Market Segmentation Across Stocks, Bonds, and Derivatives*

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February 12, 2025

Abstract

We document dealer specialization across bond, stock, and derivative markets using a unique dataset that tracks dealers' trading activities across all major Canadian financial markets. Our findings reveal that product specialization within a market is more pronounced than market specialization, though not all dealers participate in every market. While no market is frictionless enough to stop some dealers from consistently getting better prices than others, we find no evidence of cross-market trading synergies. Our results challenge the traditional view that financial intermediaries seamlessly operate across all markets, and highlight the role of market structure and product complexity in shaping market segmentation.

Keywords: Market segmentation, financial intermediaries, market design, transaction costs
JEL: G00, G10, G12, G19, D40

*The views presented are those of the authors and not necessarily the Bank of Canada. We thank Jason Allen, and the experts at the Bank of Canada and the Montreal Stock Exchange—in particular, Corey Garriott and the Triton project team. We also thank Connor Breck, Carel Chok, Costanza Didonna, Matthew Hagerty, Harrison Lynch, Brendan McLaughlin, Daniel Smith, and Joseph Wagner for excellent research assistance. Any errors are our own. Correspondence to: §Milena Wittwer (Boston College): wittwer@bc.edu, and +Andreas Uthemann (Bank of Canada): a.uthemann@gmail.com

1 Introduction

Financial markets are fragmented: stocks trade across multiple exchanges, bonds in decentralized over-the-counter (OTC) markets, and derivatives in either centralized or decentralized settings. In each market segment, most trading activity is concentrated among a small and potentially different set of financial institutions—we refer to as 'dealers'—such as exchange members for stocks or registered broker-dealers in bond markets.[1] Other investors either trade with these institutions or execute trades through them, relying on their ability to facilitate transactions.

Given the prevalence of fragmentation, a substantial theoretical literature explores its impact on trading, pricing, and efficiency—both in exchanges (e.g., Malamud and Rostek (2017); Chen and Duffie (2021); Budish et al. (2024)) and in OTC markets (see Weill (2020) for an overview). These models must take a stance on whether dealers participate in all markets or a subset and whether they trade all assets or specialize on some 'products', like government versus corporate debt. Knowing the answers to these questions is not only key to developing empirically grounded theories, but also for designing policies and regulation, as they help assess potential spillovers effects across assets and markets. However, limited data availability makes it difficult to study these questions, leaving trade segmentation across products and markets largely unexplored.

We construct a unique dataset to examine how dealer trading activities contribute to market fragmentation across equities, bonds, and derivatives in Canada. We first document the extent of cross-market and cross-product 'segmentation'—or equivalently, 'specialization'—by analyzing where, what, and how much each dealer trades. Cross-market segmentation may arise from differences in market clearing rules or entry costs, while cross-product segmentation within a market—where such frictions are absent—may instead reflect differences in trading technologies, expertise, relationships, or client preferences. We then assess whether specialized dealers systematically obtain better prices than those operating across multiple markets or products, shedding some light on the returns to specialization.

Our dataset covers all trades executed on Canada's fixed-income market and four exchanges owned by the Toronto Stock Exchange Group (TMX) from 2019 to 2022. TMX owns three stock exchanges, which account for roughly 60 percent of equity trade volume in Canada, and the country's only derivatives exchange. A key feature of this dataset is the ability to track dealers

[1] An alternative label for the institutions we analyze in this paper is 'market-maker.' We avoid this term because a significant share of their trading activity extends beyond market-making to include executing trades for clients and responding to client needs. For instance, on exchanges, only certain members are designated as market makers with a formal obligation to provide liquidity.

over time and across markets using legal entity identifiers (LEIs)—an attribute rarely available in trade-level datasets, particularly for stocks and derivatives. We link this information to public data to classify securities into products, for instance, corporate bonds, large-cap stocks, Exchange Traded Funds (ETFs), and Treasury futures. Additionally, we manually assign dealers to their parent institutions, i.e., the LEIs of their holding companies, and categorize them by type, such as primary dealers or hedge funds.

With these data, we first analyze whether dealers trade across markets. We find that cross-market segmentation is influenced by the fact that different legal sub-entities of the same parent institution (such as subsidiaries of a bank or funds of an asset manager) specialize in different markets. After removing the legal segmentation that arises within institutions, the stock and bond market appear relatively integrated—at least in terms of total trade volume. Over 80% of volume traded by dealers is executed by institutions who are active in both the stock market and fixed-income market at the holding company-level. The derivatives market is more segmented due to high-frequency traders who only trade derivatives. In general, market integration is driven by institutions who act as primary dealers for government debt, while many other dealers do not participate across all markets.

Cross-product segmentation remains prevalent, with parent institutions often specializing in specific products within markets, though this is not universal. The extent of product segmentation appears to depend on market structure—centralized, as in exchanges, versus decentralized, as in OTC markets—and the complexity of the products traded. We find that all dealers participate across all products on centralized stock exchanges, where products are standardized. However, this is not the case in the fixed-income OTC market, where products are standardized but the market is decentralized, or in the derivatives exchange, which is centralized but features less standardized products.

To compare cross-market with cross-product segmentation within markets, we introduce a segmentation measure that adapts the Theil (1967) index to account for the fact that not all dealers participate in every market segment. While the Theil index is commonly used to measure inequality in socio-economic contexts (e.g., Anand and Segal (2015)). It has not, to our knowledge, been applied to trade settings. It is useful for comparing different degrees of segmentation, as it uniquely separates within-market from cross-market segmentation. Consistent with the descriptive evidence, the Theil index decomposition reveals that, for most dealers, across-product segmentation within a market is greater than cross-market segmentation. It is not the case that dealers who are active in more markets, feature lower cross-product segmentation.

Having established evidence of trade segmentation, we investigate whether the limited

cross-market and cross-product activity of certain dealers affects their transaction costs. Alternatively, if markets are sufficiently competitive, prices—and by extension, transaction costs—may remain unaffected by dealer specialization. To address this, we compute transaction costs for each trade based on the market microstructure literature following Hendershott and Madhavan (2015); Hau et al. (2021); O'Hara and Zhou (2021); Pinter et al. (2024).

We start by analyzing whether certain dealers consistently obtain better prices than others. We show that neither the bond, stock, or derivatives market is sufficiently frictionless to prevent some dealers from systematically outperforming others. This is true even after controlling for observable confounding factors, such as trade-size, and security and time-specific fixed effects. In particular, high-frequency traders tend to outperform other dealer types on the exchanges, while dealers who serve retail investors are the least profitable types in the bond and derivatives market. On the stock market, the large dealers who are active in all markets outperform those who exclusively trade stocks. In contrast, on the (decentralized) bond and the (centralized) derivative market (which offers more complex products), specialization appears to pay off for some dealers—in line with the idea that both market structure and product complexity favor specialization.

Despite this, we find little evidence of trading synergies that enable some dealers to outperform others across markets or across products, independently of the market's structure or product complexity. For instance, dealers who consistently secure better prices for bonds do not achieve similar advantages in stocks or derivatives. One possible explanation is that, in practice, individual traders or trading desks within institutions focus on a limited set of assets and optimize trading within that selection (Lu and Wallen (2024)). From an antitrust perspective, the absence of trading synergies suggests that natural monopolies do not arise, as would be the case if the largest institutions dominated financial trading across markets and products through economies of scale.

Beyond this, our findings reveal other policy implications. Greater specialization by product rather than by market suggests that, for large financial institutions, barriers to market entry are less restrictive than factors that limit trading across products within the same market. As a result, policies aimed at lowering entry costs or membership fees—such as the recently revised fee schedule for bond dealers in Canada (CIRO (2024))—may have limited impact (unless they reduce barriers enough to attract an entirely new set of market participants). Furthermore, the dominance of large banks in trading across markets suggests that regulatory changes affecting bank balance sheets—such as adjustments to the supplementary leverage ratio to accommodate increased government debt issuance—easily impact all markets. Since the Canadian stock and bond markets are more integrated than the derivatives exchange, cross-market spillovers may

be stronger between bonds and stocks than (at least some types of) derivatives. However, this warrants further study.

We hope to inspire future research, with several additional promising avenues to explore. One direction would be to examine how product complexity and market design influence segmentation. Our findings suggest that specialized knowledge or infrastructure, particularly in derivatives and bonds, and the decentralized nature of some markets, like OTC bond trading, exacerbate segmentation. Understanding these interactions requires models that account for different market structures and product characteristics, shifting the focus beyond a single market or product, as seen in much of the existing literature. Another direction for future research is to analyze market-level equilibrium effects. While we document price differences across dealers, it remains unclear whether segmentation affects aggregate asset prices. Addressing this requires an exogenous shock to segmentation or a structural model that incorporates market clearing based on individual trading and pricing decisions. Finally, the fact that large banks dominate trading activities across markets raises concerns related about financial stability. Examining trading interconnectedness during periods of distress would help identify which types of institutions amplify negative spillovers across markets and which ones help mitigate them.

Literature. Our primary contribution is to document dealer specialization across bonds, stocks, and derivatives, and to analyze returns on specialization in terms of transaction costs. This adds to different strands of the literature.

Dating back to Markowitz (1952), a large body of work studies asset portfolios. This literature relates to our study in that portfolios include different types of assets with distinct risk characteristics like stocks and bonds. It differs from what we do in that it mostly abstract from market frictions that hinder traders from making optimal portfolio choices.

In this regard, our approach aligns more closely with the literature on financial market segmentation and fragmentation, which typically takes a theoretical perspective. For example, research on OTC markets, recently overviewed by Weill (2020), examines how decentralized market structures shape segmented trading networks; the literature on equity markets explores why stocks trade across multiple fragmented exchanges rather than a single venue (e.g., Chen and Duffie (2021); Budish et al. (2024)) and how market rules contribute to segmentation (e.g., Chao et al. (2019)). With few exceptions, such as Dougast et al. (2022), most models focus on a single market structure; and a single asset class, with the exception of studies on derivatives and their underlying assets, which date back to Kumar and Seppi (1992). We contribute to these literatures by empirically documenting the degree of market segmentation across different market structures and asset types.

Given our focus on large institution who execute trades, rather than investors who hold assets, our work further relates to a large and rapidly expanding literature on financial intermediaries and their role in financial markets. This literature analyses, for example, how different constraints that intermediaries face affect asset prices (e.g., Shleifer and Vishny (1997); Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014)), and the extent to which intermediaries arbitrage away frictions that arise from preferences of investors for specific securities (e.g., Vayanos and Vila (2021)). Empirical studies typically rely on market-level data, such as market prices or spreads, to provide evidence that intermediaries affect asset prices (e.g., Pasquariello (2014); Adrian et al. (2014); Du et al. (2018); He et al. (2017); Kargar (2021); Siriwardane et al. (2022)). Two exceptions are Siriwardane (2019), who provides evidence of segmentation in the CDS market, and Wittwer and Allen (2023), who focus on Treasury auctions. In contrast, we construct a unique dataset that allows us to zoom in how intermediaries trade so as to understand their role in connecting or segmenting different markets.

Also related is a large body of market microstructure research that analyzes trading or pricing behavior on exchanges or OTC markets for either bonds, stocks, or derivatives. Studies on equity markets often use publicly available high-frequency data, such as the Trade and Quote (TAQ) data base, where trades are anonymous, and therefore does not focus on studying dealer trading activity (e.g., Chordia et al. (2001)); Budish et al. (2024)).[2] Studies on fixed-income markets, overviewed by Bessembinder et al. (2020), consider a single type of asset, with two exceptions Üslü and Pintér (2023), and Allen and Wittwer (2024), who analyze multiple fixed-income products. Similarly, studies on derivatives focus on one market or product class at a time, for example, the foreign exchange market (e.g., Cenedese et al. (2021); Hau et al. (2021)), the markets for inflation swaps (e.g., Bahaj et al. (2023)), for credit default swaps (e.g., Riggs et al. (2020)), or for Treasury futures (e.g., Garriott et al. (2022)). We analyze trading behavior across asset classes and products, rather than focussing on one asset class.

Our cross-market and multi-asset perspective underscores the need to expand the growing literature on asset demand estimation, which was sparked by Koijen and Yogo (2019). Most

[2]A much smaller set of papers use proprietary data provided by regulators or exchanges that includes trader IDs to analyze various market-microstructure topics within the equity market (see O'Hara (2015) and Menkveld (2016) for an overview). Topics include the cost and direction of order-flows (e.g., Comerton-Forde et al. (2018); Anand et al. (2021); Battalio et al. (2023)), price pressures (e.g., Hendershott and Menkveld (2014)), the design of limit order books (e.g., Biais et al. (1995); Hollifield et al. (2004, 2006); Foucault et al. (2007)), and high-frequency trading (e.g., Brogaard et al. (2014); Budish et al. (2015); Korajczyk and Murphy (2019); Van Kervel and Menkveld (2019); Aquilina et al. (2021).

studies focus on a narrow set of assets, such as common equity, and largely constrain substitution across asset classes, thereby limiting potential spillover effects. Allen et al. (2020), Chaudhary et al. (2022), and Dix and Wittwer (2025) take initial steps in this direction, but—given the empirical patterns documented in this study—much remains to be explored.

Finally, by using an adjusted Theil index to measure market segmentation, we contribute to a long-standing literature that applies entropy-based measures in finance. Entropy is a concept from physics that explains how systems behaves. Initially identified in classical thermodynamics, the concept spans multiple disciplines, from describing microscopic behavior in statistical physics to foundational ideas in information theory. In finance, entropy has been applied to areas such as portfolio selection and asset pricing, as outlined in a literature review by Zhou et al. (2013). However, to our knowledge, the Theil index has not been employed to measure segmentation of financial markets across products and asset classes, which is one of our contributions.[3]

2 Institutional environment

Before detailing the construction of the dataset we use to examine dealer specialization, it is useful to review the key market features. The structure of Canadian financial markets closely mirrors that of other developed nations, including the United States. The three primary asset classes—bonds, stocks, and derivatives—each operate in separate markets.

Fixed-income market. Fixed-income instruments are issued in primary markets and traded in decentralized over-the-counter (OTC) markets. In traditional OTC markets, buyers must contact sellers individually to conduct bilateral trades. Consequently, these markets largely depend on large financial institutions—dealers—to intermediate between investors, such as firms public entities, and individuals. Although not all trades occur bilaterally today, the market remains fragmented.

Firms seeking to become fixed-income dealers must apply to Canadian Investment Regulatory Organization (CIRO). CIRO membership is available to Canadian entities registered to operate as dealers or advisors in any province or jurisdiction in Canada. CIRO members must satisfy CIRO's financial and operations compliance, business conduct compliance and registration requirements, including minimal capital requirements (typically C$250,000), and pay annual membership fees (CIRO website).

[3] A related but distinct study by de Guevara et al. (2007) examines interest rates and pricing disparities within the European banking system, using the Theil index to assess pricing inequalities across countries.

Table 1: Fixed-income product and sectors

Product	Trade share	Sector	Trade share
Government Bond	63.44	Public Administration	72.90
Provincial, Municipal Bond	9.33	Financial Services	20.75
Banker's Acceptance	8.81	Products and Services	2.83
Bank, Agency Paper	7.96	Missing	1.59
Corporate Bond	6.14	Media, Life Science, Transportation	1.26
ABS, MBS, CMB	4.88	Technology and Utilities	0.73
Strip	0.27	Mining and Oil/Gas	0.16

Notes: Table 1 shows the daily average share of total trade-volume, computed as the total amount of bonds traded on a day, in the bond market per product and sector. To assign industry sectors use the first two digits of the North American Industry Classification System. ABS are Asset-Backed Securities, MBS are Mortgage-Backed Securities, and CMB are Canada Mortage Bonds. Appendix Tables A1–A2 describe each product, and sector, respectively.

Fixed-income securities range from long-term to short-term money-market instruments. We classify all securities into product categories, as explained in Appendix Table A1. Government bills and bonds are traded the most, as shown in Table 1. Then we have provincial and municipal debt, and Banker's Acceptance (which is a money market instrument that is issued by a business and guaranteed by a bank), bank or agency papers (money market instruments issued by banks or agencies), and corporate debt. Mortgage- or asset-backed securities (ABS, MBS, CMB), and strip bonds (which are debt instruments in which both the principal and regular coupon payments, that have been removed, are sold separately) are relatively small.

Equity market. Equity products are in most countries traded on centralized exchanges. Exchanges differ from OTC markets in that the market clears centrally on a limit order book.

In Canada there are nine exchanges.[4] Our focus lies on exchanges that are owned by the TMX group, given our data. The TMX group owns three exchanges Toronto Stock Exchange (TSX), TSX Venture Exchange (TSXV), and TSX Alpha Exchange (Alpha). In our sample period, 2019-2022, about 58% of the total volume traded, and 63% of the total dollar value traded in an average month on any of the Canadian equity markets was traded on a TMX exchange.[5]

Only exchange members can place orders for their own account, or on behalf of non-exchange members, i.e., their clients. To become a TMX exchange member, a firm must be

[4]The nine exchanges are: NEO Exchange Inc., Canadian Securities Exchange (CSE), Instinet Canada Cross Limited (ICX), Liquidnet Canada Inc. (Liquidnet), Nasdaq CXC Limited (Nasdaq Canada), Tradelogiq Markets Inc. (TMI), TMX Group (TSX, TSXV, TSX Alpha), TriAct Canada Marketplace (Match Now).

[5]These numbers are computed with data from CIRO, accessible here: https://www.iiroc.ca/sections/markets/reports-statistics-and-other-information/reports-market-share-marketplace, accessed on 08/10/2023.

Table 2: Products and sectors on the stock exchanges

Product	Trade share
Small Stock	53.58
Large Stock	32.33
Uncommon Shares	7.41
Exchange Traded Funds	5.98
Other or Missing	0.68

Sector	Trade share
Mining and Oil/Gas	48.78
Technology, Utilities and Pipelines	13.69
Media and Life Science	10.84
Products and Services	9.95
Financial Services	9.88
ETP and Closed-End Funds	6.45
Missing	0.33
CPC and SPAC	0.04

Notes: Table 2 shows the daily average share of total trade-volume on the stock exchanges, computed as the total amount of stocks traded on a day, per product, and sector. Appendix Tables A3–A4 describe each product, and sector, respectively.

a member of a self-regulatory organization (CIRO in Canada) and have a CDS clearing agreement.[6] In addition, a firm must pay an entry cost, which is relatively high for members who seek to be eligible to trade, roughly C$65,000. To keep the membership status, each exchange member must pay a monthly membership fee (in 2023 $1,500), in addition to trading fees, which are explained on TMX's website.

Exchange members can trade a variety of products, ranging from common stocks, and ETFs to more specialized products, such Exchange Traded Receipts (which let investors own gold bullion stored in the Royal Canadian Mint Gold Reserves). We group products in five categories, as explained in Appendix Table A3: large and small common company stocks, ETFs, non-common shares, and other/missing. We also categorize symbols into industry sectors, as shown in Appendix Table A3. Table 2 shows the trade share per product and sector.

Derivatives market. Derivatives are traded bilaterally, or on exchanges. We focus on exchange-traded derivatives. In Canada, there is a single derivative exchange, the Montreal Exchange (MX). It is owned by TMX group, and operates similarly to the other TMX exchanges.

To trade on MX, a firm must become an MX exchange member. The requirements are similar to those for TMX. In particular, each MX member must be a CIRO member if the firm is Canadian and a member of the analogue regulatory entity of their nationality otherwise.[7]

[6] More specifically, there are three primary requirements that a firm must meet to become a TMX exchange member. The firm must be a member of a self-regulatory organization, for example CIRO. It must have a CDS clearing account; and/or relationship with clearing facilitator, and it must establish electronic access to TSX and/or TSX Venture Trading Engine (TMX).

[7] More specifically, requirements are different for Canadian and foreign firms. Canadian firms must be member of a Canadian self-regulatory organization (Investment Industry Regulatory Organization of Canada); must be a member of the Canadian Derivatives Clearing Corporation or conclude a clearing

Members also have to pay MX-specific monthly membership fees and trading fees.

We group the derivative products into categories, closely following the MX website, as explain in Appendix Table A5. The largest category in terms of trade volume are Treasury futures, followed by short rate derivatives (as shown Table 3). Next we have share futures and equity options. Trading activity in currency options is negligible.

Some derivative products, like Treasury futures or index futures, are highly standardized, while others are more complex. One example are 'user-defined-strategies' (UDS), which allow participants to create customized option strategies based on their individual risk management needs. We classify them under bundles and spreads since UDS tend to combine multiple assets. Even equity options and share futures are more complex than common stocks, because traders can specify their maturity and strike price, in addition to the underlying asset.

To add information about the industry sector of the underlying asset, we merge the symbol of the underlying asset to the symbols that trade on a TMX exchange. For the other types of derivatives, we assign our own sectors, for example, Public Administration to Treasury futures and Money Market to the short-term interest rate derivatives; consult Appendix Table A6 for details.

3 Data

We combine different data sources on five market segments, TSX, TSXV, Alpha, MX and the fixed-income market. These five market segments represent three markets: stock market (TSX, TSXV, Alpha), derivatives market, and the fixed-income market. The main data sources that allow us to observe trade information are proprietary to the TMX group and the Bank of Canada. We hand-collect publicly available information on CIRO and exchange members, financial products, and market conditions to enrich the data.

Fixed-income market. Our main data source for the fixed-income market is the Debt Securities Transaction Reporting System, MTRS2.0. This data base stores trades that involve at least one CIRO Member (who have an obligation to report all of their trades) since November

agreement with one of its members (MX). Foreign firms must be located in one of the following jurisdiction: United States, United Kingdom, Republic of Ireland, Israel, Jersey, the Netherlands and France; must be duly formed pursuant to the relevant laws of the country; must be registered with a securities or derivative instruments regulator, or a recognized self-regulatory organization, unless it is exempted from such registration in its jurisdiction and subject to all other applicable restriction; must have entered into a clearing agreement with a member of the Canadian Derivatives Clearing Corporation; must have a designated agent for service of process residing in Quebec (MX).

Table 3: MX Product and Sectors

Product	Trade share
Treasury Futures	37.44
Short Rate Derivatives	20.75
Share Futures	17.21
Equity Options	16.80
Bundles and Spreads	7.85
Index Futures	6.36
Basis Trades	1.69
Currency Options	0.04

Sector	Trade share
Public Administration	37.44
Money Market	20.75
Mining and Oil/Gas	9.55
Multiple	9.49
Derivative Indices	6.36
Financial Services	5.19
Products and Services	3.04
Technology, Utilities and Pipelines	2.95
ETP and Closed-End Funds	2.71
Media and Life Science	1.61
Missing	1.35
Foreign Exchange	0.04

Notes: Table 3 shows the daily average share of total trade-volume on the derivatives market, computed as the total amount of derivative contracts traded on a day, per product, and sector. Note that the amount of contracts does not reflect the value of the underlying assets. Appendix Tables A5–A6 describe each product, and sector, respectively.

2015.[8] Our sample covers trades with all Canadian fixed-income products from 2019 until 2022. Trades between two institutions or individuals who are not CIRO Members are not reported. However, these trades are rare according to market experts.

For each transaction we see which security is traded, and a series of security-characteristics which allows us to classify securities into product categories and assign industry sectors (as explained above). We also observe the quantity and price of the trade, the time at which the trade is reported, and the side of the trade (buy/sell).

A rare feature of the MTRS2.0 data relative to most of the existing datasets that cover OTC markets is that most trading firm carry a unique identifier. In this study, we focus on CIRO dealers. Traders who act as dealers in the primary market have to report their own trades with their legal identifiers (LEIs). Other CIRO dealers are allowed (but not obligated) to mask their identity when they are reporting their own trades, but not when they are reported as counterparty (with LEIs). Given that most trades occur with at least one party acting as primary dealer, masked identifiers are infrequent. Roughly 5% of trades and 1% of trade volume are reported by masked dealers in our sample.[9]

[8] A small group of Bank of Canada staff have access to the raw data, and this is anonymized before it can be shared, subject to a non-disclosure agreement, to external researchers.

[9] Whenever a masked dealer trades with a primary dealers or government distributor, it is possible to back out the identify of the masked dealer by relying on the fact that both dealers need to report the trade. The remaining trades by masked dealers are those between two masked dealers. In these cases, we cannot rule out the possibility that our data sample includes both sides of the trade due to double

Equity and derivatives market. We observe trade-level data for all exchanges that are owned by the TMX group, that is TSX, TSXV, Alpha and MX, between 2019 and 2022. Throughout the paper, we refer to 'market segments' whenever we consider the three stock exchanges separately, and to 'markets' when we pool them together.

For each trade, we the time of the trade (up to milliseconds), the security (i.e., the TMX symbol), the amount, and the price, and trading-firm IDs. For equities we also see the best national bid and ask offer for each symbol that was valid right before each trade executes. Moreover, we know whether the trade is for the exchange members's own account or a clients' account. More specifically, for stock market trades, we can distinguish between an inventory account (IN), a client account (CL), and an account that members who are designated market makers use for their market making active (ST). In addition there are some other accounts that are negligible. For trades with derivatives, we observe analogous account-types.

In order to link dealers across markets, we connect the market-specific trading-IDs to each company's LEI. We achieve this by downloading exchange member lists containing trading IDs and company names for all instances where the TMX website was archived by the Wayback Machine during our sample period. We then identify each company's Legal Entity Identifier (LEI) using `https://www.lei-lookup.com`. Doing so, we account for mergers, acquisitions, and name changes over time.

Lastly, to categorize securities into products and industry sectors, we merge the data on stock market trades with publicly available listing information for each listed symbol in December of each year in our sample, by also relying on the wayback machine. Finally, to validate data quality, we verify that we observe the same daily trade volume and nominal value as CIRO and the MX exchange report publicly for the stock markets and the derivatives exchange. See Appendix A for details.

Dealers. A distinctive feature of our data is the ability to track firms registered as CIRO dealer members in the fixed-income market or as exchange members across these markets, as we observe their LEIs. Throughout the paper, we refer to these traders as 'dealers.' It is important to note that we do not classify firms as 'dealers' based on their trading or market-making activities. Instead, our definition relies solely on firms' membership status, which grants them the ability to place trade orders on their own behalf on exchanges and to trade with clients in OTC markets, regardless of their specific role in the market. We adopt this definition because it is more exogenous—at least conditional on market entry—than classifications based

reporting. In all other cases, Bank of Canada staff has carefully removed one of the trade sides, so that each trade appears one time in the raw data.

Table 4: Dealer types

Institution type	# of LEIs	# of Parents
Asset Manager	15	21
Bank	7	17
Investment Bank	12	15
Broker	115	65
High-Frequency Trader	17	21
Mutual Fund	8	0
Pension Fund and Insurance	4	3
Retail	13	3
Other	3	2

Notes: Table 4 shows the number of LEIs and parent-LEIs of each dealer type at the LEI and parent-level. For the type classification we follow the methodology of the Bank of Canada used to classify institutions into types for the MTRS 2.0 data (explained in Appendix A). Appendix Table A7 defines each type category we observe in our data.

on endogenous trading behavior.

For each dealer LEI, we identify the LEI of its holding company parent using information from gleif.org. Doing so, we manually track mergers, acquisitions, and name changes found through Google searches to the best of our ability.

Further, we classify all LEIs and their parents into institution types: Table 4 shows that brokers constitute the largest category at the parent level, representing financial entities primarily engaged in brokerage services. Following them are asset managers and high-frequency traders, which include hedge funds, proprietary trading firms, and private equity firms. Investment banks come next, followed by other, typically smaller, banks and credit unions. At the LEI level, the dataset also includes some mutual funds and retail branches of larger institutions, such as banks, that focus on retail investing.

Summary statistics. Appendix Table A8 summarizes our trade data for stocks (TSX, TSXV, Alpha), bonds (MTRS), and derivatives (MX) to provide an overview of a typical trading day and trade in each market. The bond market is largest market in terms of trade volume. The number of dealers who actively trades on an average day is similar across markets, ranging from 48 in the derivatives market to 60 in the stock market.[10] For derivatives, trade size and volume reflect the number of contracts, not the underlying asset value. Similarly, the trade price reflects the price payed to exchange the derivative, i.e., the option fee in case the contract is an option, not the strike price.

[10]When the level of aggregation for institutions changes, the set of players adjusts slightly. This occurs because an entity identified by its LEI may not be classified as a dealer, whereas its parent institution might be.

4 Dealer specialization

We examine three types of specialization, with a particular focus on the latter two. The first type is legal in-house segmentation, where different funds or subsidiaries of the same parent institution specialize in different markets or products. The second type is specialization on different market segments, which may arise due to differences in market clearing rules and entry costs. The third type is product specialization within a market, which could stem from differences in trading expertise, or client relationships.

4.1 In-house specialization

Before analyzing market and product specialization, we assess the role of legal segmentation within institutions using our data on LEIs and assigned parent-LEIs for all dealers. While this information may be noisy for the stock and derivative markets, we still highlight its importance, though we do not focus on this type of segmentation. Similarly, we do not account for other forms of in-house specialization, such as trading desks specializing in different strategies or asset classes, as we do not observe this information.

LEIs belonging to the same parent institution typically represent either different subsidiaries (as is often the case for banks) or distinct funds, which is common among asset managers and pension funds. In some cases, the same parent institution may also have multiple LEIs in our dataset due to mergers or acquisitions. Table 5 presents the average number of LEIs per parent institution for each parent type. On average, parent banks and investment banks have the highest number of LEIs, with about 7.5 LEIs, followed by parent pension funds, and asset managers. In contrast, brokers, hedge funds, proprietary trading firms, and private equity firms (which we call high-frequency traders) typically have only one LEI each.

To assess the extent to which legal within-institution segmentation across different LEIs impacts market segmentation, we calculate the share of trade volume attributed to LEIs which are active across all markets in Table 6. To compute these shares we first sum all quantities traded by a LEI, including both sides of the trade, and then divide by the total amount of bought plus the total amount sold. For the bond (MTRS) market, where our LEI data is most reliable, we find that only 27.16% of trade volume is executed by LEIs that are also active on MX and TSX. However, when we aggregate at the parent-company level, this share rises to 59.73%, underscoring the significance of legal within-institution segmentation.

Fact 1A. *Legal within-institution segmentation plays a significant role in segmenting markets.*

To better compare within-institution segmentation across markets, we narrow the sample

Table 5: Average number of LEIs per parent-LEI by parent-institution type

Parent type	**Avg # of LEIs**
Bank	7.58
Investment Bank	7.46
Pension Fund and Insurance	6.66
Asset Manager	5.00
High-Frequency Trader	1.66
Broker	1.49
Retail	1.33
Other	1.0

Notes: Table 5 shows the average number of LEIs that belong to the same parent-LEI within institution type of the parent-LEI for all LEIs that are members at the parent-level.

to trades executed by dealers, since only dealers can trade on MX and TSX, while non-dealers may act as counterparties in OTC markets. By excluding sales or purchases by non-dealers, and calculating the total 'dealer trade volume'—the sum of quantities bought or sold by dealers—we expect to see greater market integration since non-dealers are oftentimes smaller non-financial firms.[11] Indeed, the share of dealer volume traded by dealers active across all markets is much higher than the share of total trade volume traded by such participants: 49.66% at the LEI level and 82.61% at the parent level (see column MTRS-D in Table 6).

We find the distinction between LEI-level and parent-level analysis to be most pronounced in the fixed-income market. We attribute this to two factors. First, a larger proportion of dealers on the exchanges are hedge funds, private equity firms, or proprietary trading firms compared to the fixed-income market, and these types of dealers typically have fewer sub-funds or subsidiaries. Second, some of the discrepancy may stem from differences in data reporting. In MTRS—our data source for bond trades—, institutions are required to report the LEI of the specific subsidiary conducting the trade, whereas there is no known requirement for firms to indicate which subsidiary corresponds to a specific trading ID on TSX or MX. We therefore do not focus on this empirical pattern in greater detail.

4.2 Market specialization

Next, we remove legal within-institution segmentation to analyze market specialization. Such segmentation might arise because of different market structures. Bonds trade in a decentralized market that is not directly connected to stock markets, or the derivatives exchange. Moreover,

[11]Note that 'dealer trade volume' differs from the volume dealers trade with each other, since we include all quantities bought or sold by dealers, independent of who takes the other side of the trade.

Table 6: Market intersection—fraction of trade volume (including both sides of the trade)

Lei-level	TSX	MTRS	MTRS-D	MX	Parent-level	TSX	MTRS	MTRS-D	MX
All	78.56	27.16	49.66	53.30	All	89.66	59.73	82.61	64.05
TSX and MTRS	19.52	1.6	2.92	0.0	TSX and MTRS	9.59	8.29	11.46	0.0
TSX and MX	1.15	0.0	0.0	4.63	TSX and MX	0.0	0.0	0.0	0.11
MTRS and MX	0.0	1.48	2.7	12.32	MTRS and MX	0.0	2.77	3.83	10.73
MTRS only	0.0	69.77	44.72	0.0	MTRS only	0.0	29.21	2.09	0.0
TSX only	0.77	0.0	0.0	0.0	TSX only	0.75	0.0	0.0	0.0
MX only	0.0	0.0	0.0	29.74	MX only	0.0	0.0	0.0	25.10

Notes: Table 6 shows the percentage of total volume traded in each of the three main market segments (TSX, MX, or MTRS) that is traded by dealers who trade on all segments (All), on TSX and MTRS, etc. Each column sums to 100%. The table on the LHS considers dealer at the lei-level, while we aggregate to the parent-level on the RHS. Total volume traded is computed by summing all buy-and sell-side quantities in columns (TSX), (MTRS) and (MX). In column (MTRS-D) instead compute the dealer trade volume by summing all buy-and sell-side quantities that dealers trade. This trade volume coincides with the total trade volume for the exchanges, since only dealers can execute trades on the exchange.

Table 7: Member intersection: RHS: LEI-level of members; LHS—Parent level

Intersection	TSX	ALPH	TSXV	Intersection	TSX	ALPH	TSXV
All	99.97	100.0	99.68	All	99.97	100.0	99.68
TSX and ALPH	0.0	0.0	0.0	TSX and ALPH	0.0	0.0	0.0
TSX and TSXV	0.03	0.0	0.32	TSX and TSXV	0.03	0.0	0.32
ALPH and TSXV	0.0	0.0	0.0	ALPH and TSXV	0.0	0.0	0.0
TSX only	0.0	0.0	0.0	TSX only	0.0	0.0	0.0
ALPH only	0.0	0.0	0.0	ALPH only	0.0	0.0	0.0
TSXV only	0.0	0.0	0.0	TSXV only	0.0	0.0	0.0

Notes: Table 7 shows the percentage of total volume traded in each of the three stock exchanges (TSX, TSXV, and Alpha) that is traded by brokers who trade on all segments (All), on TSX and Alpha, etc. Each column sums to 100%. Total volume traded is computed by summing all quantities of all brokers including both sides of the trade.

each market segment—the three stock exchanges, the derivatives exchange, and the fixed-income market—is characterized by different entry costs, as we have explained above.

Fact 2A (Market Participation)**.** *Not all dealers are active in all markets.*

Supporting the idea that these types of frictions might hinder universal market participation, Figure 1a highlights that not all parent LEIs (the y-axis) participate in all market segments (the x-axis). If a dealer trades at least one time in a given market segment, we plot a black line for that segment, otherwise, the line is white. Thus, if all dealers participated in every segment, the graph would be entirely black. Instead, the presence of both black and white indicates that dealers are selective in their market participation.

Even when we zoom in on the 20 largest dealers (according to the percentage of total dealer trade volume they trade in an average month in all markets) in Figure 1b, we observe differences across dealers suggesting specialization. For example, the same dealer dominates both Alpha and TSX in terms of monthly trading volume, while different dealers lead on TSXV, MTRS, and MX.[12] The largest bond dealers are all banks or investment banks, while a high-frequency trader plays a non-negligible role on the two smaller stock markets and the derivative market, but not in the bond market or the largest stock exchange.

Fact 3A (Market integration)**.** *The stock exchanges are well-integrated: Close to 100% of trade volume is traded by parent institutions who are active on all stock exchanges.*

Even though each exchange of the TMX group requires separate membership applications and costs, the three stock exchanges are well-integrated. In total, we observe 72 (66) dealers on TSX, 68 (63) on TSXV, and 64 (60) on Alpha (at the parent-level). Despite this, and the the fact that market concentration is much higher on Alpha compared to TSX, and TSXV, and that fewer traders are active on Alpha, close to 100% of the trade volume is traded by dealers who are active on all exchanges (see Table 7). In what follows, we therefore distinguish between markets rather than market segments, pooling TSX, TSXV, and Alpha together.

Fact 3B (Market integration)**.** *The stock and fixed-income markets are well-integrated: 83%–90% of dealer trade volume is executed by institutions who are active in the stock market and fixed-income market at the parent-level.*

The stock market and the fixed-income market are also highly integrated at the parent-level, in that the fraction of trade volume executed by dealers who are active in both markets is 82.61% for MTRS and 89.66% for TSX (recall Table 6). Although many dealers do not participate in all markets, as we recall from Figure 1a, a core group of dominant dealers drives the strong integration across markets.

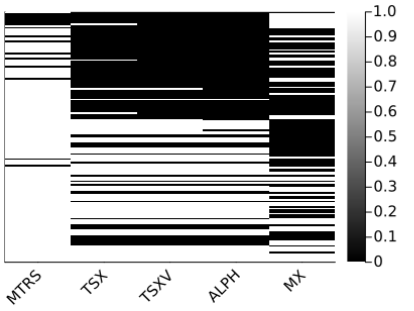
The high level of integration between the fixed-income and stock markets is partly due to exchange members not only trading for their own books or acting as market-makers but also executing trades on behalf of their clients. As a result, banks play a significant role in both markets since they serve clients who invest in both fixed-income and equities. Table 8 and Appendix Figure A1 reveal that banks and investment banks account for 86% of weekly dealer trade volume on the stock market, while high-frequency traders contribute less than 1%.

To determine the role of client-driven trades in driving stock-equity market integration, we focus on trades that are executed for a trader's inventory or the market-maker account.

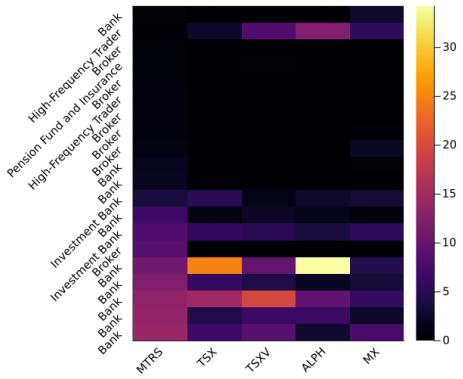
[12]The leading dealers remain consistent whether analyzed at the LEI or parent-LEI level.

Figure 1: Dealer presence and trading intensity per market segment

(a) Dealer presence



(b) Trade intensity



Notes: Figure 1a shows whether each of the dealers is present (i.e., trades at least ones) in white, and not active in black for each of the market segments, ALPHA, TSX, TSXV, MX, MTRS (at the parent-level). Figure 1b zooms in on the largest 20 brokers (at the parent-level), defined as the brokers who trade the largest fraction of dealer trade volume in an average month including all markets. It shows their average monthly trade-share in each market segments. In both cases, rows are sorted according to size, with the dealer who trades the largest dealer volume aggregated in all markets at the bottom, and the dealer who trades the lowest at the top. Given that the fixed-income market is the largest in terms of trade-volume, this sorting means that dealers who trade low fractions in the fixed-income market, but are dominant players in some of the other market segments appear at the top.

As expected, the share of stock market trades by banks decreases, while the share of trades by high-frequency traders increases when we exclude trades for client accounts, as shown in Table and Appendix Figure A1. However, banks and investment banks still trade over 50% of dealer trade volume for their own accounts.

Fact 3C (Market integration)**.** *The derivatives market remains more separated, in that roughly 25% of trade volume is traded by dealers who only trade on MX. Those dealers are primarily high-frequency traders.*

Approximately 35% of MX's trade volume is attributed to high-frequency traders when including client trades, rising to 72% when excluding them, as shown in Table 8. Around 25% of traders operate exclusively on MX, even at the parent-company level (recall Table 6). This is largely driven by hedge funds, proprietary trading firms, and private equity firms that specialize in MX trading.

Fact 4A (Who connects markets?)**.** *Banks serving as primary dealers in the Treasury market are the most important players that connect markets.*

Among all dealer types, banks acting as primary dealers are the most significant connectors across markets. We see this when comparing the fraction of monthly dealer trade volume by

Table 8: Avg. weekly share traded by dealers per type (parent-level)

Dealer type	MTRS	TSX	TSX-IN	MX	MX-IN
Asset Manager	0.27	1.70	0.98	0.68	0.00
Bank	74.13	56.05	35.77	27.12	19.05
Broker	12.32	13.47	16.46	9.12	2.02
High-Frequency Trader	0.86	10.70	24.24	34.94	72.07
Investment Bank	11.88	17.21	22.49	27.98	6.75
Other	0.00	0.00	0.00	0.11	1.11
Pension Fund and Insurance	0.50	0.23	0.03	0.00	0.00
Retail	0.02	0.60	0.00	0.07	0.00

Notes: Table 8 shows the fraction of dealer trade volume by dealer type (at the parent-level) per market in columns MTRS, TSX, and MX, respectively. In columns TSX-IN, and MX-IN we show the analogue but excluding trades for client accounts for TSX and MX.

those active in all markets, for each market, in Appendix Figure A2 with the fraction of monthly dealer trade volume by primary dealers who are active in all markets in Appendix Figure A3. We observe that essentially all omnipresent dealers on MTRS are primary dealers, and that roughly 68% of dealer trade volume on TSX is executed by primary dealers who are active in all markets, implying that $80\% - 68\% = 12\%$ of dealer trade volume is executed by dealers who are active across markets but aren't primary dealers. The share on MX is lower with roughly 40%, but even there, none of the other types of dealers play a larger role in connecting MX to the other two markets than primary dealers—at least not on the aggregate. This underscores significance of primary dealers beyond the fixed-income space and highlights contagion risks during financial distress.

4.3 Product specialization within a market

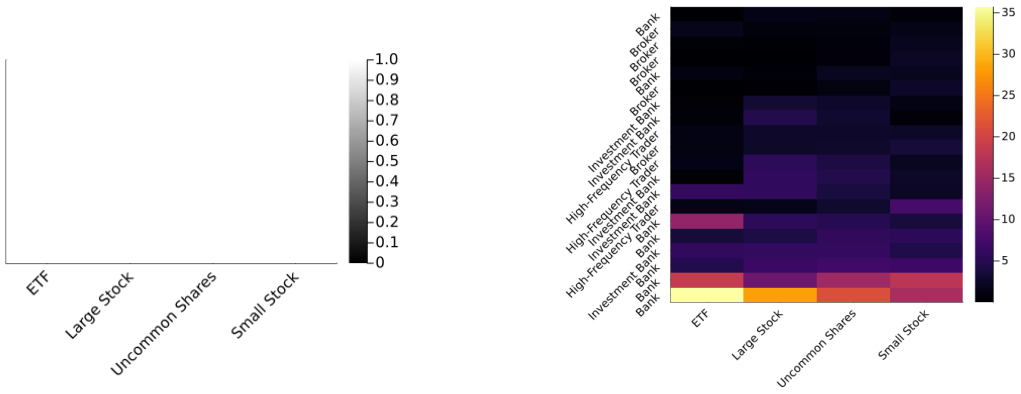
Now we examine the role of product specialization. To isolate this effect, we continue to focus on parent-level institutions, removing legal within-institution segmentation. Additionally, we account for market fragmentation by narrowing our focus to product segmentation within each market.[13]

Fact 5A (Product specialization)**.** *There is no product segmentation on the stock markets: all dealers trade all products.*

On the stock exchange almost all dealers trade all products. This is shown in Figure 2, which, on the LHS, visualizes which of the dealers active in the stock market trade which eq-

[13] Appendix Figure A4 shows the fraction of securities each dealer trades out of all securities for each market.

Figure 2: Dealer presence and trade intensity across equity products



Notes: The RHS of Figure 2 shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each product within the stock markets at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each product. We exclude the product category "Other or Missing". In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across products within a market at the bottom, and the dealer who trades the lowest at the top.

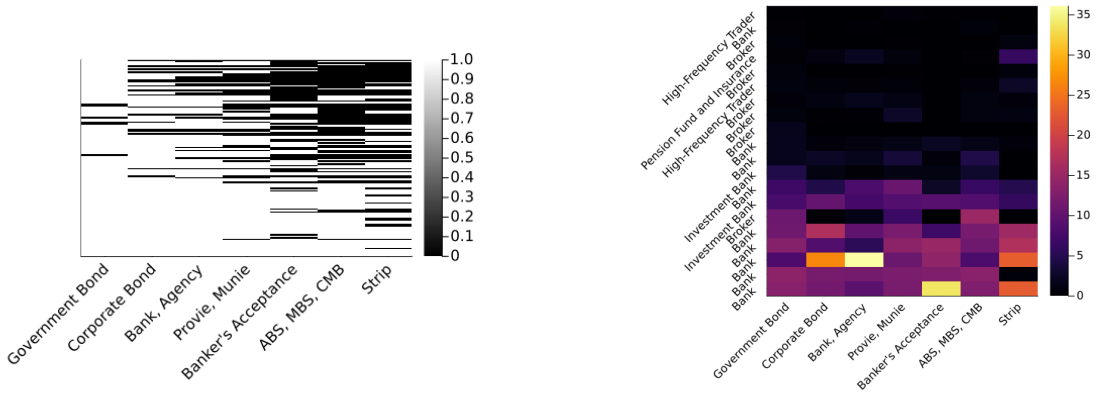
uity products (at the parent-level). The RHS of this figure zooms in on the 20 largest dealers, who trade the largest fraction of dealer volume of equities in an average month. It shows how how much these largest dealers are trading in percentage of the total amount of equities dealers are trading. We see that dealers who trade a lot of one product tend to be active across multiple products, indicating small segmentation between equity products. Two dealers dominate trading across all products, with the ETF product-segment being the most concentrated.

One explanation for the integration across equity products is that these products are sufficiently standardized so that dealers do not need to be specialized to trade these products.[14] Another explanation is the fact that these products are traded on an exchange, where all of them are available at the same time. This is not the case in the decentralized fixed-income market, where we observe substantial segmentation across products.

Fact 5B (Product specialization)**.** *There is substantial product segmentation within the fixed-income market.*

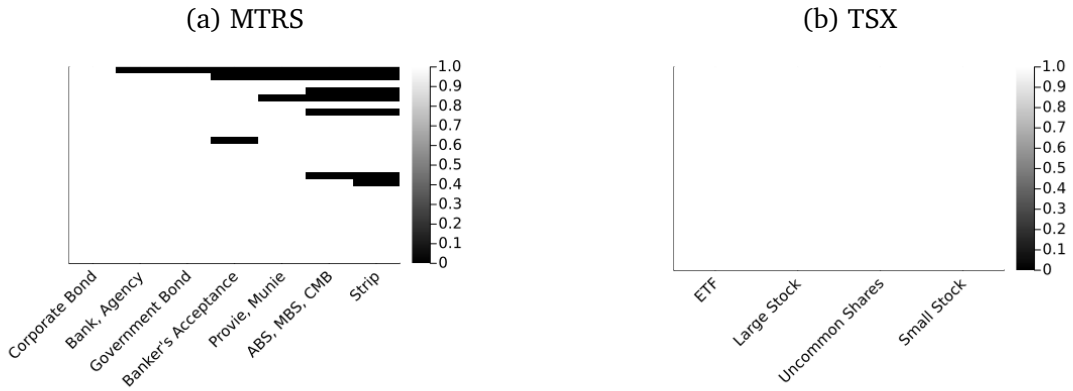
[14]We find some support for this idea, when we split the market into sectors, rather than products, as shown in Appendix Figure A6. We see that the most complex products, which are CPCs and SPAC are traded by a subset of dealers. Other uncommon shares, which include units, warrants, and notes are traded by all dealers. Moreover, when we examine different types of uncommon shares (such as preferred shares and debentures), we find that more complex products are not traded by all dealers (see Appendix Figure A5 and Appendix Table A9 for the complete list of suffices).

Figure 3: Dealer presence and trade intensity across fixed-income products



Notes: The RHS of Figure 3 shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each product within the fixed-income market at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each product. Appendix Figure A7 shows the analogous graphs for sectors instead of products. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across products within a market at the bottom, and the dealer who trades the lowest at the top.

Figure 4: Dealer presence across products of dealers present in TSX and MTRS



Notes: Figure 4 shows whether dealers who trade both stocks and bonds are active (i.e., trades at least ones) in white, versus in-active in black for each product within the fixed-income market in (a) and the stock market in (b) at the parent-level.

In the fixed-income market, not all dealers trade every product, or in every sector. This is true also when restricting to the set of dealers who are active in both the bond and stock market, and when focussing on dealers who are active in all markets, as shown in Figures 4 and 6; it holds even for those serving as primary dealers for Canadian government debt. Moreover, different dealers dominate different products, as illustrated in Figure 3. For example, the dealer responsible for over 30% of corporate debt trade volume handles less than 12% of provincial and municipal bonds. Conversely, the dealer leading in municipal and provincial bonds, with approximately 17% of that market, trades less than 7% of corporate debt.

There is no a clear division into submarkets, but a distinct hierarchy exists in terms of product popularity: most dealers trade government bonds, which account for over 50% of fixed-income trade volume. Interestingly, many dealers also trade corporate bonds, despite corporate bonds representing only 10% of the market—a share comparable to provincial bonds, municipal bonds, and bankers' acceptances, which are less widely traded. However, only a few dealers engage in products like bankers' acceptances or the smallest categories, such as bond strips or asset-backed securities/mortgage-backed securities (ABS/MBS/CMBs).

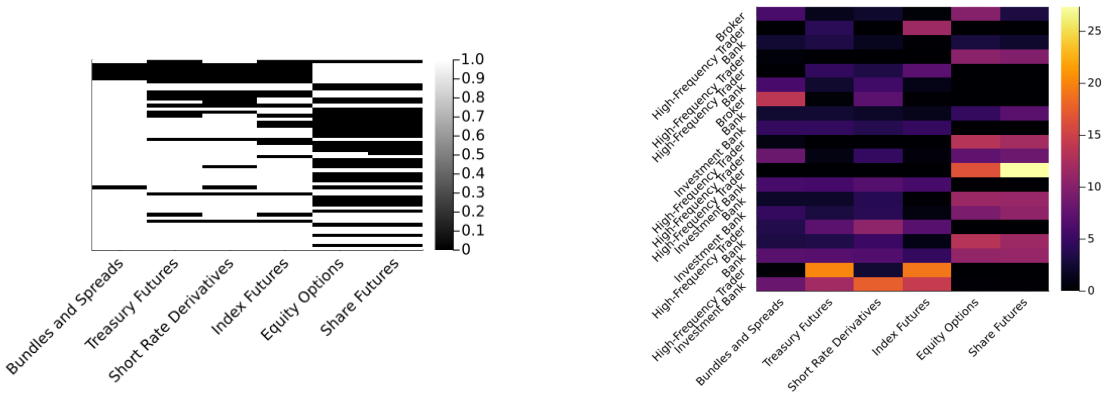
Given the decentralized nature of the fixed-income market, we hypothesize that the network structure of the OTC market and the long-term relationships dealers establish with their clients influence the products they trade. This aligns with the well-documented empirical finding that relationships play a key role in shaping trading for specific products, such as corporate bonds, in OTC markets (Di Maggio et al. (2017); Hendershott et al. (2020); Allen and Wittwer (2023); Jurkatis et al. (2023); Bak-Hansen and Sloth (2024)); and underscores the need for further research on cross-product trading (Üslü and Pintér (2023); Allen and Wittwer (2024)).

Fact 5C (Product specialization)**.** *The derivatives market splits into two main sub-segments: a more populated segment for Treasury futures, short-rate derivatives, index futures, and strategies that combine these, versus a less populated segment for equity options, and share futures.*

Although the derivative products we analyze are all traded on the same exchange, Figures 5, A8, and A11c reveal distinct segmentation among these products, and among sectors. The market splits into two main segments. The dealers with the largest market shares in equity options, and share futures differ from those dominating Treasury futures and short-rate derivatives (and spreads which tend to combine these products).

One explanation for the two-tiered market structure is that different dealers follow different types of trading strategies or serve different types of clients. However, these factors are unobservable in our data, as we do not find statistically significant differences in product traded across observable dealer types, including high-frequency traders and banks. Another possibil-

Figure 5: Dealer presence and trade intensity across derivative products



Notes: The RHS of Figure 5 shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each product within the derivative market at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each product. Here, we exclude the product categories "Basis Trades" and “Currency Options" since they are very small according to trade volume. We include these products in Appendix Figures A9. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across products within a market at the bottom, and the dealer who trades the lowest at the top.

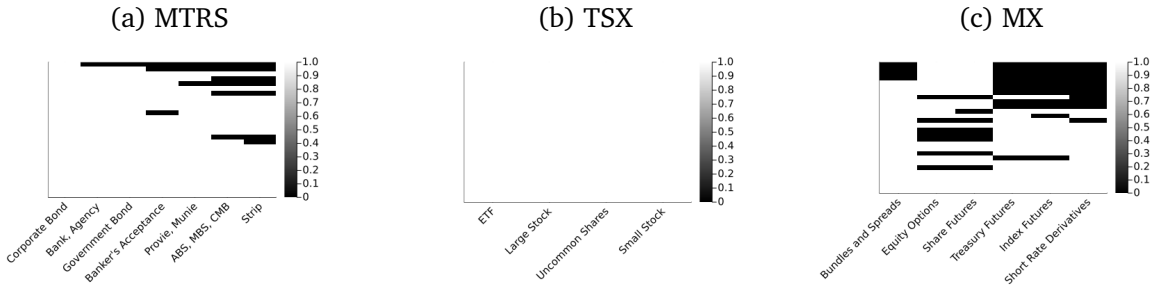
ity is that more standardized derivative products, such as Treasury futures, attract a broader set of market participants, because it’s easier to trade those products. There is no need to specify details of the contract, instead, the dealer picks form a pre-defined menu of options. In line with this idea, many more dealers are active in Treasury futures, short-rate derivatives, and index futures—which are the most standardized products—compared to options or share futures, despite these products collectively accounting for around 35% of total average daily trade volume. However, contrary to this idea, many dealers trade bundles and spreads, which are more complex, suggesting that product complexity is not the sole determining factor—a result that is unsurprising.

4.4 Comparing market and product specialization

To compare cross-market and cross-product specialization, we introduce a segmentation measure, which builds on the Theil index (Theil (1967)). The standard Theil T-Index, T_j, captures the distribution of dealer j’s market share across product-market segments. If the dealer trades the same fraction of total volume in each segment, $T_j = 0$. A positive T_j indicates segmentation, with higher values reflecting greater variation in the dealer’s activity across segments.

For our purposes, the original index is not suitable because it fails to account for the fact that non-participation by dealers in a market or market-segment increases segmentation. To

Figure 6: Dealer presence across products of dealers present in all markets



Notes: Figure 6 shows whether dealers who are present in all markets are active for a specific product in white, versus in-active in black for each product within the fixed-income market; for the TSX; and for MX (at the parent-level). For MX we exclude two small products: "Basis Trades" and "Currency Options"—Appendix Figure A11 includes them.

address this, we introduce a non-participation cost, ξ, which applies when a dealer does not trade in a market segment. Since this punishment term is chosen arbitrarily, the magnitude of our index by itself is not informative. However, it is valuable for comparing segmentation within a market across products to segmentation across different markets, which is our primary objective. To see this, note that the index decomposes into two components: one measuring within-market segmentation, T_j^w, and another measuring across-market segmentation, T_j^a:

$$T_j = T_j^a + T_j^w, \text{ with } T_j^w = \frac{1}{M}\sum_m T_{jm}^w.$$

T_{jm}^w measures the how dealer j's market share in a market-product segment is distributed across products in market m, with more uneven distributions meaning higher segmentation; and T_j^a measures how the average of this market share across products is distributed across markets. Consult Appendix B for mathematical details.

Table 9 provides the range of indices across dealers for three dealer groups, those active in all markets, those active in two out of three markets, and those active in only one market; Appendix Figure A12a shows all indices for each dealer separately. For dealers who are not active in all markets, we compute both indices subject to punishment for non-participation in the market they are not active in. In addition, we also compute the indices conditioning on non participation in the markets they are active in. This is useful to compare coss-product segmentation within a market across these dealer groups.

Fact 6A (Market versus Product Specialization)**.** *Across-product segmentation within a market is for most dealers larger than across-market segmentation.*

For most dealers, within-market segmentation is larger than across-market segmentation,

Table 9: Segmentation measures

	Across-market (T_j^a)	Across-product (T_j^w)
Dealers who participate in all markets	0.01–1.10	0.10–4.90
Dealers who participate in two markets	2.09–2.76	1.87–5.63
Conditional on being active in only two markets	0.42-1.09	0.20–3.96
Dealer who participate in one market	–	3.48–5.63
Conditional on being active in only one market	–	0.14–3.37

Notes: Table 9 reports the range of across-market segmentation indices (T_j^a) and within-market, cross-product segmentation indices (T_j^w) for a punishment term of $\xi = 5$. Dealers are grouped by activity in all markets, two markets, or one market. For dealers who are active in $K \in \{1, 2\}$ markets, ξ increases both indices by $(3-K)/3\xi$. Indices are computed with and without accounting for non-participation penalties. For single-market dealers, only cross-product indices are calculated, since the cross-market index is uninformative.

implying larger cross-product segmentation compared to cross-market segmentation. Notably, this is not driven by the fact that there are more products in a market than entire markets, like it would when considering other measures, such as the variance. Instead, the difference is driven by unequal participation across submarkets.[15]

Greater product than market specialization suggests that, for large financial institutions, barriers to market entry are less restrictive than factors that limit arbitrage across products within a given market. Given that product segmentation appears to depend on whether a market is centralized (e.g., exchanges) or decentralized (e.g., OTC markets) and on the complexity of the products traded, our findings underscore the need for theories that account for different market structures or different degrees product complexities, unlike most existing models that focus on a single market structure with standardized assets. While our analysis does not assess whether trading specialization improves welfare, it highlights the role of market design and product complexity in shaping market fragmentation.

[15]The magnitudes of the indices depend on the punishment ξ-term. However, the conclusion that within-market segmentation is larger than across market segmentation does not depend on the choice of ξ. To show this, we shut off non-participation punishments by setting ξ to zero. In that case, the average (median) within product index (across all dealers) is 0.89 (0.78), and the average across-product index is 0.91 (1.09). The indices are relatively similar in size, but this is driven by dealers who only participate in one market. For those dealers both indices are identical. When restricting attention to dealers who participate in at least two markets (for which the within-market and across market measures differ), the average (median) within product index (across all dealers) is 0.58 (0.54), which is significantly smaller than the average across-product index is 0.74 (0.80).

5 Specialization and transaction costs

So far, we have focussed on market participation. In what follows, we explore whether the limited cross-market and cross-product activity of certain dealers influences their transaction costs to get a sense of the monetary returns to specialization. The alternative hypothesis is that markets are sufficiently frictionless that trade prices remain unaffected by dealer specialization.

5.1 Returns to market specialization

We begin by analyzing whether some dealers obtain systematically better prices than others, and, in a second step, whether those dealers are active across markets, or whether they specialize in one market.

To detect systematic price differences while incorporating both sides of the trade and making magnitudes across securities with varying price levels more comparable, we draw on the market microstructure literature. Building on Hendershott and Madhavan (2015), we measure transaction costs relative to benchmark prices. Following Pinter et al. (2024) and Allen and Wittwer (2024), we use the daily average price of a security as the benchmark, as it is consistently available across all securities in our sample—an essential feature for ensuring comparability across markets. In contrast, alternatives like the inter-dealer price or the national best price valid before a trade are only available for a subset of securities—bonds and stocks, respectively—thereby limiting their applicability for our purpose.

To ensure the average price is meaningful, we focus on sufficiently liquid securities traded at least three times in a day, with results remaining qualitative robust when restricting to more liquid securities (e.g., those traded at least five times daily).[16] We also exclude approximately 2% of derivatives transactions executed at negative prices—common in certain spread types—as these would complicate the interpretation of our findings.

We call our measure 'margin'—a higher margin means that a transaction τ for security s is executed at better prices compared to the average price for that security on that day t:[17]

$$\text{margin}_{\tau} = -\ln(\text{trade price}_{\tau}/\text{average price}_{ts}) \times 100 \times \text{ trade sign}_{\tau}. \tag{1}$$

[16] This restriction is particularly stringent in the derivatives market, as symbols often include detailed and flexibly specified contract information. Our restricted dataset covers over 99% of stock market trades, approximately 88% of bond market trades, and about 54% of derivatives trades.

[17] The market-microstructure typically measures "transaction costs" of a trade, which is the negative of or margin measure. We flip the sign because it is easier to think about more and less successful traders, when the measure increases in success.

Trade sign is one when the trader buys and -1 when they sell. For trades that are close to the average price the margin essentially measures the difference between the trade price and the average price as percentage of the average price.[18] Appendix Figures A14–A17 visualize the margin distribution for each market and products. As expected, margins vary significantly more in the derivatives market, where price volatility within a day is highest, followed by the stock market, and finally the bond market, where price volatility is more moderate.

We regress our margin measure on dealer-indicator variables separately for each market:

$$\text{margin}_\tau = \alpha + \sum_j \beta_j \mathbb{I}(dealer = j) + \gamma control_\tau + \zeta_t + \zeta_{ws} + \epsilon_\tau. \tag{2}$$

If there is no systematic difference of dealers across markets, all dealer coefficients should be statistically insignificant from zero. We include a day fixed effects, ζ_t, to absorb time-varying shocks that affect the entire market, and year-week-security fixed effects, ζ_{ws}, to account for the average weekly margin of a given security.[19] This addresses two potential biases. The first arises because different dealers trade different securities, which naturally have varying margins; the second comes from the feature that the set of traded securities varies over time.

Additionally, we include control variables, though they do not significantly affect the overall pattern of the dealer coefficients. First, given prior evidence that trade size influences outcomes, we control for trade size. Second, for exchange trades, we account for the account type associated with the trade. For bond trades, we distinguish the trade type—whether it occurs between dealers (i.e., CIRO dealer members), between a dealer and an inter-dealer broker, or between a dealer and a non-dealer. Across markets, we use the same large primary dealer as the baseline for consistency.

In this and all other margin regressions, we cluster standard errors at the daily level to account for arbitrary intra-day correlations across dealers, securities, and trades. This is crucial when traders split orders throughout the day or react to price shocks that impact multiple securities.[20] Because some days feature many more trades trade than others, the day-clusters

[18] Formally, $\text{margin}_\tau \approx (\text{average price}_{ts} - \text{trade price}_\tau)/\text{average price}_{ts} \times 100 \times \text{ trade sign}_\tau$. Appendix Figure A13 shows the relationship between our main margin measure (1) and its linear approximation. Relative to the linear percentage difference, the log-measure attenuates the poor trades (which, for buyers, are those executed at higher than average prices), and amplifies the successful trades.

[19] We do not include day-security symbol fixed effects because some symbols are not traded frequently enough throughout the day. However, for robustness, we have estimated all regressions with symbol-day fixed effects, and our main conclusions remain unchanged.

[20] An alternative approach is to cluster by dealers, accounting for correlations in a dealer's trades across days while ignoring intra-day correlations across dealers. However, with fewer than 100 dealers in the stock and derivatives markets and uneven cluster sizes, we are not confident this would yield

are highly uneven in size. This can result in conventionally computed standard errors being either underestimated (MacKinnon et al. (2023)). One common solution is to compute standard errors via wild (WCR) bootstrapping following Cameron et al. (2008), and Roodman et al. (2019). Unlike standard methods, this approach does not rely on asymptotic approximations to the test statistic's distribution, which can be inaccurate when clusters are uneven or few in number. Instead, it constructs confidence intervals using bootstrap resampling, and therefore yields more reliable test statistics when clusters are small or uneven. To ensure robustness, we report coefficients that are statistically significant under both wild-bootstrapped and conventionally computed standard errors.

Our findings, shown in Figure 7 indicate that on all markets some dealers obtain systematically better prices than others. This is true when zooming in on the LEI-level—shown in the main text—and when aggregating traders to the parent-level—shown in the appendix.

On the stock market, the best dealer (a large broker) trades at margins that are roughly 0.64% better than those of the baseline dealer (a primary dealer). The worst dealer, who is also a broker, but a smaller one, realizes 0.31% worse margins than the baseline dealer. For a trade of the median trade-size (1,300 shares) and at the median price (C$ 12.24), a 1% margin difference means a payment difference of roughly C$ 160. Thus, if each trade was executed at the median price, the 0.67% margin would sum to a sizable average annual benefit of C$ 266 million for the best dealer, who trades 3.4 billion shares per (average) year. For the worst dealer, who trades 0.16 billion shares per (average) year, the annual loss would be about C$ 6 million.

On the derivative exchange, differences across dealers are more pronounced than on the stock and bond market. This is because our margin measure captures price variation within a security over the course of the day and derivative prices are volatile (Appendix Figure A14). The best dealer (a large hedge fund) is 1.38% better, and the worst dealer (a smaller proprietary trading firm) does 1.30% worse than the baseline dealer. However, given that the price for a typical derivative contract ranges around C$1, and trade volume (in units of contracts) is smaller than on the stock exchange, these margins do not sum to sizable amounts over the course of a year.

In the bond market, most dealers earn lower margins than the baseline dealer, a large primary dealer. This is unsurprising given its dominant role. However, some dealers outperform

reliable standard errors, even when boostrapping standard errors (MacKinnon et al. (2023)). Another option is to cluster at the symbol level to capture correlated shocks affecting the same symbol over time. We do not adopt this approach because many price shocks are likely correlated across symbols, making symbol-level clustering insufficient for addressing cross-symbol dependencies.

the baseline. The most successful (a large insurance company) achieves margins over 0.08% higher. In contrast, the weakest dealer, who is primarily serving retail clients, lags behind by 0.48%. Given the large trade sizes in the bond market, these percentage differences translate into substantial annual payment differences. The best dealer, trading C$20.85 billion in bond par value per year, benefits from an additional C$17 million annually compared to the baseline. In contrast, the worst dealer, with an annual trade volume of C$58 million, incurs a shortfall of C$278 thousand.

Fact 7A (Systematic Price Differences)**.** *Neither the bond, stock, or derivative market are sufficiently frictionless to prevent some dealers from systematically outperforming others.*

In Table 10, we analyze which types of dealers achieve better margins on average, using cross-dealer variation. To do so, we estimate regression (2), replacing dealer-indicator variables with dealer-type indicators, with asset managers as the baseline.

Consistent with early empirical studies on the NYSE and regional U.S. exchanges (Bernhardt et al. (2005)), we find that larger trades are executed at worse prices on exchanges, and execution prices are worse when dealers trade for client accounts than for their inventory or market-making accounts. In the bond market, we find no evidence of trade-size discounts, adding to the mixed findings in the literature, where a size discount can turn into a size penalty depending on the trader fixed effects included (Pinter et al. (2024); Allen and Wittwer (2024)). When dealers trade with clients, they realize higher margins than when trading with brokers.

High-frequency traders outperform all other trader types on the derivatives exchange and also perform well on the stock exchange, though they are ultimately dominated by a few highly successful mutual funds. Unlike on exchanges, pension funds and insurance companies—who perform the worst on stock exchanges—achieve the highest bond margins. Dealers specializing in retail clients earn the lowest margins in bonds and derivatives, while they obtain margins similar to asset managers on stock exchanges.

Fact 7B (Cross-Market Synergies)**.** *Different dealer types excel in different markets. For example, high-frequency traders outperform other types on exchanges, but not in the bond market; dealers who specialize in serving retail clients underperform in all markets compared to most other dealer types.*

Next, we analyze whether the same or different dealers are successful across markets to understand if monetary benefits of specialization drive specialization. First, we zoom in on dealers who are exclusively active in one market in Figure 8. Many of those dealers obtain worse than average prices relative to the baseline dealer. However, there is heterogeneity in

Table 10: Margin regression with dealer-types (bonds, stocks, derivatives)

Bond market	Margin	
Trade size	0.000	0.000
	(0.000)	(0.000)
Counterparty is broker	0.008**	0.008***
	(0.003)	(0.002)
Counterparty is client	0.018***	0.018***
	(0.002)	(0.002)
Bank	0.021*	0.021***
	(0.010)	(0.004)
Broker	0.003	0.003
	(0.007)	(0.002)
High-Frequency Trader	0.027	0.027
	(0.032)	(0.028)
Investment Bank	-0.049**	-0.049***
	(0.015)	(0.011)
Mutual Fund	-0.013	-0.013***
	(0.008)	(0.004)
Pension Fund and Insurance	0.101***	0.101***
	(0.008)	(0.003)
Retail	-0.160***	-0.160***
	(0.009)	(0.003)
Date-& symbol-week fes	Yes	Yes
N	6,757,118	6,757,118
R^2	0.017	0.017
Within-R^2	0.000	0.000
Standard errors	Regular	Boot

Stock market	Margin	
Trade size	-0.000***	-0.000***
	(0.000)	(0.000)
Client account	-0.069***	-0.069***
	(0.003)	(0.001)
Inventory account	-0.000	-0.000
	(0.003)	(0.002)
Market-maker account	0.070***	0.070***
	(0.003)	(0.002)
Bank	0.071***	0.071***
	(0.002)	(0.002)
Broker	0.045***	0.045***
	(0.001)	(0.001)
High-Frequency Trader	0.115***	0.115***
	(0.004)	(0.004)
Investment Bank	0.009***	0.009***
	(0.002)	(0.002)
Mutual Fund	0.159***	0.159***
	(0.019)	(0.019)
Pension Fund and Insurance	-0.046***	-0.046***
	(0.003)	(0.003)
Retail	0.026***	0.026***
	(0.002)	(0.002)
Date-& symbol-week fes	Yes	Yes
N	111,051,211	111,051,211
R^2	0.008	0.008
Within-R^2	0.001	0.001
Standard errors	Regular	Boot

Derivative market	Margin	
Trade size	-0.000***	-0.000***
	(0.000)	(0.000)
Client account	-0.275***	-0.275***
	(0.066)	(0.028)
Inventory account	1.332***	1.332***
	(0.072)	0.030
Bank	-0.304**	-0.304***
	(0.097)	(0.078)
Broker	0.388***	0.388***
	(0.034)	(0.026)
High-Frequency Trader	1.001***	1.001***
	(0.041)	(0.031)
Investment Bank	0.597***	0.597***
	(0.043)	(0.036)
Other	0.404	0.404
	(0.275)	(0.261)
Retail	-0.394***	-0.394***
	(0.067)	(0.051)
Date-& symbol-week fes	Yes	Yes
N	4,529,584	4,529,584
R^2	0.036	0.036
Within-R^2	0.006	0.006
Standard errors	Regular	Boot

Notes: Table 10 shows the estimation results from regressing trader margins (1) of stock market trades on trade-size, the account-type (client, inventory, market-market, or other—the baseline), dealer-types, and day-security fixed effects on the LHS, and for fixed-income trades in the middle, and for derivatives on the RHS. For bonds, we replace the account-type with the type of trade (dealer-broker, dealer-client, dealer-dealer—the baseline). We cluster standard errors at the dealer-level and report conventionally computed robust clustered standard errors (second column) and wild-bootstrapped standard errors (third column).

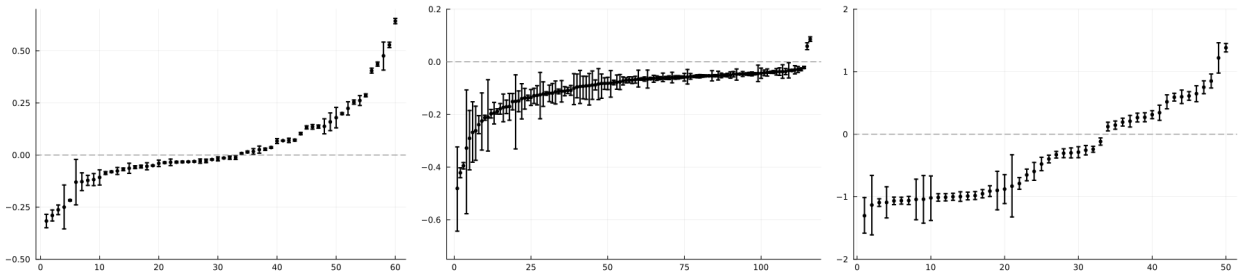
the bond and derivative market. The second best bond dealer only trades bonds, suggesting successful specialization in bonds. In contrast, the best ten stock dealers trade both bonds and stocks. This suggests that it is harder to specialize in exclusively on stocks than on bonds, possibly because bonds trade OTC where relationships matter more, or because entry costs to the stock exchanges are higher than entry cost to the bond market. For derivatives, specialization appears to pay off even more—50% of dealers who obtain positive margins only trade derivatives. This may be due to the relative complexity of derivative products compared to most equity and fixed-income products.

Second, we investigate whether synergies exist across trading bonds, stocks, and derivatives. Specifically, we assess whether dealers who excel in one market also achieve strong performance in others. As shown in Figure 9, there is little evidence to support this notion. The cross-market correlations of dealer coefficients are not statistically significant.

Fact 8A (Cross-Market Synergies)**.** *There are limited trading-synergies across markets: dealers who outperform other dealers in one market, do not tend to also outperform in other markets.*

Figure 7: Dealer coefficients that are statistically different from zero at 5% significance level

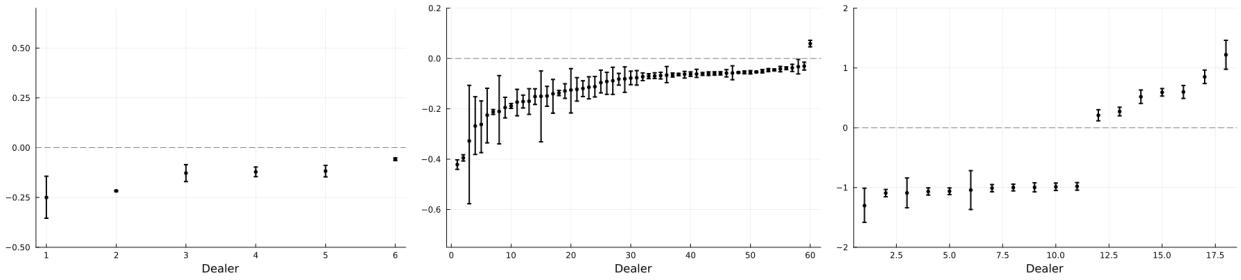
(a) Stocks (b) Bonds (c) Derivatives



Notes: Figures 7a shows the dealer coefficients, and 95% WCR bootstrapped confidence intervals when regressing margins (1) of a trade on indicator variables for each dealer active on the stock exchanges in addition to control variables (trade-size, the account-type, security-week and day fixed effects). Figures 7c shows the analogue for the derivative market. Figure 7b shows the analogue for the fixed-income market, where we replace the account-type with a variable that indicates the type of trade (dealer-dealer, dealer-client, dealer-broker). In all graphs we exclude dealer coefficients that aren't significantly different from zero at a significance level of 5% according bootstrapped and conventional inference to be conservative. We sort coefficients from small to large. Therefore, the x-axis are not comparable across markets, since they don't reflect the dealer's IDs. Appendix Figures A18 shows the analogous figures with conventionally computed confidence intervals; Appendix Figures A19 aggregates dealers to the parent-level.

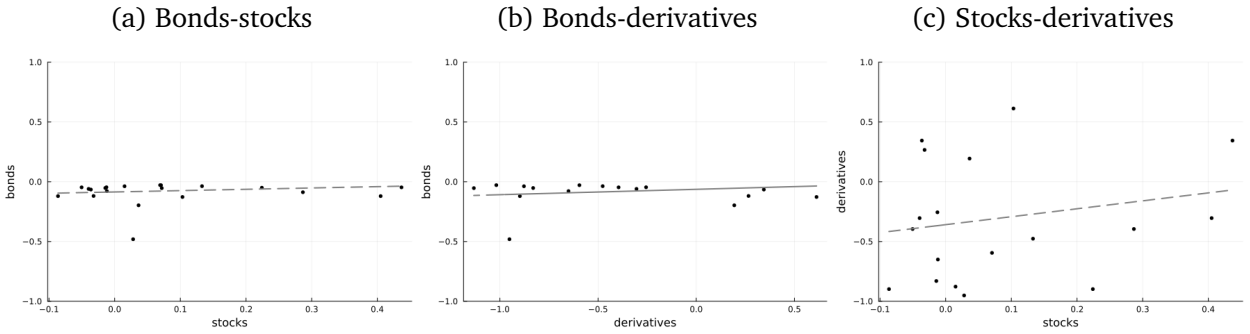
Figure 8: Dealer coefficients for dealers who exclusively trade in one market

(a) Stock market (b) Bond market (c) Derivative market



Notes: Figures 8a shows the dealer coefficients and 95% confidence intervals, which are obtained via WCR bootstrapping, when regressing margins (1) of a trade on indicator variables for each dealer that is only active on stock exchanges, and not on the bond market, (at the LEI-level) in addition to control variables (trade-size, the account-type, security-week and day fixed effects). Figure 8b shows the analogue for the fixed-income market, where we replace the account-type with a variable that indicates the type of trade. Figure 8c shows the analogue for the derivatives market. In all graphs, we exclude dealer coefficients that aren't significantly different from zero at a significance level of 5% according to bootstrapped and conventional inference to be conservative. We sort coefficients from small to large. Therefore, the x-axis are not comparable across markets, since they don't reflect the dealer's IDs.

Figure 9: Cross-market correlation between dealer coefficients of dealers active in all markets



Notes: Figure 9a shows the within-dealer correlation of coefficients in the bond (y-axis) versus stock market (x-axis), 9b and 9c show the correlation for the other two market pairs. We exclude dealer coefficients that aren't significantly different from zero at a significance level of 5% according to bootstrapped and conventional inference to be conservative. Appendix Figure A21 shows the cross-market correlation between dealer coefficients when aggregating dealer LEIs to the parent-level.

This could be for different reasons. For example, a bank that builds strong relationships with other dealers and clients in the OTC network is able to obtain better prices when trading bonds (as documented, for example, by Allen and Wittwer (2024)). Such a dealer might not have the tools to compete with high-frequency algorithmic traders on the stock exchange. Alternatively, the missing synergies might be due to the fact that different traders or trading desks are responsible for different market segments, and these traders operate separately from each other, even if they are part of the same parent-holding company.

5.2 Returns to product specialization

To detect cross-product price effects, we add product indicators to regression (2), and estimate the following regression for each market separately:

$$\text{margin}_\tau = \alpha + \sum_p \sum_j \beta_{jp} \mathbb{I}(dealer = j \text{ and } product = p) + \gamma \cdot control_\tau + \zeta_t + \zeta_{ws} + \epsilon_\tau. \quad (3)$$

If the same dealer obtains similar margins across products within a market compared to the baseline, all β_{jp} coefficients would be similar in size. If the dealer is more successful when trading some products relative to others, these coefficients would differ. As before, we include day and security-week fixed effects to avoid potential biases that arise from time-variation in the traded securities.[21] For bonds, the baseline is a large primary dealer trading government

[21] As robustness, we also estimate a specification with only include day-fixed effect to exploit variation of margins across securities within the same product category. While the size of the coefficients differs,

bonds, for stocks it is that bank trading large stocks, and for derivative it is that bank trading Treasury futures.

We clustered at the daily-level, and compute standard errors via wild-bootstrapping. This is useful not only because it circumvents issues that arise from uneven cluster sizes, but also because many indicator variables in regression (3) are zero, since dealers tend to specialize in specific products. This implies that the standard cluster-robust covariance matrix is close to singular (non-invertible) due to high correlation within some clusters with many zeros. Since wild-bootstrapping resamples residuals with cluster-dependent perturbations, and does not directly rely on inverting the covariance matrix, bootstrapping circumventing the issue.

Since estimating regression (3) is computationally intensive, especially for the stock market, we estimate it for each of the years in our sample separately, and report results for 2022. While the β estimates vary across years, the main qualitative take away is common across years: dealers generally do not outperform others across multiple products in line with the fact that product segmentation is substantial.

We visualize the estimation outcome through heatmaps, one for each market, in Figure 10. Each row in a heatmap correspond to a dealer j. A column corresponds to a product p. When dealer j obtains systematically worse margins for product p, we color the corresponding jp cell red, meaning that the β_{jp} coefficient is negative and statistically different from zero. The cell is black if the dealer outperforms the other dealers, and empty if they either do not trade product p or the coefficient is not statistically significantly different from zero. If the one dealer were to outperform (underperformed) all other dealers across products, we would observe a black (red) line for that dealer.

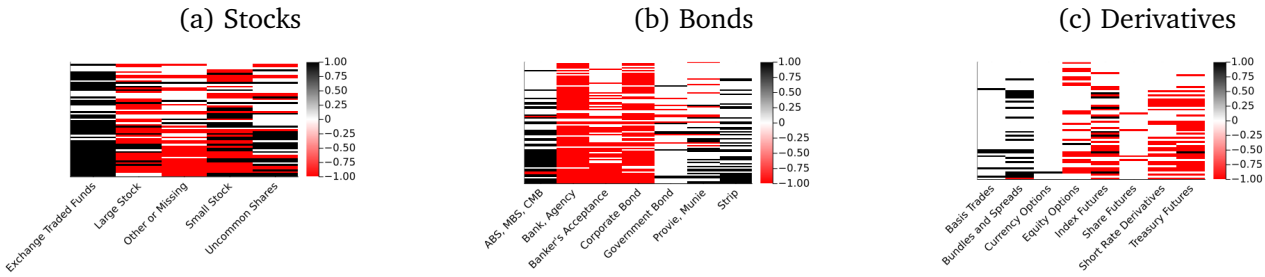
Fact 9A (Cross-Product Synergies)**.** *Dealers generally do not outperform others across multiple products, further supporting the evidence of strong product specialization.*

On the stock market (Figure 10a), some dealers achieve higher margins than the baseline bank when trading large stocks. In contrast, all dealers earn weakly higher margins when trading ETFs, suggesting that in 2022 ETFs were more profitable than large stocks, at least in terms of margins. For small stocks and other product categories, dealer performance varies, with some outperforming others.

In the bond market (Figure 10b), most dealers obtain margins similar to the baseline when trading government debt, though a few perform better and some worse. Trading strips generates weakly higher margins for all dealers, whereas bank and agency paper, bankers' acceptances, and corporate bonds yield weakly lower margins. For ABS, MBS, and CMB, as well

the main take away (Fact 9A is robust).

Figure 10: Dealer specialization across products within a market — 2022



Notes: Figure 10a visualizes the dealer-product coefficients, β_{jp}, when estimating regression (3), which regresses margins (1) of a trade on indicator variables for each dealer-product combination for dealers that are active on the stock exchanges in addition to control variables (trade-size, the account-type, security-week and day fixed effects), using data from 2022. Each row in a heatmap correspond to a dealer j. A column corresponds to a product p. When the corresponding β_{jp} is positive and statistically significant from zero, a p-j cell is black; if it is negative it is red; and empty if the coefficient is not statistically different from zero. Figure 10b and 10c show the analogue for bonds and derivatives. For bonds, the baseline β_{pj} coefficient is a large primary dealer trading government bonds; for stocks it's that bank trading large stocks, and for derivative it's that bank trading Treasury futures. In all graphs, dealers are sorted according to their trade-volume, with the dealer trading the most in the given market being at the bottom, and the dealer trading the least at the top. Standard errors are clustered at the daily-level.

as provincial and municipal bonds, dealer performance is heterogeneous—most exceed the benchmark, but some underperform.

In the derivatives market (Figure 10c), the baseline dealer earns lower margins than most others when trading Treasury futures. Margins are weakly lower for all dealers in short rate derivatives and share futures but weakly higher for most in bundles and spreads, currency options, and basis trades. Index futures exhibit the greatest heterogeneity in dealer performance.

Since the margin measure reflects price volatility over a day, this analysis does not imply that some products are inherently more profitable—we do not account for underlying trading costs. Rather, the key takeaway is that no dealer consistently outperforms all others across products, pointing towards product specialization in all markets.

In summary, we have shown that neither the bond, stock, nor derivatives markets are frictionless—if they were, no dealers would systematically outperform others. High-frequency traders are particularly successful in the stock and derivatives markets, while institutions trading on behalf of retail clients perform poorly in the bond and derivatives market. Consistent with cross-market segmentation, trading synergies across markets are limited; dealers who outperform in one market typically do not excel in others. Additionally, consistent with product specialization, dealers generally do not outperform across multiple products.

6 Conclusion

We analyze dealer specialization across bond, stock, and derivative markets using a unique dataset that tracks trading activity across all major Canadian financial markets. Our findings show that product specialization within a market is stronger than market specialization, though not all dealers participate in every market. While no market is frictionless enough to prevent some dealers from consistently securing better prices, we find no evidence of cross-market or cross-product trading synergies. These results challenge the traditional view that financial intermediaries operate seamlessly across markets and products, and underscore the importance of market structure and product complexity in driving market fragmentation.

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ONLINE APPENDIX

Market Segmentation Across Bonds, Stocks, and Derivatives

by Milena Wittwer, and Andreas Uthemann

Section A provides details regarding data cleaning.
Section B provides mathematical details for our segmentation indices.

A Data Cleaning

Data Restrictions. Our bond data includes all bond trades that are reported by CIRO-dealers to MTRS.20, excluding foreign sovereign bonds. We exclude primary market trades. In rare cases, trades are reported on a weekend. We treat those cases as trades that occur on the Monday following the weekend.

We include all stock-market trades, including those executed during the opening and closing auctions. In rare cases, trades are associated with negative trade amounts. We exclude those trades.

We keep regular derivative trades, and excludes rare cases of trades involving 'test futures'. In rare cases, trades are reported on a weekend. We treat those cases as trades that occur on the Monday following the weekend. We exclude a handful of dates where only Buy-ins are trading.

Quality Check. We compare the average monthly trade volume on the stock markets with the publically available information that is provided in CIRO's website to confirm that we observe close to 100% of the trades we should observe.

We also compare the derivative trade volume with information provided on MX's website. After restricting the raw data, as explained above, we observe roughly 90% of trade volume on average.

Type Classification for Dealers. The Bank of Canada classifies traders based on their LEIs into types following their in-house methodology. We replicate their approach to classify dealers on the stock exchanges and the derivative exchange, and to classify the parent-holding company of each LEI. Here we briefly describe their approach.

We use two types of information to classify entities – "Direct" and "Indirect" sources of information. "Direct" information refers to any information provided by the entity itself - either through its official website, internal documents, spokespersons, a regulatory organization to

which it reports, etc. “Indirect” information refers to any information which is not direct information. The latter is further broken down into two sub-types: “Reliable" or “Weakly reliable". For the dealers in this project, all information comes from reliable sources, such as Bloomberg, Yahoo Finance, CapEdge, etc.

B Theil Index

To define the dealer-specific measure, consider a fixed dealer j. Let there be M markets, indexed by m, and P_m products within each market m, and $P = \sum_m P_m$ products overall, indexed by p. Denote dealer j's share of total volume traded by dealers in product-market segment mp by $s_{jmp} \in [0,1]$. The cross-product average for a dealer within a market is given by $\bar{s}_{jm} = \frac{1}{P}\sum_p s_{jmp}$, and $\bar{s}_j = \frac{1}{M\times P}\sum_m \sum_p s_{jmp}$ the overall average.

The standard Theil T index in this setting is defined as:

$$T_j = \frac{1}{M \times P} \sum_m \sum_p \left(\frac{s_{jmp}}{\bar{s}_j}\right) \ln\left(\frac{s_{jmp}}{\bar{s}_j}\right). \tag{4}$$

This index captures the distribution of dealer j's market share across product-market segments. If the dealer trades the same fraction of total volume in each segment, $T_j = 0$. A positive T_j indicates segmentation, with higher values reflecting greater variation in the dealer's activity across segments.

For our purposes, the original index is not suitable because it fails to account for the fact that non-participation by dealers in a market or market-segment increases segmentation. The original formulation only sums the trade volume of dealers who are active in a market, ignoring those who are inactive. To address this, we introduce a non-participation cost, ξ, which applies when a dealer does not trade in market mm (i.e., when $s_{jm} = 0$):

$$T_j = \underbrace{\frac{1}{M \times P} \sum_m \sum_p \mathbb{I}(s_{jmp} > 0) \left(\frac{s_{jmp}}{\bar{s}_j}\right) \ln\left(\frac{s_{jmp}}{\bar{s}_j}\right)}_{\text{Standard Theil index conditional on participation}} + \underbrace{\frac{1}{M \times P} \sum_m \sum_p \mathbb{I}(s_{jmp} = 0)\xi}_{\text{Non-participation}}.$$

The magnitude of the index depends on the size of the penalty, ξ, which can be chosen arbitrarily. As a result, the index by itself is not informative in absolute terms. However, it is valuable for comparing segmentation within a market across products to segmentation across different markets, which is our primary objective.

To see this, note that the index decomposes into two components: one measuring within-

market segmentation, T_j^w, and another measuring across-market segmentation, T_j^a:

$$T_j = T_j^a + T_j^w, \text{ with } T_j^w = \frac{1}{M}\sum_m T_{jm}^w, \text{ where}$$

$$T_{jm}^w = \frac{1}{P}\sum_p \mathbb{I}(s_{jmp} > 0 \cup \bar{s}_{jm} > 0)\left(\frac{s_{jmp}}{\bar{s}_j}\right)\ln\left(\frac{s_{jmp}}{\bar{s}_{jm}}\right) + \xi\mathbb{I}(s_{jmp} = 0 \cup \bar{s}_{jm} > 0)$$

measures the how dealer j's market share in a market-product segment is distributed across products in market m, with more uneven distributions meaning higher segmentation; and

$$T_j^a = \frac{1}{M}\sum_m \mathbb{I}(\bar{s}_{jm} > 0)\left(\frac{\bar{s}_{jm}}{\bar{s}_j}\right)\ln\left(\frac{\bar{s}_{jm}}{\bar{s}_j}\right) + \xi\mathbb{I}(\bar{s}_{jm} = 0)$$

measures how the average of this market share across products is distributed across markets.

As for the standard Theil index, the minimum value for both measures is 0, which is the case when a dealer distributes their trading activity evenly across products in a market for T_{jm}^w, or on average across markets for T_j^a. The maximum value is given by M, P_m and ξ, namely, $\overline{T}_{jm}^w = \frac{1}{P_m}[MP_m\ln(P_m) + (P_m - 1)\xi]$, and $\overline{T}_j^a = \frac{1}{M}[M\ln(M) + (M-1)\xi]$.

Appendix Table A1: Fixed-income products

Product	Description
Government Bond	Government of Canada Bond, Government of Canada Real Return Bond, Government of Canada T-bill
Corporate Bond	Corporate Bond
Provie, Munie	Provincial Bill, Provincial Bond, Provincial Commercial Paper, Municipal Bond
Bank, Agency Paper	Bank Commercial Paper and Bank Security - Note/Bond/Debenture. Agency Bond and Agency Commercial Paper
Banker's Acceptance (BA)	Banker's Acceptance
ABS, MBS, CMB	Mortgage-Backed Security, Asset-Backed Security, Canada Mortgage Bond. In Canada CMB is a collection of MBS.
Strip	Agency Strip Bond, Bank Strip Bond, Corporate Strip Bond, Finance company Strip Bond, Government of Canada Strip Bond, Municipal Strip Bond, Provincial Strip Bond

Appendix Table A2: Fixed-income sectors

Sector	Description; NAISC Code
Public Administration	Public administration (which is essentially all government debt); 91-92
Financial Services	Finance and Insurance, Retail Trade, Wholesale Trade, Real Estate; 52, 44-45, 41-42, 53
Products and Services	Accommodation and Food Services, Administrative and Support, Waste Management and Remediation Services, Educational Services, Agriculture, Health Care and Social Assistance, Arts, Entertainment and Recreation, Other Services, Construction, Management of Companies and Enterprises; 72, 56, 61, 11, 62, 71, 81, 23, 55
Mining and Oil/Gas	Mining, quarrying, and oil and gas extraction; 21
Technology and Utilities	Utilities; 22
Median, Life Science, Transportation	Information and Culture, Professional, Scientific and Technical Services, Transportation; 51, 54, 48-49
Missing	

Notes: Appendix Table A1 describes our product classification for fixed-income products. Appendix Table A2 describes our sector classification for fixed-income products, based the first two digits of the NAISC code we observe in the raw data.

Appendix Table A3: Equity products

Product	Description
Large Stock	Symbols without suffices (i.e., common shares) that are listed with missing sp-type with more than 2 billion of quoted market value
Small Stock	Symbols without suffices (i.e., common shares) that are listed with missing sp-type with less than 2 billion of quoted market value
Exchange Traded Funds	Symbols that are listed with sp-type being Exchange Traded Funds
Uncommon Shares	Symbols which suffices that aren't listed as Exchange Traded Funds, which include the the following types: preferred stocks, class A-C, notes, debentures, equity dividends, when-issued capital pool companies, warrants, redeemable common stocks, U.S. funds, units, subscr. receipts, and stocks that trade on the NEX market
Others or Missing	Symbols without suffices that have a non-missing sp-type, which include the following sp-types: Income Trust, Fund of Equities, Commodity Funds, Exchange Traded Receipt, Split Shares, Fund of Mortgages/MBS, Fund of Debt

Appendix Table A4: Equity sectors

Sector	Description
Mining and Oil/Gas	Mining and Oil and gas
ETP and Closed-End Funds	ETP and Closed-End Funds
Products and Services	Industrial Products and Services and Consumer Products and Services
Financial Services	Financial Services and Real Estate
Technology, Utilities and Pipelines	Utilities and Pipelines, Clean Technology and Renewable Energy, Clean Technology, Technology
CPC and SPAC	SPAC, CPC
Media and Life Science	Commercial and Media, Life Science
Missing	Missing

Notes: Appendix Table A3 shows our product classification for TSX, ALPHA, or TSXV exchange; and Appendix Table shows industry sectors. In order to categorize securities into products and industry sectors, we merge the data of TMX trades with publicly available listing information for each listed symbol in December of each year in our sample, by relying on the wayback machine. The listing information contains information about the type of the equity (e.g., ETF or stock), encoded in variable "sp-type", and the quoted market value of the associated firm.

Appendix Table A5: Derivative proucts

Product	Description/Symbols if available
Treasury futures/options	Government bond futures and future options; CGZ, CGF, CGB, LGB, OGZ, OGF, OGB
Short-term derivatives	BAX futures and future options, CORRA futures; BAX, OBW, OBX, OBY, or OBZ, CRA
Equity options	Equity option, weekly option, option on ETFs
Share futures	Share futures
Currency options	Options on USD; USX
Index futures	Index futures; SXF, SCF, SXB, SXY, SXK, SXJ, SEG, SXM, SXA, SXH, SXO, SXU, SXV, SCG, SDV
Bundles and spreads	User-defined strategy, inter-group strategies, spreads
Basis Trades	Basis trade on close, index future basis trade

Appendix Table A6: Derivative sectors

Sector	Description
Public administration	Government bond futures/future options
Money market	Short-term interest rate derivates
FX	Currency options
Derivative indices	Index futures
TSX sectors of underlying	Equity options and share futures (whose underlying core-symbols match with TSX/TSXV listings information. We match 89% of (core) symbols for equity options and share futures.
Multiple	Basis trade, and bundles and spreads
Missing	Missing

Notes: Appendix Table A5 explains our product classification based on symbols we observe for the derivative exchange, and Appendix Table A6 describes the sector classification.

Appendix Table A7: Trader types classification

Broker	Financial entity whose purpose is to offer brokerage services
Investment Bank	Investment bank
Bank	Bank, retail bank or credit union, and any entity that is deposit taking
Asset Manger	Financial entity whose purpose is to manage assets (or investments) and/or offer investment advising services. Entities that manage multiple types of funds such as HF, MF or ETFs are also classified as such
Mutual Fund	Financial entity that is a mutual fund or a mutual fund manager
High-Frequency Trader	Financial entity that is a hedge fund or a hedge fund manager; Private Equity, or Proprietary Trader
Pension Fund and Insurance	Financial entity whose purpose is to manage investments (and/or provide services) related to pension, retirement, insurance, re-insurance, benefits, and superannuation funds
Retail	Financial entity whose purpose is to offer financial services to retail (non-institutional) investors
Other	This category includes all other types which we observe in our traded data. From the Bank of Canada classification we pool the following types under this category “Real Estate (a financial or non-financial entity that is involved in the construction, financing, management, or sale of commercial, industrial, or residential real estate), “Other" (Financial entity that does not fall in any of the aforementioned classifiers (e.g., Financial Planner, Financial Research Services, Execution Platform)), Uncategorized (entity that can neither be classified as a financial nor a non-financial entity due to lack of information), “Non-financial entity". We also include Buy-Ins that execute some trades on the exchanges here.

Notes: Appendix Table A7 explains the classification of trader types we adopt following the methodology of Bank of Canada staff.

Appendix Table A8: Daily trade volume, number of active dealers, trade-sizes, and prices

Variable	Mean	Median	Min	Max	Std
Daily Trade Volume					
Stocks (in mil C$)	661.053	613.824	155.859	1746.480	209.427
Bonds (in bn C$)	71.723	68.410	0.196	1,504.660	54.771
Derivatives (in k C$)	340.366	323.155	1.487	1,017.150	126.632
Number of Active Dealers (LEIs)					
Stocks	64.1574	64.0	61.0	69.0	1.630
Bonds	61.0415	62.0	5.0	84.0	7.794
Derivatives	53.6177	54.0	21.0	57.0	3.019
Number of Active Dealers (Parents)					
Stocks	60.7052	61.0	58.0	64.0	1.180
Bonds	57.3947	58.0	11.0	71.0	6.636
Derivatives	47.7374	48.0	21.0	51.0	2.668
Trade size					
Stocks (in C$)	11875.7	1300.0	0.1	7.361×10^{7}	74,694.1
Bonds (in mil C$)	10.934	1.250	$1.0/10^{6}$	7.189×10^{5}	436.1778
Derivatives (in C$)	78.143	10.0	1.0	170,478.000	667.365
Trade price					
Stocks (in C$)	27.280	12.240	0.005	2,392.400	86.936
Bonds (in C$)	102.344	100.24	1.0	980.0	12.3984
Derivatives (in C$)	20.809	1.060	-142.050	21,800.00	123.298

Notes: Appendix Table A8 summarizes trade data for stocks (TSX, TSXV, Alpha), bonds (MTRS), and derivatives (MX) from 2019 to 2022. It provides the mean, median, minimum, maximum, and standard deviation of daily trade volume, the number of active dealers ("Number of Dealers (LEI)") and parent institutions ("Parents"), trade size, and trade price. For derivatives, trade size and volume reflect the number of contracts, not the underlying asset value. There are 1,004 active trading days for stocks, 994 for derivatives, and 1,035 for bonds. Some bond trades occur on Canadian holidays, when the Investment Industry Association of Canada (IIAC) recommends pausing trading. These days, typically involving minimal activity, are excluded from the table but included in the analysis with either lower-frequency aggregation or day-fixed effects to account for special cases. The stock market features 6,449 symbols traded by 72 dealers and 66 parent institutions. The derivatives market, where symbols often include contract details like expiration dates, has 503,056 symbols traded by 64 dealers and 56 parent institutions. In the bond market, 107,516 CUSIPs are traded by 163 dealers (CIRO dealer members in the raw data) and 131 parent institutions. Only a subset of these dealers is active daily.

Appendix Table A9: Symbol Suffixes on TSX/TSXV/Alpha

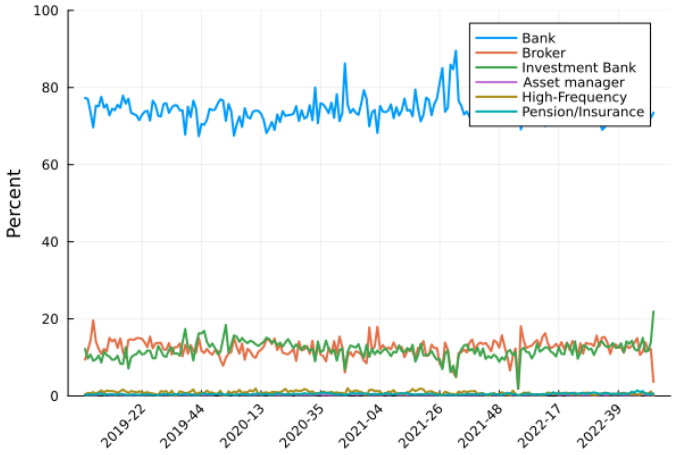
Symbol suffix	Description
None	Common shares
A, B, C	Class A, B, C of shares is typically related to voting rights, access to dividend
DB	Debenture, stock type that makes fixed payments at scheduled intervals of time, operates similar to preferred stock
E	Equity dividend
F	
G	
H	NEX market provides a trading forum for listed companies that no longer meet the TSX Venture's ongoing listing standards; designed for companies that have low levels of business activity or have ceased to carry on active business. It benefits such companies by giving their stocks a degree of liquidity and providing visibility that may attract potential acquirers or investors.
K	NEX market
IR	Installment receipts, is an equity issuance in which the purchaser does not pay the full value of the issue up front. In the purchase of an installment receipt, an initial payment is made to the issuer at the time the issue closes; the remaining balance must be paid in installments, usually within a two-year period. Although the purchaser has not paid the full value of the issue, he or she is still entitled to full voting rights and dividends.
J	
L	Legended shares. A legend is a statement on a stock certificate noting restrictions on the transfer of the stock. A stock legend is typically put in place due to the requirements established by the Securities and Exchange Commission (SEC) for unregistered securities. A stock legend may or may not be legally required on the certificate itself, depending on state laws.
M	Booms
N	Subscription receipts (second issue trading)
O	Subscription receipts (third issue trading)
NO, NS, NT	Exchange traded note (ETN) are unsecured debt securities that tracks an underlying index of securities.
P	Capital pool company (CPC) is an alternative way for private companies in Canada to raise capital and go public. The capital pool company system was created and is currently regulated by the TMX Group, and the resulting companies trade on the TSX Venture Exchange in Toronto, Canada.
Q	
PR, PF, PS	Preferred shares; similar to common shares, no maturity date, ownership, fixed distribution rate, no voting rights
PR.CLASS, PS.CLASS, PF.CLASS	Preferred class
R	Subscription receipts are defined as those limited term securities issued via prospectus, which are convertible into another security class of the issuer (predominantly common shares) at a set conversion rate based on the successful completion of a planned reorganization or transaction. Where completion is not successful, security proceeds are either returned to the subscriber or a more generous conversion rate is made available to the subscriber.
RT	Rights are instruments issued by companies to provide current shareholders with the opportunity to preserve their fraction of corporate ownership. Rights are short-term instruments that expire quickly, usually within 30-60 days of issuance. The exercise price of rights is always set below the current market price, and no commission is charged for their redemption.

S	Special U.S. terms
T	Special US trading terms (second issue trading)
U	U.S. dollar
V	U.S. dollar (second issue trading)
UN	Units are a securities that is made up of one common share and half a warrant. Units are commonly offered by special-purpose acquisition companies, or SPACs that are seeking to raise money in a public stock offering and trade on a stock exchange with the primary goal of merging with a private business and taking it public.
W	When issued
WB	
WR	
I	When issued (second issue trading)
WT	Warrants give the holder the right to purchase a company's stock at a specific price and at a specific date.
X	
Y	Redeemable common. Redeemable shares are shares that a company has agreed it will, or may, redeem (in other words buy back) at some future date. The shareholder will still have the right to sell or transfer the shares subject to the articles of association or any shareholders' agreement.

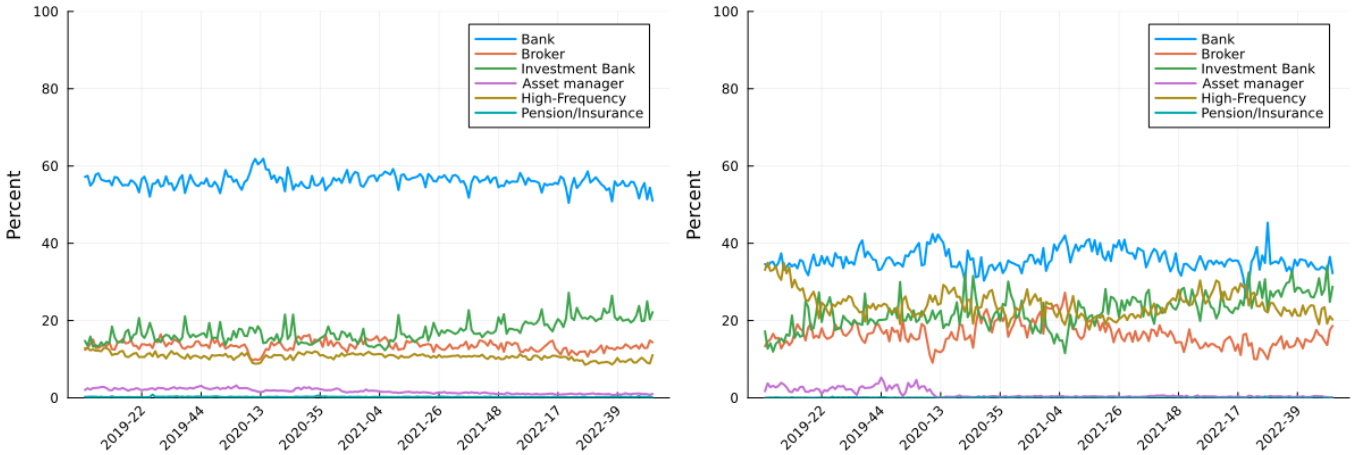
Notes: Appendix Table A9 describes the meaning of all suffixes of symbols trades on TSX, TSXV, or Alpha. An empty cell means that we were not able to find the description of a symbol that we observe in the raw data.

Appendix Figure A1: Weekly fraction of dealer trade volume by type

(a) MTRS



(b) TSX—all accounts (LHS); excluding client accounts (RHS)



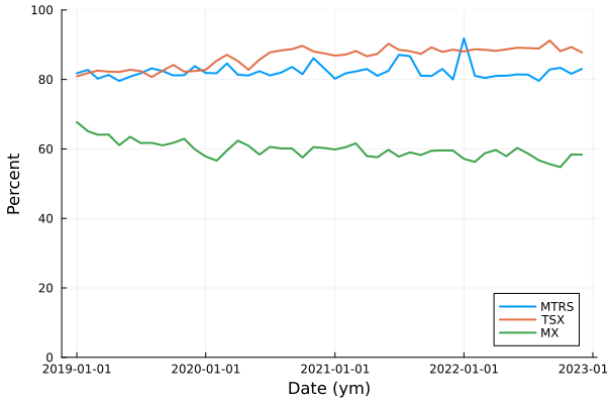
(c) MX—all accounts (LHS); excluding client accounts (RHS)



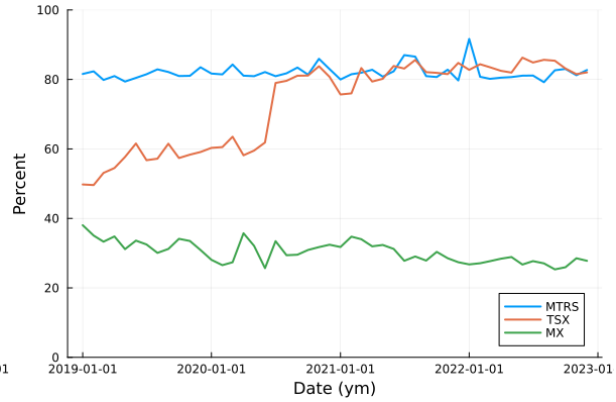
Notes: Appendix Figure A1 shows the fraction of weekly dealer trade volume that is traded by each type per market (at the parent-level). For TSX and MX we include all trades on the LHS, and focus on non-client trades on the RHS.

Appendix Figure A2: Fraction of monthly dealer trade volume by dealers active in all markets

(a) Including all trades



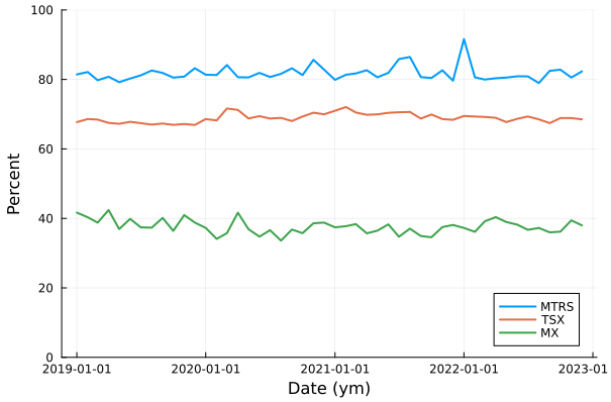
(b) Excluding client trades (for TSX/MX)



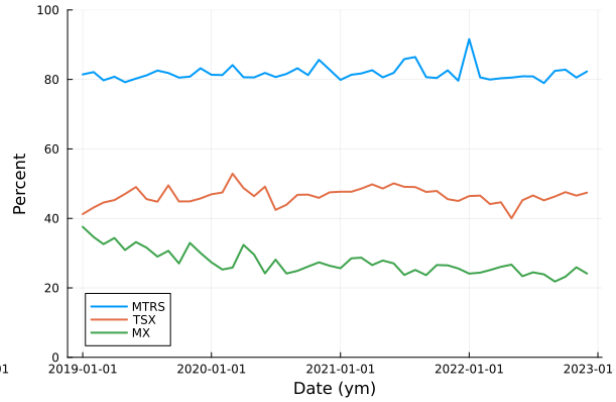
Notes: Appendix Figure A2a shows the fraction of monthly dealer trade volume by those active in all markets, for each market, including trades for all accounts. Thus, this is the analogue to row "All" in Table 6, just computed for each year-month separately, and then plotted over time. We see that about 80% of dealer trade volume on TSX is executed by dealers who also trade on MTRS and MX. Figure A2b excludes trades for client accounts. It displays an upward trend on TSX during the second half of 2020. This isn't driven by the fact that the fraction of dealer trade volume by banks or investment banks decreased during that time in light of Figure A1b. Instead, there was an increasing use of the non-client accounts among dealers who are active in all markets.

Appendix Figure A3: Fraction of monthly dealer trade volume by primary dealers active in all markets

(a) Including all trades

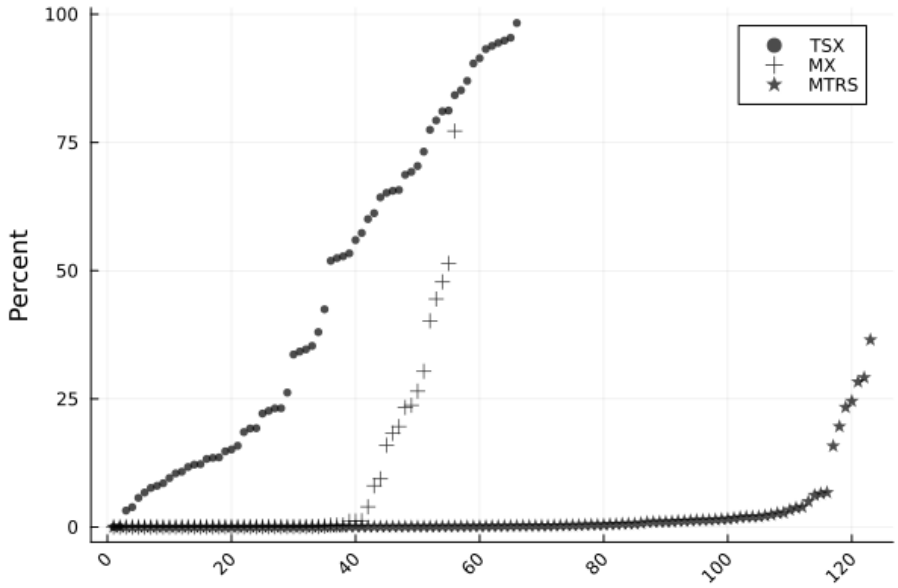


(b) Excluding client trades (for TSX/MX)



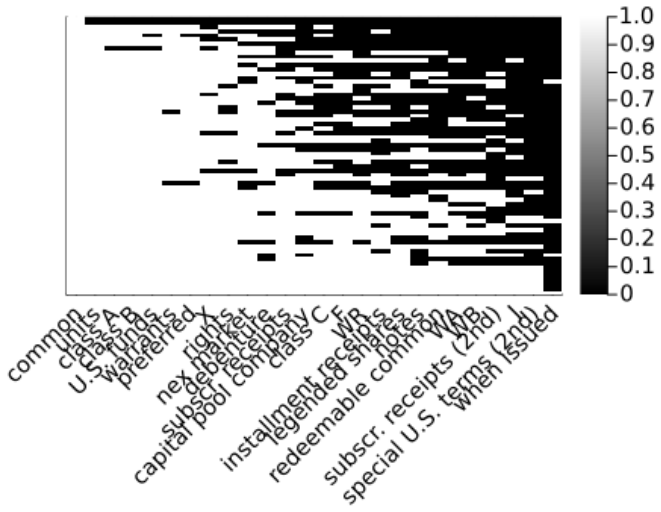
Notes: Appendix Figure A3a zooms in on primary dealers, showing the fraction of monthly dealer trade volume by dealers who are active in all markets and are primary dealers when including all trades. For example, we observe that essentially all omnipresent dealers on MTRS are primary dealers, and that roughly 68% of dealer trade volume on TSX is executed by primary dealers who are active in all markets, implying that 80%-68%=12% of dealer trade volume is executed by dealers who are active across markets but aren't primary dealers. Figure A3b excludes client trades.

Appendix Figure A4: Fraction of securities traded by each dealer out of all securities on TSX, MX, MTRS



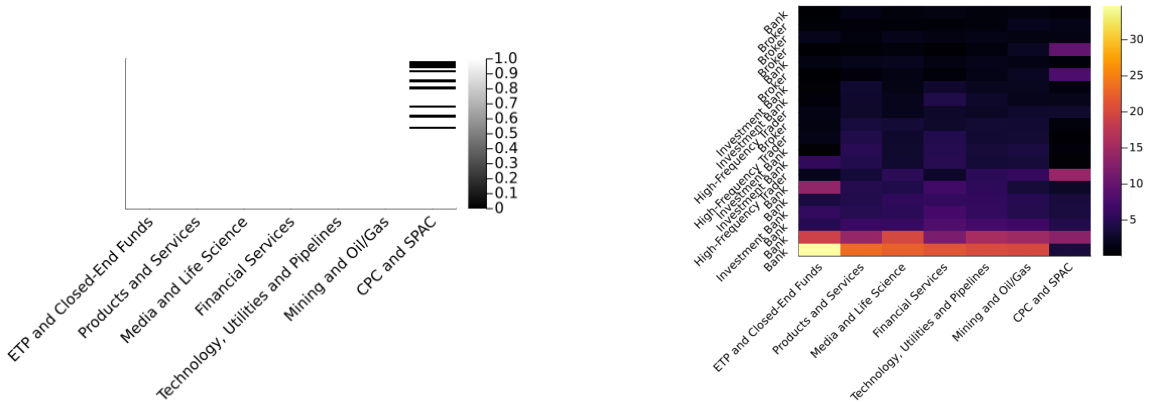
Notes: Appendix Figure A4 shows the fraction of symbols (x-axis) that each dealer trades (at the parent-level, on the y-axis) out of all traded symbols for each market. Since we sort by size within each market, the y-axis doesn't represent dealer-IDs that are common across markets. This is an alternative way of showing product differentiation: it is highest in the fixed-income market, and lowest on the stock exchange. The derivative exchange is in between.

Appendix Figure A5: Dealer presence across asset-types (defined by the symbol suffix)



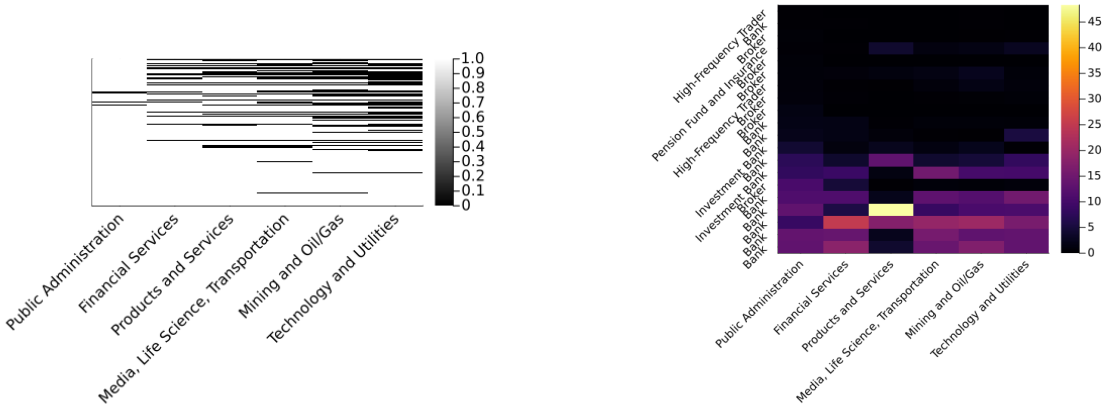
Notes: Appendix Figure A5 shows whether each of the dealers is active (i.e., trades at least ones) in yellow, versus in-active in black for each asset-class, defined according to the symbol-suffix within the stock markets at the parent-level. Suffices are explained in Appendix Table A9.

Appendix Figure A6: Dealer presence and trade intensity across equity sectors



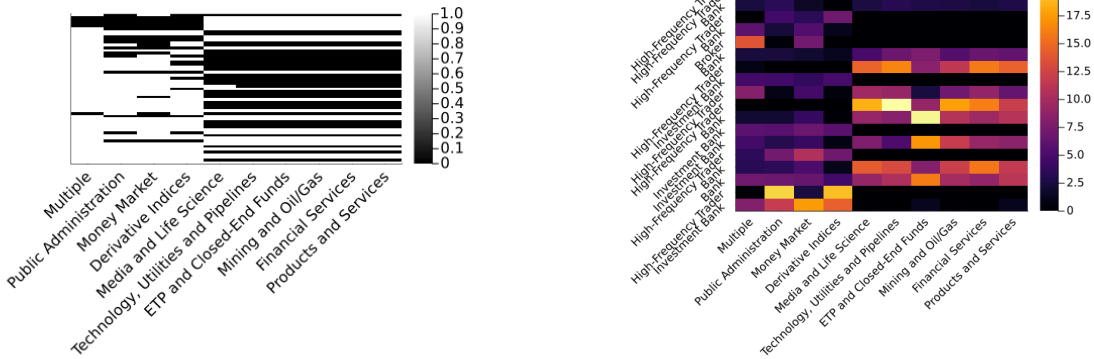
Notes: Appendix Figure A6 shows the analogous graphs for Figure 2 with sectors instead products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each sector within the stock markets at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each sector. We exclude sectors that are missing. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across sectors within a market at the bottom, and the dealer who trades the lowest at the top.

Appendix Figure A7: Dealer presence and trade intensity across fixed-income sectors



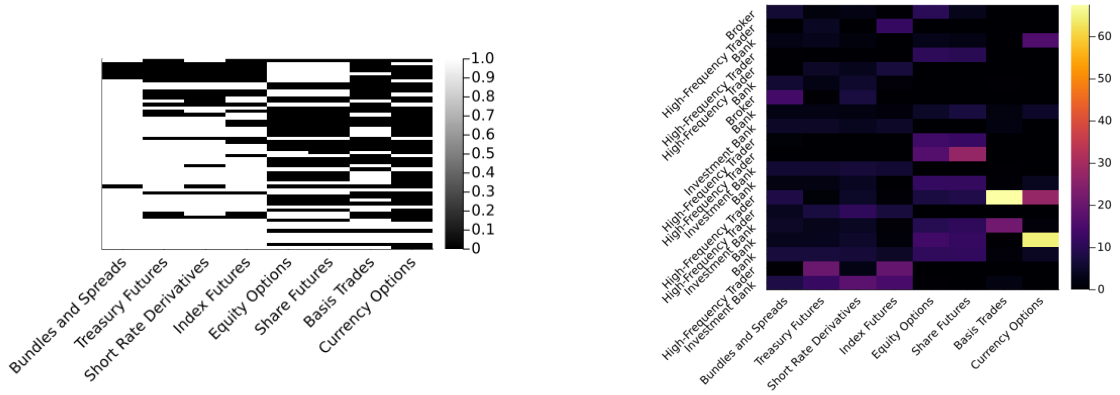
Notes: Appendix Figure A7 is analogous to Figure 3 but for sectors instead of products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each sector within the fixed-income market at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each sector. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across sectors within a market at the bottom, and the dealer who trades the lowest at the top.

Appendix Figure A8: Dealer presence and trade intensity across derivative sectors

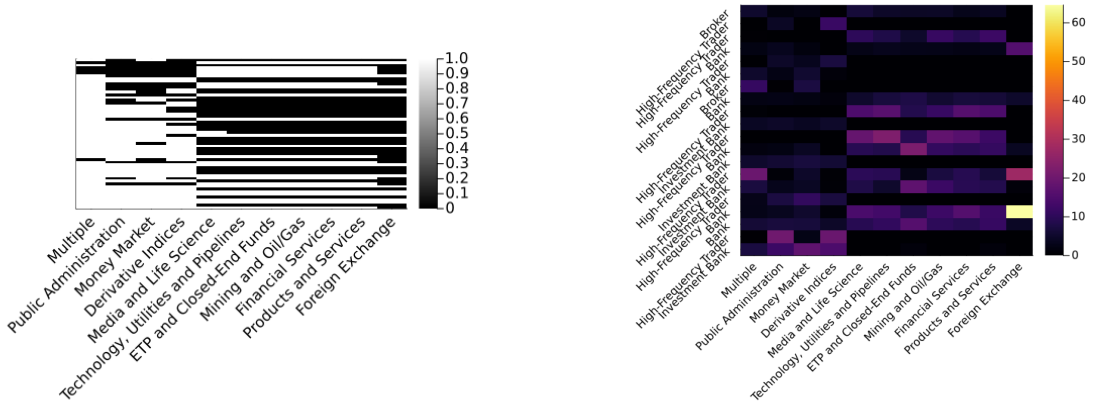


Notes: Appendix Figure A8 is analogous to Figure 5 but with sectors instead of products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each sector within the derivative market at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each sector. Here, we exclude the product categories "Basis Trades" and “Currency Options" since they are very small according to trade volume. We include these products in Appendix Figures A10. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across sectors within a market at the bottom, and the dealer who trades the lowest at the top.

Appendix Figure A9: Dealer presence and trade intensity across derivative products, including all products

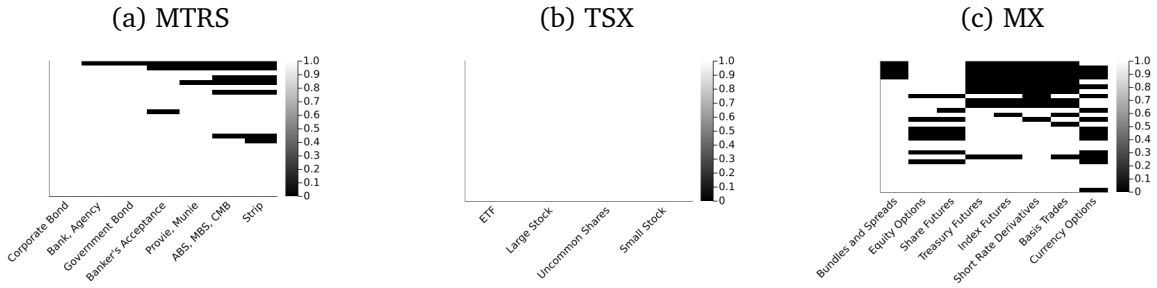


Appendix Figure A10: Dealer presence and trade intensity across derivative sectors, including all products



Notes: The RHS of Appendix Figure A9 is the analogue to Figure 5 but includes the two small products "Basis Trades" and “Currency Options". It shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in black for each product within the derivative market at the parent-level. The LHS of these figures zooms in on the 20 largest dealers, again at the parent-level, defined according to the percentage a dealer trades of the dealer trade volume within a market in an average month. It shows their average monthly trade-share for each product. In all graphs, rows are sorted according to trade size, with the dealer who trades the largest dealer volume aggregated across products (or sectors, respectively) within a market at the bottom, and the dealer who trades the lowest at the top.

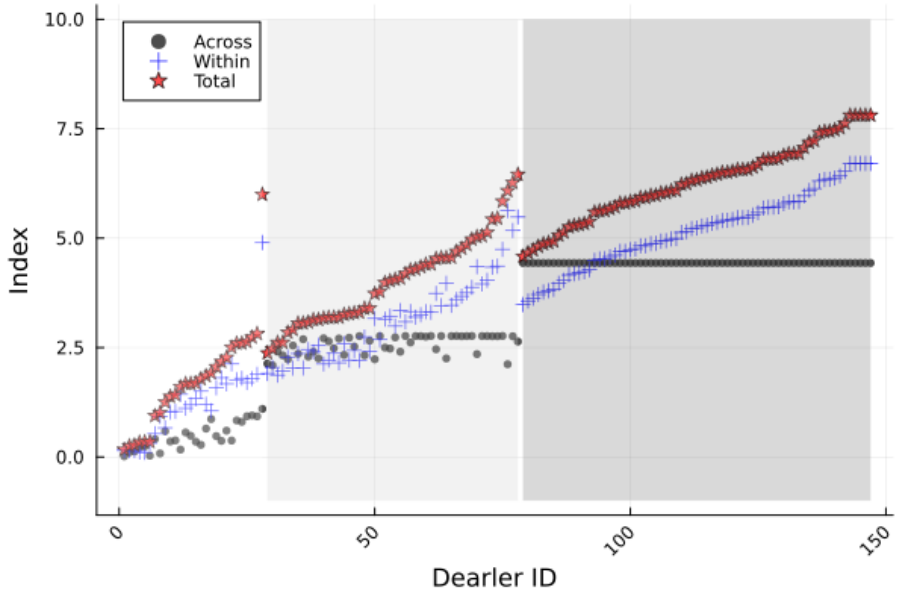
Appendix Figure A11: Dealer presence across products of dealers present in all markets



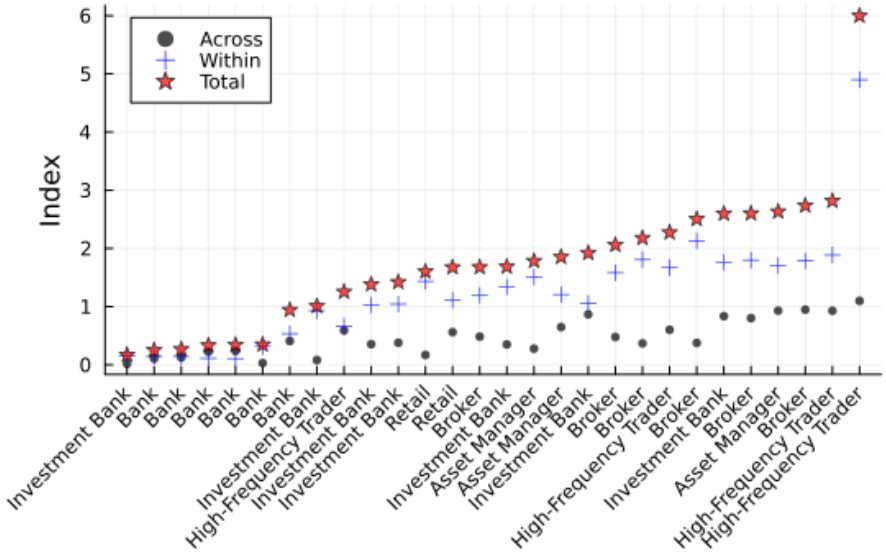
Notes: Appendix Figure A11 is the analogue to Figure 6, but includes the two small products “Basis Trades" and “Currency Options" for MX. It shows whether dealers who are present in all markets are active for a specific product in white, versus in-active in black for each product within the fixed-income market; for the TSX; and for MX (at the parent-level).

Appendix Figure A12: Within-and cross-market segmentation indices

(a) Indices of all dealers

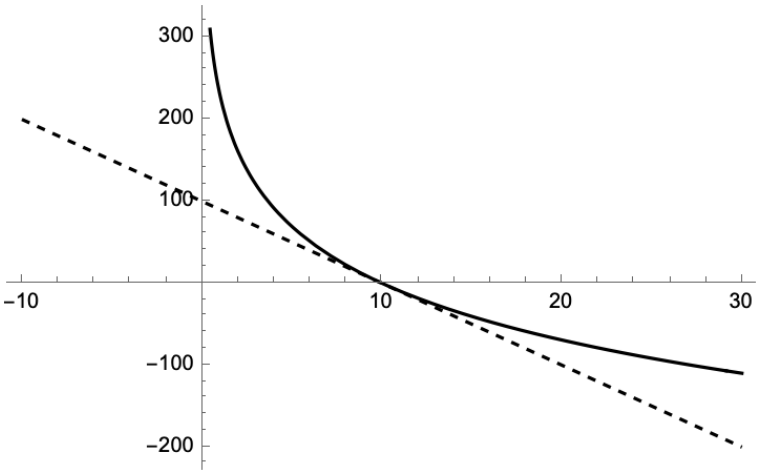


(b) Indices of largest dealers



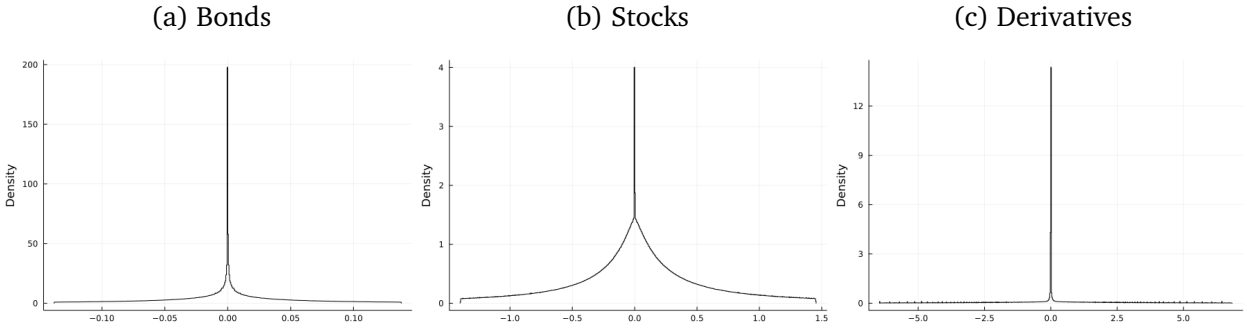
Notes: Appendix Figure A12a shows the within-market, across-market, and total adjusted Theil index for each dealer ID (at the parent-level). In the white area are dealer's who are active in all markets, in the light gray area are dealers who are active in only two markets, and in the darker gray shaded area are dealers who are active in only one market. The punishment term is 5; the maximal across market index is 4.431, and the maximal within market index is 8.82 for the stock market, 10.1234 for the bond market, and 10.6133 for the derivatives exchange. Figure A12b zooms in on the dealers who are active in all three markets.

Appendix Figure A13: Margins



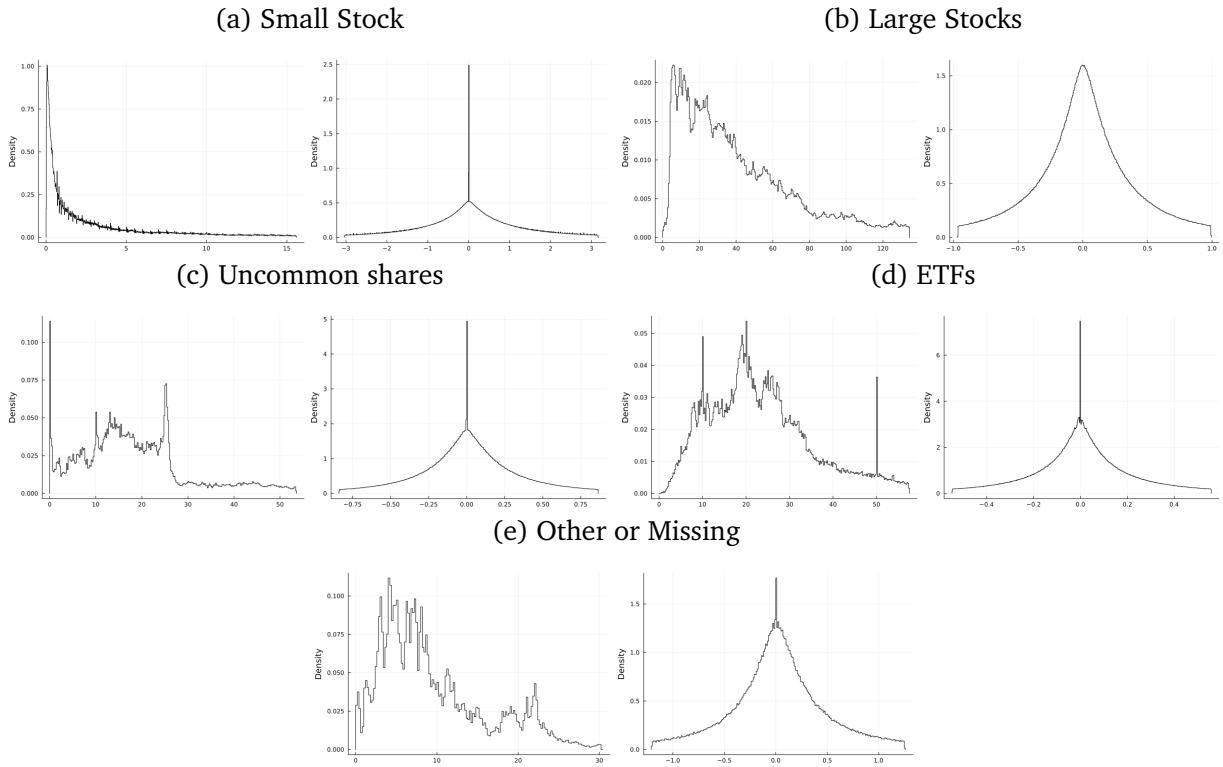
Appendix Figure A13 shows the margin (1) for an average price of 10 in black, and the linear approximation in dashed lines.

Appendix Figure A14: Margin distribution in each market



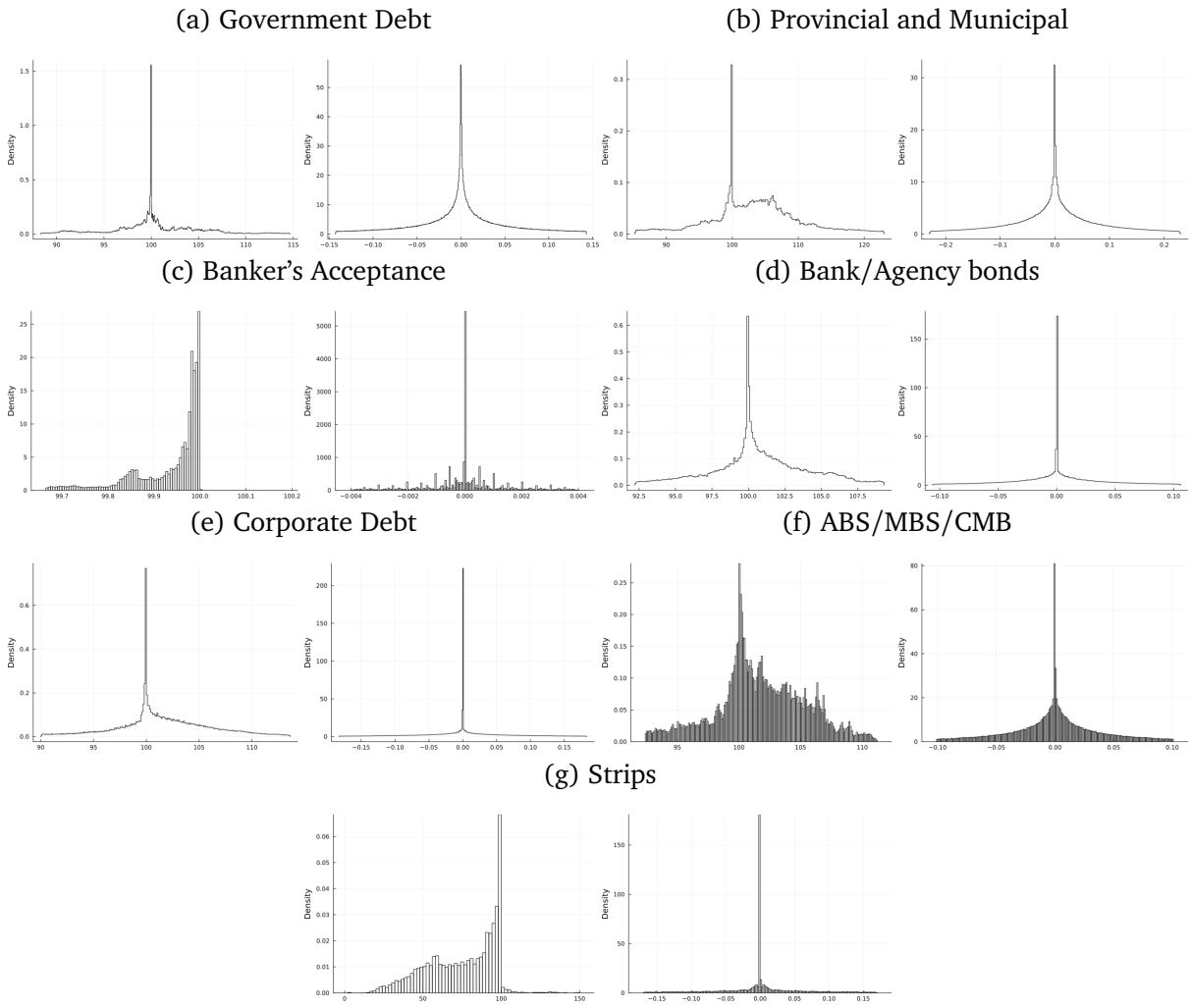
Appendix Figure A14 shows the distribution of our margin measure (1), which approximates how much less (more) a trader paid compared to the average price for a security in a day when buying (selling) for for each market. We exclude outliers, which are outside of the interquartile range. The median (average) margin is 0% for bonds, 0.005% for stocks, and 0% (0.18%) for derivatives. The standard deviation of margins is 1.59 for bonds, 2.03 for stocks, and 12.50 for derivatives. In comparison, the median trade price is C$100.29 for bonds, C$12.27 for stocks and C$1.1 for derivatives. The standard derivation in prices is 12.11 for bonds, 87.18 for stocks, and 157.35 for derivatives (where most of the variation is coming from the cross section of derivative contracts).

Appendix Figure A15: Price and margin distribution for derivatives products



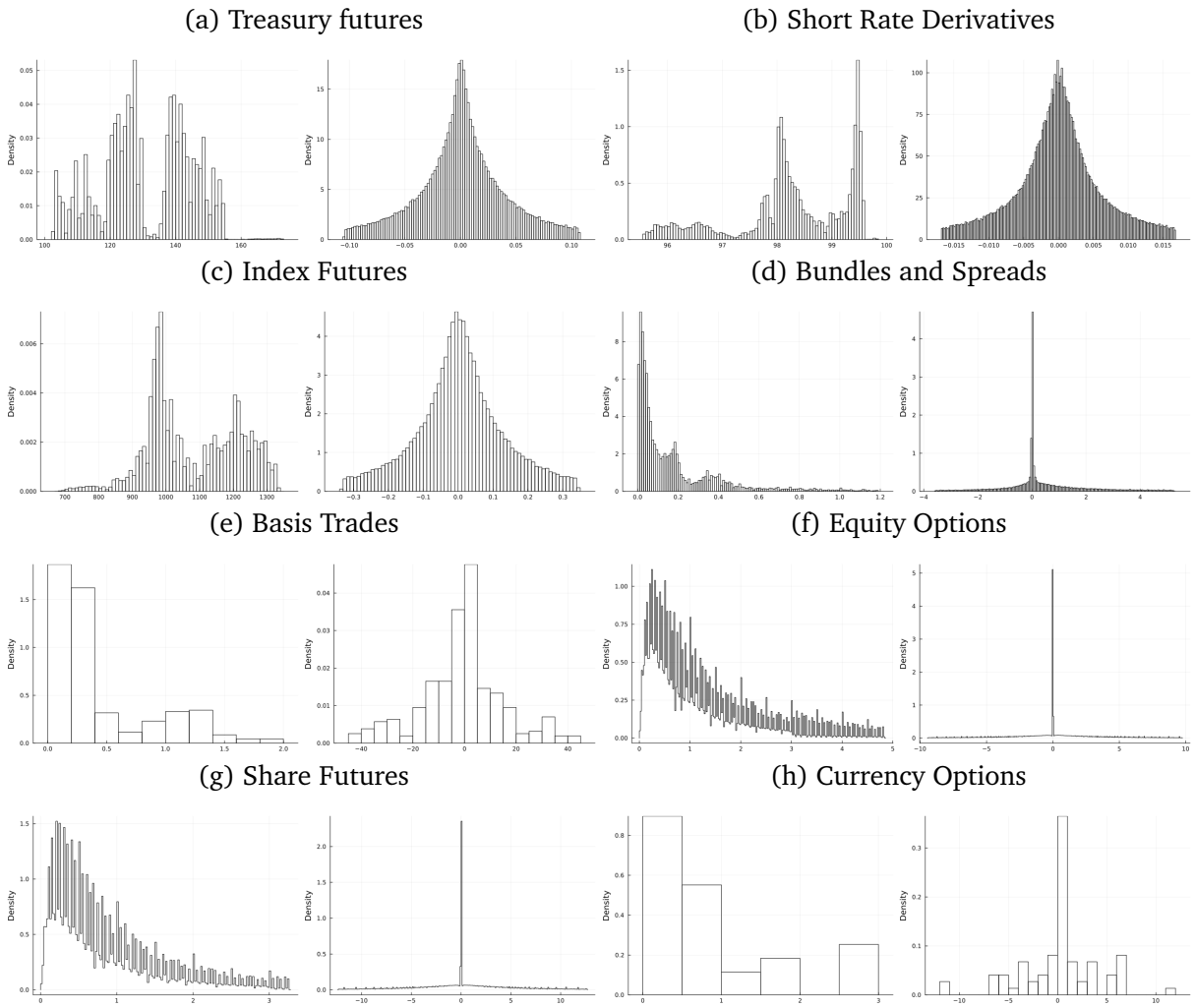
Notes: Appendix Figure A15 shows density histograms of prices for each product on TMX, excluding observations outside of the inter-quartile range.

Appendix Figure A16: Price and margin distribution for bonds



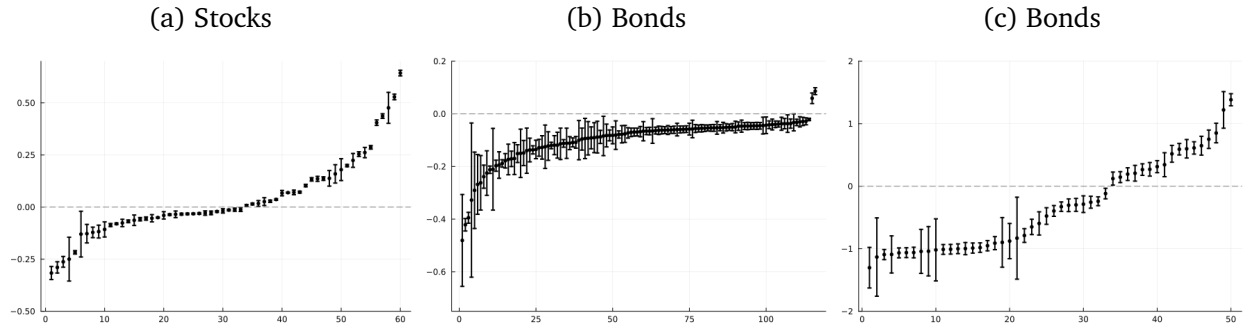
Notes: Appendix Figure A16 shows density histograms of prices for each product on the fixed-income market, excluding observations outside of the inter-quartile range.

Appendix Figure A17: Price and margin distribution for derivatives



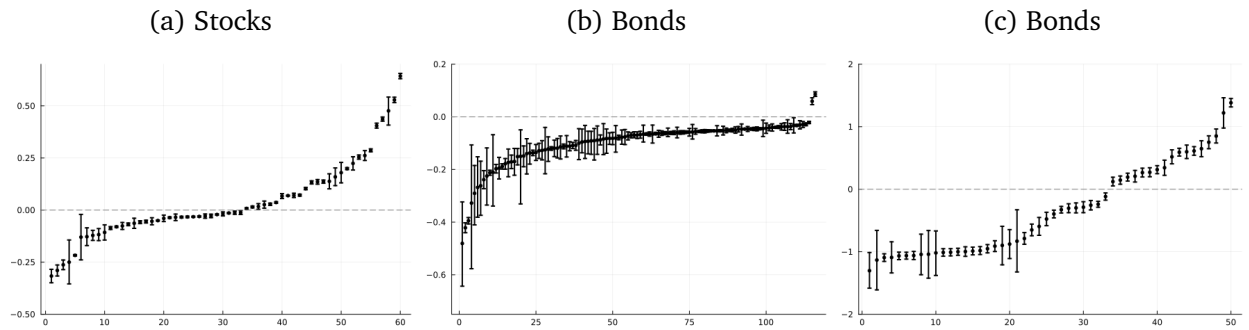
Notes: Appendix Figure A17 shows density histograms of prices for each product on MX, excluding observations outside of the inter-quartile range.

Appendix Figure A18: Robustness—Dealer coefficients that are statistically different from zero at 5% significance level (conventional inference)



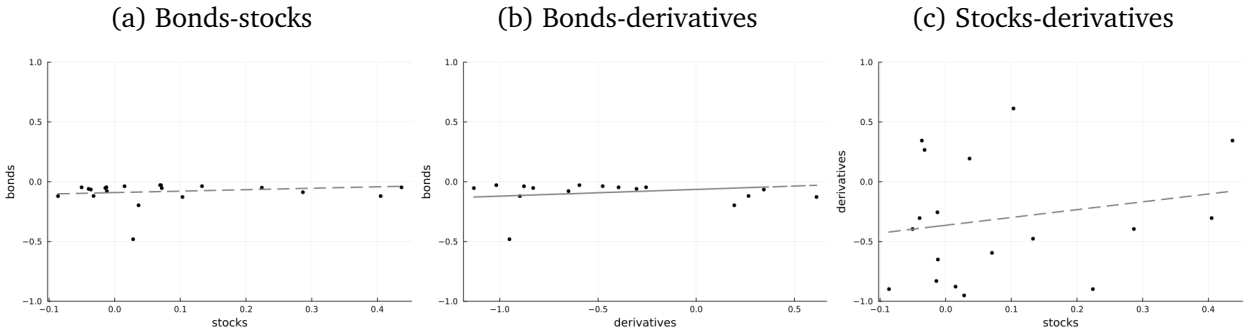
Notes: Appendix Figure A18 is the analogue to Figure 7 but with confidence intervals that are computed in the conventional way (without bootstrapping). For bonds, where clusters are most uneven in size, conventionally computed standard errors and confidence intervals differs slightly from bootstrapped confidence intervals—confirming expectations. Figure A18a shows the dealer coefficients when regressing margins (1) of a trade on indicator variables for each dealer active on the stock exchanges in addition to control variables (trade-size, the account-type, security-week and day fixed effects). Figure A18c shows the analogue for the derivatives exchange. Figure A18b shows the analogue for the fixed-income market, where we replace the account-type with a variable that indicates the type of trade (dealer-dealer, dealer-client, dealer-broker). In both graphs we exclude dealer coefficients that aren't significantly different from zero at a significance level of 5% according to bootstrapped and conventional inference. We sort coefficients from small to large. Therefore, the x-axis are not comparable across markets, since they don't reflect the dealer's IDs.

Appendix Figure A19: Robustness—Dealer coefficients that are statistically different from zero at 5% significance level (parent-level)



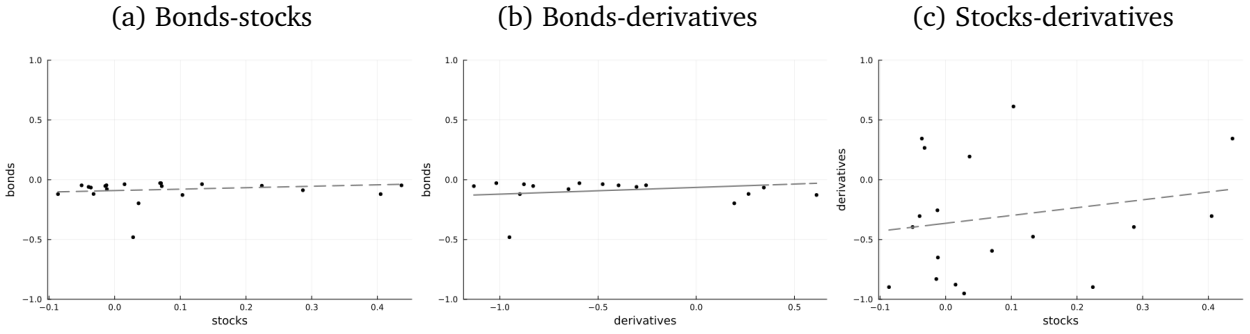
Notes: Appendix Figure A19 is the analogue to Figure 7 but aggregating dealer LEIs to the parent-level. Figure A19a shows the dealer coefficients when regressing margins (1) of a trade on indicator variables for each dealer active on the stock exchanges in addition to control variables (trade-size, the account-type, security-week and day fixed effects). Figure A19c shows the analogue for the derivatives exchange. Figure A19b shows the analogue for the fixed-income market, where we replace the account-type with a variable that indicates the type of trade (primary dealer/broker with non-primary dealer/non-broker, on-primary dealer/non-broker with non-primary dealer/non-broker, or primary dealer/broker with primary dealer/broker). In both graphs we exclude dealer coefficients that aren't significantly different from zero at a significance level of 5%. We sort coefficients from small to large. Therefore, the x-axis are not comparable across markets, since they don't reflect the dealer's IDs.

Appendix Figure A20: Robustness—Cross-market correlation between dealer coefficients of dealers active in all markets (conventional inference)



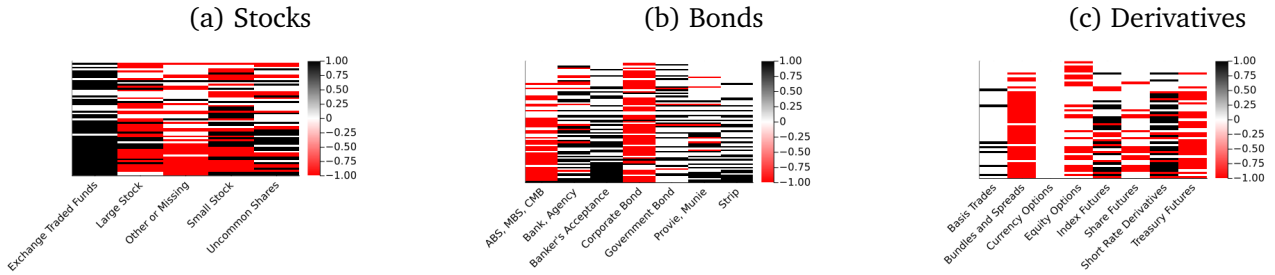
Notes: Appendix Figure A20a is analogous to Figure 9a but with confidence intervals computed in the conventional way without bootstrapping. It shows the within-dealer correlation of coefficients in the bond (y-axis) versus stock market (x-axis), (b) and (c) show the correlation for the other two market pairs. We exclude dealer coefficients that aren't significantly different

Appendix Figure A21: Robustness—Cross-market correlation between dealer coefficients of dealers active in all markets (parent-level)



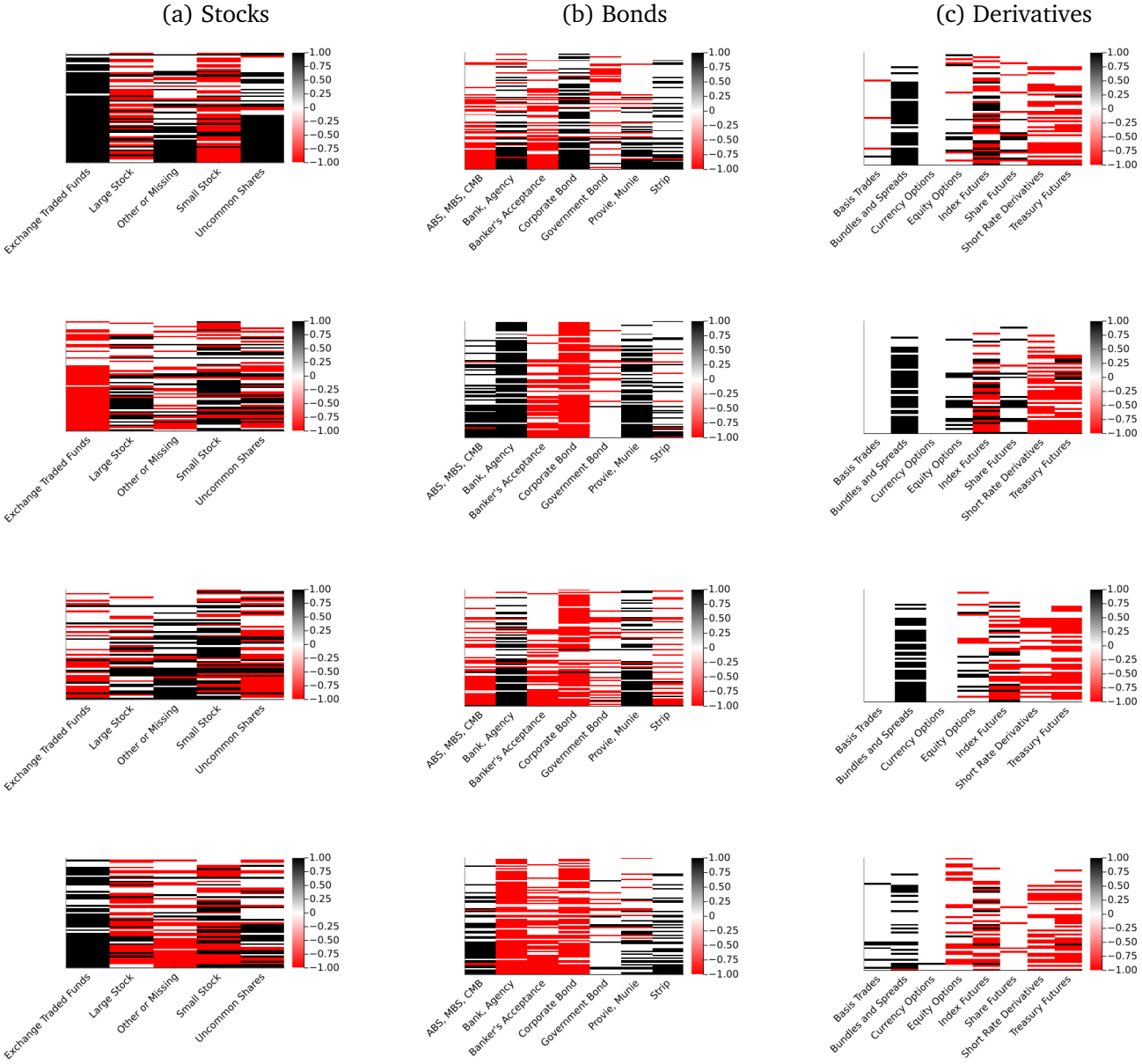
Notes: Appendix Figure A21a is analogous to Figure A21a but uses dealer LEIs to the parent-level. It shows the within-dealer correlation of coefficients in the bond (y-axis) versus stock market (x-axis), (b) and (c) show the correlation for the other two market pairs. We exclude dealer coefficients that aren't significantly different from zero at a significance level of 5%.

Appendix Figure A22: Robustness: Dealer specialization across products within a market (parent-level) — 2022



Notes: Appendix Figure A22 is analogous to Figure 10 but when aggregating dealer IDs to the parent-level. Appendix Figure A22a visualizes the dealer-product coefficients, β_{jp}, when regressing margins (1) of a trade on indicator variables for each dealer-product combination for dealers that are active on the stock exchanges in addition to control variables (trade-size, the account-type, security-week and day fixed effects), using data from 2022. Each row in a heatmap correspond to a dealer j. A column corresponds to a product p. When the corresponding β_{jp} is positive and statistically significant from zero, a p-j cell is black; if it is negative it is red; and empty if the coefficient is not statistically different from zero. Appendix Figures A22b and A22c show the analogue for bonds and derivatives. For bonds, the baseline β_{pj} coefficient is a large bank trading government bonds; for stocks it's that bank trading large stocks, and for derivative it's that bank trading Treasury futures. In all graphs, dealers are sorted according to their trade-volume, with the dealer trading the most in the given market being at the bottom, and the dealer trading the least at the top. Standard errors are clustered at the daily-level.

Appendix Figure A23: Dealer specialization across products within a market — 2019, 2020, 2021, 2022



Notes: Appendix Figure A23 is analogous to Figure 10, but for the other years in our sample. We note that dealer coefficients vary across years. However, the main takeaway that no dealer outperforms across products is robust for all years. Appendix Figures A23a visualizes the dealer-product coefficients, β_{jp}, when regressing margins (1) of a trade on indicator variables for each dealer-product combination for dealers that are active on the stock exchanges in addition to control variables (trade-size, the account-type, day fixed effects), using data from 2019, 2020, and 2021, respectively. Each row in a heatmap correspond to a dealer j. A column corresponds to a product p. When the corresponding β_{jp} is positive and statistically significant from zero, a p-j cell is black; if it is negative it is red; and empty if the coefficient is not statistically different from zero. Appendix Figures A23b and A23c show the analogue for bonds and derivatives. For bonds, the baseline β_{pj} coefficient is a large bank trading government bonds; for stocks it's that bank trading large stocks, and for derivative it's that bank trading Treasury futures. In all graphs, dealers are sorted according to their trade-volume, with the dealer trading the most in the given market being at the bottom, and the dealer trading the least at the top.