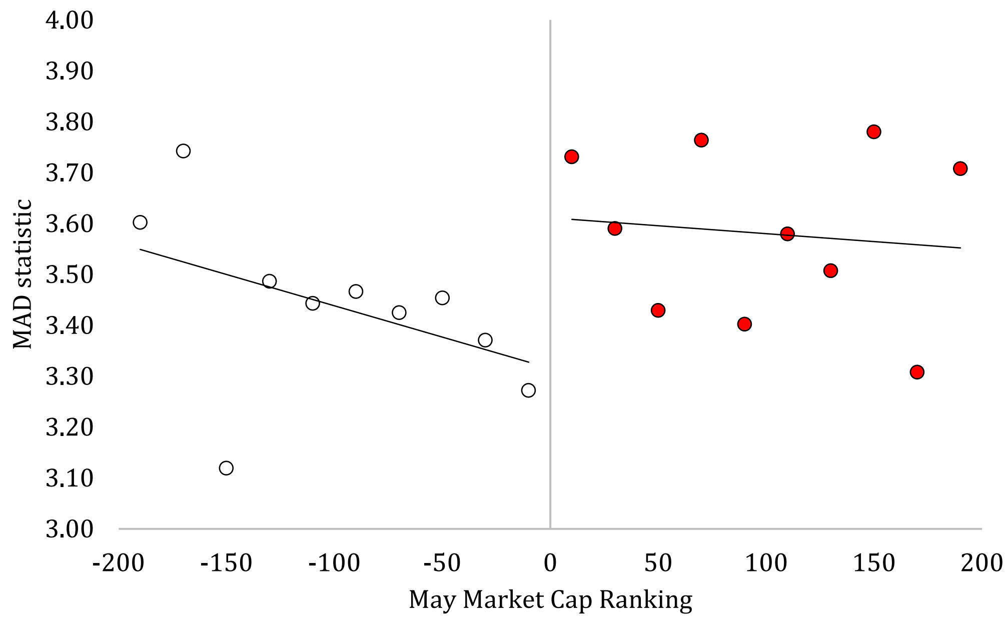


FIGURE 2: Post-reconstitution Benford's Law test statistics by partitions

This figure plots the average level of Benford's Law statistics across equal-spaced portfolio bins within a fixed 200 bandwidth around the lower (#3,000) reconstitution cutoff. Solid red dots represent deletions from the Russell 2000 Index, and hollow dots represent the counterfactuals that remained in the Russell 2000. Panel A presents the discontinuity in the mean absolute deviation (MAD) in the balance sheet and income statement items, and Panel B presents the discontinuity in the MAD statistic in the statement of cash flow items. The sample period is between 2007 and 2016.

Panel A: Balance Sheet and Income Statement MAD statistic | prior Russell 2000 members



Panel B: Statement of Cash Flows MAD statistic | prior Russell 2000 members

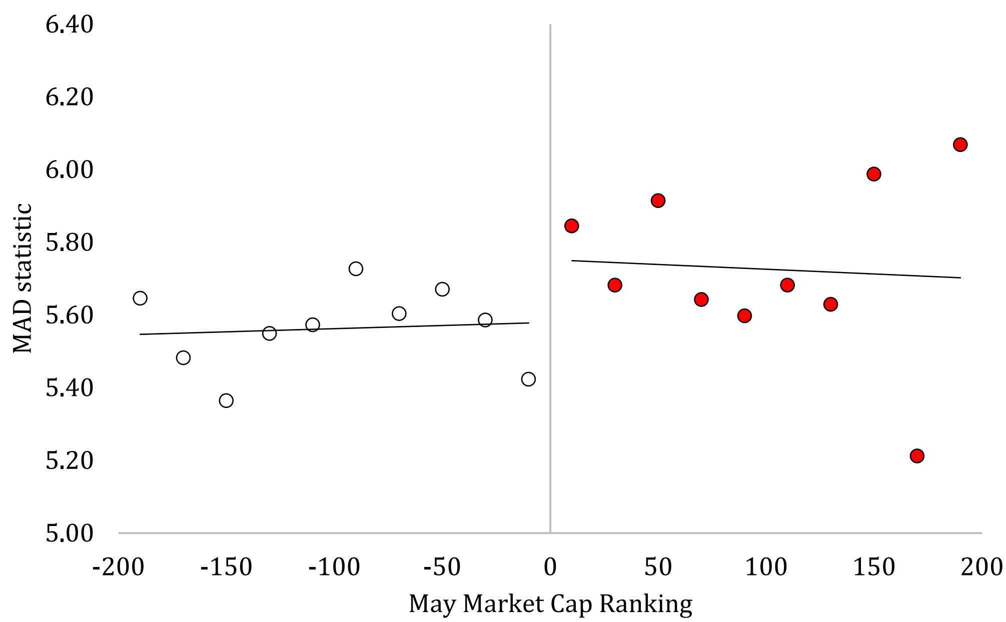
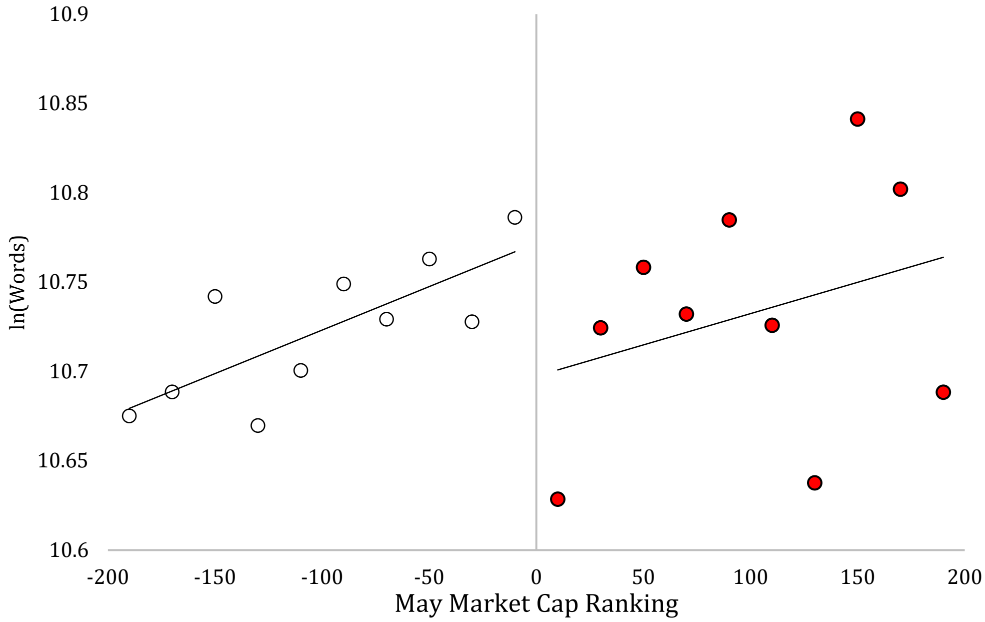


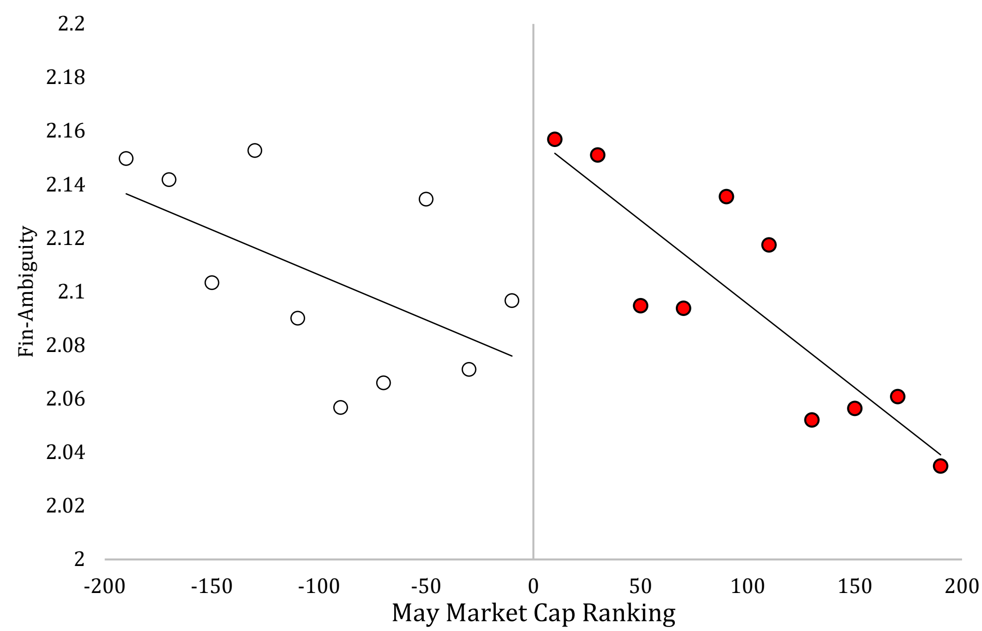
FIGURE 3: Post-reconstitution textual disclosure quality

This figure plots the average level of textual disclosure across equal-spaced portfolio bins within a fixed 200 bandwidth around the lower (#3,000) reconstitution cutoff. Solid red dots represent deletions from the Russell 2000 Index, and hollow dots represent the counterfactuals that remained in the Russell 2000. Panel A presents the discontinuity in the word count of 10-K filings, and Panel B presents the percentage of uncertainty terms and weak modal words in 10-K filings. The sample period is between 2007 and 2016.

Panel A: Length | prior Russell 2000 members



Panel B: Tone Ambiguity | prior Russell 2000 members



APPENDIX A
Variable definitions

Financial reporting quality	
MAD	The Mean Absolute Deviation (MAD) statistic is the sum of the absolute difference between the empirical and the theoretical distribution of leading digit ranging from one to nine, divided by nine. The MAD statistic is multiplied by 100 to be expressed as a percentage.
SMAD	The Standardized MAD (SMAD) statistic a la Bowler (2016) adjusts the actual MAD statistics with the benchmark MAD statistics drawn from 10,000 simulations given the number of leading digits used in the MAD calculation.
KS	The Kolmogorov–Smirnov (KS) statistic is the maximum deviation of the cumulative difference between the empirical and the theoretical distribution of the digits from one to nine. The KS statistic is multiplied by 100 to be expressed as a percentage.
I(KS Conformity)	An indicator variable that equals one if the firm-period KS statistic is not significantly different from zero at the 5% level, where the test value is calculated as 1.36 divided by the square root of the number of leading digits used.
Ln(# Items)	The natural logarithm of the number of Compustat items with non-missing values.

Textual properties	
Ln(Words)	The natural logarithm of the word counts in the 10-K/Q filings, based on words appearing in the Loughran–McDonald Master Dictionary. Data is available at Professor McDonald's website.
Ln(NetFileSize)	The natural logarithm of the net file size in megabytes of the SEC EDGAR "complete submission text file" for the 10-K/Q filings. The net file only includes text content and excludes extraneous components such as tables, exhibits, HTML, or encoded images.
Fin-Ambiguity	The number of words denoting uncertainty terms (e.g., approximate, contingency, uncertain, and indefinite) and weak modal words (e.g., might, possible, approximate, and contingent), scaled by total number words in mandatory reports. Fin-Ambiguity is multiplied by 100 to be expressed as a percentage. Data is available at Professor McDonald's website.
Fog Index	The Gunning Fog Index is computed as 0.4*(average number of words per sentence + percent of complex words), and the higher value indicates lower readability. Data is available at the WRDS SEC Analytics Suite.

Smog Index	The Smog index is computed as 1.043*square root (number of complex words*30/number of sentences) + 3.1291, and the higher value indicates lower readability. Data is available at the WRDS SEC Analytics Suite.

Institutional ownership	
Total IO	Percentage of shares outstanding held by institutions that manage over $100 million and report their quarterly holdings in SEC Form 13F and N-30Ds. Data is available from the FactSet Global Ownership Database.
Index IO	Percentage of shares outstanding held by index institutions. FactSet analysts separate index from non-index institutions using information from various sources, including fund managers, prospectuses, factsheets, audited reports, and fund accounts. Data is available from the FactSet Global Ownership Database.
ETF IO	Percentage of shares outstanding held by exchange-traded funds (ETFs) that track an index, a commodity, or a basket of assets like an index fund. Data is available from the FactSet Global Ownership Database.
Non-Index IO	Percentage of shares outstanding held by institutions (Total IO) minus the percentage of shares outstanding held by index institutions (Index IO). Data is available from the FactSet Global Ownership Database.

Information environment	
I(Analyst Coverage)	An indicator variable that equals one if at least one unique analyst covers the firm during the year of index membership. Analyst data is available from IBES detailed EPS file.
I(# Analysts >=3)	An indicator variable that equals one if at least three unique analysts cover the firm during the year of index membership.
Ln(# Analysts)	The natural logarithm of one plus the number of unique analysts issuing at least one EPS forecast during the year of index membership. Analyst data from IBES detailed EPS file.
Ln(# Analyst Forecasts)	The natural logarithm of one plus the total number of EPS forecasts during the year of index membership.
Ln(Avg Daily News)	The natural logarithm of one plus the average number of daily news articles covering the firm during the year of index membership. News coverage data is available from RavenPack News Analytics, and eligible articles require Relevance Score ≥ 75. RavenPack's Relevance Score ranges from 0 to 100, with values above 75 indicating that the news story is significantly relevant to the firm.
Ln(Total Daily News)	The natural logarithm of one plus the total number of news articles covering the firm.

Financial report preparer	
I(Big N Auditor)	An indicator variable that equals one if the firm is audited by one of the Big-N auditors during the year of index membership. The list of Big-4 (6) includes Deloitte, PwC, EY, and KPMG (and BDO Seidman and Grant Thornton). Data is available from Audit Analytics.
I(Δ Fin. Person)	An indicator variable that equals one if turnover in financial person occurs during the year of index membership. The management turnover data is available from the Director and Officer Changes database of Audit Analytics. Audit Analytics collects a director or officer change in Item 5.02 of an 8-K or 8-K/A filings and identifies the management position based on the annual title. A financial person is identified with the annual title containing keywords such as "ACCOUNT", "CFO", "CONTROL", "FINANC", or "TREASU".
I(Δ CEO)	An indicator variable that equals one if CEO turnover occurs during the year of index membership.
I(Δ CFO)	An indicator variable that equals one if CFO turnover occurs during the year of index membership.
I(Δ Audit Committee)	An indicator variable that equals one if audit committee turnover occurs during the year of index membership.

APPENDIX B
Pre-reconstitution balance test for small-cap firms

In Appendix B, I estimate the effect of stock indexing on lagged dependent variables, using 10-K and 10-Q filings with a fiscal month between last July and June. Panel A verifies the continuity in the distributional properties of annual financial statement data for stock additions and deletions. Panel B examines the partitions of financial statements, and Panel C extends analyses to quarterly financial statements. Lastly, Panel D examines the pre-reconstitution continuity in the length, readability, and tone of 10-K and 10-Q textual disclosure.

If sample firms near the reconstitution cutoff are randomly assigned, then the lagged dependent variables should not display a sign of significant discontinuity prior to the index reconstitution. The pre-existing discontinuities in lagged variables could reflect a selection bias rather than a treatment effect (see, e.g., Wei and Young' 2020 review).

Panel A: The effect of stock indexing on conformity to Benford's Law

		Additions		Deletions	
Dept. Variables	bws.	200	OPT	200	OPT
MAD	coef	0.01	0.00	0.08	0.07
	z-stat	0.10	0.04	0.71	0.67
	obs.	1,614	1,750	1,842	1,991
SMAD	coef	0.03	0.02	0.02	0.02
	z-stat	0.16	0.10	0.12	0.12
	obs.	1,614	1,767	1,842	1,849
KS	coef	-0.14	-0.16	0.20	0.11
	z-stat	-0.27	-0.31	0.42	0.26
	obs.	1,614	1,709	1,842	2,103
I(KS Conformity)	coef	0.00	0.01	-0.02	0.00
	z-stat	0.08	0.15	-0.49	-0.08
	obs.	1,614	1,819	1,842	2,374
Ln(# Items)	coef	0.02	0.01	0.00	0.00
	z-stat	0.82	0.35	-0.14	-0.11
	obs.	1,614	2,437	1,842	2,009

Panel B: The index deletion effect on conformity to Benford's Law by partitions

		BS & IS		CFS	
Dept. Variables	bws.	200	OPT	200	OPT
MAD	coef	0.20	0.15	0.06	0.07
	z-stat	1.53	1.44	0.38	0.43
	obs.	1,842	2,784	1,837	2,059
SMAD	coef	0.18	0.13	0.05	0.05
	z-stat	1.10	0.94	0.43	0.46
	obs.	1,842	2,610	1,837	1,909
KS	coef	0.51	0.26	0.80	0.60
	z-stat	1.00	0.58	1.13	0.97
	obs.	1,842	2,419	1,837	2,417
I(KS Conformity)	coef	-0.07	-0.05	0.01	0.02
	z-stat	-1.53	-1.28	0.75	0.96
	obs.	1,842	2,117	1,837	2,313
Ln(# Items)	coef	0.00	0.00	0.00	0.00
	z-stat	-0.12	-0.08	-0.48	-0.65
	obs.	1,842	1,999	1,837	2,439

Panel C: The index deletion effect on conformity to Benford's Law in 10-Q filings

		All		BS & IS		CFS	
Dept. Variables	bws.	200	OPT	200	OPT	200	OPT
MAD	coef	0.01	0.01	0.02	0.02	0.26^{*}	0.27^{**}
	z-stat	0.11	0.10	0.17	0.15	1.96	2.03
	obs.	1,901	1,974	1,901	2,008	1,899	1,971
SMAD	coef	-0.08	-0.08	-0.07	-0.07	0.15^{**}	0.15^{**}
	z-stat	-0.49	-0.48	-0.41	-0.40	2.23	2.10
	obs.	1,901	1,868	1,901	1,863	1,899	1,768
KS	coef	0.11	0.08	0.24	0.19	0.68	0.68
	z-stat	0.29	0.24	0.59	0.50	1.37	1.38
	obs.	1,901	2,053	1,901	2,111	1,899	1,913
I(KS Conformity)	coef	-0.01	-0.01	-0.02	-0.02	-0.01	-0.01
	z-stat	-0.34	-0.29	-0.59	-0.52	-0.95	-1.14
	obs.	1,901	2,029	1,901	2,017	1,899	2,174
Ln(# Items)	coef	0.00	-0.01	0.00	-0.01	0.01	0.01
	z-stat	-0.17	-0.48	-0.20	-0.52	0.69	1.28
	obs.	1,901	2,601	1,901	2,832	1,899	1,355

Panel D: The index deletion effect on textual disclosure

		10-K		10-Q	
Dept. Variables	bws.	200	OPT	200	OPT
Ln(Words)	coef	0.01	0.00	0.00	0.00
	z-stat	0.26	-0.02	0.01	-0.03
	obs.	1,778	1,592	1,846	1,767
Ln(NetFileSize)	coef	0.01	-0.01	0.00	0.00
	z-stat	0.18	-0.14	-0.02	-0.05
	obs.	1,778	1,560	1,846	1,767
Fin-Ambiguity	coef	0.00	0.00	0.03	0.03
	z-stat	0.06	0.06	0.49	0.49
	obs.	1,778	1,791	1,846	1,846
Fog Index	coef	0.09	0.10	-0.43	-0.39
	z-stat	0.80	0.97	-0.92	-0.89
	obs.	1,763	2,277	1,846	2,045
Smog Index	coef	0.06	0.06	-0.08	-0.07
	z-stat	0.72	0.89	-0.51	-0.45
	obs.	1,763	2,209	1,846	2,070