Regression Discontinuity and the Price Effects of Stock Market Indexing

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The Russell 1000 and 2000 stock indexes comprise the first 1000 and next 2000 largest firms ranked by market capitalization. Small changes in the capitalizations of firms ranked near 1000 move them between these indexes. Because the indexes are value-weighted, more money tracks the largest stocks in the Russell 2000 than the smallest in the Russell 1000. Using this discontinuity, we find that additions to the Russell 2000 result in price increases and deletions result in price declines. We then identify time trends in indexing effects and the types of funds that provide liquidity to indexers. (*JEL* G02, G12, G14)

We develop an empirical design to address several important questions on the price effects of stock market indexing. Many studies find that stocks that get added to the Standard and Poor's (S&P) 500 index, or other widely followed indexes, experience a positive risk-adjusted return (see., e.g., Shleifer 1986; Harris and Gurel 1986). For instance, the most famous of these, the S&P 500 index addition effect, is around 3% to 7% in the month following the addition announcement date, and a large fraction of the price effect is permanent (see, e.g., Beneish and Whaley 1996; Lynch and Mendenhall 1997; Wurgler and Zhuravskaya 2002).

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The traditional methodology assumes that added stocks differ from a control group of stocks that are not added—typically just the market portfolio—only because of forced buying. The preferred interpretation of this finding is that the excess risk-adjusted return is due to forced buying by passive stock index funds and by the many active institutional investors that are benchmarked to these indexes. These studies suggest that the demand curves for stocks, even large ones such as those in the S&P 500, are downward sloping. This is contrary to the central tenet of the efficient markets hypothesis, which asserts that stocks have many substitutes and hence their demand curves should be flat.

However, a number of studies call into question the plausibility of this interpretation since it is difficult to separate indexing from potential confounds such as news and investor recognition associated with S&P 500 membership.[1] Indeed, the most cleanly identified papers in the literature typically consider settings other than additions or deletions to measure downward sloping demand curves. Notably, Kaul, Mehrotra, and Morck (2000) successfully isolate the effect of index weight increases by using a one-time float rule change that reweighted firms in the Toronto Stock Exchange (TSE 300).[2]

While these studies cleverly identify the existence of downward-sloping demand curves, they leave some fundamental questions unanswered. First, they do not speak directly to the price effects of additions and deletions from indexes. That is, they tell us to expect a price effect when a stock joins an index but do not specify the size of the effect. Moreover, these studies cannot speak to whether the price effect of indexing differs between additions and deletions. The literature on S&P 500 indexing has focused on additions for the most part, since there have been fewer deletions. Indeed, the earliest studies, such as Shleifer (1986) and Harris and Gurel (1986), explicitly only look at additions because firms were often deleted due to bankruptcies, mergers, or other information-related events. The most recent studies with the largest samples of deletions find a strong addition effect but no deletion effect.

It would be valuable to see if this asymmetry is due to indexing rather than confounding factors.[3] If indexing does in fact lead to asymmetric price effects, this might suggest that it is easier for arbitrageurs or market-makers

[1] For instance, Denis et al. (2003) find that additions to the S&P 500 are associated with an increase in earnings forecasts and improvements in realized earnings. Announcements of S&P 500 membership are also widely covered in the press and might generate investor recognition (see, e.g., Merton 1987) or attention (see, e.g., Barber and Odean 2008 or Hirshleifer, Lim, and Teoh 2009).

[2] Other such studies include Greenwood (2008), who used the idiosyncratic weighting schemes in the Japanese stock exchange, and Boyer (2011), who used BARRA definitions of value and growth to establish comovement of prices of index members. The one exception is Wurgler and Zhuravskaya (2002), who used a difference-in-difference estimate to compare the addition price effects of S&P 500 stocks with close substitutes to those without close substitutes. However, these methods do not identify the mean index premium for the average addition.

[3] Chen, Noronha, and Singal (2004), the study with the largest sample of deletions, find that stocks that get deleted have no permanent negative price effect. If the observed positive price effect of addition is due to indexing or benchmarking by institutional investors, one should see a negative price effect for deletion when such demand is no longer necessary. Instead, this asymmetric price reaction seems more consistent with an investor recognition effect whereby added stocks get recognized but recognition does not go away with deletion.

to buy deleted stocks than to sell or short-sell added stocks. This highlights the role of short-selling frictions in the arbitrage process. While we know at this point that demand curves are downward sloping, specific estimates of addition and deletion effects are still highly valuable for both practitioners and academics.

The second key issue concerns the consequences of the increasing popularity of indexing among mutual funds (see, e.g., Wurgler 2011; Morck and Yang 2002). Several recent theoretical analyses suggest that, all else equal, greater demand for index stocks will lead to not only a higher index premium but also excessive comovement (relative to fundamentals) of stocks in an index (see, e.g., Vayanos and Woolley 2011; Basak and Pavlova 2013). However, frictions associated with shorting or leverage have also fallen over time, which might lead to greater arbitrage capacity to offset the effects of rising indexing demand. There are few well-identified studies on the net effects of these two trends, and studies of one-time events such as index reweightings cannot address time trends and whether these trends differ between additions and deletions.

A third and related question is who provides liquidity to the funds tracking the indexes. The existing models of indexing cited above assume that there is a class of funds that are benchmarked to an index and a separate set of arbitrageurs that are not and that instead engage in liquidity provision. But in reality there are many indexes pegged to different asset classes. As a stock moves out of one index into another, as happens when a growth stock becomes a value stock and moves from a growth-stock index to a value-stock index, perhaps funds benchmarked to these different indexes provide liquidity for each other. This question has not been addressed in the literature but might be important for understanding the adjustment of markets to rising indexing demand over time. Examining all three of these issues requires both a credible identification strategy and a large panel of additions and deletions from a major stock market index.

To address these challenges, we develop a new methodology, a set of regression discontinuity (RD) experiments associated with the Russell 2000 index, that can cleanly identify an indexing price effect. Stocks are ranked on the last trading day of May (i.e., end-of-May) based on their market capitalizations. The first 1 to 1000 are in the Russell 1000. The next 1001 to 3000 are in the Russell 2000. The end-of-May market capitalization cutoffs lock in membership for an entire year. Our methodology relies on comparing firms around the 1000 and 3000 cutoffs for Russell 2000 index membership.

Our focus is on the 1000 cutoff. The analysis of the 3000 cutoff, which is very similar, is provided in the Internet Appendix. The amounts of money benchmarked to the two indexes are comparable. But since the indexes are value-weighted, stocks with end-of-May market capitalizations just below the 1000 cutoff (i.e., stocks 1001 to 1010) end up receiving significant forced buying, while those just above the cutoff (i.e., stocks 990 to 1000) receive almost none. Indeed, the index weights for the stocks in the Russell 2000 just below the 1000 cutoff are around ten times larger than the index weights for stocks in the Russell 1000 just above the 1000 cutoff.

In other words, small and random changes in market capitalization on May 31 around the 1000 cutoff lead to large and discontinuous changes in demand due to indexing. In contrast to the S&P 500 setting, our methodology addresses the potential endogeneity of index addition (deletion) by cleanly identifying counterfactual stocks that could have entered (exited) the Russell 2000 index if their returns had been only slightly different from those observed.[4] Our identification strategy and the fact that these additions and deletions occur every year over the sample period of 1996–2012 allow us to address all three of our challenges.

Importantly, our regression discontinuity methodology differs from earlier Russell 2000 studies. These previous studies use the traditional methodology of comparing all firms that had moved into the index with those that had not (see, e.g., Madhavan 2003; Chen 2006; Petajisto 2011). These studies have the same issues as earlier S&P 500 studies and yield contradictory results. For instance, firms that move into the Russell 2000 from below the 3000 cutoff on average have experienced bigger changes in market capitalization than nonmovers, which makes an apples-to-apples comparison difficult. Our regression discontinuity methodology focuses only on stocks around the cutoff, ensuring that we are measuring only the effects of index membership. By using broad comparison groups and including stocks that would clearly move into or stay out of the index, previous Russell studies necessarily confounded new information with index membership.

Although Russell Inc. does not report the end-of-May capitalizations used to place the stocks into indexes, it is easy to predict membership using market capitalizations calculated from publicly available data. Therefore we can effectively employ a fuzzy RD design (Lee and Lemieux 2010). We verify that firm characteristics are continuous around the 1000 cutoff and then examine how our variables of interest behave around this cutoff before and after the end of May. In particular, we anticipate that most of the price effects will play out during June, immediately after the assignment of firms to indexes.

We first measure an addition effect of getting into the Russell 2000 in year t (i.e., at the end of May of year t) for stocks that were in the Russell 1000 in year $t-1$. We find that stocks from the Russell 1000 that just landed in the Russell 2000 have discontinuously higher returns in June compared with stocks that just missed making it into the Russell 2000. The economic magnitude is on the order of 5% with a t-statistic of 2.65. We find that all the price adjustments

[4] Also, in contrast to the S&P 500, where additions are widely covered in the media, index membership in the Russell 2000 does not receive much attention, thus lessening the concern that addition might also lead to higher prices because of broader recognition due to media coverage. Consistent with this perspective, we find symmetric price effects of additions and deletions.

occur in the month immediately following addition, similar to S&P 500 studies, and that there are no effects in subsequent months.

In contrast to the S&P 500 studies, we also find a deletion effect. Stocks whose market capitalization placed them above the 1000 cutoff (and hence moved into the Russell 1000) have lower returns than stocks just below the 1000 cutoff (that stayed in the Russell 2000). The economic effect of deletion is 5.4% with a t-statistic of 3, which is similar in absolute value and in statistical significance to the addition effect. Our focus on randomized assignment to indexes allows us to detect a deletion effect that is missing when the market is used as a control group, as in the S&P 500 methodology.

Another difference is that our estimate of a 5% mean price effect implies a price elasticity of around -1.5 (using estimates of the amount of assets benchmarked to the Russell 2000). This is smaller in absolute value (i.e., more inelastic demand) than most estimates found in the literature—the estimates from the literature center around -5 to -10 (see Wurgler and Zhuravskaya, 2002 for a review). For instance, the price elasticity estimate from Kaul, Mehrotra, and Morck (2000) is -10. Their set of stocks is comparable in terms of market capitalization to ours. So this contrast speaks to the need for our measure of the price effects of indexing, as opposed to extrapolating price elasticity estimates from index reweighting or other settings.

We also find that Russell 2000 membership results in more volume or trading in June, consistent with investors rebalancing because of indexing. However, there is no significant change in institutional ownership upon addition or deletion. This suggests that the price increase upon addition and the price decrease upon deletion largely compensate for market-making activities as in Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993), in which institutions with differential preferences for membership stocks trade with each other.

Our second set of findings is that even as this volume or rebalancing effect has been rising over time, consistent with the rising popularity of indexing, the demand curve has become more elastic over time. We also find some evidence that the excess comovement of index members, measured using each stock's beta with respect to the Russell 2000 index, has fallen over time. Shorting of index members (presumably by arbitrageurs and in the months after membership is determined in May) has increased slightly over time, perhaps to accommodate the growing demand from indexing. Yet it appears that the rise of indexing has not resulted in greater indexing price effects or excess comovement.

Finally and relatedly, our third set of findings points to the importance of mutual funds that own large stocks in providing liquidity for mutual funds that are indexed to the Russell 2000. Using our regression discontinuity design, we can identify which mutual funds are benchmarked to the Russell 2000 by looking at changes in their holdings around the May 31 index membership date. We focus on stocks around the 1000 cutoff. Funds that simultaneously sell stocks that have larger market capitalizations than the 1000th stock (e.g., ranked 900) and buy stocks with lower market capitalizations than the 1000th stock (e.g., ranked 1100) are identified as "Russell 2000 indexers" (where indexers are loosely defined as those benchmarked to the index) and those doing the reverse trades are identified as "liquidity providers." "Russell 2000 liquidity providers" tend to hold larger and higher market-to-book stocks and come from smaller mutual fund family complexes relative to the "Russell 2000 indexers." This finding suggests that an important set of liquidity providers for Russell 2000 funds, which moderate the price effects of indexing over our sample, might be funds benchmarked to other indexes such as the Russell 1000 rather than arbitrageurs, as is often portrayed in theories of indexing.

1. Constructing Rankings and the Empirical Design

The key to our empirical design is to verify the smoothness in market capitalization across the two cutoffs on the last trading day of May. Exact rankings are not available because Russell publishes only the reconstituted index lists and end-of-June weights, not the market capitalization rank at the end of May. Fortunately, it is possible to calculate each stock's market capitalization. The transparency of this process, in contrast to the black box approach of the S&P 500 index, is also what makes the Russell indexes attractive to many money managers for the purposes of indexing and benchmarking.

But first, we explain in detail how Russell Inc. constructs their indexes. Every year on the last trading day of May, eligible stocks are ranked by their market capitalizations. Eligible stocks include U.S. common stocks listed on major U.S. exchanges. ADR, ADS, preferred stocks, redeemable shares, warrants, rights, and trust receipts are excluded. Stocks with end-of-May closing price lower than $1.00 are also excluded. Stocks ranked 1–1000, 1001–3000, and 1–4000 constitute the member stocks for the Russell 1000, Russell 2000, and Russell 3000E, respectively. We focus on the 1000 cutoff that represents the upper end of the Russell 2000. Index reconstitution takes place on the last Friday of June, when the weights of member stocks are determined by their float-adjusted market value rank within each index. The float adjustment to outstanding shares accounts for cross-ownership by other index firms, private holdings, government holdings, etc. We obtain annual constituent lists for the Russell 1000 and Russell 2000 from Russell Inc. starting in 1996. The broadest Russell index, the Russell 3000E, is available from 2005 onward.

Starting with its 2007 reconstitution, Russell initiated a banding policy around the 1000 cutoff to mitigate index turnover. If an index member's market capitalization did not deviate far enough to warrant an index membership change, it remained in its original index. The exact methodology uses the market capitalization of stocks to create bands around the 1000 cutoff. First, all the stocks in the Russell 3000E are ranked from smallest to largest. Then a cumulative market capitalization is computed for every stock. This is the sum of the market capitalization of the stock and all the stocks that are smaller than it. This is then expressed as a percentage of the total market capitalization of the Russell 3000E. Finally, stocks switch from their current index only if they move beyond a 5% range around the cumulative market capitalization of the 1000th stock, meaning 2.5% on either side.[5] We use data on market capitalization to compute these percentiles and the implied cutoffs for every year in which banding is used.

1.1 End-of-May market capitalizations and rankings

To recreate the rankings that determine index membership, we take all 3000 firms in the Russell 3000E and use publicly available prices and shares at the end of the last trading day in May. End-of-May share prices are obtained from CRSP. To measure the number of shares at the company level, we use Compustat quarterly shares outstanding (CSHOQ). Since CSHOQ are updated only quarterly, we use the Compustat quarterly earnings report date (RDQ) to determine which quarter's CSHOQ is publicly available on the last trading day of May. For those firms with missing RDQ, the following rules are used: (1) Before 2003, the SEC required firms to file 10-Ks within 90 days of their fiscal year-ends. The policy was changed to 75 days from 2003 to 2006 for firms with market capitalizations larger than $75 million. Starting in 2007, this was further shortened to 60 days for firms with market capitalizations of at least $700 million. (2) For 10-Q filings, the SEC filing deadline was 40 days after the quarter-ends before 2003. It became 40 days for firms larger than $75 million starting in 2003. Following these rules, we obtain the most recent fiscal quarter-ends before May 31 and assume the number of shares is publicly available after these deadlines. Next, we use the monthly CRSP factor to adjust shares (FACSHR) for any corporate distribution after the fiscal quarter-ends and before May 31. For any missing prices and shares, we hand-collect the data from Bloomberg. Finally, we choose the larger of the shares obtained from this procedure and the CRSP shares.

1.2 Continuity of market capitalizations and rankings

The validity of our experiment relies on the random assignment of stocks around the upper cutoff on the last trading day of May. This is true if firms have imprecise control over which side of the cutoff they end up on. To the extent that there is local randomization, we can then perform a quasi-experiment using

5 To illustrate the effect of banding on index addition, consider the example of the stock ranked 1210 at the end of May 2007. This stock was in the Russell 1000 in the year leading up to May 2007. At the end of May its market capitalization was $1.8 billion while the stock with rank 1000 had a market capitalization of $2.47 billion. This put the cumulative market capitalization of stock 1210 at 8% of the Russell 3000E while the cumulative market capitalization of the cutoff stock was 10%. In previous years this stock would have been added to the Russell 2000. However, the implementation of the banding policy meant that a member of the Russell 1000 could switch to the Russell 2000 only if its cumulative market capitalization was less than 7.5% of the Russell 3000E. Therefore the stock remained in the Russell 1000 for the following year.

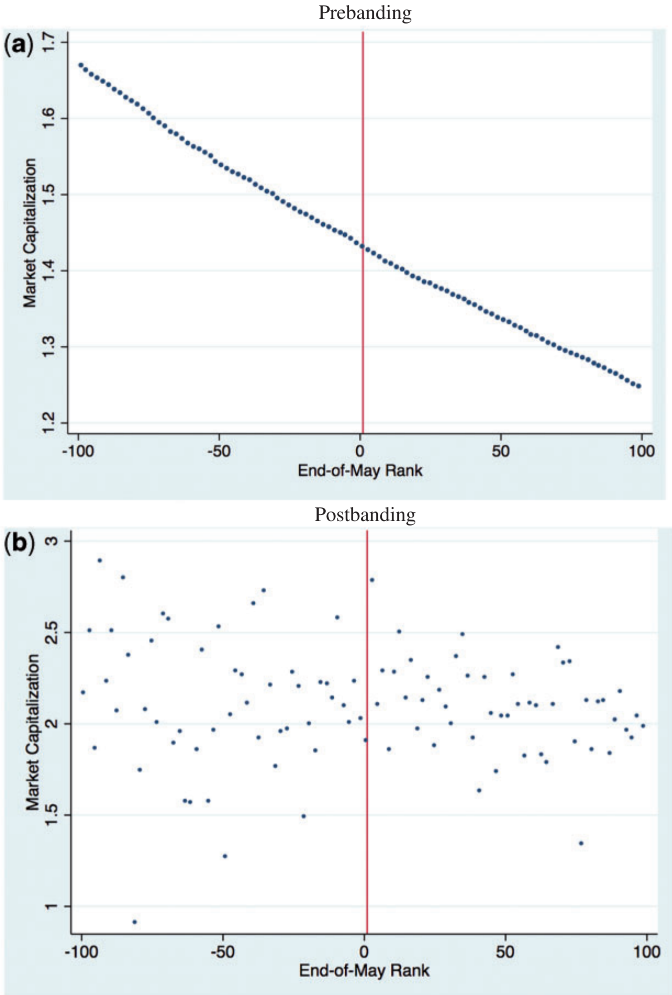


Figure 1
End-of-May market capitalization around upper cutoff
End-of-May market capitalization is measured in billions of dollars and plotted against end-of-May rankings. Firms that will end up in the Russell 1000 are on the left-hand side of the cutoff and firms that will end up in the Russell 2000 are on the right-hand side. The sample period is 1996–2006 for the prebanding period and 2007–2012 for the postbanding period.

a regression discontinuity design around this cutoff. This allows us to make causative inferences about the effect of indexing. We do the formal validity tests in a later section, but it is instructive to see that market capitalizations on the last day of May are continuous across the cutoff.

Figure 1 plots the market capitalizations of firms on either side of the upper Russell 2000 cutoff against the ranks determined by these market capitalizations, both before and after banding was implemented. Notice that market capitalizations are smoothly declining across the cutoff when banding is not in effect, supporting the assumption of random assignment. Firms on the left (right) side of the vertical line are larger (smaller) and will be in the Russell 1000 (Russell 2000) following the end-of-June reconstitution. After banding, market capitalization is not as clearly declining because smaller firms can remain in the Russell 1000 while larger firms remain in the Russell 2000. However, there is still no discontinuity at the cutoff.

1.3 Discontinuities in index weights

To demonstrate the essence of our regression discontinuity design, in Figure 2 we plot the index weights for stocks around the upper cutoff of the Russell 2000 in 2002. During the time period before banding, an average of 10% of the firms in the Russell 1000 switched to the Russell 2000 every year. Of the stocks starting in the Russell 2000, 6% switched to the Russell 1000. In 2002, 11% and 6% of firms switched indexes, respectively, making it a representative year.

In Figure 2(a) we plot the index weights of the stocks in the Russell 1000 in 2002 on the last day of May against their ranks. Notice that the index weights are smoothly declining with end-of-May ranks as one would expect in a value-weighted index. The weights are updated daily to account for changes in a firm's number of shares. The weights range from around 0.04% for the stocks around the 600 rank to a low of 0.001% for stocks at the 1400 rank. The stocks around the 1000 rank have weights around 0.01%. Notice that the number of observations declines with rank. The reason is that since we are looking at only the Russell 1000 constituents, most will tend to lie above the 1000 cutoff.

In Figure 2(b), we plot for these same stocks their end-of-June index weights. Now there is a jump in the weights at the 1000 cutoff since stocks to the right of the 1000 cutoff belong to the Russell 2000 in June and have higher weights while the stocks to the left of the cutoff remain in the Russell 1000. For the stocks just to the right of the 1000 cutoff, the weight is now 0.1% on average. This is a tenfold increase in index weights from a base of 0.01%. For the stocks above the cutoff, there is no change in weights; they remain at around 0.01%.

In Figure 2(c), we plot the end-of-May weights for the Russell 2000 members in 2002 against their ranks. Since we are looking at members of the Russell 2000, most of the observations lie below the 1000 cutoff, but there are some whose ranks have risen above 1000. The weights for the stocks at the 1000 cutoff are around 0.13%. In Figure 2(d), we see that those to the left of the cutoff experience a drop in their June weights after they become part of the Russell 1000 and have very little weight in that index. Notice that the change in weights between those to the left of the 1000 cutoff (i.e., the deletions from the Russell 2000) and those to the right of the cutoff is around 0.1%, similar to the jump upward for additions into the Russell 2000 from the Russell 1000. Therefore, we expect addition and deletion effects of equal sizes.

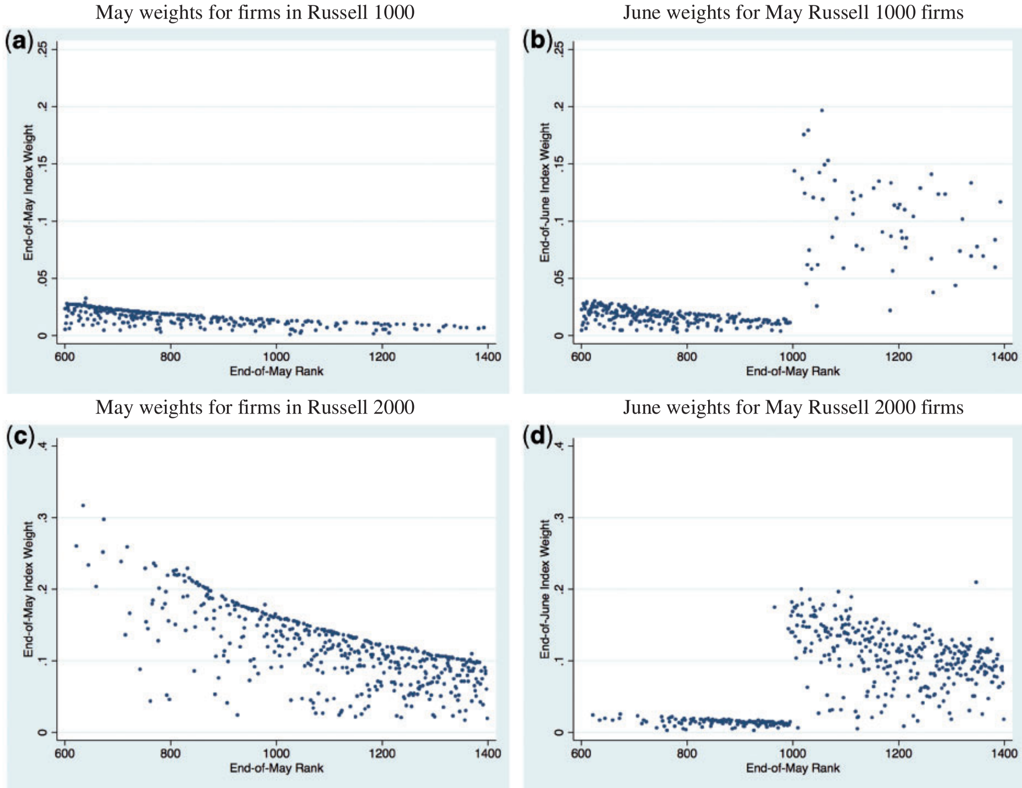


Figure 2
Index weights around upper cutoff in 2002
Index weights are measured in percent of index (in percentage points) and plotted against end-of-May market capitalization rankings. Panels (a) and (b) use firms that were in the Russell 1000 at the end of May while Panels (c) and (d) use firms that were in the Russell 2000 at the end of May. The firms that end up in the Russell 1000 are on the left-hand side of the cutoff. Those that end up in the Russell 2000 are on the right-hand side.

One take-away from this analysis is that even if there were twice as much money tracking the Russell 1000 as the Russell 2000, we would still expect a significant jump in demand for stocks below the 1000 cutoff relative to stocks above the cutoff. Figure 2 makes it clear that we should expect to find both an addition and deletion effect.

After banding is implemented, the only change is a shift in the cutoff rank. The discontinuities are no longer at 1000 but at a lower ranking for Russell 1000 firms moving into the Russell 2000. Similarly, the cutoff for Russell 2000 firms moving into the Russell 1000 is higher. There are fewer firms switching every year, as one would expect with an effective banding policy. On average, 3% of the stocks in the Russell 1000 switch to the Russell 2000 after banding. Of the stocks starting in the Russell 2000, 2% switch to the Russell 1000. However, the magnitudes of the changes in weights are similar to those before banding. As such, we still expect to find significant price effects from indexing after incorporating the postbanding sample.

1.4 Nonvalid RD using Russell index end-of-June weights

Since end-of-May market capitalization does not perfectly predict addition, one may be tempted to use index membership after reconstitution to infer the May rankings. In the Internet Appendix we show that it is not desirable to perform the RD design using end-of-June Russell index weights.

This methodology has two biases that make it much less clean than our current approach. First, among firms with market capitalizations above the 1000 cutoff, those with less tradable shares are more likely to end up with a lower Russell Index weight on the last Friday of June. Russell Inc. is not entirely transparent about how these float adjustments are made, which makes it difficult to map the final index weights to the rankings used to determine addition. We show in the Internet Appendix that this bias is significant because all the most illiquid stocks are placed at the bottom of the Russell 1000. The second bias is due to the fact that the new index weights after each year's reconstitution already encompass stock performance in June. This means that sorting on index weights is an approximate sorting on June performance itself, which again violates the assumption of random assignment and renders the RD invalid.

2. Price Effects and Demand Shocks

2.1 Assets benchmarked to Russell 1000 and 2000

In Panel A of Table 1, we report the amount of passive capital benchmarked to Russell 1000 and Russell 2000. This information is from a Russell internal report that surveys its passive clients every year at the end of June. However, these numbers are provided "as is," and Russell does not independently audit the numbers. We obtain these data from a contact at Russell's research division.[6]

[6] We thank Mark Paris of Russell for his help.

Table 1
Assets benchmarked to indexes

Panel A: Passive assets

	1996	1997	1998	1999	2000	2001	2002	2003
Russell 2000	11.6	7.6	11.0	13.6	18.9	21.5	26.9	24.6
Russell 1000	20.9	20.7	19.0	25.9	17.3	34.0	35.6	37.2
	2004	2005	2006	2007	2008	2009	2010	2011
Russell 2000	38.9	39.2	43.0	51.7	38.5	38.4	56.8	60.1
Russell 1000	84.9	93.3	151.9	175.8	144.8	104.4	137.1	125.8

Panel B: Assets benchmarked

Number of products	2002	2003	2004	2005	2006	2007	2008
S&P 500	1,009	924	919	901	888	824	685
Russell 2000	289	255	264	275	273	511	449
Russell 1000	29	43	43	48	52	52	60
Dollar amount	2002	2003	2004	2005	2006	2007	2008
S&P 500	1,679.8	1,096.9	1,431.8	1,482.9	1,576.7	1,748.6	1,412.1
Russell 2000	198.2	140.7	162.5	201.4	221.1	291.4	263.7
Russell 1000	47.6	37.3	66.9	90.0	146.1	172.7	168.6

Panel A reports the dollar amount of passive assets, in billions, benchmarked to the Russell 1000 and Russell 2000 by year. The data come from Russell's internal unaudited survey of its clients at the end of June. Panel B reports the number of products and dollar amount (in billions) of institutional assets benchmarked to the Russell 2000, Russell 1000, and S&P 500. These numbers are taken from Russell Investment's 2008 U.S. Equity Indexes: Institutional Benchmark Survey. The products surveyed are primarily institutional-oriented mutual funds, separate accounts, and commingled funds at the end of May.

Panel B of Table 1 shows the total assets benchmarked for S&P 500, Russell 1000, and Russell 2000. We show both the number of products and dollar amount benchmarked to these indexes. The data are obtained from Russell Investment's 2008 U.S. Equity Indexes: Institutional Benchmark Survey.[7] The numbers here include both passive and active benchmarking and are assessed by Russell every year from 2002 to 2008 at the end of May.

From the unaudited surveys in Panel A of Table 1, we see that the amount of passive assets is around 2 to 3.5 times bigger for the Russell 1000 index. For instance, in 2005, there was $93.3 billion tracking the Russell 1000 and $39.2 billion tracking the Russell 2000. Notice that since the index weight change from rank 1000 to rank 1001 is a tenfold increase, this difference in amount indexed is still small relative to the weight shift. In Panel B, we report the total amount of money benchmarked to these two indexes using Russell's cleaned estimates. When benchmarking is considered, the Russell 2000, at around $200 billion in 2005, is more popular than the Russell 1000, which is tracked by only $90 billion. Our contact at Russell pointed out that the estimates from the unaudited surveys for passive benchmarking are typically larger than the official numbers that Russell Inc. publishes. Notice also that there are many more products following the Russell 2000 than the Russell 1000. Of course, the interest in these two indexes is dwarfed by that in the S&P 500.

[7] This report is online at http://www.russell.com/JP/PDF/Index/2008_US_BenchmarkSurvey_E.pdf.

Since there is probably more forced buying from passive indexing than from active benchmarking, we conclude that both indexes have substantial amounts of money tied to them and that these amounts are roughly in the same ballpark. To gauge the expected effect of indexing, consider that the net indexing demand for a stock moving from the Russell 1000 to the Russell 2000 in any given year is described by the following equation:[8]

$$\Delta Demand_{it} = w_{i,R2000} BA_{R2000} - w_{i,R1000} BA_{R1000}, \tag{1}$$

where $w_{i,R2000}$ is the weight of stock i if it just makes it into the index, $w_{i,R1000}$ is its weight if it stays in the Russell 1000, and BA denotes the assets benchmarked to a particular index. We can rewrite this equation as

$$\Delta Demand_{it} = \frac{MV_i}{\sum_{R2000} MV_j} BA_{R2000} - \frac{MV_i}{\sum_{R1000} MV_j} BA_{R1000}. \tag{2}$$

Our regression discontinuity experiment comparing stocks 1001 and 1000 essentially uses stock 1000 as a counterfactual for the 1001 and captures what would have happened to the stock if it had just stayed in the Russell 1000. Therefore their market capitalization is approximately equal and we can simplify to

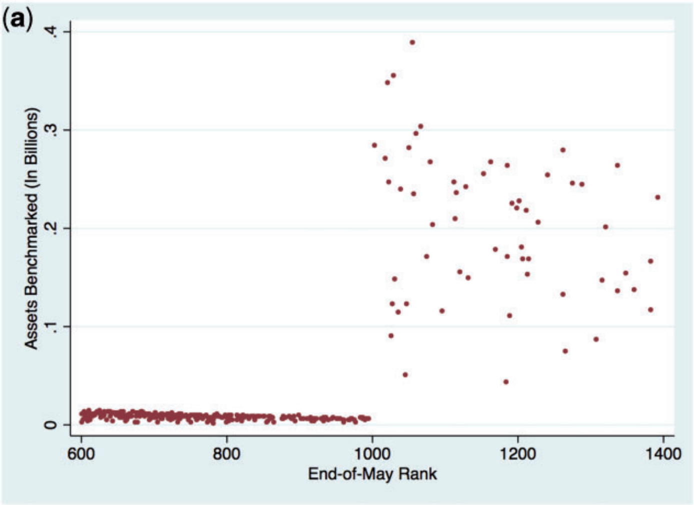
$$\%\Delta Demand = \Delta Demand_{it} / MV_i = \left(\frac{BA_{R2000}}{\sum_{R2000} MV_j} - \frac{BA_{R1000}}{\sum_{R2000} MV_j} \right). \tag{3}$$

In Figure 3 we show stock weights (w_i's) multiplied by the amount of money following their index (BA's) in June 2002. We use the dollar amount of benchmarked assets from Panel B of Table 1 to determine the relevant amount of money. In Figure 3(a) we show how the money benchmarked to stocks starting in the Russell 1000 varies by end-of-May ranking. Stocks just to the left of the 1000 cutoff have around \$5 million tracking them, whereas stocks just to the right of the cutoff have an average of \$200 million. Figure 3(b) shows similar numbers for stocks that started in the Russell 2000. This implies that the stocks that just made it into the Russell 2000 have 195 million more dollars of buying pressure. The stocks around this cutoff have an average market capitalization of \$1.4 billion.

We can translate this change in demand into a number for $\%\Delta Demand$. We estimate the assets benchmarked with the data in Panel B of Table 1. Averaging over the years 2002–2008 we get that BA_{R1000} is \$45.6 billion and BA_{R2000} is \$92.4 billion. The total market capitalization of the indexes, $\sum MV_j$, averages \$11.9 trillion for the Russell 1000 and \$1.2 trillion for the Russell 2000. Plugging these values into Equation (3) we find that $\%\Delta Demand = 7.3\%$. This is a sizable figure, so we would expect to detect some economically interesting price effects.

8 We thank the referee for suggesting the following decomposition.

Starting in Russell 1000



Starting in Russell 2000

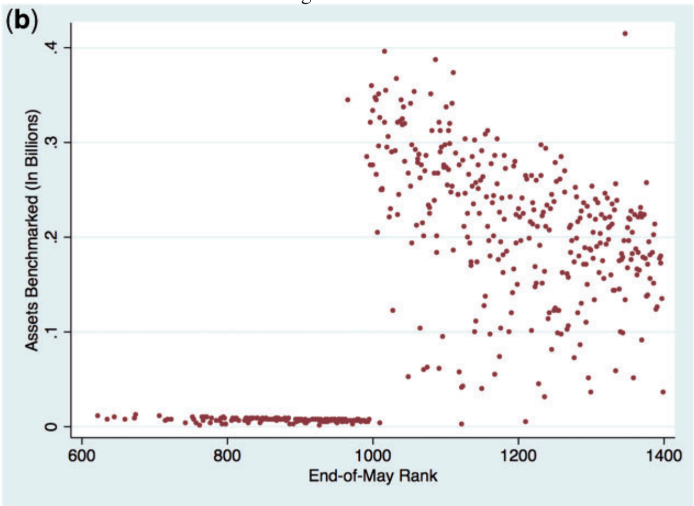


Figure 3
Assets benchmarked to stocks in 2002
Assets benchmarked are measured in billions of dollars and plotted against end-of-May market capitalization rankings. This is calculated by multiplying June index weights by the dollars benchmarked to the relevant index (from Panel B of Table 1) in 2002. Firms on the left side of the cutoff end up in the Russell 1000 in June and those on the right side end up in the Russell 2000.

2.2 Anticipation of demand shocks

Next, it is important to draw out the incentives of arbitrageurs to anticipate the Russell rebalancing. Consider stocks that are in the Russell 1000 on May 30, 2013. The last day of the month is May 31, 2013. Among these stocks, say there are two stocks A and B that are ranked 999 and 1002, respectively, using the market capitalizations of all stocks at the end of May 30. If nothing else changed between May 30 and May 31, B would move from the Russell 1000 into the Russell 2000. A would remain a Russell 1000 stock.

We find a price bump for B relative to A after the inclusion date, May 31. So why don't the arbitrageurs buy B ahead of time and move the price before May 31? The reason is that there is no incentive for hedge funds to buy B if their trades have price impact. If they buy B on May 30, the price of B will move up due to the price impact of their trades. This means that the market capitalization of B will rise and make it a larger stock. If the trade moves the stock to rank 1000, it will then move out of the Russell 2000 index.

Now consider stocks in the Russell 2000 on May 30, 2013. Take stocks C and D, which are ranked 995 and 1005, respectively. If nothing changed between May 30 and May 31, C would become a Russell 1000 stock and D would stay in the Russell 2000 index. Here the front-running strategy is to short C because the price of C falls on deletion as it goes from a high-weight stock in the Russell 2000 to no weight in the Russell 1000. But shorting the stock will make the price of C fall, lowering its market capitalization. If the price impact of the arbitrageurs moves it to a rank of 1001, it will remain in the Russell 2000 index. In this case the shorting would be self-defeating. We find a price effect on order of 5% from additions or deletions. The price impact of trades for stocks around the 1000 cutoff, which are small stocks, is easily several percentage points and most likely higher.

Anticipated demand is more of an issue for the bottom cutoff of Russell 2000; i.e., the 3000 cutoff. Here the issue might indeed be very important and might even explain why we do not seem to find as clean an indexing result. The stocks ranked just outside 3000 are prime candidates for inclusion. Here there is an incentive for front-running because buying these stocks might push them into the index and enjoy a subsequent price increase from the indexing effect.

3. Variable Definitions and Summary Statistics

All other variables for analyzing addition and deletion effects are from CRSP and Compustat. The independent variable of interest is the end-of-May rankings of stocks' market capitalizations (Mktcap). Our main dependent variables of interest include the following: Returns is the raw monthly stock return. Volume ratio for stock i in month t is defined as $VR_{i,t} = (V_{i,t}/V_i)/(V_{m,t}/V_m)$, where $V_{i,t}$ and $V_{m,t}$ are the trading volumes of stock i and of the market. V_i and V_m are the average trading volume of stock i and the market over the past six months, not including month t. Trading volume on the NASDAQ is adjusted using the Gao and Ritter (2010) procedure. SR is the monthly short interest ratio, the ratio of shares shorted to shares outstanding for each stock. Comovement is the estimated beta coefficient between daily stock returns and Russell 2000 index returns in a given month. Other fundamental variables that serve as additional validity checks include the following: ROE and ROA are the return on equity

Table 2
Summary statistics

	Russell 1000			Russell 2000		
	Median	Mean	SD	Median	Mean	SD
Returns	.00688	.00739	.121	.00479	.00972	.16
Mktcap	4.21	12.3	28.7	.473	.631	.556
IO	.709	.682	.223	.59	.598	4.11
VR	.97	1.06	.471	.953	1.12	.92
SR	.0224	.036	.0414	.0316	.0512	.0621
Comovement	.703	.842	.839	.885	.972	.793
Repurchase	1	.673	.469	0	.474	.499
ROE	.133	.0427	6.75	.0919	−.957	149
ROA	.0431	.0368	.187	.0279	−.0104	.253
EPS	1.63	1.71	4.34	.81	.676	3.61
Assets	4,794	23,396	96,193	578	1,179	2,093
C/A	.0398	.0767	.0935	.0535	.116	.148
ICR	5.25	67.1	1,058	3.03	49.8	1,322
Float	113,758	296,910	710,119	21,438	30,052	33,015
Observations	198,551			382,233		

This table reports monthly summary statistics for all member stocks in the Russell 1000 and Russell 2000. Return is monthly stock returns. Mktcap is measured in billions of dollars. IO is institutional ownership. VR is volume ratio. SR is short ratio. Comovement is the estimated beta between daily stock returns and Russell 2000 index returns, computed monthly and excluding mechanical covariance due to index membership. Repurchase is an indicator for repurchase activity in that fiscal year. ROE and ROA are return on equity and return on asset. EPS is earnings per share, excluding extraordinary items. Assets is asset book value in millions of dollars. C/A is the cash-to-asset ratio. ICR is the interest coverage ratio. Float is the number of floating shares (in thousands). The sample period is 1996–2012.

and return on assets. EPS is the earnings per share excluding extraordinary items. Float is the number of floating shares (in thousands) provided by Russell. Assets is the asset value (in millions). C/A is the cash-to-asset ratio and ICR is the interest coverage ratio.

Table 2 reports summary statistics for the Russell 1000 and Russell 2000 firms. The mean and standard deviation of returns are somewhat higher for Russell 2000 stocks than for Russell 1000 stocks. The median market capitalization (Mktcap) is \$4.21 billion for Russell 1000 stocks and around \$0.47 billion for Russell 2000 stocks. As expected, the comovement of the Russell 2000 stocks with the Russell 2000 index is stronger than the comovement of the Russell 1000 stocks with the Russell 2000 index. The top 1000 stocks have higher institutional ownership (IO) but less shorting (SR). The Russell 2000 firms are less likely to repurchase shares. They also have lower ROE, ROA, and EPS, and fewer assets. Russell 2000 stocks, not surprisingly, have fewer float shares than the top 1000 firms.

4. Results

4.1 Fuzzy RD regression specifications

To formally test the significance of addition to the Russell 2000 index, we use a fuzzy regression discontinuity design. Because our measure of market capitalization is not exactly the same as that used by Russell Inc., our rankings cannot perfectly predict membership in the index. The only factor that affects index membership, other than our rankings, is the difference between our measure of market capitalization and that used by the Russell index. Therefore treatment is determined partly by whether the ranking crosses the cutoff and partly by measurement error. As a case of local random assignment, this is an appropriate setting for fuzzy RD design. We use two-stage least-squares, as suggested by Hahn, Todd, and van der Klaauw (2001), to estimate the effect of index membership.

The instrument in this framework is an indicator variable τ for whether a firm of rank r is on the side of the cutoff c required for index membership. In the case of the upper cutoff, c is 1000 before banding and is calculated separately every year after banding is implemented. The indicator variable D identifies subsequent membership in the Russell 2000 from data on actual index constituents every year. The first-stage regression estimates

$$D_{it} = \alpha_{0l} + \alpha_{1l}(r_{it} - c) + \tau_{it}[\alpha_{0r} + \alpha_{1r}(r_{it} - c)] + \varepsilon_{it} \tag{4}$$

for each firm i and year t. The resulting estimates of α_{0r} are reported below. If our instrument τ is a perfect predictor of membership, the coefficient α_{0r} would be one. We estimate this first stage separately for addition and deletion.

For the second stage, we estimate a similar relationship between ranking and the outcome variable. For each outcome of interest Y we estimate the equation

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c)] + \epsilon_{it}. \tag{5}$$

The resulting estimates of β_{0r} are reported as the addition effect or the negative of the deletion effect.

4.2 Optimal bandwidth

We use a local linear regression to nonparametrically estimate the effects of addition and deletion close to the cutoff. The choice of bandwidth defines how many firms on either side of the cutoff are used in the estimation. This choice balances the benefits of more precise estimates as the sample size grows and the costs of increased bias. As the bandwidth increases, observations that are farther from the cutoff can influence the estimate of the change at the cutoff. Using the rule-of-thumb (ROT) bandwidth presented in Lee and Lemieux (2010), we calculate the optimal bandwidth. It varies with how we define our initial sample of Russell firms but in general it is close to 100.

To address the fact that firms 100 spots from the cutoff may be systematically different from firms 1 spot from the cutoff, we use a local linear regression. To illustrate this point, consider an alternative way to approach the RD estimate. One could compute the average value on either side of the cutoff and estimate the discontinuity by taking the difference. However, this would give equal weight to stocks 100 spots away and those 1 spot away, biasing the estimate of the discontinuity. If instead the outcome values are allowed to vary linearly on either side of the cutoff, as suggested by Hahn, Todd, and van der Klaauw

(2001), then the bias is reduced by an order of magnitude. The firms that are closest to the cutoff now contribute the most to the estimate of the discontinuity. Our preferred specification uses a bandwidth of 100 and linear functions of ranking on either side of the cutoff. However, results are robust to changes in the bandwidth and to quadratic functions of ranking.

It is important to note that it is not necessary to control for other variables or fixed effects if the RD is valid. Lee and Lemieux (2010) point out that the use of other baseline covariates in an RD design is primarily to reduce sampling variability. Firms falling above or below the 1000 cutoff are randomized, and there should not be significant differences in firm characteristics prior to the rankings. We verify that this is true in Section 5.4.3.

4.3 First-stage regressions

In Table 3, we show the first-stage regressions of the fuzzy RD design. In the top of Table 3, we present the first-stage regressions for the addition effect at the 1000 cutoff before and after the implementation of the banding policy. All stocks used in these regressions were in the Russell 1000 in year $t-1$ and were within 100 spots of the cutoff based on their end-of-May market capitalizations in year t. Before banding, the coefficient of interest α_{0r} is 0.785 with a t-statistic of 31.5. The adjusted R^2 of this regression is 0.863. After banding, the coefficient is 0.82 with a t-statistic of 12.98 and an R^2 of 0.845.

Table 3
First stage of fuzzy RD

Addition

	Upper cutoff	Upper cutoff after banding
τ	0.785***	0.820***
	(31.50)	(12.98)
N	893	164
adj. R^2	0.863	0.845
F	1,876	297

Deletion

	Upper cutoff	Upper cutoff after banding
τ	0.705***	0.759***
	(29.15)	(20.90)
N	1206	340
adj. R^2	0.817	0.878
F	1,799	815

The table reports the first-stage regression from a fuzzy RD design. The following equation is estimated.

$$D_{it} = \alpha_{0l} + \alpha_{1l}(r_{it} - c) + \tau_{it}[\alpha_{0r} + \alpha_{1r}(r_{it} - c)] + \varepsilon_{it}.$$

The outcome variable D is an indicator for addition to the Russell 2000 index. The variable τ is an indicator for whether the firm's end-of-May market capitalization ranking r_{it} predicted addition to the Russell 2000 index. We show coefficient estimates of α_{0r}, and t-statistics are reported in parentheses. All regressions use firms with end-of-May ranking within 100 spots of the predicted cutoff c. The panel identifying the addition effect only uses firms that were in the Russell 1000 at the end of May. The panel identifying the deletion effect only uses firms that were members of the Russell 2000 at the end of May. The sample period is 1996–2012. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

In the bottom half of Table 3, we present the first-stage regressions for the deletion effect at the 1000 cutoff before and after banding. All stocks were in the Russell 2000 in year $t-1$ and were within 100 spots of the cutoff based on their end-of-May market capitalizations in year t. Before banding, the coefficient is 0.705 with a t-statistic of 29.15. The adjusted R^2 of this regression is 0.817. After banding, the coefficient α_{0r} is 0.759 with a t-statistic of 20.90 and an R^2 of 0.878.

The first-stage regression is extremely strong in all cases. We cannot perfectly predict membership but on average, a firm is 70% to 80% more likely to be added to the Russell 2000 when the cutoff is crossed. The first-stage regressions are similar before and after banding, which indicates our estimates of the postbanding cutoffs are accurate.

4.4 Russell 1000 cutoff

4.4.1 Returns. In the top half of Table 4, we report the fuzzy RD results for the effect of addition on raw returns. The outcome variable is monthly stock returns and the independent variable is an indicator for addition to the Russell 2000 index. Monthly returns are shown for the month immediately before (May) and four months following index membership determination (June, July, August, and September), and t-statistics are reported in parentheses. Only firms that were members of the Russell 1000 index at the end of May are used.

Notice that the coefficient of interest for June returns is 0.05 and is significant at the 1% level. This means there is a 5% addition effect when comparing firms that just crossed the 1000 cutoff and firms that just missed it. Notice that there

Table 4
Returns fuzzy RD

Addition effect

	May	Jun	Jul	Aug	Sep
D	−0.003	0.050**	−0.003	0.035	−0.021
	(−0.14)	(2.65)	(−0.11)	(1.59)	(−0.89)
N	1055	1057	1053	1052	1047

Deletion effect

	May	Jun	Jul	Aug	Sep
D	0.005	0.054**	−0.019	−0.002	0.011
	(0.32)	(3.00)	(−0.96)	(−0.09)	(0.53)
N	1546	1545	1533	1526	1519

The table reports the results of a fuzzy RD design. The following equation is estimated.

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c)] + \epsilon_{it}.$$

The outcome variable is monthly stock returns and the independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D. We show coefficient estimates of β_{0r}, and t-statistics are reported in parentheses. The bandwidth is 100. The regression identifying the addition effect only uses firms that were in the Russell 1000 at the end of May. The regression identifying the deletion effect only uses those that were members of the Russell 2000 at the end of May. The sample period is 1996–2012. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

are no statistically significant coefficients in any other months. In particular, we should not see any noticeable return effects in May if our design is valid, given that membership is determined at the end of that month. In contrast, we might expect positive return effects not only for June but also for subsequent months if institutional investors gradually begin to track the Russell 2000 after May. Alternatively, we might expect there to be a positive effect for June followed by negative returns in subsequent months if there are reversals. The fact that we see a return effect only for June and none in following months means that there are no significant reversals.

In Figure 4, June returns are plotted against market capitalization rankings. The top two figures show only firms that were in the Russell 1000 index in May. The firms that stay in the Russell 1000 are on the left-hand side of the cutoff. The firms that move into the Russell 2000 are on the right-hand side. These are the firms that identify the addition effect. The lines drawn are linear functions of rank on either side of the cutoff. Results are shown using bin widths of 2 and 5, meaning each point represents averages over all years and either 2 or 5 ranks. We expect the just-added stocks to have a positive demand shift, and thus a higher June return. Indeed, there is a visible jump in returns in June.[9]

In the bottom half of Table 4 we report the fuzzy RD results for the deletion effect on raw returns. The outcome variable is monthly stock returns and the independent variable is an indicator for staying in the Russell 2000 index. Only firms that were members of the Russell 2000 index at the end of May are used. Note that there are more firms starting in the Russell 2000 than in the Russell 1000. Therefore the sample sizes are larger for the deletion effect.

The coefficient of interest for June returns is 0.054 and is significant at the 1% level. This means that there is a 5% deletion effect when comparing firms that crossed the 1000 cutoff with firms that did not. This point estimate is very similar to the estimate for addition, implying that the addition and deletion effects are symmetric. Note that the coefficient should be positive and not negative for deletion since we are comparing the returns of stocks that remained in the Russell 2000 to those that just got deleted, which we expect to be positive since deletion leads to lower returns.

In the bottom half of Figure 4, we plot these results for June returns. All firms shown were in the Russell 2000 index in May. The firms that moved into the Russell 1000 are on the left-hand side of the cutoff. These are the firms that identify the deletion effect. The firms that stayed in the Russell 2000 are on the right-hand side. There is a visible discontinuity in returns for stocks that stayed in versus stocks that dropped out of the Russell 2000 index.[10]

[9] Note that we are presenting raw returns. Stocks on either side of the 1000 cutoff in this addition exercise were Russell 1000 stocks in the prior year whose values fell. These stocks had negative June returns over our sample period. But just-added stocks received a positive price shock due to indexing, thereby bringing their raw returns closer to zero.

[10] Note that we are again presenting raw returns.

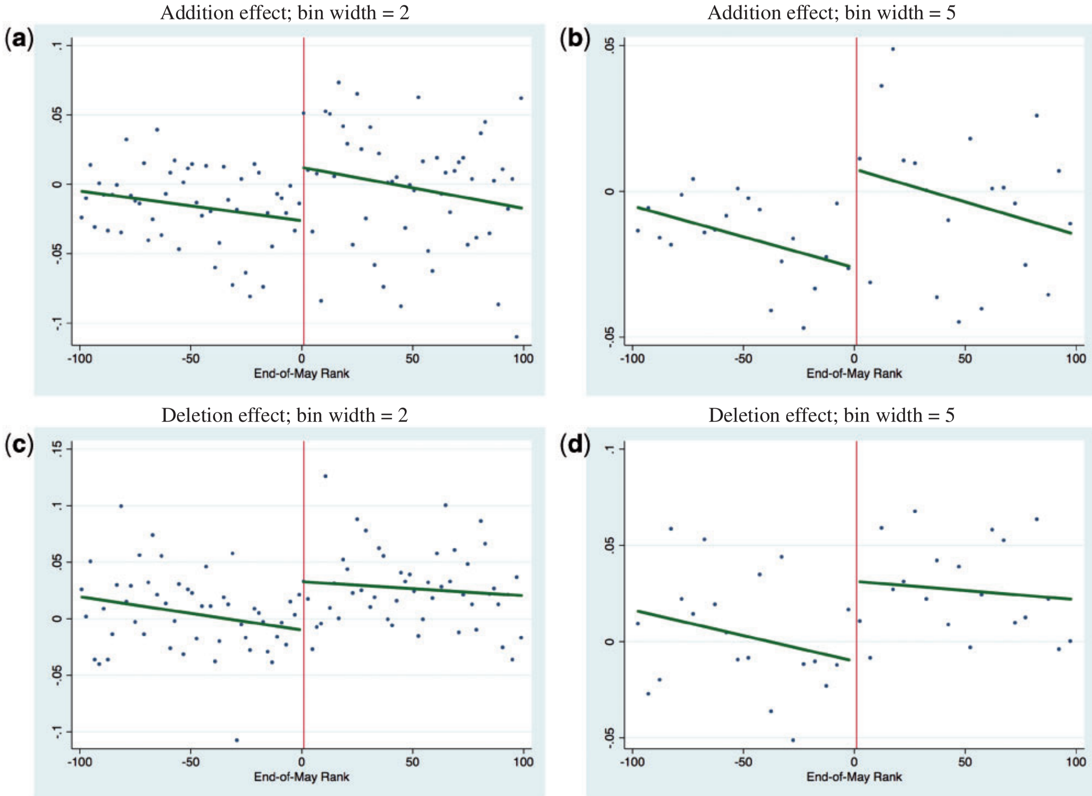


Figure 4
June returns around upper cutoff
June returns are plotted against end-of-May market capitalization ranking. The firms that end up in the Russell 1000 are on the left-hand side of the cutoff. The firms that end up in the Russell 2000 are on the right-hand side. Panels (a) and (b) use firms that were in the Russell 1000 at the end of May and these identify the addition effect. Panels (c) and (d) use firms that were in the Russell 2000 at the end of May and these identify the deletion effect. The sample period is from 1996 through 2012. The lines drawn fit linear functions of rank on either side of the cutoff. Every point represents averages over all years and over the number of ranks equal to the bin width.

Overall, the key take-away from these results is that there is both a strong addition and a strong deletion effect. This stands in contrast to the results found using the old methodology, which confounds the addition effect with earnings changes and consistently fails to find a deletion effect. One interpretation of the symmetry of the addition and deletion effects is that our method picks up a forced tracking effect whereas the old methodology is mixing both a tracking effect and a recognition effect.

To relate our results to the literature, we divide our estimate of $\Delta Return$ by $\%\Delta Demand$ to get the price elasticity associated with our demand shock:

$$Elasticity = -\frac{1}{\Delta Return/\%\Delta Demand} \tag{6}$$

(The equations for deletions would simply be a negative demand shock and lower or negative returns upon deletion.) With flat or perfectly elastic demand curves the price elasticity is $-\infty$. With downward-sloping or inelastic demand, the price elasticity approaches zero. Wurgler and Zhuravskaya (2002) provide a comprehensive review of price elasticity estimates found in the literature. Most of the estimates center around -5 to -10. For instance, the price elasticity estimate from the most cleanly identified study of Kaul, Mehrotra, and Morck (2000) is -10. Their set of stocks are comparable in terms of market capitalization to ours.

Recall that our estimate of $\%\Delta Demand$ is 7.3%. Dividing this by the negative of the $\Delta Return$ estimate of 5% yields a price elasticity of -1.46. If we use passive assets rather than assets benchmarked we get an elasticity estimate of -0.39. So this contrast of our estimates to those in the literature speaks to the need for our measure of the price effects of indexing, as opposed to extrapolating price elasticity estimates from index reweighting or other settings.

4.4.2 Trading and institutional ownership. We next discuss the findings for trading volume ratio (VR) and institutional ownership (IO) shown in Table 5. Notice that addition leads to a dramatic increase in VR in the month of June. The estimate in June is 0.478 with a t-statistic of 3.14. This effect is around 50% of a one-standard-deviation change in VR among Russell 2000 firms. As expected, there are no effects in the months preceding the reconstitution. The elevated trading after addition reflects a shift of indexing or benchmarking money into the added stocks. We also find that stocks that get deleted experience elevated trading volume in the month of June relative to stocks that stay in the index. This higher turnover makes sense as it reflects that index money is leaving the dropped stocks due to decreased demand. The coefficient is -0.263, with a t-statistic of 2.74. This is a substantial change in trading relative to the standard deviation of VR.

The observed rise or fall in demand due to indexing or benchmarking can be met by other institutional investors, ones that do not have inelastic demand for indexed stocks and can therefore sell on additions and buy on deletions, or

Table 5
Other outcome variables

Addition effect

	May	Jun	Jul	Aug	Sep
VR	−0.010	0.478**	0.114	0.097	−0.020
	(−0.13)	(3.14)	(1.44)	(1.15)	(−0.22)
IO		0.031			0.036
		(0.77)			(0.89)
N	920	921	918	915	913

Deletion effect

	May	Jun	Jul	Aug	Sep
VR	0.151	−0.263**	0.050	0.106	0.166
	(0.79)	(−2.74)	(0.55)	(1.55)	(1.64)
IO		−0.063			−0.037
		(−1.69)			(−1.02)
N	1308	1309	1300	1295	1284

The table reports the results of a fuzzy RD design. The following equation is estimated.

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c)] + \epsilon_{it}.$$

The independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D. We show coefficient estimates of β_{0r}, and t-statistics are reported in parentheses. The bandwidth is 100. The regression identifying the addition effect only uses firms that were in the Russell 1000 at the end of May. The regression identifying the deletion effect only uses those that were members of the Russell 2000 at the end of May. VR is volume ratio. IO is institutional ownership and is measured quarterly. The sample period is 1996–2012. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

it can be met by retail investors. To see who meets the changes in demand, we compare how institutional ownership levels change with addition and deletion. There appears to be a small and statistically insignificant change in institutional ownership for addition. For instance, the coefficient for addition in June is 0.031 with an insignificant t-statistic of 0.77. Recall that IO is only available quarterly. For deletion, we see a coefficient of −0.063 for June, but the result is not statistically significant. So overall it seems that the trading of indexed stocks does not result in significant changes in the level of institutional ownership. Those institutions with less inelastic demand for index member stocks provide liquidity to those with more inelastic demands for these stocks.

4.4.3 Validity tests. We now formally show that attributes determined before the end-of-May ranking are smooth across the cutoff for membership in the Russell 2000. For example, if companies with resources could manipulate their stock prices and thus qualify for a more popular Russell index, this would distort the random assignment around the index cutoff and potentially render the RD framework invalid. In this section, we perform validity checks on a host of fundamental variables. Following Lee and Lemieux (2010), we test our RD design by ensuring that all variables determined prior to the realization of the treatment are smooth. This is crucial to the assumption of local randomization.

Table 6
Validity tests

Addition effect

	Mktcap	Repurchase	ROE	ROA	EPS	Assets	ICR	C/A	Float
	.0028	–.0526	–1.25	.0664	–.174	–787	18.8	.0216	–786
	(0.06)	(–0.56)	(–0.37)	(1.32)	(–0.46)	(–1.39)	(0.22)	(1.12)	(–0.07)
N	1057	750	890	890	889	891	785	869	1057

Deletion effect

	Mktcap	Repurchase	ROE	ROA	EPS	Assets	ICR	C/A	Float
	.0315	–.0675	–.922	–.0258	.858	–95.7	–157	.0124	–2,204
	(0.41)	(–0.81)	(–0.98)	(–0.87)	(0.67)	(–0.28)	(–1.12)	(0.62)	(–0.35)
N	1546	1005	1240	1240	1240	1240	1085	1222	1546

The table reports the results of a fuzzy RD design. The following equation is estimated.

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c)] + \epsilon_{it}.$$

The independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D. We show coefficient estimates of β_{0r}, and t-statistics are reported in parentheses. The bandwidth is 100. The regression identifying the addition effect only uses firms that were in the Russell 1000 at the end of May. The regression identifying the deletion effect only uses those that were members of the Russell 2000 at the end of May. The data on fundamental variables are annual so estimates cannot be reported separately for each month. Mktcap is in billions of dollars. Repurchase is an indicator for repurchase activity in that fiscal year. ROE and ROA are return on equity and return on assets. EPS is earnings per share, excluding extraordinary items. Assets is asset book value in millions of dollars. C/A is the cash-to-asset ratio. ICR is the interest coverage ratio. Float is the number of floating shares (in thousands). The sample period is 1996–2012.

Table 6 first reports the results of a fuzzy RD design testing for an addition effect in market capitalization. The outcome variable is measured in billions of dollars at the end of May. Other regression specifications are similar to those used for the return effect tests. The independent variable is an indicator for addition to the Russell 2000 index. All regressions use firms with end-of-May ranking within 100 spots of the predicted cutoff. The regression specification includes a linear function of ranking that is allowed to vary on either side of the cutoff.

It is easy to see that there are no breaks in market capitalization. One argument that could invalidate the RD design is manipulation by the less financially constrained firms. It is conceivable that firms close to the cutoff with more financial slack can decrease their market capitalization by repurchasing shares. Firms that are more financially constrained are not able to do this and are thus stuck in the bottom of the Russell 1000. To alleviate this concern, we look at the repurchasing activities (Repurchase) of the firms around the index cutoff. We do not find discontinuities in this variable.

We then repeat the analysis with a number of other firm fundamentals around the index cutoff prior to the May ranking. These include profitability (ROE, ROA, and EPS), number of floating shares (Float), and size (Assets). One can see that there are no significant discontinuities in any of the variables we consider. Nor are there discontinuities in interest coverage ratio (ICR) or cash-over-asset ratio (C/A), which are also related to a firm's financial status.

In the bottom half of Table 6, we report analogous estimates for the deletion effect. Again there are no significant breaks across the 1000 cutoff. All the annual outcome variables reported in this table are measured in the fiscal year prior to the end-of-May ranking. We also examined the same set of variables in the fiscal year of the reconstitution and did not find any discontinuities. In the Internet Appendix we show graphically the smoothness of some firm fundamentals around the cutoff.

Finally, it is typical in studies with RD designs to conduct the McCrary (2008) test to ensure there is no "bunching" in the assignment variable. If there is manipulation, one will see a higher number of observations just passing the cutoff and fewer observations just missing it. However, in our design there is exactly one firm for each ranking position, and therefore the density of observations is always identical on either side of the cutoff.

5. Time Trends in the Effects of Indexing

Having measured the average addition and deletion effects over our sample period of 1996–2012, we now try to determine how these effects have changed over time. The motivation underlying our empirical analysis is that several recent theoretical analyses suggest that, all else equal, greater demand for index stocks will lead to a higher index premium and excessive co-movement (relative to fundamentals) of indexed stocks (see, e.g., Vayanos and Woolley 2011; Basak and Pavlova 2013). In other words, the rising popularity of indexing leads to greater nonfundamental movements in prices over time. However, these studies ignore the fact that arbitrage frictions have also fallen over time. For instance, Hanson and Sunderam (2014) document that the rise of hedge funds has been associated with more shorting and greater efficiency in markets. In other words, there are two time trends and there are few well-identified studies on the net effects of these two trends.

There has been limited prior work trying to identify these trends. The most prominent that we know of is Morck and Yang (2002), which finds some increasing indexing effects using S&P 500 additions, but their sample ends in 2002. Our approach offers a few advantages in identifying time trends. Notably, there are a greater number of additions and deletions each year in comparison to the S&P 500. Indeed, as we already mentioned, there are very few deletions throughout most of the S&P 500 sample.

To address the issue of time trends we modify our baseline regression equation. The first-stage regression specification is now given by the equation

$$D_{it}=\alpha_{0l}+\alpha_{1l}(r_{it}-c)+\alpha_{2l}t+\tau_{it}[\alpha_{0r}+\alpha_{1r}(r_{it}-c)+\alpha_{2r}t]+\varepsilon_{it},$$

where we have added a variable t to capture a linear time trend; t is the difference between the year of the observation and 1996. Both baseline returns and the estimates of the addition and deletion effects are allowed to vary linearly over time. The second-stage estimate for outcome of interest Y is now given by

$$Y_{it}=\beta_{0l}+\beta_{1l}(r_{it}-c)+\beta_{2l}t+D_{it}[\beta_{0r}+\beta_{1r}(r_{it}-c)+\beta_{2r}t]+\epsilon_{it},$$

where t is again the linear time trend. This specification estimates a baseline effect of index membership β_{0r} for 1996 and its average change over time β_{2r}.

To test whether the index effect has moved in step with demand, we change our outcome variable Y from monthly returns to returns weighted by the inverse demand change so that $Y_{it} = Return_{it}/\%\Delta Demand_{it}$. This means that β_{0r} identifies the price impact at the beginning of the period. It is positive if returns increase upon addition and decrease upon deletion. Recall that price impact is also the negative inverse of the price elasticity of demand.

If elasticity has stayed constant over time, then $\beta_{2r} = 0$, and we can conclude that the index effect has increased in step with the influx of demand. If demand for indexed stocks has become more elastic over time, then price impact has decreased in magnitude, and $\beta_{2r} < 0$. Similarly, if demand for stocks has become more inelastic, then $\beta_{2r} > 0$.

The results of the time trend regressions are displayed in Tables 7 and 8. For each variable, the first row displays the estimate for β_{0r} and represents the RD estimate of the effect of index membership on the outcome variable in the base year 1996. The second row corresponds to the estimate of β_{2r} and represents the average change in the RD estimate from 1996 to 2012. Because the data on benchmarked assets are not available for the complete time period, we instead use the $\%\Delta Demand$ calculated using passive assets. All regressions use a bandwidth of 100 and fit a linear function in rank on either side of the discontinuity, as before. The results are similar when using different polynomial specifications and bandwidths, and they are omitted for brevity.

Table 7 shows how addition effects change over time. The price impact is positive and significant but falls over time. The initial price impact of 5.85 translates to an elasticity of −0.171.[11] Using the linear time trend in price impact, after one year elasticity is −0.184, and it continues to grow in size throughout the sample period. Using our addition effect estimate of 5%, the average elasticity over the whole sample period is −0.39. In short, the force of arbitrage efficiency has increased faster than the effect of indexing, and demand has grown more elastic over time. So even though indexing has become more popular and this should lead to a higher index premium, according to recent models, we actually find the opposite result. Presumably this is because these models do not account for the rising efficiency of the arbitrage process.

In addition to returns, we also show what happens to the volume ratio over time. If more money is indexing or tracking the Russell 2000 over time and the price effects are falling, then we expect the volume ratio to be higher to reflect more rebalancing each year. This is indeed what we find. In the base year of 1996, the volume ratio is 0.329 and has a t-statistic of 2. The coefficient on VR $\times t$ is 0.023 with a t-statistic of 2.5. This implies that the volume ratio is growing by almost 7% per year.

[11] Note that the price elasticity estimates obtained using passive assets will be smaller in absolute value compared to when we use total benchmarked assets.

Table 7
Addition effect over time

	May	Jun	Jul	Aug	Sep
Returns/%Δ Demand	0.243	5.850**	–3.791	1.273	–1.761
	(0.10)	(2.76)	(–1.37)	(0.49)	(–0.61)
Returns/%Δ Demand ×t	0.088	–0.403*	0.386	0.080	0.115
	(0.50)	(–2.46)	(1.87)	(0.39)	(0.55)
N	1026	1028	1024	1023	1018
VR	–0.026	0.329*	0.055	0.166	0.015
	(–0.23)	(2.00)	(0.58)	(1.55)	(0.12)
VR ×t	0.004	0.023*	0.010	–0.009	–0.006
	(0.38)	(2.50)	(1.25)	(–0.99)	(–0.64)
N	1048	1049	1051	1047	1047
SR	–0.010	–0.013	–0.016	–0.021*	–0.018
	(–1.03)	(–1.28)	(–1.57)	(–2.10)	(–1.82)
SR ×t	0.001	0.002*	0.004***	0.004***	0.004***
	(1.41)	(2.18)	(3.44)	(3.45)	(3.59)
N	920	921	918	915	913
Comovement	0.180	0.133	–0.139	–0.102	0.145
	(0.95)	(0.88)	(–0.68)	(–0.53)	(0.70)
Comovement ×t	–0.007	–0.027*	0.017	0.037**	–0.001
	(–0.59)	(–2.28)	(1.16)	(2.64)	(–0.03)
N	1049	1050	1046	1045	1042

This table reports the results of a fuzzy RD design where the effect of the instrument is allowed to vary linearly with time. The following equation is estimated.

$$Y_{it} = \beta_{0l} + \beta_{1l}(r_{it} - c) + \beta_{2l}t + D_{it}[\beta_{0r} + \beta_{1r}(r_{it} - c) + \beta_{2r}t] + \epsilon_{it}.$$

The independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D. For each regression, we report the coefficient estimates β_{0r} and β_{2r}, and t-statistics are reported in parentheses. The bandwidth is 100. Only firms that were members of the Russell 1000 index at the end of May are used to estimate the addition effect. Returns/%Δ Demand is monthly returns weighted by the inverse demand change. VR is volume ratio. SR is short ratio. Comovement is the beta estimate between daily stock returns and Russell 2000 index returns, computed monthly and excluding mechanical covariance due to index membership. The sample period is 1996–2012. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

For the index premium to fall and the volume ratio to grow, it should also be true that the number of liquidity providers willing to sell Russell 2000 stocks is growing. One source of liquidity providers is short-selling hedge funds. We look for evidence of increased shorting by examining how the short ratio has changed for added firms over time. In the base period, a stock's short ratio did not change much in response to index addition. The coefficient on SR is -0.013 with a t-statistic of -1.28. Over the years, shorting increased significantly for added stocks in all months following the Russell 2000 rebalance. The coefficient on SR $\times t$ is 0.002 with a t-statistic of 2.18. This increase in short-supply is consistent with the diminishing effect on returns and the growth in assets benchmarked to the indexes.

Recent theories of the potentially destabilizing effects of indexing also place emphasis on excessive comovement as a measure of the impact of

Table 8
Deletion effect over time

	May	Jun	Jul	Aug	Sep
Returns/%Δ Demand	0.137	8.661***	–4.106	–1.460	1.194
	(0.05)	(3.91)	(–1.44)	(–0.53)	(0.44)
Returns/%Δ Demand $\times t$	–0.108	–0.608***	0.455*	0.056	–0.091
	(–0.44)	(–3.70)	(2.20)	(0.26)	(–0.45)
N	1473	1472	1461	1454	1447
VR	0.229	–0.057	–0.034	0.164	0.093
	(0.88)	(–0.51)	(–0.33)	(1.83)	(0.88)
VR $\times t$	–0.010	–0.028**	0.011	–0.008	0.010
	(–0.70)	(–3.08)	(1.13)	(–1.23)	(1.15)
N	1543	1545	1542	1532	1523
SR	0.007	0.003	0.002	0.006	0.007
	(0.71)	(0.34)	(0.26)	(0.59)	(0.71)
SR $\times t$	–0.000	–0.000	0.001	0.001	0.001
	(–0.64)	(–0.27)	(1.84)	(1.71)	(1.28)
N	1308	1309	1300	1295	1284
Comovement	–0.062	0.321	0.353*	–0.083	0.265
	(–0.43)	(1.92)	(2.24)	(–0.48)	(1.43)
Comovement $\times t$	0.006	–0.000	0.002	0.034**	0.004
	(0.56)	(–0.03)	(0.23)	(2.71)	(0.32)
N	1540	1540	1532	1521	1514

This table reports the results of a fuzzy RD design where the effect of the instrument is allowed to vary linearly with time. The following equation is estimated.

$$Y_{it}=\beta_{0l}+\beta_{1l}(r_{it}-c)+\beta_{2l}t+D_{it}[\beta_{0r}+\beta_{1r}(r_{it}-c)+\beta_{2r}t]+\epsilon_{it},$$

The independent variable D is an indicator for membership in the Russell 2000 index. An indicator for whether ranking r_{it} is above the cutoff c is used as an instrument for D. For each regression, we report the coefficient estimates β_{0r} and β_{2r}, and t-statistics are reported in parentheses. The bandwidth is 100. Only firms that were members of the Russell 2000 index at the end of May are used to estimate the deletion effect. Returns/%Δ Demand is monthly returns weighted by the inverse demand change. VR is volume ratio. SR is short ratio. Comovement is the beta estimate between daily stock returns and Russell 2000 index returns, computed monthly and excluding mechanical covariance due to index membership. The sample period is 1996–2012. $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

indexing. We therefore examine time trends in the comovement of index members. The baseline coefficient on Comovement is 0.133 but it is not statistically significant. The literature finds that the extra comovement from addition is around 0.3.[12] Interestingly, the coefficient on Comovement $\times t$ is -0.027 with a t-statistic of -2.28 for the month of June. We find actually a significant decline in the impact of indexing using this metric. However, the results are inconsistent across the months after addition. In August we see a positive coefficient but the other months are not statistically significant. We interpret these results as a lack of evidence that indexing

[12] For example, Barberis, Shleifer, and Wurgler (2005) find stocks added to the S&P 500 have extra comovement of 0.214. Using BARRA value/growth swithers, Boyer (2011) shows extra comovement can be as high as 0.485. Greenwood (2008) uses Nikkei 225 overweightings and estimates this measure to be 0.22.

creates more excessive comovement over time. This is consistent with arbitrage forces increasing in efficiency to overcome the effects of greater indexing.

In Table 8, we consider the same set of regressions but now applied to deletions. In the base period there was a statistically significant price impact of 8.661, which translates to an elasticity of −0.115. After one year this changes to −0.124 and continues to decrease with greater speed throughout the sample period. Using our earlier deletion effect estimate of 5.4%, the elasticity for the whole sample period is −0.364. This is again consistent with increasingly elastic demand curves. Note that there is also a slight offsetting change in July price impact. Although the base estimate does not show a significant effect of deletion in July, there is a negative point estimate consistent with a small reversal in July price impact in the early years of the Russell 2000. These reversals have disappeared over time, as evidenced by the positive coefficient on Returns$/\%\Delta Demand \times t$.

The result regarding trends in volume following deletions is symmetric to that following additions and is in line with increases in indexing. Stocks remaining in the index have significantly lower June volume over time. Again recall that the sign of VR for deletions should be the opposite of that for additions, since we expect more trading for deleted stocks. The changes in the short ratio are not significant, but the point estimates for July, August, and September are all positive, implying that shorting for stocks remaining in the Russell 2000 has increased. The evidence on comovement is again mixed. There is no strong evidence of indexing having led to more excessive comovement over time.

The trends described in these two tables are illustrated further in Figure 5. For every year displayed, observations on stocks near the cutoff are pooled from the surrounding three years. Then the usual RD estimate is calculated using our preferred specifications. Figure 5(a) shows the evolving estimate of the June price impact for stocks added into the Russell 2000. Figure 5(b) shows the June price impact for stocks that were not deleted from the Russell 2000 but remained members. Whereas the deletion effect declines gradually and almost in a linear fashion, we find that the addition has a much smaller, barely noticeable, downward trend.

Figures 5(c) and 5(d) show the changing volume ratio in June. Recall that for the deletion volume effect, we expect a negative RD estimate since we expect remaining stocks to have lower volume or rebalancing. We see that there is a larger volume ratio effect over time in deletions, consistent with indexing becoming more important. For the addition volume ratio we do not see as striking a pattern, but the linear time trend specification nonetheless suggests that on average rebalancing increases over time. In both cases, the patterns are clearer for deletions than for additions. This underscores the usefulness of using deletions to study indexing effects over time.

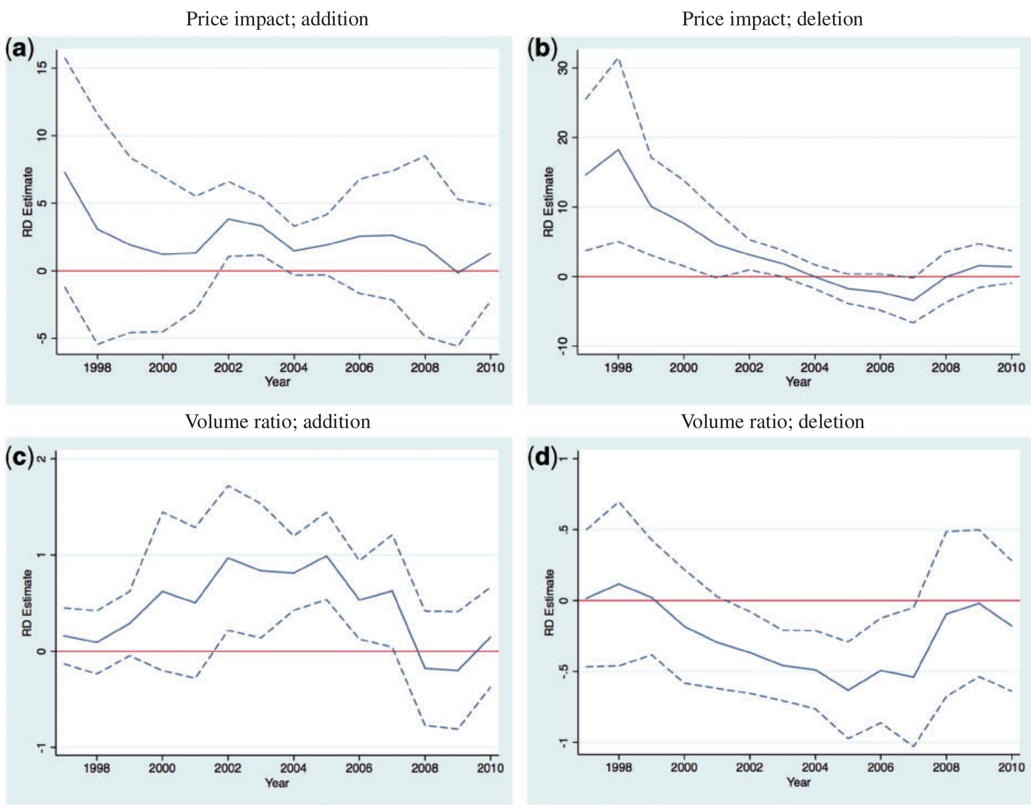


Figure 5
RD estimates over time
For each year, the RD estimate (β_{0r} in Equation (6)) is computed by pooling data with three surrounding years and estimating the RD effect of index addition or deletion. The data begin one year before and continue two years after the year posted. Price impact and volume ratio are measured in June. All regressions use firms with end-of-May ranking within 100 spots of the predicted cutoff. The regression specification is linear in ranking and is allowed to vary on either side of the cutoff. The solid line represents the point estimates of the effect of index addition or deletion. The dashed lines represent the 95% confidence interval.

6. Characteristics of Indexers and Liquidity Providers

Having established these time trends, we want to determine which types of funds are playing the role of liquidity providers for the funds tracking the Russell 2000 index. To do this, we use our RD framework to identify the domestic equity mutual funds tracking the Russell 2000 and those providing liquidity. We focus on the upper cutoff of the Russell 2000 and compare the fund characteristics of these two groups.

We use CRSP Mutual Fund Database (CRSP MFDB) for fund performance and characteristics. Fund holdings are from the Thomson-Reuters Mutual Fund Holdings database (TFN/CDA). These two databases are linked by the unique and permanent fund identifier WFICN, which we map to the fund identifier in CRSP MFDB (CRSP_FUNDNO). Note that WFICN is at the portfolio level and can be matched to multiple CRSP_FUNDNOs due to different share classes of funds that have the same holdings. In this case, we follow Wermers (2000) and measure fund performance and characteristics weighted by their most recent total net assets. Finally, we restrict our sample to funds with a valid WFICN.

6.1 Identification of indexers and liquidity providers

Every year from 1996 to 2011, we look at all funds with reporting dates that straddle Russell's annual reconstitution. We look at each fund's latest reporting date in the prereconstitution period (June of year $t-1$ to May of year t), and its earliest reporting date in the postreconstitution period (June of year t to May of year $t+1$). Funds with these report dates more than one year apart are dropped.

Next, for each fund we compare value changes in holdings for RD addition and deletion stocks around the reconstitution. Consistent with our preferred baseline results, RD stocks are defined as stocks within 100 positions of the Russell 2000 upper cutoffs. Funds with no holdings in either RD addition or deletion stocks before reconstitution are dropped. Importantly, we compute holdings value in RD stocks by multiplying the number of shares held in each stock before and after reconstitution by their closing prices before reconstitution for both the before and after dates. This allows us to separate the behavior of the fund from market price movements. We flag as an indexer any fund that simultaneously increases its holdings value in RD addition stocks and decreases its holdings value in RD deletion stocks both by more than 10%. Liquidity providers are those funds that do the opposite trades. Results using different percentage cutoffs are similar. On average, we have 3200 domestic equity funds with a valid WFICN every year, among which we classify 55 as indexers and 81 as liquidity providers. Recall that there might be many more funds. This subset consists of those that we can definitively identify using our RD methodology. In our subsequent analysis we focus on comparing the differences in characteristics across these two subsets.

6.2 Fund characteristics

We start by examining various characteristics of the funds classified as indexers or liquidity providers. Specifically, we measure the annual median market capitalization (MV, in millions) and market-to-book ratio (MtB) of each fund's holdings. These two variables capture fund style and the types of stocks funds hold in their portfolio. To calculate these variables, we use the latest report date in the period from April of year $t-1$ to March of year t. MtB is winsorized by dropping at 99.75% and assumes a five-month lag in book value. We also follow Chen, Hong, Huang, and Kubik (2004) and retrieve several other fund characteristics: total net assets (TNA, in millions), fund family total net assets (FAM TNA), turnover (TURN), age (AGE), expense ratio (EXP RATIO), and total load (LOAD). These variables are measured monthly for each fund.

Univariate comparisons (not reported for brevity) show that liquidity providers tend to hold stocks that are larger ($3.4 billion in market cap) and with higher valuation (3.8 in MtB) than indexers. In contrast, indexers hold stocks with $2.3 billion in market cap and 2.94 in MtB on average. Liquidity providers also have a larger average TNA of $1.4 billion, while that of the indexers is $1.1 billion. Other fund characteristics do not reveal significant differences across the two groups.

To more formally compare these fund characteristics in a multivariate setting, Table 9 reports OLS results from regressing indexer assignment on various fund characteristics. The dependent variable is an indicator variable for classification as an indexer. Only funds that are classified as either an indexer or a liquidity provider are included. The independent variables are defined above. We use logs of MV, MtB, TNA, and FAM TNA, and year effects are also included. The coefficients on Log(MV) and Log(MtB) are statistically significant in the entire sample period and both the subsample periods. Consistent with the univariate comparisons, indexers hold stocks with smaller market capitalizations and lower MtB, all else equal. Liquidity providers tend to own larger stocks and growth stocks. This finding makes intuitive sense because the Russell 2000 is a medium- to small-capitalization stock index. Funds that tend to own bigger stocks may be natural buyers for stocks that fall above the 1000 cutoff and might have a comparative advantage in making markets in the stocks that fall just outside the Russell 2000. Although all other differences between the two types of funds are insignificant, it is interesting to note that indexers belong to slightly larger fund families. This suggests that funds tracking the Russell 2000 are more likely to be from a large mutual fund complex.[13] Our findings here are consistent with Green and Jame (2011), who find small- and mid-cap funds provide liquidity to stocks added to the S&P 500.

[13] In the Internet Appendix, we compare the fund performance of indexers and liquidity providers and find evidence consistent with indexers under-performing liquidity providers in the month of the Russell 2000 reconstitution.

Table 9
Fund characteristics of indexers and liquidity providers

	All	1996–2003	2004–2011
Log(MV)	–0.0704***	–0.0508*	–0.0905***
	(–4.57)	(–2.50)	(–3.82)
Log(MtB)	–0.251***	–0.223***	–0.363***
	(–7.14)	(–5.47)	(–5.28)
Log(TNA)	0.00316	0.00601	–0.000540
	(0.36)	(0.50)	(–0.04)
Log(1 + FAM TNA)	0.00708	0.00366	0.0116
	(1.43)	(0.56)	(1.56)
TURN	–0.00116	0.0193	–0.0135
	(–0.13)	(1.70)	(–1.36)
AGE	–0.000270	–0.00138	0.000963
	(–0.19)	(–0.82)	(0.42)
EXP RATIO	–1.185	–4.722	5.470
	(–0.39)	(–1.25)	(1.04)
LOAD	–0.237	–0.451	0.105
	(–0.71)	(–1.04)	(0.20)
N	14838	7841	6997
adj. R^2	0.111	0.084	0.159

This table reports the OLS regression results of fund style assignment on fund characteristics. The dependent variable is an indicator variable that equals one (zero) if a fund is flagged as an indexer (liquidity provider). Log(MV) and Log(MtB) are the log of median market capitalization and market-to-book of fund holdings, measured annually using the latest report date from April of year $t-1$ to March of year t. MtB is winsorized by dropping at 99.75% and assumes a five-month lag in book value. Log(TNA), Log(1+ FAM TNA), TURN, AGE, EXP RATIO, and LOAD are a fund's lagged log total net assets (in millions), log fund family total net assets, turnover, age, expense ratio, and total load, all measured monthly. t-statistics are in reported in parentheses. The sample period is 1996–2011. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

7. Conclusion

Our new methodology contributes to the important literature on stock market indexing by delivering clean estimates of addition and deletion price effects, which differ from existing S&P 500 studies, and by showing that these price effects have fallen over time even as more money has been indexed to the Russell 2000. This is due in large part to mutual funds with large stocks and growth stocks providing liquidity to the funds that track the Russell 2000 and to a lesser degree to more shorting by hedge funds over time.

Our regression discontinuity design provides a novel approach that can be used to measure the impact of indexing on various features of stocks and firms, which might be of interest in other contexts in finance. For instance, behavioral finance models of investor behavior such as overconfidence or self-attribution bias (see, e.g., Daniel, Hirshleifer, and Subrahmanyam 1998; Gervais and Odean 2001) predict that investors misattribute random past performance to their skill. Our design could provide random shocks to past performance that, when combined with brokerage house trading data, could be used to test and discriminate among various behavioral theories of investor behavior.

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