Market and Product Specialization in Financial Markets*

Milena Wittwer⋆, and Andreas Uthemann+

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Abstract

Intermediary asset pricing theories assume integrated markets—akin to Walrasian auctions—with homogeneous assets. In reality, market fragmentation and product diversity introduce frictions that may influence asset prices. Using a unique dataset linking trades of intermediaries across Canadian stock, bond, and derivative markets, we analyze where, what and at what prices intermediaries trade to assess the extent of market and product specialization. We find that intermediaries concentrate their trading activity unevenly across markets and products, indicating specialization. More specialized intermediaries consistently secure better prices, particularly in the decentralized bond market and the derivatives market that offers more complex products. Our findings highlight two aspects—market and product specialization—that future asset pricing models could explore, and underscore the role of market structure and product complexity in shaping financial intermediation.

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1 Introduction

Intermediary asset pricing theory suggests that frictions faced by financial intermediaries—dealers—can constrain arbitrage and influence asset prices (e.g., Shleifer and Vishny (1997); Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); He and Krishnamurthy (2013); Brunnermeier and Sannikov (2014)). Most models assume frictionless markets, akin to a Walrasian auction. Consequently, the related empirical literature largely overlooks frictions arising from market fragmentation (e.g., Pasquariello (2014); Adrian et al. (2014); Du et al. (2018); He et al. (2017); Siriwardane et al. (2022)).[1] This contrasts with the fragmented nature of financial markets, where different asset classes trade in distinct venues (Malamud and Rostek (2017); Weill (2020); Chen and Duffie (2021); Budish et al. (2024)). Moreover, since financial assets are treated as homogenous, the literature tends to overlook the diversity of financial products and, consequently, the role of product specialization (Babus et al. (2024); Mota and Siani (2024)).

We introduce a unique dataset to study the role of market and product 'segmentation'—or equivalently, 'specialization'—in financial markets. Our goal is to provide novel stylized facts to inform future asset pricing models. By linking trades across Canadian stock, bond, and derivative markets, we assess the extent of cross-market and cross-product segmentation by analyzing where and what dealers trade in the first part of the paper. 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 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,

[1] Unlike this paper, empirical studies in intermediary asset pricing typically rely on market-level data, such as prices or spreads. While effective for identifying broad market trends and average patterns, this approach limits the ability to examine segmentation drivers at a more granular level. Two exceptions are Siriwardane (2019), which focuses on the CDS market, and Wittwer and Allen (2023), which examines Treasury auctions.

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.

We start by showing that cross-market fragmentation 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 legal segmentation within institutions, the stock and bond markets appear integrated at the aggregate-level, with over 80% of volume traded by dealers executed by institutions active in both. The derivatives market remains more distinct, with some high-frequency traders only trading derivatives.

Crucially for this study, however, even after aggregating dealers to the parent-company level to remove in-house segmentation, dealers allocate their trading activity—measured by their share of total trade volume—unevenly across markets, specializing in certain markets over others. Banks are more active in the bond market, while high-frequency traders focus on the derivative exchange. Institutions that act as primary dealers for government debt trade across markets, while many other dealers do not participate across all markets.[2]

Similarly, trading activity is unevenly distributed across products within a market, indicating product specialization. The degree of product specialization appears to depend on market structure—centralized, as in exchanges, versus decentralized, as in OTC markets—as well as the complexity of the products traded. On centralized stock exchanges, where products are highly standardized, all dealers participate across all products. In contrast, segmentation is more pronounced in the fixed-income OTC market, where products are standardized but trading is decentralized, and 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.

The Theil index decomposition reveals that, for most dealers, across-product segmentation

[2]From a policy perspective, 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—impacts 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.

within a market is greater than cross-market segmentation. 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 moderately changing entry costs or membership fees—such as the recently revised fee schedules for registered broker-dealers in the U.S. and Canada (FINRA (2024); CIRO (2024))—may have limited impact on market participation.

Having provided evidence of trade specialization, we investigate whether market or product specialization affects transaction costs. Alternatively, if markets are sufficiently competitive, prices—and by extension, transaction costs—remain unaffected by any type of specialization. To address this, we compute transaction costs for each trade following the market microstructure literature (e.g., Hendershott and Madhavan (2015); Hau et al. (2021); O'Hara and Zhou (2021); Pinter et al. (2024)). Since we are interested in understanding monetary benefits associated with specialization, we refer to our transaction cost measure as 'margin'—a higher margin means that a transaction for a security is executed at better prices compared to the average price for that security on that day.

We begin by analyzing whether certain dealers consistently obtain higher margins than others—a necessary condition for specialization to be profitable. 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-year-week and day fixed effects. 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. This suggests that different types of institutions excel in different markets. At the individual dealer level, we find that in the decentralized bond market and the centralized derivatives market—where products are more complex—some dealers who trade exclusively within these markets outperform those who trade across all markets—in line with the idea that both market structure and product complexity favor specialization.

Consistent with the importance of specialization, 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 explanation, consistent with the idea of specialization, is that, in practice, individual traders or trading desks within institutions focus on a limited set of assets and optimize trading within that set (Lu and Wallen (2024)). From an antitrust perspective, the absence of trading synergies suggests that natural monopolies do not arise (under the current regulatory regime), as would be the case if the largest institutions dominated financial trading across markets and products through economies of scale.

Finally, we examine whether more specialized dealers secure higher margins than less specialized ones, highlighting potential returns to specialization. To account for a possible size effect—where dealers with broader trading activity obtain better prices—we construct market and product specialization scores, ranging from zero for dealers who do not trade in a given market or product to one for those who trade exclusively within it.

We first document a positive correlation between both product and market specialization and trade margins, controlling for potential confounders such as trade size, dealer type, account type, and security-year-week and day fixed effects. The correlation is stronger for product specialization than for market specialization in the stock and bond markets, whereas the opposite holds for the derivatives exchange. This aligns with our finding that the derivatives market is the most segmented of the three.

While these correlations are suggestive, they do not establish causality. Specifically, it remains unclear whether dealers achieve better prices because they are specialized or whether better prices drive specialization. Moreover, omitted variables such as dealer sophistication or efficiency could bias OLS estimates. To address these concerns, we seek an instrument that influences dealer margins only through specialization. While exogenous variation is challenging to identify in financial trade settings, our data allows us to track trades executed for client accounts in the stock and derivatives exchanges. Using these client flows as exogenous shocks to dealer trading activity, our IV estimates confirm that both market and product specialization enhance margins, with the strongest effects observed in the derivatives market.

Together, our findings underscore the importance of market and product specialization in intermediary asset pricing. We show that dealers specialize in trade volume and that this specialization translates into better prices. We hope to inspire future research by highlighting several promising avenues that contribute to various strands of the literature, from theoretical foundations to empirical analysis.

One direction for future research 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. With few exceptions, such as Dougast et al. (2022), existing models focus on a single market structure; and a single asset class, with the exception of studies on derivatives and their underlying assets, dating back to Kumar and Seppi (1992).

Another direction for future research is to analyze market-level equilibrium effects. While we document systematic differences in transaction costs across dealers, it remains unclear whether segmentation affects aggregate asset prices. Addressing this question requires either an exogenous shock to segmentation, or a structural model that generalizes Vayanos and Vila (2021) to account for product complexity and differences in market structure, such as centralized versus decentralized trading.

A further avenue for future research is to broaden the focus of empirical market microstructure research, and the large and growing literature on asset demand estimation (Koijen and Yogo (2019)) to move beyond isolated markets or individual products within a market.[3] Our cross-market and multi-asset perspective underscores the importance of this shift. Most existing studies in both literatures focus on a narrow set of assets, such as one type of bond, or common equity, and largely constrain substitution across asset classes, thereby limiting potential spillover effects. Allen et al. (2020), Chaudhary et al. (2022), Üslü and Pintér (2023), Allen and Wittwer (2024), 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. Similarly, though more distantly related, the extensive asset pricing literature on factor structures has primarily focused on asset-class-specific factors but has been shifting away from this emphasis in search for joint factors that span across asset classes (e.g., Chen et al. (2024)) .

A final direction for future research is to examine how trading interconnectedness evolves during periods of distress. Our finding that large banks dominate trading activities across markets raises concerns about financial stability. Investigating which types of institutions amplify negative spillovers and which help mitigate them would contribute to the extensive literature on contagion, following Allen and Gale (2000).

[3] For an overview on trading in OTC fixed-income markets see Bessembinder et al. (2020). 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)) 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).

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).

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

[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).

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.

(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 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.

[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.

[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).

Table 2: Products and sectors on the stock exchanges

Product	Trade share	Sector	Trade share
Small Stock	53.58	Mining and Oil/Gas	48.78
Large Stock	32.33	Technology, Utilities and Pipelines	13.69
Uncommon Shares	7.41	Media and Life Science	10.84
Exchange Traded Funds	5.98	Products and Services	9.95
Other or Missing	0.68	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.

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] 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

[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 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	Sector	Trade share
Treasury Futures	37.44	Public Administration	37.44
Short Rate Derivatives	20.75	Money Market	20.75
Share Futures	17.21	Mining and Oil/Gas	9.55
Equity Options	16.80	Multiple	9.49
Bundles and Spreads	7.85	Derivative Indices	6.36
Index Futures	6.36	Financial Services	5.19
Basis Trades	1.69	Products and Services	3.04
Currency Options	0.04	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.

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

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]

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

[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 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.

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 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

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.

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.

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.

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.

[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.

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.

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

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

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.

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).

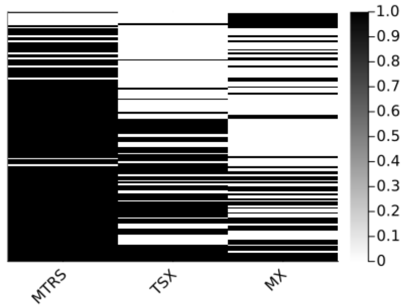
We find the distinction between LEI-level and parent-level analysis to be most pronounced in the fixed-income market. We attribute this to two factors. First, a larger proportion of dealers on the exchanges are hedge funds, private equity firms, or proprietary trading firms compared to the fixed-income 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.

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, each market is characterized by different entry costs. Here, and going forwards, we distinguish between markets rather than market segments, pooling TSX, TSXV, and Alpha together, because the three stock exchanges are well integrated, likely because they are all owned by the same company and share similarities. Close to 100% of the

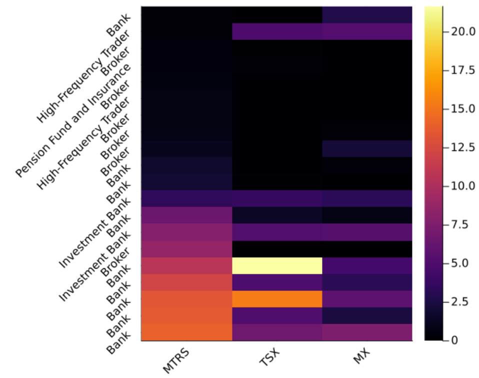
[11] Note that 'dealer trade volume' differs from the volume dealers trade with each other, since we include all quantities bought or sold by dealers, independent of who takes the other side of the trade.

Figure 1: Dealer presence and market share per market segment

(a) Dealer presence



(b) Market shares



Notes: Figure 1a shows whether each of the dealers is present (i.e., trades at least ones) in black, and not active in white 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 annual 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.

trade volume is traded by dealers who are active on all exchanges (see Appendix Table A9).

Supporting the idea that frictions or market-specific preferences 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, we plot a black line for that market, otherwise, the line is white. Thus, if all dealers participated in every market, the graph would be entirely black. Instead, the presence of both black and white indicates that dealers are selective in their market participation. Market activity, also when measured in trading volumes, is uneven across markets, further pointing towards market specialization. For the largest 20 dealers, we see this in Figure 1b, which shows us the fraction of dealer trade volume traded by each dealer (a row) in each market.

Zooming in more closely on the correlation of trading activities across markets, Figure 2 illustrates the pairwise correlation between each dealer's market share, calculated as the fraction of a dealer's trade volume in a given market relative to all other dealers. The distribution of points in the figure reveals several patterns, which remain consistent when examined at the LEI level and when trades for client accounts on the exchanges are excluded (as shown in Appendix Figures A2 and A3).

First, most dealers concentrate their trading activity in specific markets rather than distributing their participation evenly; if market shares were uniform across markets, the points would align along the 45-degree line. Second, smaller dealers tend to specialize more strongly, as indicated by points near the axes, suggesting they transact almost exclusively in one market. Among larger dealers, a subset focuses more heavily on the bond market, primarily banks that act as primary dealers (see Appendix Figure A1a).

To control for the overall market size of a dealer, we normalize market shares by each dealer's aggregate market share, summing market shares across all markets,

$$\text{specialization}_{yjm} = \frac{s_{yjm}}{\sum_m s_{yjm}} \in [0, 1], \tag{1}$$

in Figure 3a; here s_{yjm} is the fraction of dealer volume dealer j trades in market m compared to all other dealers. Dealers who only trade in one market have a specialization score of 1; those that don't trade in one of the three markets lie along the x- or y axis; and those that only trade in two out of three markets line up on the decreasing diagonal connecting the 1 (full specialization) on the x-axis with the 1 on the y-axis.

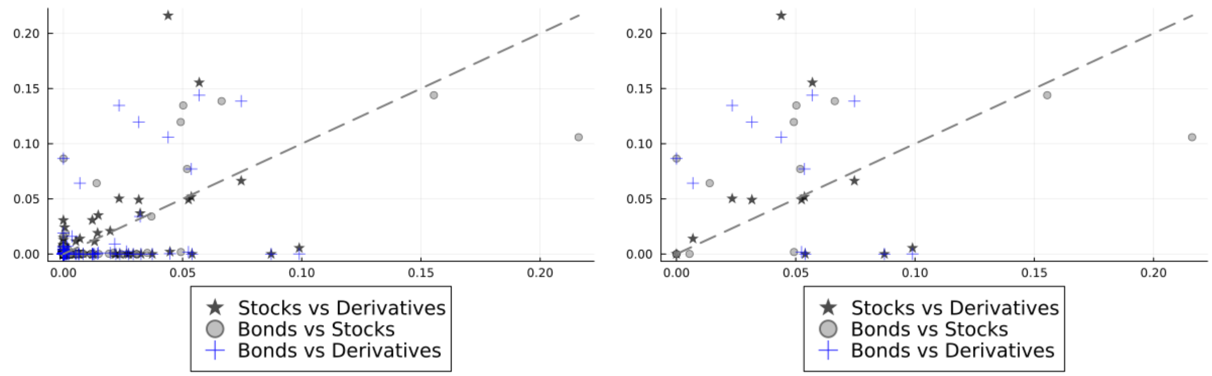
Third, the derivatives market stands out as the most detached, with some dealers—particularly high-frequency traders—engaging almost exclusively in derivatives, even when their overall trading volume exceeds 5% (see Appendix Figure A1b). In total, approximately 35% of MX's trade volume is attributed to high-frequency traders when including client trades, rising to 72% when excluding them, as shown in Appendix Table A10. 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 2 (Market specialization)**.** *Dealers distribute their trading activity unevenly across markets—they specialize. Banks are more active in the bond market, while high-frequency traders focus on the derivative exchange.*

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 those active in all markets, for each market, in Appendix Figure A5 with the fraction of monthly dealer trade volume by primary dealers who are active in all markets in Appendix Figure A6. 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

Figure 2: Dealer market shares, $s_{yjm} \in [0,1]$, in an average year (parent-level)

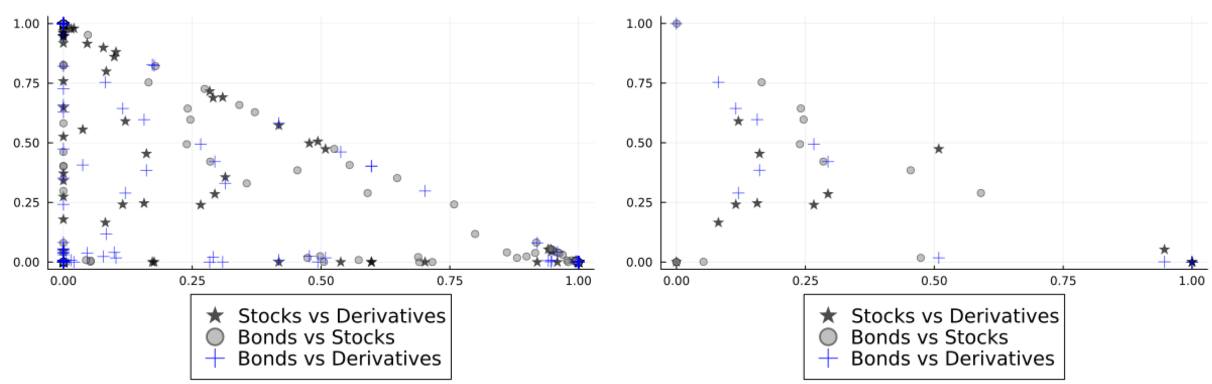
(a) All dealers (b) Largest dealers



Notes: Figure 2a plots all dealer j's market shares, $s_{yjm} \in [0,1]$, for each market m, averaged across years. The stars show each dealer's stock market share on the y-axis and their derivatives market share on the x-axis; the circles show the stock versus bond market shares and the crosses the bond versus derivative market shares, on the y-axis and x-axis respectively. Figure zooms in on dealers who trade at least 5% of the market share in one of the three markets.

Figure 3: Market specialization

(a) All dealers (b) Largest dealers



Notes: Figure 3a plots all dealer j's market specialization scores, $\text{specialization}_{yjm} = s_{yjm}/\sum_m s_{yjm} \in [0,1]$, for each market m, averaged across years. The stars show each dealer's stock market score on the y-axis and their derivatives market score on the x-axis; the circles show the stock versus bond market shares and the crosses the bond versus derivative market score, on the y-axis and x-axis respectively. Figure zooms in on dealers who trade at least 5% of the market share in one of the three markets.

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.

Product specialization. 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.[12]

To examine the extent of product specialization within each market, we visualize dealer participation and product market shares among the largest dealers across products in Figure 4. Product market shares are measured as the fraction of trade volume a dealer transacts within a given product-market segment, capturing their trading intensity in that segment.

Figure 5 presents the pairwise correlation of product market shares, normalized by a dealer's total size in the market:

$$\text{specialization}_{yjmp} = \frac{s_{yjmp}}{\sum_p s_{yjmp}} \in [0,1], \tag{2}$$

where s_{yjmp} represents the fraction of dealer j's trading volume in product p within market m, relative to all other dealers. Since each market contains more than three products, the figure is less intuitive than, and not directly comparable to, Figure 3a. However, as with market specialization, dealers with scores near the x- or y-axis—or at the extreme value of 1 which means that the dealer only trades one product—demonstrate higher degrees of product specialization.

Comparing across markets, product specialization is lowest in the stock market, where all dealers trade all products. This is evident from the right-hand side of Figure 4a, which appears completely black, and from the left-hand side, where colors remain more consistent within dealers (horizontally) than across dealers (vertically), indicating a more even distribution of market shares.

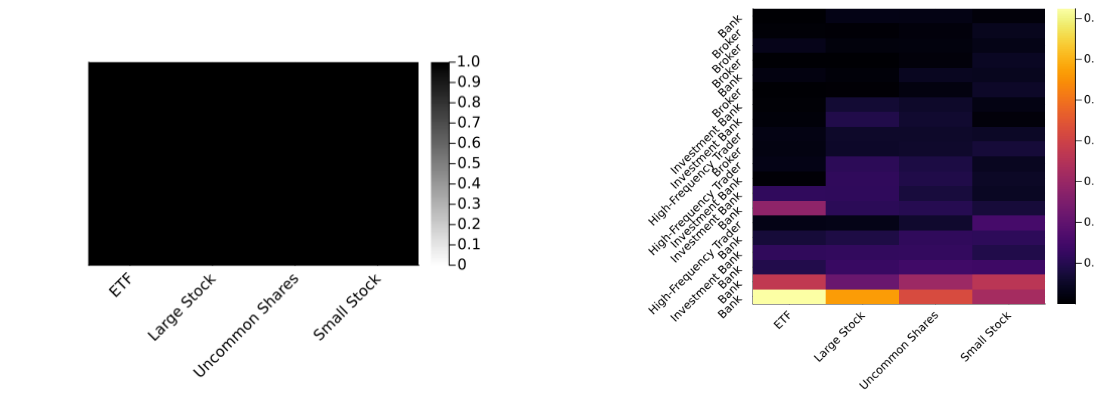
In contrast, product specialization is more pronounced in the bond and derivatives markets, both in terms of dealer participation and trading concentration. This is further illustrated in Figure 5, where product specialization scores in the stock market (blue crosses) tend to be more moderate, whereas scores in the bond and derivatives markets are more frequently close to 1 or 0, reflecting stronger specialization.

Fact 3 (Product specialization)**.** *Dealers specialize in different products in all markets. However, product specialization is less pronounced on the stock market than in both the decentralized bond*

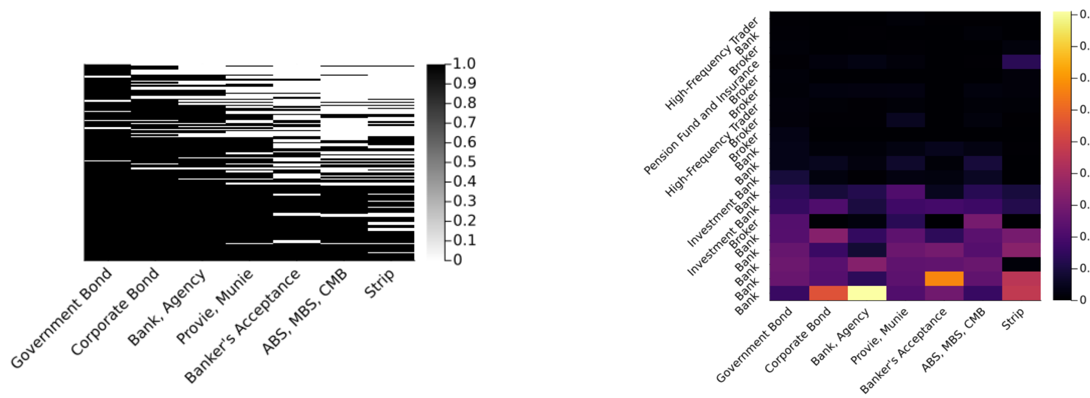
[12] Appendix Figure A7 shows the fraction of securities each dealer trades out of all securities for each market.

Figure 4: Dealer presence and market share across products in each market

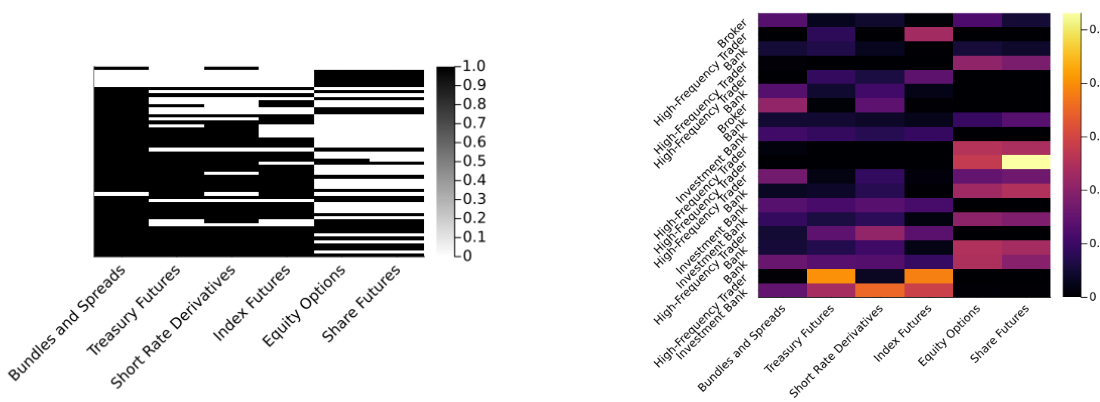
(a) Stock market



(b) Bond market



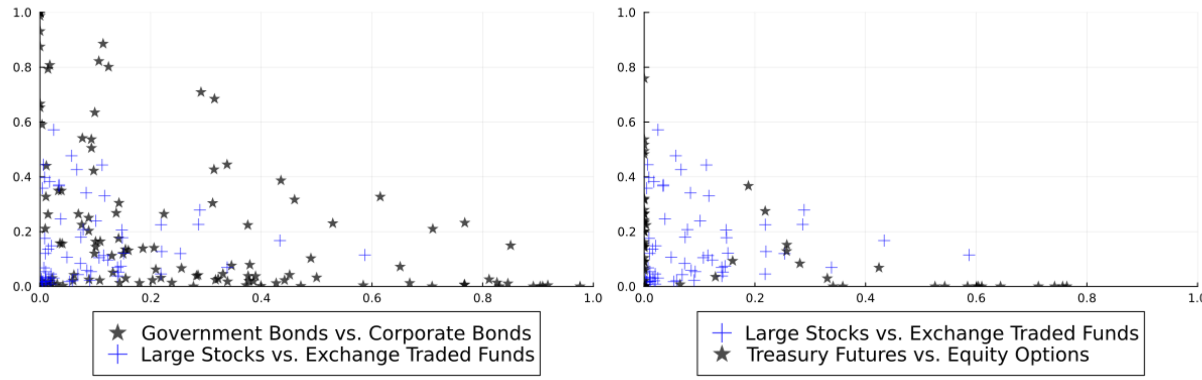
(c) Derivatives market



Notes: Figure 4 visualizes dealer activity (on the RHS) and market shares (on the LHS) of the largest dealers for each market. The RHS of Figure 4 shows whether each of the dealers is active (i.e., trades at least ones) in black, versus in-active in white for each product within a 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 annual 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 within a market at the bottom, and the dealer who trades the lowest at the top. For the stock market, we exclude the product category "Other or Missing". For the derivatives exchange. 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 A12.

Figure 5: Product specialization

(a) Bond and stock market (b) Stock and derivatives market



Notes: Figure 5 plots all dealer j's product specialization scores, $\text{specialization}_{yjmp} = s_{yjmp}/\sum_p s_{yjmp} \in [0, 1]$, for a subset of products p for each market m, averaged across years. In 5a we compare bonds versus stocks and in 5b we compare stock market versus derivative products. The stars show the specialization scores for large stocks on the y-axis and ETFs on the x-axis. The stars in 5a show the scores for government bonds the y-axis and for corporate bonds on the x-axis. In 5b they show the scores for Treasury futures versus equity options.

and centralized derivative exchange.

Our interpretation of these empirical patterns is that product specialization is influenced by both market structure—OTC versus exchange—and product complexity. On the centralized stock exchange, where products are largely standardized, specialization is minimal.[13] In contrast, it is more pronounced in the decentralized bond market and the derivatives exchange, which includes both standardized and complex products.

One reason for decentralized markets to feature higher product specialization is that trading is more strongly dictated by the network structure among dealers and clients. In particular, we know from existing studies that dealers form long lasting relationships with clients, and that clients tend to have tastes for specific bonds (Di Maggio et al. (2017); Hendershott et al. (2020); Jurkatis et al. (2023); Allen and Wittwer (2024)). Both features taken together could attribute to stronger product specialization in OTC markets compared to stock markets where network structures and relationships are less relevant.

The derivatives exchange accommodates both standardized products, like Treasury futures,

[13]To further support our idea, we split the market into sectors, rather than products, as shown in Appendix Figure A9. 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 A8 and Appendix Table A11 for the complete list of suffices).

and more complex derivative contracts. Standardized products are likely to attract a broader set of dealers, similar to the universal dealer presence in stock markets, as they require minimal customization—dealers simply select from a predefined menu. Consistent with this, many more dealers trade Treasury futures, short-rate derivatives, and index futures—the most standardized derivatives—compared to options or share futures, despite the latter accounting for around 35% of total average daily trade volume. However, this pattern does not hold universally. Many dealers trade bundles and spreads, which are more complex, suggesting that product complexity alone does not determine specialization.

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)). Loosely speaking, this measure integrates the specialization scores from Figures 3 and 5 in a way that allows for direct comparison.

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 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 product market shares in each market are distributed across markets. Consult Appendix B for mathematical details.

Table 7 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 A15a shows all indices for each dealer separately. For dealers who are not

Table 7: 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 7 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.

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 4 (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, 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.[14]

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

[14]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).

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.

5 Specialization and transaction costs

We now 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.

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).[15] 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

[15]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.

executed at better prices compared to the average price for that security on that day t:[16]

$$\text{margin}_\tau = -\ln(\text{trade price}_\tau/\text{average price}_{ts}) \times 100 \times \text{ trade sign}_\tau. \tag{3}$$

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.[17] Appendix Figures A17–A20 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:

$$\text{margin}_\tau = \alpha + \sum_j \beta_j \mathbb{I}(\text{dealer} = j) + \gamma \text{control}_\tau + \zeta_t + \zeta_{ws} + \epsilon_\tau. \tag{4}$$

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.[18] 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.

[16] 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.

[17] 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 A16 shows the relationship between our main margin measure (3) 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.

[18] 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.

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.[19] Because some days feature many more trades trade than others, the day-clusters 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 (Figure 6) show that some dealers consistently secure better prices across all markets, both at the LEI- and parent-level. In the stock market, the best dealer (a large broker) achieves margins 0.64% better than the baseline (a primary dealer), while the worst (a smaller broker) lags by 0.31%, translating into an annual benefit of approximately C$266 million for the best dealer and a C$6 million loss for the worst.[20] Dealer differences are more pronounced in the derivative market due to price volatility, with the best (a large hedge fund) outperforming by 1.38% and the worst (a proprietary trading firm) underperforming by 1.30%, though total payment differences remain modest given contract prices and trade volumes. In the bond market, most dealers earn lower margins than the dominant primary dealer baseline, yet the best (a large insurance company) outperforms by 0.08%, gaining C$17 million annually, while the worst (serving retail clients) underperforms by 0.48%, losing C$278 thousand.

Table 8 examines which dealer types achieve better margins using cross-dealer variation by

[19] 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 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.

[20] 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.

Table 8: 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

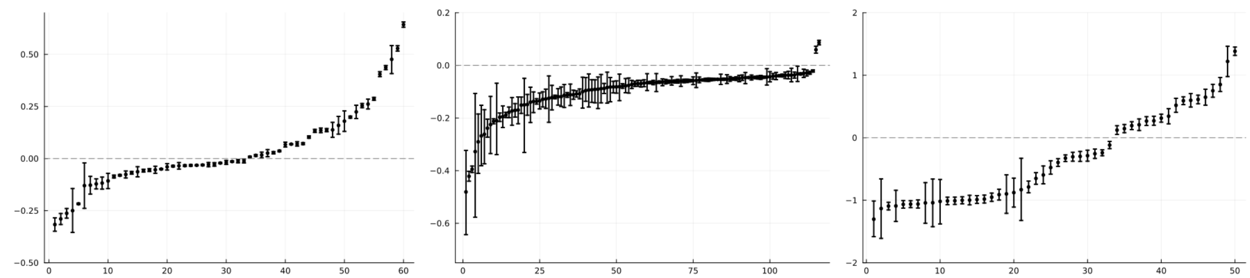
Notes: Table 8 shows the estimation results from regressing trader margins (3) of stock market trades on trade-size, the account-type (client, inventory, market-market, or other—the baseline), dealer-types, and day- and security-week fixed effects on the LHS, and for fixed-income trades in the middle, 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 daily-level and report conventionally computed robust clustered standard errors (second column) and wild-bootstrapped standard errors (third column).

estimating regression (4) with dealer-type indicators, setting asset managers as the baseline. Consistent with prior studies (Bernhardt et al. (2005)), larger trades receive worse prices on exchanges, and execution prices are worse for client trades than for inventory or market-making accounts. In the bond market, we find no trade-size discounts, aligning with mixed literature (Pinter et al. (2024); Allen and Wittwer (2024)). Dealers earn higher margins trading with clients than with brokers. High-frequency traders outperform other types in derivatives and perform well in stocks, though mutual funds dominate. Pension funds and insurance companies, the weakest performers in stocks, achieve the highest bond margins. Dealers specializing in retail clients earn the lowest margins in bonds and derivatives but perform comparably to asset managers in stocks.

Fact 5 (Systematic Price Differences)**.** *Neither the bond, stock, or derivative market are sufficiently frictionless to prevent some dealers from systematically outperforming others. 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*

Figure 6: Dealer coefficients that are statistically different from zero at 5% significance level

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



Notes: Figures 6a shows the dealer coefficients, and 95% WCR bootstrapped confidence intervals when regressing margins (3) 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 6c shows the analogue for the derivative market. Figure 6b 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 A22 shows the analogous figures with conventionally computed confidence intervals; Appendix Figures A23 aggregates dealers to the parent-level.

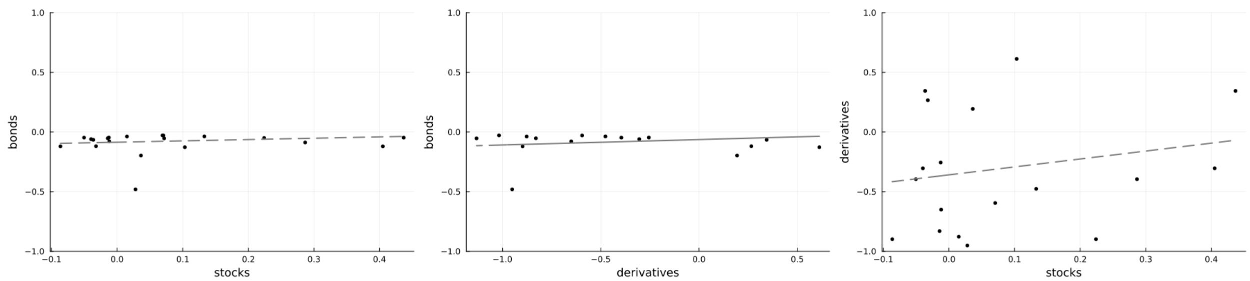
underperform in all markets compared to most other dealer types.

To examine market specialization, we assess whether the same dealers succeed across markets or if success varies by market. First, Appendix Figure A21 zooms in on dealers who are exclusively active in one market—an extreme form of market specialization, which does not account for the overall market presence of the dealer. Many of those dealers obtain worse than average prices relative to the baseline dealer. However, there is heterogeneity in 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, Figure 7 shows that dealers who excel in one market do not also achieve strong performance in other markets—the cross-market correlations of dealer coefficients are not statistically significant. This is in line with the notion that market specialization is prominent, and could be for different reasons. For example, a bank that builds strong relationships with other

Figure 7: Cross-market correlation between dealer coefficients of dealers active in all markets

(a) Bonds-stocks (b) Bonds-derivatives (c) Stocks-derivatives



Notes: Figure 7a shows the within-dealer correlation of coefficients in the bond (y-axis) versus stock market (x-axis), 7b and 7c 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 A25 shows the cross-market correlation between dealer coefficients when aggregating dealer LEIs to the parent-level.

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.

Fact 6 (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, supporting the notion of market specialization.*

Product specialization. To detect cross-product price effects, we add product indicators to regression (4), and estimate the following regression for each market separately:

$$\text{margin}_\tau = \alpha + \sum_p \sum_j \beta_{jp} \mathbb{I}(\text{dealer} = j \text{ and product} = p) + \gamma \cdot \text{control}_\tau + \zeta_t + \zeta_{ws} + \epsilon_\tau. \quad (5)$$

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 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 (5) 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 (5) 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.

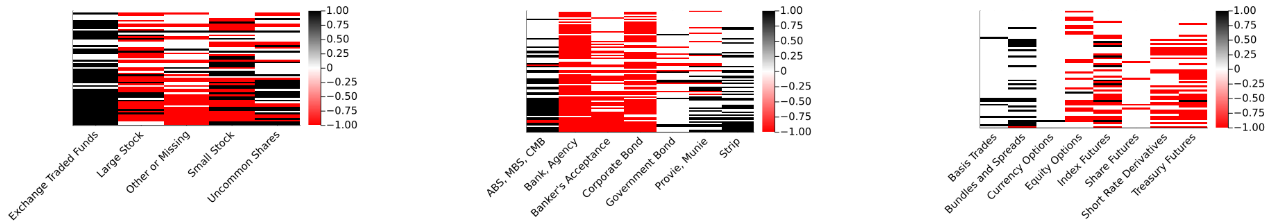
We visualize the estimation outcome through heatmaps, one for each market, in Figure 8. Each row in a heatmap correspond to a dealer j. A column corresponds to a product p. When dealer j obtains systematically worse margins for product p, we color the corresponding jp cell red, meaning that the β_{jp} 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.

Across markets, dealer performance varies by product category. In the stock market (Figure 8a), some dealers achieve higher margins than the baseline bank for large stocks, while all earn weakly higher margins on ETFs, suggesting ETFs were more profitable in 2022. Performance in small stocks and other categories is mixed. In the bond market (Figure 8b), most dealers earn margins similar to the baseline on government debt, while strips yield weakly higher margins for all. Margins are weaker for bank and agency paper, bankers' acceptances, and corporate bonds, whereas performance in ABS, MBS, CMB, and provincial and municipal bonds is more heterogeneous. In the derivatives market (Figure 8c), most dealers outperform the baseline in Treasury futures, while margins are weakly lower across short rate derivatives and share

[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, the main take away (Fact 7 is robust).

Figure 8: Dealer specialization across products within a market — 2022

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



Notes: Figure 8a visualizes the dealer-product coefficients, β_{jp}, when estimating regression (5), which regresses margins (3) 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 8b and 8c 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.

futures but higher for bundles, spreads, currency options, and basis trades. Index futures show the greatest variation in dealer performance.

Fact 7 (Cross-Product Synergies). *Dealers generally do not outperform others across multiple products, supporting the notion of strong product specialization.*

Comparing market and product specialization in terms of margins. So far, we have examined transaction costs at the dealer-level to assess whether certain dealers consistently obtain better prices and whether their advantage could stem from broad activity across markets and product segments or from specialization. To complete this analysis, we now compare the relationship between market-wide and product-specific specialization scores (1) and (2) and margins (3) across dealers.

In theory, the relationship between dealer specialization and trading margins is ambiguous. Greater specialization might enable dealers to trade at lower transaction costs. However, it could also be that specialized dealers are more efficient than their less specialized counterparts and, as a result, are willing to trade at margins that less specialized dealers avoid.

To determine the direction of the correlation, we examine the relationship between margins and specialization (market or product) by estimating the following regressions separately for each market:[22]

$$\text{margin}_\tau = \alpha + \beta \text{specialization}_\tau + \gamma \text{controls}_\tau + \zeta_t + \zeta_{ws} + \epsilon_\tau, \tag{6}$$

with specialization$_\tau$ being either market specialization (1) or product specialization (2).

To mitigate endogeneity concerns—arising from reverse causality (where dealers specialize because they are successful) or omitted variables—we include the same control variables as in previous specifications (Table 8), i.e., trade size, account type, and dealer type, along with fixed effects for trade date and security-week-year.

Table 9 shows that both forms of specialization tend to be positively correlated with margins, implying that specialized dealers secure better prices (or that dealers who earn higher margins specialize). Importantly, the evidence so far does not establish a causal relationship—for example, successful dealers may trade more, or increased trading may lead to greater success. More generally, the estimates might be biased as a result, or more broadly the fact that both prices and quantities are determined endogenously in equilibrium.

To address endogeneity concerns, we implement an instrumental variable (IV) approach. For the stock exchange, we use dealer client flows as exogenous shocks to the margins dealers obtain for their own accounts. If these client flows—conditional on our controls and fixed effects for the two exchanges where client accounts are observed—are unrelated to the margins dealers earn for their own accounts, the IV regression isolates a causal effect of specialization on margins. For the derivatives exchange, we apply a similar approach but, recognizing that derivatives are less liquid than stocks, we include trades from all accounts rather than only the dealer's own account. For the bond market, we cannot follow this approach since we don't observe trader accounts.

The IV-estimates, reported in Tables 10 and 11 for the stock exchange and the derivatives exchange, respectively, suggest that more specialized dealers obtain better prices on both exchanges. The OLS estimates are either smaller than or not statistically different from the IV estimate. The downward bias in OLS could stem from omitted variables that introduce a negative correlation between the error term and specialization. For instance, more specialized dealers may be more efficient and thus willing to trade at lower margins.

The impact of specialization on margins varies across markets. In the derivatives market, where both product and market specialization are pronounced, the effects are strongest: a one-percentage-point increase in market (product) specialization raises the average margin

[22]We analyze markets separately for clearer interpretation. However, we also estimate a specification that stacks all markets into a single regression or includes both specialization measures in one regression (see Appendix Table A12.

Table 9: Correlation between margins and specialization scores

	(TSX)		(MTRS)		(MX)	
market specialization	0.022***		0.007		0.438***	
	(0.002)		(0.005)		(0.040)	
product specialization		0.388***		0.062***		0.259***
		(0.004)		(0.009)		(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	111,051,211	111,051,211	6,757,118	6,757,118	4,529,584	4,529,584
R^2	0.008	0.009	0.017	0.017	0.036	0.036
Within-R^2	0.000	0.001	0.000	0.000	0.000	0.000

Table 9 shows the estimation results from regressing margins (3) on our specialization measures (1) and (2),respectively, for each market separately (TSX, MTRS, MX) using all trades. In all regressions we include the same control variables and fixed effects as in regression (8): trade size, account-types for the exchange, trade-type for the bond market, dealer-types, date fixed effects and security-year-week fixed effects.

by approximately 1.7 (2.6) basis points. This is substantial increase. On the stock exchange, the effect is more modest, around 0.3 basis points. In the decentralized bond market, the estimated effects are even smaller, though only OLS estimates are available, which may be subject to either downward or upward bias.

Fact 8. *Dealers specializing in specific markets or products within a market consistently achieve better margins than those who do not, indicating that specialization provides monetary benefits.*

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. An instrumental variable regression, leveraging client orders as exogenous shocks to dealer trading activity, suggests that the returns to specialization are substantial.

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

Table 10: IV regressions of margins on specialization scores for TSX

	(First Stage)	(OLS)	(IV)
s^c_{yjm}	-0.442***		
	(0.003)		
Market specialization		0.134***	0.385***
		(0.004)	(0.024)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	27,300,881	30,356,466	27,300,881
R^2	0.349	0.124	0.126
Within-R^2	0.012	0.000	0.000

	(First Stage)	(OLS)	(IV)
s^c_{yjmp}	-0.206***		
	(0.002)		
Product specialization		0.335***	0.284***
		(0.008)	(0.037)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	27,300,881	30,356,466	27,300,881
R^2	0.349	0.124	0.126
Within-R^2	0.012	0.000	0.000

Table 11: IV regressions of margins on specialization scores for MX

	(First Stage)	(OLS)	(IV)
s^c_{yjm}	-1.291***		
	(0.061)		
Market specialization		0.438***	1.701***
		(0.040)	(0.258)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	2,911,209	4,529,584	2,911,209
R^2	0.426	0.036	0.126
Within-R^2	0.038	0.000	0.000

	(First Stage)	(OLS)	(IV)
s^c_{yjmp}	-0.491***		
	(0.021)		
Product specialization		0.259***	2.589***
		(0.052)	(0.352)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	2,911,209	4,529,584	2,911,209
R^2	0.426	0.036	0.126
Within-R^2	0.038	0.000	0.000

Tables 10 and 11 show the IV estimation results for the stock market, and the derivatives market, respectively. Consider the LHS of 10. In column (First Stage), we show the first stage of the two stage least square estimator—regressing the market specialization score (1) on the fraction of all client-orders dealer j executes in market m in year y relative to other dealers, $s^c_{yjm} \in [0,1]$. In column (OLS) we present the OLS coefficient from regressing margins on market specialization, using trades for the dealer's own account for the stock market, and all trades for the derivatives market. In column (IV) we depict the corresponding IV estimate. The table on the RHS shows the analogous for product specialization, where the instrument is the fraction of all client-orders for product p dealer j executes in market m in year y relative to other dealers, $s^c_{yjmp} \in [0,1]$. In all regressions we include the same control variables and fixed effects as in regression (8): trade size, account-types for the exchange, dealer-types, date fixed effects and security-year-week fixed effects.

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:

$$T_j = \frac{1}{M \times P}\sum_m \sum_p \left(\frac{s_{jmp}}{\bar{s}_j}\right) \ln\left(\frac{s_{jmp}}{\bar{s}_j}\right). \tag{7}$$

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: 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: Appendix Table A9 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.

Appendix Table A10: 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

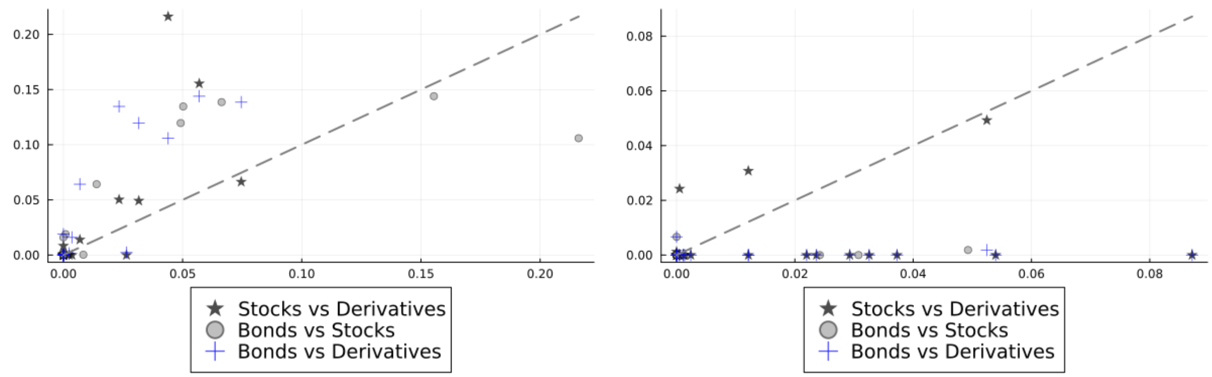
Notes: Appendix Table A10 shows the fraction of dealer trade volume by dealer type (at the parent-level) per market in columns MTRS, TSX, and MX, respectively. In columns TSX-IN, and MX-IN we show the analogue but excluding trades for client accounts for TSX and MX.

Appendix Table A11: 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.

Appendix Figure A1: Dealer market shares, $s_{yjm} \in [0,1]$, in an average year (parent-level)

(a) Banks (b) High-frequency traders



Notes:
Appendix Figures A1a and A1b are analogous to Figure 2a but only includes banks, and high-frequency traders, respectively. It plots all bank/high-frequency dealer j's market shares for each market m, averaged across years. The stars show each dealer's stock market share on the y-axis and their derivatives market share on the x-axis; the circles show the stock versus bond market shares and the crosses the bond versus derivative market shares, on the y-axis and x-axis respectively.

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.

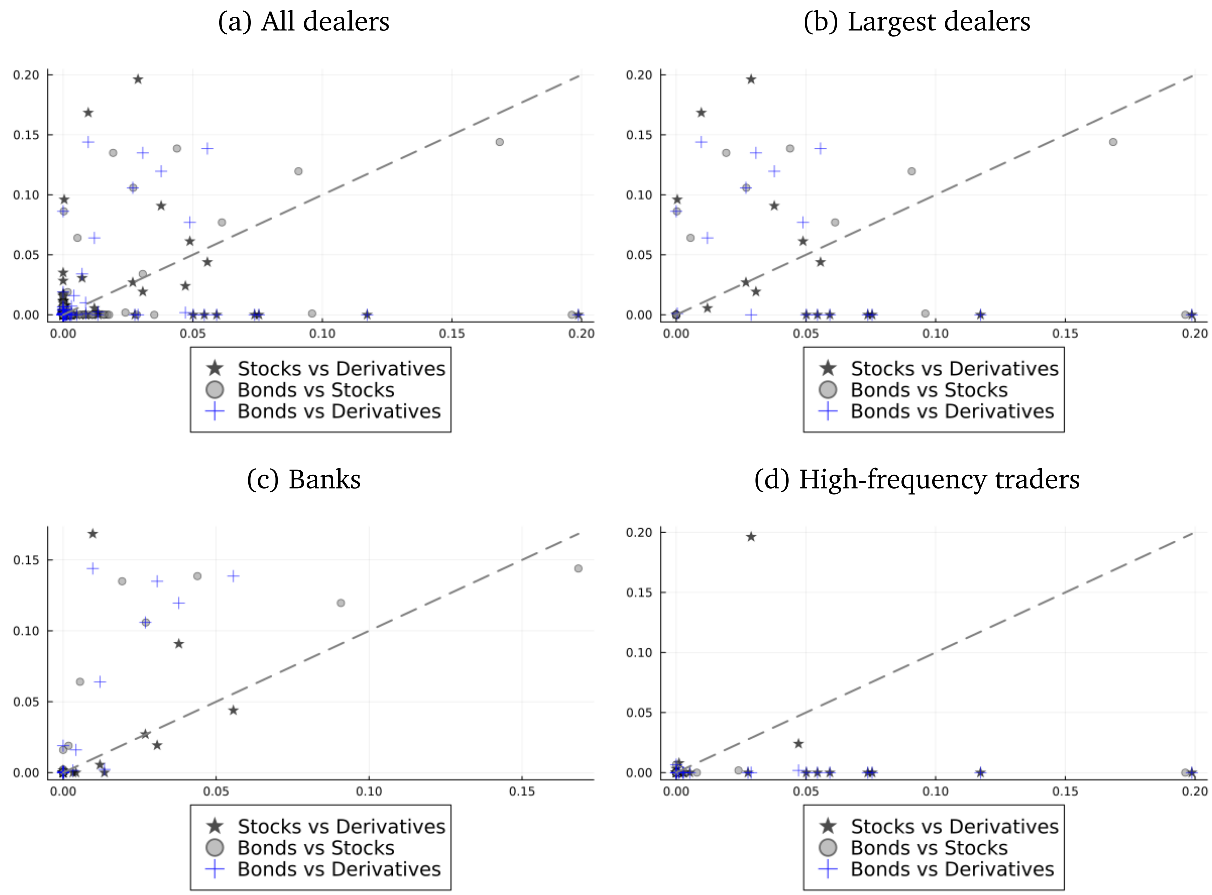
Notes: Appendix Table A11 describes the meaning of all suffixes of symbols trades on TSX, TSXV, or Alpha. An empty cell means that we were not able to find the description of a symbol that we observe in the raw data.

Appendix Table A12: Stacked OLS regression: Margins on product and market specialization

	(All trades)	(Own-account)
Product specialization × Stocks	0.395***	0.287***
	(0.004)	(0.007)
Product specialization × Bonds	0.063***	0.063***
	(0.009)	(0.009)
Product specialization × Derivatives	0.019	-0.361***
	(0.052)	(0.063)
Market specialization × Stocks	-0.016***	0.103***
	(0.002)	(0.003)
Market specialization × Bonds	0.009*	0.009
	(0.004)	(0.005)
Market specialization × Derivatives	0.431***	0.298***
	(0.039)	(0.054)
Controls × market	Yes	Yes
Fixed effects	Yes	Yes
N	122,337,913	39,416,713
R^2	0.025	0.201
Within-R^2	0.000	0.000

Notes: Appendix Table A12 is similar to Table 9, with two difference. First, the regression includes both product and market specialization scores, (1) and (2), as independent variables. Second, the regression stacks all trades into a single regression, multiplying all independent variables by market-indicator variables. In column (All trades) we include all trades, in column (Own-account) we exclude trades for client-accounts. In all regressions we include the same control variables and fixed effects as in regression (8), but multiplied by a market-indicator variable: trade size× market, account-types for the exchange/trade-types for the bond $market$×market, dealer-types× market, date fixed effects × market and security-year-week fixed effects.

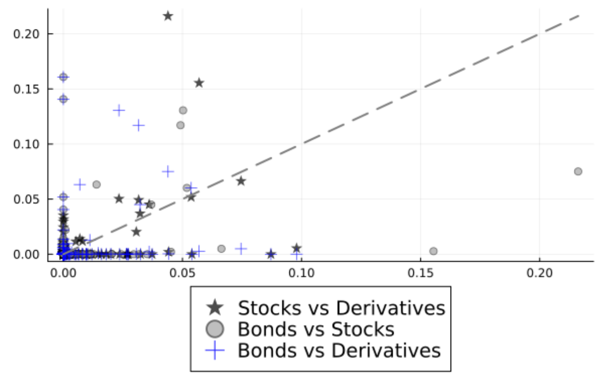
Appendix Figure A2: Dealer market shares, excluding client-accounts, in an average year



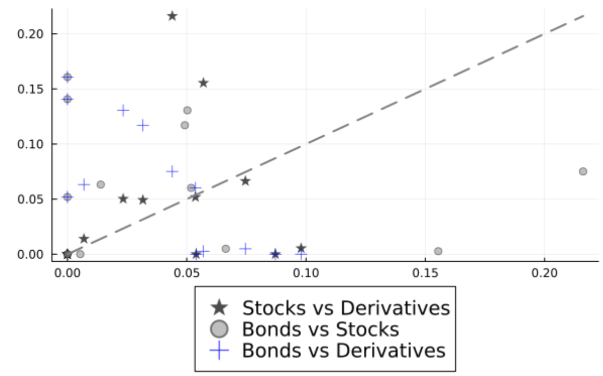
Notes: Appendix Figure A2a is analogous to Figure 2a but excludes trades for client accounts on the exchanges. It plots all dealer *j*'s market shares (of trades for non-client accounts) for each market *m*, averaged across years. The stars show each dealer's stock market share on the y-axis and their derivatives market share on the x-axis; the circles show the stock versus bond market shares and the crosses the bond versus derivative market shares, on the y-axis and x-axis respectively. Figure zooms in on dealers who trade at least 5% of the non-client market share in one of the three markets. In Figures A2c and A2d we only consider banks, and high-frequency traders, respectively.

Appendix Figure A3: Dealer market shares, excluding client-accounts, in an average year (LEI-level)

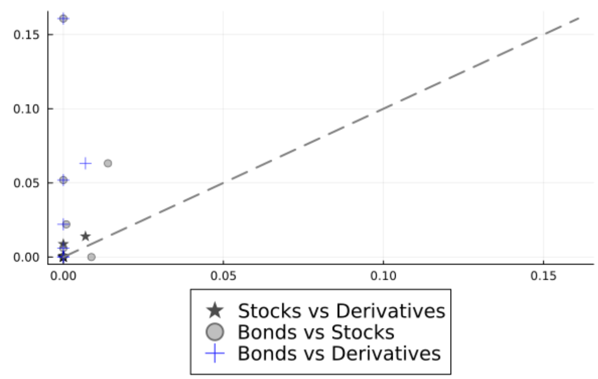
(a) All dealers



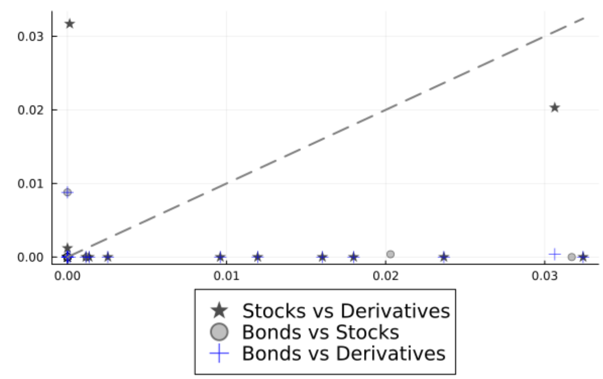
(b) Largest dealers



(c) Banks



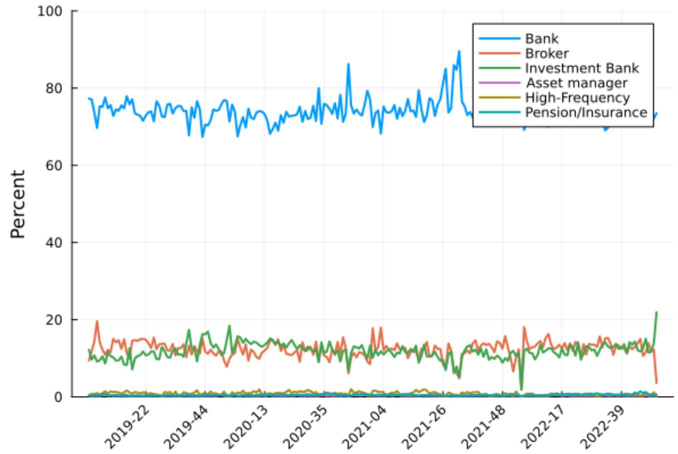
(d) High-frequency traders



Notes: Appendix Figure A3 is analogous to Figure 2a but for dealers at the LEI-level rather than the parent-level. It plots all dealer j's market shares for each market m, averaged across years. The stars show each dealer's stock market share on the y-axis and their derivatives market share on the x-axis; the circles show the stock versus bond market shares and the crosses the bond versus derivative market shares, on the y-axis and x-axis respectively. Figure zooms in on dealers who trade at least 5% of the non-client market share in one of the three markets. In Figures A3c and A3d we only consider banks, and high-frequency traders, respectively.

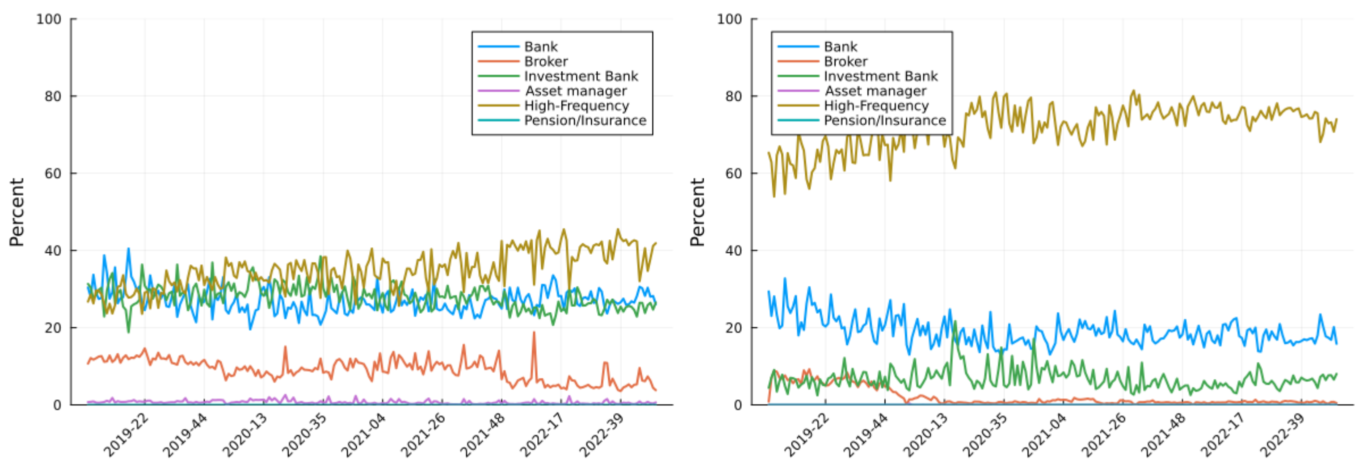
Appendix Figure A4: Weekly fraction of dealer trade volume by type

(a) MTRS



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

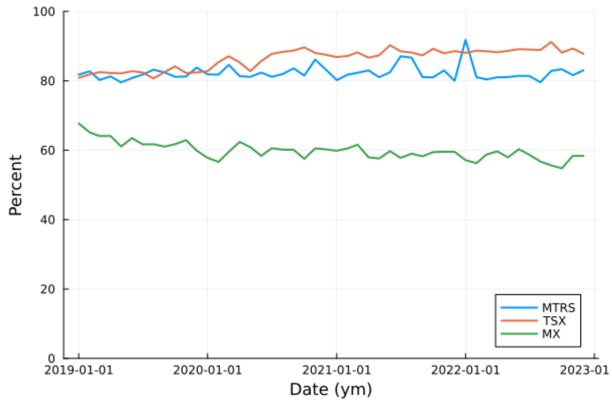
(c) MX—all accounts (LHS); excluding client accounts (RHS)



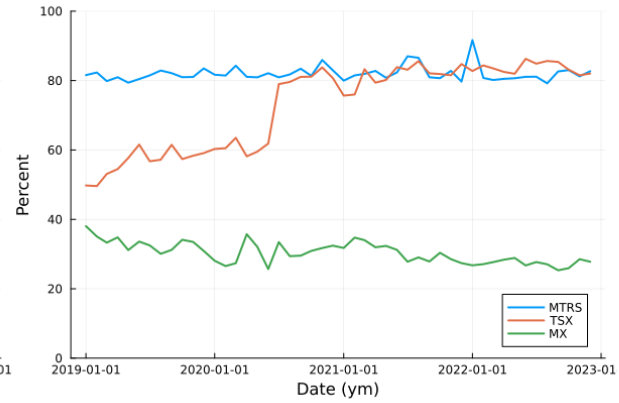
Notes: Appendix Figure A4 shows the fraction of weekly dealer trade volume that is traded by each type per market (at the parent-level). For TSX and MX we include all trades on the LHS, and focus on non-client trades on the RHS.

Appendix Figure A5: Fraction of monthly dealer trade volume by dealers active in all markets

(a) Including all trades



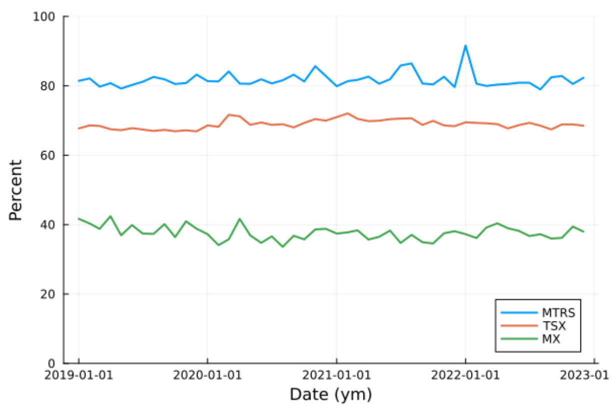
(b) Excluding client trades (for TSX/MX)



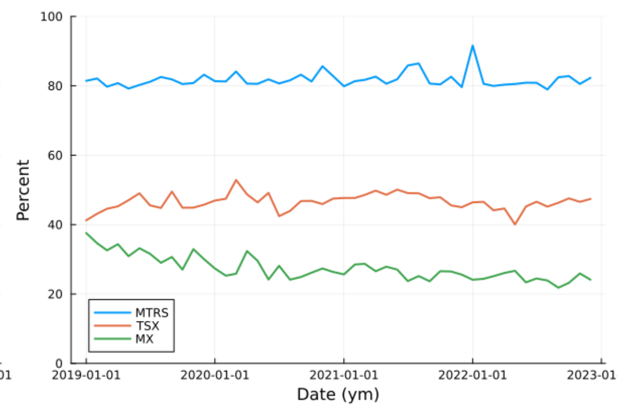
Notes: Appendix Figure A5a shows the fraction of monthly dealer trade volume by those active in all markets, for each market, including trades for all accounts. Thus, this is the analogue to row "All" in Table 6, just computed for each year-month separately, and then plotted over time. We see that about 80% of dealer trade volume on TSX is executed by dealers who also trade on MTRS and MX. Figure A5b 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 A4b. Instead, there was an increasing use of the non-client accounts among dealers who are active in all markets.

Appendix Figure A6: Fraction of monthly dealer trade volume by primary dealers active in all markets

(a) Including all trades

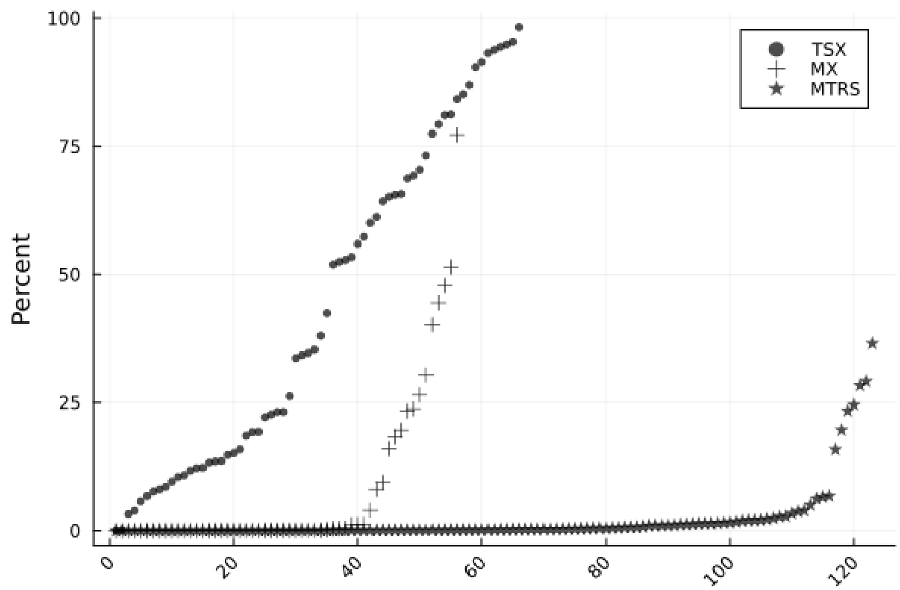


(b) Excluding client trades (for TSX/MX)



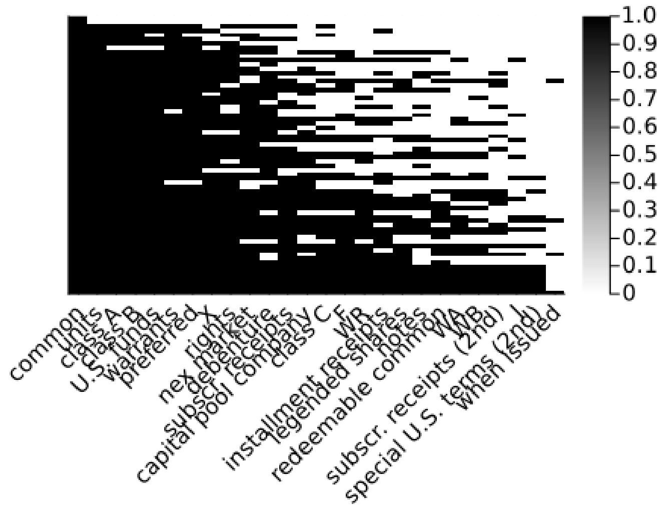
Notes: Appendix Figure A6a zooms in on primary dealers, showing the fraction of monthly dealer trade volume by dealers who are active in all markets and are primary dealers when including all trades. For example, we observe that essentially all omnipresent dealers on MTRS are primary dealers, and that 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 A6b excludes client trades.

Appendix Figure A7: Fraction of securities traded by each dealer out of all securities on TSX, MX, MTRS



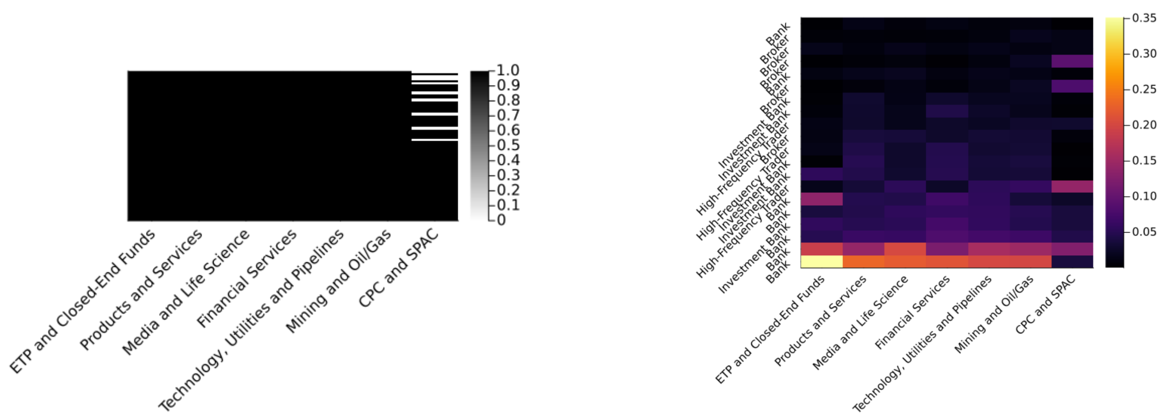
Notes: Appendix Figure A7 shows the fraction of symbols (x-axis) that each dealer trades (at the parent-level, on the y-axis) out of all traded symbols for each market. Since we sort by size within each market, the y-axis doesn't represent dealer-IDs that are common across markets. This is an alternative 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 A8: Dealer presence across asset-types (defined by the symbol suffix)



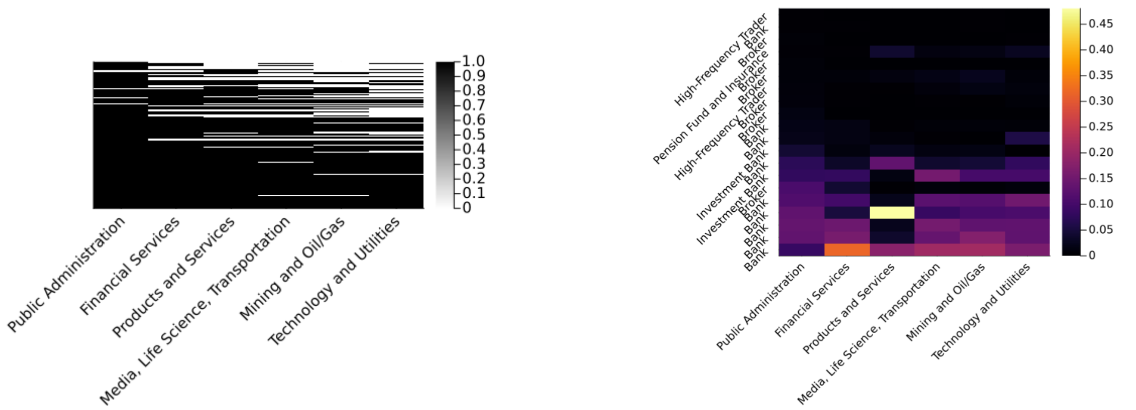
Notes: Appendix Figure A8 shows whether each of the dealers is active (i.e., trades at least ones) in white, versus in-active in white for each asset-class, defined according to the symbol-suffix within the stock markets at the parent-level. Suffices are explained in Appendix Table A11.

Appendix Figure A9: Dealer presence and market share across equity sectors



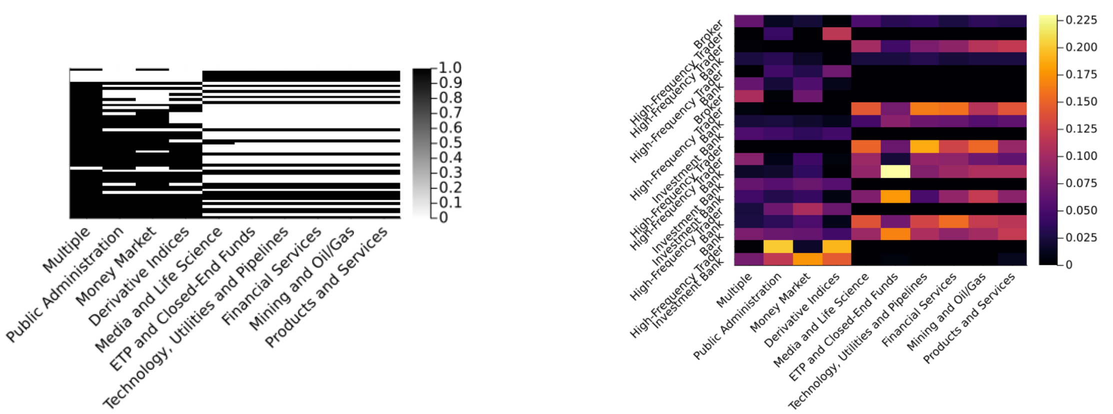
Notes: Appendix Figure A9 shows the analogous graphs for Figure 4a with sectors instead products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in black, versus in-active in white for each sector within the stock markets at the parent-level. The LHS of these figures 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 annual 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 A10: Dealer presence and market share across fixed-income sectors



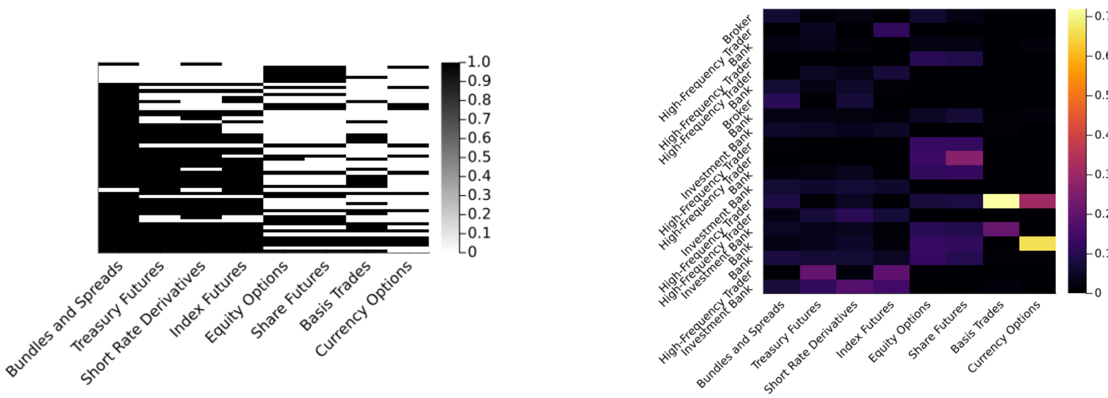
Notes: Appendix Figure A10 is analogous to Figure 4b but for sectors instead of products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in black, versus in-active in white for each sector within the fixed-income market at the parent-level. The LHS of these figures zooms 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 annual 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 A11: Dealer presence and market share across derivative sectors

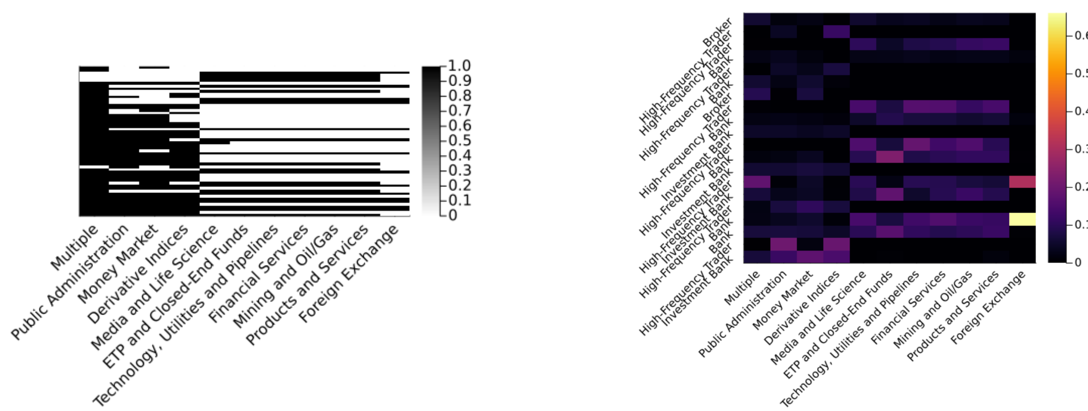


Notes: Appendix Figure A11 is analogous to Figure 4c but with sectors instead of products. The RHS shows whether each of the dealers is active (i.e., trades at least ones) in black, versus in-active in white for each sector within the derivative market at the parent-level. The LHS of these figures zooms 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 annual 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 A13. 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 A12: Dealer presence and market share across derivative products, including all products



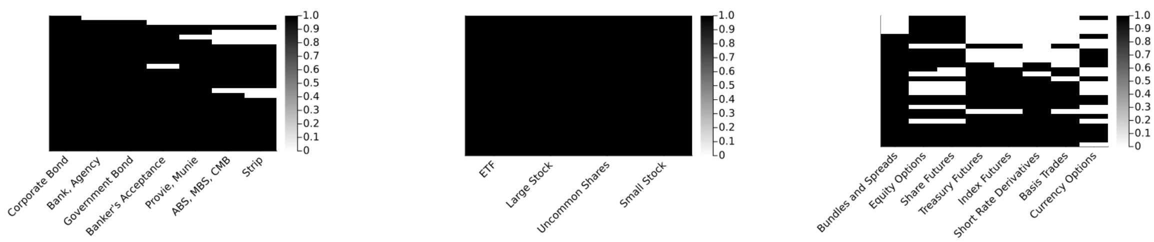
Appendix Figure A13: Dealer presence and market share across derivative sectors, including all products



Notes: The RHS of Appendix Figure A12 is the analogue to Figure 4c 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 black, versus in-active in white 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 annual 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 A14: Dealer presence across products of dealers present in all markets

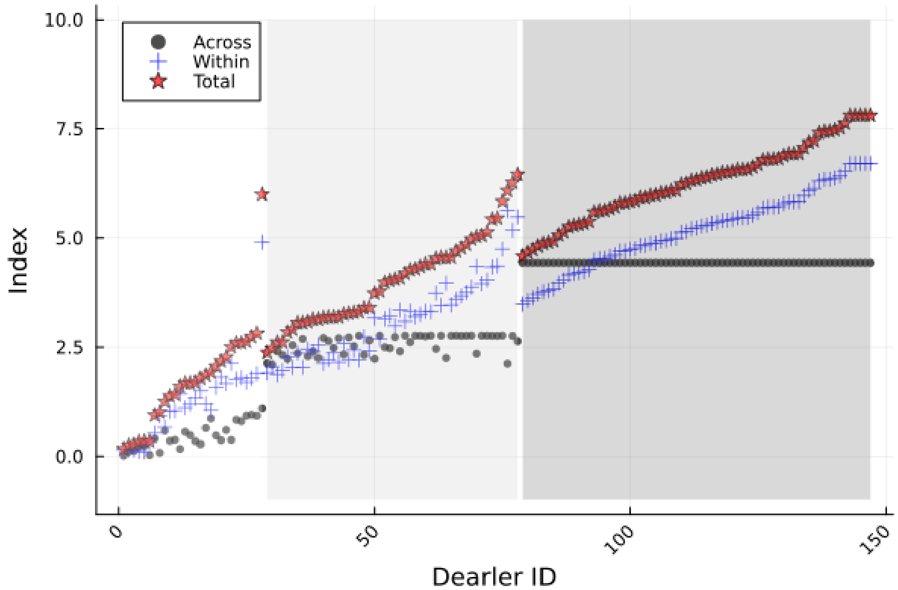
(a) MTRS (b) TSX (c) MX



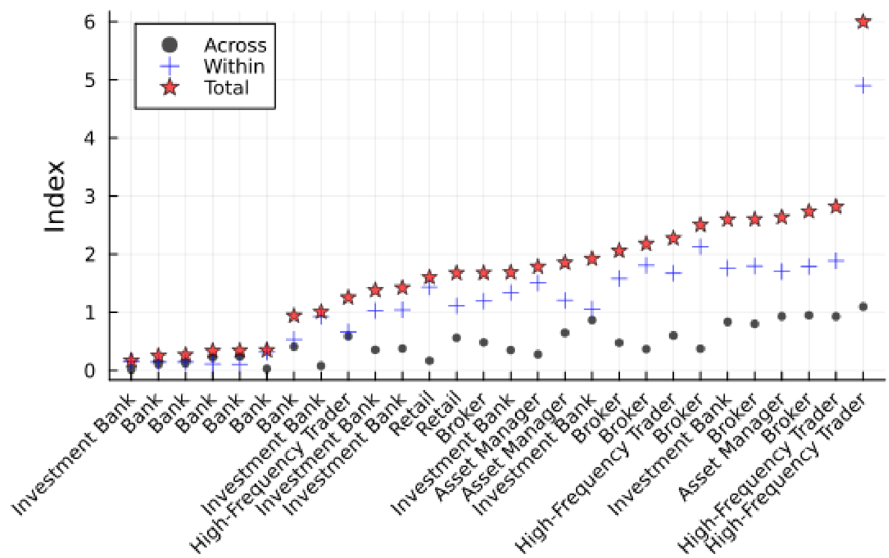
Notes: Appendix Figure A14 is the analogue to Figure 4, but includes the two small products “Basis Trades" and “Currency Options" for MX. It shows whether dealers who are present in all markets are active for a specific product in black, versus in-active in white for each product within the fixed-income market; for the TSX; and for MX (at the parent-level).

Appendix Figure A15: Within-and cross-market segmentation indices

(a) Indices of all dealers

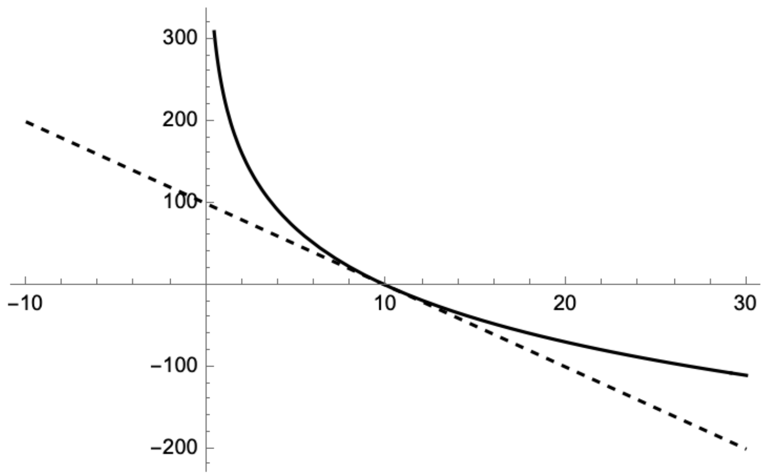


(b) Indices of largest dealers



Notes: Appendix Figure A15a 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 A15b zooms in on the dealers who are active in all three markets.

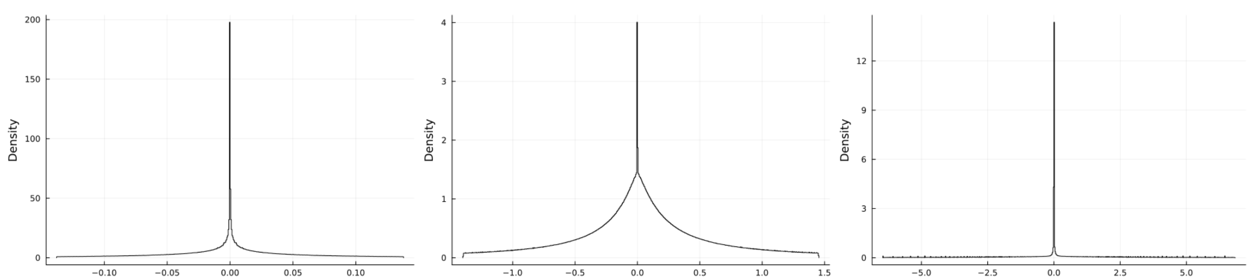
Appendix Figure A16: Margins



Appendix Figure A16 shows the margin (3) for an average price of 10 in black, and the linear approximation in dashed lines.

Appendix Figure A17: Margin distribution in each market

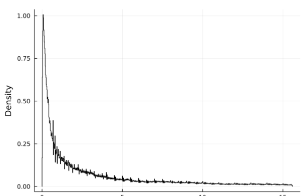
(a) Bonds (b) Stocks (c) Derivatives



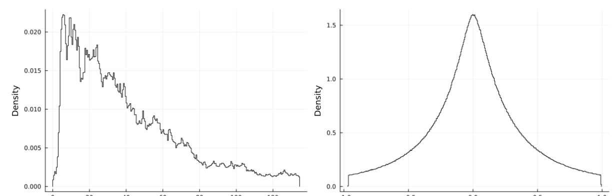
Appendix Figure A17 shows the distribution of our margin measure (3), which approximates how much less (more) a trader paid compared to the average price for a security in a day when buying (selling) for for each market. We exclude outliers, which are outside of the interquartile range. The median (average) 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 A18: Price and margin distribution for derivatives products

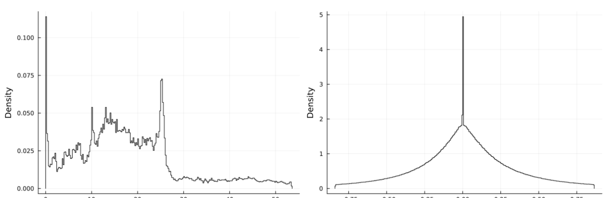
(a) Small Stock



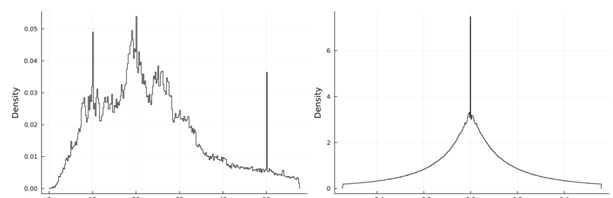
(b) Large Stocks



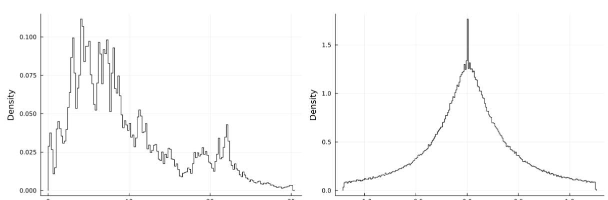
(c) Uncommon shares



(d) ETFs



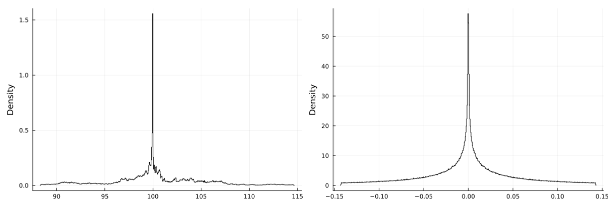
(e) Other or Missing



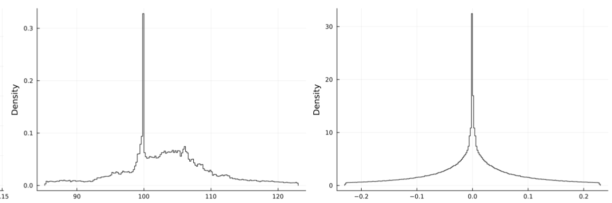
Notes: Appendix Figure A18 shows density histograms of prices for each product on TMX, excluding observations outside of the inter-quartile range.

Appendix Figure A19: Price and margin distribution for bonds

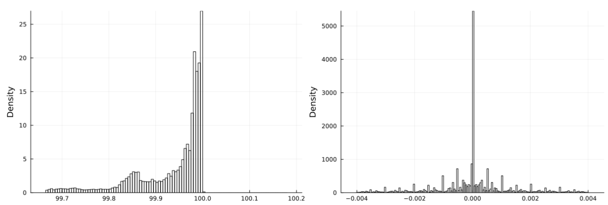
(a) Government Debt



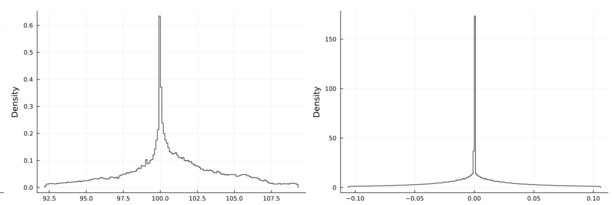
(b) Provincial and Municipal



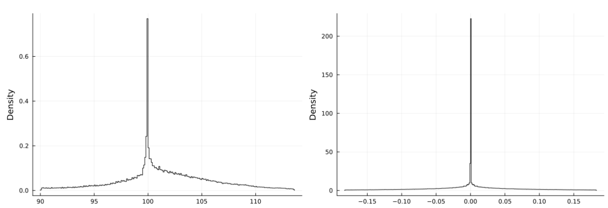
(c) Banker's Acceptance



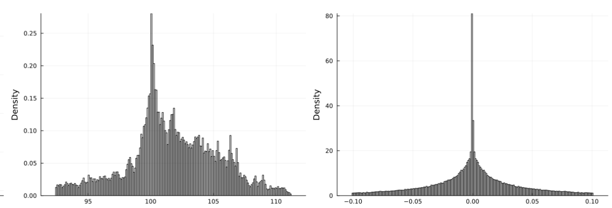
(d) Bank/Agency bonds



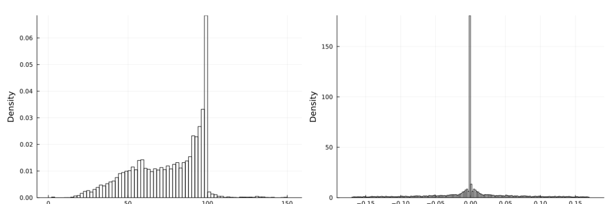
(e) Corporate Debt



(f) ABS/MBS/CMB



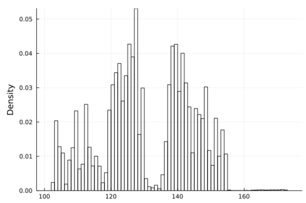
(g) Strips



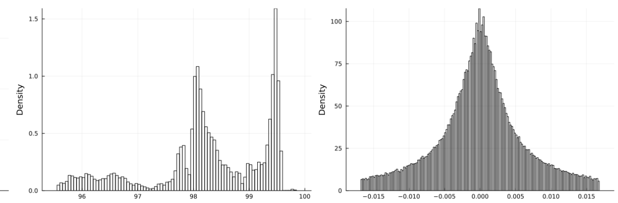
Notes: Appendix Figure A19 shows density histograms of prices for each product on the fixed-income market, excluding observations outside of the inter-quartile range.

Appendix Figure A20: Price and margin distribution for derivatives

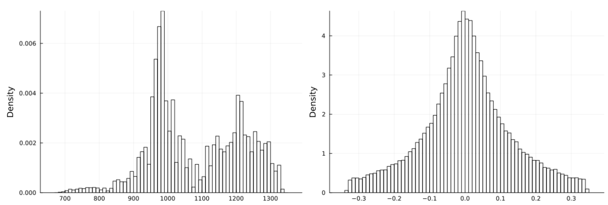
(a) Treasury futures



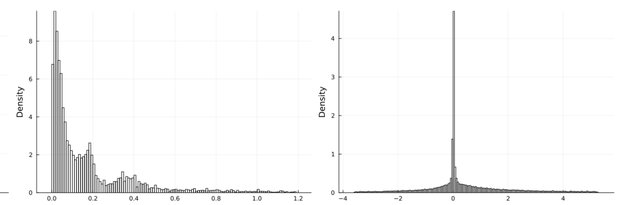
(b) Short Rate Derivatives



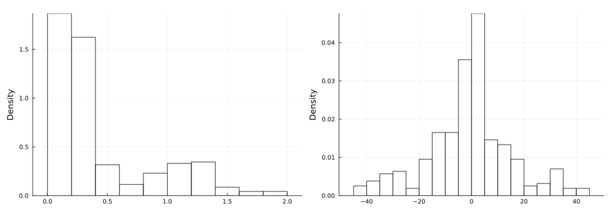
(c) Index Futures



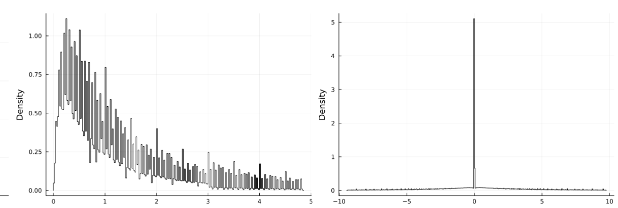
(d) Bundles and Spreads



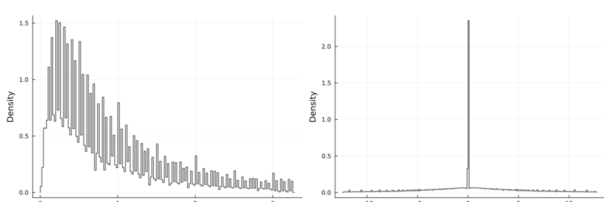
(e) Basis Trades



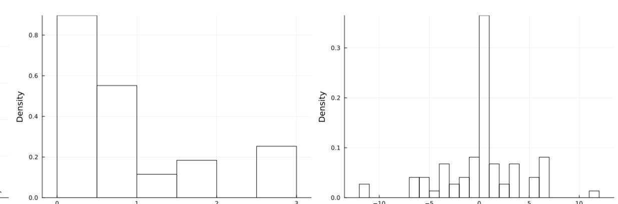
(f) Equity Options



(g) Share Futures



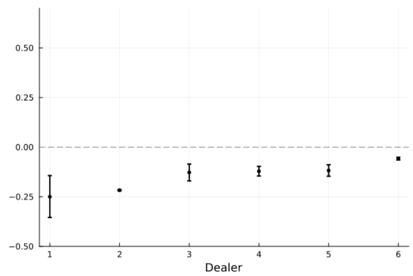
(h) Currency Options



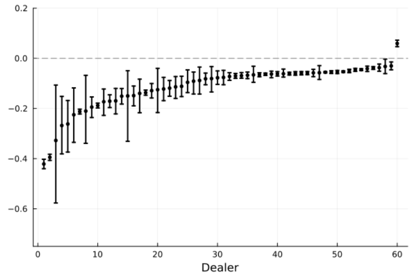
Notes: Appendix Figure A20 shows density histograms of prices for each product on MX, excluding observations outside of the inter-quartile range.

Appendix Figure A21: Dealer coefficients for dealers who exclusively trade in one market

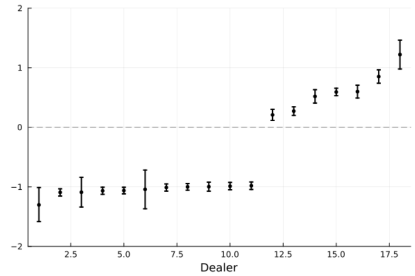
(a) Stock market



(b) Bond market



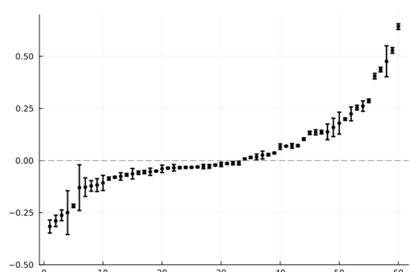
(c) Derivative market



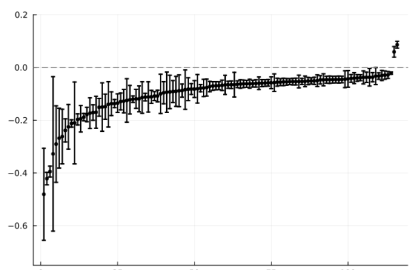
Notes: Appendix Figures A21a shows the dealer coefficients and 95% confidence intervals, which are obtained via WCR bootstrapping, when regressing margins (3) of a trade on indicator variables for each dealer that is only active on stock exchanges, and not on the bond market, (at the LEI-level) in addition to control variables (trade-size, the account-type, security-week and day fixed effects). Figure A21b shows the analogue for the fixed-income market, where we replace the account-type with a variable that indicates the type of trade. Figure A21c 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.

Appendix Figure A22: Robustness—Dealer coefficients that are statistically different from zero at 5% significance level (conventional inference)

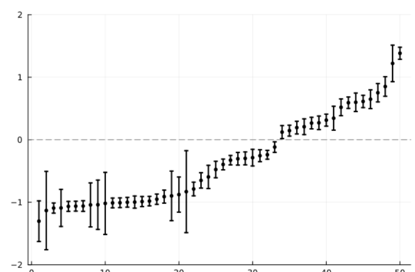
(a) Stocks



(b) Bonds



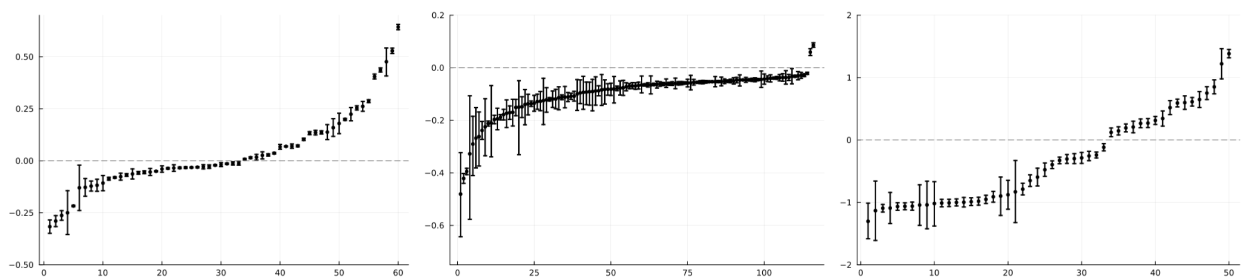
(c) Bonds



Notes: Appendix Figure A22 is the analogue to Figure 6 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 A22a shows the dealer coefficients when regressing margins (3) 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 A22c shows the analogue for the derivatives exchange. Figure A22b 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 A23: Robustness—Dealer coefficients that are statistically different from zero at 5% significance level (parent-level)

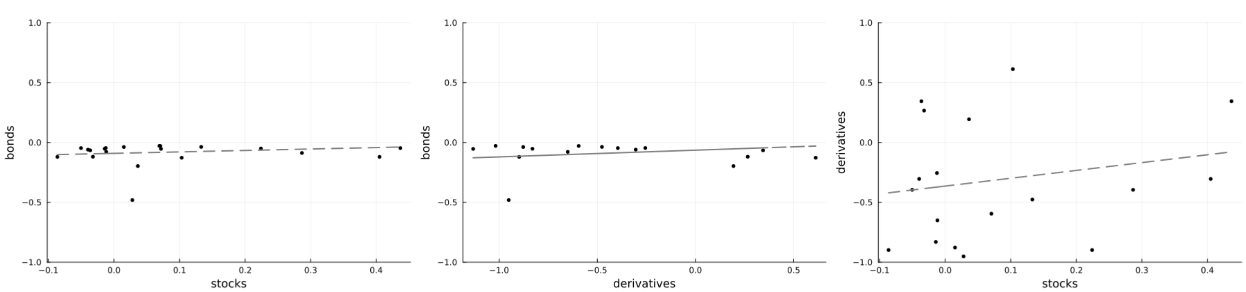
(a) Stocks (b) Bonds (c) Bonds



Notes: Appendix Figure A23 is the analogue to Figure 6 but aggregating dealer LEIs to the parent-level. Figure A23a shows the dealer coefficients when regressing margins (3) 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 A23c shows the analogue for the derivatives exchange. Figure A23b 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 A24: Robustness—Cross-market correlation between dealer coefficients of dealers active in all markets (conventional inference)

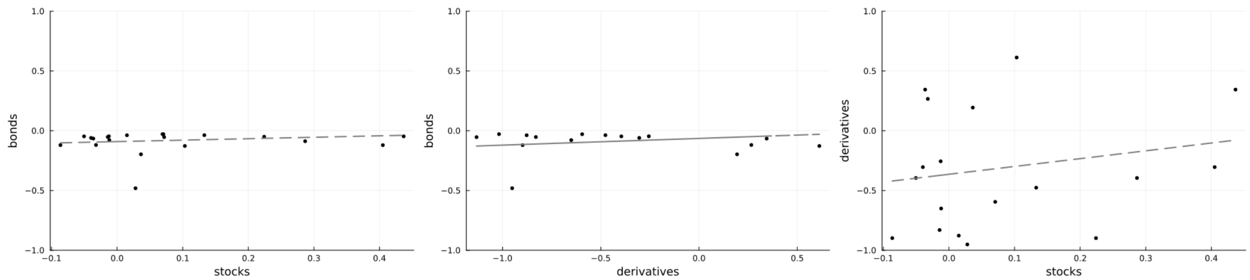
(a) Bonds-stocks (b) Bonds-derivatives (c) Stocks-derivatives



Notes: Appendix Figure A24a is analogous to Figure 7a 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 A25: Robustness—Cross-market correlation between dealer coefficients of dealers active in all markets (parent-level)

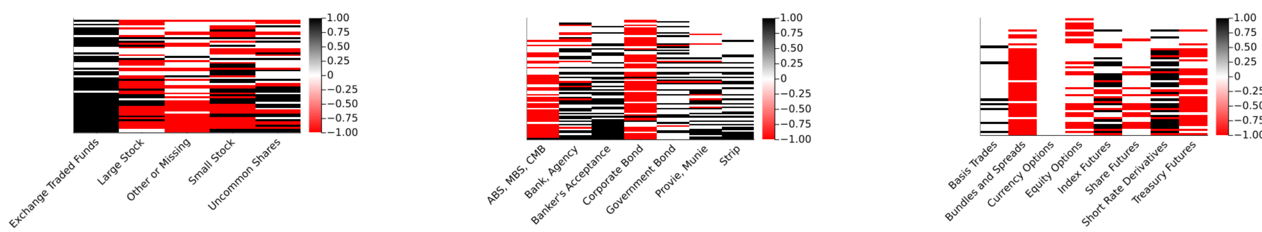
(a) Bonds-stocks (b) Bonds-derivatives (c) Stocks-derivatives



Notes: Appendix Figure A25a is analogous to Figure A25a 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 A26: Robustness: Dealer specialization across products within a market (parent-level) — 2022

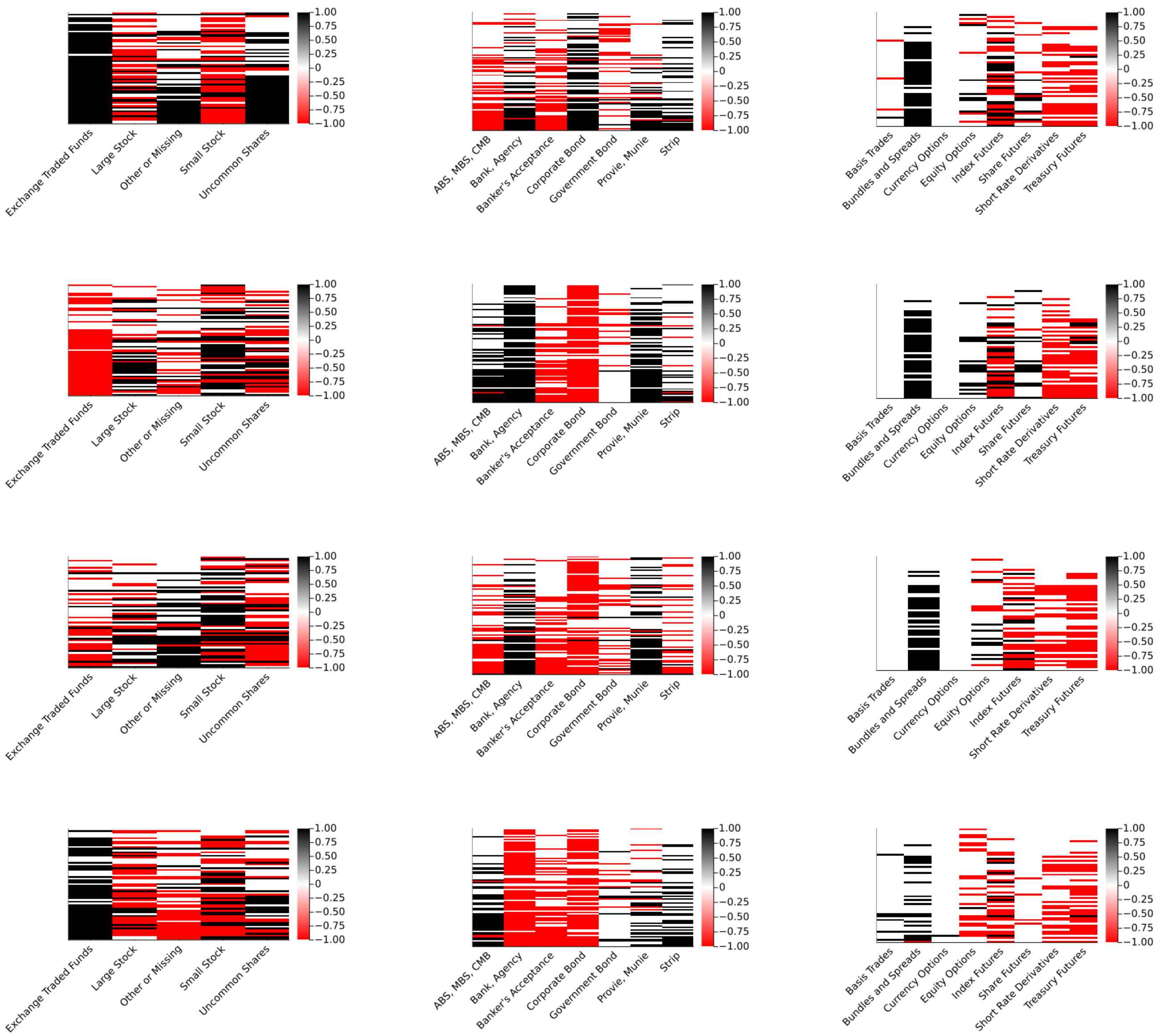
(a) Stocks (b) Bonds (c) Derivatives



Notes: Appendix Figure A26 is analogous to Figure 8 but when aggregating dealer IDs to the parent-level. Appendix Figure A26a visualizes the dealer-product coefficients, β_{jp}, when regressing margins (3) 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 A26b and A26c 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 A27: Dealer specialization across products within a market — 2019, 2020, 2021, 2022

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



Notes: Appendix Figure A27 is analogous to Figure 8, 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 A27a visualizes the dealer-product coefficients, β_{jp}, when regressing margins (3) 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 A27b and A27c 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.