The Liquidity of Credit Default Index Swap Networks

Richard Haynes[1] and Lihong McPhail[2]

June 2017

Abstract

Recent regulatory reforms like the mandatory clearing of standardized swap contracts and mandatory trading on centralized execution platforms have significantly changed the derivatives landscape. These reforms have, in certain cases, led the market to increasingly trade on multilateral platforms, potentially affecting the average cost of execution. Prior research has examined the effects of centralized trading on execution costs and has generally found reduced costs, especially for entities with higher transaction volumes or greater execution flexibility. We use detailed information on the trading of credit index swaps, the most actively traded credit derivatives instrument, between May 2014 and Sep 2016. We find that the customers who trade with a higher number of dealers (high network degree) and those who trade with the most active dealers (high network centrality) incur lower trading costs; for at least the less liquid indices, this cost improvement increases as trade size increases. We also identify a few liquidity trends: measures like average daily volumes, average price impact, and price dispersion have remained steady or have improved. However, during the same period, trade sizes for certain indices may have declined slightly.[3]

Keywords: OTC Market, Liquidity, Credit Default Index Swaps, Network, Execution Cost

JEL Classification: G10, G12, G14, G20, G23, C13

---

[1] Supervisory Economist, CFTC rhaynes@cftc.gov

[2] Senior Economist, CFTC. lmcphail@cftc.gov

[3] The Office of the Chief Economist and CFTC economists produce original research on a broad range of topics relevant to the CFTC's mandate to regulate commodity future markets, commodity options markets, and the expanded mandate to regulate the swaps markets pursuant to the Dodd-Frank Wall Street Reform and Consumer Protection Act. These papers are often presented at conferences and many of these papers are later published by peer-review and other scholarly outlets. The analyses and conclusions expressed in this paper are those of the authors and do not reflect the views of other members of the Office of Chief Economist, other Commission staff, or the Commission itself.

Introduction

Recent regulatory reforms like the mandatory clearing of standardized swap contracts and mandatory trading on centralized execution platforms (e.g., Swap Execution Facilities) have significantly changed the derivatives landscape. Highly liquid products, like fixed-floating interest rate swaps and credit default index swaps, are subject to the most comprehensive changes. Because of this, certain market structure changes, as well as liquidity and efficiency gains may be the most noticeable for these products. In order to better understand these structural changes, we focus our analyses on highly standardized credit index products.

Credit index swaps are the most actively traded credit-related instrument in the global derivative market. Credit indices were first introduced in 2001 and provide a means of diversified credit protection. In the years since introduction, credit indexes have expanded dramatically, with credit index trading now often above $10 trillion notional per week. By 2004, two major credit indices had been established: the CDX index set, which cover North America and emerging markets, and the iTraxx index set, which cover Europe, Asia, Australia and Japan. Within the CDX and iTraxx benchmarks, individual indices often reference a specific quality of credit protection. For instance, both the CDX and iTraxx have an index that references firms of investment grade credit quality and another that references firms of high yield credit quality.[4] Both index sets are now owned and managed by Markit.[5]

Understanding customer trading costs in these markets are critical to investors in credit markets, because these swaps often provide the most efficient way to hedge or speculate on portions of credit markets. Trading costs affect the effectiveness of a hedge or the profitability of trading in general. Investors incur these costs when they establish and exit their positions, and often seek to time their trades to minimize the slippage related to these costs. If costs become too high relative to the expected returns, a market may lose marginal investors, leading to higher concentration, less risk transfer and greater challenges in finding timely counterparties.

Recent research examining trading costs in derivatives markets has been limited due to the lack of detailed swap transaction data. Using participant-identified information on credit index swap trades reported to the Bloomberg Swap Data Repository, we are able to take a detailed look into customer trading cost trends in some of the most liquid credit index swaps. We find that customer trading costs have been stable or decreasing over our sample period; decreases in

[4] http://www.markit.com/Documentation/Product/CDX
[5] http://www.markit.com/Product/CDX

trading costs have been strongest for the entities who trade most frequently and with the most counterparties.

Prior to the Dodd-Frank reforms, credit indices in the U.S. were often traded "over-the-counter" (OTC). These OTC swap executions could take a number of different forms: trades over the phone between dealer and customer, through inter-dealer brokers (IDB), or, more recently, using more automated methods on electronic platforms where customers can follow indicative price streams through the day. In most cases, swaps executed OTC prior to recent regulatory reforms were not cleared, exposing each of the counterparties to the potential default of the other. These potential losses were, in cases, mitigated by the exchange of initial and variation margins, covering liquidation and mark-to-market costs. In recent years margin exchange has become more common a practice, and is now required for a subset of institutions.

The Dodd-Frank Act introduced significant changes to derivatives markets: more standardized forms of execution for formerly OTC products and mandatory clearing for a subset of standardized products. The first clearing mandate was finalized by the CFTC in December 2012 and covered: 1) interest rate swaps denominated in super-major currencies and 2) certain credit index swaps. Central clearing has transformed the trading of derivatives by removing bilateral counterparty credit exposure. This change standardizes risk management and may help provide participants access to a wider range of trading counterparties. In certain cases, this transformation in trading has led, like equities and futures, to a broader set of liquidity providers.[6]

Related to the mandatory platform trading requirement, Dodd-Frank established swap-execution facilities (SEFs). SEFs are multilateral trading platforms which must have both an open limit order book (LOB) as well as a request for quote (RFQ) mechanism. Order books are similar to execution methods used on futures or equity exchanges: all-to-all with anonymous quoting. In contrast, RFQ is closer to prior OTC methods; customers send price requests to a set of potential counterparties, usually on a non-anonymized basis, and choose to trade, or not, depending on the set of responses. As of now, RFQ is the more popular method of execution, though a few hybrid approaches have become increasingly popular. At the moment, there are more than a dozen swap execution facilities registered with the CFTC; for the credit asset class, the Bloomberg platform is currently the largest SEF, representing around 80 percent of total credit SEF trading volume.[7] After execution, the trade is then sent for clearing (often required) and trade details are sent to a Swap Data Repository (SDR) for public dissemination.[8]

These market structure changes in execution methods, in data dissemination, and in clearing have been shown, in recent academic literature, to have had effects on market efficiency and

[6] https://www.ft.com/content/22b83fa4-8c6e-11e5-8be4-3506bf20cc2b
[7] https://www.clarusft.com/cds-record-volumes-expiring-swaptions-and-bloomberg/
[8] https://www.bloombergsdr.com/ticker

pricing. Centralizing counterparties on platforms can encourage new liquidity providers, help customers reduce search costs and may increase trading efficiencies by pooling liquidity. Pre- and post-trade transparency may also benefit liquidity by reducing information asymmetry across participants; however, these effects may differ by participant type.

In this paper we analyze how liquidity on centralized platforms may be related to the relative trading activity, and connections, of market takers (customers) and market makers (dealers). We find an inverse correlation between transaction cost and customer activity/connections. As customers increase their relative strength in the network their trading costs fall, possibly because this allows customers more flexibility to demand "higher quality" execution or they can more easily search out improved pricing. After constructing measures related to customers and dealers for daily credit index transaction activity, we find, mirroring other recent research, that increases in the strength of customers does, on average, reduce their execution costs. Interestingly, there does not seem to be as direct a relationship between average dealer strength and transaction costs.

More generally, we find that trading conditions have generally been stable or improving, as measured by a few common liquidity measures: average daily volumes, average price impacts, and price dispersion. However, CDX trade sizes may have declined slightly, a trend seen in other markets as traders optimize trade size for best execution. In cases when customers execute large size trades, price impact increases (Figure 6). For example, over our sample period, the average price impact of executing a CDX HY trade with over $500mn notional is about 0.3 bps, about 0.5% of the average credit spread and roughly twice as large as the average price impact of a small trade of $5 to 10mn. Over our sample period, for the CDX investment grade index (CDX IG), average price impacts for the 10 largest customers were 13% lower than the full sample average (0.42 bps vs 0.483 bps, Table 2). For the indices with the lowest level of liquidity, the cost difference between the two groups increases as trade size increases (Figure 10).

The rest of the paper is organized as follows. The next section provides an overview of relevant literature. This is followed by a description of the data used in the analysis, and a general overview of swap activity on the platform. We then provide details of our market concentration and transaction cost measures; followed by a summary of how trade costs change relative to customer and dealer characteristics. We conclude with a discussion of the regression results.

Literature Review

A few recent papers have examined how regulatory reforms such as mandated SEF trading and public trade reporting affect liquidity in the swap market. The Bank of England staff, using data provided by a European clearinghouse, found that the introduction of SEFs improved liquidity in interest rate swap markets, including a reduction in transaction costs and intraday price dispersion. Using the public reports of credit index swap transactions, Loon and Zhong (2016) found that execution cost related measures fell around 0.5% after the introduction of the public price feed. The authors attribute this partially to reduced information asymmetry, with customers better able to compare quotes to recent transaction prices.

Other recent papers have examined how market structure change affects search and execution costs in OTC markets. Hendershott and Madhavan (2015) found that electronic trading technology that enables investors to simultaneously search across many bond dealers (similar to RFQ-style trades), a compromise between bilateral search in OTC markets and continuous double auctions in electronic limit order books, reduces search costs and improves execution quality. Bessembinder et al (2006) found that an increase in price transparency through the TRACE system for corporate bonds reduced transaction costs even for related bonds that are not eligible for TRACE reporting. Conversely, Du et al (2016) found no evidence that costs associated to central clearing increased transaction spreads. Onur et al (2017) investigated the customer trading behavior on credit SEFs and find, at the level of individual trades, that transaction costs are higher for trades where more dealers are contacted. In contrast, we find that participants who trade with more counterparties generally face lower average transaction costs.

In a theoretical paper on OTC markets, Duffie et al (2005) find that bid-ask spreads are lower when investors have low-cost access to multiple market makers. They attribute this relationship in part to the relative bargaining power of investors and market makers. As investors are able to force market makers to compete on price, execution costs fall. Increased centralization of trading presumably aids in raising the relative power of investors, potentially helping to decrease costs. Babus and Hu (2016) show in a theoretical model that a star network in which one agent intermediates all transactions is an efficient and stable trading network, but the central agent in this case of concentrated intermediation can demand higher fees, given the pricing power his centrality provides.

The research closest to our analysis has examined how the trading network affects liquidity in other OTC markets, though no prior study has looked specifically at the credit index swap market. Li and Schurhoff (2014) examined the network effects in OTC municipal bond markets and found that central dealers could help provide execution immediacy partly through their ability to hold higher levels of inventory. However, as dealer centrality increases, trading costs for customers also increase, possibly leading customers to balance the speed and cost of execution. Similarly, Iercosan and Jiron (2017) found that counterparty trading networks and relationships affect execution costs in the single-name CDS market. Specifically, they found that less central clients, including those that trade with fewer counterparties, are faced with higher average transaction costs.

Data and Sample Description

In order to investigate these relationships, we use transaction level data for credit index trades executed on the Bloomberg SEF from May 1, 2014 to September 19, 2016, a period of just under two and a half years. Bloomberg is currently the most active U.S. credit trading platform, and it acts as a data repository for swap trades done on its platform; execution details are saved in the repository and are available to regulators for purposes of market oversight. The regulatory data stream includes information on the traded product, the trade counterparties, and the size and time of the trade. For the analysis below, we restrict to the primary price discovery contracts where risk transfer is greatest, the on-the-run series for the most active credit indices: CDX IG, CDX HY and iTraxx Europe.

In order to ensure a clean data set, we include a number of data filters. To isolate trading effects on absolute, rather than relative, price levels we filter out any trades that have multiple legs (e.g. a CDX IG/CDX HY spread). We also filter out block trades, where the execution and reporting process is unique and reported execution times may not match execution times for the equivalent non-block trades; related, we filter out far "off-market" trades, where we assume that execution times may be in error, leading to prices out-of-sync with the rest of the trade ticker. In addition to these general filters, we also restrict our observations by trade size and time. We omit all trades with notional less than $5 million to avoid substantial noise in price impact measures. Finally, we exclude trades that occur outside of "primary" market hours. The market windows we use are 14:00-20:00 GMT for the two CDX indices and 8:00-16:00 GMT for the iTraxx index. Figure 1, a summary of average trade volumes for every fifteen minute period, provides a quantitative justification for our window selection. After applying these filters we are left with 32,208 CDX IG trades, 43,884 CDX HY trades, and 35,170 iTraxx Europe trades for our analysis.

Market Overview

Before turning to transaction costs directly, we provide a brief overview of credit index trading trends over the last few years. Figure 2 shows the five day moving average trading volumes in the three primary indices. CDX IG is the most active of the three, followed by iTraxx Europe and CDX HY. Average trade volume has been stable over the sample period, possibly indicating relatively stable liquidity conditions. From May 2014 to September 2016, CDX IG had an aggregate average daily volume (ADV) of $7.05 billion notional, representing an average of 108 trades per day. On Feb 9th, 2016, trade volume peaked at $22.7 billion (331 trades), coinciding with strong declines in equity and commodity markets and increased market volatility. Similar trends exist for the other two indices, though at lower base levels.

In contrast to the stable trade volumes, the average size of CDX index trades may have experienced minor declines (Figure 3).[9] Declining trade size has been cited as evidence that buy-side institutions have found it more difficult to execute large trades and so split orders to reduce price impact. Trade size trends may also represent market evolutions similar to those for equities and futures, where higher levels of automation have led to faster markets with smaller individual risk transfer.

With this as background, we turn to our primary variables of interest. In order to estimate transaction costs and market liquidity we calculate both an average daily price impact and a daily price dispersion measure. For both, we restrict our attention to dealer-to-customer trades, trades where we can distinguish between the price maker and the price taker. The vast majority of trades represent this counterparty pairing, with dealer-to-dealer trades (after applicable filters) only accounting for roughly 15% of volume on the BSEF platform for CDX IG and iTraxx Europe and 8% of volume for CDX HY during our period.

Our daily average price impact measure is constructed in the spirit of Amihud (2002) and is defined as:

$$PriceImpact_i = \frac{1}{(N_i - 1)} \sum_{t=2}^{N_i} \frac{(|P_{i,t} - P_{i,t-1}|)}{Q_{i,t}}$$

where $P_{i,t}$ and $Q_{i,t}$ represent the price and the quantity of the *t*-th trade on day *i* and N_i represents the total number of trades on day *i*. Figure 4 presents the five day moving average price impacts over our sample.[10] Price impact levels peaked in early 2016 for CDX IG and CDX HY although, in general, price impacts have been stable over the sample period, a trend similar to market volumes.

In addition to average cross-day trends, price impact levels adjust relative to the time of day of the trade and the size of the trade. Impacts are larger during off-market hours and for trades where the notional size is large. Figure 5 shows how average price impact changes throughout the day. For CDX HY, price impacts are the smallest and relatively stable from 1 to 11 PM

[9] Note that trade size calculations differ from Onur et al (2017) because we do not exclude large size trades.
[10] The average time between consecutive trades for all three indices is roughly on the order of a few minutes, so price changes are likely due primarily to liquidity demand rather than an accumulation of fundamental price changes due to information.

London Time. The time range is similar for the CDX IG, whereas prime market hours for the more European-focused iTraxx are shifted earlier.[11]

Figure 6 shows the average absolute price difference of trades, as broken down by trade size. Generally, impact measures have a positive correlation with size, as expected; however, there do appear to be exceptions to this relationship. For instance, the average cost of trades between \$10-25mn notional for the CDX HY index and trades between \$25-50mn for the other two indices appear low relative to other size buckets. In Figure 7, a histogram of trade sizes, we can see that these buckets are some of the most active for the respective index. Traders, not surprisingly, appear either to choose to trade at efficient sizes, or market makers are more comfortable providing liquidity at expected size levels.

The other liquidity measure, volume-weighted price dispersion, matches a measure in similar OTC studies: Loon and Zhong (2014) and the Bank of England (2016). This measure captures the average percentage deviation of individual trades from a selected price benchmark (the end of day price). Specifically,

$$DispVW_{i,t} = \sqrt{\sum_{k=1}^{N_{i,t}} \frac{Vlm_{k,i,t}}{Vlm_{i,t}} (\frac{P_{k,i,t} - \bar{P}_{i,t}}{\bar{P}_{i,t}})^2}$$

where $N_{i,t}$ is the total number of trades executed for contract *i* on day *t*, $P_{k,i,t}$ is the execution price of transaction *k*, $P_{k,i,t}$ is the average execution price on contract *i* and day *t*, $Vlm_{k,i,t}$ is the volume of transaction/notional *k* and $Vlm_{i,t} = \sum_k Vlm_{k,i,t}$. Figure 8 presents the five-day moving average volume-weighted price dispersion metric for dealer-to-customer trades. On average, price dispersions for CDX HY, CDX IG, and iTraxx Europe are about 0.5%, 0.58%, and 0.8% respectively. Price dispersion levels were generally stable throughout our sample; however, iTraxx Europe experienced significantly higher dispersion in early 2016 when concerns were raised about the credit quality of European banks; all three markets experienced high dispersion around October 15, 2014.

Further details about these liquidity measures can be found in Table 1. Generally, dealer-to-customer trades are larger than that for dealer-to-dealer trades (DTD) and are associated with slightly lower price impact values. For instance, the average price impact of a \$100 million notional dealer-to-customer CDX IG trade is 0.48 bps, versus a 0.62 bps cost for the equivalent dealer-to-dealer trade. This comparison contrasts with some earlier CDS research such as Iercosan and Jiron (2017), but the disparity may be due to the fact that, by concentrating only on Bloomberg SEF transactions, we cover only a small fraction of total dealer-to-dealer activity.

[11] These values also validate the choice of market hours outlined above.

Because of this skew, the regressions below focus strictly on dealer-to-customer activity, where the coverage is much less likely to be biased.

We have hypothesized that these liquidity measures are affected by the strength and distribution of network connections in the credit swap market. In order to test this, we compute a set of daily concentration measures for both dealers and customers: the Herfindahl-Hirschman Index and two network-related measures, vertex degree and Bonacich centrality (introduced in Bonacich (1987)). These two concentration measures will act as our primary covariates. The Herfindahl-Hirschman Index (HHI) is defined as the sum of the squared market share of each active firm (calculated as firm's volume divided by market volume), and takes values between 0 and 1. HHI is close to 1 when the market is dominated by only one firm (monopolistic). HHI is closer to 0 when the market has a more even distribution of activity across a larger number of firms. The US Department of Justice considers a market with an HHI of less than 0.15 to be a competitive marketplace, an HHI of 0.15 to 0.20 to be a moderately concentrated marketplace, and an HHI of 0.25 or greater to be a highly concentrated marketplace.

The final two concentration measures are measures that take into account not just the activity of individual firms but the distribution of trade linkages. We define the trade counterparty network as the set of bilateral relationships in a given index on a given day; the activity between two participants is aggregated at a gross notional level for the given product-day. Our simplest network measure is participant degree, the number of unique counterparties for the participant on that product-day. Somewhat more complex is the eigenvector centrality, which follows the calculation of Bonacich (1987). This centrality measure takes into account the strength of both direct and indirect links. A firm is important if it is strongly connected to other firms that are important, prioritizing closer to more distant connections. After calculating degree and centrality for each active firm, both measures are then averaged across the customer and dealer groups separately. These averages represent the average number of connections, and the average network strength, of dealers/non-dealers on each product-day.

Table 2 compares the daily average price impacts for all customers to those for the top 10 customers (as measured by HHI). We find that the price impacts for the top 10 customers are, on average, about 13%, 7.2%, and 1.6% lower for the CDX IG, CDX HY, and ITRAXX Europe indices respectively. In all cases, average price impacts for more central customers are lower than that for all customers. For average trades sizes, this difference is often about 5-10 percent of total trade costs.

Methodology

We are interested in identifying factors that may drive the cost of trading for customers on swap trading platforms. Our focus is on measures related to the strength of customer firms relative to those of dealer firms in a given contract. The analysis in the prior section gave a first indication that there is a relationship between customer size and transaction cost. Below, we construct a few regressions to more formally test this hypothesis and include a number of market level factors as controls. These controls include:

Trade Volume: Liquidity is commonly defined as the ability to transact quickly at relatively low cost. As liquidity increases, more market participants will find execution attractive and choose to trade in a given, liquid product. Because of this, trade volumes are often used as a proxy for liquidity levels, and are often endogenous to liquidity. If a lot of participants trade often, this is often taken as a sign that the market is liquid and that execution costs are low enough to be acceptable to a broad range of firms. We use trade volume as a control for general market liquidity, and the level of trading interest of the average participant. If trading costs are low (i.e. liquidity is high), trade volume should be high on a market-wide basis.

Index spreads: CDX spreads represent the expected creditworthiness of the basket of institutions that make up the index (e.g. 125 North American firms for CDX IG). Spreads increase as aggregate default expectations increase and decrease as they fall. Often, spread movements are correlated with more general market dynamics - as market sentiment improves, economic concerns abate and spreads fall. During the 2008-2009 Financial Crisis, spreads for CDX indices hit all-time highs, peaking at around 235 bps for IG and 1800 bps for HY. Because of this relationship, we use spreads both as a broad credit market control and as a control for market sentiment. Like other market sentiment gauges, we expect liquidity levels to decrease as spreads increase, leading to increases in transaction costs.

VIX: The VIX represents the average expected short-term volatility of the S&P 500 index – it is calculated as a weighted average of S&P options. Like credit spreads, the VIX is often used as a proxy for general market sentiment, increasing as concerns about the economy increase. Prior financial network papers such as Li and Shurhoff (2014) use the VIX as a control. We include spreads and the VIX to control for general market conditions.

Concentration Measures

The remaining regression covariates represent our spectrum of concentration measures. Table 3 summarizes our concentration measures across each of the index products. It includes the Herfindahl-Hirschman Index (HHI), degree and centrality measures and breaks down each measure into customer and dealer groups. In general, all three index markets have low concentration, with HHI measures at or below 0.05 for all groups.

Unsurprisingly, average dealer degree is significantly higher than the degree of non-dealers, roughly at a ratio of 3:1 across products (with some variation). Dealers, as market intermediaries and liquidity providers, will naturally trade with more participants. The same comparison is true for the standard deviation of the degree measures (even as a percentage of the average) – indicating that there is a bit more heterogeneity in dealer compared to customer connections (e.g.

larger dealers vs smaller dealers). The same is true for the centrality measures, with dealer centrality much higher on an absolute basis than that for non-dealers. In general, the numbers are highest for CDX IG, which has the highest market volumes and lowest price impacts. Over the sample period, the daily average swap dealer weighted centrality experienced small declines for all three markets, indicating an increasingly competitive marketplace for swap dealers while the daily average customer weighted centrality remained stable. Figures 14 and 15 provide examples of trading networks on an active day and an inactive day respectively.

Results

Table 4 summarizes the regression results for the price impact measure, including the effects of our concentration metrics. All of our control variables are significant and have the expected signs, as seen in Models 1 and 2. Price impact measures are low on days when trade volumes are high, indicating that participants are more likely to trade on days when execution costs are low. When market uncertainty is high, such as when the VIX index or credit spreads are high relative to historical averages, trading costs are also high. Market-makers, concerned about potential adverse selection risk during times when the market expects unusually large price moves, react by charging more for liquidity provision. After including these three controls, along with index fixed effects, we explain a significant portion of the variance in daily average price impact (88%).

Beyond our market controls, we also find that concentration (or lack of it) amongst our participant categories is often highly predictive of trading costs. This is true for both our network and non-network based concentration measures. Interestingly, however, this relationship seems to hold only for the levels of customer concentration; the relative level of dealer concentration does not appear to have separate explanatory power for the average cost of dealer-to-customer trades. This may signal a higher variance in the day-to-day customer activities – where any individual dealer is likely to be active in each index on each day, the trading interests of the average customer are likely to be much less consistent. Model 3 indicates that the higher the average HHI for customers, the lower the cost of an average trade. So, on days when more concentrated customers trade in the market (measured by their trading volume), these customers face, or perhaps demand, reduced trading costs. This is consistent with findings by Iercosan and Jiron (2017): higher levels of trading activity by clients lowers the average execution costs for these clients.

The same is true for the network-based measures. In Model 4 we find that the more counterparties the average customer trades with, the lower the average customer's trading cost. This is consistent with Duffie et al (2005)'s finding that execution costs such as bid-ask spreads are lower when investors can have easy access to multiple market makers. The authors attribute this relationship in part to the relative bargaining power of investors and market makers. As investors are able to force market makers to compete with each other, execution costs fall for investors. Centralizing trading between investors and market makers on one or a few platforms presumably aids in raising the relative power of investors, potentially helping to decrease costs. The same directional relationship holds for the weighted direct and indirect connections for an average customer. Simply put, the more influential customers trade in the market, the lower the average cost of trading for customers. These results support the hypothesized link between trading power (as expressed by network connections) and liquidity levels.

Concentration and network measures for dealers do not seem to have a significant effect on liquidity. The fairly stable dealer participation over the last few years is a possible cause; recently, a few non-traditional institutions have either started to act as market-makers in credit index swaps, or have announced their intention to. Over time, this increase in the number and type, of swap dealers may lead to a more direct relationship between concentration in market making and execution costs.

Robustness Checks

Defining and measuring liquidity is challenging, as well-established liquidity measures can often represent only segments of execution efficiency. To further test our results, we run regressions with the same covariates on our alternative liquidity measure, the volume weighted price dispersion measure defined above. Table 4 presents the regression results using price dispersion as dependent variable. In almost all cases, the results for the less granular price dispersion measure match those for the price impact measure in Table 3. One exception to this is the slightly less explanatory power attributable to the measures and controls we include in the regressions. This is likely due to the fact that the daily price dispersion measure is less precise an estimate of transaction costs than price impact. In addition, in Table 4 the network measures no longer have a significant effect on price dispersion. Still, the HHI results mirror those from the prior set of regressions, bolstering our argument that customer power within the trading network can affect their ability at getting more favorable execution terms.

Conclusions

Credit index swap trading has gone through dramatic structural changes in recent years, including reforms such as mandatory clearing, SEF trading and reporting, and the entrance of new liquidity providers. Because market health is often highly correlated with the ease with which market participants can trade at reasonable size over a reasonable period of time, it is important to analyze where market liquidity currently stands after this evolution. Many recent research papers have looked at changes in market liquidity in derivatives markets relative to market changes and have, on balance, not found significant liquidity deteriorations. In some cases, liquidity improvements may have been identified.

In this paper, we use quantity-based and price-based liquidity measures to examine factors behind credit index trading costs executed on the largest CDS trading platform over a sample period of two and a half years. Using this data, we see that trading conditions have generally been stable or have improved, as measured by liquidity metrics such as daily volumes, price impacts, and price dispersion. However, we also observe that trade sizes may have declined slightly, perhaps due to automation or customers' optimizing trade size for best execution. Finally, our regressions point to the possibility that more active trading customers incur lower trading costs. In addition, we find that customers trading with more dealers (high network degree) and having connections with more active dealers (high network centrality) incur lower trading costs. Though we cannot speak directly to the effect of specific market changes, this does provide some evidence that in cases where customers are able to reach more intermediaries they may be able to mitigate the cost of their trades.

References

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-section and Time-series Effects. Journal of Financial Markets 5, 31-56.

Benos, E., Payne, R., and Vasios, M. (2016). Centralized Trading, Transparency and Interest Rate Swap Market Liquidity: Evidence from the Implementation of the Dodd-Frank Act. Bank of England Staff Working Paper No. 580.

Babus, A., and Hu, T. (2016). Endogenous Intermediation in Over-the-Counter Markets, Available at http://www.anababus.net/research/otc.pdf.

Bessembinder, H., Maxwell, W., and Venkataraman, V. (2006). Market Transparency, Liquidity Externalities, and Institutional Trading Costs in Corporate Bonds. Journal of Financial Economics 82 (2).

Bonacich, P. (1987). Power and Centrality: A Family of Measures. American Journal of Sociology 92 (5).

Du, W., Gadgil, S., Gordy, M., and Vega, C. (2016). Counterparty Risk and Counterparty Choice in the Credit Default Swap Market. FEDS Working Paper.

Duffie, D., Garleanu, N., and Pedersen, L. (2005). Over-the-Counter Markets. Econometrica 73 (6).

Hendershott, T., and Madhavan, A. (2015). Click or Call? Auction versus Search in the Over-the-Counter Market. Journal of Finance 70 (1).

Iercosan, D. and Jiron, A. (2017). The Value of Trading Relationships and Networks in the CDS Market. Available at SSRN: https://ssrn.com/abstract=2901743

Li, D. and Schürhoff, N. (2014). Dealer Networks. Available at https://www.federalreserve.gov/econresdata/feds/2014/files/201495pap.pdf

Long, Y. and Zhong, Z. (2016). Does Dodd-Frank Affect OTC Transaction Costs and Liquidity? Evidence from Real-time CDS Trade Reports, Journal of Financial Economics 119 (3).

Onur, E., Reiffen, D., Riggs L., and Zhu H. (2017). Mechanism Selection and Trade Formation on Swap Execution Facilities: Evidence from Index CDS Trades. MIT and CFTC Working Paper.

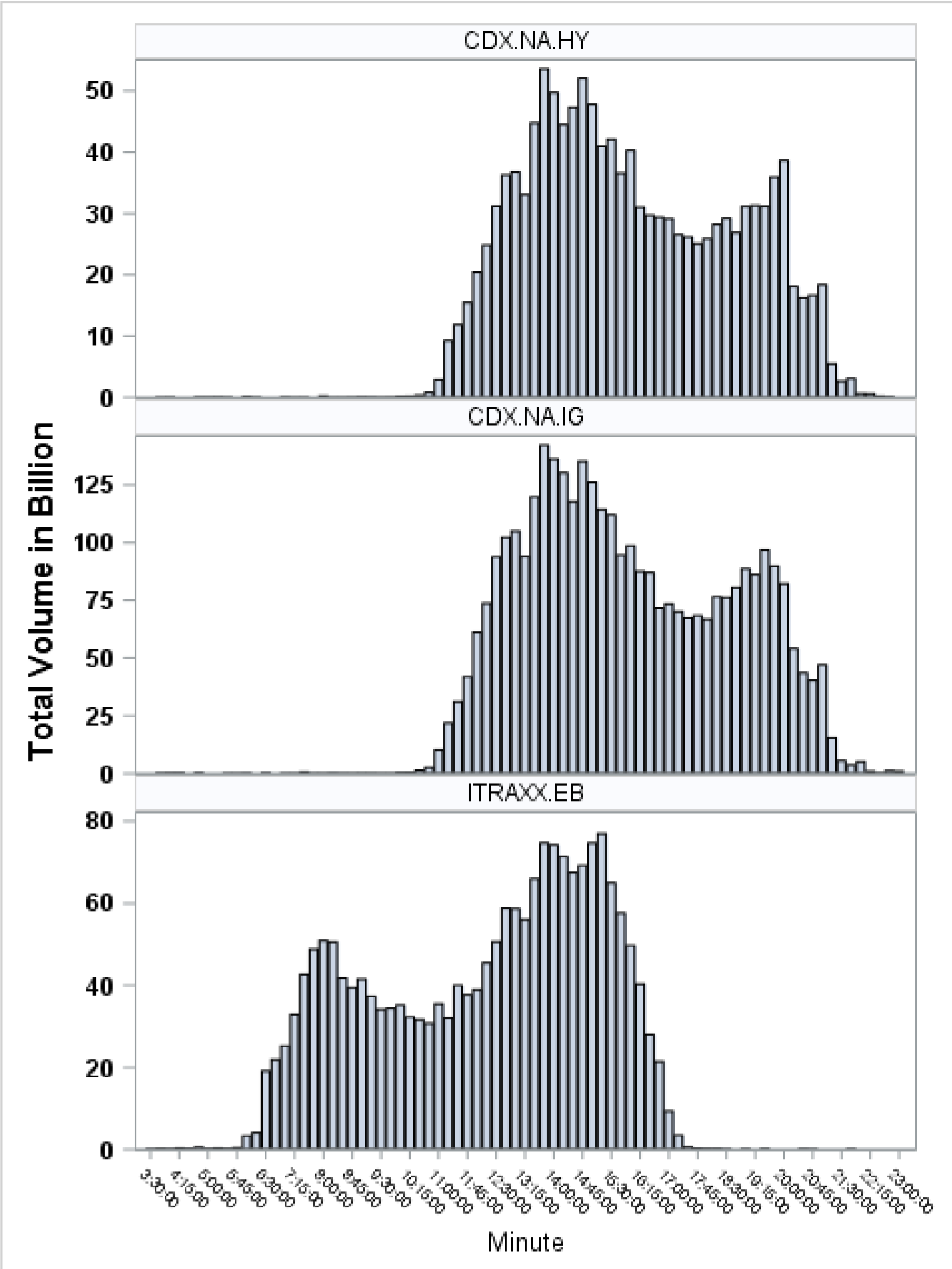

Figure 1 Total Volume ($ for CDX.NA.HY and CDX.NA.IG and € for ITRAXX.EB) by 15-minute Window (GMT) from Oct 2014 to Sep 2016

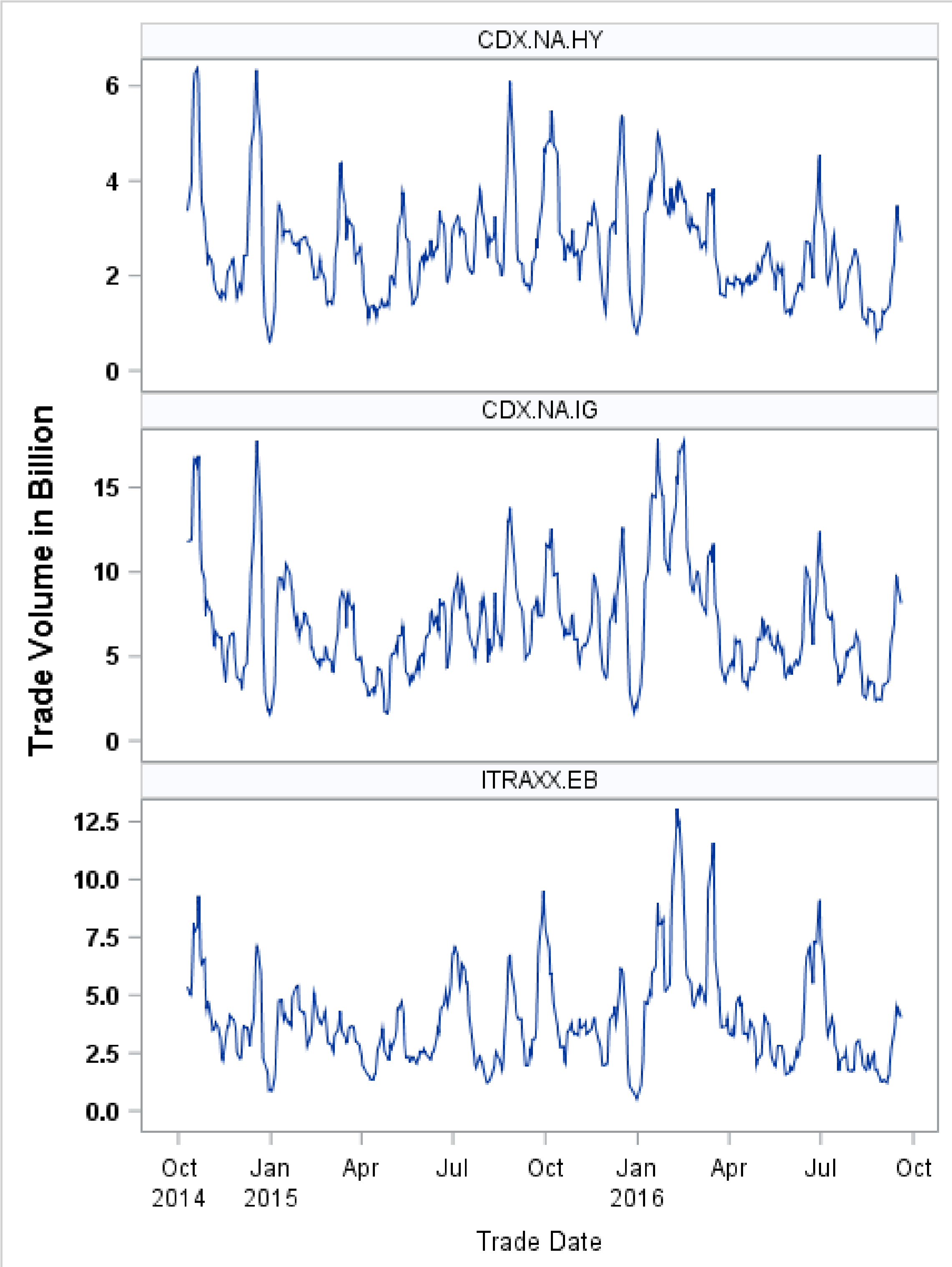

Figure 2 Five Day Moving Average Trade Volume ($ for CDX.NA.HY and CDX.NA.IG and € for ITRAXX.EB) on BSEF Including both Dealer To Dealer (DTD) and Dealer To Customer (DTC) Trades

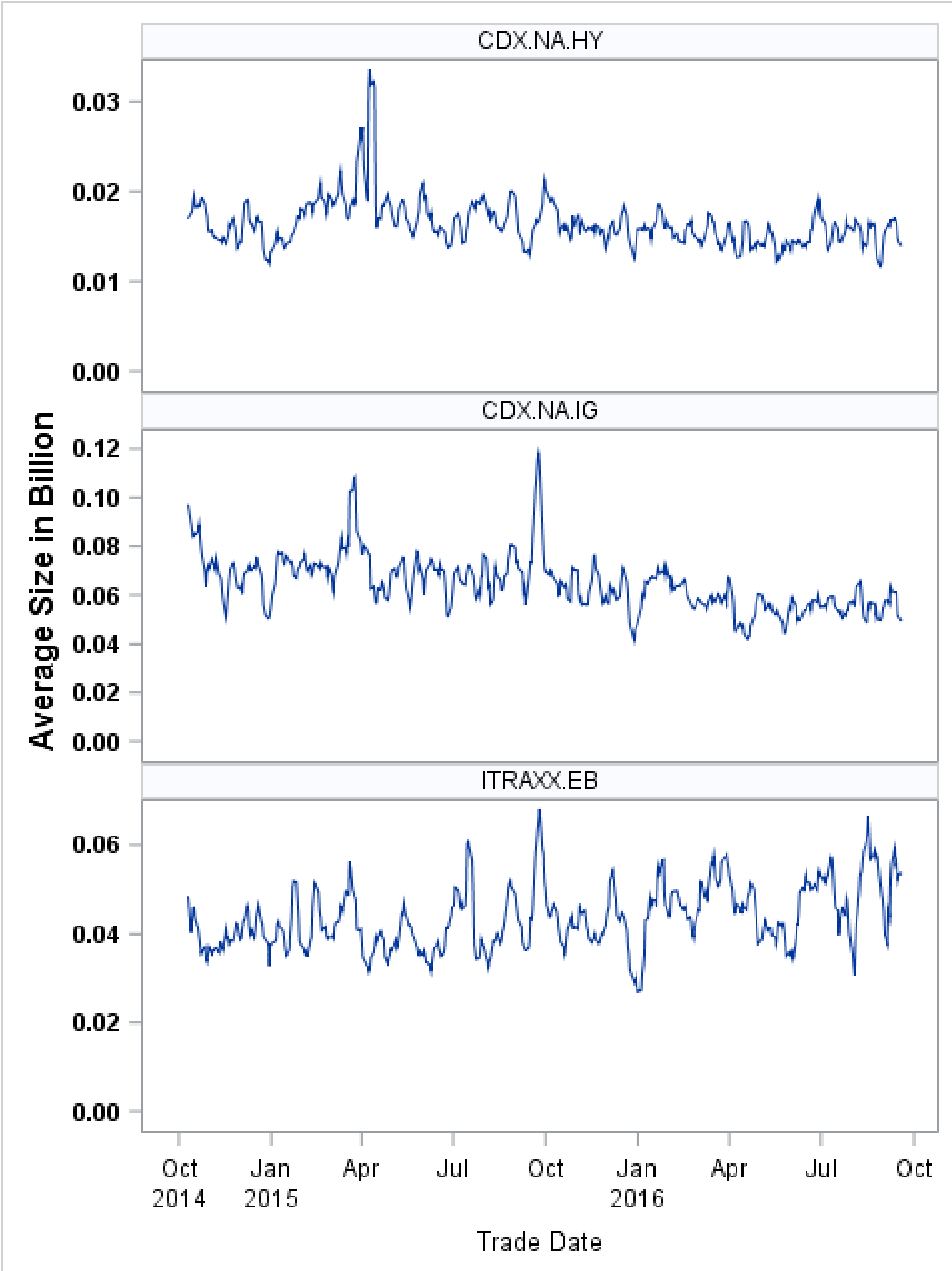

Figure 3 Five Day Moving Average Trade Size for Dealer to Customer Trades (in $ for CDX.NA.HY and CDX.NA.IG and € or ITRAXX.EB)

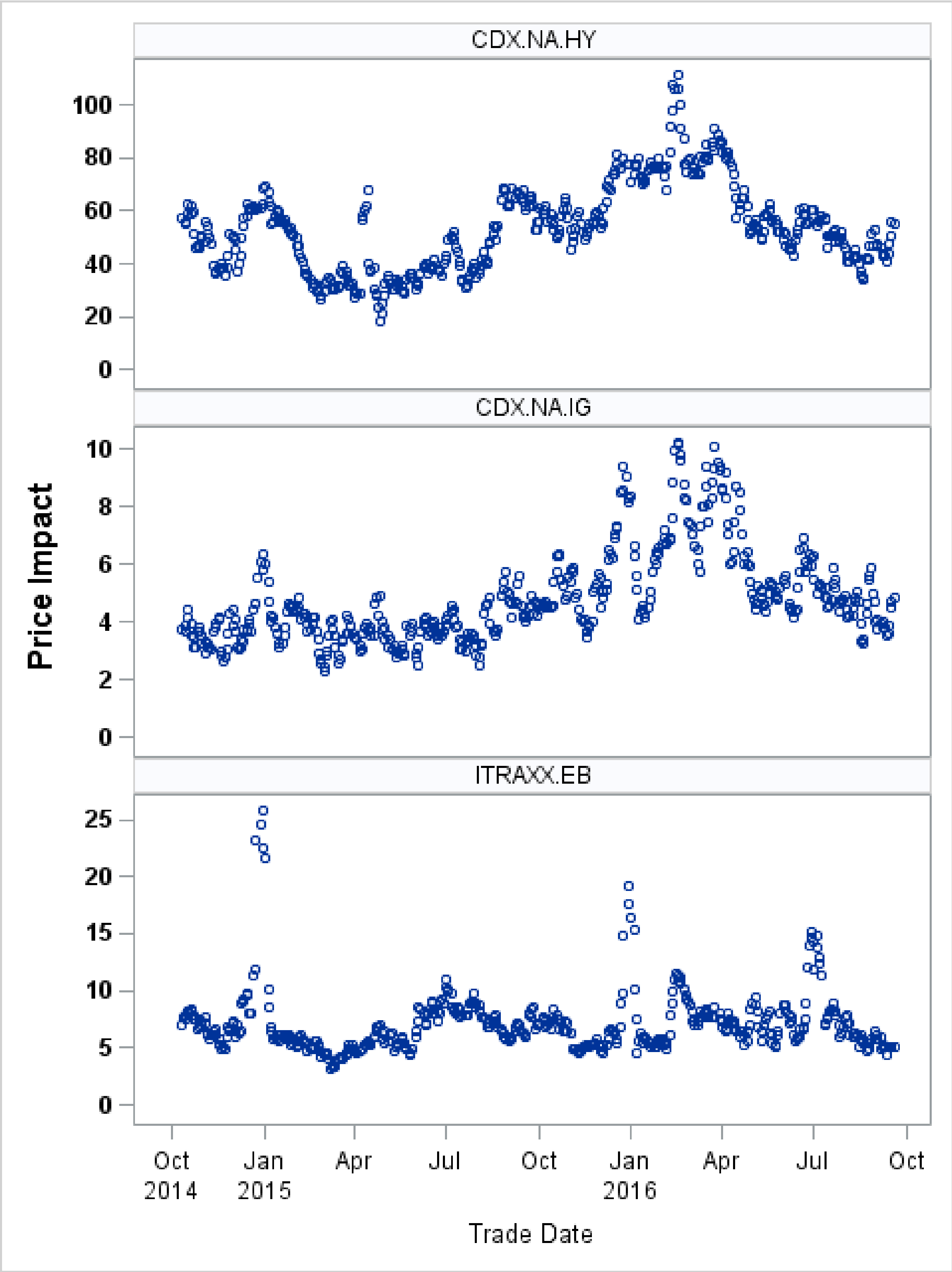

Figure 4 Five Day Moving Average Price Impact for Dealer to Customer Trades using Spreads (bps)

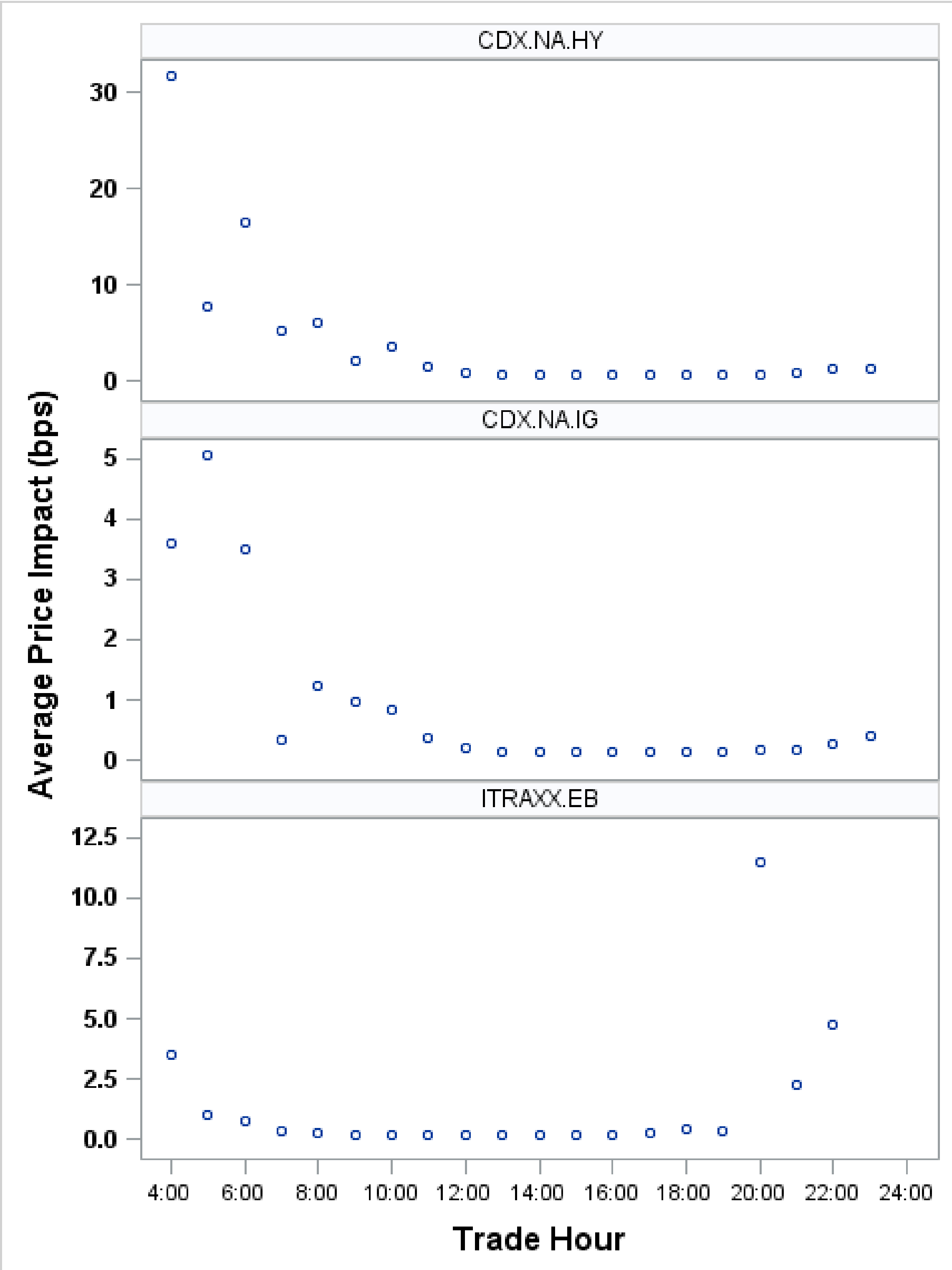

Figure 5 Average Price Impact by Trade Hour (GMT) from Oct 2014 to Sep 2016

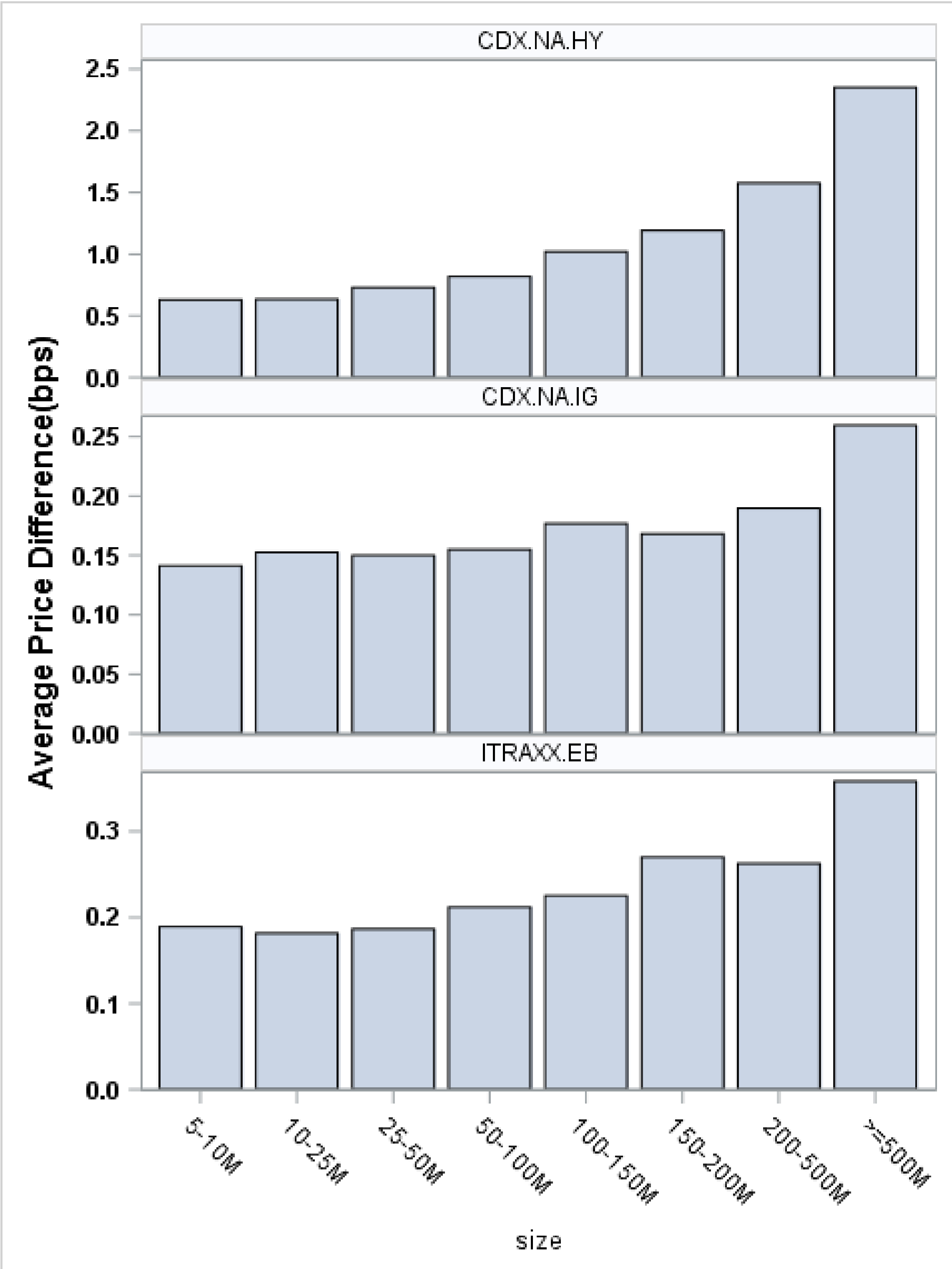

Figure 6 Price Impact measured by Absolute Spread Difference between Current and Previous Trade by Size Using Trades Oct 2014 to Sep 2016

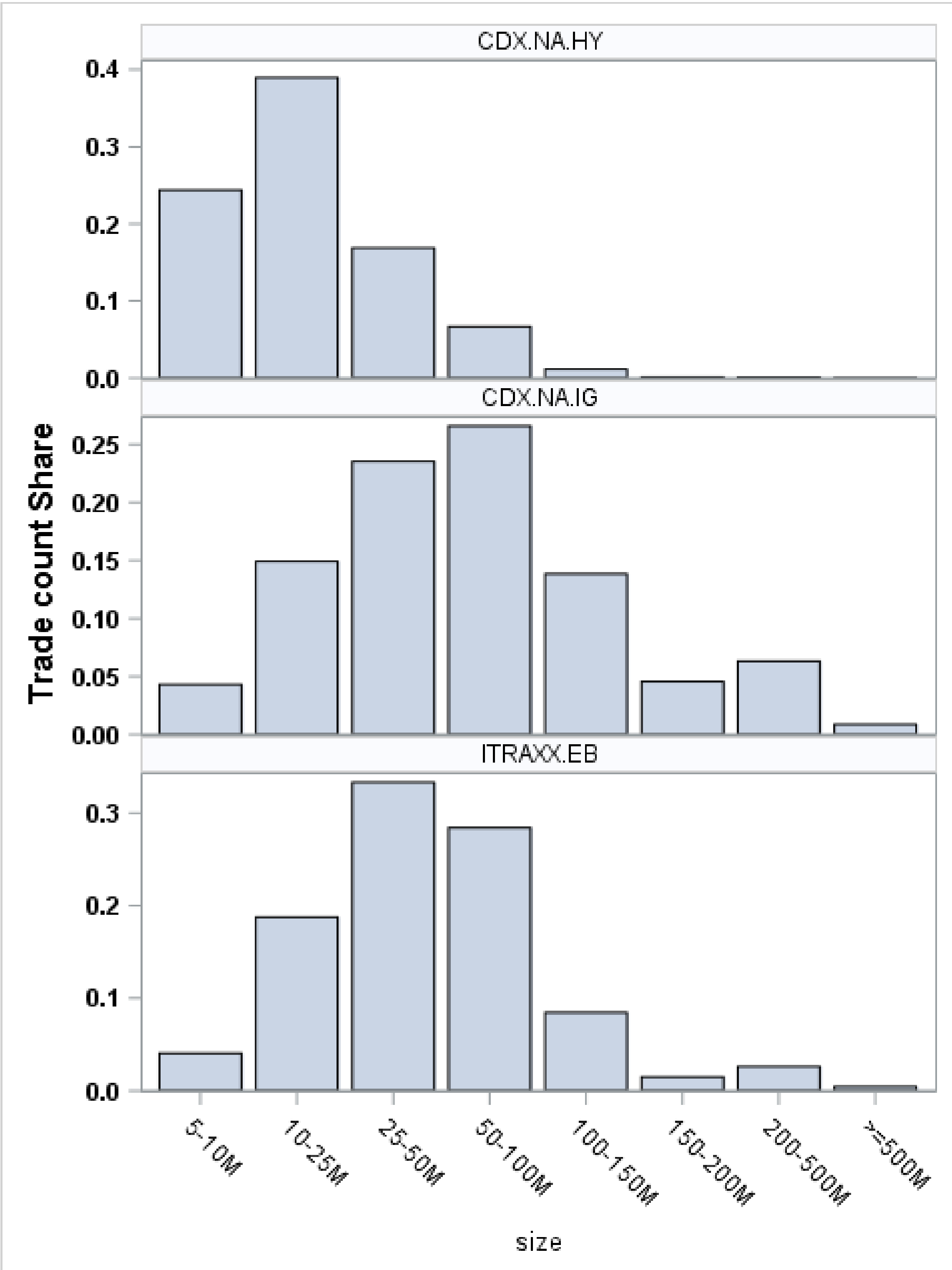

Figure 7 Dealer to Customer Trade Size Distribution: Percentage of Trade Counts in Each Size ($ for CDX and € for ITRAXX)

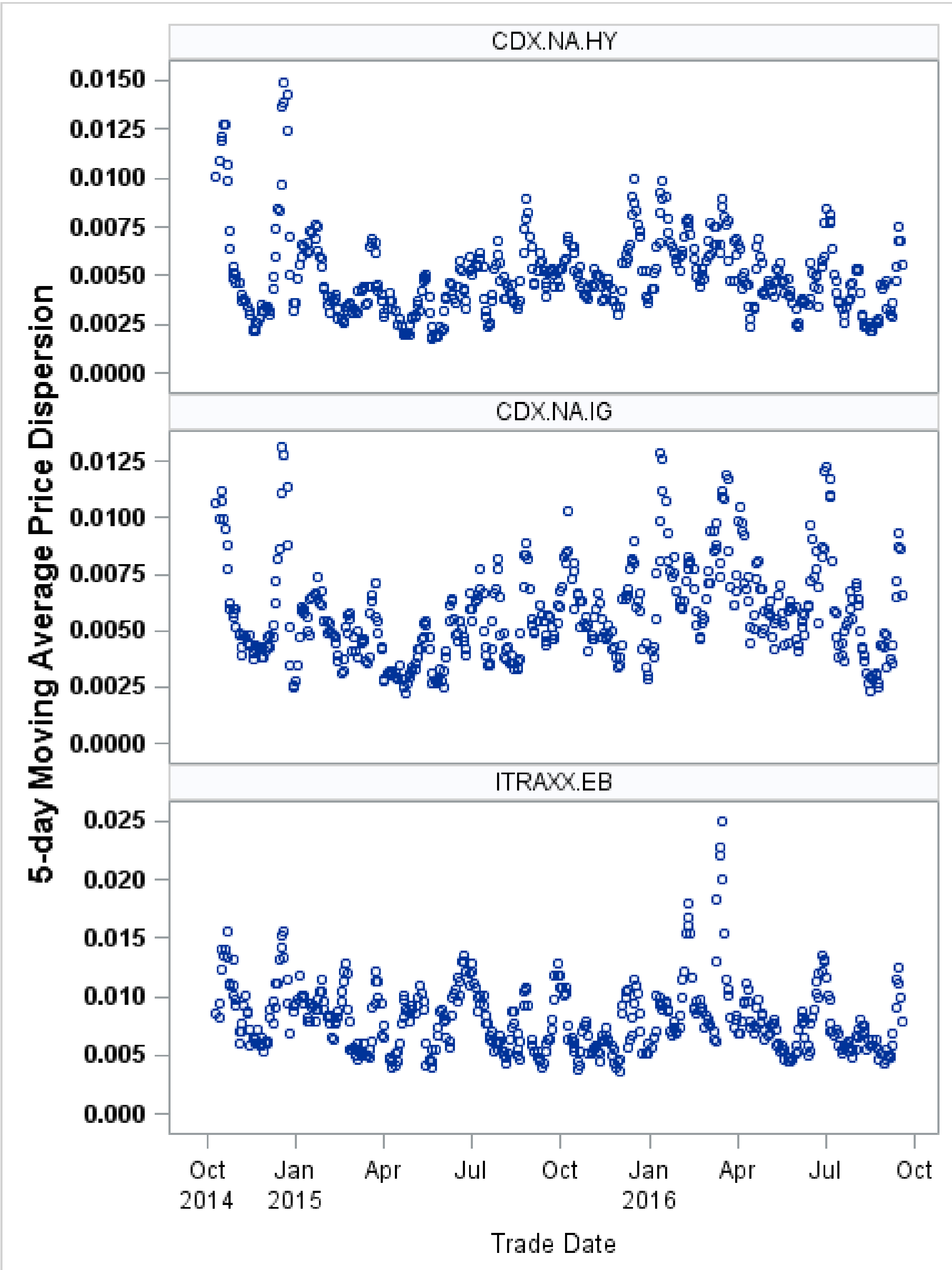

Figure 8 Five-Day Moving Average Volume-Weighted Price Dispersion for Dealer-to-Customer Trades

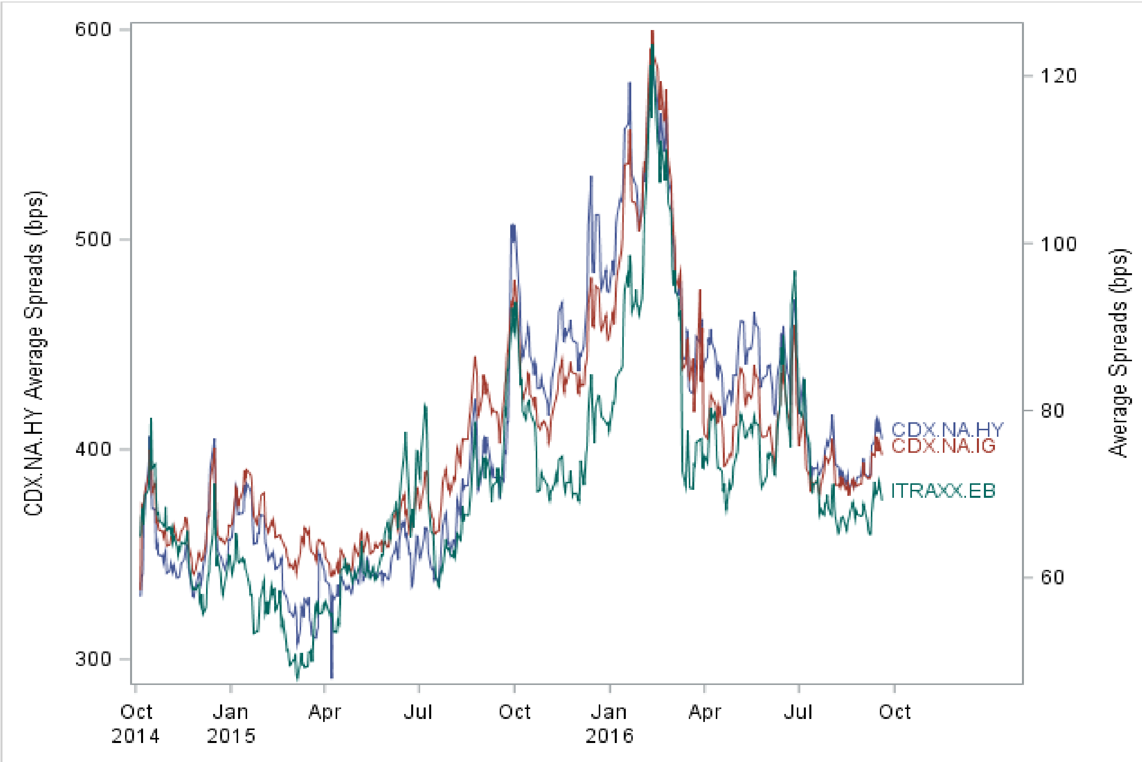

Figure 9 Average Daily Spreads

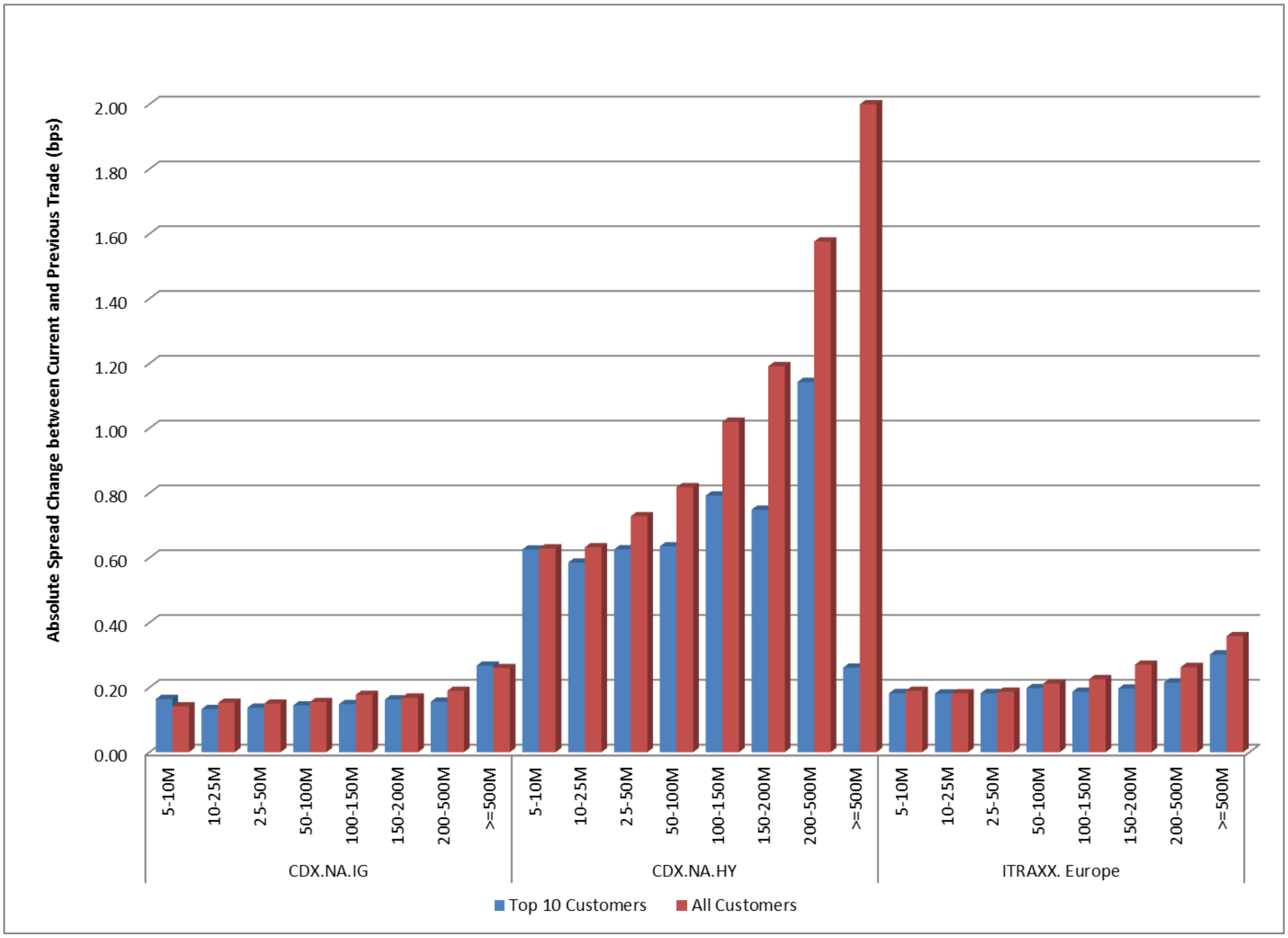

Figure 10 Price Impact for Top 10 Customers vs All Customers by Size

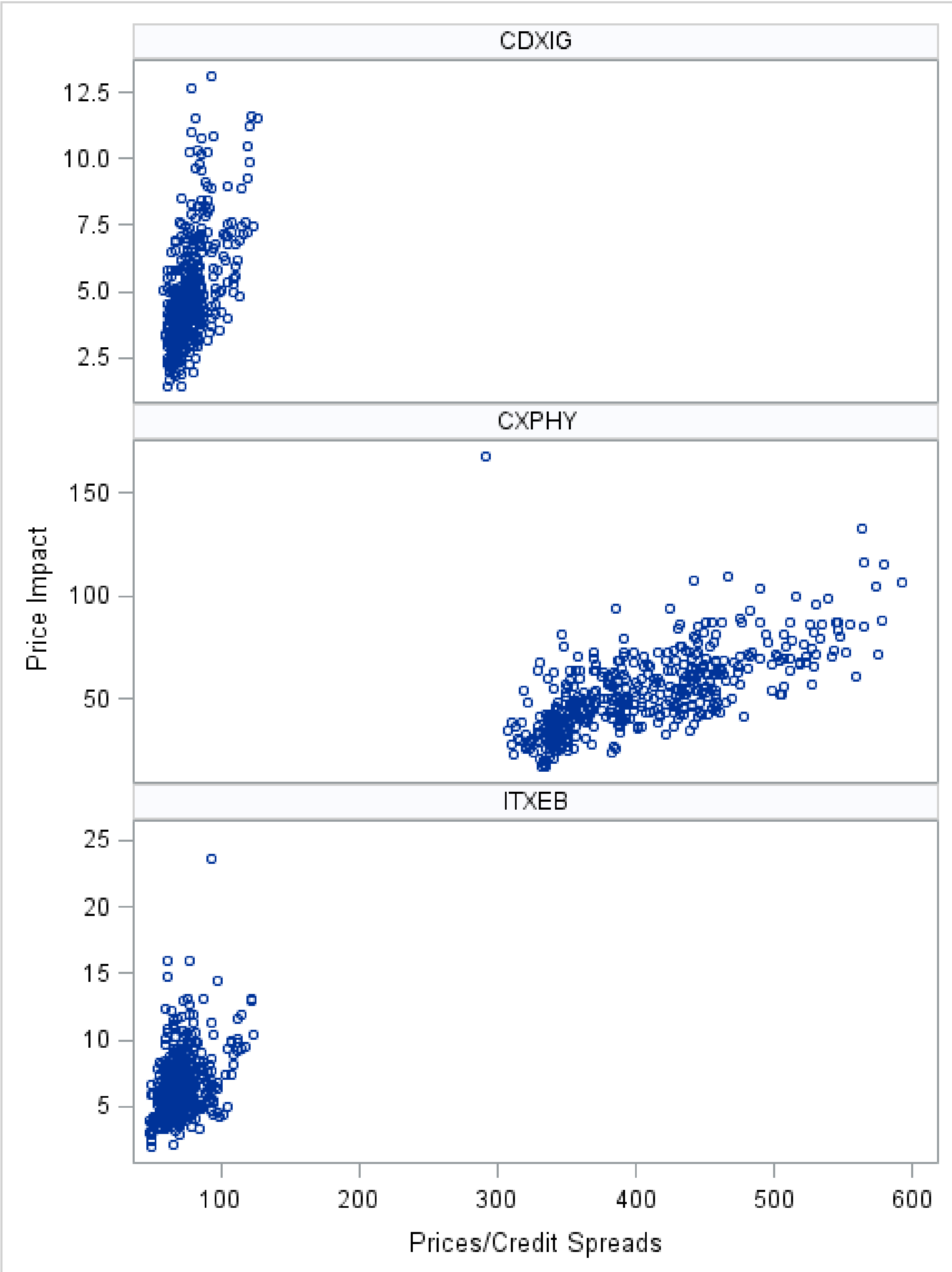

Figure 11 Daily Price Impact vs Daily Average Spreads

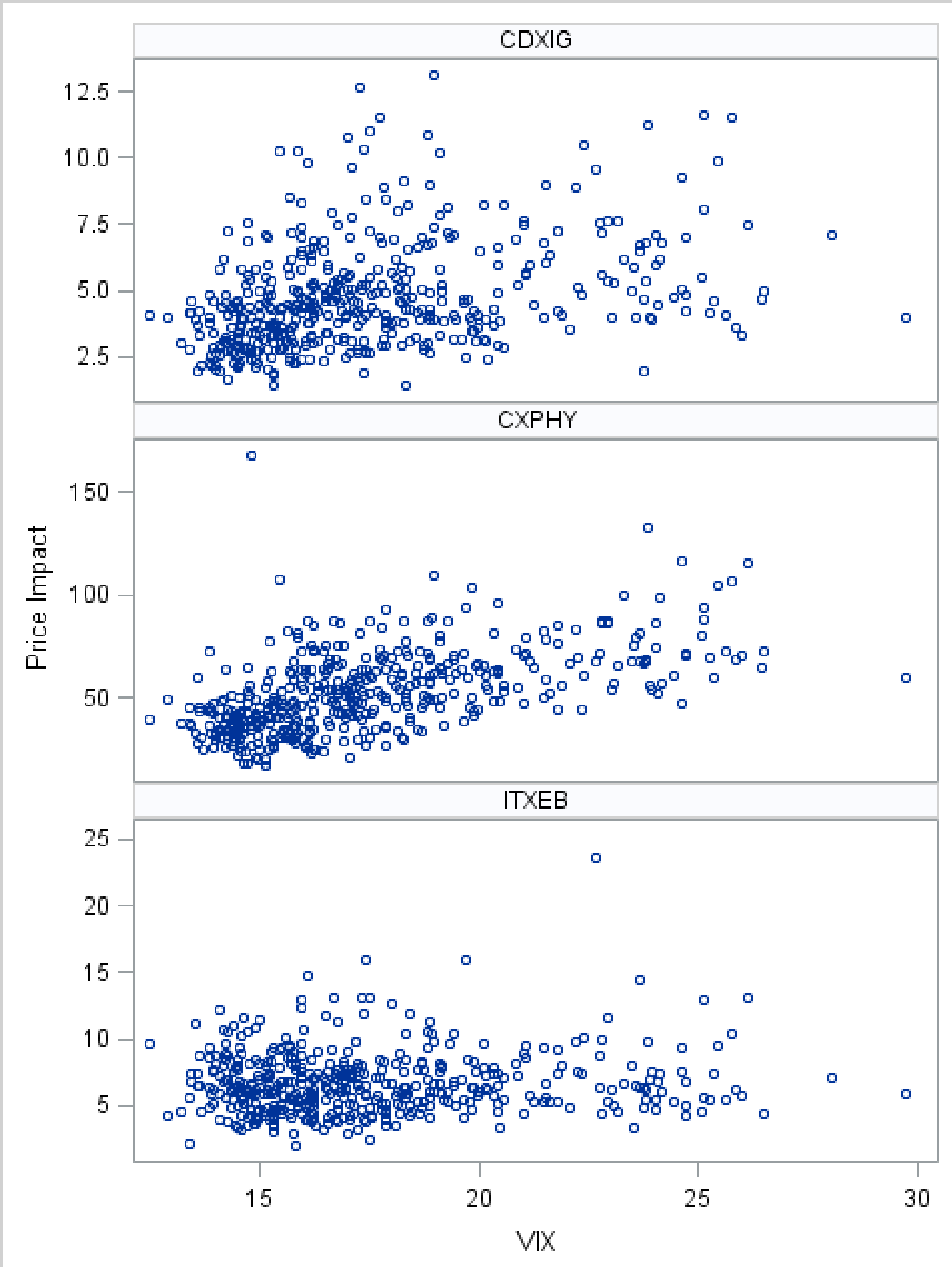

Figure 12 Daily Average Price Impact vs VIX Settlement Price

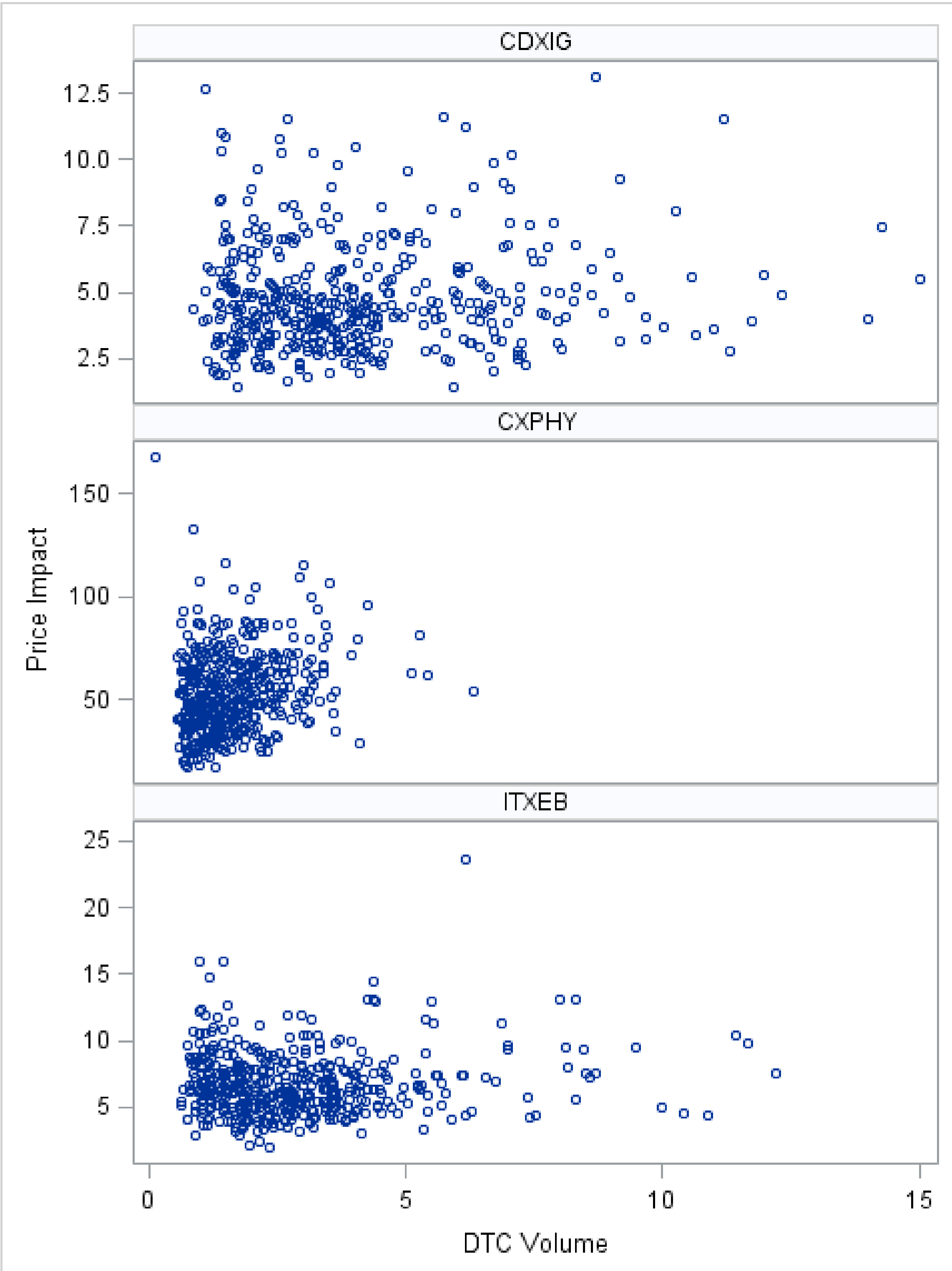

Figure 13 Daily Average Price Impact vs Daily Volume

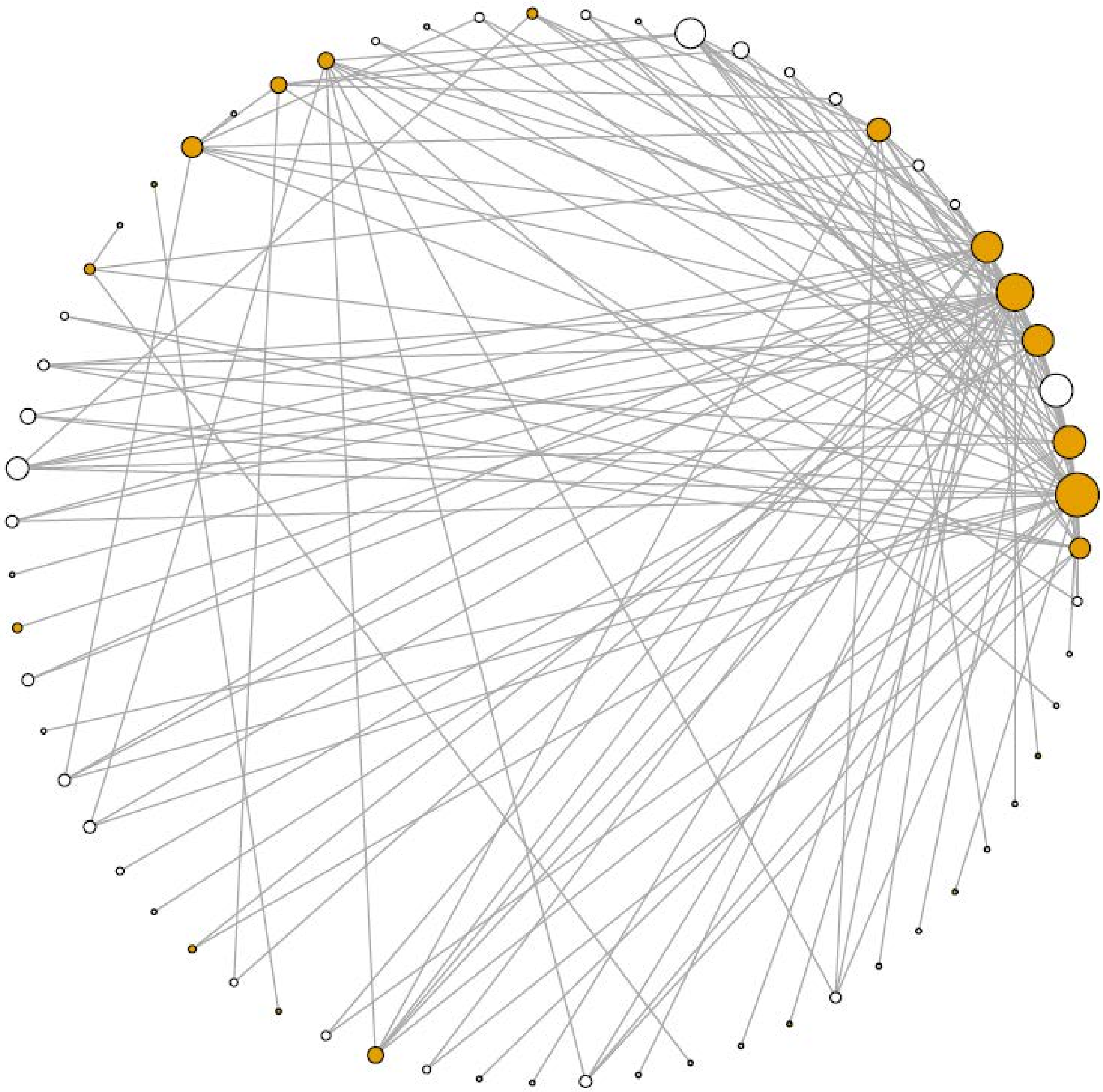

Figure 14 CDX Trading Network on Oct. 15, 2014: Vertex Breakdowns into Dealer (Orange) and Non-dealer (White) Categories

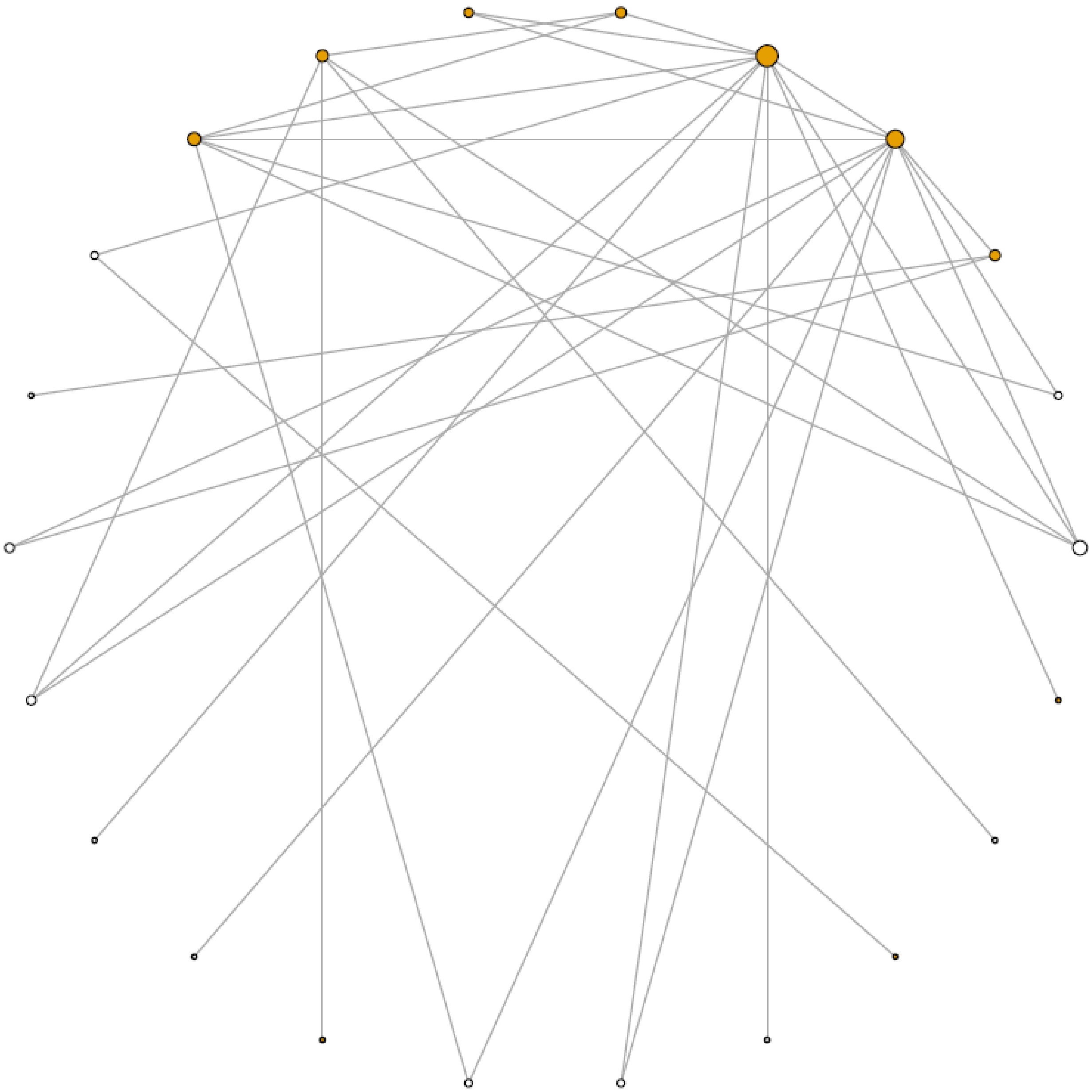

Figure 15 CDX Trading Network on Jan. 2, 2015: Vertex Breakdowns into Dealer (Orange) and Non-dealer (White) Categories

Table 1 Daily Measures for Dealer to Dealer and Dealer to Customer (DTC) Trades

Series	Daily measures	Dealer to dealer (DTD)	Dealer to customer (DTC)
CDX IG	Market trade count	12.15	53.79
	Market trade notional ($ bil.)	0.69	3.84
	Average trade size ($ bil.)	0.05	0.07
	Price impact (bps/$BN)	6.28	4.83
CDX HY	Market trade count	8.34	81.63
	Market trade notional ($ bil.)	0.13	1.55
	Average trade size ($ bil.)	0.02	0.02
	Price impact (bps/$BN)	80	53.67
ITRAXX	Market trade count	16.72	54.53
	Market trade notional (€ bil.)	0.54	2.72
	Average trade size (€ bil.)	0.03	0.05
	Price impact (bps/€ BN)	10.21	7.1

Table 2 Daily Average Price Impacts for All Customers versus Top 10 Customers

	CDX IG	**CDX HY**	**ITRAXX**
All Customers (bps/$bn)	4.83	53.64	7.1
Top 10 Customers (bps/$bn)	4.2	49.78	6.98
Difference (%)	13.04	7.19	1.6

Table 3 Summary Statistics for Regression Variables

	CDX.NA.HY		CDX.NA.IG		Itraxx.Europe	
	Mean	StDev	Mean	StDev	Mean	StDev
Price Impact (per $bn)	53.64	19.82	4.83	2.06	7.10	3.98
DTC Volume ($bn)	1.55	0.86	3.82	2.43	2.72	1.89
Daily Average Spread	403.69	62.47	76.60	13.15	71.30	13.00
Dealer HHI	0.04	0.02	0.05	0.01	0.05	0.02
Avg Dealer Degree	8.34	2.52	5.97	1.91	4.62	1.54
Avg Dealer Centrality	0.11	0.03	0.10	0.03	0.10	0.03
Non-dealer HHI	0.02	0.01	0.02	0.01	0.03	0.02
Avg Non-dealer Degree	2.13	0.29	1.99	0.35	2.18	0.42
Avg Non-dealer Centrality	0.04	0.02	0.05	0.02	0.07	0.03

Table 4 Price Impact Regression Results

	Model 1	Model 2	Model 3	Model 4
DTC Volume	-0.80*	-0.70*	-0.53*	-0.98*
VIX	1.47*	0.28*	0.19*	0.19*
Daily Average Price		0.20*	0.21*	0.20*
Dealer HHI			176.78	
Non-dealer HHI			-59.02*	
Avg Dealer Degree				0.72
Avg Dealer Centrality				36.15
Avg Non-dealer Degree				-2.31*
Avg Non-dealer Centrality				-41.34*
Index FE	Yes	Yes	Yes	Yes
R-squared	0.82	0.88	0.89	0.89

Note: estimates with * are significant at 1% level.

Table 5 Price Dispersion Regression Results

	Model 1	Model 2	Model 3	Model 4
DTC Volume	0.000818*	0.000820*	0.000792*	0.000455*
VIX	0.000109*	0.000083*	0.000071*	0.000024
Daily Average Price		0.000004*	0.000004*	0.000002
Dealer HHI			-0.00302	
Non-dealer HHI			-0.039300*	
Avg Dealer Degree				0.000530*
Avg Dealer Centrality				-0.000128
Avg Non-dealer Degree				0.000207
Avg Non-dealer Centrality				-0.002047
Index FE	Yes	Yes	Yes	Yes
R-squared	0.18	0.18	0.19	0.22

Note: estimates with * are significant at 1% level.