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Essays on Liquidity Costs and Equity Index Effects

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Summary

This dissertation examines three research topics from financial market microstructure and corporate finance. First, I assess the impacts of equity funds' liquidity-motivated trading behavior on overall stock market liquidity.[1] Using a unique order volume-weighted liquidity measure for the German stock market, I find that liquidity-motivated trading from mutual funds—measured by their net cash flows—improve overall stock market liquidity. In addition, my analysis suggests that the information-processing ability of fund managers drives the positive impact from equity mutual funds on overall stock market liquidity. Second, I analyze the liquidity effects associated with index revisions of German Prime Standard indexes. Applying a difference-in-differences estimator, I find that stocks newly included in a "higher level" index enjoy lower liquidity costs than do stocks that could have been added to the "higher level" index based on index selection criteria. Third, I use exogenous index events as identification to assess index effects on corporate financial leverage. Using both difference-in-differences estimator and regression discontinuity design, I find that firms increase their financial leverage after being exogenously added to an index. Overall, I find evidence that investor awareness is an important driver of a firm's stock liquidity and debt supply.

[1] In this dissertation, I use the term "I" in the introduction and conclusion. It does not necessarily refer to me directly as the first and third essay are joint work with my coauthors.

Zusammenfassung

Diese Dissertation untersucht drei Forschungsthemen in den Bereichen Finanzmarktmikrostruktur und Unternehmensfinanzierung. Zuerst analysiere ich die Auswirkungen von liquiditätsmotiviertem Handelsverhalten von Aktienfonds auf die gesamte Marktliquidität. Unter Verwendung eines vom Auftragsvolumen abhängigen Liquiditätsmaßes für den deutschen Aktienmarkt zeige ich, dass liquiditätsmotiviertes Handeln von Publikumsfonds die Liquidität des gesamten Aktienmarktes verbessert. Liquiditätsmotiviertes Handeln wird hierbei anhand der Nettogeldflüsse der Fonds gemessen. Des Weiteren zeigt meine Analyse, dass der positive Effekt von Aktien-Publikumsfonds auf die gesamte Marktliquidität von der Informationsverarbeitungsfähigkeit der Fondsmanager getrieben ist. Daraufhin erforsche ich Liquiditätseffekte, die mit Indexanpassungen der deutschen Primärstandardindizes verbunden sind. Durch Differenz-in-Differenzen-Schätzungen finde ich heraus, dass jene Aktien, die kürzlich in einen "höheren" Index aufgestiegen sind, niedrigere Liquiditätskosten haben, als jene Aktien, die gemäß Indexauswahlkriterien auch in den "höheren" Index hätten aufsteigen können, jedoch im bisherigen Index verblieben sind. Abschließend verwende ich exogene Indexevents als Identifikation, um die Indexeffekte hinsichtlich der Fremdkapitalquoten der Unternehmen zu analysieren. Sowohl mittels Differenz-in-Differenzen-Schätzungen als auch mittels Regressions-Diskontinuitäts-Analysen zeige ich, dass Unternehmen nach der exogenen Inklusion in einen Index die Fremdkapitalquote erhöhen. Im Allgemeinen finde ich Indizien dafür, dass die Beachtung durch Investoren einen bedeutenden Einfluss auf die Aktienliquidität und Kapitalstruktur eines Unternehmens hat.

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Nomenclature

AuM	Assets under Management
cf.	confer
diff-in-diff	difference-in-differences
e.g.	exempli gratia
et al.	et alii
etc.	et cetera
ETF	Exchange Traded Fund
FE	Fixed Effects
i.e.	id est
OLS	Ordinary Least Squares
OTC	Over-The-Counter
M&A	Mergers and Acquisitions
NAV	Net Asset Value
RDD	Regression Discontinuity Design
S&P	Standard & Poor's
U.S.	United States
USD	United States Dollar
XLM	Xetra Liquidity Measure

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1 Introduction

Financial market liquidity risk has been gaining increasing attention from both practitioners and academia during the last decade. Liquidity shortages of hedge funds and banks have accompanied many recent financial crises, such as the collapse of Long-Term Capital Management (LTCM) and the sub-prime crisis. Before these crises, many funds and banks had held large risky positions, which they could not liquidate in a short time without negative price impact. When the financial crises arose, many funds and banks started to sell positions in the same underlying stocks without sufficient market demand at that time.

Increasingly often, we observe short period price jumps from single stocks, including blue chip stocks. For example, Volkswagen stock lost almost 40% of its value (from about 167 euro per share on September 18, 2015 to 105 euro per share on September 23, 2015) within 3 trading days when an emission scandal became public on September 18, 2015 in the U.S. In addition to the price correction due to expected financial penalties, another driver of the sharp price drop might be so-called "flight-to-liquidity" behavior, which especially has received more attention from both practitioners and academia since Lehman Brothers' bankruptcy (cf. e.g., Chordia et al., 2000; Rösch and Kaserer, 2013). Past evidence indicates that investors prefer to hold liquid stocks and sell illiquid stocks when they are facing uncertainty.

Meanwhile, exchange traded funds (ETFs) have been celebrated as another financial market innovation in the past years. The market size of ETFs reached 2.95 trillion USD in

2015, and market researchers expect it to keep growing in the years ahead.[1] Given that ETFs basically follow a "buy and hold" strategy, ETF providers have far lower costs in terms of information acquisition and transaction. Even if ETFs face net cash flow changes, they use several mechanisms to avoid market trades,[2] and therefore, transaction costs. Referring to these mechanisms, ETF providers often claim that the financial market liquidity environment has almost no effect on their activities. On the other hand, because ETFs track their benchmark indexes and do not actively manage their portfolio positions, ETFs' performance is expected to be pro-cyclical. Hence, there are concerns about potential liquidity shortages caused by the ETF market if there is a fire sale of ETFs.[3]

Accompanying the growth of the ETF market, leading indexes, especially equity indexes, play an increasingly important role in capital markets. These indexes are not only the underlying indexes for ETFs, but also serve as the benchmark indexes for actively managed funds. Cremers et al. (2016) find international evidence that about 20% of actively managed mutual funds worldwide in fact passively follow certain indexes. Firms associated with leading indexes have a larger share of institutional shareholders and more media attention than those without index membership do. Harris and Gurel (1986) and Erwin and Miller (1998) find evidence that stocks enjoy higher prices, trading volumes, and lower liquidity costs when they are constituents of the S&P 500. These "index benefits" set the basis for easier access to stock financing. Cao et al. (2016) conclude that index membership allows firms to issue more equity. However, Faulkender and Petersen (2006) suggest that members of the S&P 500 have higher leverage ratios than the US market average.

The aim of this dissertation is to clarify the abovementioned ambiguous arguments and empirical findings. It consists of three essays that aim at shed light on capital market interdependency, especially regarding liquidity costs and index effects. Next, after a brief overview of the theoretical background and evidence presented in Section 1.1, the research questions on these two topics are introduced in Section 1.2.

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[1] Source: ETF Annual Review & Outlook, January 21, 2016, Deutsche Bank Market Research.

[2] Such mechanisms include creation/redemption procedure, borrowing/lending stocks, transactions through market makers; details cf. Section 2.1.

[3] Source: Exchange-traded funds: Emerging Trouble in the Future? October 25, 2014, The Economist.

1.1 Theoretical background and previous evidence

1.1.1 Liquidity costs

In this dissertation, liquidity is defined from an investor's perspective as the "ease of trading an asset."[4] Liquidity cost is then the cost of trading an asset relative to its fair value.[5] Some researchers have developed theoretical frameworks and liquidity measures (e.g., Kyle, 1985; Chordia et al., 2009), but most literature uses empirical approaches to measure liquidity costs.

One of the most widely used liquidity measures is the illiquidity measure of Amihud (2002), the so-called *ILLIQ*. The *ILLIQ* of a stock is defined as the average ratio of daily absolute stock return to its trading value,[6] where the latter is the aggregation of the number of shares traded multiplied by the corresponding trading prices. The annual illiquidity of stock i in year y is defined as

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}} \sum_{d=1}^{D_{i,y}} \frac{|R_{i,y,d}|}{TV_{i,y,d}}, \tag{1.1}$$

where $D_{i,y}$ is the number of trading days in year y, when return data of stock i are available, $R_{i,y,d}$ and $TV_{i,y,d}$ are the daily return and trading value, respectively, of stock i on day d in year y. This formula can form the basis for calculating quarterly or monthly averages of illiquidity, and works for other time intervals as well. *ILLIQ* measures the price change as a response to one currency unit of trading. The higher *ILLIQ* is, the higher the liquidity cost is—in other words, the more illiquid the stock is. By its construction, *ILLIQ* is positively correlated with the absolute value of stock returns and negatively correlated with trading value. Although no theoretical model developed so far precisely explains the design of *ILLIQ*, empirical tests widely support its use, especially the inclusion of trading value in the illiquidity measure (cf. Chordia et al. (2009)).

Compared to the illiquidity measure of Amihud (2002), another broadly used liquidity

[4] Cf. Longstaff (1995)

[5] Cf. Amihud and Mendelson (2006)

[6] Amihud (2002) calls it *dollar volume*.

measure is that of Pastor and Stambaugh (2003), who add the aspect of order flow direction in the liquidity measure. This is defined as the ordinary least squares (OLS) estimate of $\gamma_{i,t}$ in the following regression for stock i in month t

$$R^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} R_{i,d,t} + \gamma_{i,t} sign(R^e_{i,d,t}) \cdot TV_{i,d,t} + \epsilon_{i,d+1,t},\ d = 1, ..., D_{i,t}, \tag{1.2}$$

where $R_{i,d,t}$ and $TV_{i,d,t}$ are the daily return and trading value of stock i on day d in month t. The excess return $R^e_{i,d,t}$ is defined as $R_{i,d,t} - R_{m,d,t}$, where $R_{m,d,t}$ is the value-weighted market return on day d in month t. $D_{i,t}$ is the number of trading days in month t for which data of stock i are available. The basic idea behind this approach is to use trading value along with the sign of the excess return of the stock serving as a proxy for *order flow*. The greater is the expected reversal for a given order flow, the lower is the stock's liquidity. In general, one would expect a negative $\gamma_{i,t}$ and larger magnitude, when the stock is more illiquid.

Both Amihud (2002) and Pastor and Stambaugh (2003) argue that higher liquidity costs, in other words, illiquidity, have to be compensated through higher expected returns on assets. Uninformed investors are afraid of adverse selection due to information asymmetry and require higher returns from illiquid stocks. This fits the information paradigm of Kyle (1985), which suggests that informed traders pass liquidity costs to uninformed traders.

Kyle (1985) divides market liquidity into three components: *tightness*,[7] *depth*, and *resiliency*. Brennan and Subrahmanyam (1996) use intraday data to measure stock liquidity costs and find empirical evidence supporting the theory Kyle (1985) developed. Brennan and Subrahmanyam (1996) highlight the benefits of using a liquidity measure dependent on trade size and find a significant relationship between required rates of return and illiquidity measured by intraday transaction data.

Using intraday transaction data allows for better reflection of market breadth (tightness) and depth in the liquidity measure. Nonetheless, this measure can provide only an ex post observation. In addition, the prevalence of electronic trading platforms reduces the portion

[7] Tightness is also called as *breadth*.

of quoted trades in the overall exchange trading, especially for liquid stocks. Therefore, researchers suggest the use of information from limit order books to measure stock liquidity costs, which not only provides an ex ante liquidity measure considering market breadth and depth, but also better reflects the increasing importance of electronic trading platforms in recent years.

Irvine et al. (2000) are the first to measure the cost of round-trip transactions using limit order book data. A round-trip transaction of a share describes the hypothetical situation in which one submits a buy order and a sell order for the same share at the same time. Based on limit order book data, Gomber and Schweickert (2002) introduce the volume-weighted spread for a round-trip trade. For a round-trip trade at time t of euro-denominated volume size q, Gomber and Schweickert (2002) defines the volume-weighted spread as

$$WS_t(q) = \frac{\frac{1}{n_t}\left(\sum_i a_{i,t}n_{i,t} - \sum_j b_{j,t}n_{j,t}\right)}{P_{mid,t}} \cdot 10,000 \tag{1.3}$$

where $a_{i,t}$ and $n_{i,t}$ are the ask price and corresponding number of shares, respectively, of the order i, $i = 1, 2, \ldots$, in the limit order book at time t sorted according to price priority (from low to high). n_t is the number of shares required to fulfill an order with volume q and mid-price $P_{mid,t}$, that is, $n_t = q/P_{mid,t}$. The individual limit orders $n_{i,t}$ are added in the sorted order of i until the sum of $n_{i,t}$ equals n_t. The bid price $b_{j,t}$ and corresponding number of shares of order j $n_{j,t}$, $j = 1, 2, \ldots$, are defined analogously but in the reverse order (from high to low).

1.1.2 Index effects

In the late 20th century, many studies discovered the so-called "index effect" due to the growing importance of equity indexes and increasing market volume of equity indexing funds. Harris and Gurel (1986) and Schleifer (1986) provide evidence of abnormal price and trading volume increases for stocks added to the S&P 500. In addition, Erwin and Miller (1998) and Hegde and McDermott (2003) find abnormal bid–ask spread declines for stocks that have been added into the S&P 500. There is some consensus in the literature about the existence of index effects, especially about the positive price impact on stocks added to a leading index. However, the literature has developed different theories about the cause of index effects, which the following subsections describe.

Information signaling hypothesis

The information signaling hypothesis assumes that the capital market is efficient and the demand curve for stocks is horizontal; hence, there would be an immediate and permanent price adjustment of a stock if new information about the underlying firm or other relevant information (e.g., news about the belonging industry and competitors) became available. Although publicly available information mostly informs index revisions, stock exchanges might have access to superior information about the affected firms and might send signals about positive or negative development prospects of these firms to the capital markets by including or deleting the stocks into or from a certain index. Therefore, the information signaling hypothesis indicates an immediate and permanent price increase for the stocks that are added to an index, as well as an immediate and permanent price drop for the stocks deleted from an index (cf. e.g., Schleifer, 1986; Jain, 1987).

Imperfect substitutes hypothesis

The imperfect substitutes hypothesis originates from Scholes (1972), and assumes a long-term downward-sloping demand curve for stocks. Each stock is a unique asset, and stocks added to or deleted from an index cannot be substituted by a portfolio of other stocks. In the case of index revisions, the demand for newly added or deleted stocks changes. Hence, the demand curve of the affected stock shifts until it reaches the new equilibrium price. As a result, one expects permanent price and trading volume changes for stocks with index revisions (cf. e.g., Harris and Gurel, 1986; Wilkens and Wimschulte, 2005).

Price pressure hypothesis

According to the price pressure hypothesis, index revisions do not reveal new information about affected stocks. An unbalanced supply and demand relationship driven by investors that follow index strategies causes the immediate price and volume changes of these stocks. Market liquidity providers are motivated by immediate price changes associated with short-term demand shifts of the affected stocks, until prices of these stocks reverse to their full-information levels. Therefore, the price pressure hypothesis assumes a short-term downward-sloping demand curve and a long-term horizontal demand curve for stocks. In other words, price changes caused by index revisions are only temporary (cf. e.g., Harris and Gurel, 1986).

Information costs/liquidity hypothesis

According to the information costs/liquidity hypothesis, index inclusion increases analyst coverage and media attention, and thereby generates better public availability of information about the affected stocks. Thus, index inclusion reduces information acquisition costs for investors and increases stock liquidity. Because liquidity costs reduce future expected cash flows, reduction of liquidity costs increases stock prices. Hence, the information costs/liquidity hypothesis declares there are permanent price changes of stocks affected by index revisions (cf. e.g., Schleifer, 1986; Wooldrige and Ghosh, 1986; Edmister et al., 1996).

1.2 Research questions

In addition to liquidity cost measurement and assessment, existing literature on stock liquidity often addresses topics in the area of asset pricing. For example, Wagner and Winter (2013) and Amihud et al. (2015) add an additional liquidity factor to the Carhart (1997) four-factor model, and both find strong evidence that liquidity risk is an important factor explaining market excess returns of equities. These findings support the hypothesis of Amihud (2002) and Pastor and Stambaugh (2003) that investors are willing to take more liquidity risk only when they are compensated by higher expected returns. Another subject in stock liquidity is market microstructure. Chordia et al. (2000) are the first to study liquidity commonality instead of attributes of single assets. Brunnermeier and Pedersen (2009) provide a theoretical market liquidity model, which predicts "flight to quality" or "flight to liquidity" as a result of liquidity commonality during recessions. The findings of Rösch and Kaserer (2013), for instance, support the model of Brunnermeier and Pedersen (2009).

Thus far, the literature has studied liquidity commonality mostly empirically for stressed market situations, because it is much easier to find a market liquidity shortage event, such as in the aftermath of the bankruptcy of Lehman Brothers, than a positive surprise with similar market magnitude. Moreover, most studies focus on reactions of investors to certain market liquidity events. Researchers have hardly investigated the reverse situation, that is, how investors' behavior affects overall market liquidity. As a start to close the research gap, my first research question links equity fund activities and stock market liquidity, and aims to find evidence of liquidity effects from mutual funds and ETFs on the overall stock market.

As introduced in Section 1.1.2, a large number of past studies examine the abnormal price and trading volume development of stocks associated with index additions or deletions. Most of these studies, however, do not control for possibly present positive development trends of the affected stocks. Although positive index effects on these stocks are widely agreed on in the research, it is possible to overestimate the magnitude of index effects owing to endogeneity, that is, a firm's own positive development rather than the index inclusion might contribute some part of observed index effects. My second research question addresses the precise measurement of index effects on stock liquidity. Using a difference-in-differences approach and a unique order-volume weighted liquidity measure, I was enabled to isolate the "pure" index effects on stocks that have been added into or deleted from a benchmark index.

Some recent studies have extended research on index effects to institutional shareholder activism and corporate governance topics in order to account for transparency and sometimes predictability of index revisions (e.g., Duggal and Millar, 1999; Boone and White, 2015; Crane et al., 2016). Nonetheless, endogeneity of firms' development trends often still affects these studies. In addition, all these studies investigate the U.S. market, and most of them examine only the equity side. To reduce this gap, my third research question focuses on exogenous index events in an international sample. I analyze the causal inference of index effects on firms' capital structure using both difference-in-differences and regression discontinuity estimators. The findings shed light on the interplay between equity and debt markets.

1.2.1 Do mutual funds improve stock market liquidity and ETFs harm it?

Actively managed equity mutual funds not only seek positive returns to outperform the respective benchmark, but also provide liquidity services to their customers. Mutual fund investors can pay into or redeem from the equity fund at the daily closing price mostly without bearing any liquidity costs.[8] Although many studies suggest that actively managed mutual funds do not outperform the overall market after consideration of management fees (cf. e.g., Carhart, 1997; Wermers, 2000), Edelen (1999) provides evidence that actively managed mutual funds do outperform the stock market if one considers their liquidity services. He further shows that inflows and outflows of mutual funds cause liquidity-motivated trading, that is, mutual fund managers buy or sell stocks in order to rebalance their holdings purely because of clients' investments and redemptions and not owing to changes in the target asset allocation. Clarke et al. (2007) and Shawky and Tian (2011) find that mutual funds intend to buy less liquid stocks when they are facing substantial and sustained cash inflows, and prefer to sell more liquid stocks when they are experiencing the reverse situation. This asymmetric behavior is mostly motivated by the fundamental target of maximizing fund value, because less liquid stocks provide higher

[8] Management fees and other compensation of mutual funds are usually not directly linked to transaction costs of individual fund-holding positions.

expected returns (cf. e.g., Brennan and Subrahmanyam, 1996; Amihud, 2002; Pastor and Stambaugh, 2003) and selling illiquid stocks goes in hand with higher transaction costs. At the same time, this behavior benefits the overall stock market owing to its "side effect" as an automatic liquidity-providing mechanism, as selling (buying) less liquid stocks encounters greater downward (upward) price pressures. Therefore, I hypothesize that equity mutual funds improve overall market liquidity when conducting liquidity-motivated trades.

Meanwhile, stock market liquidity seems to be a less important issue in the management process of ETFs than that of mutual funds. Although ETFs have less reaction time to cash flow injection and redemption from their customers compared to mutual funds, the market liquidity situation does not affect or only marginally affects ETFs' creation and redemption procedures. First, ETFs buy or sell holding positions only if there is at least one unit of creation or redemption (usually about 50,000 shares). When they create or redeem their positions, they trade a diversified portfolio simultaneously. Second, ETFs can always choose to trade either at the primary or secondary market, that is, ETFs can buy or sell ETF shares instead of underlying stocks. Finally, ETF providers have various alternatives to trade their positions, such as internal trading platforms and borrowing or lending stocks from or to investment banks. I eliminate synthetic ETFs from the research, because they often use swaps and other financial products to construct their portfolios instead of physically owning stocks. Considering the abovementioned purchase and sale options for ETFs, I hypothesize that when capital inflows or outflows from investors induce ETF trades, these trades do not have an impact on overall stock market liquidity.

To test these two hypotheses, I use daily net cash flows of open-ended equity funds as proxy for their liquidity-motivated trades. Although this proxy works in general for ETFs with physical replication, it works only if the selected equity mutual funds have very low target cash ratios and are indeed sensitive to cash inflows and outflows. Therefore, I select equity mutual funds that invest in comparably liquid stocks in Germany (DAX, MDAX, SDAX, and TecDAX stocks). Owing to competition, these funds aim to conduct trades within 1 or 2 days after net cash inflows or outflows, in order to maintain target cash positions in the range of 1–2% of their total holdings. I aggregate the absolute values of all daily net cash flows for all equity mutual funds that mainly invest in one of the previously mentioned indexes, and proceed analogously for ETFs.

For accurate measurement of stock market liquidity, I use the Xetra Liquidity Measure (XLM) provided by Deutsche Börse AG. For every stock traded at Xetra platform, XLM measures the daily average weighted round-trip liquidity costs for different order volumes based on limit order book data (cf. Irvine et al., 2000; Gomber and Schweickert, 2002). Hence, XLM is able to consider the whole depth of the limit order book and measures order volume-dependent liquidity costs, which is much more precise than standard bid–ask spreads. I use the XLM values for the order volume class of 100,000 euros, which is reasonable for open-ended equity funds. Finally, I calculate aggregated daily XLM values for the DAX, MDAX, SDAX, and TecDAX as average XLM values of all index member stocks weighted by their market capitalization.

I regress the overall stock market liquidity costs per index on the corresponding aggregated net cash flow variables of mutual funds and ETFs, as well as other well-established market liquidity variables, and time- and index-fixed effects. My study covers the period from July 1, 2002, when Deutsche Börse AG started to calculate XLM, to December 31, 2014. I find that liquidity motivated trades of mutual funds improve overall stock market liquidity by 2% if aggregated net cash flows increase by one standard deviation. Meanwhile, I find no statistically significant relationship between ETFs' cash flow changes and market liquidity. Because many market variables can drive funds' cash flows, which might be omitted variables in the baseline model, I conduct several robustness tests. All tests support that my findings are robust to various model specifications.

In addition, I observe the strongest liquidity contribution from mutual funds on the overall stock market during the financial crisis in 2008/2009 when liquidity was needed mostly. The results further attribute the positive liquidity impact from mutual funds to mutual fund managers with better liquidity-timing abilities, that is, better ability to process information.

1.2.2 Liquidity effects associated with revisions of German Prime Standard indexes

My second study presented in Chapter 3 aims to measure "pure" liquidity effects associated with index revisions, and supports the liquidity hypothesis introduced in Subsection 1.1.2. Although many studies of the late 20th century find evidence of liquidity improvement for stocks added to the S&P 500 (cf. e.g., Erwin and Miller, 1998; Hegde and McDermott, 2003; Chen et al., 2004), they all face three potential issues. First, these studies do not control for positive development trends of examined stocks and, thus, potentially overestimate the index effects for stocks added to leading benchmark indexes. Second, the liquidity measure used in these past studies, bid–ask spread, is representative only of small order volumes. Bid–ask spreads for constituents of popular benchmark indexes have become very small since the introduction of electronic trading platforms in the late 20th century. Therefore, it is difficult to measure liquidity cost changes using bid–ask spreads for recent years. Finally, the event study design from Campbell et al. (1997), which is popular for many index effect studies, is not suitable for long-term studies, given that it assesses only changes of variables of interest and neglects development of other potential influencing factors during the event window.

To account for these concerns, I apply a difference-in-differences event study design, and compare liquidity cost changes of stocks that experienced an index change with liquidity cost changes of stocks that could have had an index change based on index constituent selection criteria, but – in the end – did not change the index. As an accurate measure of liquidity costs, I use the Xetra Liquidity Measure from Deutsche Börse AG again. In addition, I apply established market variables and fixed effects to control for other influencing factors of stock liquidity costs, and undertakes a long-term event study.

My analysis considers index changes among three German Prime Standard indexes, namely, the DAX, MDAX, and SDAX.[9] This scope eliminates liquidity effects driven by reporting standards (cf. Healy and Palepu, 2001) given that all these Prime Standard

[9]For clarification of "index upgrade" and "index downgrade", I also remove the TecDAX from the observation sample, as its classification basis is industry instead of size.

indexes require the same reporting standards from their member stocks. From July 1, 2002 to December 31, 2014, 117 stocks moved within these three indexes. Based on entry and exit rules of these indexes, I identify 931 stocks (with replacement) that could have experienced index changes but remained unchanged.

Applying the difference-in-differences estimator to these 117 stocks and their control group stocks, I find that an index upgrade reduces liquidity costs of affected stocks by 15–18% compared with their control group stocks, even after controlling for market liquidity factors, such as market capitalization, trading volume, return, return volatility, and stock- and time-fixed effects. The results are statistically significant and robust to various specifications. Meanwhile, the coefficients for downgraded stocks are small and statistically insignificant. I argue that investor awareness causes this asymmetry. Investors devote more attention to stocks that have been upgraded to a higher-level index because of increasing media and analyst coverage. Nonetheless, it is unlikely that investors suddenly become "unaware" of affected stocks after a downgrade.

Finally, I use analyst following and news coverage as two proxies for information availability. It turns out that information availability can at least partially explain the liquidity improvement of stocks that have experienced an index upgrade, which is consistent with the information costs/liquidity hypothesis.

1.2.3 Index membership and capital structure

The abovementioned information cost hypothesis suggests it is less costly for investors to acquire information about firms that have been added to a benchmark index. This applies to both equity and public debt investors.[10] Hence, both equity and debt investors tend to be more willing to buy shares and public debt from these firms, because it is easier and cheaper to monitor the companies. However, this raises the question whether index inclusion affects a firm's capital structure. My third study focuses on the influence of index membership on firms' capital structure using exogenous index events as identification.

[10] Private debt holders, such as banks, might have superior access to firm information, and therefore, are less affected by changes of firms' publicly available information.

Transparent rules usually form the foundation for regular index revisions of most benchmark indexes; such rules include rankings of market capitalization and trading volume. Therefore, firms could hypothetically influence index revision results by taking action beforehand, such as mergers and acquisitions. To solve this potential endogeneity issue, I include only "exogenous" index events in the data sample, so that it is unlikely that firms could predict these events or even affect them. I consider the following four types of index events as exogenous:

1. **Launch/closure**: Formation of a new equity index or discontinuation of an existing index
2. **Universe change**: Change in the eligible index universe, such as country and industry
3. **Number change**: Increase or decrease in the number of index constituents
4. **Ranking methodology change**: Change of index selection criteria or change of criteria weightings

I use index providers' press releases, including archived press releases, as primary source for finding eligible events. By screening more than 54,000 press releases covering more than 7,000 indexes from 32 major index providers worldwide, I find 226 exogenous index events comprising more than 8,000 firms in total. These events across 21 countries provide a unique opportunity to study international differences of index effects.

Moreover, I apply both difference-in-differences estimation and regression discontinuity design separately for the event sample to find causal effects from index membership on firms' capital structures. For the difference-in-differences study, I select control group firms from the same country and industry by using propensity score matching based on main influencing factors of capital structure that Frank and Goyal (2009) identify, that is, size, profitability, tangibility, and market-to-book ratio. For the regression discontinuity design, I rank firms based on index methodologies published by index providers, and select firms *just* below the index selection thresholds as control firms. For both approaches, I further control for the abovementioned influencing factors of capital structure, as well as firm- and time-fixed effects.

Using both approaches (difference-in-differences and regression discontinuity design), I find that firms increase their financial leverage, defined as the relationship of total debt to total assets, by 1–3 percentage points after being exogenously added to a benchmark index. I further conclude that an increase of public debt drives growth of financial leverage. This supports my hypothesis that index membership reduces public information acquisition costs for investors, and therefore, increases the willingness of investors to lend money to firms that have been added to an index.

1.3 Contribution

Overall, this dissertation contributes to a better understanding of the interplay between liquidity-motivated trading from open-ended funds and overall market liquidity, as well as index effects on stock liquidity and firms' capital structure. I enlarge the existing data sample by mostly using non-U.S. market data and provide international evidence. In particular, this dissertation contributes to the existing literature in the following aspects:

First, I employ a unique order volume-weighted liquidity measure, which uses data from the limit order book of the Xetra electronic trading platform provided by Deutsche Börse AG. This measure especially considers the whole depth of the limit order book, and therefore, provides a more accurate measure of liquidity costs compared to bid–ask spreads, which are representative only of very small order volumes, and can hardly measure real liquidity costs in the age of electronic trading. The volume-weighted liquidity measure especially enables selection of different order volume classes for different research targets, for example, large order volume classes can better represent institutional trading activities.

Second, I explore the relationship between overall stock market liquidity and liquidity-motivated trading from open-ended equity funds. Using net cash flows as a proxy for liquidity-motivated trading, I find a positive impact of liquidity-motivated trading from actively managed equity mutual funds on the overall stock market. This supports the view of mutual funds as liquidity service providers (cf. Edelen, 1999). Meanwhile, I find neither significantly positive nor significantly negative effects of net cash flows from ETFs on the stock market.

Third, I measure the "pure" index effect in terms of liquidity cost changes of stocks added to or deleted from equity indexes. To do so, I apply a difference-in-differences design, which compares the effects on stocks that experienced an index revision with stocks that could have experienced an index revision according to index methodology, but were not revised in the end. In this way, I avoid potential overestimation caused by firms' development trends and other influencing factors. In addition, I use up-to-date data containing more than 10 years of observation from Germany, which augments the mainly US-focused data used by research until now.

Fourth, I collect a valuable international data set of exogenous index events by screening more than 54,000 press releases covering more than 7,000 equity indexes. In these more than 200 exogenous events, firms can hardly affect index constitution by their own actions beforehand. Therefore, these events provide an excellent basis for the analysis of index effects. This international sample further supports cross-country studies.

Finally, using the exogenous index events outlined above, I analyze the interplay between equity and debt markets by observing capital structures of affected firms before and after index events. Based on this exogenous identification, I assess the causal relationship between index membership and firms' capital structure. The results show evidence that equity index membership has a positive impact on debt financing.

Overall, this dissertation contributes to an improved understanding of capital market operations by examining the relationships between stock market liquidity and liquidity-motivated trading by open-ended funds, index membership, and stock liquidity, as well as index membership and firms' capital structure.

1.4 Structure

The structure of the remaining part of this dissertation is as follows. Chapter 2 examines the relationship between liquidity-motivated trading from open-ended equity funds and overall stock market liquidity. Chapter 3 measures liquidity effects associated with index revisions. Chapter 4 studies index effects on firms' capital structure. Chapter 5 concludes and provides avenues for future research.

2 Do Mutual Funds Improve Stock Market Liquidity and ETFs Harm It? — New Evidence from the German Stock Market

Abstract

This essay examines the impact of liquidity-motivated trading by equity funds on overall stock market liquidity. Using a unique volume-weighted spread for the German stock market, this study finds strong evidence that liquidity-motivated trading by actively managed mutual funds, as measured by their net cash flows, improves stock market liquidity. A one-standard-deviation increase of funds' net cash flows reduces the weighted spread of small and medium caps by up to 45 basis points. This is an economically important effect. Moreover, this study observes the strongest liquidity contribution exactly when it is most needed, that is, during times of crisis. In addition, we find evidence that high-skilled fund managers mostly drive this beneficial liquidity service. Finally, this study finds no impact or even a negative impact for ETFs, which is not surprising given the creation/redemption mechanisms governing their inflows and outflows.

Keywords: Stock market liquidity, liquidity-motivated trading, open-ended fund, equity fund's cash flow, Xetra Liquidity Measure

JEL Codes: G11, G14

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2.1 Introduction

Open-ended mutual funds play an important role as liquidity providers. This is because they have to satisfy redemptions or injections from their customers at very short notice based on fixed net asset values (NAVs). As their target cash ratios are typically in the 1%-range, portfolio managers of equity funds most likely respond to these net inflows or outflows by appropriate buying or selling transactions.[1] In fact, Edelen (1999) finds evidence that in-/outflows of mutual funds induce liquidity-motivated trading. Coval and Stafford (2007) suggest that liquidity-motivated trading of mutual funds is more likely to occur if the in-/outflows are unexpected. Moreover, Clarke et al. (2007) observe that mutual fund managers prefer to buy less liquid stocks experiencing substantial and sustained cash inflows, while they tend to sell more liquid stocks when facing substantial and sustained cash outflows. Shawky and Tian (2011) find the same asymmetric liquidity preference in the small-cap equity mutual fund segment, independent of in-/outflows. The liquidity-induced price impact motivates these findings, as less liquid stocks face greater downward (upward) price pressures when selling (buying) them. There is substantial research on the negative correlation between liquidity and expected return, for example, by Brennan and Subrahmanyam (1996), Amihud (2002), Pastor and Stambaugh (2003), and more recently, for an international sample, by Amihud et al. (2015).

Based on these findings, the first hypothesis in this study is that liquidity-motivated trading by mutual funds improves market liquidity. The reason is that to benefit from downward price pressures when buying shares, mutual fund managers offer their liquidity where it is most needed, that is, in those stocks where order book demand curves are either very steep or order book depth is completely missing. At the same time, when shares have to be sold because of new outflows, mutual fund managers withdraw liquidity from those stocks that need it less, that is, where order book offer curves are rather flat and deep. While it is obvious that equity fund managers have an interest in exploiting the liquidity-induced price impact for their own advantages, it is less clear whether they

[1] Mutual funds might also engage on futures markets in order to avoid mimicking each single cash flow. However, due to cost and risk issues, this typically covers only a very limited amount of net in-/outflows.

are able to do so. Interestingly, in a recent study, Cao et al. (2013) find that mutual fund managers are able to time market liquidity. We argue that fund managers engage in collecting information with respect to individual stocks' liquidity. By doing so, however, they offer a service that is beneficial to the overall market liquidity.

Exchange-traded fund (ETF) managers do not offer a similar service for at least two reasons. First, ETFs' net in-/outflows do not necessarily lead to stock market transactions owing to the involvement of market makers. Market makers usually borrow/lend stocks from/to investment banks or other financial institutions, as long as the accumulated net in-/outflows do not exceed certain limits, such as one creation/redemption unit, which usually includes 50,000 shares. Even if the net in-/outflows exceed one creation/redemption unit, market makers could choose between buying/selling the underlying stocks or the ETF shares. If they choose to buy the stocks instead of the ETF shares, there is no discretion to react to the different liquidity of different stocks, as each stock has a given weight in the ETF. Second, the ETF manager has only weak incentives to exploit the liquidity-induced price impact, as this would increase the tracking error of the fund. Therefore, the second hypothesis is that trading by ETFs does not impact market liquidity or, to the extent the ETFs are crowding out mutual funds, the former can even harm market liquidity.

Although researchers confirmed the existence of liquidity-motivated trading more than a decade ago, to the best of our knowledge, ours is the first study to investigate the impact of liquidity-motivated trading by equity funds on the overall market liquidity. The main reason for the lack of research on this topic is the difficulty in measuring market-wide liquidity, especially as far as stock market depth is concerned. Most research in the past used bid–ask spreads, which are relevant only for small trading volumes and are less adequate for order sizes from equity mutual funds or ETFs. This study uses the unique order volume-weighted liquidity measure—Xetra Liquidity Measure (XLM)—of Deutsche Börse (Germany's stock exchange), which considers the whole depth of the limit order book.

This paper focuses on the German Prime Standard stock market, that is, the DAX, MDAX, SDAX, and TecDAX. Stocks from these four indexes constitute 88% of the German stock market, according to market capitalization as of December 2014.[2] The sample includes daily observations of all stocks within these indexes from July 1, 2002 to December 31, 2014. For funds' net cash flows, we choose equity funds that invest only in German stocks, that is, actively managed mutual funds with an investment focus on Germany and ETFs with a German underlying index. Because mutual funds have to react to both cash inflows and outflows within 1 to 2 days of receiving the deposit/redemption requests from private investors, this study uses the absolute value of net cash flows of mutual funds on day t to assess their impact on the market liquidity on day $t + 1$ and $t + 2$. Similarly, this study uses the absolute value of net cash flows of ETFs on day t to assess their impact on the market liquidity on day $t + 1$, because the measurements for ETF tracking error are on a daily basis and market makers have to react faster than mutual fund managers.

We regress stock market liquidity costs on the abovementioned parameters and additional market variables. In the regression models, we further control for index- and time-fixed effects as well as for persistence of liquidity costs. According to the hypotheses, we find a significant influence of the net cash flows of actively managed mutual funds on the liquidity costs of the stock market—they indeed reduce liquidity costs and improve overall stock market liquidity. This effect is economically strong, as a one standard deviation increase of total net cash flows reduces overall market liquidity costs by 2% on average. Moreover, these results are in line with previous findings about liquidity-motivated trading and liquidity preferences of mutual fund managers. At the same time, this study finds no effect of ETFs' net cash flows on stock market liquidity. We further corroborate the beneficial role of equity mutual funds by observing that their liquidity contribution was greatest during the stock market crisis in 2008/2009. Finally, we use two approaches to assess the mutual fund managers' skills in terms of their information processing ability. We find that those managers with greater information-processing abilities drive the liquidity contribution from mutual fund managers.

In summary, this paper contributes to the literature by presenting empirical evidence for

[2] Source: Banking statistics, Supplement 2, Deutsche Bundesbank; Deutsche Börse

the positive impact of liquidity-motivated trading by mutual funds on overall stock market liquidity. At the same time, we do not find a similar impact by ETFs. Using a unique order volume-weighted spread measure that considers the whole depth of the limit order book, the liquidity measure in this study is both timely and accurate. Therefore, our paper extends the existing research about liquidity-motivated trading by equity fund managers and its interdependency with overall market liquidity.

The structure of the remaining parts of this paper is as follows. Section 2.2 reviews the existing literature on liquidity measures, mutual funds' liquidity-timing ability, and empirical design using fund cash flows. We further derive the main hypotheses at the end of Section 2.2. Section 2.3 presents the data used in this research. Section 2.4 introduces the test models in this study and provides empirical results. Finally, Section 2.5 summarizes, concludes, and provides a brief outlook.

2.2 Literature review and hypothesis

Previously, liquidity risk research has mainly focused on measuring liquidity costs of market transactions. Models have been developed based on bid–ask spread data (e.g., Amihud and Mendelson (1986)), volume or transaction data (e.g., Amihud (2002), Pastor and Stambaugh (2003)), or limit order book data (e.g., Irvine et al. (2000)).

Irvine et al. (2000) and Gomber and Schweickert (2002) are the first to use round-trip transaction costs to measure liquidity costs (details cf. Subsection 1.1.1). Deutsche Börse implemented the volume-weighted spread from Gomber and Schweickert (2002) to assess the liquidity costs of stocks traded on its platform.

Since July 2002, Deutsche Börse has calculated every minute during trading hours for different order volume classes (from 3,000 euros up to 5 million euros)[3] a volume-weighted round-trip spread, the so-called *Xetra Liquidity Measure* (XLM), for all stocks traded on the Xetra trading platform. Xetra is a fully electronic trading platform from Deutsche

[3]The maximum available order volume class depends on the depth of the limit order book.

Börse, which aggregates and automatically matches buy and sell orders according to their price and quantity. Xetra processed more than 90% of the entire stock trading on the German exchanges in 2014.[4]

The calculation of XLM considers the whole depth of the limit order book and includes the entire size of the so-called "iceberg" orders, which are only partially visible for traders. Therefore, XLM is able to measure the implied round-trip spread for large orders that is normally much higher than the reported bid–ask spread. This order volume-dependent measure not only allows us to better measure the impact of order size but also to measure liquidity risk more precisely. Using XLM, Stange and Kaserer (2010) find evidence that even for liquid stocks, liquidity costs could increase total market price risk by more than 25%. This effect is measurable only because of the observation of the entire market depth. Hence, we use XLM as the liquidity measure for the empirical analysis in Section 2.4. More details on XLM and its advantages as a measure of liquidity costs for high order volumes is available in Stange and Kaserer (2010) and Rösch and Kaserer (2013).

In recent years, some researchers have started to analyze the liquidity-timing ability of specific market participants, especially fund managers. One common approach is to decompose fund returns into well-established stock return risk factors (e.g., Fama–French factors) and additional liquidity factors. Cao et al. (2013) add the liquidity measure from Pastor and Stambaugh (2003) as a liquidity factor to the standard Carhart (1997) four-factor model to assess the liquidity-timing ability of mutual funds. The authors find strong evidence at both the portfolio level and the individual fund level that mutual fund managers actively time market-wide liquidity. Similarly, Wagner and Winter (2013) add the illiquidity measure ILLIQ from Amihud (2002) and another factor for idiosyncratic risk to the Carhart (1997) four-factor model and find significant factor sensitivity concerning liquidity.

Shawky and Tian (2011) use quarterly holding data of small-cap equity mutual funds and record a significant pattern of buying less liquid stocks and selling more liquid stocks. The authors argue that liquidity effects are stronger in small-cap stocks than in large-

[4]Source: Major business figures 2014, Deutsche Börse

cap stocks, and provide evidence that small-cap equity mutual funds achieve, on average, an additional 1.5% return per year as compensation for holding less liquid stocks after controlling for other standard risk factors.

There are several reasons that researchers have rarely conducted analysis of a fund's liquidity-timing ability and liquidity preferences at a microstructure level. First, the detailed holding structures of mutual funds are mostly unavailable on a daily or weekly basis, as the data reports for these holdings are only on a monthly basis or even less frequently. Second, even if one had access to the daily holding structure, it is almost impossible to separate trades driven by stock preferences (information-motivated trading) from those driven by liquidity preferences (liquidity-motivated trading). In reality, fund managers consider both stock and liquidity preferences simultaneously and make decisions either using quantitative optimization models or based on their experiences or beliefs in market developments.

To conduct microstructure liquidity research, some researchers use an external "trigger" that "forces" mutual fund managers to trade within a short period of time and analyze the trading behavior accordingly. Besides individual event studies, one frequently used "trigger" is the fund in-/outflow because of the short investment and redemption time constraints of open-ended funds, which Section 2.1 mentions. Edelen (1999) shows that liquidity-motivated trading induced by fund flows accounts for a considerable fraction of the funds' overall trading activities. Coval and Stafford (2007) argue that in-/outflows, especially unexpected in-/outflows drive fund managers to buy/sell, especially sell, some stocks that are not their first choice. Because of the limited reaction time, fund managers are unlikely to collect new information about the traded stocks. Therefore, liquidity motivations mainly drive the trading decisions. This study uses equity funds' cash flows as the "trigger" of liquidity-motivated trades in the empirical research in Section 2.4.

Clarke et al. (2007) discover that mutual funds prefer to sell more liquid stocks when they experience substantial and sustained redemption of at least 10% of the funds' total assets under management. At the same time, mutual funds avoid buying more liquid stocks when they face the same size of cash inflow. This result is only partly significant[5] in the dataset of Clarke et al. (2007), which might lead to the lack of daily data. Bollen and Busse (2001) suggest that using daily data instead of monthly data could greatly enhance the quality of research on funds' timing ability. Furthermore, the authors argue that monthly data are the reason for the insignificant results of previous research.

The abovementioned literature suggests that mutual funds are subject to a significant amount of liquidity-motivated trading and that their managers are able to actively time market liquidity to some extent. Following this literature, we argue that fund managers engage in collecting information with respect to individual stocks' liquidity to exploit the liquidity-induced price impact for the fund's benefit. Consequently, we propose two main hypotheses regarding the impact of liquidity-motivated trading, as the equity funds' net cash flows measure, on overall market liquidity.

1. *Net cash flows of equity mutual funds improve stock market liquidity.*

   Portfolio managers of actively managed mutual funds process market information and consider liquidity costs while making trading decisions. To maximize their portfolio returns, it is important for mutual fund managers to try to minimize the liquidity costs of stock trading activities, especially when they face a "forced trading" situation, such as investor net cash in-/outflows. At this time, the liquidity costs receive much attention from fund managers, and they tend to buy stocks that need the fund's liquidity most (i.e., stocks where the order book demand curves are either very steep or the order book depth is completely missing). In cases in which fund managers have to sell shares because of new outflows, the managers withdraw liquidity from those stocks that need it less (i.e., where order book offer curves are rather flat and deep). Consequently, mutual fund managers tend to sell more liquid stocks when they face net cash outflows, while they tend to buy less liquid stocks when they experience net cash inflows.[6] This liquidity-motivated trading behavior

[5]The result is significant within the CRSP data set for January 2003 to November 2005, but not within the Thomson data set for January 1995 to September 1999.

[6]According to Amihud (2002) and Pastor and Stambaugh (2003), the illiquidity of stocks is compensated by higher returns.

of mutual fund managers reduces the overall liquidity costs of trading on the stock market[7] and improves stock market liquidity.

2. *Net cash flows of equity ETFs have no significant impact on stock market liquidity.*

   In contrast to mutual funds, market makers process the net cash flows of ETFs via creation and redemption procedures. Normally, this does not lead to direct trading activities, as long as the accumulated net cash flows do not exceed one creation/redemption unit. In addition, market makers often borrow/lend stocks from/to investment banks, for example, to avoid trading activities and reduce transaction and liquidity costs. Even if market makers choose to buy stocks instead of ETF shares, there is no discretion to react to the different liquidity of different stocks, as each stock has a given weight in the ETF. Second, the ETF manager has only weak incentives to exploit the liquidity-induced price impact, as this would increase the tracking error of the fund. Therefore, our second hypothesis is that trading by ETFs does not impact market liquidity or, to the extent that they crowd out mutual funds, might even harm market liquidity.

3. *High-skilled fund managers mainly drive the beneficial impact of liquidity-motivated trading.*

   Hypothesis 1 assumes that fund managers engage in collecting information with respect to individual stocks' liquidity and have the ability to exploit this information. Most likely, there is correlation between this liquidity-timing ability of an individual fund manager and with his or her ability to handle fundamental information. Based on this assumption, we hypothesize that mutual fund managers with higher information-processing abilities (higher skills) should make a greater contribution to overall market liquidity.

We empirically test these hypotheses in Section 2.4 using German stock market data,

[7]One might argue that mutual fund managers do not necessarily trade on stock exchanges and instead engage in over-the-counter (OTC) trading. We argue that the liquidity situation in both markets should be highly correlated, especially for relatively liquid stocks, because otherwise arbitrage possibility will exist for market makers and other traders.

which the next section describes.

2.3 Data description

This study focuses on the German stock market from July 1, 2002 to December 31, 2014. This period includes the recent financial crisis in 2008 and 2009 as well as the ongoing euro crisis. The dataset in this study comprises four main German stock indexes: the DAX, MDAX, SDAX, and TecDAX. The daily data, therefore, comprise 160 major German stocks. We renew the observed stocks when there is a member change in the indexes. In total, there are 329 stocks in the database in this study.

Because the focus of our paper is the impact of equity funds' cash flows on overall market liquidity, we aggregate the data at the index level, that is, aggregate data for the DAX, MDAX, SDAX, and TecDAX.

2.3.1 Dependent variable: liquidity data

We use the Xetra Liquidity Measure (XLM) as the liquidity cost measure, which Section 2.2 introduces. We calculate daily weighted averages of XLM for the DAX, MDAX, and SDAX by stock market capitalization from July 1, 2002 to December 31, 2014, which represents 3,181 trading days. For the TecDAX, we start the observations from the index's launch on March 24, 2003 and end them on December 31, 2014. For the analysis, we use one of the most available limit order volume classes from the XLM database (100,000 euros),[8] because this is more relevant than the other volume classes for the equity funds in the observations.[9]

Figure 2.1 presents the development of (market value-)weighted index level XLM for the

[8]There is one missing value for the MDAX and TecDAX in the data set, and five missing values for the SDAX. The reason for the missing values could be lack of limit orders for high volume classes.

[9]The mutual funds in this study's observations have an average daily absolute net in-/outflow of about 0.5 million euros per fund with an average standard deviation of about 2 million euros. 100,000 euros is more likely to be in the range of real order sizes than the smaller order volume classes are. For ETFs that usually have a creation/redemption unit of 50,000 shares, 100,000 euros per share is closer to real order sizes. In addition, we test volume classes of 25,000 euros and 50,000 euros, and achieve similar results.

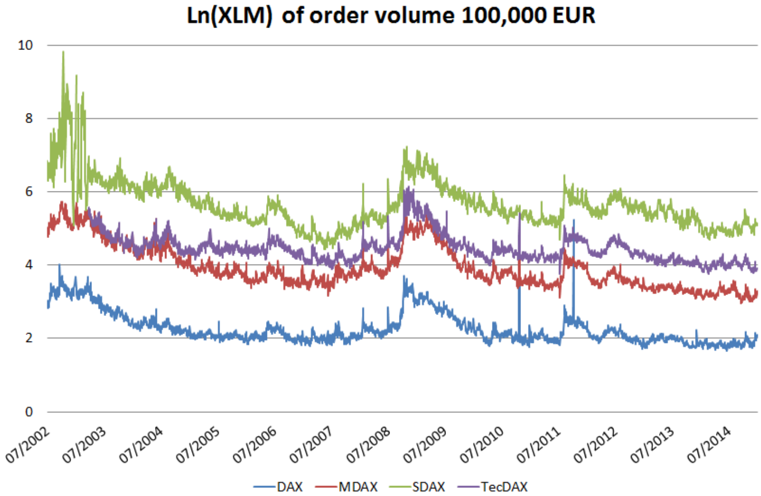

Figure 2.1: (Log-)XLM development by index

limit order volume class of 100,000 euros in the dataset. We show the natural logarithm of XLM for a better comparison between different indexes. For all indexes, XLM shows a long-term declining trend, with the exception of the recent financial crisis, in which the peak came after the bankruptcy announcement of Lehman Brothers in September 2008. The maximum value of the weighted XLM for the SDAX almost reached 1,400 basis points, which represents a liquidity cost from 14% of the stocks' mid-price for a round-trip trade. Even for the most liquid index, the DAX, the XLM value was above 40 basis points after the Lehman insolvency.[10] In addition, the smaller is the market value of the index constituents, the higher is the XLM value. After the introduction of the new Prime Standard segment on March 24, 2003 (the launch of the TecDAX, including foreign issuers in the Prime Standard indexes, as well as the downsizing of the MDAX from 70 to 50 stocks),[11] the XLM value and volatility of the DAX, MDAX, and SDAX declined immediately. The strongest effect is at the SDAX.

We control for the differences among indexes by including the index-fixed effects in the regression analysis in Section 2.4. The time-fixed effects control the long-term trends of

[10]There are an additional three outlier values of XLM on October 21 and 22, 2010 as well as October 5, 2011. XLM values on these 3 days are up to 30 times as much as the day before and after. We include these values in the regressions in Section 2.4 and use time-fixed effects as a control. In addition, we test the data set without these outliers. The outliers do not affect the test results.

[11]Source: Guide to the equity indices of Deutsche Börse AG, Version 6.31, Deutsche Börse

XLM and XLM's correlation to the economic state variables, such as the financial crisis. In addition, we control for the effect of the abovementioned market capitalization and other influential factors in the regressions, which Subsection 2.3.3 introduces.

2.3.2 Independent variables: cash flow data

We use daily estimated fund-level net flow from Morningstar (aggregated from the various share classes) as inputs for the fund net cash flows. The share class net cash flow is calculated as the change in total net asset values between 2 trading days that cannot be explained by the return of the share class, that is, for equity fund i, share class j, on trading day t, the net cash flow is

$$\text{net cash flow}_{i,j,t} = TNA_{i,j,t} - TNA_{i,j,t-1} \cdot (1 + R_{i,j,t}), \tag{2.1}$$

where $TNA_{i,j,t}$ and $R_{i,j,t}$ are the total net assets and return of stock i in share class j on trading day t. Then, we aggregate the fund-level net cash flow from all share classes, that is,

$$\text{net cash flow}_{i,t} = \sum_{j} \text{net cash flow}_{i,j,t}. \tag{2.2}$$

If a fund reports only the total net assets at the fund level, then we use the return of the oldest share class. This follows the net cash flow definition of Coval and Stafford (2007).

For mutual funds, we choose all equity funds with an investment focus entitled "Germany" from Morningstar, including dead funds to adjust for survivorship bias. We find a total of 120 funds up to the last record day (December 31, 2014). Then, we check the funds' holding structures and investment strategies and classify these funds into one of the four relevant indexes (DAX, MDAX, SDAX, and TecDAX). We select only funds with the majority of their investments in one of the four indexes of this study. For example, we exclude from the fund list one fund with the benchmark designation "Germany small/mid-cap equity" and a diversified asset allocation in the MDAX, SDAX, and TecDAX, because, in this case, the fund manager could choose to freely trade stocks in all three indexes, depending on the fund's strategy and stocks' liquidity, and we cannot clearly allocate its cash flow through induced trading to one of the three indexes. This selection process ensures that the net cash flows can only (or rather have to) be invested into/disinvested from the corresponding index. As a result, 103 mutual funds fulfill all the criteria of this study.

There are 40 ETFs with underlying indexes related to DAX, MDAX, SDAX, or TecDAX to December 31, 2014. We eliminate the synthetic ETFs from the analysis to ensure that net cash flows potentially cause real stock trades instead of only trades related to swaps or other financial derivatives. Similar to the selection of mutual funds, we exclude ETFs from the sample if we could not allocate their underlying index clearly to one of the four indexes. For example, we exclude one ETF with the underlying index of the HDAX, because it includes all stocks from the DAX, MDAX, and TecDAX. Consequently, 18 ETFs fulfill all the criteria.

As both positive and negative net cash flows of a mutual fund trigger trading activities by the fund manager, the absolute values of the net cash flows determine the trading volume. Therefore, we modify the definition from Equation (2.2) with the absolute value and define net cash flow (NCF) as

$$NCF_{i,t} = |\text{net cash flow}_{i,t}| \tag{2.3}$$

for equity fund i on trading day t. Next, we sum up the daily NCFs from all mutual funds with the corresponding benchmark index to calculate the daily index-level mutual fund NCF. Similarly, we define the daily index-level ETF NCF as the sum of the daily NCFs from all ETFs with the same corresponding underlying index.

Table 2.1 gives an overview of the daily index-level NCFs. Mutual funds and ETFs with the DAX as the benchmark/underlying index have a much higher daily NCF compared with funds with other benchmark/underlying indexes. Compared with the mutual funds with the same underlying index, ETF NCFs have higher relative standard deviations. In addition, all NCF variables in the dataset show, as expected, strong skewness in their distributions, especially ETF NCFs. Therefore, we use the logarithm of the NCFs for the regressions in Section 2.4.

Table 2.1: Fund NCF summary

Index	Variable	Observations	Mean	Std. dev.	25%-percentile	Median	75%-percentile
DAX	Mutual fund NCF	3,150	28.46	36.10	10.40	21.13	36.34
	ETF NCF	2,423	83.42	348.87	0.40	15.04	49.10
MDAX	Mutual fund NCF	2,465	3.39	6.68	0.87	2.00	3.97
	ETF NCF	3,115	2.14	6.35	3.82e-03	0.01	0.05
SDAX	Mutual fund NCF	3,101	0.75	1.47	0.05	0.30	0.88
	ETF NCF	896	0.14	1.62	1.27e-05	2.70e-05	4.71e-05
TecDAX	Mutual fund NCF	2,436	0.09	0.41	5.31e-03	0.02	0.06
	ETF NCF	2,927	0.56	2.29	0.02	0.05	0.09

This table shows the descriptive statistics of the daily index-level NCF of mutual funds and ETFs from July 1, 2002 to December 31, 2014 for DAX, MDAX, SDAX, and TecDAX. This study calculates the daily index-level mutual fund/ETF NCF as the sum of all absolute values of net cash flow from all mutual funds/ETFs with the corresponding benchmark/underlying index. The fund-level net cash flow data are from Morningstar. For every variable, the table presents the number of observations, mean, standard deviation, 25% percentile, median, and 75% percentile. The cash flows are in million euros.

There are fewer observations for ETF NCFs, especially with the SDAX as the underlying index, because the first such ETF launched in 2011. In the mutual fund sample, the average accumulated yearly NCFs (the sum of the daily absolute value of net cash flows) are equal to approximately two-thirds of the average yearly net asset value (NAV). For ETFs, this ratio equals about 160%. This demonstrates that high NCF-to-NAV ratios can occur for average funds, which forces fund managers to conduct liquidity-motivated trading. There is an obvious connection between the very high ratio for ETFs and the rapid growth in the ETF market.

2.3.3 Control variables: market data

Previous research shows that some simple observable market parameters at least partially explain the liquidity costs. This literature often uses these parameters as proxies of liquidity determinants. Besides market capitalization, which we discuss in Subsection 2.3.1, commonly used market parameters in cross-sectional analyses are trading volume (number of traded shares), stock price, stock return, and return (or price) volatility. These parameters contain information that has close relationships to order processing, inventory risk, and information asymmetry, which, according to Stoll (2000) and Corwin (1999), determine liquidity cost. While there is a positive correlation between liquidity and market capitalization, trading volume, stock price, and return, there is a negative correlation between liquidity and return (or price) volatility (cf., e.g., Copeland and Galai (1983), Stoll (2000), Pastor and Stambaugh (2003), Chordia et al. (2009)).

We use the index-level market value (MV) from Datastream as the input for market capitalization. Instead of trading volume and stock price, we use the daily total trading value of all constituents in one index, as our analysis focuses on index-level market development. We calculate the daily trading value of each stock as the product of the daily trading volume (TV) and the end price (P) from Datastream. Then, we aggregate stock trading values to the index level based on index constitution lists. According to Chordia et al. (2009), information included in trading value is probably more important than that in trading volume. Some liquidity measures, including the Amihud (2002) illiquidity measure, also use trading value instead of trading volume. We use the index-level daily discrete return; we derive these data from Datastream's total return index (RI) for each relevant index.[12] To estimate the daily volatility of the four indexes, we use the volatility estimator from Rogers, L. C. G. and Satchell (1991) using daily high, low, open, and close values of the indexes. This study defines daily volatility as

$$\begin{aligned} Vola_{i,t} = &(ln(High_{i,t}) - ln(Open_{i,t}))(ln(High_{i,t}) - ln(Close_{i,t})) \\ &+ (ln(Low_{i,t}) - ln(Open_{i,t}))(ln(Low_{i,t}) - ln(Close_{i,t})) \end{aligned} \tag{2.4}$$

for index i, day t, where $High_{i,t}$ and $Low_{i,t}$ are the intraday high and low values, respectively, of index i on day t, and $Open_{i,t}$ and $Close_{i,t}$ are the open and close values, respectively, of index i on day t. This estimation is drift-independent and has a low estimation variance (cf., e.g., Rogers, L. C. G. et al. (1994), Yang and Zhang (2000)).[13]

[12]We run all regressions with daily continuous return as well. There is no substantial difference between the regression results.

[13]In addition, we test further volatility estimators from Yang and Zhang (2000). The different volatility estimators do not lead to significant change in the regression results. Furthermore, we test the 5-, 10-, and 30-day rolling return volatility. The regression results are less significant, because all other variables are daily data.

Table 2.2 exhibits some basic characteristics of the four most important stock indexes in Germany. Compared with the other three indexes, the DAX shows much higher total market capitalization and daily trading values, on average, while the average return and volatility are comparable with other indexes. Interestingly, the TecDAX has a much higher daily average trading value than the SDAX does, although they have similar total market capitalization. This is further reflected in the higher XLM value of the SDAX in Figure 2.1, in contrast to the TecDAX, and confirms that the trading value is one of the most important determinants of market liquidity—even more important than market capitalization. Besides returns, the distributions of all other variables show positive skewness. For this reason, we use the logarithm of market capitalization, trading value, and return volatility for the regression analysis in Section 2.4.

Table 2.2: Control variable summary

Index	Variable	Observations	Mean	Std. dev.	25% percentile	Median	75% percentile
DAX	Market capitalization	3,181	684,897.80	154,012.30	565,727.10	677,492.40	790,288.40
	Trading value	3,181	3,944.00	2,085.11	2,709.94	3,318.22	4,462.17
	Return	3,181	0.04	1.53	-0.65	0.09	0.75
	Volatility	3,181	1.61	3.52	0.29	0.63	1.48
MDAX	Market capitalization	3,181	138,401.50	49,470.92	98,591.74	136,302.60	175,960.40
	Trading value	3,181	411.52	252.63	244.61	362.60	504.28
	Return	3,181	0.06	1.38	-0.56	0.13	0.74
	Volatility	3,181	1.02	2.31	0.16	0.38	1.01
SDAX	Market capitalization	3,181	24,389.51	10,472.54	17,415.58	22,058.84	30,930.82
	Trading value	3,181	36.27	28.42	16.52	29.40	48.07
	Return	3,181	0.04	1.05	-0.40	0.11	0.58
	Volatility	3,181	0.45	1.36	0.10	0.20	0.40
TecDAX	Market capitalization	2,996	29,789.02	7,979.66	24,592.40	27,293.88	34,843.14
	Trading value	2,996	132.33	80.03	75.90	116.59	170.21
	Return	2,996	0.06	1.55	-0.68	0.13	0.87
	Volatility	2,996	1.34	2.80	0.25	0.56	1.36

This table shows the descriptive statistics of the daily index-level market data from July 1, 2002 to December 31, 2014 from DAX, MDAX, SDAX, and TecDAX, including market capitalization, trading value, return, and volatility. Market capitalization and trading value are in million euros, while return and volatility are in percent. All databases are from Datastream. The market capitalization directly for each index; index-level trading value is calculated as the sum of all index constituents' trading values, that is, trading volume (number of traded shares) multiplied by stock end price. The daily index-level return is derived from the return index for each index. The daily volatility is calculated as Rogers, L. C. G. and Satchell (1991) volatility using daily high, low, open, and close value of the indexes. For every variable, the table presents the number of observations, mean, standard deviation, 25% percentile, median, and 75% percentile.

In addition, we illustrate the development of these four market variables during the observation period in Figure 2.2. We use the natural logarithm for market value, trading value, as well as volatility for a better comparison among the indexes. In general, market capitalization and trading value show an increasing trend in the long run. Similar to the XLM development presented in Figure 2.1, the co-movement of the four indexes again reveals the impact of the overall macro financial environment on the stock market. All four indexes experienced huge losses of market capitalization during the recent financial crisis and reached their bottom a few months after the bankruptcy announcement of Lehman Brothers. The trading value shows less sensitivity toward the macro financial environment compared to the market value, but higher volatility over the entire observation period. Notably, the daily total trading values of DAX stocks stay almost in the same range during the last 12 years, with the exception of the boom phase from 2006 to 2008 before the financial crisis, while the total market capitalization of DAX stocks increased from 593 billion euros on July 1, 2002 to 966 billion euros on December 31, 2014, which corresponds to more than a 60% increase. The figures clearly show a similar increase for the MDAX. The indexes demonstrate high volatility during the market-distressed phases, that is, the stock market downturn in 2002 as a result of the dotcom bubble, the recent financial crisis in 2008/2009, and the euro crisis in 2011/2012.

2.4 Empirical results

To analyze the impact from equity funds' cash flows on market liquidity, we regress the market-wide XLM against the lagged NCF variables. We include 1 and 2 trading-day lags[14] of mutual fund cash flows, because the equity mutual funds in our data set have "t+1" or "t+2" for redemption, which means that the mutual fund managers have to trade within 1 to 2 trading days after the in-/outflows if the managers want to maintain the target cash ratios of their portfolios. For ETFs, we use NCFs with a 1-day lag. Because ETF's performance is measured by the tracking error, which is calculated on a daily basis, market makers of ETFs are motivated to trade within 1 day after the in-/outflows if the accumulated net cash flow amount exceeds one creation/redemption unit.

[14] For simplification, we use *1- and 2-day lags* for *1- and 2-trading day lags.*

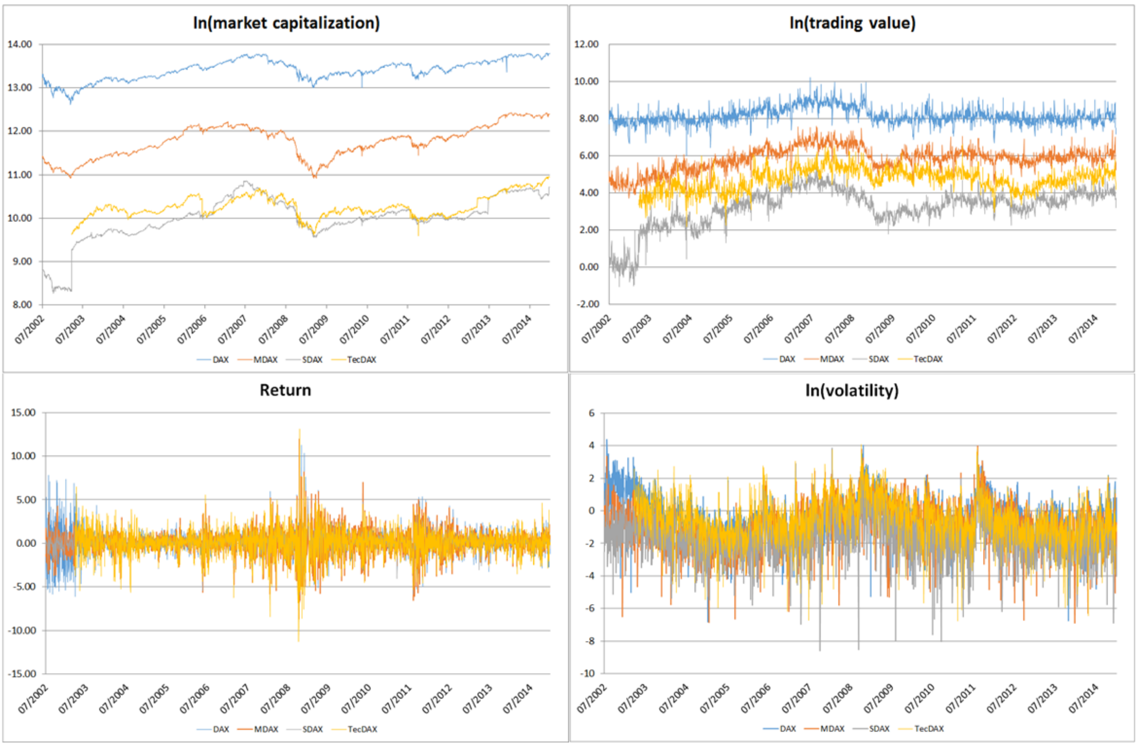

Figure 2.2: Development of market variables

As expected, Figure 2.3 shows the persistence of XLM based on its nature. Therefore, we include the 1-day lag of XLM in the regression model.[15] To control for other influential factors on market liquidity, as Subsection 2.3.3 introduces, we add return, volatility, trading value, and market capitalization to the regression.

The formula for the regression model is

$$\begin{aligned} ln(XLM_{i,t}) =& \alpha + \beta_1 \cdot ln(MFNCF_{i,t-1}) + \beta_2 \cdot ln(MFNCF_{i,t-2}) + \beta_3 \cdot ln(ETFNCF_{i,t-1}) \\ & + \beta_4 \cdot ln(XLM_{i,t-1}) + \beta_5 \cdot R_{i,t} + \beta_6 \cdot ln(Vola_{i,t}) + \beta_7 \cdot ln(TV_{i,t}) \\ & + \beta_8 \cdot ln(MC_{i,t}) + \gamma_t \cdot \mathrm{I}_t + \delta_i \cdot \mathrm{I}_i + \epsilon_{i,t}, \end{aligned} \tag{2.5}$$

where $XLM_{i,t}$ and $XLM_{i,t-1}$ are the (market value-)weighted XLM values on days t and t-1 for the order volume class of 100,000 euros in index i in basis points. $MFNCF_{i,t-1}$

[15] We include up to six lags in the regression for the robustness check. This does not influence the significance of the regression coefficients. The absolute value of the coefficients changes only marginally.

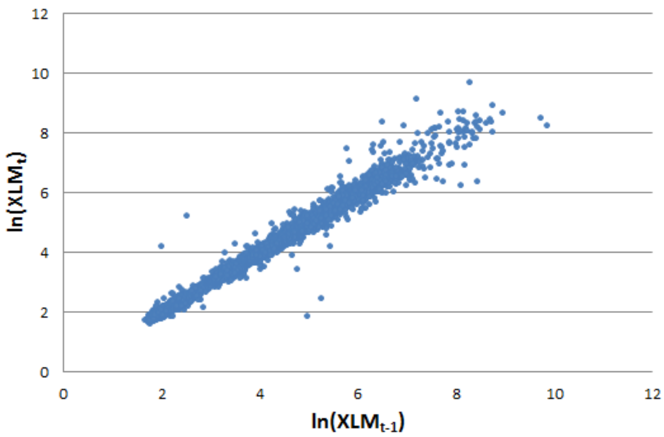

Figure 2.3: Autocorrelation of XLM

and $MFNCF_{i,t-2}$ are the sum of the absolute values of the mutual funds' net cash flows, whose holding majority are stocks from index i on days t-1 and t-2, respectively, in million euros. $ETFNCF_{i,t-1}$ is the sum of the absolute values of ETFs' net cash flows, whose underlying index is index i, on day t-1 in million euros. $R_{i,t}$ is the discrete return in percent. $Vola_{i,t}$ is the Rogers, L. C. G. and Satchell (1991) volatility calculated from the open, close, high, and low values of index i on day t, which Equation (2.4) defines in percent. $TV_{i,t}$ is the total trading value (aggregation of the number of shares traded multiplied by the end price for each stock) on day t for index i in million euros, $MC_{i,t}$ is the total market capitalization (aggregated market value from the index constituents) on day t for index i in million euros. Index i belongs to one of the following indexes: DAX, MDAX, SDAX, and TecDAX. In addition, we include index- and weekly time-fixed effects to control for unobservable index-specific effects, as well as macro financial environmental changes during the observation period. See Section 2.3 for more details and descriptive statistics.

We use the natural logarithm due to the high skewness of the distribution of most variables, with the exception of daily returns. To solve the potential issues caused by multicollinearity, we standardize all regressors, except the lagged XLM, and orthogonalize the control variables against the cash flow variables. Using these techniques, we are able to reduce the maximum variance inflation factor to less than two. At this level, we are confident that potential multicollinearity issues do not affect the regression results. A drawback of using orthogonalization is that we cannot directly interpret the value of regression coefficients of the orthogonalized regressors. Fortunately, in the case of this study, this problem affects only the control variables, not the main variables of interest. The orthogonalization of the control variables does not affect the regression coefficients of the cash flow variables. Table 2.3 shows the pairwise correlation among all standardized regressors (except the lagged XLM). By design, there is high correlation between mutual fund NCFs with 1- and 2-day lags. Furthermore, the correlation between the funds' NCFs and trading values as well as between the funds' NCFs and market capitalization is relatively high, as expected. The highest correlation among the control variables is between the trading value and market capitalization. Figure 2.2 directly shows this. Using orthogonalization eliminates the correlation between the cash flow variables and control variables and, therefore, excludes the effect of potential collinearity driven by the control variables from the regression. Considering potential heteroscedasticity and autocorrelation of the residuals, we use the Driscoll–Kraay estimator[16] for standard errors, which accounts for cross-sectional dependence.

[16]Cf. Driscoll and Kraay (1998)

Table 2.3: Pairwise correlation of regressors

	Mutual fund NCF with 1-day lag	Mutual fund NCF with 2-day lags	ETF NCF with 1-day lag	XLM with 1-day lag	Return	Volatility	Trading value	Market capitalization
Mutual fund NCF with 1-day lag	1.0000							
Mutual fund NCF with 2-day lags	0.6243*	1.0000						
ETF NCF with 1-day lag	0.0768*	0.0632*	1.0000					
XLM with 1-day lag	-0.1450*	-0.1457*	-0.0571*	1.0000				
Return	0.0073	0.0075	-0.0123	0.0042	1.0000			
Volatility	-0.0549*	-0.0575*	0.0935*	0.1295*	-0.2168	1.0000		
Trading value	0.4042*	0.4061*	0.0755*	-0.1961*	-0.0246	0.1621*	1.0000	
Market capitalization	0.4678*	0.4684*	0.1471*	-0.3190*	0.0211*	-0.2387*	0.5945*	1.0000

This table presents the pairwise correlation between the regression variables. The study uses the natural logarithm of the variables with an exception of return, and standardizes all variables (except lagged XLM). * indicates significance at the 5% level or better.

2.4.1 Main test results

Table 2.4 shows the regression results. Model 1 represents the results from Equation (2.5), where all three cash flow variables are included in the regression. Models 2–4 each include only one of the cash flow variables as a robustness check. All three cash flow variables are statistically significant in Model 1. The regression coefficients of the mutual fund NCFs remain significant at the 1% level in both Models 2 and 3; however, the coefficient of the ETF NCF is statistically insignificant at the usual significance levels (i.e., 1%, 5%, and 10%) in Model 4. Even in Model 1, the absolute value of the coefficient for ETF NCF is only about one-fifth of that for mutual fund NCFs, while the relative standard error of the ETF NCF's coefficient is much higher than those of the mutual fund NCFs. Overall, the regression coefficients of the mutual fund NCFs are robust in all models, while this result applies only to a lesser extent to the coefficient of the ETF NCF. The coefficients of the mutual fund NCFs with 1- and 2-day lags both have a negative sign, which is in line with the first hypothesis. An increase in the net in-/outflows of equity mutual funds reduces the weighted liquidity costs and therefore, increases the overall market liquidity. At the same time, the coefficients for the ETF NCF's are positive, indicating that an increase in their net in-/outflows increases the liquidity costs and therefore, reduces overall market liquidity. This is in accordance with the second hypothesis from Section 2.2.

Table 2.4: Cash flow impact on stock market liquidity costs

Variable	Model 1	Model 2	Model 3	Model 4
Main variables				
Mutual fund NCF with 1-day lag	-0.0186***	-0.0211***		
	(0.00294)	(0.00340)		
Mutual fund NCF with 2-day lags	-0.0206***		-0.0227***	
	(0.00387)		(0.00420)	
ETF NCF with 1-day lag	0.00385***			0.00188
	(0.00117)			(0.00116)
XLM with 1-day lag	0.586***	0.607***	0.605***	0.633***
	(0.0595)	(0.0580)	(0.0589)	(0.0571)
Control variables				
Return	-0.0220***	-0.0226***	-0.0226***	-0.0233***
	(0.00279)	(0.00281)	(0.00274)	(0.00276)
Volatility	0.0376***	0.0311***	0.0319***	0.0234***
	(0.00413)	(0.00325)	(0.00357)	(0.00257)
Trading value	-0.0208***	-0.0148***	-0.0153***	-0.00724**
	(0.00441)	(0.00364)	(0.00384)	(0.00291)
Market capitalization	-0.0330***	-0.0232***	-0.0245***	-0.0101***
	(0.00631)	(0.00482)	(0.00528)	(0.00350)
Observations	7,980	7,980	7,980	7,980
Within R-squared	0.938	0.936	0.937	0.935
Adjusted R-squared	0.993	0.992	0.992	0.992
Time-fixed effects	Yes	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes	Yes

This table reports the regression results on the impact of equity funds' net cash flows on German stock market liquidity costs during July 1, 2002 to December 31, 2014. For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observation of the following variables to the index level and uses them as regression inputs. The dependent variable stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for the order volume class of 100,000 euro in basis points. The main independent variables include mutual fund NCF with 1- and 2-day lags, ETF NCF with 1-day lag, as well as XLM with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euro. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euros). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Furthermore, this study controls for index- and time-fixed effects in the regression. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In addition, the values of the regression coefficient of the NCFs with 1- and 2-day lags are very similar. Both values are about -2% after controlling for autocorrelation of XLM and market influence factors. The absolute value of the second coefficient is only marginally higher than the first. There is a minor increase in both coefficients of the mutual fund NCF variables in the single cash flow variable tests compared to Model 1, owing to the correlation between these two variables. According to the regression results, the overall market liquidity costs decreases by about 2% on day t if the mutual funds' NCFs 1 or 2 trading days before day t increase by one standard deviation. For the average liquidity cost of DAX stocks, this means only half a basis point, but, for the MDAX, TecDAX, and SDAX stocks, 2% equates to 5, 8, and 45 basis points, respectively. This is an economically strong effect.

Finally, even if it is necessary to interpret the coefficients of the control variables very carefully, the regression results show, as expected, that there is a positive association between market liquidity cost and volatility and a negative link between market liquidity cost and return, trading value, and market capitalization.

2.4.2 Robustness tests

We conduct several robustness tests in order to rule out that (1) the potential interaction between the lagged XLM and the cash flow variables drives the results, and (2) that some specific sub-periods included in the analysis, such as the financial crisis, drive the results.

Regarding the first problem, we execute the following additional tests. First, we run an AR(1) regression for $ln(XLM)$ and regress the residuals on the cash flow and control variables. Appendix A presents the regression results, which are very similar to the results in Table 2.4 in terms of statistical significance and the sign of the coefficients. Next, we use the first difference of $ln(XLM)$ as the dependent variable to remove the autocorrelation of $ln(XLM)$ from the regression models. Appendix B shows the test results. Although the signs of the cash flow variables' coefficients remain the same, their statistical significance somewhat decreases, compared to the results in Table 2.4. A possible reason is unobservable noise in the first-difference regression, which this study cannot control for. Nevertheless, both tests support the main hypotheses and underline the robustness of the results presented in Table 2.4.

With respect to the second problem, that is, whether some specific sub-periods drive the results, we investigate how the equity funds' cash flows influence market liquidity in different market periods. The data sample includes the greatest stock market crisis of the last decade, the recent global financial crisis, which intensified after the bankruptcy of Lehman Brothers. We consider the period from August 1, 2008 to March 31, 2009 as the core financial crisis. Specifically, we divide the data set into three sub-periods for the analysis: the pre-financial crisis period (July 1, 2002 to July 31, 2008), the financial crisis period (August 1, 2008 to March 31, 2009), and the aftermath of the financial crisis (April 1, 2009 to December 31, 2014).

Table 2.5 presents the descriptive statistics of these three sub-periods. The average daily NCF of mutual funds reaches its lowest value during the financial crisis compared to the other time periods, while its relative standard deviation (ratio of standard deviation to the mean) is higher than the level before the crisis and comparable to the ratio after the financial crisis. High relative volatility during the stock market crisis indicates high probabilities of unexpected in-/outflows and, therefore, liquidity-motivated trading. At the same time, the NCFs of ETFs reached their highest daily average during the stock market crisis. In all three sub-periods, the NCF standard deviation of ETFs is much higher than that of mutual funds. During the financial crisis, the German stock market underwent an average daily loss of 28 basis points, while the volatility in this period was much higher than in the before and after periods. In the sub-period after the financial crisis, the average daily return reached 9 basis points, which was almost double the level before the crisis, while the volatility remained at a similar level. Compared to the period before the financial crisis, there are high trading values and even higher corresponding standard deviations during the financial crisis. Interestingly, the average daily trading value after the financial crisis and its standard deviation are much lower than before and during the crisis. The crisis recovery, a low interest rate environment, and the ongoing euro crisis might have driven this.

Table 2.5: Fund NCF and market data summary by sub-period

Variable	Pre-financial crisis (07/01/2002-07/31/2008)	Financial crisis (08/01/2008-03/31/2009)	Post-financial crisis (04/01/2009-12/31/2014)
Mutual fund NCF	8.34	5.87	9.92
	(18.45)	(14.39)	(26.76)
ETF NCF	10.83	30.69	29.77
	(107.66)	(186.91)	(217.08)
Return	0.05	-0.28	0.09
	(1.28)	(2.83)	(1.24)
Volatility	0.98	3.97	0.90
	(2.44)	(5.82)	(2.02)
Trading value	1,304.58	1,397.28	953.41
	(2,256.63)	(2,535.17)	(1,450.18)
Market capitalization	211,345.00	181,835.60	237,938.90
	(272,290.10)	(244,943.20)	(301,866.10)
Trading days	1,551	168	1,462

This table shows the descriptive statistics of the daily index-level NCFs of mutual funds and ETFs, as well as index-level market data (market capitalization, trading value, return, and return volatility) from July 1, 2002 to December 31, 2014 for DAX, MDAX, SDAX, and TecDAX, in three sub-periods (pre-financial crisis, financial crisis, and after financial crisis in 2008/2009). The daily index-level mutual fund/ETF NCF is calculated as the sum of all absolute value of net cash flows from all mutual funds/ETFs with the corresponding benchmark/underlying index. The fund-level net cash flow data are from Morningstar. All market databases are from Datastream. The market capitalization is collected directly for each index. Index-level trading value is calculated as the sum of all index constituents' trading values, that is, trading volume (number of traded shares) multiplied by stock end price. The daily index-level return is derived from the return index for each index. The daily volatility is calculated as Rogers, L. C. G. and Satchell (1991) volatility using daily high, low, open, and close value of the indexes. For every variable, the table presents the mean and standard deviation in parentheses. The NCF, market capitalization, and trading value are in million euros; return and volatility are in percent.

Table 2.6 presents the regression results. In all three sub-periods, mutual fund NCFs with 1- or 2-day lags reduced overall market liquidity costs at the 1%-significance level. ETF NCFs do not have a significant impact on overall market liquidity, although they show a strong statistical significance in the time period after the stock market crisis. The absolute values of the regression coefficients of the mutual fund NCFs with 1- and 2-day lags are very similar to each other before and after the financial crisis. During the financial crisis, however, the absolute value of the coefficient of the mutual fund NCF with a 1-day lag is almost one-third higher than the coefficient of the mutual fund NCF with a 2-day lag. A potential explanation is that mutual fund managers reacted faster to in-/outflows during the financial crisis than in the other two sub-periods. One driver for this feature could be the high uncertainty during the crisis, as the case of redemptions shows; redemptions occurred more often during the financial crisis than in the other two sub-periods. The share price of a mutual fund is calculated based on the closing price of stock holdings on the redemption day. The longer a fund manager waits, the more he or she exposes the fund to market risk. If market risk is high, as during a crisis period, this risk becomes perceptible and, hence, fund managers try to avoid or reduce the risk. As a result, a fund manager might sell their positions faster after receiving a redemption request during a financial crisis. Furthermore, the absolute values of the mutual fund NCFs' coefficients during the financial crisis were about twice as high as the coefficients in the other time periods. This could be explained by the fact that there was a flight-to-quality effect during the crisis, as corroborated by Rösch and Kaserer (2013). Therefore, liquidity becomes more unequally distributed among different stocks, making the potential impact of injecting liquidity in the less liquid stocks even stronger.

Table 2.6: Cash flow impact on stock market liquidity costs by sub-period

Variable	Pre-financial crisis (07/01/2002-07/31/2008)	Financial crisis (08/01/2008-03/31/2009)	After financial crisis (04/01/2009-12/31/2014)
Mutual fund NCF with 1-day lag	-0.0140***	-0.0382***	-0.0176***
	(0.00394)	(0.0113)	(0.00415)
Mutual fund NCF with 2-day lags	-0.0150***	-0.0303***	-0.0204***
	(0.00456)	(0.0108)	(0.00543)
ETF NCF with 1-day lag	0.00182	0.00504	0.00463***
	(0.00178)	(0.00808)	(0.00145)
XLM with 1-day lag	0.528***	0.299***	0.591***
	(0.0530)	(0.101)	(0.0853)
Observations	2,383	491	5,106
Within R-squared	0.805	0.933	0.908
Adjusted R-squared	0.993	0.990	0.993
Control variables	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes

This table reports the regression results on the impact of equity funds' NCFs on German stock market liquidity costs during July 1, 2002 to December 31, 2014 in three sub-periods (pre-financial crisis, financial crisis, and after financial crisis in 2008/2009). For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observation of the following variables to the index level and uses them as regression inputs. The dependent variable stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for the order volume class of 100,000 euro in basis points. The main independent variables include mutual fund NCF with 1- and 2-day lags, ETF NCF with 1-day lag, as well as XLM with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euros. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euros). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Index- and time-fixed effects are also controlled for in the regression. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

2.4.3 The impact of information-processing abilities

This study bases its main hypothesis on the assumption that fund managers engage in collecting information with respect to individual stock liquidity and have the ability to exploit this information. Even though it is difficult to think of a variable that measures this liquidity timing ability of individual fund managers, there might be an indirect way to test this assumption. For this purpose, we assume that there is correlation between a fund manager's liquidity-timing ability and his or her ability to handle fundamental information. Based on this assumption, we hypothesize that mutual fund managers with better information-processing abilities (higher skills) should make a greater contribution to overall market liquidity. To verify this hypothesis, we separate the observed mutual funds into two groups based on their information-processing abilities. For later comparisons, we choose two different factors to represent the fund manager's information-processing ability: the abnormal return derived from the standard Carhart (1997) four-factor model and the information ratio.

In the first analysis, we use the mutual fund's abnormal returns—which the standard risk factors from Carhart (1997) cannot explain—as a proxy for the fund manager's information-processing ability. For that purpose, we run a Carhart (1997) four-factor regression that includes the market factor (market excess return), size factor (small minus big), value factor (high minus low), and momentum factor (winner minus loser) for each mutual fund and each year from 2002 to 2014. We use the daily market risk factors for German stocks from the Frankfurt Stock Exchange (FSE) top segment[17] that Brückner et al. (2014) provide. For each year and each benchmark index, we then sort the mutual funds based on their abnormal returns (alpha). We categorize the mutual funds into two groups (one with high alphas [upper 50%] and one with low alphas [lower 50%]). The categories are renewed every year based on the regression results.[18] Using the aggregate NCF data and market data, we conduct the following regression:

$$
\begin{aligned}
ln(XLM_{i,t}) =& \alpha + \beta_1 \cdot ln(MFNCF_{i,t-1,high\ alpha}) + \beta_2 \cdot ln(MFNCF_{i,t-1,low\ alpha}) \\
&+ \beta_3 \cdot ln(MFNCF_{i,t-2,high\ alpha}) + \beta_4 \cdot ln(MFNCF_{i,t-2,low\ alpha}) \\
&+ \beta_5 \cdot ln(XLM_{i,t-1}) + \beta_6 \cdot R_{i,t} + \beta_7 \cdot ln(Vola_{i,t}) + \beta_8 \cdot ln(TV_{i,t}) \\
&+ \beta_9 \cdot ln(MC_{i,t}) + \gamma_t \cdot \mathrm{I}_t + \delta_i \cdot \mathrm{I}_i + \epsilon_{i,t},
\end{aligned}
\tag{2.6}
$$

where $MFNCF_{i,t-1,high\ alpha}$ and $MFNCF_{i,t-2,high\ alpha}$ are the sum of the absolute values

[17] All four indexes we consider belong to the FSE top segment. For further information regarding FSE segmentation, cf. Brückner et al. (2014).

[18] To ensure "fair" comparison between mutual funds with high and low abnormal return, we drop NCF observations out of the regression sample for one index, if either of the NCF variables is missing for one index. This especially affects the SDAX and TecDAX, because there is sometimes only one mutual fund with the SDAX or TecDAX as the benchmark index in the sample. This is particularly the case in the early period of the observation.

of the net cash flows of the mutual funds with high abnormal returns based on the Carhart (1997) four-factor model (upper 50%) on days t-1 and t-2, respectively, for index i, and $MFNCF_{i,t-1,low\ alpha}$ and $MFNCF_{i,t-2,low\ alpha}$ are the sum of the absolute values of net cash flows of the mutual funds with low abnormal returns based on the Carhart (1997) four-factor model (lower 50%) on days t-1 and t-2, respectively, for index i. All other variables are defined as in Equation (2.5).

Table 2.7 presents the descriptive statistics of mutual fund NCFs sorted by abnormal returns. The NCFs of funds with high abnormal returns have lower means, with the exception of the DAX, and higher standard deviations, with the exception of the TecDAX, compared to funds with low abnormal returns. For all indexes, the relative volatility (ratio of the standard deviation to the mean) of the NCFs of funds with high alphas is higher than that of the NCFs of funds with low alphas. This implies that fund managers that achieve high abnormal returns are more likely to face unexpected in-/outflows and, therefore, conduct more liquidity-motivated trading.

Table 2.7: Mutual fund NCF summary by abnormal returns

Index	Variable	Observations	Mean	Std. dev.	25% percentile	Median	75% percentile
DAX	NCF (high alphas)	3,133	16.11	30.58	3.96	10.13	19.89
	NCF (low alphas)	3,133	11.88	15.48	3.31	7.57	14.27
MDAX	NCF (high alphas)	2,435	1.27	5.14	0.21	0.56	1.27
	NCF (low alphas)	2,435	2.15	4.19	0.33	0.95	2.53
SDAX	NCF (high alphas)	2,437	0.24	1.05	0.01	0.03	0.15
	NCF (low alphas)	2,437	0.44	0.93	0.02	0.11	0.45
TecDAX	NCF (high alphas)	936	0.02	0.04	0.00	0.01	0.03
	NCF (low alphas)	936	0.04	0.09	0.00	0.01	0.02

This table shows the descriptive statistics of the daily index-level net cash flows of mutual funds by abnormal return (alpha) from July 1, 2002 to December 31, 2014 for DAX, MDAX, SDAX, and TecDAX. The mutual funds are categorized into two groups by alphas (upper and lower 50%) as a regression result from the Carhart four-factor model. The regressions are conducted for each year from 2002 to 2014, and thus, is the constitution of each category. The daily index-level mutual fund NCF of each group is calculated as the sum of absolute value of net cash flows from all mutual funds in the group with the corresponding benchmark index. The fund-level net cash flow data are from Morningstar. For every variable, the table presents the number of observations, mean, standard deviation, 25% percentile, median, and 75% percentile. The cash flows are in million euros.

Table 2.8 presents the regression results. Model 1 is the regression test of Equation (2.6). Models 2–4 test the robustness of the coefficients using one of the cash flow variables. All test models lead to consistent results in terms of statistical significance. The coefficients of mutual funds with high alphas are statistically significant at the 1% level and the coefficients of mutual funds with low alphas are not significant at the 10% level or better. This suggests that managers with higher skills mainly drive the liquidity contribution of actively managed mutual funds. The coefficients of the NCFs of funds with high abnormal returns in Models 2 and 4 do not differ much from the test results of Model 1, which indicates no strong interaction effect between the variables with a 1-day lag and those with a 2-day lag for the funds with high alphas. On the other hand, the coefficients of the NCFs of funds with low abnormal returns in Models 3 and 5 deviate strongly from the regression coefficients for the other test models. This provides further evidence of the robustness of the regression coefficients. The coefficients of the regressors with 1- and 2-day lags do not greatly differ from each other, which is in line with the test results in Table 2.4, which shows there is no preference from the mutual fund managers between trading on the 1st or 2nd day after the in-/outflows.

Table 2.8: Mutual funds' cash flow impact on stock market liquidity costs by abnormal returns

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
NCF with 1-day lag of funds	-0.0168***	-0.0120***			
with high alpha	(0.00273)	(0.00184)			
NCF with 1-day lag of funds	-0.0107		-0.000976		
with low alpha	(0.00711)		(0.00645)		
NCF with 2-day lags of funds	-0.0192**			-0.0142***	
with high alpha	(0.00535)			(0.00211)	
NCF with 2-day lags of funds	-0.0111				-0.00158
with low alpha	(0.00653)				(0.00553)
XLM with 1-day lag	0.694***	0.718***	0.731***	0.716***	0.731***
	(0.0741)	(0.0658)	(0.0689)	(0.0681)	(0.0689)
Observations	8,637	8,637	8,637	8,637	8,637
Within R-squared	0.947	0.946	0.945	0.946	0.945
Adjusted R-squared	0.994	0.994	0.994	0.994	0.994
Control variables	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the regression results on the impact of equity mutual fund net cash flows on German stock market liquidity during July 1, 2002 to December 31, 2014. The mutual funds are categorized into two groups by abnormal return alphas (upper and lower 50%) as a regression result from the Carhart four-factor model. The regressions are conducted for each year from 2002 to 2014, and thus, they form the constitution of each category. For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observations of the following variables to the index level and uses them as regression inputs. The dependent variable stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for the order volume class of 100,000 euro in basis points. The main independent variables include mutual fund NCF with 1- and 2-day lags, ETF NCF with 1-day lag, as well as XLM with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euros. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euros). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Index- and time-fixed effects are also controlled for in the regression. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The test results are in line with our hypothesis that fund managers with better information-processing skills also have superior liquidity-timing skills. It is noteworthy, however, that we cannot rule out that another effect drives the results. As funds with above-average abnormal returns have above-average NCF standard deviations, it follows that these fund managers have to engage more in liquidity-motivated trading. In addition, even if they only have average liquidity-timing skills, their relative positive impact on market liquidity would be above average.

To investigate this issue further, we perform a second approach for comparing the impact of funds with different liquidity timing skills. For that purpose, we use the information ratio as a measure of the fund manager's ability to generate excess returns compared to the benchmark index based on information analysis. According to Grinold and Kahn (1992), the information ratio most directly captures the investment value-added generated by the information and it is the most important statistic for investment information analysis. Similar to the first approach, we calculate the information ratio for each mutual fund and each year from 2002 to 2014 by dividing the fund's average excess return by its tracking error. The excess return is the difference between the fund's return and the return of its benchmark index. The tracking error is the standard deviation of the excess return. For each year and each benchmark index, we then sort the mutual funds based on their information ratios (IR). We categorize the mutual funds into two groups (one with a high information ratio [upper 50%] and one with a low information ratio [lower 50%]) and renew the categories every year based on the new information ratio rankings.[19] Using the aggregate NCF data and market data, we conduct the following regression:

$$\begin{aligned} ln(XLM_{i,t}) =& \alpha + \beta_1 \cdot ln(MFNCF_{i,t-1,high\ IR}) + \beta_2 \cdot ln(MFNCF_{i,t-1,low\ IR}) \\ &+ \beta_3 \cdot ln(MFNCF_{i,t-2,high\ IR}) + \beta_4 \cdot ln(MFNCF_{i,t-2,low\ IR}) \\ &+ \beta_5 \cdot ln(XLM_{i,t-1}) + \beta_6 \cdot R_{i,t} + \beta_7 \cdot ln(Vola_{i,t}) + \beta_8 \cdot ln(TV_{i,t}) \\ &+ \beta_9 \cdot ln(MC_{i,t}) + \gamma_t \cdot \mathrm{I}_t + \delta_i \cdot \mathrm{I}_i + \epsilon_{i,t}, \end{aligned} \tag{2.7}$$

where $MFNCF_{i,t-1,high\ IR}$ and $MFNCF_{i,t-2,high\ IR}$ are the sum of the absolute values of the NCFs of mutual funds with high information ratios (upper 50%) on days t-1 and t-2, respectively, for index i, and $MFNCF_{i,t-1,low\ IR}$ and $MFNCF_{i,t-2,low\ IR}$ are the sum of the absolute values of the net cash flows of mutual funds with low information ratios (lower 50%) on days t-1 and t-2, respectively, for index i. All other variables are defined

[19] To ensure "fair" comparison between mutual funds with high and low information ratio, we drop NCF observations out of the regression sample for one index, if either of the NCF variables is missing for one index. This especially affects the SDAX and TecDAX, because there is sometimes only one mutual fund with the SDAX or TecDAX as the benchmark index in the sample. This is particularly the case in the early period of the observation in this study.

as in Equation (2.5).

Table 2.9 presents the descriptive statistics of mutual fund NCFs by information ratios. For the DAX, the mean and standard deviation of mutual fund NCFs are comparable with the statistics in Table 2.7, and so is the mean of the NCFs of mutual funds with the MDAX as the benchmark index. For the SDAX and TecDAX, the mean of the mutual fund NCFs does not differ between the funds with a high or low information ratio. In contrast to the mutual fund NCFs sorted by abnormal returns, the standard deviations of the NCFs of mutual funds with high information ratios are smaller than those with low information ratios, as well as the ratios of the standard deviations to the mean, with the exception of mutual funds with the DAX as the benchmark index. This suggests that mutual funds with lower information ratios are more likely to experience unexpected in-/outflows and, therefore, might conduct more liquidity-motivated trading.

Table 2.9: Mutual fund net cash flow summary by information ratios

Index	Variable	Observations	Mean	Std. dev.	25% percentile	Median	75% percentile
DAX	NCF (high IR)	3,133	16.82	30.49	3.56	10.70	21.11
	NCF (low IR)	3,133	11.18	15.81	3.22	7.23	13.92
MDAX	NCF (high IR)	2,440	1.37	2.26	0.23	0.60	1.62
	NCF (low IR)	2,440	2.04	6.30	0.23	0.73	2.10
SDAX	NCF (high IR)	2,442	0.34	0.83	0.01	0.08	0.33
	NCF (low IR)	2,442	0.34	1.14	0.01	0.05	0.25
TecDAX	NCF (high IR)	936	0.03	0.04	0.01	0.02	0.03
	NCF (low IR)	936	0.03	0.10	2.53e-03	0.01	0.01

This table shows the descriptive statistics of the daily index-level net cash flows of mutual funds by information ratios from July 1, 2002 to December 31, 2014 for DAX, MDAX, SDAX, and TecDAX. For each year, the mutual funds are categorized into two groups by their information ratios (upper and lower 50%). The daily index-level mutual fund NCF of each group is calculated as the sum of absolute value of net cash flows from all mutual funds in the group with the corresponding benchmark index. The fund-level net cash flow data are from Morningstar. For every variable, the table presents the number of observations, mean, standard deviation, 25% percentile, median, and 75% percentile. The cash flows are in million euros.

Table 2.10 presents the regression results. Model 1 is the regression based on Equation (2.7). Both regression coefficients for the mutual funds with high information ratios have higher absolute values than those of the funds with low information ratios, which means that mutual funds with high information ratios contribute more to the reduction of market-wide liquidity costs. It is noteworthy, however, that this difference is statistically insignificant at the usual levels. Nevertheless, the significance of the cash flow variables from mutual funds with low information ratios disappears in the single cash flow variable tests (Models 2–5), while the significance of the cash flow variables from mutual funds with high information ratios remains unchanged. This further corroborates the hypothesis that high-skilled managers mainly drive the liquidity service offered by actively managed funds. The coefficients of the NCFs of funds with high information ratios in Models 2 and 4 do not differ much from the test results of Model 1, which indicates that there is no strong interaction effect between variables with a 1-day lag and variables with a 2-day lag for the funds with a high information ratio. On the other hand, the coefficients of the NCFs of funds with lower information ratios deviate sharply from the regression coefficients of the other test models. This provides additional evidence for the robustness of the regression coefficients. The coefficients of the regressors with a 1- and 2-day lag do not greatly differ from each other, which implies again that there is no clear preference for mutual fund managers to trade on the 1st or 2nd day after the in-/outflows.

Table 2.10: Mutual funds' cash flow impact on stock market liquidity costs by information ratios

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
NCF with 1-day lag of funds	-0.0142***	-0.0106***			
with high IR	(0.00281)	(0.00228)			
NCF with 1-day lag of funds	-0.00541**		0.000733		
with low IR	(0.00228)		(0.00173)		
NCF with 2-day lags of funds	-0.0120***			-0.00857***	
with high IR	(0.00317)			(0.00241)	
NCF with 2-day lags of funds	-0.00989***				-0.00341
with low IR	(0.00282)				(0.00223)
XLM with 1-day lag	0.713***	0.724***	0.730***	0.725***	0.729***
	(0.0460)	(0.0444)	(0.0440)	(0.0446)	(0.0441)
Observations	8,622	8,622	8,622	8,622	8,622
Within R-squared	0.946	0.946	0.945	0.946	0.945
Adjusted R-squared	0.994	0.994	0.994	0.994	0.994
Control variables	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports the regression results on the impact of equity mutual fund NCFs on German stock market liquidity during July 1, 2002 to December 31, 2014. For each year, the mutual funds are categorized into two groups by their information ratios (upper and lower 50%). For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observations of the following variables to the index level and uses them as regression inputs. The dependent variable stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for the order volume class of 100,000 euro in basis points. The main independent variables include mutual fund NCF with 1- and 2-day lags, ETF NCF with 1-day lag, as well as XLM with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euros. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euros). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Index- and time-fixed effects are also controlled for in the regression. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Overall, the test results provide evidence of the contribution from the NCFs of mutual funds with high information ratios toward market liquidity and confirm its robustness. At the same time, the contribution from the NCFs of mutual funds with low information ratios is smaller and not robust. Similar to the results in Table 2.8, the results can again, be explained by better information-processing ability of the mutual fund managers who are able to achieve higher information ratios as well as to better time market liquidity. Therefore, these managers not only benefit from their liquidity-timing ability, but also improve the overall market liquidity based on their liquidity service in terms of liquidity-motivated trading. In contrast to the analysis based on mutual fund abnormal returns, the NCFs of mutual funds with high information ratios do not have higher standard deviations. This reveals that the higher contribution to market liquidity from the mutual funds with high information ratios cannot be explained by more liquidity-motivated trading, but is likely due to better information-processing ability.[20]

2.5 Conclusion

In our paper, we analyzed the impact from the cash flows of open-ended equity funds on stock market liquidity using daily stock market data from four major German stock indexes (DAX, MDAX, SDAX, and TecDAX) in the time period from July 2002 to December 2014. We find that liquidity-motivated trading by actively managed mutual funds, as measured by their net cash flows, improves the overall stock market liquidity. For ETFs, we do not find such a positive impact, and in some cases, it is even negative. Moreover, the effect is economically important. A one standard deviation increase of total net cash flows reduces overall market liquidity costs by 2% on average. Expressed as an absolute impact for DAX stocks, this means only a liquidity cost reduction of half a basis point, but for small and medium caps (i.e., MDAX, TecDAX, or SDAX stocks), this equates to 5, 8, or 45 basis points, respectively.

Overall, the results confirm our hypothesis that actively managed mutual funds provide an important liquidity service to the stock market. It fits into the observation in which the strongest liquidity contribution is during the financial crisis in 2008/2009. In addition, we find evidence that mutual fund managers' skills in terms of information-processing ability can explain the contribution to the overall market liquidity. At the same time, we do

[20] One drawback of the information ratio is that a higher tracking error could result in a higher information ratio for equal excess returns if the excess return is negative. This issue does not affect the analysis in this study as long as more than one-half of the mutual funds with the same benchmark index have positive excess returns. In this study's sample, there are a few years for certain indexes when this is not the case, unfortunately. We conduct tests without observations from these years within corresponding indexes. The findings do not change in the test results. Because our desire is to use the information ratio as a comparison to verify the test results based on abnormal returns, we do not go further into each single information ratio ranking in this paper.

not find a similar impact for ETFs, which is not surprising given the creation/redemption mechanisms governing their inflows and outflows.

We believe that these findings have implications for stock exchanges, asset managers, and financial policymakers. There is general belief that preserving or even increasing stock market liquidity is beneficial for price discovery and market efficiency. Therefore, the significant and ongoing shift in market shares from actively managed mutual funds to ETFs could raise some broader questions. Even though we do not propose any policy measures here, this paper aims to be a piece of the evidence on the potential unintended consequences related to the increase of ETF market shares.

3 Liquidity Effects Associated with Revisions of German Prime Standard Indexes

Abstract

This study examines the liquidity effects associated with index revisions of three German prime standard indexes: the DAX, MDAX, and SDAX. I apply a difference-in-differences design that compares the liquidity cost changes of 117 stocks that experienced an index change and stocks that could have been subject to an index change. Using a unique order volume-weighted spread measure, I assess the liquidity effects for different order volume classes individually. Even after controlling for the established liquidity determinants, I find evidence of a 15–18% liquidity cost reduction for stocks with an index upgrade compared with their control group stocks. Meanwhile, I find no statistically significant effects associated with index downgrades. Using analyst coverage as a proxy, I further discover that information availability partially explains liquidity effects associated with index upgrades.

Keywords:	Index effect, liquidity costs, Xetra Liquidity Measure, information costs, analyst coverage
JEL Codes:	G10, G14

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Current Status: Working paper

3.1 Introduction

Stocks belonging to benchmark indexes benefit from their index membership and attract demand from investors, especially since the boom of passive investment strategies in the last decade. Global exchange traded fund (ETF) assets experienced record growth of 17% in 2014, reaching a volume of 2.64 trillion USD. This is especially driven by new cash inflows into the ETF market, which account for 14.6% of the 17% increase[1]. There is no sign that this development will slow soon. Although the pace of ETF market development in Europe is not as rapid as in the US, ETFs have become one of the most popular investment products. In Germany, ETFs accounted for approximately 10% of the entire mutual fund market volume in 2014, whereas the European average was approximately 3%.[2] Besides explicitly indexed equity products (e.g., ETFs), Cremers et al. (2016) find evidence that many mutual funds in different countries claim to manage funds actively but actually follow passive strategies. According to Cremers et al. (2016), approximately 20% of the management of worldwide mutual fund assets follows "closet indexing" strategies (i.e., having less than an active share[3] of 60% in the portfolio). In their sample, 34% of German domiciled mutual funds and 24% of mutual funds sold in Germany belong to the group of closet indexing. Finally, even true actively managed funds often have benchmark indexes and invest a significant share of their assets in stocks belonging to those benchmarks.

At the same time, index revision causes trading activities of index funds and other investors without providing new information to the stock market. The rapid growth of ETFs and the widespread use of actively managed closet indexing funds lead to significant trading volumes among the affected stocks. Although index revisions are based on publicly available information and are, to some extent, "foreseeable," the trading activities induced by index revisions result in so-called "index effects," which are reflected in key stock figures, such as price and trading volume. The positive abnormal returns and

[1]Source: Deutsche Bank Market Research, ETF Annual Review & Outlook, January 26, 2015
[2]Source: BVI report 2015
[3]Active share measure: cf. Cremers and Petajisto (2009).

trading volumes for stocks added to a leading index (e.g., S&P 500 and NASDAQ) are well documented (cf. e.g., Harris and Gurel, 1986; Elliott and Warr, 2003). Some actively managed funds (e.g., Candriam Index Arbitrage and Laffitte Index Arbitrage) even follow a simple index arbitrage strategy by buying stocks that are going to be included in leading benchmark indexes after the announcements and selling them after the effective date. On the other hand, most studies do not show the effects for stocks deleted from a leading index or cannot find statistically significant effects. Harris and Gurel (1986) explain the asymmetric finding by different reasons of deletion from an index (e.g., merger, tender offer, and failure to fulfill index eligibility criteria).

Schleifer (1986), Wooldrige and Ghosh (1986), and Edmister et al. (1996) explain the price and volume impact of index inclusion by information costs/liquidity hypothesis (i.e., the costs for acquiring information regarding a stock decline if the stock is included in a leading index). This is a result of higher analyst coverage and media coverage of the stock. In addition, the decrease in information costs reduces the overall transaction costs, that is, increases stock liquidity. Given that the future payment to investors increases through reduction in transaction costs, the present value of the stock increases. Hence, one would expect that addition to a benchmark index would result in a positive and permanent effect on stock liquidity and price, whereas deletion from the index should lead stock liquidity and price in the opposite direction. Several researchers have documented the positive liquidity impact of addition to the S&P 500 (cf. e.g., Erwin and Miller, 1998; Hegde and McDermott, 2003; Chen et al., 2004). However, they merely establish the opposite liquidity effects for deletion, and if present, the effects are very weak. Chen et al. (2004) explain these asymmetric findings by investor awareness; that is, inclusion in a benchmark index creates new investor awareness about the involved stocks. On the contrary, investors do not suddenly become “unaware” of stocks after their deletion from an index. Gregoriou and Ioannidis (2006) is the only study to find statistically significant liquidity decline for stocks deleted from the FTSE 100 in the 1984–2001 period. However, the study does not control for common liquidity determinants (e.g., trading volume) in its liquidity analysis. A decreasing trading volume could drive the increase of liquidity spreads, which Gregoriou and Ioannidis (2006) find in their sample.

There are three main issues in the previous research regarding index liquidity effects. First, most literature does not consider the positive or negative development trends of the examined stocks; thus, endogeneity issues could affect their results. Previous research considers only stocks experiencing index changes and lacks controls for positive or negative trends of the stocks. The observed index effects, therefore, could be partially explained by increasing or decreasing liquidity trends of the involved stocks. Current research measures the market-driven index effects caused by, for example, an index funds' trading activities and, hence, does not answer the question of whether a "pure" index effect exists, that is, whether stocks benefit from being members of indexes after controlling for associated market effects and trends. Second, the liquidity measures in the existing literature cannot accurately reflect the true liquidity costs of trading. Insufficient liquidity measures are one cause of the lack of evidence for liquidity effects. The popular bid–ask spread is representative of only small order volumes (cf. Stange and Kaserer, 2010). It is very difficult for bid–ask spreads to measure liquidity changes nowadays, owing to increased market liquidity. Finally, most empirical research focuses on short-term effects. The standard event study design as Campbell et al. (1997) describes is not applicable for long-term studies. My research design, introduced below, aims to bypass these issues and find the "pure" index effects.

This study analyzes the liquidity effects associated with index revisions after controlling for market variables (trading volume, return, return volatility, and market capitalization) and individual fixed effects (time- and stock-fixed effects). I apply a difference-in-differences event study approach to control for positive or negative trends of the affected stocks. The control group consists of stocks that fulfill at least one of the index selection criteria from Deutsche Börse and could, therefore, potentially face an index change. I measure liquidity cost differences between stocks that experienced an index change and stocks of their control group after controlling for the aforementioned market variables and fixed effects. This approach allows us to measure the liquidity effects that are purely the result of the index changes.

Using a unique order volume-weighted liquidity measure, I am able to measure the liquidity effects for different order volume classes. Xetra Liquidity Measure (XLM), provided by Deutsche Börse, calculates the weighted round-trip spreads for different order volume classes every minute during the trading hours based on the limit order book data. XLM considers the entire depth of the limit order book of the Xetra trading platform,[4] including the so-called "iceberg orders," which are not visible for stock traders. Hence, I can measure the round-trip liquidity costs for different order volume classes more precisely.

To accomplish meaningful comparison and exclude potential liquidity effects caused by reporting or information disclosure standard differences (cf. Healy and Palepu, 2001), my event study focuses on index member changes among the DAX, MDAX, and SDAX. These three indexes all belong to the family of German Prime Standard indexes. Stock relocations within these three indexes do not cause shifts in the required reporting standards. Meanwhile, index revisions within the DAX family exclude stock inclusion or deletion following changes in index eligibility, such as changes in free float ratios. Hence, this study has a clean sample to measure the real liquidity effects that index changes among the DAX, MDAX, and SDAX cause.[5] The sample contains 117 events from July 1, 2002 to December 31, 2014. For each event, I observe the daily XLM value, trading volume, return, and market capitalization from 3 months before the announcement date to 3 months after the effective date. Therefore, I can access the long-term liquidity effects for a sufficiently long period in detail.

I find empirical evidence for positive liquidity effects associated with an index upgrade but no statistically significant effects associated with index downgrades. After controlling for market variables and fixed effects, the round-trip trading costs reduced by 15–18% for stocks upgraded to a more popular index compared with stocks that could potentially be upgraded as well. This effect is consistent for different order volume classes. Chen

[4]Xetra's average daily order book volume was approximately 4.6 billion euros in 2014, which corresponds to more than 90% of all order books from Deutsche Börse. (Source: Major business figures 2014, Deutsche Börse)

[5]Of course, the potential index effect for a stock without any index membership moving into the SDAX could differ from a stock moving from the SDAX to MDAX, but this study cannot isolate the index effect from other confounder effects in the first case.

et al. (2004) find similar asymmetric price effects associated with index revisions without a difference-in-differences study design. The authors find a permanent price increase for stocks added to the S&P 500 but no permanent price decrease for the deleted stocks. Chen et al. (2004) explain this finding by investor awareness, that while inclusion of a stock into the S&P 500 makes more investors aware of the stock, its deletion does not make investors suddenly "unaware" of the stock.

Motivated by the information cost/liquidity hypothesis, I further assess the information coverage changes associated with index revisions as well as the relation between index liquidity effects and information coverage. I use two different proxies for information coverage: analyst following and news coverage. Some empirical studies use the same proxies and find a positive relationship between information coverage and stock liquidity. Brennan and Subrahmanyam (1995), for example, provide evidence that greater analyst following improves stock liquidity by reducing adverse selection costs. Roulstone (2003) derives similar results and further argues that analyst following improves stock liquidity by revealing public information. Fang and Peress (2009) find a negative relationship between stock liquidity and media coverage in terms of newspaper articles. To the best of my knowledge, my study is the first to analyze the relationship between information coverage and liquidity in the context of index revision using a difference-in-differences design.

In the sample of this study, the analyst following of stocks that experienced an index upgrade increases by 33%, or three to four analysts on average, compared with the control group. Indeed, the change of analyst coverage can explain about 10% of the liquidity effects from the difference-in-differences results for the upgraded stocks. Similar to the main liquidity difference-in-differences regressions, I find no significant results for stocks that experienced an index downgrade. Similarly, I find no comparable significant changes in the data sample using media coverage. There is probably too much noise in the news dataset in the observation time windows around the index revisions.

The findings are robust to sub-sample tests, placebo tests, as well as different choices of control groups in terms of selection criteria and stock number per control group. My study contributes to the existing literature in the following aspects. First, the difference-in-differences approach, with additional control for market activities, quantifies the "pure" liquidity effects associated with index revision.[6] Second, the order volume-weighted spread measure used in my study not only ensures more accurate liquidity measurement, but also allows us to conduct order volume-dependent analysis. Furthermore, my additional analysis connects stock liquidity with information availability during index revisions. Finally, this is the first such long-term study using longer periods of German stock market data.[7] Overall, I extend the existing research about index effects and provide new evidence in support of the information costs/liquidity hypothesis.

The remaining parts of this paper proceed as follows. Section 3.2 provides background information of German prime standard equity indexes, introduces ranking and selection criteria of the DAX, MDAX, and SDAX, and summarizes observed index change events. Section 3.3 explains the difference-in-differences event study design, including the selection criteria for the control groups. Section 3.4 describes liquidity, market, and information coverage data this study uses and presents summary statistics. Section 3.5 presents the event study results. Section 3.6 concludes.

3.2 German prime standard equity indexes

Deutsche Börse AG[8], the only large stock exchange group in Germany, offers an index universe (DAX index universe) from more than 100 equity indexes.[9] The second largest ETF in Europe, iShares Core DAX, with a fund size of about 8.7 billion euro[10] ranked by assets under management, is based on the DAX.

Deutsche Börse calculates its equity indexes based on the following principles: representativeness, tradability, replicability, stability, rules-based methodology, predictability, and

[6]Most existing studies focus on revisions of the S&P 500, which does not have regular index reviews; rather, committee decisions determine revisions. Their results could be endogenous.

[7]Wilkens and Wimschulte (2005) focus on one major index restructuring in Germany in 2003; Deininger et al. (2002) do not analyze stock liquidity changes.

[8]hereafter, Deutsche Börse

[9]As of December 31, 2014

[10]As of December 31, 2014

transparency (Deutsche Börse (2015), p.9). In particular, the last three principles ensure that public information and transparency rules determine all index selection/deletion decisions, and are to some extent foreseeable. In addition, Deutsche Börse announces the index revision decisions with adequate notification periods, so that investors have sufficient time to make investment decisions and adjust their portfolios, even before the effective date of the index revision. Hence, the DAX index universe from Deutsche Börse provides an excellent environment for research on index revision effects, because it yields all decision-relevant information ahead of the index revision announcement and enables this study to integrate this information into the research design.

The DAX index universe comprises four blue-chip indexes: DAX (30 largest and most traded German stocks at the Frankfurt Stock Exchange); MDAX (50 mid-cap stocks from traditional sectors[11] at the Frankfurt Stock Exchange and ranked below DAX stocks in terms of free float market capitalization and turnover); SDAX (next 50 stocks from traditional sectors[12] at the Frankfurt Stock Exchange and ranked below MDAX stocks based on free float market capitalization and turnover); and TecDAX (30 largest and most traded technology sector stocks at the Frankfurt Stock Exchange beneath the DAX). These indexes are the most important German (selection) indexes. All stocks from these four indexes belong to the Prime Standard segment, which applies the highest accounting, reporting, and stock-issuing requirements in the German stock market[13].

For the analysis of index revision effects, I choose the DAX, MDAX, and SDAX as the corresponding indexes for the following three reasons. First, all stocks from these indexes belong to the Prime Standard segment and therefore, have high transparency in terms of stock and corporate information. Second, these three indexes have a long history available for event studies.[14] Third, these three indexes are ranked by stock size and turnover. As a result, the market perceives an index change of a security among these three indexes as either an “upgrade” or “downgrade,” which enables me to assess the index revision effects

[11]This includes all sectors excluding technology.
[12]This includes all sectors excluding technology.
[13]Such as minimum market capitalization, share quantity, and free float.
[14]The DAX launched in 1988, the MDAX in 1996, and the SDAX in 1999, and the TecDAX in 2003.

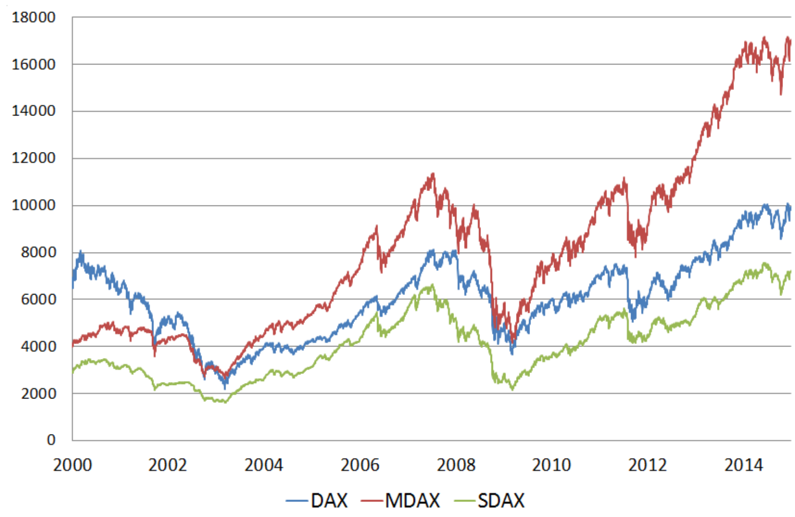

Figure 3.1: Development of major German Prime Standard indexes

both at upgrade and downgrade events. On the other hand, the index changes between the TecDAX and other indexes as "upgrade" or "downgrade," because the TecDAX can include only stocks from the technology sector. Furthermore, there are only seven index change events between the TecDAX and other prime standard indexes[15] since the introduction of the TecDAX on March 24, 2003 until the end of 2014. Hence, I do not lose a large number of observations owing to exclusion of the TecDAX from the research.

Figure 3.1 shows the development of the DAX, MDAX, and SDAX since 2000. In the long run, all three indexes have grown in the past 15 years. There is obviously high correlation between the development of these three indexes and all three suffered from various market stress phases, such as the dotcom bubble, the 2008/2009 financial and stock market crisis, as well as the ongoing euro crisis. The DAX, MDAX, and SDAX cover at least 130 of the largest and most traded stocks at the Frankfurt Stock Exchange,[16] and together account for more than 85% of market capitalization in Germany.[17]

To prepare for stock selection from the abovementioned four blue-chip indexes, Deutsche Börse ranks continuously traded stocks from the Prime Standard segment at the end

[15] Five stocks moved from the MDAX to TecDAX, one stock from the DAX to TecDAX, and one stock from the TecDAX to DAX.

[16] The MDAX had 70 components before March 2003 and the SDAX had 100 components before June 2002.

[17] Source: Banking statistics, Supplement 2, Deutsche Bundesbank; Deutsche Börse, as of December 31, 2014

of every month. The exchange considers only a stock that has traded for at least 30 trading days and whose free float percentage exceeds the minimum threshold[18]. Deutsche Börse ranks only the biggest share type if both common and preferred shares fulfill the abovementioned requirements. For shares that meet all these prerequisites, Deutsche Börse conducts three rankings each month: DAX ranking (all German stocks), MDAX and SDAX ranking (all stocks from traditional sectors, excluding those from DAX), as well as TecDAX ranking (all stocks from the technology sector, excluding those from DAX).

The order book turnover and free float market capitalization determine the monthly equity index ranking. The first criterion, order book turnover, considers the total trading volume at the Frankfurt Stock Exchange, including Xetra electronic trading platform, in the previous 12 months. If a stock has traded for less than 12 months, then Deutsche Börse cuts off the turnover data for the first 20 trading days and linearly projects the remaining data for 12 months. The second criterion, free float market capitalization, is calculated as the product of the number of free float shares on the last trading day of a month and the average daily volume-weighted average price of the last 20 trading days of the month based on prices at the Xetra platform (cf. Deutsche Börse (2015), p.18f).

Table 3.1 summarizes the current selection rules and frequencies for the DAX. Deutsche Börse reviews quarterly index constituents on the basis of stock ranking results (all German stocks) from the last available month. There are two types of entry/exit rules: fast entry/exit and regular entry/exit. Except in September, an ordinary index adjustment takes place only if one or more stocks meet all criteria for the fast entry/exit rule.

- *Fast entry.* A stock is included into the DAX if both its free float market capitalization and turnover rank at least 25th.[19]
- *Fast exit.* A stock is excluded from the DAX if either its free float market capital-

[18] In December 2008, the threshold increased from 5% to 10%.

[19] This stock replaces the existing DAX member stock with a ranking worse than 35th in one criterion and the lowest free float market capitalization. If no such stock exists, then the stock with the lowest free float market capitalization is excluded from the index.

ization or turnover ranks worse than 45th.[20]

As a result of the regular review in September, a stock is included in/excluded from the DAX if it fulfills the regular entry/exit rules, as follows.

- *Regular entry.* A stock is included in the DAX if both its free float market capitalization and turnover rank at least 30th.[21]

- *Regular exit.* A stock is excluded from the DAX if either its free float market capitalization or turnover ranks worse than 40th.[22]

Deutsche Börse (2015), p.27f contains detailed rules for ordinary and extraordinary adjustments of the DAX.

Table 3.1: Selection rules and frequencies for the DAX

Rule	Turnover	Free float market capitalization	Review months
Fast Entry	25	25	March, June, September, December
Fast Exit	45	45	March, June, September, December
Regular Entry	30	30	September
Regular Exit	40	40	September

Source: Deutsche Börse (2015), p.29

Table 3.2 illustrates the selection rules and frequencies for the MDAX, similar to the DAX. There is a quarterly review of the membership of the MDAX from the monthly ranking results (all stocks from traditional sectors excluding those from the DAX) from the last available month. Likewise, the fast entry/exit and regular entry/exit rules determine the decision of inclusion into/exclusion from the MDAX. The index committee can make an ordinary index adjustment after the quarterly review if one or more stocks meet all criteria for the fast entry/exit rule.

- *Fast entry.* A stock can be included in the MDAX if both its free float market

[20]This is only if one stock outside the DAX ranks at least 35th in turnover and 45th in free float market capitalization.

[21]This is the case only if one DAX member stock ranks worse than 35th in one of the two criteria.

[22]This is only if one stock outside the DAX ranks at least 35th in both turnover and free float market capitalization.

capitalization and turnover rank at least 40th.[23]

- *Fast exit.* A stock might be excluded from the MDAX if either its free float market capitalization or turnover ranks worse than 75th.[24]

As a result of the regular review in March or September, a stock can be included in/excluded from the MDAX if it fulfills the regular entry/exit rules, as follows.

- *Regular entry.* A stock can be included in the MDAX if both its free float market capitalization and turnover rank at least 60th.[25]
- *Regular exit.* A stock may be excluded from the MDAX if its free float market capitalization and turnover rank worse than 60th.[26]

Deutsche Börse (2015), p.29ff presents detailed rules for ordinary and extraordinary adjustments of the MDAX. In general, the index committee has more flexibility regarding stock selection for the MDAX than for the DAX owing to selection criteria and thresholds. If more than one stock or no stock fulfills both criteria, then free float market capitalization outweighs turnover in the committee decision.

Table 3.2: Selection rules and frequencies for the MDAX

	Turnover	Free float market capitalization	Review months
Fast Entry	40	40	March, June, September, December
Fast Exit	75	75	March, June, September, December
Regular Entry	60	60	March, September
Regular Exit	60	60	March, September

Source: Deutsche Börse (2015), p.27

[23]This stock replaces an existing MDAX member stock with a worse turnover or free float market capitalization ranking. The free float market capitalization primarily determines the decision if more than one stock qualifies.

[24]A stock with better turnover or free float market capitalization ranking and fulfilling fast entry criteria is then included in the MDAX. The free float market capitalization primarily determines the decision if more than one stock qualifies. If no stock meets the abovementioned criteria, then the largest company by free float market capitalization is included.

[25]This stock replaces an existing MDAX member stock with a worse turnover or free float market capitalization ranking. The free float market capitalization primarily determines the decision if more than one stock qualifies.

[26]A stock with better turnover or free float market capitalization ranking and fulfilling regular entry criteria is then included in the MDAX. The free float market capitalization primarily determines the decision if more than one stock qualifies. If no stock meets abovementioned criteria, then the largest company by free float market capitalization is included.

To ensure enough reaction time for shareholders, Deutsche Börse announces the ordinary index revision decisions on the first Wednesday in March, June, September, and December after the trading close.[27] The revisions become effective on the third Monday after the announcement. For extraordinary changes (e.g., M&As), there are at least 2 trading days between the announcement and effective date.

In the sample time period from July 2002 to December 2014, there are 124 index member changes within German Prime Standard indexes, of which 117 are among the DAX, MDAX, and SDAX. Table 3.3 presents an overview of these events.

Table 3.3: Overview of index member changes

Event type	Description	Number of events (treatment stocks)	Number of stocks in control groups
Index upgrade	from MDAX to DAX	14	40
	from SDAX to MDAX	37	592
Index downgrade	from DAX to MDAX	13	48
	from MDAX to SDAX	53	251

This table shows the overview of all index member changes within DAX, MDAX, and SDAX from July 1, 2002 to December 31, 2014.

My event study focuses on two event types: index upgrade (51 events) and index downgrade (66 events). During the observation period, the stock number of the MDAX declined from 70 to 50 in March 2003, at the time when Deutsche Börse introduced the TecDAX. The index number change of the MDAX resulted in 20 index downgrade events from the MDAX to the SDAX. In addition, 13 index member changes from the observation are not the result of quarterly index reviews. All of these cases are induced by low free float rates of MDAX shares caused by takeovers or tender offers and disqualification for status of Prime Standard stocks, resulting in stock relocation from the SDAX to the MDAX.

In the observed 117 events, more than 40% of index changes occur passively, that is, the stocks are selected to replace other stocks that fulfill entry or exit rules although these

[27] Before September 2004, the decisions were announced 6 weeks before the effective date.

stocks themselves do not meet all selection criteria. In particular, deletion of stocks from the DAX or MDAX induce almost 60% of stocks moving from the MDAX to DAX or from the SDAX to MDAX. In these cases, one or more stocks fulfill the *fast exit* or *regular exit* criteria, do not meet the required free float minimum, or are involved in spinoff processes, among other reasons, and have to be deleted from the DAX or MDAX. Even though no stock from the MDAX or SDAX fulfills the entry criteria of the DAX or MDAX, the index committee has to select a more suitable stock to replace the existing stock. Stocks' own performances do not drive these passive index changes and nor do these changes reveal new information of the involved stocks. Therefore, these passive index changes serve as excellent events for assessing index effects.

3.3 Event study design

This study uses the index revision as an identifier to assess the index effect on stock liquidity. To control for stock performance trends (i.e., stocks experiencing index upgrades/downgrades are normally those with good/bad performance in the past and stronger growth/decline during the index revision), I apply a difference-in-differences approach for the event study. In the difference-in-differences study, the treatment group includes stocks that experience 1 of the 117 index changes as listed in Table 3.3.

For each treatment stock, I build a control group of stocks that could have faced an index change, but remain in the previous index. Thanks to the guiding principle of rules-based stock selection and transparency of index revision from Deutsche Börse, I can build the control groups based on monthly ranking results. All stocks from a control group fulfill at least one of the two criteria regarding free float market capitalization and turnover. If one stock meets both criteria, then it will be selected twice for the control group (selection with replacement). If no stock fulfills either criterion, then I select stocks with the closest free float market capitalization ranking or turnover ranking for the control group. Hence, I have at least two stocks in the control group for each treatment stock in the treatment group.

As Table 3.3 presents, I select more stocks into control groups for stocks moving between the MDAX and SDAX compared with stocks moving between the DAX and MDAX. This leads back to the selection rules of the DAX and MDAX, as Section 3.2 explains. For the robustness check, I use different control groups, including nearest neighbor, maximum three stocks per control group, and maximum five stocks per control group (see Section 3.5.3 for more details).

Every month, Deutsche Börse publishes the index ranking based on the criteria explained in Section 3.2. Unfortunately, only the newest six rankings are publicly available. A sizable number of older ranking results are deleted and not available for purchase. In the event study time window, I collect index rankings that are used as a base for the regular reviews between September 2004 and September 2009 directly from Deutsche Börse. There are 48 relevant index change events in this time period. For the 35 events after September 2009, I use Bloomberg data and rank all Prime Standard stocks based on free float market capitalization and turnover using the same methodology as Deutsche Börse (2015). The free float market capitalization data from Bloomberg are closer to those used by Deutsche Börse for equity rankings compared with the data provided by Datastream.[28] Unfortunately, these are not available before October 2005. For the 34 events before September 2004, I use Datastream free float market capitalization data for the ranking.[29] The turnover data from Bloomberg and Datastream are almost identical. For a robustness check, I conduct the analysis with sub-sample events separately for different ranking data sources. The results do not differ significantly from each other and are consistent with the results presented in Section 3.5.

For each event, I collect relevant data for the treatment and control group stocks for the time period starting in the 3rd month before the index revision announcement date and until the 3rd month after the effective date due to the quarterly review frequency

[28]Both Bloomberg and Datastream calculate the free float share of public stocks based on their own definitions of free float. There could be minor differences between the free float definitions.

[29]Datastream started to report the free float market capitalization for German stocks in April 2002 and is this study's only available source of free float market capitalization for German stocks before October 2005. For some stocks the free float market capitalization is available since August or September 2002. In these cases, I use the earliest available percentage of the free float shares of the stocks to calculate the free float market capitalization before August or September 2002. In total, this calculation affects 26 stocks.

of Deutsche Börse. More precisely, the observation period starts on the 62nd trading day before the announcement date (AD) and ends on the 62nd trading day after the effective date, assuming 21 trading days per month. I then divide this period into five observation windows: the 2nd and 3rd months before the announcement date $[AD - 62, AD - 21]$, the last month before the announcement date $[AD - 20, AD]$, the days between the announcement and effective dates (AD, ED), the first month after the effective date $[ED, ED + 20]$, and the 2nd and 3rd months after the effective date $[ED + 21, ED + 62]$.[30] The first observation window is defined as the reference time window of this study.

To measure the liquidity effects "purely" associated with index revisions, I control for established influencing factors on stock liquidity in the difference-in-differences analysis, such as market capitalization, trading volume, return, and return volatility.[31] While stock liquidity is positively correlated with the first three factors, it is negatively correlated with return volatility (cf. e.g., Copeland and Galai, 1983; Stoll, 2000; Pastor and Stambaugh, 2003; Chordia et al., 2009). Since the boom of ETF products and actively managed indexeing funds, I expect the abnormal return and trading volume for stocks experiencing index relocation to be larger. Therefore, it becomes even more important to control for the abovementioned factors to separate the pure index effect from the liquidity impact driven by market activities during the index revisions.

Based on the information cost hypothesis, information availability should at least partly explain the liquidity effect associated with index revision. The main challenge of testing the information cost hypothesis is the measurement of information availability. Two information sources about a company are available from an investor's perspective: first, reports and press releases from the company; and second, reports and news about the company from external analysts and media. Given that all DAX, MDAX, and SDAX stocks belong to the Prime Standard segment and have the same reporting standard, there is no change

[30]In addition, I conduct an analysis using monthly observation windows for the months before the announcement date and after the effective date. The results suggest high similarity between the 2nd and 3rd months before the announcement date, as well as between the 2nd and 3rd months after the effective date, and do not reveal more insights. Therefore, I combine each 2-month period into one observation window.

[31]I choose market capitalization over stock price, because the first is not influenced by stock issue and repurchase.

of information disclosure from the company side with regard to, for example, reporting frequency and covered content in standard accounting reports. Changes of press releases are more endogenous and in this case, it is almost impossible to solve for the omitted variable issue. Therefore, I use two proxies generated by external sources to measure the information availability: analyst coverage and news coverage. Existing literature finds a positive relationship between these two factors and stock liquidity (cf. e.g., Brennan and Subrahmanyam, 1995; Roulstone, 2003; Fang and Peress, 2009), but does not analyze these factors during index revisions. If the information cost hypothesis holds, then there should be significant changes of information availability associated with index revision. Therefore, I first apply the same difference-in-differences approach to assess the changes of information coverage associated with index revision. In addition, I use information coverage as an explanatory variable in the difference-in-differences liquidity analysis.

3.4 Data

The event study examines index revisions from July 1, 2002 to December 31, 2014. Based on the event study design, I collect three types of data: liquidity data, market data, and information data. In total, I collect data for 117 treatment stocks that experienced an index change and 931 stocks from their control groups (with replacement), consisting of stocks that fulfill at least one of the entry/exit criteria for the DAX or MDAX, but did not experience changes during the index revisions. The following subsections present data explanations, sources, and summaries.

3.4.1 Liquidity data

The bid–ask spread is a commonly used measure to evaluate liquidity costs and has been established for about 30 years (cf. Amihud and Mendelson, 1986). Although the bid–ask spread reflects stock liquidity costs directly, it is valid only for a certain size of order volume, which is normally rather small. As the equity market becomes more liquid and big orders occur more often, the bid–ask spread becomes less sensitive to market changes and does not present accurate liquidity costs. Therefore, researchers have developed liquidity measures based on trading volume, transaction data, or daily high/low prices (cf. e.g., Amihud, 2002; Pastor and Stambaugh, 2003; Corwin and Schultz, 2012).

In recent years, electronic trading platforms have replaced traditional trading floors, especially for continuously traded shares. In Germany, trades on the Xetra electronic platform account for more than 90% of the total equity trading volume on Deutsche Börse stock exchanges in 2014.[32] As a result, the limit order book from such a platform reflects the trading behavior from the majority of market participants most suitably.

Irvine et al. (2000) introduce a round-trip transaction cost measure using limit order book data (cf. Subsection 1.1.1). Based on their work, Gomber and Schweickert (2002) further develop the volume-weighted round-trip transaction cost measure, which the Deutsche Börse implements.

In July 2002, Deutsche Börse started to compute every minute the volume-weighted round-trip transaction costs defined as above, the so-called *XLM*, for different order sizes (from 3,000 euros up to 5 million euros)[33]) of all stocks traded at the Xetra electronic trading platform. I use the average daily XLM values to assess the order volume-dependent liquidity costs of stocks in the analysis.

An essential advantage of XLM is that it takes the whole depth of the limit order book into account, including so-called "iceberg" orders, which are only partially visible to equity traders. As a result, XLM measures liquidity costs more accurately. In particular, it measures different liquidity costs for different order sizes precisely. This is particularly important for institutional investors, such as mutual funds and ETFs, because their order sizes are usually larger than what a normal bid–ask spread could represent. More details and advantages about XLM are in Stange and Kaserer (2010).

This study considers three different order volume classes: 25,000 euros, 50,000 euros, and 100,000 euros, given that their historical time series belong to the most available order

[32]Source: Major business figures 2014, Deutsche Börse

[33]The maximum available order volume class depends on the depth of the limit order book for each stock and trading day.

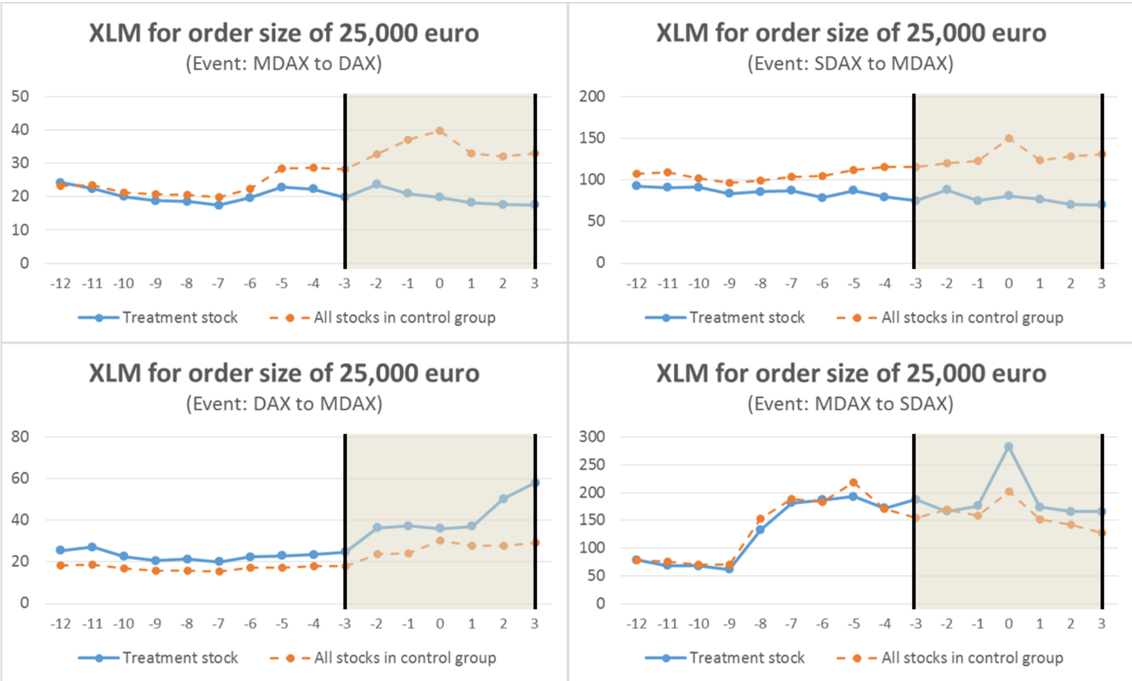

Figure 3.2: Development of XLM for the order volume class of 25,000 euros

volume classes and they represent different groups of market participants. The last order volume class is especially interesting for institutional investors.

Figure 3.2 illustrates the development of the average XLM values for the order size of 25,000 euros from four different treatment stock groups that experienced index changes and their control groups during the event observation window, as Section 3.3 defines). The graphs start in the 12th month before the announcement date and end in the 3rd month after the effective date. Month 0 represents the time period between the announcement date and the effective date. Again, this study assumes 21 trading days per month. The time periods highlighted by gray background are the observation time periods in this study.

All graphs imply parallel development of treatment stocks and their control groups in the first months of the observation. Although the differences between the liquidity costs of stocks experiencing an index upgrade and their control groups already became bigger before the observation window, I first observe a clear non-parallel development in the month before the announcement date. A placebo test in Subsection 3.5.3 further supports the parallel trend assumption of the treatment and control groups. In the case of an index upgrade, the liquidity costs of the treatment stocks are, on average, lower than those of their control group stocks.[34] The opposite relationship holds only for the downgrade events from the DAX to MDAX. The liquidity costs of stocks downgraded from the MDAX to SDAX and their control groups lie very close to each other. The XLM values of the treatment stocks become continuously higher than those of the control group stocks only from the month before the announcement date. The differences between the liquidity costs of treatment stocks and control group stocks become larger in the observation window for all four event types. The development of XLM for the other two order volumes is similar to Figure 3.2.

3.4.2 Market data

As mentioned in Section 3.3, I include market capitalization, trading volume, return, and return volatility as control variables into this study. I collect the daily market capitalization, trading volumes, and stock prices of all treatment stocks and control group stocks from Datastream. The trading volumes are those from the Xetra platform, because this study calculates the liquidity measure XLM based on the limit order book from the Xetra platform. I use the continuous daily return. The return volatility is then calculated as 5-day rolling return volatility.

Table 3.4 summarizes the development of the key market factors from the treatment stocks and their control group stocks during the observation time windows. The table shows the mean values. Stocks experiencing index upgrades show increasing trading volume while those experiencing downgrades have decreasing trading volume. Meanwhile, the trading volumes of all control group stocks remain at a stable level. Except for control group stocks downgraded from the DAX to MDAX, all other control group stocks have notably lower average trading volumes in the time window between the announcement date and effective date, compared with the other time intervals. This might explain the high liquidity costs for these stocks between the announcement and effective dates, as Figure 3.2 shows. I can

[34] The single exception is the 12th month before the announcement date for stocks upgraded from the MDAX to DAX.

derive no clear pattern of development from the other three market factors based on the descriptive statistics. In summary, the development of stock trading volumes seems to be the main driver for the liquidity cost changes of the observed stocks.

Table 3.4: Development of market data by event type

MDAX to DAX	[AD-62, AD-21]	[AD-20, AD]	(AD, ED)	[ED, ED+20]	[ED+21, ED+62]
			Market capitalization (million euros)		
Treatment stocks	6,787	7,017	6,420	6,486	6,403
Control group stocks	7,485	7,563	6,773	7,208	7,326
			Trading volume (thousand euros)		
Treatment stocks	922	906	1,366	1,230	969
Control group stocks	623	418	408	434	471
			Return (%)		
Treatment stocks	0.06	0.07	-0.35	-0.18	0.04
Control group stocks	-0.17	-0.14	-0.16	-0.08	-0.04
			Return volatility (%)		
Treatment stocks	2.42	2.46	2.34	2.24	1.99
Control group stocks	2.29	2.22	2.19	2.11	2.33
SDAX to MDAX	[AD-62, AD-21]	[AD-20, AD]	(AD, ED)	[ED, ED+20]	[ED+21, ED+62]
			Market capitalization (million euros)		
Treatment stocks	1,271	1,327	1,463	1,353	1,450
Control group stocks	724	727	625	726	708
			Trading volume (thousand euros)		
Treatment stocks	144	163	206	197	261
Control group stocks	164	160	133	150	152
			Return (%)		
Treatment stocks	0.15	0.17	-0.13	-0.05	-0.04
Control group stocks	-0.03	-0.06	0.07	-0.07	-0.14
			Return volatility (%)		
Treatment stocks	1.84	1.95	2.33	2.14	2.15
Control group stocks	2.14	2.20	2.08	2.08	2.20
DAX to MDAX	[AD-62, AD-21]	[AD-20, AD]	(AD, ED)	[ED, ED+20]	[ED+21, ED+62]
			Market capitalization (million euros)		
Treatment stocks	5,772	5,147	4,485	4,943	4,853
Control group stocks	5,263	5,081	4,207	5,028	5,031
			Trading volume (thousand euros)		
Treatment stocks	2,610	1,356	1,390	998	812
Control group stocks	2,156	1,860	2,301	2,260	2,045

Continued on next page.

Table 3.4 (continued)

			Return (%)		
Treatment stocks	-0.47	-0.24	0.30	-0.56	-0.16
Control group stocks	-0.32	-0.38	-0.23	-0.06	-0.06
			Return volatility (%)		
Treatment stocks	3.21	3.10	2.88	2.45	2.75
Control group stocks	2.32	2.67	2.39	2.93	2.39
MDAX to SDAX	[AD-62, AD-21]	[AD-20, AD]	(AD, ED)	[ED, ED+20]	[ED+21, ED+62]
			Market capitalization (million euros)		
Treatment stocks	690	676	509	666	682
Control group stocks	508	500	339	505	548
			Trading volume (thousand euros)		
Treatment stocks	249	219	134	174	159
Control group stocks	104	91	114	131	110
			Return (%)		
Treatment stocks	-0.29	-0.18	-0.21	0.24	-0.03
Control group stocks	0.01	-0.25	0.05	0.33	0.38
			Return volatility (%)		
Treatment stock	2.09	2.17	2.15	2.37	1.88
Control group stocks	2.11	2.15	2.29	2.44	2.28

This table presents the development of the average daily market capitalization, trading volume, return, and 5-day rolling return volatility of the treatment stocks and control group stocks during the five observation time windows of this study by event type. All market data are collected or derived from Datastream. The continuous return is presented and used for the calculation of the return volatility. (AD = Announcement Date; ED = Effective Date)

3.4.3 Information data

As Section 3.3 describes, I use analyst and news coverage to reflect information availability. I collect the numbers of analysts covering a stock, which it defines as the number of analysts who submitted earnings forecasts for the underlying stock, from the Institutional Brokers' Estimate System (I/B/E/S). The monthly update in I/B/E/S records the data values on the Thursday prior to the third Friday of every month. Meanwhile, the effective date of index revision during a regular review, which Section 3.2 introduces, is always the Monday following the third Wednesday of the month. Therefore, the number of analysts from the

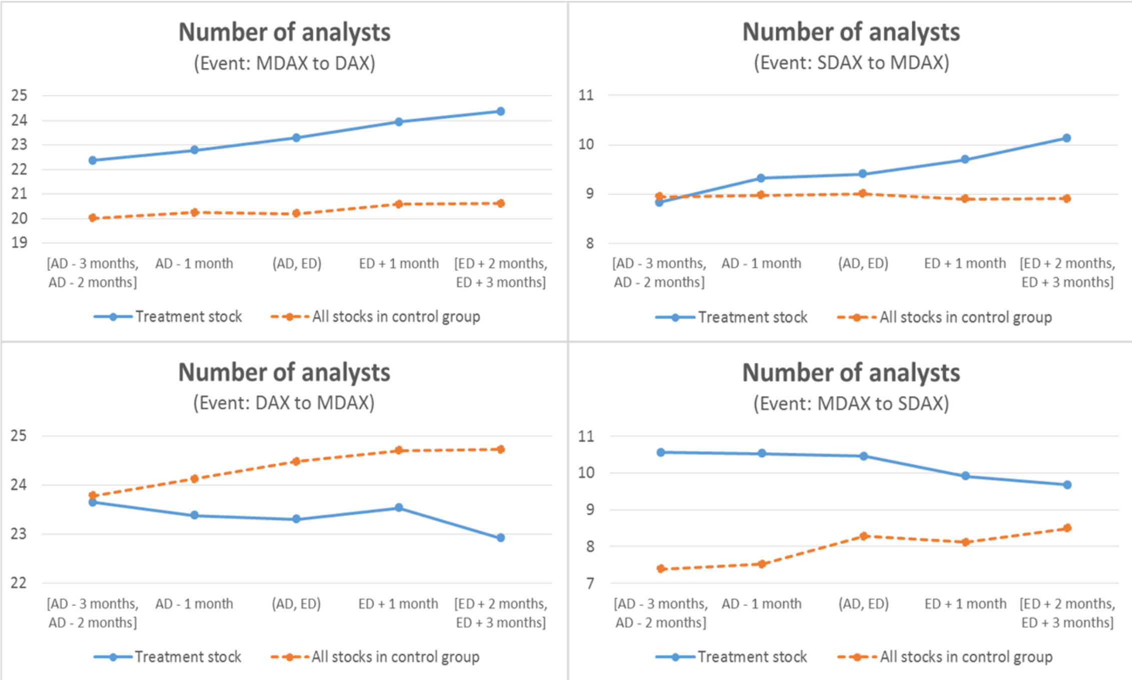

Figure 3.3: Development of analyst coverage by event type

I/B/E/S covering each stock in a regular review month reports the value after the index revision announcement date and before the revision effective date if there is an index revision. I further obtain numbers of analysts covering each treatment and control stock for the 3 months before the month of index revision announcement as well as the 3 months after the index revision effective month.

Applying the event study observation window definition, I then calculate the average number of analysts for the 2nd and 3rd months before the announcement month, and, likewise, the 2nd and 3rd months after the effective month. Figure 3.3 illustrates the development of the average number of analysts for each event type. While more than 20 analysts, on average, cover the large cap stocks in Germany, only about 10 analysts, on average, cover the mid to small-sized stocks. As expected, there is a slight increasing trend of analyst following. This is evident especially for almost all control group stocks. Most importantly, there is, on average, an increase of analyst numbers covering upgraded stocks as well as a decrease of analysts covering downgraded stocks.

As demonstrated by Figure 3.3, the average analyst coverage changes only slowly in the observation window (i.e., one to two analysts) because it takes time for investment firms to start covering new stocks. Therefore, I introduce another measure for information availability that reacts faster to index revisions than the number of analysts: news coverage.

I define the number of news articles from external public news sources as news coverage and obtain the number of news articles as search results from the Factiva database. Thus, I consider all available news sources in German and English from Factiva, excluding newswires, companies' own press releases, and mandatory announcements, such as ownership, shareholder, and board changes.[35] Thus, I count only news from external sources, excluding government bureaus and services that only collect news from other media. To eliminate irrelevant news, I apply the same news filter criteria that Tetlock et al. (2008) use, that is, the firm's official name has to appear in the first 25 words of the article (including headline), the popular name of the firm has to be mentioned at least twice within the full text, and the news has to contain at least 50 words.

Using the abovementioned filter criteria, I search for news about each treatment and control group stock for the following time periods: [announcement date − 3 months, announcement date − 1 month), [announcement date − 1 month, announcement date), [announcement date, effective date], (effective date, effective date + 1 month], and (effective date + 1 month, effective date + 3 months]. I then document the numbers of found articles for each time period as news coverage for each period. For news coverage, I classify the announcement and effective dates as dates of the 3rd observation time period, which differs from the approach in Subsection 3.4.1 and Subsection 3.4.2. This approach for news coverage does not introduce inconsistency into the study for two reasons: first, although the announcement of index revision decisions is after close of trading, the news still comes out on the same day; second, on the effective day, there is a relationship between most news about the observed stocks and the index revision instead of companies' fundamental information. Finally, I normalize all observation window periods to 30 days for the study, that is, the number of news articles found in each observation window period is multiplied

[35] I exclude only companies' own announcements and those from government bureaus, such as the commercial register. If other media report these announcements, I count the news from these media.

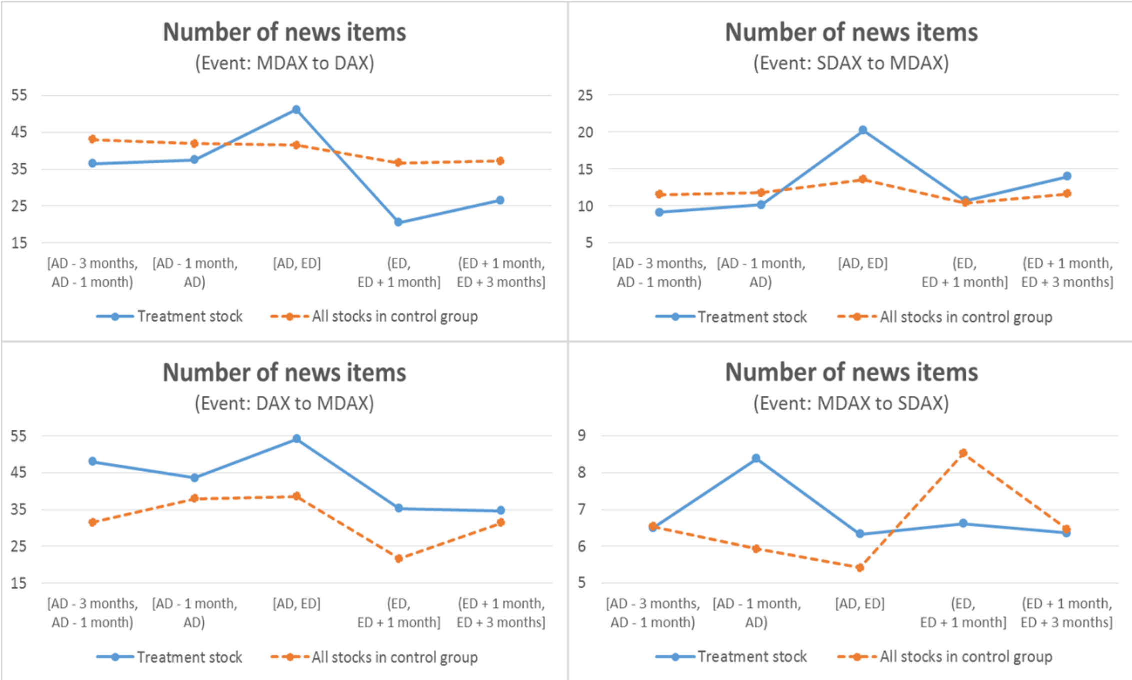

Figure 3.4: Development of news coverage by event type

by a factor of $\frac{30}{\text{number of days counted in observation window period}}$. Through this normalization, I ensure comparability of the collected numbers of news articles.

Figure 3.4 illustrates the averaged normalized numbers of news articles about treatment and control stocks. As expected, news coverage about treatment stocks peaks between the announcement and effective dates, except stocks that experienced a downgrade from the MDAX to SDAX.[36] In general, the development of news coverage on control group stocks seems less volatile than on treatment stocks, again except for downgrading stocks from the MDAX to SDAX. Overall, I do not discover a clear pattern of the development of news coverage associated with index revision.

[36]Deutsche Börse reduced the number of MDAX member stocks from 70 to 50 on March 24, 2003. This led to the immediate downgrading of 20 stocks from the MDAX to SDAX. Given that the companies' performances and characteristics did not cause the changes, news articles did not focus on individual stocks and I eliminate them by the screening criteria based on Tetlock et al. (2008). I conduct the regressions from Subsection 3.5.1 without these 20 events. The test results do not change substantially.

3.5 Empirical results

As Section 3.3 describes, I apply a difference-in-differences approach to measure the liquidity effect associated with index revisions. Subsection 3.5.1 presents the results. In Subsection 3.5.2, I further explore the potential driving factor of the liquidity effect based on the information cost hypothesis. Finally, I demonstrate the robustness of the test results in Subsection 3.5.3.

3.5.1 Difference-in-differences tests

First, I conduct the following regression separately for stocks (treatment and control stocks) associated with an index upgrade and stocks associated with an index downgrade:

$$\begin{aligned} ln(XLM_{i,t}) =& \alpha + \beta_1 \cdot ln(TV_{i,t}) + \beta_2 \cdot R_{i,t} + \beta_3 \cdot ln(Vola_{i,t}) + \beta_4 \cdot ln(MC_{i,t}) \\ &+ \gamma_1 \cdot \mathrm{I}_{[AD-20,AD]} + \gamma_2 \cdot \mathrm{I}_{(AD,ED)} + \gamma_3 \cdot \mathrm{I}_{[ED,ED+20]} + \gamma_4 \cdot \mathrm{I}_{[ED+21,ED+62]} \\ &+ \delta_1 \cdot \mathrm{I}_{[AD-20,AD]} \cdot \mathrm{I}_{treatment} + \delta_2 \cdot \mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment} \\ &+ \delta_3 \cdot \mathrm{I}_{[ED,ED+20]} \cdot \mathrm{I}_{treatment} + \delta_4 \cdot \mathrm{I}_{[ED+21,ED+62]} \cdot \mathrm{I}_{treatment} \\ &+ \theta_i \cdot \mathrm{I}_i + \phi_t \cdot \mathrm{I}_t + \epsilon_{i,t}, \end{aligned} \tag{3.1}$$

day $t \in [AD-62, ED+62]$, which is the observation time window. $XLM_{i,t}$ is the XLM of stock i on day t. I test for the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros individually. $TV_{i,t}$ is the trading volume of stock i on day t on the Xetra electronic platform in thousand euros. $R_{i,t}$ is the continuous return of stock i on day t in percent. $Vola_{i,t}$ is the 5-day rolling return volatility in percent. $MC_{i,t}$ is the market capitalization of stock i on day t in million euros. $\mathrm{I}_{(AD,ED)} = 1$ if $t \in (AD, ED)$, otherwise $\mathrm{I}_{(AD,ED)} = 0$. This study defines the other binary variables analogously and includes stock-fixed effects and quarterly time-fixed effects to control for stock individual characteristics as well as changes in the overall financial market environment. I choose the quarterly time-fixed effects because the regular index review takes place every 3 months and thus, have the most time lags among the starting days of the observation time windows. The reference time period in the regression contains the 2nd and 3rd months before the announcement date, that is, $[AD - 62, AD - 21]$. This study assumes 21 trading days per month.

For the regression, I use the natural logarithm of all continuous variables due to observed high skewness in variable distributions, with the exception of daily returns. I further center all control variables to prevent multicollinearity causing potential problems. Centering of the variables does not affect the regression coefficients and the variance inflation factors of all regressors are less than 2 afterwards, which indicates that multicollinearity does not bias the regression results. Moreover, this study reports the heteroscedasticity- and autocorrelation-consistent standard errors that the Driscoll and Kraay (1998) estimator calculates, which considers cross-sectional dependence.

Table 3.5 shows the regression results of Equation (3.1) separately for index upgrades and downgrades. After controlling for the established liquidity determinants (trading volume, return, return volatility, and market capitalization) as well as stock- and time-fixed effects, this study still identifies statistically significant and sustainable liquidity effects for all order volume classes in the case of an index upgrade. The effect is already observable in the month before the index upgrade announcement. For the order volume class of 100,000 euros, the liquidity cost reduction is even statistically significant at the 1% level. In addition, the absolute value of the coefficient for the order volume class of 100,000 euros is higher than the other coefficients. This indicates that investors that submit higher order volumes—normally institutional investors—anticipate index revision earlier and more strongly than other investors do. After the announcement date, the liquidity effects increase over time and differ only marginally among different order volume classes. This confirms that liquidity effects associated with index upgrades exist for all order volume classes. The time trend within the observation time periods does not drive the observed effects, as no observation time period dummy has a significant coefficient. Overall, the results reveal strong and persistent liquidity effects, that is, liquidity costs decline 17–18% on average in the 2nd and 3rd months after the index change if one converts the coefficient of logarithm back to the standard decimal system. These findings support the information costs/liquidity hypothesis.

Table 3.5: Liquidity effects associated with index revisions: difference-in-differences regressions

	Index upgrade			Index downgrade		
Dep. variable	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)
Difference-in-differences variables						
$\mathrm{I}_{[AD-20,AD]} \cdot \mathrm{I}_{treatment}$	-0.0447**	-0.0450**	-0.0569***	0.0519**	0.0447	0.00818
	(0.0192)	(0.0190)	(0.0201)	(0.0256)	(0.0299)	(0.0336)
$\mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment}$	-0.124***	-0.123***	-0.130***	0.0443	0.0226	0.0933**
	(0.0210)	(0.0210)	(0.0241)	(0.0292)	(0.0292)	(0.0443)
$\mathrm{I}_{[ED,ED+20]} \cdot \mathrm{I}_{treatment}$	-0.168***	-0.160***	-0.179***	0.0211	0.0235	0.0124
	(0.0180)	(0.0178)	(0.0187)	(0.0315)	(0.0370)	(0.0441)
$\mathrm{I}_{[ED+21,ED+62]} \cdot \mathrm{I}_{treatment}$	-0.202***	-0.196***	-0.191***	0.00835	-0.0233	-0.00511
	(0.0169)	(0.0171)	(0.0190)	(0.0254)	(0.0309)	(0.0382)
Observation time period variables						
$\mathrm{I}_{[AD-20,AD]}$	0.00702	0.00397	-0.00708	-0.0597**	-0.0506*	-0.00636
	(0.0129)	(0.0140)	(0.0160)	(0.0301)	(0.0289)	(0.0244)
$\mathrm{I}_{(AD,ED)}$	0.00316	-0.000885	-0.0165	-0.0600*	-0.0523	-0.0956**
	(0.0138)	(0.0153)	(0.0180)	(0.0351)	(0.0350)	(0.0376)
$\mathrm{I}_{[ED,ED+20]}$	0.00577	-0.00326	-0.0150	-0.0264	-0.0327	0.00870
	(0.0132)	(0.0145)	(0.0171)	(0.0371)	(0.0384)	(0.0436)
$\mathrm{I}_{[ED+21,ED+62]}$	-0.00322	-0.0120	-0.0413	0.0147	0.0499	0.0580
	(0.0202)	(0.0227)	(0.0286)	(0.0444)	(0.0531)	(0.0573)
Control variables						
ln(trading volume)	-0.133***	-0.143***	-0.159***	-0.110***	-0.124***	-0.149***
	(0.00422)	(0.00478)	(0.00557)	(0.0109)	(0.0120)	(0.0153)
return	-0.00218***	-0.00230***	-0.00135	0.00412**	0.00454**	0.00529**
	(0.000827)	(0.000886)	(0.000877)	(0.00207)	(0.00216)	(0.00256)
ln(return volatility)	0.134***	0.145***	0.154***	0.125***	0.136***	0.147***
	(0.00706)	(0.00795)	(0.00899)	(0.0116)	(0.0131)	(0.0176)
ln(market capitalization)	-0.613***	-0.677***	-0.757***	-0.873***	-1.065***	-1.145***
	(0.0284)	(0.0321)	(0.0343)	(0.0728)	(0.103)	(0.135)
Observations	84,664	84,004	82,337	47,761	47,394	45,386
Adjusted R-squared	0.867	0.872	0.862	0.924	0.915	0.903
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. Trading volume (in thousand euros), return (in percent), 5-day rolling return volatility (in percent), and market capitalization (in million euros) are collected or derived from Datastream. All control variables are centered. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

On the other hand, most coefficients of the difference-in-differences variables for index downgrades are not statistically significant. Almost all coefficients have the expected positive sign, which indicates an increase in liquidity cost; however, only two coefficients are significant at the 5% level. The significance disappears in the subsequent observation time periods. Therefore, no statistically significant and persistent change of liquidity costs occurs with an index downgrade. This result coincides with past findings based on stocks deleted from the S&P 500, as Section 3.1 outlines. Interestingly, the first two observation time period dummy variables both have a negative coefficient. Some of the coefficients are statistically significant at the 5% or 10% level. This could be the result of market relief, as the control group stocks have not been downgraded to another index. Therefore, the reaction is not persistent and disappears after the effective date.

All control variable coefficients are statistically significant at the 1% level, with the exception of return. As expected, there is a positive correlation between the liquidity costs and return volatility and a negative correlation between the liquidity costs and trading volume and market capitalization. Although most coefficients of return are statistically significant at the 1% or 5% level, the sign of these coefficients is different for index upgrades and index downgrades. Under normal market conditions, an increase of return reduces the inventory risk of holding a stock. Given that inventory risk determines liquidity costs according to Stoll (2000), an increase of return should reduce liquidity costs. Although this is the case for order volumes of 25,000 and 50,000 euros in the index upgrade regressions, the coefficient for an order volume of 100,000 euros is not statistically significant. The coefficients in the index downgrade regressions even imply the opposite. I argue that unbalanced liquidity demand and supply for the treatment stocks in the observation time window cause this result. Domowitz et al. (2005) argue that liquidity costs and return can move without correlation, because different economic forces determine them. While liquidity supply and demand drive liquidity costs, order flows drive returns. In the case of an index downgrade, more investors want to sell than buy the affected stocks. An increase of return raises the stock price and prevents liquidity providers from buying these stocks.

Next, I run the difference-in-differences regressions separately for the upgrade events from the MDAX to DAX and from the SDAX to MDAX to further investigate the liquidity effects associated with index upgrades. As Table 3.6 shows, the overall results are similar to the left part of Table 3.5. Compared with the control group stocks, an index upgrade significantly reduces liquidity costs of treatment stocks after controlling for established liquidity determinants. This liquidity cost change is persistent over time. Although statistically significant liquidity effects are already evident in the month before the announcement date for stocks upgrading from the MDAX to DAX, I first discover similar effects for stocks upgrading from the SDAX to MDAX after the index revision announcement. Relying on the upgrade/downgrade mechanism that Section 3.2 outlines, I argue that higher uncertainty of upgrade decisions for stocks from the SDAX to MDAX causes this difference. As Table 3.3 presents, there are more stocks in the control group per treatment stock (16 stocks per treatment stock on average) for index upgrades from the SDAX to MDAX compared with upgrades from the MDAX to DAX (3 stocks per treatment stock on average). It is easier for the market to anticipate the index changes of the latter group of upgrades and even to react before the official announcement. The liquidity cost reductions for stocks upgrading from the SDAX to MDAX are stronger (about 18%) than from the MDAX to DAX (15–16%). Again, the percentage level of liquidity cost reduction for both index upgrade cases are independent of order volume. For the average XLM value of treatment stocks, it means a 3–6 basis point reduction for stocks upgrading from the MDAX to DAX and a 15–29 basis point decline for stocks upgrading from the SDAX to MDAX.

Table 3.6: Liquidity effects associated with index upgrade: difference-in-differences regressions

	MDAX to DAX			SDAX to MDAX		
Dep. variable	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)
Difference-in-differences variables						
$I_{[AD-20,AD]} \cdot I_{treatment}$	-0.0930***	-0.0965***	-0.101***	-0.0273	-0.0251	-0.0365
	(0.0302)	(0.0301)	(0.0348)	(0.0222)	(0.0222)	(0.0243)
$I_{(AD,ED)} \cdot I_{treatment}$	-0.163***	-0.170***	-0.184***	-0.0982***	-0.0946***	-0.101***
	(0.0317)	(0.0337)	(0.0405)	(0.0264)	(0.0273)	(0.0321)
$I_{[ED,ED+20]} \cdot I_{treatment}$	-0.119***	-0.117***	-0.122***	-0.165***	-0.159***	-0.190***
	(0.0372)	(0.0373)	(0.0403)	(0.0228)	(0.0227)	(0.0241)
$I_{[ED+21,ED+62]} \cdot I_{treatment}$	-0.169***	-0.164***	-0.174***	-0.197***	-0.197***	-0.203***
	(0.0273)	(0.0283)	(0.0333)	(0.0206)	(0.0213)	(0.0233)
Observation time period dummy variables						
$I_{[AD-20,AD]}$	0.0239	0.0258	0.0205	0.00579	0.00245	-0.00880
	(0.0251)	(0.0251)	(0.0275)	(0.0132)	(0.0144)	(0.0165)
$I_{(AD,ED)}$	-0.00634	0.00372	0.0120	0.00287	-0.00251	-0.0206
	(0.0246)	(0.0247)	(0.0281)	(0.0141)	(0.0158)	(0.0191)
$I_{[ED,ED+20]}$	-0.0557	-0.0504	-0.0403	0.00830	-0.00238	-0.0163
	(0.0387)	(0.0387)	(0.0398)	(0.0132)	(0.0146)	(0.0176)
$I_{[ED+21,ED+62]}$	-0.0522	-0.0453	-0.0356	-0.00184	-0.0127	-0.0458
	(0.0420)	(0.0423)	(0.0450)	(0.0205)	(0.0232)	(0.0294)
Control variables						
ln(trading volume)	-0.118***	-0.133***	-0.150***	-0.133***	-0.143***	-0.160***
	(0.0143)	(0.0144)	(0.0151)	(0.00441)	(0.00505)	(0.00592)
return	-0.00242*	-0.00224*	-0.00148	-0.00209**	-0.00225**	-0.00131
	(0.00129)	(0.00124)	(0.00123)	(0.000838)	(0.000915)	(0.000921)
ln(return volatility)	0.112***	0.111***	0.108***	0.136***	0.148***	0.159***
	(0.0177)	(0.0183)	(0.0197)	(0.00754)	(0.00861)	(0.00972)
ln(market capitalization)	-0.670***	-0.776***	-0.928***	-0.614***	-0.672***	-0.745***
	(0.0441)	(0.0449)	(0.0532)	(0.0292)	(0.0332)	(0.0351)
Observations	7,217	7,217	7,217	77,447	76,787	75,120
Adjusted R-squared	0.878	0.891	0.893	0.826	0.829	0.816
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade (treatment group) and stocks that could have had an index upgrade (control group) during index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. Trading volume (in thousand euros), return (in percent), 5-day rolling return volatility (in percent), and market capitalization (in million euros) are collected or derived from Datastream. All control variables are centered. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Similarly, I separately conduct difference-in-differences regressions for the downgrades from the DAX to MDAX and from the MDAX to SDAX. Table 3.7 presents the results. The liquidity costs increase when the stocks are downgraded from the DAX to MDAX compared with the control group stocks. In the 2nd and 3rd months after the effective date, the liquidity costs difference between the treatment and control group stocks is 14–22% higher than before the index downgrade, that is, a 4–14 basis point increase of XLM depending on order volume class. This increase is statistically significant at the 1% level. In contrast to index upgrades, the level of liquidity cost difference change depends on the order volume class. The larger is the order size, the more the liquidity cost difference increases and the earlier the increase appears. Given that institutional investors most likely submit the orders with high volume, the results imply that these investors are more sensitive to index downgrades, require higher liquidity spreads for trading after index downgrades, and react faster than average market participants react. Meanwhile, I discover a liquidity cost reduction in the month before the announcement date and in the time period between the announcement and effective dates for all stocks in the regression. I argue that market relief drives this effect following the expectation and announcement about no index change of control group stocks. Therefore, this effect is stronger after the announcement date and does not persist over time.

Table 3.7: Liquidity effects associated with index downgrade: difference-in-differences regressions

	DAX to MDAX			MDAX to SDAX		
Dep. variable	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)
Difference-in-differences variables						
$I_{[AD-20,AD]} \cdot I_{treatment}$	0.0349	0.0389	0.0303	0.0565**	0.0468	0.00805
	(0.0389)	(0.0420)	(0.0466)	(0.0281)	(0.0326)	(0.0382)
$I_{(AD,ED)} \cdot I_{treatment}$	0.0156	0.0443	0.0679	0.0494	0.0178	0.0997**
	(0.0423)	(0.0483)	(0.0562)	(0.0324)	(0.0322)	(0.0487)
$I_{[ED,ED+20]} \cdot I_{treatment}$	0.0243	0.0721*	0.116**	0.0167	0.00996	-0.0143
	(0.0349)	(0.0399)	(0.0475)	(0.0354)	(0.0406)	(0.0475)
$I_{[ED+21,ED+62]} \cdot I_{treatment}$	0.127***	0.171***	0.199***	-0.0379	-0.0993***	-0.0912**
	(0.0330)	(0.0384)	(0.0455)	(0.0275)	(0.0328)	(0.0456)
Observation time period variables						
$I_{[AD-20,AD]}$	-0.0328*	-0.0379**	-0.0412*	-0.0775**	-0.0690*	-0.0181
	(0.0174)	(0.0191)	(0.0223)	(0.0376)	(0.0363)	(0.0298)
$I_{(AD,ED)}$	-0.0574**	-0.0670**	-0.0801**	-0.0815*	-0.0811*	-0.131***
	(0.0228)	(0.0268)	(0.0326)	(0.0429)	(0.0429)	(0.0447)
$I_{[ED,ED+20]}$	-0.000635	-0.00667	-0.0125	-0.0312	-0.0410	0.0126
	(0.0329)	(0.0383)	(0.0461)	(0.0417)	(0.0416)	(0.0413)
$I_{[ED+21,ED+62]}$	-0.0183	-0.0193	-0.0255	0.0563	0.120*	0.145**
	(0.0363)	(0.0409)	(0.0478)	(0.0512)	(0.0620)	(0.0654)
Observations	8,163	8,163	8,163	39,598	39,231	37,223
Adjusted R-squared	0.944	0.943	0.939	0.850	0.834	0.819
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

The table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index downgrade (treatment group) and stocks that could have had an index downgrade (control group) during index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before announcement date (AD) to 3 months after effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. Trading volume (in thousand euros), return (in percent), 5-day rolling return volatility (in percent), and market capitalization (in million euros) from Datastream. All control variables are centered. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

On the other hand, this study can derive no clear pattern about liquidity cost change from the difference-in-differences regressions with stocks downgraded from the MDAX to SDAX and their control group stocks. Most difference-in-differences variables have a positive sign, but only two of them are statistically significant and these do not persist over time. The coefficients of the difference-in-differences variable for the 2nd and 3rd months after the index downgrade effective date are even negative. The coefficients for higher-order volumes are at least statistically significant at the 5% level. Similar to the difference-in-differences regression results with stocks downgraded from the DAX to MDAX and their control groups, I again observe liquidity cost reductions for all stocks in the month before the announcement date and in the observation time period between the announcement date and the effective date. In addition, the liquidity costs of all stocks in the regressions increase in the 2nd and 3rd months after the effective date of index revision, which is statistically significant for the larger order volume classes.

3.5.2 Information tests

The difference-in-differences regression results from Subsection 3.5.1 indicate that there is a substantial and persistent liquidity cost reduction for stocks that experienced an index upgrade compared with their control group stocks, and this even holds after controlling for the market liquidity drivers. Meanwhile, the results show a liquidity cost increase of downgraded stocks compared with their control group stocks only from stocks downgraded from the DAX to MDAX.

Based on the information cost hypothesis, the reduction of information-acquiring costs should mainly drive the abovementioned liquidity changes. After an index upgrade, stocks receive more analyst and media attention, and vice versa. For example, about 32 analysts follow a DAX stock on average, 19 follow an MDAX stock, and only 8 follow an SDAX stock, as of December 2014.[37] Analysts publish overviews, earnings forecasts, and investment recommendations on covered stocks. As a result, it is cheaper and faster for investors to acquire information about DAX stocks compared with, for example, MDAX stocks. In other words, liquidity costs have to reflect less information-acquiring costs. Therefore, investors are willing to trade DAX stocks with lower liquidity spreads compared with

[37]This study defines analyst following/coverage as submission of an earnings forecast in the I/B/E/S system.

MDAX stocks.

If the information cost hypothesis is true, then the following propositions should hold.

1. There is significant information availability changes of the treatment stocks compared with stocks from their control groups.

2. The changes of information availability at least partially explain the changes of liquidity costs.

As Section 3.3 and Subsection 3.4.3 introduce, I use analyst and news coverage to measure information availability. To test the first proposition above, I conduct the following difference-in-differences regression using the number of analysts following stock i:

$$
\begin{aligned}
ln(\#\text{ of analyst}_{i,t}) =& \alpha + \gamma_1 \cdot \mathrm{I}_{AD-1\ month} + \gamma_2 \cdot \mathrm{I}_{(AD,ED)} + \gamma_3 \cdot \mathrm{I}_{ED+1\ month} \\
& + \gamma_4 \cdot \mathrm{I}_{[ED+2\ months,ED+3\ months]} + \delta_1 \cdot \mathrm{I}_{AD-1\ month} \cdot \mathrm{I}_{treatment} \\
& + \delta_2 \cdot \mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment} + \delta_3 \cdot \mathrm{I}_{ED+1month} \cdot \mathrm{I}_{treatment} \\
& + \delta_4 \cdot \mathrm{I}_{[ED+2\ months,ED+3\ months]} \cdot \mathrm{I}_{treatment} + \theta_i \cdot \mathrm{I}_i + \phi_t \cdot \mathrm{I}_t + \epsilon_{i,t},
\end{aligned}
\tag{3.2}
$$

day $t \in [AD - 3\ months, ED + 3\ months]$, which is the observation time window. I use the natural logarithm because of the skewness of the data set. $\mathrm{I}_{(AD,ED)} = 1$ if $t \in (AD, ED)$, and $\mathrm{I}_{(AD,ED)} = 0$ otherwise. This study defines the other binary variables analogously. I include stock-fixed effects and yearly time-fixed effects to control for stock individual characteristics as well as changes in the overall financial market environment. The reference time period in the regression contains the 2nd and 3rd months before the announcement date, that is, $[AD - 3\ months, AD - 2\ months]$.

I run the test for index upgrades and downgrades separately, as well as for different event types. Table 3.8 presents the results. I find that more analysts follow stocks experiencing an index upgrade already before the announcement compared with stocks from their control group. The increase of analyst numbers persists and becomes stronger over time, and finally reaches about one-third in the 2nd and 3rd months after the effective date.

The separate analyses for stocks upgrading from the MDAX to DAX and from the SDAX to MDAX show that the latter group mainly drives the increase of analyst coverage for upgrading stocks. In the 2nd and 3rd months after the index revision, about 41% more analysts follow stocks upgrading from the SDAX to MDAX compared with their control group stocks. For the average treatment stock, this means an increase of 3.6 analysts. Meanwhile, there is no time trend in the data set. Although the difference-in-differences variables of all stocks upgraded from the MDAX to DAX have a positive sign, they are not statistically significant. A possible explanation is that there are larger numbers of analysts who already follow the treatment stocks and, therefore, there is low potential for additional growth. Furthermore, there is weak and slow growth in the data set over time.

Table 3.8: Analyst coverage changes during index revisions: difference-in-differences regressions

	Index upgrade	Index downgrade	MDAX to DAX	SDAX to MDAX	DAX to MDAX	MDAX to SDAX
Dep. variable	ln(# of analysts)	ln(# of analysts)	ln(# of analysts)	ln(# of analysts)	ln(# of analysts)	ln(# of analysts)
Difference-in-differences variables						
$I_{AD-1month} \cdot I_{treatment}$	0.117**	0.0245	0.0227	0.147**	-0.0112	0.0345
	(0.0457)	(0.0190)	(0.0259)	(0.0616)	(0.0330)	(0.0228)
$I_{(AD,ED)} \cdot I_{treatment}$	0.132**	-0.0547*	0.0515	0.155**	-0.0318	-0.0570
	(0.0541)	(0.0328)	(0.0457)	(0.0725)	(0.0491)	(0.0391)
$I_{ED+1month} \cdot I_{treatment}$	0.190***	-0.0847**	0.0543	0.231***	-0.0425	-0.0937**
	(0.0635)	(0.0363)	(0.0368)	(0.0857)	(0.0396)	(0.0439)
$I_{[ED+2months,ED+3months]} \cdot I_{treatment}$	0.288***	-0.198***	0.107	0.344***	-0.0622	-0.227***
	(0.0750)	(0.0484)	(0.0756)	(0.0984)	(0.0587)	(0.0580)
Observation time period variables						
$I_{AD-1month}$	0.00143	-0.0548***	0.0200*	-0.000878	0.0234	-0.0802***
	(0.00629)	(0.0155)	(0.0103)	(0.00678)	(0.0143)	(0.0228)
$I_{(AD,ED)}$	-0.000607	0.0319*	0.0268	-0.00361	0.0505**	0.0189
	(0.00893)	(0.0178)	(0.0208)	(0.00947)	(0.0228)	(0.0246)
$I_{ED+1month}$	-0.00344	0.0348**	0.0460*	-0.00739	0.0733***	0.0160
	(0.0110)	(0.0175)	(0.0249)	(0.0116)	(0.0259)	(0.0239)
$I_{[ED+2months,ED+3months]}$	-0.00183	0.115***	0.0552*	-0.00634	0.0883***	0.108***
	(0.0134)	(0.0199)	(0.0320)	(0.0141)	(0.0325)	(0.0260)
Observations	3,346	1,781	270	3,076	305	1,476
Adjusted R-squared	0.954	0.947	0.961	0.948	0.964	0.916
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare analyst coverage changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of the DAX, MDAX, and SDAX from July 2002 to December 2014. The numbers of analysts who submit earnings forecast in the I/B/E/S database represent analyst coverage. The observation time window from 3 months before announcement date (AD) to 3 months after effective date (ED) is divided into five time intervals, where $[AD-2months, AD-1month]$ is the reference time window. This study scales analyst coverage as monthly average. Heteroscedasticity-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Coefficients of the difference-in-differences variables in the index downgrade regression present a statistically significant and sustained decline in the number of analysts, although the decrease is first measurable after the announcement date and less strong (about 18% decline in the 2nd and 3rd months after the effective date) compared with the case of an index upgrade. Stocks downgraded from the MDAX to SDAX again drive this change. Stocks downgraded from the MDAX to SDAX have, on average, 20% (or 2.1) analysts less in the 2nd and 3rd month after the effective date compared with their control group stocks. The difference-in-differences variables of stocks downgraded from the DAX to MDAX have a negative sign as this study expects; however, these are not statistically significant. In general, there is slow growth of analyst numbers in the dataset over time, with the exception of the month before the announcement. The growth is statistically more significant compared with the case of an index upgrade.

The results in Table 3.8 provide evidence for the first proposition. To test the second proposition, I add the natural logarithm of the number of analysts ln(# of analysts) and its interaction term with treatment ln(# of analysts)$\cdot I_{treatment}$ as additional independent variables into Equation (3.1). Given that the number of analysts is collected for each calendar month and all other variables are available on a daily basis, this study assumes the calendar months are in line with the trading months defined in the observation windows. As Subsection 3.4.3 describes, the number of analysts for the month with index revision reflects the number of analysts between the announcement and effective dates in the case of a regular index review. I then match the previous months and the following months in a sorted order.

Table 3.9 presents the regression results for index upgrades and downgrades, including analyst coverage as an explanatory variable. In general, the results indicate a negative relationship between liquidity costs and analyst coverage. In the case of an index upgrade, the liquidity costs for the order volume classes of 25,000 and 50,000 euros reduce by about 5% if the ln(number of analysts) increases by one unit. This is statistically significant at the 5% level. Interestingly, a similar effect for the order volume class of 100,000 euros, which normally is only relevant for institutional investors, is not statistically significant. In other words, the information effect driven by analyst coverage on liquidity cost is evident only in smaller order volume classes. This could be the result of different information-collection processes from different investor groups. While institutional investors often have their own research teams and dedicated portfolio managers per investment segment, private and corporate investors rely predominantly on publicly available information, such as analyst reports. Meanwhile, the interaction variables between analyst coverage and treatment dummy are all statistically insignificant. This implies that the positive effect from analyst coverage on liquidity does not depend on index revision. Compared with the results from Table 3.5, the absolute values of difference-in-differences variable coefficients decline by 10% on average. The coefficients of the first difference-in-differences variable for the order volume classes of 25,000 and 50,000 euros become even less significant. These findings indicate there is a relationship between changes of liquidity costs and changes of analyst coverage, and that information availability represented by analyst coverage can partially explain the liquidity effect associated with index upgrade. Therefore, the second proposition holds in the case of an index upgrade.

Table 3.9: Impact of analyst coverage on stock liquidity associated with index revisions: difference-in-differences regressions

	Upgrade			Downgrade		
Dep. variable	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)
Information variables						
ln(# of analysts)	-0.0515**	-0.0518**	-0.0376	-0.0859	-0.112	-0.326**
	(0.0225)	(0.0240)	(0.0251)	(0.0790)	(0.107)	(0.152)
ln(# of analysts) $\cdot \mathrm{I}_{treatment}$	-0.0555	-0.0485	-0.0198	0.0636	0.0893	0.281*
	(0.0431)	(0.0437)	(0.0463)	(0.0641)	(0.109)	(0.145)
Difference-in-differences variables						
$\mathrm{I}_{[AD-20,AD]} \cdot \mathrm{I}_{treatment}$	-0.0370*	-0.0370*	-0.0518***	0.0508*	0.0400	-0.00247
	(0.0197)	(0.0192)	(0.0201)	(0.0268)	(0.0315)	(0.0357)
$\mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment}$	-0.115***	-0.115***	-0.125***	0.0381	0.0121	0.0704
	(0.0213)	(0.0211)	(0.0243)	(0.0286)	(0.0292)	(0.0467)
$\mathrm{I}_{[ED,ED+20]} \cdot \mathrm{I}_{treatment}$	-0.155***	-0.147***	-0.170***	0.0157	0.0155	-0.00866
	(0.0187)	(0.0181)	(0.0189)	(0.0312)	(0.0373)	(0.0452)
$\mathrm{I}_{[ED+21,ED+62]} \cdot \mathrm{I}_{treatment}$	-0.179***	-0.174***	-0.176***	-0.00130	-0.0358	-0.0389
	(0.0182)	(0.0176)	(0.0201)	(0.0264)	(0.0324)	(0.0462)
Observation time period dummy variables						
$\mathrm{I}_{[AD-20,AD]}$	0.00728	0.00410	-0.00685	-0.0647**	-0.0532*	-0.00330
	(0.0130)	(0.0141)	(0.0162)	(0.0310)	(0.0306)	(0.0253)
$\mathrm{I}_{(AD,ED)}$	0.00271	-0.00149	-0.0165	-0.0610*	-0.0506	-0.0819**
	(0.0140)	(0.0155)	(0.0181)	(0.0347)	(0.0356)	(0.0392)
$\mathrm{I}_{[ED,ED+20]}$	0.00573	-0.00348	-0.0154	-0.0290	-0.0342	0.0193
	(0.0133)	(0.0145)	(0.0172)	(0.0368)	(0.0389)	(0.0452)
$\mathrm{I}_{[ED+21,ED+62]}$	-0.00283	-0.0122	-0.0417	0.0150	0.0515	0.0803
	(0.0205)	(0.0230)	(0.0289)	(0.0465)	(0.0560)	(0.0645)
Observations	83,522	82,965	81,492	46,724	46,368	44,520
Adjusted R-squared	0.864	0.870	0.861	0.925	0.916	0.905
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. This study collects numbers of analysts from I/B/E/S on a monthly basis and matches them to the trading month. Driscoll–Kraay heteroscedasticity-, autocorrelation- and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

On the other hand, for index downgrades, I find a significant effect of analyst coverage only for the order volume of 100,000 euros. The insignificance of the analyst coverage coefficients for the order volume classes of 25,000 and 50,000 euros could be due to the nature of the data. First, the XLM values for these two order volume classes are smaller and less volatile compared with the order volume class of 100,000 euros. Second, monthly data form the basis of the variable analyst coverage, and these have less explanatory power than daily data do. Nevertheless, the significance of the difference-in-differences variables is lower than that of the results in Table 3.5, which could provide a clue that the changes of liquidity costs associated with an index downgrade are related to the changes of analyst coverage. Overall, the regression results in the case of an index downgrade only indirectly support the second proposition.

As Table 3.8 indicates, stocks that have index changes between the SDAX and MDAX mainly drive the effect of analyst coverage changes. I repeat the difference-in-differences regressions only for these stocks and their control groups. The results that Table 3.10 presents are similar to those in Table 3.9. In the case of an upgrade from the SDAX to MDAX, the absolute values of the difference-in-differences variables drop even more than 10%, on average, compared with those from Table 3.6. This implies that changes of analyst coverage have higher impact on liquidity costs of stocks upgrading from the SDAX to MDAX compared with all upgrading stocks, which is plausible owing to overall lower analyst coverage for SDAX stocks compared with DAX and MDAX members.

Table 3.10: Impact of analyst coverage on stock liquidity associated with index revisions between the SDAX and MDAX: difference-in-differences regressions

	SDAX to MDAX			MDAX to SDAX		
Dep. variable	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)
Information variables						
ln(# of analysts)	-0.302**	-0.263**	-0.226*	-0.108	-0.152	-0.385**
	(0.119)	(0.117)	(0.130)	(0.0796)	(0.110)	(0.158)
ln(# of analysts) $\cdot I_{treatment}$	0.291**	0.351**	0.488***	0.0801	0.115	0.323**
	(0.147)	(0.154)	(0.172)	(0.0663)	(0.114)	(0.154)
Difference-in-differences variables						
$I_{[AD-20,AD]} \cdot I_{treatment}$	-0.0934***	-0.100***	-0.111***	0.0563*	0.0422	-0.00538
	(0.0298)	(0.0297)	(0.0348)	(0.0296)	(0.0349)	(0.0411)
$I_{(AD,ED)} \cdot I_{treatment}$	-0.163***	-0.175***	-0.199***	0.0422	0.00512	0.0696
	(0.0316)	(0.0339)	(0.0410)	(0.0325)	(0.0326)	(0.0520)
$I_{[ED,ED+20]} \cdot I_{treatment}$	-0.124***	-0.129***	-0.147***	0.0101	-0.000685	-0.0395
	(0.0368)	(0.0366)	(0.0394)	(0.0354)	(0.0416)	(0.0501)
$I_{[ED+21,ED+62]} \cdot I_{treatment}$	-0.178***	-0.184***	-0.217***	-0.0524*	-0.120***	-0.138**
	(0.0288)	(0.0296)	(0.0349)	(0.0292)	(0.0349)	(0.0567)
Observation time period dummy variables						
$I_{[AD-20,AD]}$	0.0230	0.0253	0.0206	-0.0862**	-0.0750*	-0.0165
	(0.0246)	(0.0247)	(0.0272)	(0.0383)	(0.0385)	(0.0312)
$I_{(AD,ED)}$	-0.00627	0.00387	0.0123	-0.0853**	-0.0813*	-0.117**
	(0.0240)	(0.0243)	(0.0279)	(0.0425)	(0.0440)	(0.0462)
$I_{[ED,ED+20]}$	-0.0510	-0.0450	-0.0331	-0.0345	-0.0417	0.0268
	(0.0384)	(0.0384)	(0.0395)	(0.0413)	(0.0425)	(0.0433)
$I_{[ED+21,ED+62]}$	-0.0432	-0.0359	-0.0245	0.0599	0.127**	0.180**
	(0.0416)	(0.0419)	(0.0446)	(0.0533)	(0.0647)	(0.0744)
Observations	7,217	7,217	7,217	76,305	75,748	74,275
Adjusted R-squared	0.879	0.891	0.894	0.821	0.826	0.814
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of MDAX and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. This study collects numbers of analysts from I/B/E/S on a monthly basis and matches them to the trading month. Trading volume (in thousand euros), return (in percent), 5-day rolling return volatility (in percent), and market capitalization (in million euros) are collected or derived from Datastream. All control variables are centered. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Next, I conduct the same tests for the second proxy for information availability: news coverage. News coverage reacts faster to index revision than analyst coverage does and might provide more insight into the relationship between stock liquidity and information availability. Nevertheless, we should be aware of noises associated with the number of news items. Although I filter the "noisy" news in all conscience as Subsection 3.4.3 introduces, the test results require cautious interpretation.

I replace the number of analysts in Equation (3.2) by the number of news articles. Table 3.11 summarizes all regression results. The coefficients of the difference-in-differences variables for stocks experiencing an index upgrade indicate higher news coverage on treatment stocks between the announcement and effective date, as well as in the 2nd and 3rd months after the effective date. Again, the stocks upgrading from the SDAX to MDAX mainly drive this. Given an index downgrade, more articles cover the treatment stocks before the announcement date and fewer articles in the month after the effective date compared with the control group stocks. While the downgraded stocks from the MDAX to SDAX behave similarly, the downgraded stocks from the DAX to MDAX present a different picture. In this case, all difference-in-differences coefficients have a negative sign and are statistically significant at least at the 5% level in the month before the announcement date and in the 2nd and 3rd months after the effective date. In general, the coefficients of the observation time period dummy variables suggest a slight increase of news coverage over time in most cases.

Table 3.11: News coverage changes during index revisions: difference-in-differences regressions

	Index upgrade	Index downgrade	MDAX to DAX	SDAX to MDAX	DAX to MDAX	MDAX to SDAX
Dep. variable	ln(# of articles)	ln(# of articles)	ln(# of articles)	ln(# of articles)	ln(# of articles)	ln(# of articles)
Difference-in-differences variables						
$\mathrm{I}_{[AD-1month,AD)} \cdot \mathrm{I}_{treatment}$	-0.00389	0.396***	0.192	-0.0344	-0.613**	0.653***
	(0.138)	(0.147)	(0.250)	(0.167)	(0.279)	(0.165)
$\mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment}$	0.700***	0.174	0.444	0.912***	-0.0224	0.237
	(0.183)	(0.145)	(0.294)	(0.218)	(0.299)	(0.168)
$\mathrm{I}_{(ED,ED+1month]} \cdot \mathrm{I}_{treatment}$	-0.0632	-0.350**	-0.564*	0.153	-0.0146	-0.407**
	(0.167)	(0.145)	(0.289)	(0.194)	(0.228)	(0.170)
$\mathrm{I}_{(ED+1month,ED+3months]} \cdot \mathrm{I}_{treatment}$	0.302***	-0.146	-0.181	0.473***	-0.471***	-0.0593
	(0.113)	(0.142)	(0.181)	(0.128)	(0.149)	(0.177)
Observation time period dummy variables						
$\mathrm{I}_{[AD-1month,AD)}$	0.164***	-0.259***	0.0324	0.171***	0.224	-0.386***
	(0.0450)	(0.0866)	(0.102)	(0.0479)	(0.147)	(0.114)
$\mathrm{I}_{(AD,ED)}$	0.429***	-0.00115	0.133	0.461***	0.0733	-0.0531
	(0.0542)	(0.0915)	(0.126)	(0.0580)	(0.183)	(0.118)
$\mathrm{I}_{(ED,ED+1month]}$	0.135***	0.336***	0.131	0.136***	-0.435***	0.460***
	(0.0493)	(0.0903)	(0.108)	(0.0525)	(0.152)	(0.115)
$\mathrm{I}_{(ED+1month,ED+3months]}$	0.160***	0.0985	0.242**	0.155***	0.197*	0.0304
	(0.0439)	(0.0803)	(0.0976)	(0.0466)	(0.111)	(0.108)
Observations	2,899	1,686	269	2,630	297	1,389
Adjusted R-squared	0.624	0.518	0.690	0.577	0.565	0.302
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare news coverage changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. The number of qualified articles from the Factiva database represents news coverage, using the criteria in Subsection 3.4.3 as a basis. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-2months, AD-1month]$ is the reference time window. This study scales news coverage as monthly average. Heteroscedasticity-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

In summary, Table 3.11 offers no clear picture regarding the relationship between the change of news coverage and index revisions. The changing signs and significance of the difference-in-differences coefficients imply noise in the dataset. Thus, we can find almost no meaningful result.

To complete the analysis, I show results of difference-in-differences regressions, including news coverage as an explanatory variable in Appendix C, although the results yield no clear implications. None of the news coverage's coefficients are statistically significant. There is a positive relationship between the interaction term of news coverage and treatment dummy and liquidity cost, which contradicts this study's hypotheses and theories from the existing literature. The following two points provide some explanation.

(1) This study is unable to eliminate "noise," as the media cover both positive and negative news while analysts tend to cover "winning" stocks only. In addition, the media are more likely looking for "eye-catching" stories and usually publish either highly positive or negative news. This behavior might create an imbalance between stock demand and supply and, therefore, reduces liquidity of the affected stock.

(2) Analyst reports generate more transparency about the covered stock than lack of such reports, even if they do not reveal insider information (cf. Roulstone (2003)), whereas media news always reveals new information, or at least is induced by new information. Therefore, analyst coverage reduces liquidity cost by increasing transparency about the underlying enterprise. At the same time, the effect of news coverage on the stock is more complicated, because news coverage not only generates transparency, but also reveals changes in the fundamental factors of the companies.

For further research using news coverage, additional clusters of positive/negative/neutral news might be necessary to separate news items that increase information transparency from those that create unbalanced demand and supply in the market. This measure might be better for long-term analysis using yearly averages, since noises from monthly data are reduced.

3.5.3 Robustness of test results

The fundamental prerequisite for this study is the parallel assumption of liquidity development of treatment and control group stocks before the event window. Although the control groups consist of stocks that could have been subject to an index change based on predefined criteria from Deutsche Börse, one might still argue that the treatment stock usually has a higher or lower ranking compared with most control group stocks and the choice for treatment (index change) is not completely random. Hence, in addition to the graphical illustration in Figure 3.2, which indicates high parallelism of the XLM development, I conduct a placebo test.

Given that the time period between the announcement date and effective dates is 3 to 6 weeks in the data sample for regular index reviews, which means the observation window for one event could extend to about 7.5 months, I shift the observation windows backwards by at least 8 months for the placebo test. In addition, the time period of the placebo test should not coincide with the regular index revision time periods when both treatment and control stocks could be candidates for the revisions. Therefore, I shift the panel data by, for example, 180 trading days backwards. Table 3.12 shows the results. All difference-in-differences coefficients on the left side of the table (index upgrade) become insignificant. This implies no significant difference between liquidity costs for treatment and control stocks after controlling for market variables and fixed effects. Thus, the parallel assumption holds. Meanwhile, almost all the difference-in-differences coefficients on the right side of the table (index downgrade) have a negative sign and some of them are even highly statistically significant. However, the coefficients become statistically insignificant when I use other time windows for the placebo test. I test further random dates for the placebo test and the parallel assumption holds for the case of index upgrades.

Table 3.12: Liquidity effects associated with index revisions: placebo test

	Index upgrade			Index downgrade		
Dep. variable	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)	ln(XLM25k)	ln(XLM50k)	ln(XLM100k)
			Difference-in-differences variables			
$I_{[AD-200,AD-180]} \cdot I_{treatment}$	0.00619	0.0131	0.0189	0.00480	-0.0218	-0.0233
	(0.0223)	(0.0227)	(0.0231)	(0.0225)	(0.0255)	(0.0306)
$I_{(AD-180,ED-180)} \cdot I_{treatment}$	0.0170	0.0206	0.0169	-0.0487	-0.0645*	-0.0389
	(0.0284)	(0.0280)	(0.0351)	(0.0313)	(0.0382)	(0.0468)
$I_{[ED-180,ED-160]} \cdot I_{treatment}$	-0.0224	-0.0161	-0.00598	-0.0791***	-0.129***	-0.154***
	(0.0223)	(0.0216)	(0.0236)	(0.0236)	(0.0271)	(0.0329)
$I_{[ED-159,ED-118]} \cdot I_{treatment}$	-0.0197	-0.0238	-0.0258	0.0363*	-9.41e-06	-0.0456
	(0.0186)	(0.0186)	(0.0195)	(0.0219)	(0.0246)	(0.0293)
			Observation time period variables			
$I_{[AD-200,AD-180]}$	-0.0249**	-0.0287**	-0.0329**	-0.0686***	-0.0595***	-0.0722***
	(0.0109)	(0.0123)	(0.0132)	(0.0151)	(0.0164)	(0.0192)
$I_{(AD-180,ED-180)}$	-0.00378	-0.00449	0.00202	-0.0407*	-0.0361	-0.0637*
	(0.0139)	(0.0144)	(0.0193)	(0.0214)	(0.0238)	(0.0327)
$I_{[ED-180,ED-160]}$	-0.0119	-0.0154	-0.0269	0.0440	0.0841**	0.0977**
	(0.0163)	(0.0164)	(0.0178)	(0.0309)	(0.0342)	(0.0450)
$I_{[ED-159,ED-118]}$	0.0132	0.0128	-0.00175	-0.0505	-0.00956	0.0141
	(0.0184)	(0.0188)	(0.0210)	(0.0327)	(0.0345)	(0.0467)
Observations	78,487	78,127	77,023	33,514	33,142	31,529
Adjusted R-squared	0.851	0.854	0.850	0.941	0.939	0.928
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports placebo test coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) for index revisions of DAX, MDAX, and SDAX from July 2002 to December 2014. This study conducts the placebo test for the observation time periods shifted by 180 trading days backwards. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window is defined as time window from Equation (3.1) shifted backwards by 180 trading days, where $[AD-242, AD-201]$ is the reference time window assuming 21 trading days per month. Trading volume (in thousand euros), return (in percent), 5-day rolling return volatility (in percent), and market capitalization (in million euros) are collected or derived from Datastream. All control variables are centered. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Even though the parallel assumption holds, one might still argue that the probabilities of individual control group stocks experiencing an index change are not equal. To verify the robustness of the test results, I change the control group specifications, as Table 3.13

summarizes. In its equity guideline, Deutsche Börse defines only the threshold of trading value and free float market capitalization ranking, and indicates that the latter has a higher weight in the final decision if no stock reaches both thresholds. There is no predefined rule about the weightings of each criterion and the index committee makes the final decisions. Therefore, this study introduces two ranking methods in terms of weightings for trading value and free float market capitalization: equal weights and two-thirds weight for free float market capitalization (one-third weight for trading value). Furthermore, I change the maximum number of stocks per control group: nearest neighbor, maximum three stocks, and maximum five stocks. The test results are robust to all these different specifications.

Table 3.13: Variations of control group specifications

	Equal weights for free float market capitalization and trading value	2/3 weight for free float market capitalization and 1/3 weight for trading value
Nearest neighbor	Yes	Yes
Max. 3 stocks	Yes	Yes
Max. 5 stocks	Yes	Yes

3.6 Conclusion

This study examines the liquidity effect associated with the revisions in German Prime Standard indexes. Using a difference-in-differences study design, I compare liquidity cost changes from stocks that experienced an index change and stocks that could have had an index change during index revisions of the DAX, MDAX, and SDAX from July 2002 to December 2014. Furthermore, I use a unique order volume-weighted spread measure to assess order volume-dependent liquidity cost changes.

I find asymmetric liquidity effects associated with index revisions. Compared with their control group stocks, liquidity costs of stocks that experienced an index upgrade decline for 17–18% on average in the 2nd and 3rd months after the index change. The percentage changes are independent of the order volume classes. The sub-sample analysis shows that the liquidity costs for a round-trip trade of a stock that upgraded from the MDAX to the DAX reduce, on average, by 3–6 basis points depending on their order volume class, compared with their control group stocks. The same liquidity cost differences decline even by 15–29 basis points for stocks upgraded from the SDAX to the MDAX. On the other hand, I find no clear liquidity cost increases for stocks that experienced an index downgrade compared to their control group stocks. I find statistically significant liquidity cost rises only for stocks that downgraded from the DAX to the MDAX in the 2nd and 3rd months after the effective date. Their liquidity costs for a round-trip trade increase by 14–22% or 4–14 basis points compared with their control groups. The findings are robust to various specifications, including placebo tests and variations of stock numbers within a control group.

These asymmetric findings are in line with most past research, which mainly focuses on price effects of inclusion into and deletion from the S&P 500 index. I explain these liquidity effects by company information availability. I find statistically significant changes of analyst coverage for both upgraded and downgraded stocks using the same difference-in-differences design. In the case of an index upgrade, analyst coverage shows a positive impact on stock liquidity and explains about 10% of the difference-in-differences liquidity effect associated with an index upgrade. The effects are more significant for smaller order volume classes. It is almost impossible to test the opposite effects for index downgrades, because this study finds no generally valid significant index effect on liquidity. In addition, I conduct the same study using news coverage and find no clear evidence. The potential cause of this is the nature of news coverage, as Subsection 3.5.2 discusses.

This study contributes to the literature in several aspects. First, the difference-in-differences approach with additional control for market activities quantifies the "pure" liquidity effects associated with index revision and largely bypasses the endogeneity issue. The additional placebo test shows that the potential selection bias due to stock development trends does not affect the regressions. Second, this study's unique order volume-weighted spread measure considers the whole depth of the limit order book and provides more accurate liquidity measurement. In addition, it allows us to find order volume-dependent evidence in terms of liquidity cost changes. Finally, the findings about the connection between information availability and stock liquidity support the information cost hypothesis. Overall, this study extends current research regarding index effects and information costs/liquidity hypothesis theory.

In addition, the findings might have implications for stock exchanges and enterprises. Stocks benefit clearly from the inclusion of indexes in terms of liquidity costs, without improving any fundamental characteristics of the companies. However, the degrees of the liquidity change for stocks moving between different indexes are very different. Stock exchanges should design index construction rules in a way that liquidity jumps among different indexes are as small as possible. Potential means to do so are, for example, adjustment of constituent numbers or the introduction of banding rules for stocks around the selection threshold. Meanwhile, public companies should be interested in attracting more analysts to follow their stocks, because higher analyst coverage effectively reduces the liquidity costs of covered stocks and, hence, reduces the cost of equity. Furthermore, enterprises should think of financing analysts for coverage (similar to the rating agency model for bonds). However, this study does not provide any measures to address these implications and there is a need for further research in this regard.

4 Index Membership and Capital Structure: International Evidence

Abstract

How much do shocks to the information environment in equity markets matter for debt supply and the financing of firms? We find that the use of debt increases by about 1–3 percentage points following exogenous additions of stocks to an index. The leverage response is primarily in public debt markets: Borrowing costs in these markets decrease, while bond liquidity increases. These results suggest that index additions affect leverage, because an increase in public information reduces information asymmetries for lenders and increases their willingness to buy information-sensitive debt. Indeed, stocks added to an index are followed by more equity analysts. Overall, we support the view that information production in equity markets spills over into debt markets.

Keywords:	index membership, investor awareness, debt supply, capital structure
JEL Codes:	G14, G15, G32

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4.1 Introduction

Investigating and monitoring informationally opaque borrowers is both costly and imperfect. Thus, an important research question is to determine the extent to which information frictions and supply considerations affect debt financing of firms. We make progress on this question by examining shocks to the information environment that result in greater firm transparency. If information asymmetries are critical for lending, then debt levels should increase as a firm becomes less opaque. How important are information frictions in debt supply considerations? Do they matter for leverage?

To address these questions, this study examines exogenous additions and deletions of stocks to equity indexes that cause large sudden changes to a firm's information environment. As a firm becomes a part of a major stock index, it becomes better known and more visible. Ownership by institutions increases, because institutions often benchmark to these indexes. Institutions value public information, which results in greater demand for analyst services. In addition, institutions specialize in monitoring and evaluating firms, which further increases the amount of information produced on indexed firms. Overall, we expect index membership to result in a richer information environment for firms.[1]

As the information environment improves, monitoring and screening costs that lenders incur decrease. Consequently, firms become less constrained in their ability to issue debt. This can occur directly through a quantity channel, because lenders are willing to lend more when transparency increases. However, firms also can become less constrained indirectly through a price channel, as they now have greater access to cheaper capital. While index membership might facilitate purchases by institutional investors and specialized funds that require firms whose debt they purchase to be a member of an index, this study is more interested in the information effects in equity markets and how they spill over to debt markets.

In particular, we expect arm's length lenders with coarser and more costly screening and monitoring technologies to find it feasible to lend now. Firms that previously could borrow

[1] See, for example, Boone and White (2015) and Crane et al. (2016).

only from financial intermediaries with an information advantage (e.g., banks) could now access public debt markets.[2] In fact, Faulkender and Petersen (2006) suggest that a firm's visibility is important in its ability to issue public debt. If a firm is better known and more visible, it is easier for investment banks to sell their bonds to investors. Thus, we expect shocks to the information environment to matter more for the amount of public debt that firms can issue.

From a theoretical perspective, the effects of equity index membership on capital *structure* are not clear. Even though firms might find it easier to increase debt levels following equity index membership, leverage could nevertheless decrease because the cost of equity might be more sensitive to *equity* index membership than the cost of debt. According to the pecking-order theory of debt (Myers, 1984), information frictions result in a hierarchy of financing—internal funds, debt, and then equity. Ultimately, the empirical question is then whether firms are operating at the internal funds versus debt margin or at the debt versus equity margin. Leverage increases would be consistent with firms being at the former margin, while the literature expects firms operating at the latter margin to switch from debt issuance to equity issuance. In addition, leverage increases, for example, would be consistent with the trade-off theory of debt (Kraus and Litzenberger, 1973). In this view, firms are under-leveraged because of financial frictions. A reduction in those frictions allows firms to move toward their optimal debt ratios.

The ideal situation we would like is random assignment of firms to an index in order to infer the causal effects of indexing on debt ratios. In practice, firm size and past performance often determine index membership. This makes firms that are added to an index different to firms not in the index.[3] Furthermore, given that index ranking methodologies and review dates are well known, firms could influence index membership by increasing size through acquisitions, for example.

We overcome these difficulties by considering only changes in index membership that result

[2] Banks are good at investigating and monitoring borrowers, because they interact with borrowers over time and across different products, which gives them a unique advantage in collecting information about firms (Brealey et al., 1977; Diamond, 1984; Fama, 1985; Boyd and Prescott, 1986).

[3] Becker-Blease and Paul (2006) show that stocks to be included in the S&P 500 index had both higher return on assets and higher returns compared to their control group in the year prior to inclusion.

from (1) the formation of a new equity index or discontinuation of an existing index, (2) changes in the eligible index universe, such as country and industry, (3) increases or decreases in the number of index constituents, or (4) changes in index selection criteria or changes in criteria weightings. We construct this sample by screening more than 54,000 press releases, including archived press releases, related to 7,356 equity indexes from 32 major index providers across 21 countries. This results in a sample of more than 200 events that satisfy our screening criteria affecting 8,000 (treatment) stocks. Compared to previous literature that exploits the quasi-random assignment into Russell 1000 and 2000 stock indexes, our approach has the advantage that announcements of changes in index methodology and the creation of new indexes are usually on relatively short notice.[4] For example, in our data set, announcements of index changes, formations, or discontinuations are on average 44 days (median: 23 days) before the index event, while the announcements of the exact stocks that event affects are 25 days later (median: 1 day). In addition, the events are of meaningful importance. For example, for the subset of newly created indexes, the market capitalization of the stocks in the index amounts to about 15% of a country's total market capitalization at that point of time. By comparison, at the end of 2015, the market capitalization of the Dow Jones Industrial Average Index amounted to about 21% of the total market capitalization of U.S. firms. Thus, we can exploit these exogenous changes in index membership for identification purposes.

This study shows that firms added to an index increase leverage by about 1–3 percentage points relative to control firms that are observationally identical to treatment firms with respect to country, industry, year, and various firm characteristics. Furthermore, we find that much of the increase in leverage around index additions is attributable to an increase in public debt. By contrast, private debt ratios show no statistical change following index additions. Furthermore, we observe that borrowing costs in public debt markets decrease, while bond liquidity increases simultaneously. The results are in line with the view that index additions have a stronger impact on a firm's ability to access public debt. Public debt investors for whom monitoring is more costly exhibit a greater supply response as a

[4]See, for example, Chang et al. (2014), Boone and White (2015), Crane et al. (2016), and Schmidt and Fahlenbrach (2017).

firm's information environment improves, and firms increase their issuance of public debt relatively more compared to bank debt, as they can access external debt markets.[5]

We find that the main result is robust to alternative estimation methodologies. In particular, we implement a regression discontinuity design that compares firms that, based on the underlying index methodology, have just been included in the index to firms that have not just been included in the index. This is a step closer to a quasi-random selection into treatment and non-treatment stocks. Based on this approach, we observe comparable magnitudes of leverage increases around index additions. Furthermore, we rule out that the results are driven by strategic behavior of index providers. Index providers might have an incentive to create or change indexes in a way so that they include "winner" stocks but exclude "loser" stocks and, accordingly, index providers set the size of a new or modified index to reflect these expectations. Therefore, in a robustness test, we restrict the data set to index families whose indexes all have the same number of constituents and index families whose constituents are from the same universe of stocks and the same ranking methodology. In these cases, it is less likely that future expectations from a single industry drive index size. In addition, we restrict the data set to indexes with a round number of index constituents (e.g., 20, 30, 50, and 100) and considers only a small number of stocks around the index inclusion threshold. When doing so, index providers cannot always perfectly distinguish stocks with good and bad prospects. Even though the number of observations drops considerably, we still observe a positive and highly significant effect of *marginal* index inclusion on leverage. Thus, we conclude that the main result does not stem from strategic index creation by index providers.

In the second part of the paper, we conduct several tests to shed light on the underlying mechanisms. Around the exogenous addition to an index, we find that the number of analysts following a firm increases relative to control stocks, which is consistent with the notion that index membership increases investor awareness and reduces information costs. In line with Boone and White (2015), we document that liquidity costs, approximated by average relative bid–ask spreads, decrease when a stock is exogenously included in

[5] See, for example, Krishnaswami and Subramaniam (1999) and Gomes and Phillips (2012).

an index. Finally, we exploit the cross-country variation by examining how institutional differences across countries amplify debt responses to changes in information environment. We expect shocks to the information environment to engender a greater debt response in countries with weak disclosure laws and worse accounting standards. This is because greater production of public information by investors and analysts is of greater value when the overall information environment is weak. Consistent with this argument, we find that leverage increases in response to exogenous additions to an index are smaller for firms in countries with stronger disclosure requirements and better accounting standards. These results support the view that incremental effects of greater public information production are greater when firms operate in a relatively poor information environment.

The paper adds to the literature along several dimensions. First, by looking at exogenous effects of equity index events on debt financing, we shed light on the under-researched interplay of equity and bond markets (e.g., Campbell and Ammer, 1993; De Jong and Driessen, 2012). We provide evidence that significant spillovers occur from equity markets to bond markets. Second, the paper contributes to the growing literature on the supply of debt financing as an important determinant of capital structure (Faulkender and Petersen, 2006; Leary, 2009; Tang, 2009; Sufi, 2009; Rice and Strahan, 2010; Saretto and Tookes, 2013). Third, the paper contributes to the literature on how information asymmetry affects debt financing (Brealey et al., 1977; Myers, 1984; Chang et al., 2006). Finally, related to works such as Rajan and Zingales (1995) and Korajczyk and Levy (2003), we are able to document international variation in the "index effect," helping to understand whether the institutional environment affects corporate financing decisions.

The studies closest to ours are Cao et al. (2016) and Cheung et al. (2017). Cao et al. (2016) examine the effects of financing decisions for a sample of small U.S. firms around the Russell 2000 threshold. The authors find that, as a result of lower information acquisition cost, index membership lets firms issue more equity. In contrast to their findings, we find that equity index membership results in more public debt, highlighting the interplay of equity and debt markets. Cheung et al. (2017) find that increases in stock liquidity due to decimalization and Russell index reconstitution result in higher leverage. By contrast, we argue that greater information production as a result of index membership reduces adverse selection costs, which lets firms borrow more. Furthermore, we follow a different empirical approach by looking at exogenous changes in index membership due to index formations or index methodology changes. Compared to regular updates to Russell 2000 membership, these events are even more difficult to influence for firms, for example, because of the suddenness of their announcement. Finally, due to the internationality of the data set, we can document cross-country variation in the effects of index membership on corporate financing decisions. In addition, this study is related to Michaely et al. (2014), who argue that the increased presence of institutional investors, such as mutual funds, can help to explain the deleveraging of U.S. firms since 1992. By contrast, Lu (2013) argues that institutional ownership reduces bank loan spreads, facilitating borrowing.

The structure of the remainder of this paper is as follows. Section 4.2 describes the identification strategy. Section 4.3 presents the data. Section 4.4 discusses the empirical results. Section 4.5 concludes.

4.2 Identification

Publicly available information usually determines index construction. Furthermore, most index providers disclose their index methodology in a transparent way that one can easily reconstruct by using market data provided by established data vendors. Hence, many studies have employed equity index revisions for event studies (e.g., Harris and Gurel, 1986; Erwin and Miller, 1998; Becker-Blease and Paul, 2006). These events, however, are subject to endogeneity concerns. First, firms can influence index revision results and, therefore, index membership, because index review dates and methodologies are very transparent and known in advance. For example, in September 2015, Vonovia SE acquired two firms and, therefore, increased its market capitalization shortly before its inclusion in the DAX, an index of 30 German blue chip stocks. Without the acquisitions by Vonovia SE, ProSiebenSat.1 Media SE, a media firm, would have been included in the DAX instead. Second, around regular index revisions, there might be underlying trends.

For instance, stocks to be included in equity indexes often grow faster than those not to be included, which is why they are to be included in the first place. In this regard, Becker-Blease and Paul (2006) show that stocks to be included in the S&P 500 index had both higher return on assets and higher returns compared to their control group in the year prior to inclusion. Consequently, other endogenous factors partially affect the index effects that the past literature measures; these index effects do not reflect only the effects of index membership itself.

This study relies on exogenous events affecting index membership. In particular, we look at the following four types of index events.

- We examine formations of new equity indexes or discontinuations of existing indexes (**launch / closure**). For example, after 2000, the Dow Jones launched various country and regional Titan indexes consisting of blue chip stocks.

- We study changes in the eligible index universe, such as country and industry (**universe change**). In this regard, NASDAQ-100 first included foreign stocks listed on the NASDAQ in 1998, while foreign companies have not been eligible for inclusion in the S&P 500 since July 2002.

- We analyze increases or decreases in the number of index constituents (**number change**). For instance, the number of constituents of the Dow Jones US Select Dividend Index increased from 50 to 100 at the end of 2004.

- We investigate changes in index selection criteria or changes of criteria weightings (**ranking methodology change**). For instance, the Dow Jones changed ranking methodologies by reducing the number of index criteria from five to three in 2002 to increase transparency.

The intuition behind exploiting these events for identification is that it is unlikely that firms can anticipate these events and influence index membership in advance, because changes in index methodology and the creation of new indexes are usually on relatively short notice. This makes it very difficult for firms to influence index membership. For example, in this study's data set, announcements of index changes, formations, or discontinuations are on average 44 days (median: 23 days) before the index event, while the announcements of the exact stocks that are affected by the event are 25 days later (median: 1 day). Therefore, from the perspective of an individual firm that is included in or removed from a certain index for these reasons, index membership is exogenous. Furthermore, even if economic development could drive these index events (e.g., strong growth of the Chinese stock market as the driver for introducing many Chinese stock indexes), which could affect a firm's financial leverage decisions (e.g., Baker and Wurgler, 2002), this study's difference-in-differences approach eliminates these effects by matching within country, year, and industry, as well as by performing propensity score matching along several firm characteristics.[6] Finally, we complement the analysis with a regression discontinuity design that considers stocks near the index inclusion threshold that have *just* been included in an index to mitigate concerns related to firms anticipating changes in index membership (e.g., Chang et al., 2014; Boone and White, 2015; Crane et al., 2016, for the Russell 1000/2000 indexes).

4.3 Data

To identify exogenous index events, we search for all available press releases, including archived press releases, from major index providers worldwide. We start with the 45 countries included in the sample of Amihud et al. (2015). However, owing to only a small number of exogenous events, a low number of affected stocks, or missing information on index constituents in 24 of the countries, we restrict the sample to index events in 21 countries. In addition, we exclude strategic indexes, such as short indexes, indexes that only cover financial firms, and customized indexes whose methodologies and constituents are not publicly available. Overall, we identify 226 index events from January 1996 to June 2014, for which we are able to determine index constituents before and/or after the respective events. Index constituent lists are obtained from press releases, Datastream,

[6]Firms must be available throughout the full time window around the index events for inclusion in the data set.

Table 4.1: Overview of exogenous equity index events

Event type	**Number of events** (1)	**Number of stock inclusions** (2)	**Number of stock deletions** (3)
Launch/closure	168	7,534	503
Index universe change	22	132	51
Number change	19	452	207
Ranking methodology change	17	31	40
Total	**226**	**8,149**	**801**

This table shows all identified exogenous equity index events from 21 countries from January 1996 to June 2014. The last two columns show the number of stocks affected by an index event. Launch/closure refers to the introduction of a new equity index or closing of an existing index. Index universe change refers to a change in the eligible index universe, such as country and industry. Number change captures events based on an increase or decrease in the number of index constituents. Ranking methodology change considers the change of index selection criteria and change of criteria weightings. Index events are identified via screening of press releases, including archived press releases, from major index providers. The sample includes only events with available constituents details. Index constituent lists are collected from index providers and external data vendors, such as Datastream, Bloomberg, and newswires.

Bloomberg, or newswires, depending on data availability. Table 4.1 provides an overview of these events.

The 226 events we find are based on the screening of more than 54,000 press releases for 7,356 equity indexes from 32 index providers. After excluding financial firms, the events refer to about 9,000 individual non-financial stocks. To show that the sample of equity indexes is representative and not subject to selection bias, we apply the same filtering criteria to the Morningstar database. Thereby, we are able to identify about 8,000 active and dead equity indexes as of December 2015, which is close to the number of indexes for which we screen press releases.

Table 4.2 presents the distribution of the stocks affected by the events across countries, which Figure 4.1 also illustrates. The 23 stock exchange groups[7] we look at have a total domestic market capitalization of about 62.7 trillion USD as of December 2015, which corresponds to more than 93% of the total worldwide stock market capitalization.[8] The events themselves are also of meaningful importance. For example, for the newly created subset of indexes, the market capitalization of the stocks in the index amounts to about

[7]For example, we assume that NYSE and AMEX represent one exchange group.
[8]Source: World Federation of Exchanges.

Table 4.2: Country distribution of event stocks

Country	**Number of stock inclusions**	**Number of stock deletions**	**Total number of stocks**
Australia	44	13	57
Canada	82	20	102
China	1,633		1,633
France	543	66	609
Germany	439	162	601
Greece	448	66	514
Hong Kong	1,060	13	1,073
India	211		211
Israel	174	27	201
Japan	590	97	687
Netherlands	55	7	62
Poland	229		229
Portugal	20	6	26
Singapore	393	27	420
South Korea	131		131
Spain	122	15	137
Sweden	87	69	156
Switzerland	94	13	107
Taiwan	120	2	122
United Kingdom	633	22	655
United States	1,041	176	1,217
Total	**8,149**	**801**	**8,950**

This table shows the country distribution of stocks affected by exogenous index events from 21 countries from January 1996 to June 2014.

15% of each country's total market capitalization at that point of time. By comparison, at the end of 2015, the market capitalization of the Dow Jones Industrial Average Index amounted to about 21% of the total market capitalization of U.S. firms.[9]

Looking at an international sample of index events entails several advantages. First, most leading equity indexes in the United States exist for very long histories and recently, have experienced hardly any exogenous changes. Second, this study's sample represents a substantial portion of worldwide stock market capitalization. Therefore, it enables meaningful comparison among different economic regions and development stages.

For firm financial data, we rely on the Worldscope database. We stick to Frank and Goyal (2009) for variable definitions. Detailed data on debt structure is from Capital IQ. Analyst forecast data are from I/B/E/S. Finally, stock market data are from Datastream.

[9]Firm-level market capitalization is from the Worldscope database. Country-level stock market capitalization comes from the World Bank database.

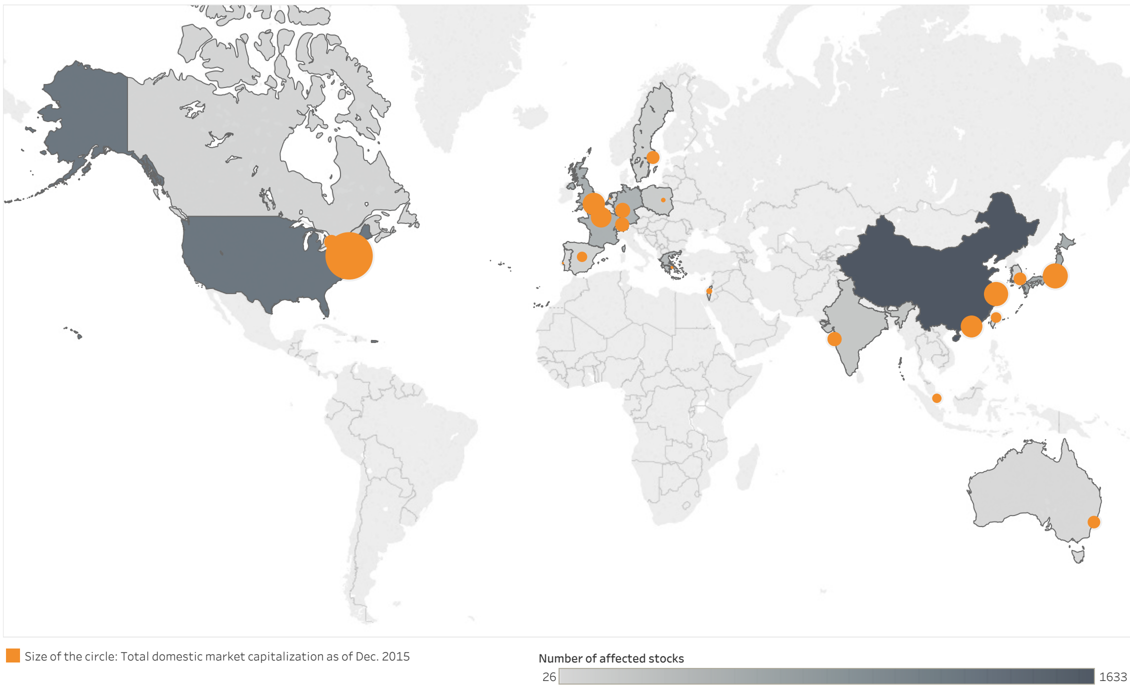

Figure 4.1: International stock exchange coverage and number of affected stocks per country

Appendix D provides more information on definitions and sources of all variables.

4.3.1 Difference-in-differences sample

For the empirical analysis, we first construct a difference-in-differences sample consisting of treatment and control group stocks. We define stocks exogenously added to an index from Table 4.1 as treatment stocks. When performing the propensity score matching, we select control stocks within the same country, industry,[10] and year that have similar size, profitability, tangibility, and market-to-book ratios. The stocks are matched based on all available stocks included in the respective Worldscope country lists, except for the treatment stocks. We then include the nearest neighbor for each treated stock in the control group.

Overall, we match 6,463 treated stocks that have been exogenously added to an index. In the last part of this paper, we look at 700 stocks that have been exogenously deleted from

[10]We apply the ICB super-sector classification (2-digits) as industry definition. The findings hold for the ICB sector (3-digits) and sub-sector (4-digits) classifications as well.

an index. Table 4.3 presents descriptive statistics for the difference-in-differences sample before and after the propensity score matching. As suggested by Imbens and Wooldridge (2009), we look at normalized differences between treatment and control stocks. We consider normalized differences not exceeding one-fourth to be not significantly different from zero. After the matching procedure, differences between treated and control stocks become economically small and are not statistically significant. Regarding profitability and tangibility, however, the normalized differences are close to the threshold of one-fourth. Thus, we apply a regression discontinuity design that compares firms that are close to the index inclusion threshold as well as a Cochran and Rubin (1973) caliper restriction.

Table 4.3: Propensity score matching

Variable	Before matching				After matching			
	Mean (treated)	Mean (unmatched control)	Difference	Normalized difference	Mean (treated)	Mean (matched control)	Difference	Normalized difference
Size	14.14	11.71	2.43	0.31	14.14	13.57	0.57	0.12
Profitability	0.12	0.02	0.10	1.29	0.12	0.11	0.01	0.23
Tangibility	0.31	0.29	0.03	0.24	0.31	0.28	0.03	0.20
Market-to-book ratio	3.31	3.20	0.11	0.00	3.31	3.35	-0.04	-0.01

This table reports descriptive statistics for 6,463 non-financial stocks exogenously added to an index and their nearest neighbor control stocks before and after propensity score matching. The control stocks are from the same country, year, and industry as the treated stocks, and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. The matching basis for control stocks are all stocks in the Worldscope country lists, excluding the stocks in the treatment group. Tis table presents the MEAN of treated and (unmatched and matched) control stocks, the mean DIFFERENCE between treated and control stocks, and the normalized difference in coefficients according to Imbens and Wooldridge (2009). Normalized differences not exceeding one-fourth are considered to be not significantly different from zero.

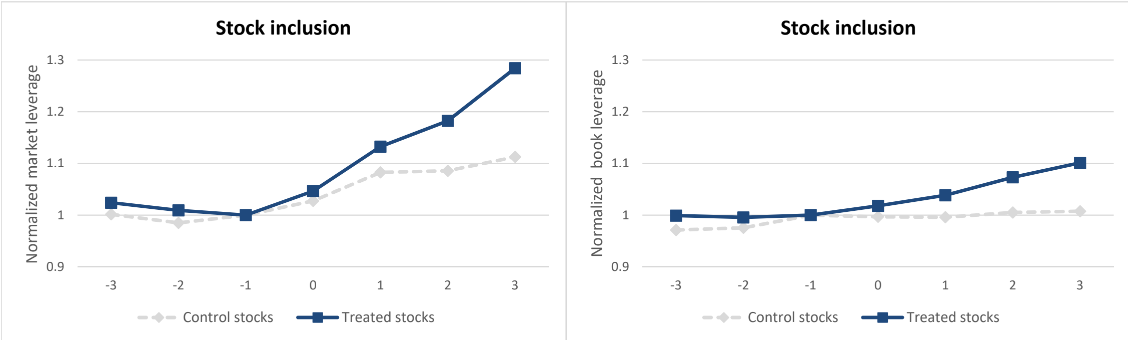

Figure 4.2: Development of mean financial leverage around exogenous index events Index inclusion is during $t = 0$. Values are normalized relative to the value in the year before the event.

Figure 4.2 illustrates the development of mean market leverage and mean book leverage of treatment and control firms around the index events. Year 0 is the fiscal year of the corresponding index event. Leverage is normalized based on year -1. The graphs suggest that treated firms increase both market and book leverage relative to the control firms after index inclusion. In addition, it is important to note that financial leverage in the years before year 0 follows a parallel development for both treated and control firms, indicating that the data sample does not violate the parallel trends assumption.

4.3.2 Regression discontinuity sample

In addition, we apply a regression discontinuity design around index events for which we are able to replicate stock rankings based on the index methodology guidelines published by the index providers. Overall, we are able to retrieve index ranking methodologies for 128 events with 3,150 stock additions.[11] We restrict the sample to index events with available index methodology guidelines, because we can then identify the firms that just have not been included in the index from the eligible firm universe (e.g., all firms in the Datastream Worldscope lists for a given country). Henceforth, these firms will be referred to as the control stocks.

Specifically, we define n as the number of treated stocks per index event ("bandwidth").

[11]Unfortunately, due to the low number of observations, we cannot perform a meaningful regression discontinuity design analysis around stock deletions.

Table 4.4: Descriptive statistics RDD

Variable	N	Mean	SD	25%-percentile	Median	75%-percentile
Market leverage	6,675	0.23	0.22	0.04	0.16	0.36
Book leverage	6,674	0.32	0.24	0.10	0.31	0.50
Size	6,675	13.28	2.00	12.06	13.24	14.53
Profitability	6,483	0.10	0.14	0.06	0.10	0.16
Tangibility	6,636	0.29	0.23	0.10	0.24	0.44
Market-to-book ratio	6,673	3.31	3.97	1.19	2.08	3.76

This table reports descriptive statistics for firms used for the regression discontinuity sample. The sample consists of stocks near the threshold that have *just* been included or not included in an index. This study considers only firms that rank within the full bandwidth around the threshold. The full bandwidth is defined as the number of affected stocks per index event, that is, if an index with a size of 30 is created, 60 stocks will be considered. This table presents the number of observations (N), mean, standard deviation (SD), 25%-percentile, median, and 75%-percentile for the market leverage, book leverage, natural logarithm of the dollar value of total assets (size), profitability, tangibility, and the market-to-book ratio.

For each index event, we further include the n stocks below the index inclusion threshold as the control group. For example, if there is a new index launch with 50 stocks, the "all" bandwidth means that we refer to these 50 stocks as the treated ones, and add the next 50 stocks that have not been included in the index as control stocks to the sample, based on the index ranking methodology. In this regard, a bandwidth of "all" means that the bandwidth is set to the number of all affected stocks for an event. In addition, we perform robustness tests, setting the bandwidth to "1/2," which means that in the above example, we would take only 25 treated and 25 control stocks into account. The advantage of this approach is that we restrict the sample to firms closer to the index inclusion threshold, resulting in a higher degree of exogeneity. However, this procedure reduces the statistical power of the analysis. In this regard, both bandwidths are consistent with prior literature. For example, Boone and White (2015) look at the ± 50 to ± 200 firms around the Russell 1000/2000 threshold, while the corresponding numbers for Crane et al. (2016) are ± 100 to ± 750 firms.

Table 4.4 presents descriptive statistics for the regression discontinuity sample. Overall, mean values for the covariates are close to those that Table 4.3 reports.

4.4 Empirical results

In this section, we first focus on stocks exogenously added to an index. Section 4.4.1 summarizes the difference-in-differences regression results of financial leverage around exogenous index events. Section 4.4.2 presents the results using a regression discontinuity design. Section 4.4.3 examines the robustness of the findings. Section 4.4.4 reports additional results regarding the drivers of the index effects as well as international variation. Section 4.4.5 presents test results for stocks exogenously deleted from an index.

4.4.1 Difference-in-differences results

We apply the following difference-in-differences regression:

$$\begin{aligned} \text{Lev}_{i,t} =& \alpha \cdot \text{Treated}_i \cdot \text{Post}_t + \beta \cdot \text{Post}_t + \vec{\gamma} \cdot \vec{X}_{i,t-1} \\ & + \delta_1 \cdot I_i + \delta_2 \cdot I_t + \delta_3 \cdot I_t \cdot I_j + \delta_4 \cdot I_t \cdot I_k + \epsilon_{i,t}, \end{aligned} \tag{4.1}$$

where $\text{Lev}_{i,t}$ is the market leverage of firm i in year t. Similar to Frank and Goyal (2009), we use market leverage as the main dependent variable, because this measure is more forward looking and takes market expectations into account. In addition, we report results using book leverage in Appendix E. Treated_i equals one if firm i belongs to the treatment group, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Post_t equals one if year $t > 0$, and zero otherwise. Index inclusion is in $t = 0$ so that financial statements at the end of that year might already reflect short-term effects of index inclusion.[12] $\vec{X}_{i,t-1}$ is a vector of control variables, as Frank and Goyal (2009) suggest. The vector includes the most important determinants of financial leverage, that is, FIRM SIZE, PROFITABILITY, TANGIBILITY, and the MARKET-TO-BOOK RATIO. Appendix D summarizes variable definitions. Control variables are lagged by 1 year. I_i, I_j, I_k, and I_t are firm, industry, country, and year fixed effects. $\epsilon_{i,t}$ is the error term.

[12] We perform robustness tests and set Post_t equal to one if year $t \geq 0$, and obtain similar results.

Table 4.5 shows the empirical results. The sample is restricted to firm-year observations in the time windows that the column titles represent. The analysis does not include the event year (0). According to Models 1–3, which do not consider control variables, firms included in an equity index increase market leverage by 1.6–2.2% compared to control firms with similar firm characteristics. These changes become smaller (1.1–1.7%) when we take control variables into account (Models 4–6), but the statistical significance of the difference-in-differences term remains at 1%. If we compare years 2 and 3 with year -1 (Models 7 and 8), the increase of financial leverage becomes even greater in magnitude. Overall, we find that firms included in an equity index increase market leverage by 1–2% compared to the control group.

Table 4.5: Market leverage: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5	6	7	8
Window (years)	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: Market leverage								
Treated x Post	**0.0155*** **	**0.0222*** **	**0.0218*** **	**0.0108** **	**0.0151*** **	**0.0172*** **	**0.0191*** **	**0.0264*** **
	(0.00431)	**(0.00542)**	**(0.00705)**	**(0.00421)**	**(0.00486)**	**(0.00606)**	**(0.00548)**	**(0.00714)**
Post	-0.00181	-0.00513	-0.00908*	-0.00343	-0.00454	-0.00968**	0.000479	-0.0140**
	(0.00420)	(0.00402)	(0.00528)	(0.00405)	(0.00366)	(0.00460)	(0.00440)	(0.00701)
Size				0.0660***	0.0715***	0.0768***	0.0742***	0.0845***
				(0.00687)	(0.00513)	(0.00476)	(0.00662)	(0.00753)
Profitability				-0.207***	-0.236***	-0.261***	-0.318***	-0.314***
				(0.0283)	(0.0234)	(0.0234)	(0.0261)	(0.0423)
Tangibility				0.105***	0.135***	0.152***	0.114***	0.116***
				(0.0232)	(0.0230)	(0.0223)	(0.0263)	(0.0271)
Market-to-book ratio				-0.0029**	-0.0028***	-0.0033***	-0.0030***	-0.0036***
				(0.00121)	(0.000740)	(0.000602)	(0.000940)	(0.00107)
Observations	23,499	39,568	54,800	22,460	38,433	51,439	19,510	16,161
Adjusted R^2	0.897	0.865	0.812	0.910	0.881	0.843	0.898	0.873
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. MARKET LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for stocks added to an index, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. This study matches control stocks from the same country, year, and industry based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

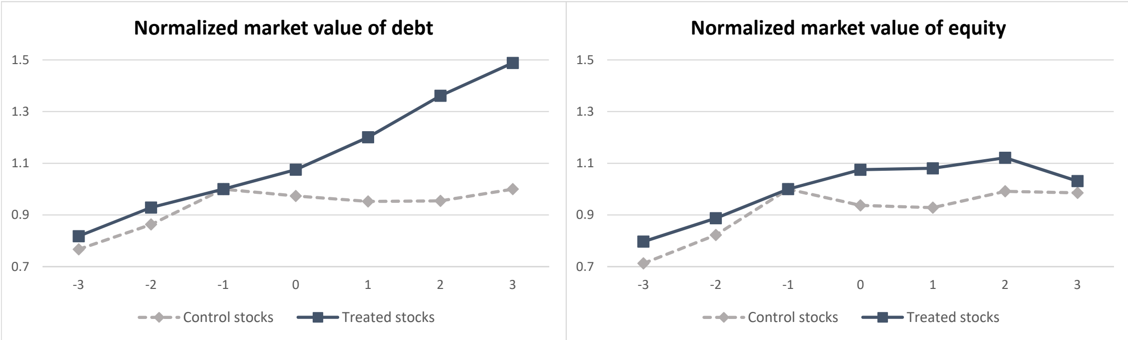

Figure 4.3: Development of median normalized debt and equity values around exogenous index events
Index inclusion is during $t = 0$. Values are normalized relative to the value in the year before the event.

To examine the drivers of the changes in leverage, we look at the development of median total debt and median market value of equity around the index events. We normalize both variables based on their values in year -1 for each firm in the sample. Figure 4.3 displays the results. The graphs suggest a parallel development of debt and equity until the event year (0) for both treatment and control stocks. While there is only a small increase in normalized equity relative to control stocks after the treatment, the debt level of treatment stocks increases much more relative to the control group. Therefore, we conclude that the issuance of new debt drives the increase in market leverage. In the following, we examine the robustness of the results and then shed light on why firms increase leverage after being exogenously added to an index.

4.4.2 Regression discontinuity results

This section reports the results for the regression discontinuity design. The idea behind this approach is to mitigate concerns related to unbalanced treatment and control samples due to the nature of the index assignment procedures that often correlate with different proxies of firm size (e.g., market capitalization). The regression discontinuity model is specified as follows:

$$
\begin{aligned}
\Delta \mathrm{Lev}_{i,t_1,t_2} =& \alpha + \beta \cdot \mathrm{Treated}_i + \vec{\gamma} \cdot \Delta \vec{X}_{i,t_1,t_2} + \sum_{p=1}^{4} \theta_p \cdot D_i^p + \sum_{p=1}^{4} \vartheta_p \cdot D_i^p \cdot \mathrm{Treat}_i \\
&+ \delta_1 \cdot I_j + \delta_2 \cdot I_k + \delta_3 \cdot I_t + \delta_4 \cdot I_t \cdot I_j + \delta_5 \cdot I_t \cdot I_k + \epsilon_{i,t},
\end{aligned}
\tag{4.2}
$$

where $\Delta\mathrm{Lev}_{i,t_1,t_2}$ is the change of market leverage of firm i from year t_1 to year t_2. α is a constant. $\mathrm{Treated}_i$ equals one if firm i belongs to the treatment group, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but rank *just* below the inclusion threshold based on the respective index methodologies. $\Delta\vec{X}_{i,t_1,t_2}$ is a vector of changes in control variables from year t_1 to year t_2. D_i is the assignment variable, defined as the threshold of index inclusion minus the index ranking based on the index methodology. Thus, the cutoff point is defined as the ranking of the lowest ranked firm from the treatment group, that is, $D_i \geq 0$ if firm i belongs to the treatment group, $D_i < 0$ if not. p refers to the order of the polynomial. We employ polynomials of order 1, 2, and 4. I_j, I_k, and I_t are industry, country, and year fixed effects. $\epsilon_{i,t}$ is the error term.

Figure 4.4 shows graphical results. The figure shows a regression discontinuity plot with a linear fit and the corresponding 90% confidence interval. The y-axis represents the change in market leverage from the fiscal year before the index event to the 3rd fiscal year after the event. The x-axis is the distance from the respective index threshold. The greater is the absolute value of the x-axis, the greater is the distance of the stock from the cut-off. Dots on the right-hand side of the cutoff point represent stocks that have been added to indexes, while dots on the left-hand side represent those that have not been included in an index. The dots can be interpreted as the average change in leverage for all observations in the same bin. The bin size is five. One can observe that firms that have just been included in an index increase leverage by about 4% relative to those firms that have not been included in an index. Interestingly, if one goes farther away from the threshold, confidence intervals widen up. This is because the number of observations per bin decreases, as there are few index events that affect a large number of stocks.

Figure 4.4: Regression discontinuity plot around index threshold
The figure shows a regression discontinuity plot with linear fit and the corresponding 90% confidence interval. The bin width is five. The x-axis displays the distance from the respective index thresholds. Positive (negative) values refer to firms that are (not) included in an index. The y-axis shows the mean market leverage change from 1 year before the event to 3 years after the event

Table 4.6 reports regression results of Equation (4.2). The dependent variable is the change in MARKET LEVERAGE over the time windows presented in the column titles. Following Lee and Lemieux (2010), we use different polynomials and bandwidths for robustness. A bandwidth of "all" refers to all affected treatment stocks, while "1/2" refers to half of the number of affected treatment stocks. Overall, the regression results confirm the findings from the difference-in-differences regressions. The results are robust to using different polynomials and bandwidths. With a magnitude of 1–3%, the coefficients for the treatment dummy even suggest a greater impact of equity index membershiop on leverage changes compared to the results based on the difference-in-differences estimator.

Table 4.6: Market leverage: Regression discontinuity design for stock inclusions

Model	1	2	3	2a	2b	3a	3b
Window (years)	1 vs. -1	2 vs. -1	3 vs. -1	2 vs. -1	2 vs. -1	3 vs. -1	3 vs. -1
Polynomial	One	One	One	Four	Two	Four	Two
Bandwidth	All	All	All	All	1/2	All	1/2
Dep. variable: Change in market leverage							
Treated	**0.0122****	**0.0222*****	**0.0285*****	**0.0254****	**0.0295****	**0.0249***	**0.0287****
	(0.00582)	**(0.00694)**	**(0.00822)**	**(0.0125)**	**(0.0120)**	**(0.0152)**	**(0.0143)**
Change in size	0.0957***	0.104***	0.101***	0.104***	0.117***	0.101***	0.122***
	(0.00786)	(0.00765)	(0.00757)	(0.00765)	(0.0109)	(0.00758)	(0.0109)
Change in profitability	-0.291***	-0.364***	-0.357***	-0.364***	-0.328***	-0.357***	-0.332***
	(0.0287)	(0.0335)	(0.0348)	(0.0335)	(0.0444)	(0.0349)	(0.0435)
Change in tangibility	0.190***	0.188***	0.245***	0.188***	0.104***	0.246***	0.209***
	(0.0324)	(0.0294)	(0.0304)	(0.0295)	(0.0363)	(0.0304)	(0.0385)
Change in	-0.00385***	-0.00223**	-0.00355***	-0.00228**	-0.00137	-0.00354***	-0.00145
market-to-book ratio	(0.00118)	(0.00103)	(0.00119)	(0.00104)	(0.00146)	(0.00119)	(0.00154)
Observations	4,340	3,806	3,615	3,806	2,267	3,615	2,147
Adjusted R^2	0.346	0.401	0.361	0.400	0.400	0.360	0.381
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients based on a regression discontinuity design for stock inclusions. The dependent variable is the change in MARKET LEVERAGE over the time windows that the column titles represent. A bandwidth of "all" refers to the number of affected treatment stocks, while "1/2" refers to half of the number of affected treatment stocks. TREATED is a dummy variable set to one for stocks added to an index, and zero otherwise. Control variables are based on first differences for the time windows presented in the column titles. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4.7: RDD robustness: Covariates around the threshold

Window (years)	3 vs. -1	3 vs. -1	3 vs. -1	3 vs. -1
Polynomial	Two	Two	Two	Two
Bandwidth	All	All	All	All
Dep. variable:	Change in SIZE	Change in PROFITABILITY	Change in TANGIBILITY	Change in MARKET-TO-BOOK
Treated	**0.00474**	**-0.00260**	**0.00982**	**0.19283**
	(0.0375)	**(0.01035)**	**(0.00817)**	**(0.25267)**
Observations	3,724	3,616	3,718	3,724
Adjusted R^2	0.171	0.208	0.126	0.224
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes

This table reports regression coefficients based on a regression discontinuity design for stock inclusions. The dependent variables are the control variables from Table 4.6. A bandwidth of "all" refers to the number of affected treatment stocks. TREATED is a dummy variable set to one for stocks added to an index, and zero otherwise. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

To ensure that changes in the covariates do not drive the findings from Table 4.6, we apply the regression discontinuity design to all control variables from Equation (4.2). Table 4.7 reports the regression results for changes from years -1 to 3, second degree polynomials, and a bandwidth that corresponds to all affected treatment stocks. The results confirm that the control variables do not drive the leverage changes around the threshold, since we do not detect statistically significant changes in the covariates around the index events. Unreported regressions using other specifications concerning time windows, polynomials, and bandwidths yield the same conclusion.

Next, we examine whether strategic behavior of index providers drives the results. For example, it could be that index creators are able to distinguish prospective "winner" from "loser" stocks in a certain country or industry and, accordingly, they will set the size of a new or modified index to reflect these expectations. Specifically, an index provider could expect that there will be high investor demand for the 10 largest industrial stocks from Germany (e.g., BMW and Siemens) and, therefore, the index provider will create a new index with these 10 firms. In other words, it could be that underlying unobserved trends explain the results and not index inclusion itself.

Even though the above analysis reveals no violation of the parallel trends assumption and that the covariates are balanced across the treatment and control samples, we perform additional tests to rule out this alternative explanation. To this end, we exploit two aspects of the data set. First, we restrict the data set to index families. For example, some index providers create several related industry indexes at the same time. When these indexes all have the same size, it is less likely that expectations from a single industry drive index size definition.[13] Furthermore, several indexes in this study's data set have constituents selected from the same universe and the same ranking methodology.[14] Second, in many cases, index providers choose round index sizes (e.g., 20, 30, 50, and 100). When doing so, index providers are not always able to perfectly distinguish stocks with good versus bad prospects. For example, there could also be strong demand for only 7 or even 13 large industrial stocks from Germany.

Therefore, we restrict the sample to these index categories. In addition, we apply a smaller bandwidth of only one-third to look at a relatively small number of stocks around the inclusion threshold. Table 4.8 presents the results.[15] Even though the number of observations drops considerably, there is still a positive and highly significant effect of *marginal* index inclusion on leverage in all models. Thus, we conclude that the main result does not stem from strategic index creation by index providers.

[13] Potential examples are, among others, the DJ Titans Const&Materials 30 Index, the DJ Titans Health Care 30 Index, the DJ Titans Oil&Gas 30 index, etc.

[14] For example, the CSI 300 Consumer Staples, CSI 300 Energy index, and CSI 300 Health Care index are, among others, selected from the CSI 300 index.

[15] Difference-in-differences regressions yield similar results.

Table 4.8: RDD robustness: Index threshold manipulation

Model	1a	1b	2a	2b	3a	3b	4a	4b
Window (years)	2 vs. -1	2 vs. -1	2 vs. -1	2 vs. -1	3 vs. -1	3 vs. -1	3 vs. -1	3 vs. -1
Polynomial	One	One	Two	Two	One	One	Two	Two
Bandwidth	1/2	1/3	1/2	1/3	1/2	1/3	1/2	1/3
Dep. variable: Change in market leverage								
Treated	**0.0284****	**0.0379*****	**0.0313****	**0.0394****	**0.0274*****	**0.0405*****	**0.0295****	**0.0342****
	(0.0121)	**(0.0146)**	**(0.0145)**	**(0.0190)**	**(0.00980)**	**(0.0140)**	**(0.0123)**	**(0.0169)**
Change in size	0.119***	0.118***	0.119***	0.118***	0.104***	0.131***	0.104***	0.132***
	(0.0124)	(0.0157)	(0.0124)	(0.0156)	(0.00961)	(0.0130)	(0.00963)	(0.0130)
Change in profitability	-0.417***	-0.465***	-0.417***	-0.469***	-0.378***	-0.385***	-0.377***	-0.389***
	(0.0720)	(0.0945)	(0.0712)	(0.0933)	(0.0473)	(0.0600)	(0.0472)	(0.0597)
Change in tangibility	0.0915**	0.0400	0.0905**	0.0366	0.243***	0.212***	0.243***	0.210***
	(0.0433)	(0.0443)	(0.0431)	(0.0444)	(0.0387)	(0.0463)	(0.0387)	(0.0459)
Change in	-0.00283	-0.00322	-0.00290	-0.00339	-0.0055***	-0.00415**	-0.0054***	-0.00416**
market-to-book ratio	(0.00219)	(0.00226)	(0.00217)	(0.00226)	(0.00158)	(0.00208)	(0.00158)	(0.00207)
Observations	1,531	980	1,531	980	2,597	1,480	2,597	1,480
Adjusted R^2	0.435	0.494	0.435	0.494	0.354	0.406	0.354	0.406
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Country FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes
Year x Country FE	yes	yes	yes	yes	yes	yes	yes	yes
Year x Industry FE	yes	yes	yes	yes	yes	yes	yes	yes

This table reports regression coefficients based on a regression discontinuity design for stock inclusion. The dependent variable is the change in MARKET LEVERAGE over the time windows presented in the column titles. A bandwidth of “1/2” refers to half the number of affected treatment stocks, while “1/3” refers to one-third of the number of affected treatment stocks. TREATED is a dummy variable set to one for stocks added to an index, and zero otherwise. Control variables are based on first differences for the time windows presented in the column titles. Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4.3 Additional robustness tests

This section performs additional robustness tests. In addition to market leverage, we run all regressions in this paper with book leverage as the dependent variable. Appendix E presents the results. The main result remains robust.

As a result of the ranking methodologies of many indexes, which are often based on market capitalization or free float, firms included in an index are often larger than firms that are not. In addition, the normalized differences of profitability and tangibility in Table 4.3 are close to the rule of thumb, as Imbens and Wooldridge (2009) describe. Therefore, in addition to the regression discontinuity analysis, we employ different calipers to the propensity score matching procedure to reduce potential matching bias (Cochran and Rubin, 1973). Following this approach, we consider observations only if the difference between propensity scores of treated and control firms is smaller than the caliper. Appendix F presents a tight matching result that reduces more than 99% of matching bias Cochran and Rubin (e.g., 1973). Overall, we are able to match 3,815 treated stocks that are added to an index to control stocks. After the matching, mean differences between treated and untreated stocks become very close to zero, and absolute values for the normalized differences are close to zero. Appendix G presents corresponding regression results. The findings of this study regarding changes in market leverage remain the same. In addition, in unreported tests, we also apply a variety of different calipers and all results remain unchanged.

Moreover, we conduct placebo tests to examine the validity of the parallel trends assumption. Appendix H presents test results for the treatment and control firms from Table 4.5. In contrast to before, however, we now look at different time windows around year -7 so that there is no overlap with the time window from the main analysis. For most time windows, there are no significant differences between treatment and control firms. The only statistically significant coefficient for TREATED X POST in Model 1 even exhibits a negative sign, which is opposite to this study's main findings. Overall, the results in Appendix H suggest a parallel trend of treatment and control firms before the main event time window.

Furthermore, the findings remain unchanged when we exclude the first type of events (launch), which includes most observations in the sample. Sub-sample tests, excluding countries with the most observations, such as the U.S. or China, provide robust results as well. In addition, we vary the number of control stocks per treatment stock (up to five control stocks per treated stock) and obtain very similar regression results. The results of this study are robust to different industry classification methodologies (up to ICB 4-digits). All results are available upon request.

4.4.4 Channel

In this section, we show that changes in investor awareness and production of information drive the changes in financial leverage. Unfortunately, one can measure investor awareness only indirectly. Following Chen et al. (2004), Irani and Oesch (2013), and Chen et al. (2015), we use two different variables to approximate investor awareness: the number of following analysts and stock liquidity costs. The first variable signals the level of information production and monitoring of a stock by analysts. The second variable is the result of market reactions to changes in information availability, for example, reports generated by analysts. An increase in information availability reduces the cost of acquiring information, lowers adverse selection costs, increases familiarity to investors, and therefore, reduces liquidity costs.

Analysts

First, we apply the same difference-in-differences estimator, but employ the number of following analysts as the dependent variable, defined as the natural logarithm of the number of analysts following a stock. Table 4.9 presents the results. We find that the number of analysts who follow treatment stocks increases relative to control stocks after index inclusion. Compared to their control group, about 10% more analysts follow stocks that have exogenously been included in an index.[16] This result is consistent with the view that index

[16]This result is in line with Denis et al. (2003), Barber and Odean (2008), and Hirshleifer et al. (2009).

Table 4.9: Analyst following: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5
Window (years)	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: Analysts					
Treated x Post	**0.0723*** **	**0.107*** **	**0.137*** **	**0.0999*** **	**0.0621**
	(0.0261)	**(0.0270)**	**(0.0308)**	**(0.0342)**	**(0.0393)**
Post	-0.0550**	-0.0500**	-0.103***	-0.0556*	0.00142
	(0.0249)	(0.0227)	(0.0248)	(0.0289)	(0.0339)
Size	0.356***	0.384***	0.398***	0.372***	0.389***
	(0.0357)	(0.0270)	(0.0229)	(0.0355)	(0.0377)
Profitability	0.746***	0.701***	0.617***	0.943***	1.111***
	(0.155)	(0.110)	(0.102)	(0.167)	(0.184)
Tangibility	0.224	0.239**	0.179*	0.199	0.127
	(0.138)	(0.108)	(0.0957)	(0.146)	(0.149)
Market-to-book ratio	0.00423	0.0106**	0.0159***	0.0136**	0.0168***
	(0.00575)	(0.00486)	(0.00383)	(0.00591)	(0.00613)
Observations	15,594	27,298	36,232	13,818	11,434
Adjusted R^2	0.895	0.872	0.852	0.881	0.874
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. The dependent variable is ANALYSTS, defined as the natural logarithm of the number of analysts following a stock, collected from the I/B/E/S database. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

inclusion increases investor attention and reduces adverse selection cost through greater analyst coverage, resulting in greater debt supply. This, in turn, results in increases in leverage.

Liquidity cost

Next, we look at a firm's liquidity cost. According to the information cost hypothesis by Shleifer (1986), Wooldrige and Ghosh (1986), and Edmister et al. (1996), index inclusion increases information availability, and, hence, reduces information-acquiring costs. This further reduces adverse selection costs and, in turn, improves stock liquidity. In this regard, Hegde and McDermott (2003) and Chen et al. (2004) find that liquidity costs decrease after inclusion in the S&P 500 index; the authors argue that their findings are driven by increasing information availability and greater investor awareness.

If greater investor awareness were to reduce adverse selection costs, we would expect that firms might benefit from improved stock liquidity after exogenous index inclusion. Table 4.10 presents difference-in-differences results for stock liquidity costs. The dependent variable, LIQUIDITY COSTS, is defined as the average daily relative bid–ask spread (bid–ask spread divided by mid-price) in a given fiscal year. Following the literature on liquidity costs (e.g., Copeland and Galai, 1983; Stoll, 2000; Pastor and Stambaugh, 2003; Chordia et al., 2009), we include MARKET CAPITALIZATION, TRADING VOLUME, RETURN, and RETURN VOLATILITY as control variables. Appendix D summarizes the variable definitions. Consistent with the notion that index membership increases investor awareness and reduces information costs (e.g., Wooldrige and Ghosh, 1986; Edmister et al., 1996; Chen et al., 2004), we find lower relative bid–ask spreads once a firm is exogenously added to an index. For example, the table suggests that bid–ask spreads decrease by about 18 basis points in the year after the index inclusion (Model 1).

Table 4.10: Liquidity costs: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5
Window (years)	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: Liquidity costs					
Treated x Post	**-0.0450*****	**-0.0477*****	**-0.0509****	**-0.0603*****	**-0.0512****
	(0.0163)	**(0.0178)**	**(0.0224)**	**(0.0193)**	**(0.0228)**
Post	0.0435***	0.0374***	0.0499***	0.0421***	0.0604***
	(0.0133)	(0.0125)	(0.0147)	(0.0143)	(0.0174)
Market capitalization	-0.315***	-0.323***	-0.318***	-0.341***	-0.350***
	(0.0173)	(0.0167)	(0.0179)	(0.0181)	(0.0210)
Trading volume	-0.225***	-0.218***	-0.218***	-0.212***	-0.214***
	(0.0127)	(0.0108)	(0.0125)	(0.0147)	(0.0179)
Return	0.187***	0.175***	0.160***	0.216***	0.218***
	(0.0182)	(0.0135)	(0.0135)	(0.0178)	(0.0213)
Return volatility	0.973***	1.275***	0.923***	1.080***	0.814***
	(0.181)	(0.121)	(0.132)	(0.149)	(0.234)
Observations	17,978	31,330	42,338	15,750	13,061
Adjusted R^2	0.966	0.959	0.950	0.966	0.967
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. The dependent variable is LIQUIDITY COSTS, defined as the natural logarithm of the average relative bid–ask spreads in basis points in a fiscal year. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm years after a change in index membership. MARKET CAPITALIZATION is defined as the natural logarithm of market capitalization in million USD at fiscal year-end; TRADING VOLUME as the natural logarithm of the total number of shares traded in the fiscal year; RETURN as the cumulative stock return in basis points in the fiscal year; and RETURN VOLATILITY as the standard deviation of monthly returns in the fiscal year, in basis points. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Public and private debt

If the increase in leverage is due to increasing debt supply caused by increasing investor awareness, one might expect that increasing public debt supply primarily drives the change, because private debt suppliers, such as banks, have their own monitoring channels, and do not primary rely on analyst reports and public information. Hence, in Table 4.11, we further examine whether increases in public or private debt cause increases in leverage due to exogenous additions to stock indexes. If increased investor attention were to cause higher leverage, we would expect that firms primarily would increase their public debt ratio, while private debt would remain unchanged. To check this, we perform separate difference-in-differences regressions for public and private debt ratios. Public debt is defined as the ratio of public debt to the market value of total assets, while private debt is the ratio of private debt to the market value of total assets. In line with this study's hypothesis, Table 4.11 shows that firms increase their public debt ratio around exogenous index inclusions, while the private debt ratio stays constant.[17]

[17] In untabulated regression, we also find that the result holds when one deflates public debt by total debt and not the market value of assets.

Table 4.11: Debt structure: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5	6
Window (years)	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]
Dep. variable:	Public debt ratio			Private debt ratio		
Treated x Post	**0.0140*** **	**0.0125*** **	**0.00973** **	**-0.00275**	**0.00279**	**0.00125**
	(0.00415)	**(0.00458)**	**(0.00485)**	**(0.00636)**	**(0.00592)**	**(0.00716)**
Post	-0.008***	-0.010***	-0.00731*	9.01e-05	0.00169	-0.00112
	(0.00295)	(0.00344)	(0.00384)	(0.00508)	(0.00458)	(0.00531)
Observations	21,277	39,105	56,260	21,277	39,105	56,260
Adjusted R^2	0.813	0.764	0.744	0.864	0.828	0.798
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. PUBLIC DEBT LEVERAGE and PRIVATE DEBT LEVERAGE are the dependent variables, defined as the ratios of public debt or private debt to the market value of total assets. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Public debt financing

This section examines why firms increase their public debt ratios. For this, we test whether the cost of public debt decreases following exogenous equity index membership. We rely on two sources for bond-related data. First, we search the Capital IQ database for all bonds that can comprise the sample firms. For the matching, we rely on firm-level identifiers (e.g., ISINs) as well as a final manual screening based on bond and firm names. In total, we identify more than 24,000 bonds for which we obtain information on their notional values from Capital IQ. Furthermore, we calculate equal-weighted coupon rates and average coupon rates based on the notional values of the outstanding bonds.

Second, for the 24,000 bonds, we download daily closing prices from Bloomberg. Using these data, we calculate four liquidity measures:

1. **Roll**: Roll (1984) approximates the bid–ask spread based on $2\sqrt{-cov(R_t, R_{t-1})}$, where R_t and R_{t-1} denote daily consecutive returns. The measure is missing if the covariance is positive (Dick-Nielsen et al., 2012). The measure is calculated daily for rolling 21-trading day windows. Then, the median observation for a given financial year form the basis for annual values.

2. **Roll_Zero**: Following Schestag et al. (2016), we alternatively calculate the Roll (1984) measure where we set positive covariance to zero.

3. **FHT**: Proxy for bid–ask spreads, as defined by Fong et al. (2017); calculated as $2\sigma N^{-1}(\frac{1+Zero\_Ret}{2})$. σ is a bond's standard deviation of daily returns in a financial year and N^{-1} is the inverse function of the cumulative normal distribution.

4. **Zero_Ret**: Fraction of zero returns relative to the number of trading days in a financial year, as defined by Schestag et al. (2016).

Table 4.12 provides the results. In the first two models of the table, which is based on firm-year observations, firms that are exogenously added to an index experience a decrease in their average coupons by about 0.13%, which corresponds to about 2.1% of the average coupon payment (6.05%).

Table 4.12: Public debt financing

Model	1	2	3	4	5	6
Window (years)			[-3,3]			
Dep. variable:	Coupon	Coupon (weighted)	Roll	Roll_Zero	FHT	Zero_Ret
Treated x Post	**-0.137*** **	**-0.134** **	**-0.0475** **	**-0.0462** **	**-0.0710** **	**-0.0423** **
	(0.0520)	**(0.0563)**	**(0.0211)**	**(0.0185)**	**(0.0340)**	**(0.0193)**
Post	0.126**	0.153***	0.0802	0.0326	0.0135	-0.000222
	(0.0497)	(0.0575)	(0.0549)	(0.0422)	(0.0891)	(0.0438)
Size	-0.0966	-0.114	0.0159*	0.0222**	0.00930	0.00303
	(0.0621)	(0.0695)	(0.00872)	(0.00991)	(0.00876)	(0.00472)
Profitability	0.258	0.325	-0.0572	-0.0563*	-0.0456	-0.0634
	(0.270)	(0.289)	(0.0539)	(0.0341)	(0.0930)	(0.0700)
Tangibility	-0.494	-0.578*	0.0822***	0.0620**	0.107***	0.0157
	(0.324)	(0.341)	(0.0260)	(0.0291)	(0.0403)	(0.0188)
Market-to-book ratio	-0.0152*	-0.0142	0.00127**	0.00136*	0.000686	0.000247
	(0.00871)	(0.00934)	(0.000608)	(0.000705)	(0.000678)	(0.000397)
Book leverage	0.380*	0.428*	-0.0553	-0.0273	-0.114	-0.101**
	(0.222)	(0.231)	(0.0421)	(0.0261)	(0.0724)	(0.0509)
Bonds Outstanding	-0.232***	-0.290***				
	(0.0625)	(0.0683)				
Observations	4,677	4,677	30,408	31,590	34,338	52,861
Adjusted R^2	0.630	0.623	0.120	0.091	0.100	0.100
Firm FE	yes	yes	no	no	no	no
Bond FE	no	no	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Year x Country FE	yes	yes	yes	yes	yes	yes
Year x Industry FE	yes	yes	yes	yes	yes	yes

This table reports coefficients from difference-in-differences regressions. The dependent variables that the column titles represent are different measures of coupon rates and bond liquidity. See Section 4.4 for more information. Models 1 and 2 are based on firm-year observations, while all other models are at the bond-year level. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks (bonds) experience exogenous index inclusion, while control stocks (bonds) do not experience an index change but have similar firm characteristics. Control stocks (bonds) are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. For the bond-level sample, we match along coupon rates and the notional amounts. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Model 3 to 6 are based on bond-year level observations. When performing the matching of treatment bonds to control bonds, we also match along the coupon rate and the notional amount. All models also include bond fixed effects. In the model, both Roll (1984) measures, the FHT measure, and the fraction of zero returns (Zero_Ret) decrease by about 25% for the treatment bonds. The result is consistent with the view that equity index membership improves bond liquidity, resulting in lower cost of public debt, which improves, in turn, a firm's access to debt.

International variation

In this section, we examine whether institutional differences moderate the effect of index membership on capital structure. We expect that the better is the information environment in a country, the less pronounced is the effect of equity index membership on capital structure. Stronger disclosure requirements and better accounting standards reduce public bond investors' information acquisition cost, resulting in lower adverse selection cost and, hence, enabling firms to borrow more. Therefore, information production through equity index membership is less important. In addition, we conjecture that more developed stock markets strengthen the effect of equity index membership on debt levels. Investor awareness is higher in more developed capital markets, resulting in greater production of information that is also available to debt investors, amplifying the consequences of equity index membership. Empirically, we look at a country's disclosure requirements (La Porta et al., 2006), the quality of accounting statements (La Porta et al., 1998), and the size of its stock market. In all models, we control for two classical measures of investor protection, namely, the protection of minority shareholders (La Porta et al., 2008) and the protection of creditors (Djankov et al., 2007). Appendix D presents all definitions.

Table 4.13 presents the regression results. In Models 1 and 2, firms increase leverage less when the information environment in a country is better, as the negative and significant coefficients for the three-way interactions based on DISCLOSURE and ACCOUNTING suggest. In addition, we find that in more developed stock markets, firms increase leverage more after they are added to an index, possibly owing to greater investor awareness. Finally, the protection of minority investors (ADRI) and creditors (CR) does not moderate the index membership effect. Overall, the result is consistent with the view that the index effect is less (more) pronounced in countries with better information availability (more developed equity markets). The findings suggest that index additions reduce the cost of financing and increase the supply of capital.

Table 4.13: Market leverage: International variation in the index effect

Model	1	2	3	4	5	6
Window (years)			[-2,2]			
Dep. variable:			Market leverage			
Treated x Post	0.0704**	0.245***	0.00502	0.0472	0.168***	5.95e-05
	(0.0246)	(0.0367)	(0.0140)	(0.0351)	(0.0488)	(0.0125)
Post	-0.0352	-0.230***	-0.0103	-0.0388	-0.174***	-0.0119
	(0.0241)	(0.0498)	(0.0147)	(0.0273)	(0.0537)	(0.0136)
Post x Disclosure	0.0142			0.0229		
	(0.0239)			(0.0344)		
Treated x Post x Disclosure	**-0.0654***			**-0.0490***		
	(0.0159)			**(0.0232)**		
Post x Accounting		0.00389***			0.00324**	
		(0.00107)			(0.00113)	
Treated x Post x Accounting		**-0.0039***			**-0.0029***	
		(0.000774)			**(0.000826)**	
Post x CR			0.0113*			0.00908
			(0.00593)			(0.00594)
Treated x Post x CR			**-0.00760**			**-0.00630**
			(0.00649)			**(0.00598)**
Post x ADRI	0.00276	-0.00275	-0.00568*	0.00303	-0.00560	-0.00428
	(0.00721)	(0.00516)	(0.00298)	(0.00596)	(0.00717)	(0.00321)
Treated x Post x ADRI	**-0.00248**	**0.00146**	**0.00520***	**-0.00147**	**0.00291**	**0.00548***
	(0.00704)	**(0.00625)**	**(0.00287)**	**(0.00648)**	**(0.00677)**	**(0.00282)**
Market Cap to GDP	-0.000212	-0.0611***	-0.00376	-0.00587	-0.0621***	-0.00656
	(0.00455)	(0.0201)	(0.00893)	(0.00585)	(0.0180)	(0.00636)
Treated x Market Cap to GDP	-0.00152	-0.00926	0.00315	0.00219	-0.00210	0.00389
	(0.00292)	(0.0129)	(0.00455)	(0.00299)	(0.0123)	(0.00287)
Post x Market Cap to GDP	0.00143	-0.0342*	-0.000551	-0.00148	-0.0347**	-0.00249
	(0.00118)	(0.0171)	(0.00206)	(0.00149)	(0.0159)	(0.00161)
Treated x Post x Market Cap to GDP	**0.00484***	**0.0292**	**0.00404***	**0.00656***	**0.0283**	**0.00516***
	(0.00156)	**(0.0126)**	**(0.00213)**	**(0.00130)**	**(0.0103)**	**(0.00179)**
Observations	26,880	21,670	36,928	26,864	21,654	36,912
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	No	No	No	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. MARKET LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by country are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4.5 Stock deletions

Due to a low number of observations, we can draw only limited causal inference from tests based on stocks that are exogenously deleted from an index. Nevertheless, Table 4.14 presents difference-in-differences regression results for stock deletions based on Equation (4.1). As described in Section 4.3, we match treatment firms to comparable control stocks from the same country, year, and industry, and then match them based on a propensity score using firm size, profitability, tangibility, and the market-to-book ratio. Most regression results for stocks deleted from an index or included in a discontinued index are statistically not different from zero, although all difference-in-differences coefficients show the expected negative sign.

This asymmetric result is consistent with existing literature about equity index effects on stock prices, trading volumes, and liquidity costs (e.g., Harris and Gurel, 1986; Hegde and McDermott, 2003; Chen et al., 2004). This literature does not find significant or weak index effects for index deletions. For example, Chen et al. (2004) argue that asymmetric index effects stem from investor awareness, that is, one would not become suddenly "unaware" about certain stocks just because they are deleted from an index. Therefore, one can find only weak, if any, index effects on stocks deleted from equity indexes.

Table 4.14: Market leverage: Difference-in-differences regressions for stocks exogenously deleted from an index

Model	1	2	3	4	5	6	7	8
Window (years)	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: market leverage								
Treated x Post	**-0.00291**	**0.00674**	**-0.00126**	**-0.00505**	**-0.00195**	**-0.00435**	**-0.00883**	**-0.0234***
	(0.00822)	**(0.00950)**	**(0.0105)**	**(0.00790)**	**(0.00839)**	**(0.00951)**	**(0.00948)**	**(0.0125)**
Post	-0.0271*	-0.0157	0.0145	-0.0143	-0.0101	0.0187	0.0153	0.00165
	(0.0157)	(0.0205)	(0.0201)	(0.0194)	(0.0204)	(0.0182)	(0.0392)	(0.0595)
Size				0.0860***	0.0810***	0.0705***	0.0793***	0.0695***
				(0.0252)	(0.0185)	(0.0112)	(0.0206)	(0.0223)
Profitability				0.0223	-0.120**	-0.210***	-0.418***	-0.357***
				(0.0941)	(0.0477)	(0.0321)	(0.0645)	(0.0917)
Tangibility				0.213**	0.124***	0.225***	0.117*	0.0101
				(0.0858)	(0.0481)	(0.0542)	(0.0664)	(0.0894)
Market-to-book ratio				-0.000438	-0.00208	-0.00210	-0.00240	-0.00687*
				(0.00185)	(0.00156)	(0.00146)	(0.00178)	(0.00410)
Observations	2,448	4,423	6,891	2,349	4,316	6,531	2,177	2,019
Adjusted R^2	0.937	0.912	0.881	0.949	0.924	0.896	0.935	0.915
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions. MARKET LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window that the column titles represent. The analysis does not include the event year (0). TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index deletion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry; and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.5 Conclusion

This paper examines the effects of index membership on debt policy and thereby, sheds light on spillover effects of equity markets on debt markets. Specifically, we argue that exogenous addition to an index expands a firm's investor base, because improved monitoring by analysts and institutional shareholders increases production of information, which is also available to potential investors in a firm's debt securities. This lowers the cost of debt and allows firms to borrow more, resulting in higher leverage.

For identification, we rely on exogenous shocks to equity index membership as a result of the formation of new equity indexes or discontinuation of an existing index, increases or decreases in the number of index constituents, or changes in index selection criteria. The intuition behind this approach is that, in contrast to regular index updates, firms cannot influence index membership, in particular because of the suddenness of the events.[18] To identify exogenous shocks in index membership, we manually screen more than 54,000 press releases related to 7,356 equity indexes from 32 major index providers across 21 countries. Thereby, we arrive at more than 200 exogenous index events from January 1996 to June 2014 that have no relationship to firm characteristics. These index events affect about 8,000 (treatment) stocks.

Based on a difference-in-differences estimator, we find that exogenous addition to an index results in an increase in leverage by about 2 percentage points. The results are robust across several empirical specifications, such as placebo tests and applying a regression discontinuity design.

Furthermore, this study sheds light on the underlying mechanisms. Around the exogenous addition to an index, we find that the number of analysts following a firm increases relative to control stocks, which is consistent with the notion that index membership increases investor awareness and reduces information costs. In addition, increases in leverage around the index events mainly stem from increases in the public debt ratio and not the private

[18] For example, in this study's data set, index changes, formations, or discontinuations are announced on average 44 days (median: 23 days) before the index event, while the announcement of the exact stocks that the event affects are 25 days later (median: 1 day).

debt ratio. This is in line with greater access to public debt as a result of lower monitoring cost for public investors, who generally face higher monitoring costs than private lenders. Furthermore, borrowing costs in public debt markets decrease, while bond liquidity increases. Finally, we exploit the internationality of the data set to show that the effect is less pronounced in countries with stronger disclosure requirements. Overall, the findings suggest that index additions reduce the cost of financing and increase the supply of capital. Furthermore, the results suggest that the institutional environment affects corporate financing decisions.

This study has three important implications. First, it shows that equity markets influence public debt markets. Second, it highlights the importance of equity index membership on debt financing. Firms might want to pursue active policies to become members of equity indexes when they want to increase their financial leverage. Third, better access to debt as a result of index membership might provide firms with a competitive advantage. In this regard, sufficiently successful firms included in an index might be awarded additional benefits through their index membership, thereby leaving less successful firms even more behind. This is particularly relevant in times of ETF markets, which are ever more important. For example, global ETF markets experienced steady growth in the last decade, and their total assets under management reached almost 3 trillion USD in 2015.[19] Against this background, regulators should critically examine the role of indexes that goes well beyond "pure" relevance for investors.

[19]Source: ETF Annual Review & Outlook, 21 January 2016, Deutsche Bank Market Research.

5 Conclusion

In the last decade, the exchange traded fund (ETF) market has celebrated one record of total asset under management after another. At the same time, performance pressure relative to benchmark indexes is forcing many actively managed funds to follow an indexing strategy (cf. Cremers et al., 2016). Consequently, index constituents benefit from their index membership with respect to lower liquidity costs and higher analyst coverage. The abovementioned capital market developments motivate this dissertation, which aims to contribute to a better understanding of interdependency between capital market operations and activities of market participants. It consists of three studies that focus on three specific, yet related, research questions. The first study, which Chapter 2 presents, examines the relationship between overall stock market liquidity and liquidity-motivated trading from open-ended equity funds. The second study, which Chapter 3 presents, assesses the liquidity effects associated with index revisions. Finally, the third study, which Chapter 4 presents, analyzes the index effect on firms' capital structure.

5.1 Main results

5.1.1 Do mutual funds improve stock market liquidity and ETFs harm it?

Edelen (1999) finds evidence of liquidity services offered by actively managed equity funds to their customers, and links funds' cash flows to liquidity-driven trading. Since then, some studies have provided additional evidence on liquidity-motivated trading from mutual funds induced by funds' cash flows, and liquidity preferences from mutual funds (e.g., Clarke et al., 2007; Coval and Stafford, 2007; Shawky and Tian, 2011). In addition, physically replicating ETFs have to react to funds' cash flows to keep the tracking error low. However, researchers know little about the impact from open-ended funds' liquidity-motivated trading behavior on overall stock market liquidity.

The first study in this dissertation assesses the impacts of liquidity-motivated trading from open-ended equity funds on stock market liquidity in Germany. To do so, I use daily net cash flows as a proxy for liquidity-motivated trading volumes for all open-ended equity funds with focus on the German stock market. Using the Xetra Liquidity Measure (XLM) for order volume of 100,000 euros, I then regresses aggregated stock market liquidity costs of four major stock indexes (DAX, MDAX, SDAX, and TecDAX) on aggregated absolute value of funds' net cash flows and established market liquidity factors, such as market capitalization, trading volume, return, and return volatility. The observation time period starts on July 1, 2002 and ends on December 31, 2014.

As result, I find liquidity-motivated trading by actively managed mutual funds indeed positively affects overall stock market liquidity. This finding has a significant economic interpretation, as well. A one standard deviation increase of aggregated (absolute values of) net cash flows decreases the round-trip liquidity costs for an order volume of 100,000 euros by 2% on average, which corresponds to 0.5, 5, 8, and 45 basis points for the DAX, MDAX, TechDax, and SDAX, respectively. Meanwhile, I find no significant impacts from ETFs' net cash flows on overall stock market liquidity. This is not surprising considering the creation/redemption and other trading mechanism of ETFs. The results are persistent over time. Interestingly, I find the strongest effects from liquidity-motivated trading by actively managed equity mutual funds on overall stock market liquidity when it is most needed, that is, during the recent financial crisis. This underpins the importance of liquidity services provided by actively managed mutual funds.

Based on the assumption that there is a positive correlation between liquidity timing ability of a fund manager and her or his ability to process fundamental information, I hypothesize that fund managers with higher information-processing abilities can better time market liquidity, and therefore, contribute more to overall stock market liquidity given their liquidity preferences (buy relatively illiquid and sell liquid stocks). To test this hypothesis, I use two variables approximating the information-processing ability of fund managers. First, I sort all actively managed mutual funds in the sample into two groups by their yearly average information ratios, that is, upper 50% and lower 50%, and adjust the groups every year. I find the liquidity contribution by actively managed mutual funds is mainly driven by funds with higher information ratios. The results are confirmed when using the alpha (abnormal return) from the Carhart (1997) four-factor model instead of information ratio. Test results using both proxies suggest that fund managers that can better process information drive mutual funds' positive liquidity contribution.

5.1.2 Liquidity effects associated with revisions of German Prime Standard indexes

Benchmark indexes have gained high importance in worldwide capital markets. According to Cremers et al. (2016), almost half of worldwide equity funds by assets under management either follow a "direct indexing" strategy[1] or a "closet indexing" strategy.[2] It is commonly agreed that the so-called "index effect" exists—that is, stocks added to a benchmark index experience abnormal returns and trading volumes in the aftermath of their index events. However, there are many different hypotheses to explain the cause of the index effect. According to one of these, the information costs/liquidity hypothesis, an addition to a benchmark index reduces costs for information acquisition, and thereby, increases stock liquidity. As a result, the affected stocks experience an immediate price and trading volume increase (cf. e.g., Schleifer, 1986; Wooldrige and Ghosh, 1986; Edmister et al., 1996). Evidence supporting the liquidity hypothesis mostly focuses on the U.S. market, especially investigating the S&P 500 (e.g., Erwin and Miller, 1998; Hegde and McDermott, 2003; Chen et al., 2004). Given that most existing studies do not address potential endogeneity issues, such as firms' own development trends, these studies might

[1]An example is ETFs.

[2]These involve funds that have less than a 60% actively managed share in their portfolios.

overestimate the index effect.

In the second study, I apply a difference-in-differences event study design comparing stocks that experienced an index change with stocks that could have experienced an index change but remained in their index in the end. I consider all index changes among the DAX, MDAX, and SDAX from July 2002 to December 2014, and find 117 index events in total, that is, 117 stocks that have moved within these three indexes. Based on the index selection rules of Deutsche Börse AG, I find 931 control group stocks that could have had to change index membership during the sample period, but ultimately did not.

I find significant positive liquidity effects for stocks that moved to a "higher" level index, that is, from the MDAX to the DAX, or from the SDAX to the MDAX. Compared to their control group stocks, an upgrade to a higher-level index reduces stock liquidity costs by 17–18% on average. This corresponds to 3–6 basis points for stocks upgraded from the MDAX to the DAX, and even 15–29 basis points for stocks upgraded from the SDAX to the MDAX. In addition, the magnitude of liquidity effects is independent of order volume classes. Meanwhile, the liquidity costs increase for downgraded stocks is low and statistically not significant, compared to their control group stocks.

These asymmetric findings are in line with past studies that focus on the U.S. market. Existing literature explains the asymmetry among others with investor awareness. While investors become increasingly aware about stocks upgraded into higher-level indexes, they cannot suddenly become "unaware" about certain stocks that have been downgraded into lower level indexes. Given that investor awareness is difficult to measure, I assume investor awareness increases when company information availability improves, and test for changes of company information availability around index revisions. Using analyst coverage as the measure, I find statistically significant changes in the number of analysts covering stocks that experienced an index revision, compared to their control stocks. Changes in analyst coverage explain about 10% of the liquidity effects. In addition, I conduct the same analysis with news coverage measured by the number of news articles as a proxy for information availability. Unfortunately, I am unable to find significant effects owing to the noisy data nature around index revisions. More sophisticated news filtering might help future research.

5.1.3 Index membership and capital structure

Besides direct index effects, such as price, trading volume, and liquidity effects, index membership has implications for firms' corporate finance. As shown in the second study, equity index membership reduces liquidity costs of the stock, and therefore, lowers firms' costs of equity. At the same time, firms added to an equity index obtain easier access to debt markets. Several reasons are behind this. First, index member firms have higher analyst coverage (cf. the second study), which means there is more information available about these firms. Second, firms that belong to an index usually have more institutional shareholders, both ETFs and actively managed funds, which are expected to fulfill the monitoring role better (cf. e.g., Boone and White, 2015). Finally, fixed income investors might become aware of such firms for the first time when they enter a benchmark index. As a result, there is a positive relationship between index membership and both equity and debt finance opportunities. However, it is unclear which financing source firms would prefer after index inclusion, which could lead to changes in firms' capital structure.

The third study in this dissertation analyzes the effect of index membership on firms' capital structure. To do so, I use exogenous index events as identification, such as index formation or discontinuation, index eligible universe change, number change of index constituents, and index selection methodology change. During these exogenous events, firms did not likely foresee index selection results and therefore, were unlikely to influence them beforehand, such as they could do during regular index revisions. After manually screening more than 54,000 press releases related to 7,356 equity indexes around 21 countries, I find more than 200 exogenous index events from January 1996 to June 2014, affecting more than 8,000 stocks.

Using a difference-in-differences estimator, I find firms increase their financial leverage by 1–2 percentage points relative to control group stocks after exogenously being added to an index. The control group stocks are selected by a propensity score match based on established determinants for financial leverage, after controlling for other influencing factors and fixed effects. Applying regression discontinuity design, I obtain similar results.

I argue that improved investor awareness and company information availability drive the increase in financial leverage. Given the difficulties of measuring investor awareness, I use analyst coverage and stock liquidity costs as proxies for information availability. In the data sample, I find a statistically significant increase of analyst coverage and a decrease of liquidity costs for firms exogenously added to an index relative to their control stocks. If superior information availability drives the observed increase in financial leverage, one might expect that this affects public debt more than private debt, because banks usually have better information access and own monitoring channels. Additional tests regarding public and private debt show that, in fact, the increase in debt ratios is mainly driven by increases in public debt. Finally, I find that the effects on financial leverage are stronger in countries where less information disclosure requirements and reporting standards exist.

5.2 Contribution and implications

Overall, this dissertation contributes to a better understanding of several capital market phenomena with respect to stock liquidity costs and equity index effects. My research addresses the interplay between liquidity-motivated trading from open-ended funds and overall stock market liquidity, as well as index effects on stocks' liquidity costs and firms' capital structure. Detailed contributions and implications regarding each topic are as follows.

First, I employ a unique order-volume weighted round-trip spread measure, the XLM provided by Deutsche Börse AG as a more accurate liquidity cost measurement than bid–ask spread. XLM relies on the limit order book from the Xetra Electronic Trading Platform, and considers the whole depth of the limit order book which even includes so-called "iceberg" orders that are not visible to traders. XLM especially provides order-volume dependent spreads, which can be assessed individually for different research purposes (e.g., spreads referring to large order volumes are more suitable for studies on institutional trading). Using XLM, I am able to assess liquidity cost development of a specific stock for different order volume classes, which is not possible when using the traditional bid–ask spread measure.

Second, I find evidence of a relationship between liquidity-motivated trading from open-ended equity funds and overall stock market liquidity. The analysis shows that there is a positive relationship between stock market liquidity and liquidity-motivated trading from actively managed mutual funds, as measured by their net cash flows. A one standard deviation increase in mutual funds' net cash flows reduces the overall market liquidity costs by up to 45 basis points. At the same time, there is no statistically significant effect from ETFs' net cash flows on overall stock market liquidity. These results emphasize the importance of actively managed mutual funds for stock markets due to their role as liquidity service providers. These findings might be of importance to stock exchanges and financial regulators, which both prefer high stock market liquidity.

Third, I quantify the "pure" liquidity impact from index revisions on affected constituents. Applying a difference-in-differences event study design, I compare liquidity cost changes from stocks that experienced an index change with those stocks that could have had an index change, and find a liquidity cost reduction of 15–18%, which corresponds to 3–30 basis points, depending on the indexes. This finding is consistent across different order volume classes, and therefore, affects both private and institutional investors. My study provides additional support for the liquidity hypothesis regarding index effects that originated from Schleifer (1986), and especially extends empirical evidence by recent data outside the U.S. market.

Fourth, I provide a hand-collected, valuable international data set of more than 200 exogenous equity index events with about 8,000 affected stocks, in which individual firms could not likely influence index constituent selection. I manually collect these events by screening more than 54,000 press releases related to 7,356 indexes from 21 countries. This screening filters out regular index revisions that endogeneity issues could potentially influence; such issues include firms' development trends and M&A activities. In addition, the international sample provides opportunities to examine cross-country differences regarding index effects, and does not focus on the U.S. market only.

Finally, based on the abovementioned exogenous data sample, I find casual impact from index membership on firms' capital structure. The study shows that firms increase their financial leverage on average by 1–2 percentage points after being exogenously added to an index, compared to their control stocks. This result is robust using both difference-in-differences estimation and regression discontinuity design. In addition, my findings suggest equity index membership benefits firms' debt financing, even during exogenous index events, where no changes have occurred at the affected firms themselves except for being "surprisingly" included in a benchmark index. The importance of index membership has several implications for financial regulators, given that index funds keep growing steadily. Governments should pay more attention to the role of benchmark indexes that go beyond their "benchmarking" function.

5.3 Avenues for future research

In this dissertation, I find evidence that liquidity-motivated trading from actively managed mutual funds, as measured by their net cash flows, improves overall stock market liquidity, and therefore, provides important liquidity services to the market. Researchers could gain additional insights by investigating how exactly actively managed mutual funds provide their liquidity services, for example, by assessing their fund holdings on a daily basis, and relating their trading behavior to their net cash flows and liquidity costs of holding stocks. Although my study suggests that ETFs do not influence overall stock market liquidity, the result could be different if the data set were to contain fire sales of ETFs in Germany. To understand the liquidity risks stemming from ETF markets better, it would be worthwhile to model the case of fire sales of ETFs, which has not occurred so far in global financial markets.

In addition, this dissertation provides new empirical evidence supporting the liquidity hypothesis of index effects. To categorize different index effects further, it would be necessary to separate "passive" index changes from "active" index changes. With an "active" index change the stock itself fulfills all index selection criteria to be added to or deleted from an index. With a "passive" index change, the affected stock does not fulfill all index selection criteria but still experiences an index revision as replacement for another stock. The magnitudes of index effects for these two groups of stocks are potentially different. My study does not observe clear evidence for changes of news coverage associated with index revisions. This could be a result of data noise. A more sophisticated pre-screening of news articles, for example, to limit news articles to only those from business newspapers, might lead to different results. This could help to find a clearer relationship between news coverage and index effects.

Finally, using hand-collected exogenous identification, I find evidence of index effects on firms' capital structure. It is worth directly comparing equity and debt issuing, as well as costs of equity and costs of debt, before and after index events. This could further shed light on the drivers behind the change in financial leverage. Moreover, this data set could address many additional topics, providing exogenous identification to examine causal inferences in the areas of asset pricing, corporate governance, and corporate finance.

Overall, my dissertation examines the importance of the role benchmark indexes play in capital markets. This raises questions that financial regulators might consider thoroughly, such as how many constituents a leading benchmark index should have; how to limit the benefits that firms could have being a member of an index; or how to eliminate changes for firms to manipulate their inclusion in a benchmark index. Meanwhile, questions regarding index effects are important for corporations, and of particular importance is how firms should pre-act and react to index revisions when expecting changes in shareholder structures, corporate disclosure, or related matters.

Appendix

Appendix A: Robustness test: Residual regressions

Variable	Model 1	Model 2	Model 3	Model 4
Main variables				
Mutual fund NCF with 1-day lag	-0.0111*	-0.0132**		
	(0.00363)	(0.00336)		
Mutual fund NCF with 2-day lags	-0.0140***		-0.0156***	
	(0.00172)		(0.00195)	
ETF NCF with 1-day lag	0.00408**			0.00266
	(0.00111)			(0.00156)
Control variables				
Return	-0.0253***	-0.0254***	-0.0254***	-0.0256***
	(0.00189)	(0.00184)	(0.00185)	(0.00189)
Volatility	0.0301**	0.0261**	0.0271**	0.0214**
	(0.00723)	(0.00651)	(0.00674)	(0.00634)
Trading value	-0.0106	-0.00725	-0.00796	-0.00289
	(0.00472)	(0.00396)	(0.00354)	(0.00321)
Market capitalization	-0.0189*	-0.0135**	-0.0151**	-0.00530
	(0.00641)	(0.00420)	(0.00450)	(0.00305)
Observations	7,980	7,980	7,980	7,980
Adjusted R-squared	0.864	0.864	0.864	0.864
Time-fixed effects	Yes	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes	Yes

This table reports the regression results on the impact of equity funds' net cash flows on German stock market liquidity costs during July 1, 2002 to December 31, 2014. For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observation of the following variables the index level and uses them as regression inputs. The stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for order the volume class of 100,000 euro in basis points. The dependent variable is the residual of AR(1) regression of $ln(XLM_t)$. The main independent variables include mutual fund NCF with 1- and 2-day lags, as well as ETF NCF with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euros. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euros). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Furthermore, this study controls for index- and time-fixed effects in the regression. Heteroscedasticity-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix B: Robustness test: First-difference regressions

Variable	Model 1	Model 2	Model 3	Model 4
Main variables				
Mutual fund NCF with 1-day lag	-0.00145	-0.00193*		
	(0.000893)	(0.000719)		
Mutual fund NCF with 2-day lags	-0.00566*		-0.00550*	
	(0.00204)		(0.00196)	
ETF NCF with 1-day lag	0.00438**			0.00401*
	(0.00116)			(0.00137)
Control variables				
Return	-0.0295***	-0.0296***	-0.0295***	-0.0296***
	(0.00223)	(0.00219)	(0.00218)	(0.00225)
Volatility	0.0206**	0.0190**	0.0203**	0.0181**
	(0.00608)	(0.00557)	(0.00596)	(0.00537)
Trading value	0.00244	0.00372	0.00261	0.00463
	(0.00344)	(0.00352)	(0.00326)	(0.00391)
Market capitalization	-0.000924	0.000609	-0.00146	0.00298
	(0.00286)	(0.00181)	(0.00264)	(0.00222)
Observations	7,980	7,980	7,980	7,980
Adjusted R-squared	0.0583	0.0573	0.0568	0.0581
Time-fixed effects	Yes	Yes	Yes	Yes
Index-fixed effects	Yes	Yes	Yes	Yes

This table reports the regression results on the impact of equity funds' net cash flows on German stock market liquidity costs during July 1, 2002 to December 31, 2014. For each index from DAX, MDAX, SDAX, and TecDAX, this study aggregates the daily observation of the following variables to the index-level and uses them as regression inputs. The stock market liquidity costs are represented by the (market value-)weighted Xetra Liquidity Measure (XLM) for the order volume class of 100,000 euro in basis points. The dependent variable is the daily change of liquidity costs defined as $ln(XLM_t/XLM_{t-1})$. The main independent variables include mutual fund NCF with 1- and 2-day lags, as well as ETF NCF with 1-day lag. The NCFs are calculated as the sum of absolute value of funds' net cash flows in million euros. Daily return, volatility, trading value, and market capitalization are included as control variables (return and volatility are in percent, while trading value and market capitalization are in million euro). Except return, all variables are logarithmized. All net cash flow and control variables are then standardized. In addition, the control variables are orthogonalized. Furthermore, this study controls for index- and time-fixed effects in the regression. Heteroscedasticity-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix C: Impact of news coverage on stock liquidity associated with index revisions: difference-in-differences regressions

	Upgrade			Downgrade		
Dep. variable	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)	ln(xlm25k)	ln(xlm50k)	ln(xlm100k)
Information variables						
ln(# of articles)	-0.000339	0.00410	-0.00330	-0.0173	-0.00114	-0.00217
	(0.00463)	(0.00515)	(0.00656)	(0.0137)	(0.0227)	(0.0240)
ln(# of articles)$\cdot \mathrm{I}_{treatment}$	0.0409***	0.0345***	0.0350***	-0.00512	-0.0211	-0.00538
	(0.0102)	(0.0108)	(0.0110)	(0.0152)	(0.0242)	(0.0254)
Difference-in-differences variables						
$\mathrm{I}_{[AD-20,AD]} \cdot \mathrm{I}_{treatment}$	-0.0489**	-0.0497***	-0.0633***	0.0774***	0.0725**	0.0346
	(0.0193)	(0.0192)	(0.0203)	(0.0287)	(0.0328)	(0.0327)
$\mathrm{I}_{(AD,ED)} \cdot \mathrm{I}_{treatment}$	-0.160***	-0.157***	-0.148***	0.0248	-0.0221	0.0405
	(0.0243)	(0.0253)	(0.0278)	(0.0306)	(0.0337)	(0.0386)
$\mathrm{I}_{[ED,ED+20]} \cdot \mathrm{I}_{treatment}$	-0.156***	-0.149***	-0.169***	0.00243	0.0147	0.00757
	(0.0193)	(0.0190)	(0.0199)	(0.0303)	(0.0351)	(0.0439)
$\mathrm{I}_{[ED+21,ED+62]} \cdot \mathrm{I}_{treatment}$	-0.214***	-0.211***	-0.205***	0.0345	0.00775	0.0116
	(0.0178)	(0.0185)	(0.0203)	(0.0225)	(0.0268)	(0.0361)
Observation time period dummy variables						
$\mathrm{I}_{[AD-20,AD]}$	0.01000	0.00716	-0.00170	-0.0683**	-0.0600**	-0.0195
	(0.0140)	(0.0151)	(0.0169)	(0.0296)	(0.0271)	(0.0206)
$\mathrm{I}_{(AD,ED)}$	0.0131	0.00875	-0.0119	-0.0278	0.00511	-0.0250
	(0.0167)	(0.0188)	(0.0218)	(0.0349)	(0.0356)	(0.0367)
$\mathrm{I}_{[ED,ED+20]}$	0.00417	-0.00499	-0.0151	-0.0162	-0.0303	0.00245
	(0.0145)	(0.0157)	(0.0179)	(0.0415)	(0.0399)	(0.0411)
$\mathrm{I}_{[ED+21,ED+62]}$	0.00415	-0.00436	-0.0306	0.00639	0.0449	0.0511
	(0.0217)	(0.0244)	(0.0296)	(0.0446)	(0.0536)	(0.0547)
Observations	77,330	76,824	75,440	44,844	44,534	42,620
Adjusted R-squared	0.867	0.873	0.864	0.927	0.918	0.906
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Stock-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

This table reports coefficients from difference-in-differences regressions that compare liquidity cost changes of stocks that experienced an index upgrade/downgrade (treatment group) and stocks that could have had an index upgrade/downgrade (control group) during index revisions of DAX, MDAX and SDAX from July 2002 to December 2014. The Xetra Liquidity Measure (XLM) represents the liquidity cost, and calculates the order volume-weighted round-trip transaction cost for different order volume classes. This study uses the order volume classes of 25,000 euros, 50,000 euros, and 100,000 euros as dependent variables. The observation time window from 3 months before the announcement date (AD) to 3 months after the effective date (ED) is divided into five time intervals, where $[AD-62, AD-21]$ is the reference time window assuming 21 trading days per month. Numbers of articles are collected from Factiva for each observation window and scaled on a monthly basis. Driscoll–Kraay heteroscedasticity-, autocorrelation-, and cross-sectional dependence-robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix D: Definition of variables

Variable	Description
Main variables	
Market leverage	Total debt [WC03255] / (total debt [WC03255] + market value of common equity [WC08001]). Source: Worldscope.
Book leverage	Total debt [WC03255] / (total debt [WC03255] + book value of common equity [WC03501]). Source: Worldscope.
Analyst	Natural logarithm of the total number of estimates for earnings per share ending in the next fiscal year-end. Source: I/B/E/S.
Liquidity costs	Average relative bid–ask spread (bid–ask spread / mid-price) in a fiscal year. Source: Datastream.
Public debt ratio	(Senior bonds and notes + subordinated bonds and notes) / market value of total assets. Source: Capital IQ.
Private debt ratio	(Term loans + capital lease + revolving credit + commercial paper + other borrowings) / market value of total assets. Source: Capital IQ.
Coupon	Average coupon for all bonds outstanding in percent. Source: Capital IQ.
Roll, Roll_Zero, FHT, Zero_Ret	Various measures of bond liquidity. See Section 4.4 for more information. Source: Bloomberg.
Control variables	
Size	Natural logarithm of total assets [WC02999] in USD. Source: Worldscope.
Profitability	Earnings before interest, tax, depreciation, and amortization (EBITDA) [WC18198] / total assets [WC02999]. Source: Worldscope.
Tangibility	Property, plant and equipment [WC02501] / total assets [WC02999]. Source: Worldscope.
Market-to-book ratio	Market value of common equity [WC08001] / book value of common equity [WC03501]. Source: Worldscope.
Market capitalization	Natural logarithm of market capitalization in USD. Source: Datastream.
Trading volume	Natural logarithm of the total number of shares traded in a fiscal year. Source: Datastream.
Return	Cumulative stock return in the fiscal year. Source: Datastream.
Return volatility	Standard deviation of monthly returns in a fiscal year. Source: Datastream.
Bonds outstanding	Natural logarithm of the amount of bonds outstanding in USD. Source: Capital IQ.
Other variables	
Industry classification	Industry Classification Benchmark (ICB) supersector (2-digits). Source: Datastream.
Disclosure	Disclosure requirements index, as defined by La Porta et al. (2008). Higher values imply better company disclosure.
Accounting	Quality of accounting standards, as defined by La Porta et al. (1998). Higher values imply better accounting standards.
ADRI	Antidirector rights index, as defined by La Porta et al. (2008). Higher values imply better protection of minority shareholders.
Market capitalization to GDP	Market capitalization of listed domestic companies deflated by a country's GDP. Source: The World Bank.
CR	Creditor rights index, as defined by Djankov et al. (2007). Higher values imply better creditor protection.

Appendix E: Book leverage: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5	6	7	8
Window (years)	[-1,1]	[-2,2]	[-3,3]	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: book leverage								
Treated x Post	**0.0196*** **	**0.0201*** **	**0.0208*** **	**0.0141*** **	**0.0141*** **	**0.0186*** **	**0.0164*** **	**0.0210*** **
	(0.00408)	**(0.00483)**	**(0.00595)**	**(0.00387)**	**(0.00441)**	**(0.00544)**	**(0.00515)**	**(0.00611)**
Post	-0.00981**	-0.00523	-0.00925*	-0.00824**	-0.00378	-0.00969**	-0.00383	-0.00607
	(0.00405)	(0.00413)	(0.00511)	(0.00385)	(0.00376)	(0.00454)	(0.00501)	(0.00683)
Size				0.0511***	0.0599***	0.0673***	0.0628***	0.0743***
				(0.00696)	(0.00548)	(0.00495)	(0.00755)	(0.00774)
Profitability				-0.252***	-0.243***	-0.269***	-0.338***	-0.324***
				(0.0327)	(0.0260)	(0.0237)	(0.0322)	(0.0403)
Tangibility				0.116***	0.142***	0.141***	0.147***	0.115***
				(0.0234)	(0.0213)	(0.0190)	(0.0280)	(0.0267)
Market-to-book ratio				0.00407***	0.00493***	0.00563***	0.00684***	0.00795***
				(0.00105)	(0.000842)	(0.000737)	(0.00129)	(0.00139)
Observations	23,499	39,568	54,799	22,460	38,433	51,439	19,510	16,161
Adjusted R^2	0.892	0.858	0.812	0.904	0.873	0.837	0.884	0.864
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports coefficients from difference-in-differences regressions. BOOK LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window presented in the column titles. The event year (0) is not included in the analysis. TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry, and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix F: Propensity score matching with caliper specification

	Before matching				After matching			
Variable	Mean (treated)	Mean (unmatched)	Dif.	Norm. dif.	Mean (treated)	Mean (matched)	Dif.	Norm. dif.
Size	13.24	11.71	1.54	0.23	13.24	13.18	0.06	-0.01
Profitability	0.11	0.02	0.09	1.12	0.11	0.11	0.00	-0.01
Tangibility	0.30	0.29	0.01	0.10	0.30	0.27	0.02	0.11
Market-to-book ratio	3.30	3.20	0.11	0.00	3.30	3.37	-0.07	0.00

The table reports descriptive statistics for 3,815 non-financial stocks exogenously added to an index and their nearest neighbor control stocks before and after propensity score matching using an additional caliper specification. The control stocks are from the same country, year, and industry as the treated stocks, and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. The matching basis for control stocks are all stocks in the Worldscope country lists without those from the treatment group. The MEAN of treated and (unmatched and matched) control stocks, the mean DIFFERENCE between treated and control stocks, and the normalized difference in coefficients according to Imbens and Wooldridge (2009) are presented in the table. Normalized differences not exceeding a quarter are considered to be not significantly different from zero.

Appendix G: Robustness: Difference-in-differences regressions based on propensity score matching with caliper specification

Model	1	2	3	4	5
Window (years)	[-1,1]	[-2,2]	[-3,3]	2 vs. -1	3 vs. -1
Dep. variable: Market leverage					
Treated x Post	**0.0107****	**0.0158*****	**0.0141****	**0.0206*****	**0.0261*****
	(0.00453)	**(0.00526)**	**(0.00638)**	**(0.00607)**	**(0.00774)**
Post	-0.00625	-0.00407	-0.00277	-0.00216	-0.00660
	(0.00487)	(0.00421)	(0.00459)	(0.00545)	(0.00778)
Size	0.0744***	0.0733***	0.0812***	0.0742***	0.0872***
	(0.00844)	(0.00685)	(0.00576)	(0.00832)	(0.00871)
Profitability	-0.179***	-0.191***	-0.212***	-0.266***	-0.258***
	(0.0303)	(0.0255)	(0.0236)	(0.0300)	(0.0388)
Tangibility	0.118***	0.135***	0.139***	0.104***	0.107***
	(0.0289)	(0.0298)	(0.0287)	(0.0341)	(0.0356)
Market-to-book ratio	-0.0034***	-0.0032***	-0.0034***	-0.0034***	-0.0054***
	(0.000979)	(0.000826)	(0.000684)	(0.00124)	(0.00125)
Observations	13,296	22,036	29,538	11,212	9,267
Adjusted R^2	0.902	0.869	0.836	0.886	0.866
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes

The table reports coefficients from difference-in-differences regressions. MARKET LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window presented in the column titles. The event year (0) is not included in the analysis. TREATED is a dummy variable set to one for treatment stocks, and zero otherwise. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry, and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, the market-to-book ratio, and additional caliper specification. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%levels, respectively.

Appendix H: Placebo test: Difference-in-differences regressions for stocks exogenously added to an index

Model	1	2	3	4	5
Window (years)	[-8,-6]	[-9,-5]	[-10,-4]	-5 vs. -8	-4 vs. -8
Dep. variable: Market leverage					
Treated x Post	**-0.0208***	**-0.0143**	**-0.0138**	**-0.0146**	**0.0169**
	(0.0114)	**(0.0105)**	**(0.0129)**	**(0.0118)**	**(0.0164)**
Post	0.0203***	-0.0115	0.000865	-0.0146	0.0224*
	(0.00763)	(0.00828)	(0.00945)	(0.0106)	(0.0124)
Size	0.0559***	0.0718***	0.0912***	0.0950***	0.128***
	(0.00950)	(0.00808)	(0.00819)	(0.0107)	(0.0133)
Profitability	-0.187***	-0.114***	-0.193***	-0.243***	-0.416***
	(0.0474)	(0.0338)	(0.0396)	(0.0543)	(0.0673)
Tangibility	0.125**	0.189***	0.237***	0.0907*	0.0900
	(0.0509)	(0.0434)	(0.0434)	(0.0537)	(0.0650)
Market-to-book ratio	-0.000868	-0.00120	-0.0038***	-0.00172	-0.00417
	(0.00128)	(0.000779)	(0.00107)	(0.00179)	(0.00277)
Observations	6,162	8,699	9,911	4,468	3,246
Adjusted R^2	0.910	0.888	0.864	0.907	0.901
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Year x Country FE	Yes	Yes	Yes	Yes	Yes
Year x Industry FE	Yes	Yes	Yes	Yes	Yes

The table reports coefficients from placebo difference-in-differences regressions (from year -10 to year -4). MARKET LEVERAGE is the dependent variable. The sample is restricted to firm-year observations in the time window presented in the column titles. The pseudo event year (-7) is not included in the analysis. Treatment stocks experience exogenous index inclusion, while control stocks do not experience an index change but have similar firm characteristics. Control stocks are from the same country, year, and industry, and are matched based on a propensity score using the natural logarithm of the dollar value of total assets, profitability, tangibility, and the market-to-book ratio. POST is a dummy variable set to one in firm-years after a change in index membership. Control variables are lagged by 1 year. Huber/White robust standard errors clustered by firm are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10%levels, respectively.

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