What Do Bank Trading Desks Do?*

Lina Lu
Federal Reserve Bank of Boston

Jonathan Wallen
Harvard Business School

November 14, 2024

Abstract

Bank trading desks earn profits from intermediating customer trading volume. Across a broad set of asset markets, we document that the trading desks of large U.S. dealer banks behave as financial intermediaries that profit from toll-taking as in Duffie et al. (2005). Despite having large inventories and earning large profits, bank trading desks bear little to no market risk. Risk is primarily idiosyncratic and diversifies across desks, resulting in high profitability, profits per unit of risk. In the cross-section of large U.S. dealer banks, the profitability of trading desks differs, even within the same asset class and trading activity. Trading desks exhibit economies of scale, where profitability is increasing in trading desk size.

JEL Classifications: G21; G32; G12

Keywords: Banks; Market Making; Financial Intermediation; Search Frictions

*For insights that made the paper better, we thank Jeremy Stein and Adi Sunderam. We further express our gratitude to Markus Brunnermeier, John Campbell, Darrell Duffie, Sam Hanson, Jonathan Lewellen, and Arvind Krishnamurthy for their excellent comments. We thank seminar participants at Dartmouth and Princeton. The views expressed in this paper are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Boston, the Federal Reserve System, or any of its staff. Emails: lina.lu@bos.frb.org and jwallen@hbs.edu.

1 Introduction

A large theoretical literature characterizes many forms of financial intermediation for different types of asset markets. One such prominent theory is search-based market making, where financial intermediaries match buyers with sellers. In the search model of Duffie et al. (2005), one can think of intermediaries as effectively being toll takers who earn rents on the customer relationships that allow them to locate buyers and sellers. Given this relationship capital, there is no need for the intermediaries to bear market risk in order to earn these rents. However, there is little empirical evidence of the prevalence and profitability of such toll-taking across asset markets.

In this paper, we characterize how large U.S. dealer banks behave as intermediaries across many asset markets. We use regulatory data from the Federal Reserve, which includes daily information on individual trading desks within large U.S. dealer banks from 2014 to 2023. For the 5 large U.S. dealer banks, Bank of America, Citigroup, Goldman Sachs, JP Morgan, and Morgan Stanley, we have about 500 trading desks, spanning commodity, credit, equity, foreign exchange (FX), mortgage backed securities (MBS), and rates markets. For each trading desk, we observe mark to market trading profits, trading volume with customers, and risk-metrics.

To fix ideas, we begin with a discussion of theories of financial intermediation with a focus on differing empirical predictions. In a broad class of theories, intermediaries earn profits to compensate them for bearing risk. We label this type of financial intermediary as a "specialized risk bearer". In He and Krishnamurthy (2013), households invest in the risky asset through the balance sheets of intermediaries, resulting in the intermediary sector being long the risky asset. The core empirical prediction of models of risk-bearing financial intermediaries is that the profits of intermediaries depend on the returns of the risky asset.

In an alternative class of theories, financial intermediaries profit from charging a bid-ask spread on customer trading volume. We label this type of financial intermediary as a "toll-taker". In Grossman and Miller (1988), intermediaries supply immediacy by absorbing order imbalances. If there are more sellers than buyers, intermediaries buy and temporarily hold the risky asset until more buyers arrive to the market. In this model, bid-ask spreads are compensation for holding risky inventories. Duffie et al. (2005) extends this to a setting with search frictions, where intermediaries have market power and earn bid-ask spreads, despite not bearing any inventory risk. The core empirical prediction of this class of models is that intermediation profits depend on customer trading volume.

A second and more subtle distinction between these models is the relationship between profitability and size. In Grossman and Miller (1988) and He and Krishnamurthy (2013), financial intermediaries are homogeneous and earn the same return per unit of risk. More generally, a large literature documents diseconomies of scale in earning excess returns from bearing risk (Berk and Green, 2004; Chen et al., 2004). In contrast, search models of financial intermediation permit heterogeneity in how well connected a dealer is; Wang (2016) explains how larger dealers that are better connected with customers can more quickly match buyers and sellers. Therefore, in search models, there are positive economies to financial intermediation.

From publicly available information, these dealer banks may appear to be specialized risk bearers because they have large inventories and earn large profits. Figure 1 shows that in 2023 these dealer banks have 2.2 trillion in trading assets, comprised of Treasuries, mortgage backed securities, loans, other debt instruments, derivatives and other assets. In 2023, these dealer banks also earned $133 billion in trading revenue and fees and commissions from securities brokerage.[1]

Using regulatory data at the trading-desk level, we show that these dealer banks are actually toll-taking financial intermediaries. Despite having large inventories, trading desks bear little market risk and their profits tend to be driven by customer trading volume. Their profits are large and profits per unit of risk varies across banks, even for desks within the same asset market and trading activity. An important driver of this heterogeneity is positive economies of scale, where trading desk profitability is increasing in desk size.

[1]The public data on bank trading assets and trading profits is from Schedules HC-D and HI of the FR Y-9C, respectively.

Our first fact is that bank trading profits are not compensation for bearing market risk. There is little to no relationship between trading profits of a bank in an asset market and the returns of that asset. Bank trading profits have little exposure to commodity returns, credit spreads, equity returns, the dollar exchange rate, MBS spreads, short-term interest rates, and term premia. For example, a one standard deviation increase in equity market returns is associated with a 5 percent decrease in equity market trading profits. This association is small and negative, which is evidence against trading profits being compensation for bearing equity market risk.

In addition to this evidence on average exposures, we show that dealer banks do not have large time varying positive or negative exposures to credit risk or interest rates. Trading desks report DV01, the effect of a one bps change in the level of interest rates on trading profits, and similarly for credit spreads (CS01). For interest rates, trading profits are on average nearly insensitive to when yields rise or fall by 1 bps, but this sensitivity varies between -26 and 19 million. In dollar notional terms, this is an exposure that ranges between long \$29 billion to short \$21 billion of 10-year Treasuries yielding 2%. This dollar exposure is an order of magnitude smaller than the average trading inventory of Treasuries (\$273 billion). We also find similarly small sensitivities to credit spreads.[2]

Of particular interest is how dealer banks respond to periods of financial distress. Our sample includes one such period, the "dash for cash" in March 2020, when COVID-19 was declared a global pandemic, and Treasury and corporate bond yields widened and these markets became illiquid (Duffie, 2023; O'Hara and Zhou, 2021). Dealer bank trading inventories increased by \$207 billion (13%), but there was little to no change in their exposure to interest rate or credit risk. Furthermore, trading profits were abnormally high during this period as shown in Figure 2. Therefore, bank trading profits are unlikely to be compensation for bearing systematic tail risk.

This is not to say that bank trading desks take no risk, but rather that much of the risk

[2] For credit spreads, trading profits decrease by 4.8 million when spreads widen by 1 bps, and this ranges from -18 to 9 million.

appears to be idiosyncratic. Bank trading desks, at times, experience substantial idiosyncratic losses. We group trading desks by bank and asset market and we identify 68 events where a bank made an extreme trading loss in an asset market. We define an extreme trading loss as 5 standard deviations large (hereafter 5-sigma loss days).[3] These events include cases where there is counterparty failure, such as the failure of Archegos Capital Management and the London Metal Exchange Nickel crisis.

For a 5-sigma loss day, the bank on average loses \$148 million, which is 3-weeks of trading profits for the bank in that asset market. These losses tend to be idiosyncratic to the bank; other dealer banks in the same market earn an average positive trading profit of \$4 million on the same day. Although large for the trading desk, these losses are small compared to the total trading profits of the bank holding company. On average, a 5-sigma loss day in an asset market is only 1.6 trading days of profit for the bank holding company. The bank that experienced the loss does not appear to change its trading behavior in the market for which it experienced the loss: profits and customer trading volume are similar to that of other dealer banks in the weeks following the event. This lack of response seems to be efficient because intermediation is highly profitable and losses are idiosyncratic and small to the bank holding company.

In sum, U.S. dealer banks have large inventories, earn large trading profits, but do not bear standard forms of risk, such as exposure to asset market returns, interest rate risk, and credit spreads. This evidence suggests that U.S. dealer banks are not specialized bearers of market risk. We then explore the extent to which U.S. dealer banks behave as toll-takers.

We empirically test the core prediction of toll-taking intermediation, which is that profits depend on customer trading volume. We find that a one percent increase in customer trading demand is associated with a 0.81 percent increase in trading profits. In weekly changes, customer trading volume is 48 percent correlated with bank trading profits. Furthermore,

[3] We measure the standard deviation to daily trading profits for the past quarter (lagged by one day). If trading profits were normally distributed, a 5 standard deviation event is less likely to happen than one in a million.

we show that this customer demand for trading is correlated across markets. For the asset markets with the largest trading profits (equity, credit, FX, and rates), the average pairwise correlation of trading volume is 65 percent. This suggests that customer trading volume is economically important for the trading profits of dealer banks.

We next show that there is substantial cross-sectional heterogeneity in the profitability of financial intermediation across trading desks and across dealer banks. We measure profitability as trading profits per unit of risk. We consider two measures of risk: (i) the time-series standard deviation of trading profits and (ii) the 99% Value-at-Risk (VaR). If trading profits were normally distributed, then the two measures would be isomorphic. However, we have shown that trading desk profits have idiosyncratic, negative tails. We refer to the ratio of average trading profits to its standard deviation as the Sharpe ratio and the latter as the profit to VaR ratio.

For both measures, we find that bank trading profitability is large and heterogeneous across banks. The annualized average Sharpe ratio for our dealer banks is 16 and the difference between the ratio of the most profitable and least profitable bank is 4. Trading desks on average earn \$0.88 per unit of VaR and this varies by \$0.48 across banks.

To be clear, these large and heterogeneous profitability ratios do not prove that trading desks are excessively profitable or leaving money on the table. There are large and difficult to measure variable costs associated with customer acquisition and maintaining existing relationships. To shed some light on this, we measure the association between labor inputs and trading profits. We measure labor as the number of traders for each bank within each asset market. Trading profits are 64 percent correlated with the number of traders. Controlling for bank by time and market by time fixed effects, one additional trader at a trading desk is associated with \$13 million of additional profits per year, which is an order of magnitude larger than the average annual compensation of a trader. This is not an estimate of the marginal productivity of labor because trading desks are unlikely to be scaleable. Trading profits depend on customer demand for trading and competing to acquire a larger share of customers may decrease the trading profits earned from each customer. However, this does suggest that trading profits are too large to be explained by direct labor costs associated with operating trading desks.

For trading desks that perform the same market making activity within the same asset market and geographic region, profitability ratios are persistently different across banks. This suggests that trading desks are heterogeneously profitable depending on their parent bank, which is inconsistent with models of competitive and homogeneous financial intermediaries.

At the desk-level, we find positive economies of scale: profitability is increasing in trading desk size. Trading desks that trade more volume with customers earn higher Sharpe ratios and more profits per unit of VaR. Such positive economies of scale is a feature of toll-taking financial intermediation, where risk does not scale linearly with trading profits. Larger trading desks can better match buyers and sellers and earn larger profits with less inventory risk.

Furthermore, profitability ratios are higher for trading desks whose profits are more correlated with that of the aggregate trading profits of their bank. This implies that dealer banks require riskier trading desks to earn more per unit of risk. The riskiness of trading desks within the same asset market differs across banks because of their heterogeneous specialization across asset markets. Equity trading desks within a bank specialized in the equity market are riskier to that bank compared to equity trading desks within a bank specialized in other asset markets.

This paper seeks to make two contributions. First, we characterize how large U.S. dealer banks behave as financial intermediaries. They earn large trading profits that depend on customer trading volume, and not market risk, which implies that their trading desks behave more like toll-takers and less like specialized bearers of risk. This contrasts with historical evidence that documents an association between the health of the intermediary sector and the price of risk across many asset markets. Adrian et al. (2014) and He et al. (2017) show that from 1968 to 2012, changes in the equity of the intermediary sector is a priced risk factor across many asset classes. This difference many be explained by the migration of proprietary trading desks from dealer banks to hedge funds after the financial crisis of 2008. Following the financial crisis of 2008, regulations have limited the ability of U.S. dealer banks to bear risk. Most notably, the Volcker Rule restricts U.S. dealers from engaging in proprietary trading and was implemented in 2014. Whether this regulation had any effect on how U.S. dealer banks intermediate financial markets is unknown. Duffie (2012) explains that there is no economic distinction between market making and proprietary trading and that this rule is therefore difficult to enforce. However, Falato et al. (2019) show that the riskiness of bank trading assets have decreased after the implementation of the Volcker rule.

This is not to say that dealer banks are unimportant financial intermediaries. These large U.S. dealer banks may be taking duration and credit risk by intermediating credit in their affiliated commercial bank divisions.[4] Although large dealer banks may not directly price market risk, their financial constraints have been shown to be important for understanding arbitrage spreads (Andersen et al., 2019; Anderson et al., 2021; Du et al., 2018; Duffie and Krishnamurthy, 2016; Siriwardane et al., 2022). Furthermore, the financial constraints of dealers is important for liquidity: Duffie et al. (2023) show that Treasuries are less liquid when the intermediation capacity of dealers is more constrained.

Our second contribution is to highlight that the equity capital of U.S. dealer banks is unlikely to be pricing risk in asset markets. This has important implications for our understanding of how the balance sheet constraints of financial intermediaries matter for asset prices. For example, this implies that quantitative easing is unlikely to affect term premia by relaxing the risk-bearing constraints of large U.S. dealer banks. Furthermore, it also suggests that it is the risk bearing capacity of non-bank financial intermediaries that matters for pricing risk in asset markets. This is relevant for a broad set of financial markets, where we have seen significant growth of non-bank financial intermediaries: the mortgage market (Buchak et al., 2018), credit market (Irani et al., 2021), insurance market (Koijen and Yogo, 2016), and

[4] Drechsler et al. (2021) argue that commercial banks do not bear duration risk due to the stickiness of deposit rates. Greenwood et al. (2022) show that growth in bank lending and compressed credit spreads can predict financial crises.

money markets (Sunderam, 2015). This highlights the importance of understanding the risk bearing capacity and leverage of non-bank financial intermediaries (Aramonte et al., 2023).

The rest of the paper is organized as follows. In Section 2, we describe the theoretical literature on financial intermediation with an emphasis on the empirical differences between risk bearing and toll-taking theories of financial intermediation. In Section 3, we describe the data and institutional details about dealer bank trading desks. In Section 4, we characterize how dealer banks behave as financial intermediaries and show evidence consistent with toll-taking. Section 5 concludes.

2 Theories of Financial Intermediation

In this section, we discuss two groups of models of financial intermediation: (i) specialized bearers of risk, and (ii) toll-takers that profit from search frictions. The goal of the simple characterizations of these models is to illustrate the different empirical predictions under each type of model of financial intermediation.

2.1 Specialized Risk Bearing Theory of Financial Intermediation

In risk bearing theories of financial intermediation, intermediaries hold risky assets and earn a risk premium for doing so. In He and Krishnamurthy (2013), households invest in risky assets through the balance sheets of financial intermediaries. Risk premia are

$$E[r] - r_f = \alpha^I \mathrm{Var}(r)$$

where $E[r] - r_f$ is the risk premium (excepted return minus the risk-free rate), α^I is the leveraged exposure of the intermediary sector to the risky asset, and $\mathrm{Var}(r)$ is the riskiness of the asset. The leverage of the intermediary sector depends on its wealth. When intermediary wealth is low and their leverage is high, as is the case during periods of financial distress, the expected return to the risky asset is high. Financial intermediaries are homogeneous and earn the same expected risk premium.

The realized profits of financial intermediaries is

$$\pi = r_f + \alpha^I (r - r_f) \tag{1}$$

and depends on the realized return of the risky asset (r).

From this risk-bearing model of financial intermediation, we take two empirical predictions to the data. First, that the realized profits of the intermediary sector depend on the realized returns of risky assets. This empirical test is a more high powered than most asset pricing tests because it does not rely on average realized returns being a good proxy for expected returns (Merton, 1980).

Second, intermediaries are homogeneously profitable: intermediaries earn the same compensation for bearing the same risk. There may be time-series variation in the risk premium that the intermediary sector earns, but in the cross-section, big and small intermediaries earn the same compensation for bearing the same risk.

2.2 Toll-Taking Theory of Financial Intermediation

In toll-taking theories of financial intermediation, intermediaries profit from spreads earned from customer trading volume. Grossman and Miller (1988) provides a canonical such model, where financial intermediaries supply immediacy to investors by absorbing temporary order imbalances. The expected return to the risky asset is

$$E[r] = X\gamma \text{Var}(r)$$

where X is the intermediary position in the risky asset, γ is their risk aversion, and $\text{Var}(r)$ is the riskiness of the asset. If there are more buyers than sellers, then intermediaries are short ($X < 0$) and the expected return to the risky asset is negative ($E[r] < 0$). For short-lived order imbalances, this expected return can be conceptualized as a bid-ask spread. Therefore, the profits of financial intermediaries depends on the demand for immediacy and the size of bid-ask spreads.

Duffie et al. (2005) provides a model of toll-taking financial intermediation where intermediaries match buyers and sellers in a market with search frictions. Financial intermediaries are assumed to be able to perfectly hedge (or offload) their inventory risk. Intermediary profits are thus determined by the matching intensity (ρ), the minimum of the number of buyers or sellers (μ) and the equilibrium bid ask spread ($A - B$) they charge:

$$\pi = \rho\mu(A - B).$$

The bid-ask spread is a rent that intermediaries earn from being a local monopolist; there is a search friction to the customer finding another intermediary to transact with. The realized profits of toll-taking depend on the number of customers that intermediaries transact with, not the realized returns of risky assets. Intermediaries that transact with more customers earn more profits without bearing additional risk.

The toll-taking models of financial intermediation provide two juxtaposing empirical predictions. First, realized profits of the intermediary sector depend on trading volume with customers and not on the realized returns of risky assets. In toll-taking models of financial intermediation, profits are not compensation for bearing risk.

Second, there are positive economies of scale to being a financial intermediary that is well-connected to customers. Wang (2016) explains how intermediaries that match more buyers with sellers are more profitable, earn more profits per unit of risk. Therefore, a feature of search models is positive economies of scale: profitability is increasing in dealer size.

In the following sections, we empirically test both of these juxtaposing predictions of the risk bearing and toll-taking theories of financial intermediation.

3 Data and Institutional Details

In this section, we introduce the data and provide background on the organizational structure of trading desks within our sample of large U.S. dealer banks. Furthermore, we present summary statistics about trading desks across markets and banks.

3.1 Data

We use confidential FR VV-1 data collected by the Federal Reserve to monitor compliance with the Volcker rule. U.S. banks with $20 billion in average gross trading assets and liabilities over the past calendar year are required to report data on trading activities. We focus our analysis on the sample of the following U.S. bank holding companies: Bank of America, Citigroup, Goldman Sachs, JP Morgan, and Morgan Stanley.

The data is at the daily frequency and spans from July 2014 to September 2023. Each observation is for a trading desk by date. For each trading desk, we classify it by asset market, trading activity, and geography as described in Section 3.2 and in Appendix Section C.

For the full sample, we have data on daily trading profits for each trading desk within each bank. Trading profits are marked-to-market and net of funding costs but not other costs, such as labor costs. The trading profits are similar in magnitude and closely correlated to that of trading revenues fees and commissions from securities brokerage, which are publicly reported at the quarterly frequency in Schedule HI of the FR Y-9C.

From January 2016 to September 2023, we have daily data on trading desk risk metrics. We have 99% VaR for a 1-day holding period, interest rate sensitivity (DV01), and credit spread sensitivities. These risk measures are self-reported by trading desks. For a subsample from January 2021 to September 2023, we have data on daily transaction volumes in securities and derivatives with customers for each trading desk within each bank.[5]

[5]We have data on the 30-day moving averages of trading volume, which is the sum of derivatives trades and securities trades with customers, from July 2014 to December 2020. The variation in this series is likely to be dominated by that of derivatives trades because the notional of derivatives trades are an order of magnitude larger than that of securities transactions.

From Trade Reporting and Compliance Engine (TRACE), we obtain data on secondary market trading volume for corporate bonds. This data is at the daily frequency and spans our sample from July 2014 to September 2023.

From Revelio Labs, we obtain data on the LinkedIn profiles of people employed by our sample of banks. We identify traders based on their job title and classify traders by asset market using their job title and description as described in Appendix Section D.

3.2 Organization of Bank Trading Desks

The average bank holding company in our sample has 86 trading desks, which we organize by the asset market that they operate in. We classify trading desks into 7 asset markets: commodity, credit, equity, FX, MBS, rate, and other.[6]

We further subcategorize trading desks based on how the dealer banks organize their trading desks. In doing this we follow self-reported structures by the dealer banks. A subset of the dealer banks have trading desk names where the first part refers to an asset market and the second part to a trading activity. For example, we group equity desks by the following activities: hedging, underwriting, derivatives, prime brokerage, trading.[7] These activities are at times further subdivided by region: Asia-pacific (APAC), Europe and the Middle East (EMEA), Latin America (LATAM), and North America (NA).[8] In Section C in the Appendix, we describe in detail how we use the name and description of the trading desks to classify each trading desk.

3.3 Market Return Measures

To construct measures of market risk, we obtain Bloomberg data on the market returns for each of the asset markets that bank trading desks operate in. For the commodity market, we

[6]The "other" market category is comprised of legacy assets that are in the process of being run down and municipal bond market trading activities.

[7]The trading category captures all residual activities that cannot be classified into any other activity.

[8]In the case of the trading desk operating globally or without a specified region, the region category is left blank.

measure returns to the Bloomberg commodity index. For the credit market, we proxy for market returns as the change in the credit spread of investment grade bonds, which is the yield on an investment grade bond index minus the yield of a maturity-matched Treasury. For the equity market, we measure the return to the SP 500 index. For the FX market, we measure the change in the USD exchange rate against a basket of currencies (DXY index), such that an increase in the exchange rate is an appreciation of the USD. For the mortgage market, we measure returns as changes to the credit spread of MBS, which is the yield of the MBS index minus the yield of a maturity-matched Treasury. For the rates market, we measure returns as changes to the term premia spread, which is the 10-year Treasury yield minus the 1-year Treasury yield. We measure the risk-free rate as the yield on the 1-year T-bill.

3.4 Summary Statistics

Table 1 presents summary statistics for bank trading profits by market. For each week, the 5 dealer banks in our sample, in sum, earn 1.65 billion in trading profits. The equity and credit markets make up the majority of these trading profits with respective shares of 38 and 18 percent. The dealer banks earn 17 percent of their profits in the rate market, 14 percent in the FX market, 6 percent in the MBS market, 5 percent in the commodities market, and 2 percent in the residual other category.

These trading profits are volatile, but rarely negative, as shown by Figure 2. At the weekly frequency, the standard deviation to trading profits is 608 million, which is 37 percent of the average weekly trading profit of 1.65 billion. This ratio is even higher within each market. For example, in the commodity and MBS market the weekly standard deviation in trading profits is greater than the average trading profit.

The trading profits for each market are not heavily concentrated in any one of the five banks. The average HHI of annual trading profits by market varies from a low of 0.23 to a high of 0.26.[9] The most concentrated market is the FX market, where on average, the bank with the largest share of profits has 36 percent of profits.

Although concentration levels are similar across markets, the dealer banks heterogeneously specialize across markets. For each bank, we measure the share of the bank's profits within each market and report the mean and range of these estimates in Table 1. For example, dealer banks on average earn 38 percent of their profits in the equity market, but the range is 29 percent. The bank that most specializes in the equity market earns 29 percent more of its profits in the equity market than the bank that least specializes in the equity market. Across markets, the range of bank profit weights is similar in magnitude to the average profit weight in each market.

The cross-market differences in trading profits strongly correlate with the number of traders employed in each asset market. For example, 1308 traders work in equity market related desks, which is 32% of traders. Equity market trading desks earn 38% of trading profits. Credit desks have 23% of traders and 18% of trading profits. On the other end, commodity trading desks have 6% of traders and 5% of trading profits and MBS trading desks have 2% of traders and 6% of trading profits.

Each trading desk reports a 99% VaR and the fraction of this limit that they utilize. In Table 1, we report the sum of the 99% VaR across trading desks within each asset market. This is difficult to interpret because VaR is not additive: i.e. the sum of the equity trading desks have a smaller VaR than 242 million because their trading profits are not perfectly correlated. However, we can interpret the average VaR utilization, which ranges between 25% to 36% across asset markets. This implies that trading desks on average have significant buffers to their VaR limits.

The trading profits by dealer banks are positively correlated across markets but this correlation is far from 1. Figure 4 shows the correlation of the sum of weekly trading profits across dealer banks between asset markets. The pairwise average correlation between markets

[9] For these and the following statistics, we exclude the other market category.

is 44 percent. The largest correlation is between the FX and the commodity market (71 percent). Table 1 shows more granular average pairwise correlations. Within a market, the average pairwise correlation of weekly changes to trading profits of dealer banks varies from 11 percent (credit market) to 37 percent (equity market). Despite engaging in similar market making activities within the same asset class, the trading profits of dealer banks are far from perfectly correlated. Furthermore, the weekly changes to trading profits of bank i in market j is on average 19 percent correlated with the trading profits of the same bank i in other markets. This suggests that there is significant variation in trading profits across dealer banks and across markets. In the following section, we study this variation to characterize the behavior of bank trading desks.

4 Empirical Results

In this section, we characterize how large U.S. dealer banks behave as financial intermediaries. We empirically test the two juxtaposing hypotheses of risk bearing and toll-taking financial intermediation as described in Section 2.

4.1 Exposure to Risk

Under risk bearing theories, financial intermediary profits are compensation for bearing risk. In this subsection, we empirically characterize the extent to which the trading profits of large U.S. dealer banks can be explained by risk exposures.

An empirical challenge with testing this hypothesis is that we do not observe the positions of bank trading desks in risky assets. The exposures of bank trading desks to risky assets may be time varying and these risky assets may be complex spread trades, which makes it difficult to measure the risky asset return, r in equation (1). Despite this limitation, we can empirically evaluate the extent to which trading desks are exposed to standard risk exposures, such as market returns for each market that trading desks operate in and interest rate risk.

Furthermore, we have self-reported estimates of time-varying exposures to interest rate risk and credit risk.

4.1.1 Realized Market Returns

We begin with the most standard form of risk, market risk. For each asset market m, we empirically estimate the weekly association between trading profits and the returns of the asset market:

$$\Delta\text{Profits}_{t,m} = \alpha_m + \beta_m \text{Market Ret}_{t,m} + \gamma_m \Delta\text{RF Rate}_t + \epsilon_{t,m} \tag{2}$$

where $\Delta\text{Profits}_{t,m}$ is the weekly percent change in trading profits at time t in asset market m summed across our 5 dealer banks.[10] We measure the market return (Market $\text{Ret}_{t,m}$) for the specific asset market in which the bank earns the trading profits. Section 3.1 describes how we measure market returns for each asset market. The risk free rate (RF Rate_t) is the 1-year T-bill rate. We estimate this association at the weekly frequency and standard errors are robust.

Table 2a shows the estimates for equation (2). To better compare estimates across markets, we standardize weekly market returns such that one unit is one standard deviation. We also standardize the dependent variable by dividing by the average profits earned in the market in the previous trading year.[11] For the equity market, where 38 percent of trading profits are earned, a one standard deviation increase in equity market returns is associated with a 5 percent decrease in trading profits. This effect is small compared to a standard deviation in weekly changes of equity market trading profits, which is 39 percent (Table 1). A one standard deviation increase in equity market returns is a 0.128 standard deviations decrease

[10] The denominator to the weekly percent change is the 1-week lagged average trading profit over the past year. This addresses the issue of trading profits being negative for some weeks and the volatility of weekly levels of trading profits.

[11] For the first week of January, the numerator would be the average of bank trading profits in the first week of January minus the average of bank trading profits in the last week of December. The denominator would be the 1-week lagged average of weekly average trading profits for the past year.

in equity trading profits. Changes in equity market returns and the risk-free rate explain 1 percent of the variation in equity trading returns. For the commodity, credit, FX, and rates markets, we find similarly small associations between market returns and trading profits. For the MBS markets, we find a small association between trading profits and market returns, but a larger sensitivity to the risk-free rate.

The risk-bearing models of financial intermediation imply that the level of profits are determined by market returns as in equation (1). However, our primary analysis uses weekly changes, rather than levels of profits. We do this because there is a positive trend to the level of bank trading profits as shown in Figure 2. From January 2020 to September 2023, bank trading profits are, on average, 50 percent larger than that of January 2014 to December 2019. As robustness, we show the association between the levels of trading profits and market returns in appendix Table B.2. The estimated effects of market returns on the level of trading profits are very similar to that of the changes estimates. For market returns, we cannot reject the null that any of the level estimates are statistically significantly different from the changes estimates.

Even though these trading desks may not on average bear market risk, they may be long market risk at times, while short at other times. This would imply that bank trading profits are volatile when market returns are volatile. To empirically test this, we estimate whether the absolute value of weekly changes in trading profits are associated with the absolute value of market returns:

$$|\Delta \text{Profits}_{t,m}| = \alpha_m + \beta_m |\text{Market Ret}_{t,m}| + \gamma_m |\Delta \text{RF Rate}_t| + \epsilon_{t,m}. \tag{3}$$

Table 2b shows the estimates for equation (3). We similarly standardize the absolute value of market returns such that one unit is one standard deviation. For the equity market, a one standard deviation increase in the magnitude of equity market returns is associated with a 6 percent increase in the absolute value of trading profits in the equity market. We find estimated associations that tend to be more positive and more significant to that of equation (2). However, the economic magnitudes continue to be small, except for the MBS and FX market. In the MBS, a one standard deviation increase in the absolute value of MBS credit spreads is associated with a 35 percent increase in the absolute value of trading profits. Similarly, for the FX market a one standard deviation increase in the absolute value of changes in the term spread is associated with a 22 percent increase in the absolute value of changes in trading profits.

We empirically test whether financial intermediaries are non-linearly exposed to market risk, in particular whether they are exposed to tail market returns. We define tail market returns as those that are in the top 10 percent largest returns (positive or negative). Table 2c shows the estimates for equation (2) conditional on a subsample of tail market returns. We find similar estimates to that of the unconditional sample, which implies that bank trading profits are unlikely to be compensation for bearing tail risk.

4.1.2 Time Varying Exposures to Risk

So far, we have shown that on average, there is an economically small association between bank trading profits and market risk. However, this is not informative about whether bank trading desks ever take large economic exposures to market risk. To evaluate this, we use estimates from the trading desks of their exposure to interest rate risk and credit spread risk. Bank trading desks report their DV01, which is the effect of a one bps shift in the yield curve on their trading profits, and their CS01, which is the effect of a one bps increase in credit spreads on their trading profits.

Figure 3a shows the sum of trading desk DV01 over our sample of banks.[12] Trading desk DV01 is on average -1.3 million, but ranges from -26 to 19 million. Therefore, a one standard deviation weekly increase in the level of interest rates (11 bps) would on average change bank trading profits by -14 million or -7.3 percent of average weekly trading profits for the Rates

[12]This sample of dealer banks excludes one of the banks, which does not report trading desk DV01 or CS01. The percents of average weekly trading profits are adjusted for this change in sample.

trading desks. This estimate is within the standard errors of the -10 percent estimate in Table 2a (Rates column).[13]

At either extreme of DV01 exposure, this is the equivalent of dealer banks being long \$29 billion or short \$21 billion in 10 year Treasuries yielding 2%. This is dwarfed by the trading assets of the dealer banks, which includes \$273 billion is Treasuries (16%) and \$181 billion in MBS (11%). Trading desks have large inventories of assets with duration risk but have little exposure to duration risk, which implies that they hedge their inventory risk.

Similarly, Figure 3b shows the sum of trading desk CS01, which is on average -4.8 million, but ranges from -18 to 9 million. Therefore, a one standard deviation weekly increase in investment grade credit spreads (5.4 bps) would on average change bank trading profits by -26 million or -10 percent of average weekly trading profits for the Credit trading desks. This estimate is larger than the -2 percent estimate in Table 2a (Credit column), but within the standard errors of the estimate. This difference may be because the investment grade credit spread is a noisier proxy of the tailored credit spread metrics that each trading desks uses when reporting their CS01 exposure. At either extreme of CS01 exposure, the effect of a standard deviation change in credit spreads range from 19 to 37 percent of the average weekly profit of the credit trading desks.

These findings suggest that the trading desks of dealer banks do not take large interest rate risk or credit risk, even during periods of financial distress when risk premia are large. Therefore, trading profits are unlikely to be compensation for time-varying exposures to risk.

4.1.3 Idiosyncratic Risk

Despite not bearing market risk or systematic tail-risk, Figure 2 shows that there is variation to bank trading profits and sometimes losses. For example, on March 8th 2022, trading profits were on average -731 million. These trading losses were primarily from the credit

[13] An increase in the level of interest rates that does not change the slope of the yield curve would be captured by an increase in the risk-free rate (RF coefficient of -10) and a zero change in the term premia (market return coefficient of 0.15).

market, where there was a one-day loss of \$1,346 million. This loss was not evenly distributed among banks, but rather entirely due to a desk from one of the five banks. This is the largest such event in the data, but there are other similar tail-events in the data.

To characterize these large trading losses, we estimate rolling standard deviations over a quarter of daily trading profits at the bank-market level. We study trading losses that are more than 5 standard deviations large (estimated with a one day lag). There are 68 such events in the data, and they span all asset markets and banks. The equity market has the fewest number of such events (5) and the MBS market has the most (22). The bank with the highest number of such events has 22 and the bank with the fewest has 8 events.

We estimate the difference in trading profits for a bank with a 5-sigma trading loss compared to other dealer banks for the 10 trading days before and after that event:

$$\text{Profit}_{i,t} = \alpha_t + \sum_{t \in -10,-9,\ldots,10} \beta_t \mathbb{1}_{\{\text{5-sigma loss bank}\}} + \epsilon_{i,t}. \tag{4}$$

We cluster standard errors by trading date. Figure 5a shows the estimated difference in trading profits. Dealer banks that experience a 5-sigma trading loss at event time 0 on average lose \$148 million of trading profits more than the other dealer banks. In fact, other dealer banks on average earn a positive trading profit of 4 million in the same market as the bank that experienced a 5-sigma trading loss. For the 10 trading days prior and afterwards, the dealer bank's trading profits is insignificantly different from that of other dealer banks. This suggests that these extreme large trading losses are idiosyncratic to the bank.

These idiosyncratic trading losses are large, and economically significant to trading-desks. On average, they wipe out 15 trading days or 3-weeks of trading profits for the dealer bank in the affected asset market. To evaluate the impact of these extreme losses on the dealer bank's market making, we estimate equation (4) for the bank's securities trading volume with customers. Figure 5b shows that there is no significant difference in customer trading volume by the dealer bank with the 5-sigma trading loss. This suggests that the dealer bank does not change its market making activities in response to the large loss. This may seem surprising, but this response may be efficient if the trading loss is idiosyncratic. Furthermore, the trading loss is on average a much smaller fraction of total trading profits of the affected dealer bank (1.6 trading days).

In sum, we have shown that bank trading desks have little exposure to market risk or systematic tail risk, even during periods of financial distress. Furthermore, the idiosyncratic risk of individual trading desks is small compared to the total trading profits of the dealer bank. This weak association between market returns and trading profits implies that bank trading desks do not earn their profits from exposure to market risk. In the next section, we explore the extent to which customer trading volume can explain variation in bank trading profits.

4.2 Exposure to Customer Trading Volume

Under toll-taking theories of financial intermediation, profits are from intermediating customer trading volume. In this subsection, we empirically characterize the extent to which customer trading volume is important for trading desk profits.

To empirically measure the association between bank trading profits and customer trading volume, we estimate by OLS:

$$\Delta\text{Profits}_{t,m} = \alpha + \beta\Delta\text{Security Volume}_{t,m} + \gamma\Delta\text{Derivative Volume}_{t,m} + \epsilon_{t,m} \qquad (5)$$

where $\Delta\text{Profits}_{t,m}$ is the weekly percent change in bank trading profits for market m and $\Delta\text{Security Volume}_{t,m}$ is the weekly change in customer trading volume in securities and $\Delta\text{Derivative Volume}_{t,m}$ is the weekly percent change in customer trading volume in derivatives for market m.

Table 3a shows the estimates for equation (5). For the equity market, a one percent increase in trading volume with customers in securities is associated with a 0.59 percent increase in trading profits in the equity market. In the equity market there is no association between derivatives volume and trading profits. For the credit market, a one percent increase in customer trading volume in securities is associated with a 0.97 percent increase in trading profits in the credit market. For the MBS, market we find a similarly positive association between customer trading volume in securities and trading profits. For the commodity and FX markets, derivatives trading volume with customers is significantly associated with trading profits. For the rates market, we find positive but insignificant associations between customer trading volume and trading profits.

The magnitudes of these estimates are economically significant because the sum of the coefficient to changes in securities volume and derivatives volume is close to one in many markets. This implies that without customer trading volume in securities or derivatives, trading profits would be near zero. For commodity, credit, FX, MBS, and rates markets, we cannot reject the null that the sum of coefficients is equal to 1. Only for the equity market, do we have a combined coefficient of 0.54, which is significantly less than 1. Furthermore, for credit, equity, and FX markets, we have an r-squared between 13 to 15 percent.

A limitation of these estimates is that we have a much shorter sample period where we observe securities and derivatives trading volume with customers: January 2021 to September 2023. However, we observe that weekly changes in securities trading volume with customers is strongly positively correlated across markets as shown by Figure 6. For the four largest markets by trading profits (equity, credit, FX, and rates) that make up 87 percent of trading profits, the average pairwise correlation of trading volume is 65 percent. Therefore, we use dealer to customer trading volume in the secondary market for corporate bonds (Credit Volume$_t$) as a proxy for customer trading demand. For our subsample, where our measures overlap, we find that the two measures are 57 percent correlated.

We estimate in a time series regression, the association between percent changes in our proxy for customer trading demand and percent changes in dealer bank trading profits:

$$\Delta\text{Profits}_t = \alpha + \beta\Delta\text{Credit Volume}_t + \epsilon_t \tag{6}$$

Table 3b shows the estimated coefficient for equation (6). A one percent increase in credit volume is associated with a 0.81 percent increase in bank trading profits. Weekly changes in credit volume is 48 percent correlated with weekly changes in bank trading profits. Figure 7 plots this relationship in the data where each point is a decile of changes in corporate bond trading volume and the average change in trading profits for this decile.

These findings imply that bank trading profits are strongly related to customer trading volume, which is evidence in favor of toll-taking theories of financial intermediation. In the following section, we empirically evaluate the second juxtaposing prediction of risk-bearing and toll-taking theories of financial intermediation: economies of scale.

4.3 The Profitability of Dealer Bank Trading Desks

In this subsection, we empirically characterize the profitability of dealer bank trading desks. For each trading desk, we measure profitability as profits per unit of risk. We consider two measures of risk: (i) the standard deviation of trading profits at the weekly frequency, and (ii) the 99% VaR. If trading profits were normally distributed, then these measures of risk would be isomorphic. However, we show in Section 4.1.3 that there are fat left tails to trading desk profits.

The standard deviation of trading profits measures the total risk of the trading desk. The ratio of average trading profits to the standard deviation of trading profits is similar to that of a Sharpe ratio, but measured for dollar profits rather than returns. The dollar trading profits are net of the cost of funding, which is greater than that of the risk-free rate.[14] We refer to this profitability measure as a Sharpe ratio.

[14] Another difference between a Sharpe ratio in returns rather than dollars is the time series variation of the size of trading profits.

Table 4a shows that dealer banks have an average annualized Sharpe ratio of 16. However, when measured for each trading-desk, the average Sharpe ratio is 3.9. This reflects how idiosyncratic risks at the desk-level are diversified at the bank-level. Much of this diversification happens across asset markets: Sharpe ratios increase by 6.6 when going from a Sharpe ratio computed as the sum of trading desks within a bank by market (9.4) to a Sharpe ratio computed from the sum of all trading desk within a bank (16). Another important component of aggregation is that larger trading desks tend to earn more per unit of risk. The profit weighted average Sharpe ratio of trading desks is 4.2 larger than that of the equal-weighted average Sharpe ratio of trading desks. Finally, the small difference between bank by market and desk weighted average Sharpe ratios imply that there are small diversification gains across desks within the same market.

The ratio of trading profits to VaR is economically relevant because bank trading desks have explicit VaR limits. Figure 8 shows the average VaR utilization across trading desks over time. On average, trading desks utilize about 25% to 40% of their VaR limits. Although VaR limits are far from binding, trading desks may prefer to have precautionary buffers because VaR limits mechanically become tighter during volatile periods. Indeed, VaR utilization reached 70% for MBS trading desks during the financial distress of capital markets in March 2020 Figure A.1. On average, desks earn trading weekly profits of \$0.88 for every dollar of VaR.

These profitability measures suggest that bank trading profits are likely to be too large to be explained by compensation for risk. However, these profitability ratios do not account for the many fixed and variable costs of operating bank trading desks. Many of these costs are difficult to estimate due to data limitations, but in the following section we measure one important variable input, which is labor.

4.3.1 Trading Profits per Trader

An important labor cost to operating a trading desk is hiring traders. For each month, we measure the number of employed traders for each bank and asset market. On average over our sample, our dealer banks in sum have about 4 thousand traders. Table 1 shows the average number of traders for each asset market. The share of traders employed in an asset market is similar to the share of profits earned in each market. Excluding the other category, the correlation between these two shares is 92 percent.[15] The top two asset markets by share of trader employment are equities (32 percent) and credit (23 percent) and these two markets are also the top two share of profits: 38 percent for equities and 18 percent for credit. Similarly, the bottom two asset markets by profit share are MBS and commodity markets, which also make up the bottom two shares of employment.

The average trading profit per trader is 0.42 million per week or 21.3 million per year. This average profit per trader omits other variable inputs that are likely positively correlated with the number of employed traders, such as information technology investments, compliance costs, and general overhead. We make progress on these difficult to measure other costs through fixed effects:

$$\text{Profit}_{i,m,t} = \alpha_{i,t} + \alpha_{m,t} + \beta \text{Number of Traders}_{i,m,t} + \epsilon_{i,m,t}$$

where $\alpha_{i,t}$ is a bank by time fixed effect, $\alpha_{m,t}$ is a market by time fixed effect and Number of Traders$_{i,m,t}$ is the number of traders employed by dealer bank i in asset market m and month t. To support comparability of the estimates with previous tables, trading profits are divided by four so as to be weekly averages for the month.

Table 5 shows that for each additional trader, the trading desk earns on average an additional \$0.25 million per week or \$13 million per year (column 5). This estimate includes bank by time and market by time fixed effects. Bank by time fixed effects capture all time

[15]We exclude the other category because it has an outsized share of employment because it includes all of the traders for which we could not classify, which is 17 percent.

varying costs that are at the bank-level, which includes bank-level information technology investments and general overhead. Market by time fixed effects captures all time varying costs that are common to an asset market, such as compliance costs. This estimate is 40 percent smaller than the unconditional average trading profit per trader, which reveals that there are likely large omitted costs that positively covary with the number of traders. Despite this, the fixed effects and the number of traders explains a large fraction of the variation (63 percent) in the weekly level of bank trading profits across asset markets. The number of traders alone explains 41 percent of the variation.

We do not interpret this estimate as a the marginal productivity of labor for trading desks. From industry estimates, the average total compensation of traders is less than 1 million, which is an order of magnitude smaller than the estimated $13 million earned per trader. This suggests that trading profits are too large to be entirely explained by labor costs associated with paying traders. This also implies that these trading profits are not scaleable: hiring an additional trader does not increase trading profits by $13 million per year. This suggests that trading desk profits are too large to be explained by labor costs and may reflect rents from customer relationships.

4.3.2 Heterogeneity in Trading Desk Profitability and Economies of Scale

In addition to trading desks being on average highly profitable, their profitability varies across dealer banks. Table 4a shows that the range of bank-level Sharpe ratios to trading profits is 4.2. Even within the same asset market, Table 4b shows that dealer banks are differentially profitable. For example, in the credit market, where the average Sharpe ratio across our dealer banks is 8.6, the range is 4.4. Averaged across markets, the range of dealer bank Sharpe ratios is 63 percent of the average Sharpe ratio.[16]

We estimate the extent to which observable characteristics can explain the cross-sectional

[16] We exclude the other category; including the other category would increase the average ratio to 83 percent.

heterogeneity in dealer bank Sharpe ratios:

$$\text{SR}_{d,i} = \alpha_i + \alpha_{sm(d)} + \alpha_{\tau(d)} + \beta\text{Volume}_{d,i} + \gamma\text{Number of Traders}_{m(d),i} + \rho\text{Profit Corr}_{d,i} + \epsilon_{d,i}$$

where $\text{SR}_{d,i}$ is the Sharpe ratio of trading desk d belonging to bank i, α_i is a bank fixed effect, $\alpha_{sm(d)}$ is a fixed-effect for the sub-market the desk operates in, $\alpha_{\tau(d)}$ is a fixed-effect for the years that the desk operated, $\text{Volume}_{d,i}$ is the log total trading volume done with customers, $\text{Number of Traders}_{m(d),i}$ is the log number of traders for the bank in the asset market for which the desk operates ($m(d)$), $\text{Profit Corr}_{d,i}$ is the correlation between desk trading profits and bank trading profits.[17] For ease of interpretation, we standardize $\text{Volume}_{d,i}$ and $\text{Number of Traders}_{m(d),i}$ such that one unit is one standard deviation.

Table 6 shows the dispersion of dealer bank Sharpe ratios estimated with increasingly granular fixed effects. Without any fixed effects (column 1), the dealer bank with the highest average Sharpe ratio has a 2.3 larger Sharpe ratio than that of the dealer bank with the lowest average Sharpe ratio.[18] Adding control variables related to trading desk size (customer trading volume), labor intensity (number of traders) and riskiness (correlation of trading desk profits with that of aggregate trading profits) does not significantly decrease the cross-sectional dispersion in dealer bank Sharpe ratios (column 2). We cumulatively add fixed effects for the dealer bank (column 2), for the years that the desk operated (column 3), for the asset market the desk operates in (column 4) and the submarket that the desk operates in (column 5). The submarket contains information about the desk's particular trading activities and the region the desk operates in.[19] For example, we are comparing investment grade credit trading desks of different banks operating in North American credit markets. At this level of granularity, the range of average trading desk Sharpe ratios across dealer banks is 1.2.

[17]We compute this correlation excluding the own desk's trading profits from that of the bank holding company to avoid any confounding effect from trading desk size, but the results are not sensitive to this exclusion because there are on average about 86 trading desks per bank.

[18]This is slightly different from that of the range of 2.6 reported in the "Bank-Market" column in Table 4a because it does not include trading desks in the "Other" category for which we do not have a good measure for the number of Traders and because the regression is equal weighted.

[19]See Appendix Section C for details about this sub-market classification.

Table 6 shows that the Sharpe ratio of trading desks is increasing in the size of the trading desk as measured by their trading volume with customers. For a trading desk that does one standard deviation more in customer trading volume, its Sharpe ratio is on average 1.05 higher (column 5). Figure 9 illustrates this positive association between the Sharpe ratio of trading desks and customer trading volume by asset market. This shows that larger trading desks are more profitable, which is evidence in favor of toll-taking theories of financial intermediation where there are economies of scale.

We control for differences in labor intensity and riskiness of dealer bank trading profits. Table 6 shows that trading desks that have a one standard deviation higher number of traders earn a 0.45 higher Sharpe ratio (column 3). With sub-market fixed effects, this association shrinks to 0.32, which is positive but insignificant. We measure the riskiness of trading desk profits as its correlation with that of total trading profits of the bank. Trading desks that have riskier profits on average earn higher Sharpe ratios. A desk whose trading profits have a correlation of one with that of the bank's trading profits earns a Sharpe ratio that is 1.6 higher than that of an trading desk with uncorrelated profits. This suggests that there is an internal capital asset pricing model: trading desks with riskier profits to the dealer bank are required to earn a higher Sharpe ratio.

Table 7 shows the estimates for profitability measured as trading profits per unit of VaR. The cross-sectional dispersion of profits to VaR is even larger than that of the difference in Sharpe ratios. In column 5, we show that after controlling for desk characteristics, the bank with the highest average profits to VaR earns \$0.48 more than that of the bank with the lowest ratio. This estimate is large compared to the unconditional average profit to VaR ratio of \$0.88. Furthermore, there is evidence of positive economies of scale: profits to VaR is significantly increasing in trading desk size. A trading desk with 1 standard deviation larger trading volume with customers earns \$0.29 more per unit of VaR. Similarly, a trading desk with a 1 standard deviation larger number of traders earns \$0.56 more per unit of VaR.

In sum, we have shown that there is substantial cross-sectional heterogeneity in the profitability of trading desks and that profitability in increasing in desk size. For trading desks operating within the same asset market and the same number of traders, larger desks that trade more with customers earn more profit per unit of risk. These findings of heterogeneity and positive economies of scale are consistent with toll-taking theories of financial intermediation and not with risk-bearing theories.

5 Concluding Discussion

We have seen that large U.S. dealer bank trading desks earn profits primarily from customer trading volume and not from exposure to market risk. Trading desks are highly profitable, and this profitability is persistently different across dealer banks, even within the same asset market and trading activity. Furthermore, trading desks exhibit economies of scale in profitability: trading desks that trade more with customers earn more profits per unit of risk. Therefore, U.S dealer banks are more similar to the toll-taking financial intermediaries of Duffie et al. (2005), rather than the specialized risk bearing intermediaries of other theories.

Understanding the nature of dealer bank financial intermediation is important for the design of market regulation. Since the Volcker Rule, large dealer banks have little exposure to market risk from their trading activities. This suggests that regulation may have been successful in decreasing the riskiness of financial intermediation. However, we show that there are large profits and positive economies to scale, which raises the concern about competition in financial intermediation. Toll-taking financial intermediation may be a natural monopoly.

These findings are not necessarily inconsistent with prior literature that documents that the wealth of the intermediary sector is a priced risk factor. Prior such literature, Adrian et al. (2014) and He et al. (2017) study quarterly samples from 1968 to 2009 and 1970 to 2012, respectively. Following the financial crisis of 2008 and the implementation of the Volcker rule in 2014, proprietary trading desk activities migrated from dealer banks to hedge funds. This has resulted in dealer bank trading desks behaving much more like volume-driven toll-takers rather than specialized bearers of market risk. Therefore, other economic agents than dealer banks are likely bearing market risk. Indeed, He and Krishnamurthy (2013) broadly define their set of financial intermediaries to also include hedge funds, mutual funds, insurance companies, and pensions. The equity of these non-dealer bank financial intermediaries may now be the relevant factor for pricing risk premia.

Of interest for future work is whether this separation of risk bearing from market making has caused risk premia to become more segmented. If non-bank intermediaries, such as hedge funds, mutual funds, insurance companies, and pensions are the primary risk bearing financial intermediaries, then their specializations may partially segment capital across asset markets. Such partial segmentation could cause risk premia to differ across markets in a manner similar to what is found for arbitrage spreads in Siriwardane et al. (2022).

References

Adrian, T., E. Etula, and T. Muir (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance 69*(6), 2557–2596. (Cited on pages 6 and 29.)

Andersen, L., D. Duffie, and Y. Song (2019). Funding value adjustments. *The Journal of Finance 74*(1), 145–192. (Cited on page 7.)

Anderson, A. G., W. Du, and B. Schlusche (2021). Arbitrage capital of global banks. *National Bureau of Economic Research*. (Cited on page 7.)

Aramonte, S., A. Schrimpf, and H. S. Shin (2023). Non-bank financial intermediaries and financial stability. *Research Handbook of Financial Markets*, 147–170. (Cited on page 8.)

Berk, J. B. and R. C. Green (2004). Mutual fund flows and performance in rational markets. *Journal of political economy 112*(6), 1269–1295. (Cited on page 2.)

Buchak, G., G. Matvos, T. Piskorski, and A. Seru (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of financial economics 130*(3), 453–483. (Cited on page 7.)

Chen, J., H. Hong, M. Huang, and J. D. Kubik (2004). Does fund size erode mutual fund performance? the role of liquidity and organization. *American Economic Review 94*(5), 1276–1302. (Cited on page 2.)

Drechsler, I., A. Savov, and P. Schnabl (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance 76*(3), 1091–1143. (Cited on page 7.)

Du, W., A. Tepper, and A. Verdelhan (2018). Deviations from covered interest rate parity. *The Journal of Finance 73*(3), 915–957. (Cited on page 7.)

Duffie, D. (2012). Market making under the proposed volcker rule. *Rock Center for Corporate Governance at Stanford University Working Paper* (106). (Cited on page 7.)

Duffie, D. (2023). Resilience redux in the us treasury market. *Jackson Hole Symposium, Federal Reserve Bank of Kansas City*. (Cited on page 3.)

Duffie, D., M. J. Fleming, F. M. Keane, C. Nelson, O. Shachar, and P. Van Tassel (2023). Dealer capacity and us treasury market functionality. *FRB of New York Staff Report* (1070). (Cited on page 7.)

Duffie, D., N. Gârleanu, and L. H. Pedersen (2005). Over-the-counter markets. *Econometrica 73*(6), 1815–1847. (Cited on pages 1, 2, 10, and 29.)

Duffie, D. and A. Krishnamurthy (2016). Passthrough efficiency in the fed's new monetary policy setting. In *Designing Resilient Monetary Policy Frameworks for the Future. Federal Reserve Bank of Kansas City, Jackson Hole Symposium*, pp. 1815–1847. (Cited on page 7.)

Falato, A., D. Iercosan, and F. Zikes (2019). Banks as regulated traders. *FEDS Working Paper No. 2019-005R1*. (Cited on page 7.)

Greenwood, R., S. G. Hanson, A. Shleifer, and J. A. Sorensen (2022). Predictable financial crises. *The Journal of Finance 77*(2), 863–921. (Cited on page 7.)

Grossman, S. J. and M. H. Miller (1988). Liquidity and market structure. *the Journal of Finance 43*(3), 617–633. (Cited on pages 1, 2, and 9.)

He, Z., B. Kelly, and A. Manela (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics 126*(1), 1–35. (Cited on pages 6 and 29.)

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *American Economic Review 103*(2), 732–70. (Cited on pages 1, 2, 8, and 30.)

Irani, R. M., R. Iyer, R. R. Meisenzahl, and J.-L. Peydro (2021). The rise of shadow banking: Evidence from capital regulation. *The Review of Financial Studies 34*(5), 2181–2235. (Cited on page 7.)

Koijen, R. S. and M. Yogo (2016). Shadow insurance. *Econometrica 84*(3), 1265–1287. (Cited on page 7.)

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of financial economics 8*(4), 323–361. (Cited on page 9.)

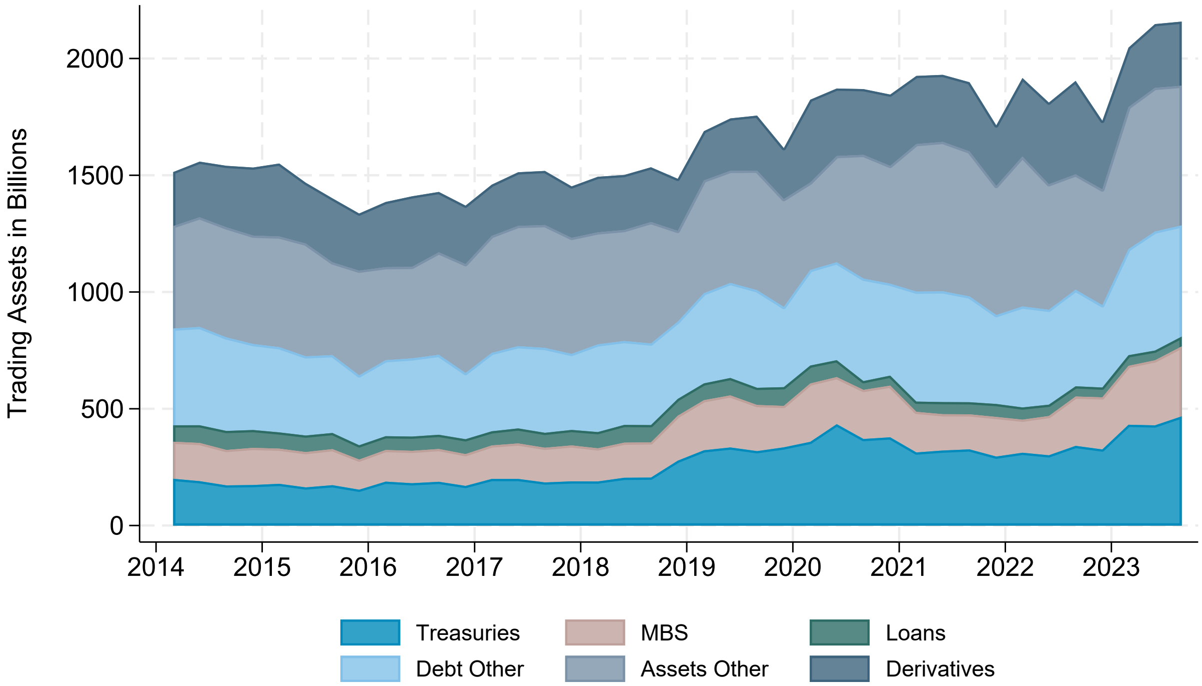
O'Hara, M. and X. A. Zhou (2021). Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis. *Journal of Financial Economics 142*(1), 46–68. (Cited on page 3.)

Siriwardane, E., A. Sunderam, and J. L. Wallen (2022). Segmented arbitrage. *National Bureau of Economic Research*. (Cited on pages 7 and 30.)

Sunderam, A. (2015). Money creation and the shadow banking system. *The Review of Financial Studies 28*(4), 939–977. (Cited on page 8.)

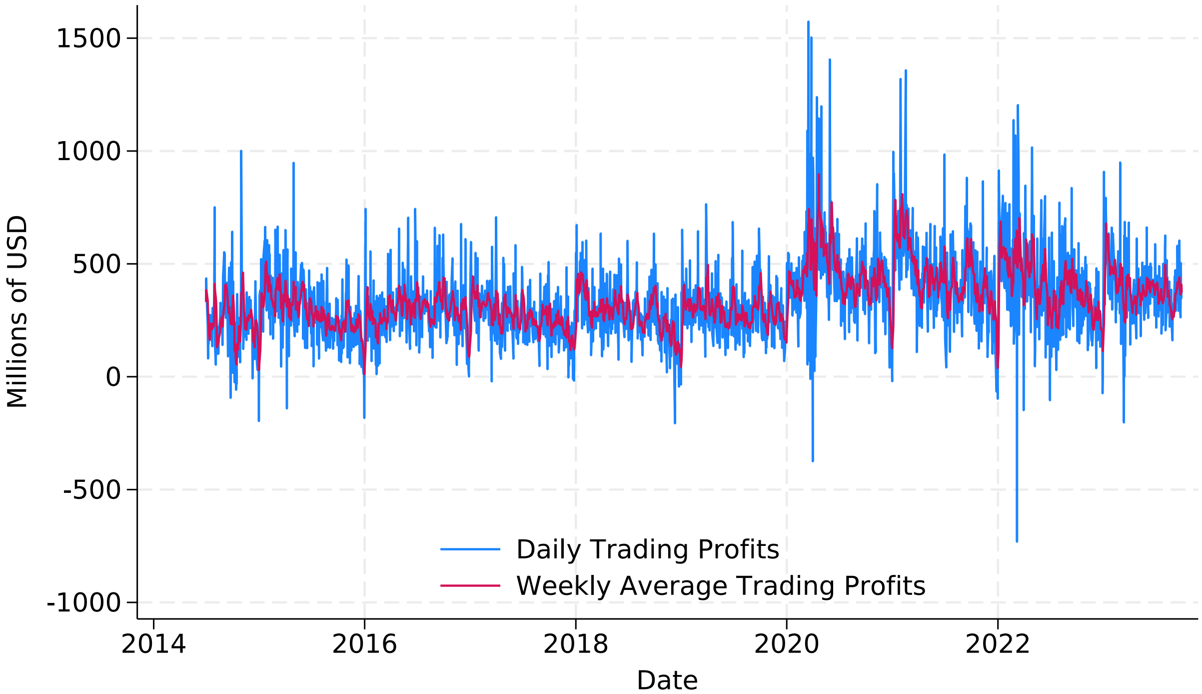
Wang, C. (2016). Core-periphery trading networks. *Available at SSRN 2747117*. (Cited on pages 2 and 10.)

Figure 1: Time Series of Bank Trading Assets



Notes : Figure 1 shows the sum of trading assets for our sample of US banks at the quarterly frequency from 2014Q2 to 2023Q3 by asset type. The asset types include Treasuries (16%), MBS (11%), loans (4%), other debt (23%), other assets (30%), and derivatives (16%). Treasuries are primarily Treasury securities (90%), but also include agencies and munis. MBS includes residential and commercial mortgage backed securities. Loans include commercial, industrial, real estate, and household loans. Other debt includes structured products, asset backed securities and other debt securities. Derivatives are not the notional exposure of derivatives, but rather the positive mark to market value of derivative positions. Other assets is a residual category for all other trading assets. For more details see Schedule HC-D of FR Y9-C.

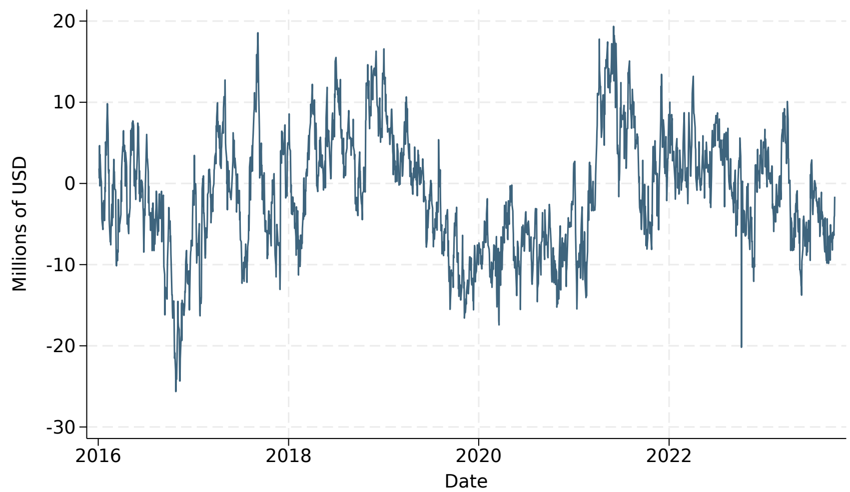
Figure 2: Time Series of Bank Trading Profits



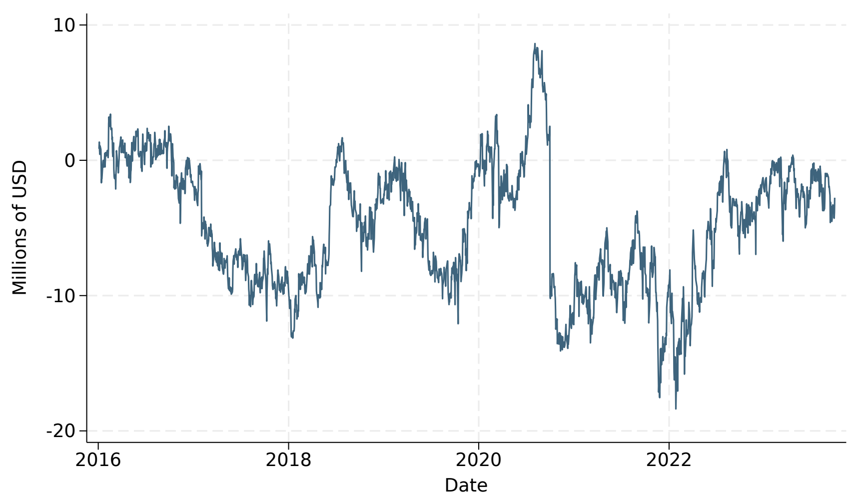
Notes : Figure 2 shows the sum of daily trading profits for our sample of US banks at the daily frequency and weekly frequency. From July 2014 to Dec 2019, profits were on average 283 million per day and from Jan 2020 to Sept 2023, profits were on average 429 million per day.

Figure 3: Exposure to Credit Spreads and Interest Rates

(a) Interest Rate Exposure

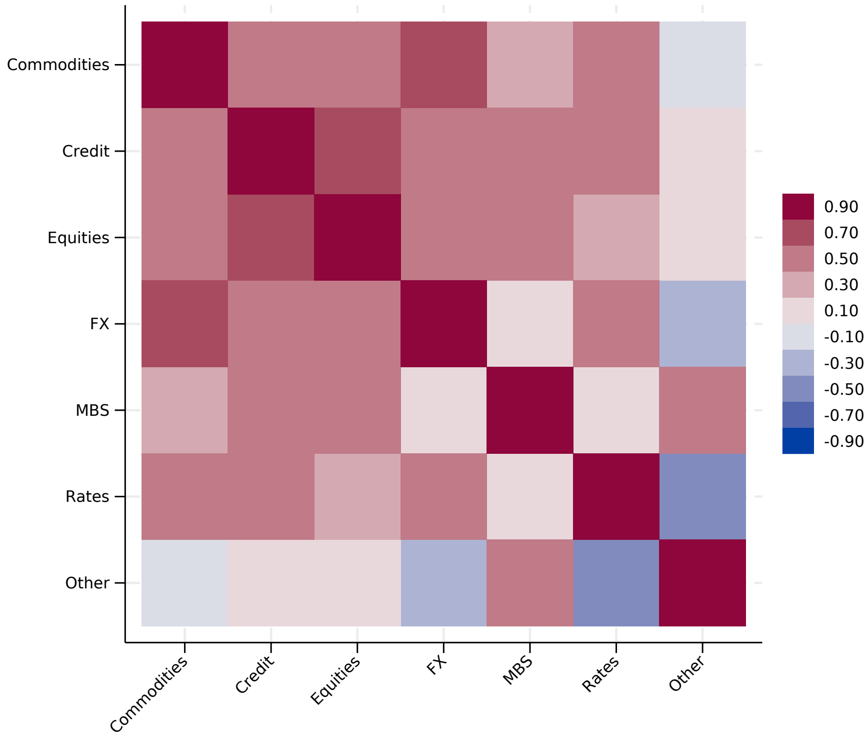


(b) Credit Spread Exposure



Notes : Figure 3a shows the sum of bank trading desk profit sensitivity to a basis point increase in the yield curve or the DV01 of the sample of banks. Figure 3b shows the sum of bank trading desk profit sensitivity to a basis point increase in credit spreads or the CS01 of the sample of banks. The sample is at the daily frequency and spans from January 2016 to September 2023.

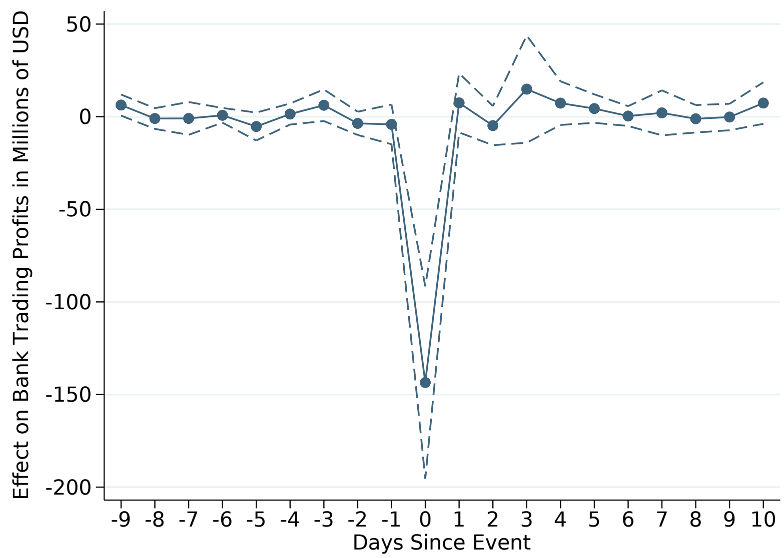
Figure 4: Cross Market Correlation of Trading Profits



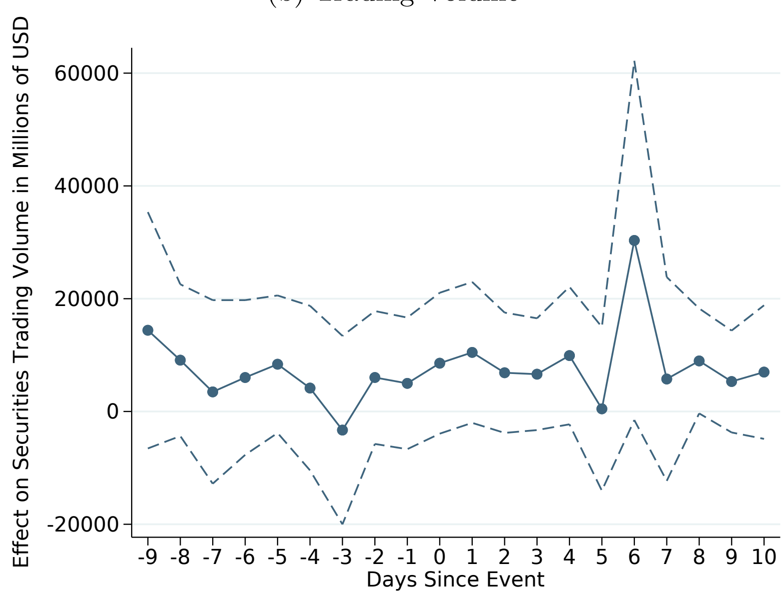
Notes : Figure 4 shows the cross-market correlation of bank trading profits at the weekly frequency. We measure weekly bank trading profits as the sum of trading profits over a week and across our sample of 5 banks. We measure this for each of our 5 asset markets (and the residual other category). We have weekly data from January 2014 to September 2023 and the markets include the follow asset classes: commodities, credit, equity, foreign exchange, MBS, and rates. See Section C for a description of how trading desks are grouped by asset class. The pair of markets where bank trading profits are the highest are the commodity and FX markets with a correlation of 71 percent.

Figure 5: Trading Profits and Volume Conditional on Large Losses

(a) Trading Profits

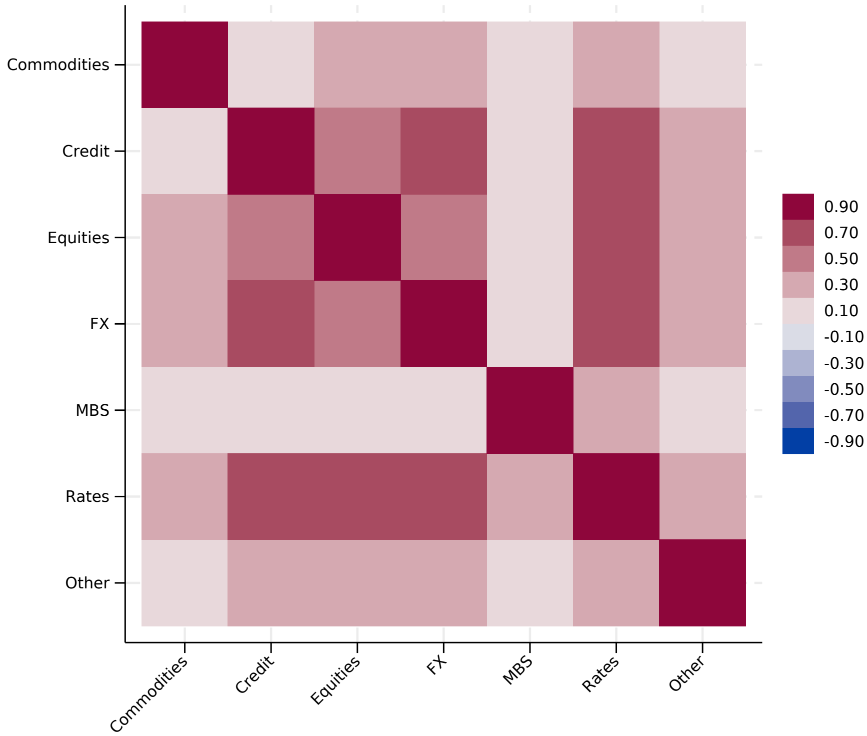


(b) Trading Volume



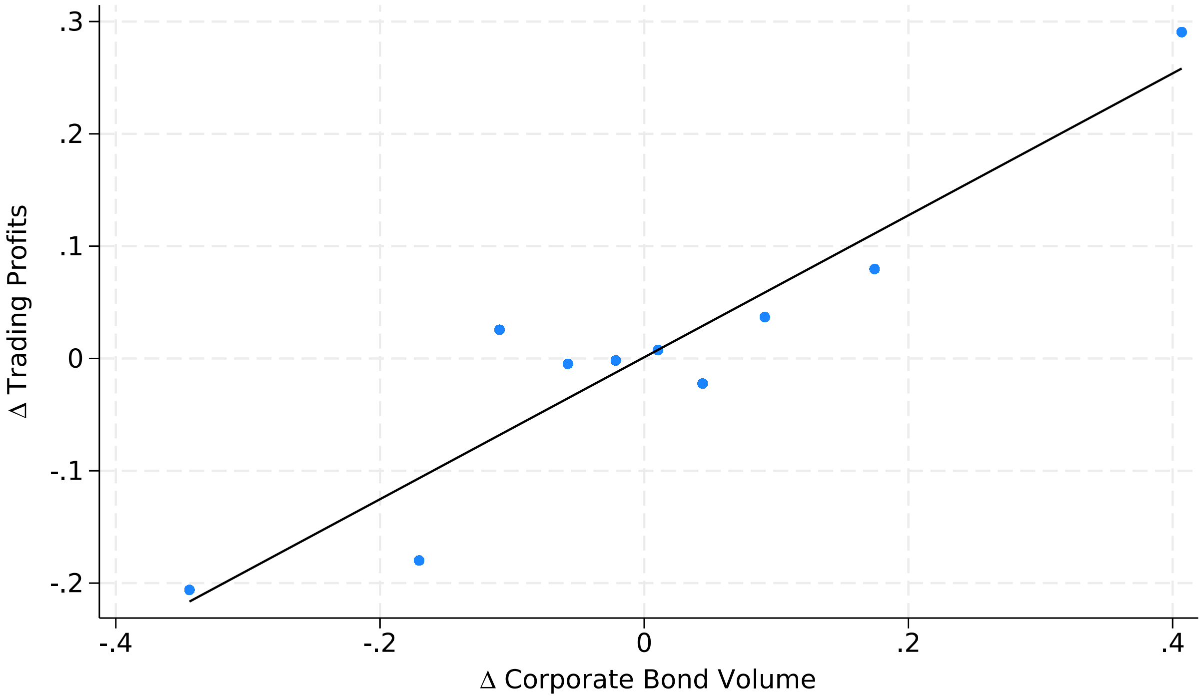
Notes : Figure 5a shows the effect of a 5-sigma trading profit loss on a bank's trading profits in a market compared to that of other bank's trading profits in the same market. Figure 5b shows the effect of a 5-sigma trading profit loss on a bank's trading volume in a market compared to that of other bank's trading volume in the same market.

Figure 6: Cross Market Correlation of Bank Trading Volume with Customers



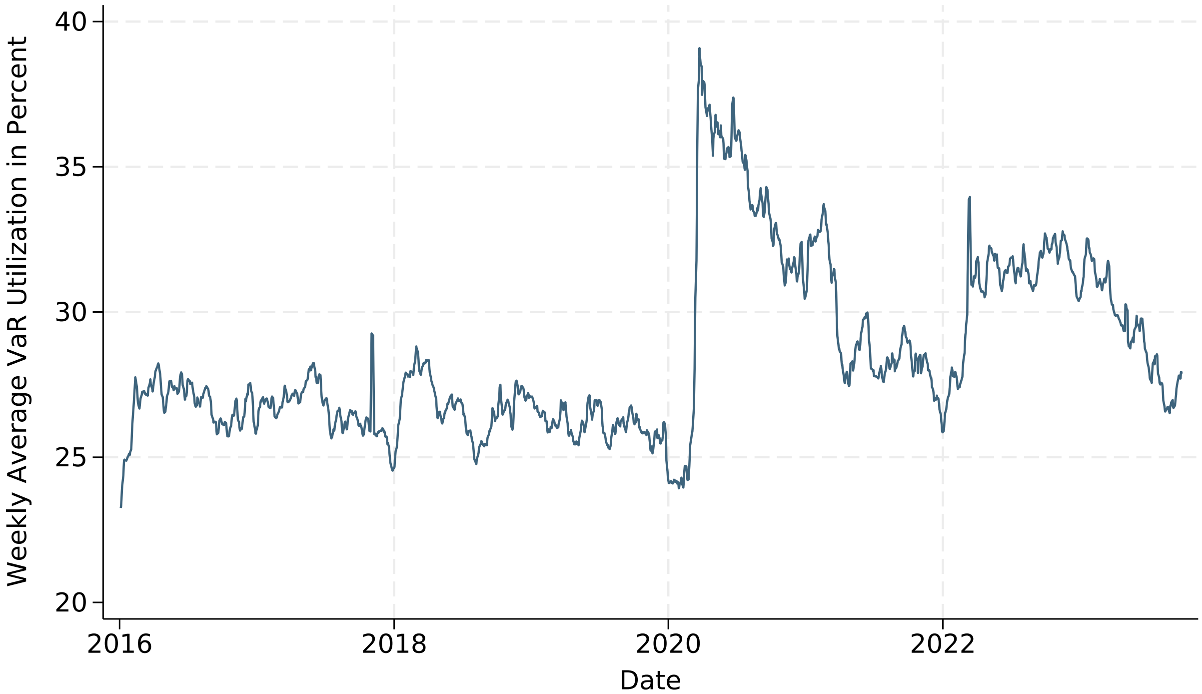
Notes : Figure 6 shows the cross-market correlation of changes in bank trading volume with customers at the weekly frequency. We measure weekly volume as the sum of the market value of securities transactions with customers over a week and across our sample of 5 banks. We measure this for each of our 5 asset markets (and the residual other category). We have weekly data from January 2021 to September 2023 and the markets include the follow asset classes: commodities, credit, equity, foreign exchange, MBS, and rates. See Appendix C for a description of how trading desks are grouped by asset class. The pair of markets with the largest correlation is rates and credit markets with a correlation in volume of 78 percent.

Figure 7: Trading Profits and Volume



Notes : Figure 7 shows the association between weekly changes in bank trading profits and weekly changes in secondary market dollar trading volume in corporate bonds. Each point is a decile of weekly changes in corporate bond volume and the average change in trading profits for this decile.

Figure 8: Average VaR Limit Utilization



Notes : Figure 8 shows average VaR utilization (usage divided by limits) across trading desk over the sample from January 1st 2016 to September 30th 2023.

Figure 9: Sharpe Ratios and Customer Trading Volume

Notes : Figure 9 shows the association between trading desk Sharpe ratios and customer trading volume. Each unit of observation is the average Sharpe ratio and customer trading volume of a cluster of trading desks within the same asset market, where they are grouped into by decile of customer trading volume. Trading desk Sharpe ratios are measured as the average trading profits of the desk divided by the standard deviation of trading profits. Customer trading volume is the log notional dollars traded with customers (derivatives and securities).

Table 1: Summary Statistics

	Cmdty	Credit	Eq	FX	MBS	Rates	Oth
Profit Mean	94.03	300.67	628.65	226.10	90.83	277.10	33.49
Profit SD	100.89	156.82	253.99	110.81	99.79	192.69	56.28
Δ Profit SD	1.34	0.61	0.39	0.58	1.45	0.75	2.66
HHI	0.23	0.23	0.23	0.26	0.23	0.25	0.42
Top Share	0.31	0.30	0.28	0.36	0.31	0.32	0.45
Profit Weight	0.05	0.18	0.38	0.14	0.06	0.17	0.02
Range of Profit Weight	0.04	0.11	0.29	0.18	0.03	0.17	0.07
Traders Mean	247.83	932.64	1308.32	381.54	78.36	385.89	702.89
Traders Weight	0.06	0.23	0.32	0.10	0.02	0.09	0.17
Range of Traders Weight	0.01	0.09	0.11	0.04	0.02	0.05	0.05
VaR	126	778	242	182	250	307	114
VaR Limit Usage	0.34	0.25	0.25	0.30	0.36	0.35	0.25
Rho within Mkt	0.18	0.11	0.37	0.25	0.21	0.30	0.03
Rho within Bank	0.13	0.28	0.22	0.15	0.17	0.20	0.14

Notes: Table 1 shows summary statistics by market for the sum of bank trading profits. The sample includes 5 US banks and spans from January 2014 to September 2023. Profit Mean is the average weekly trading profit in millions. Profit SD is the standard deviation of weekly trading profit. Δ Profit SD is the standard deviation of weekly changes to trading profit divided by the last year's average trading profit. HHI is the Herfindahl-Hirschman Index for bank trading profits measured at the annual frequency and averaged over the years of our sample. Top share is the average market share of the greatest market share across banks measured at the annual frequency and averaged over the years of our sample. Profit Weight is the average across banks of their share of profits in the market. Range of Profit weight is the difference between the bank with the highest and lowest profit weight in the market. Traders Mean is the average number of traders employed by our sample of 5 banks for each market. Traders Weight is the average across banks of their share of traders for each market. Range of Traders Weight weight is the difference between the bank with the highest and lowest Traders weight in the market. VaR is the 99th percentile value at risk. VaR limit usage is the average fraction of the VaR limit utilized by trading desks. Rho within Mkt is the average pairwise correlation of weekly changes to bank trading profits within a market. Rho within Bank is the average correlation of bank i's weekly changes to trading profits in market j with the weekly changes in the total of bank i's trading profits (excluding the profits in market j).

Table 2: Weekly Changes in Trading Profits and Market Returns

(a) Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rate
Mkt Return	0.03	-0.02	-0.05*	0.08***	0.11	0.15**
	(0.07)	(0.05)	(0.02)	(0.03)	(0.12)	(0.06)
Δ RF Rate	-0.05	-0.02	0.02	-0.02	0.36***	-0.10*
	(0.05)	(0.03)	(0.01)	(0.02)	(0.07)	(0.06)
Adjusted R^2	-0.00	-0.00	0.01	0.01	0.07	0.03
N	481	481	481	481	481	481

(b) Absolute Value of Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rate
|Mkt Return|	0.11	0.08***	0.06*	0.09***	0.35***	0.22***
	(0.09)	(0.02)	(0.03)	(0.03)	(0.12)	(0.06)
|Δ RF Rate|	0.00	0.01	-0.02	-0.02	0.16**	-0.02
	(0.03)	(0.02)	(0.01)	(0.01)	(0.07)	(0.03)
Adjusted R^2	0.00	0.04	0.02	0.02	0.09	0.06
N	481	481	481	481	481	481

(c) Tail Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rate
Mkt Return	0.08	-0.05	-0.10***	0.15***	0.19	0.07
	(0.09)	(0.05)	(0.03)	(0.05)	(0.18)	(0.14)
Δ RF Rate	-0.26*	-0.04	-0.01	-0.05	0.14	-0.06
	(0.15)	(0.05)	(0.03)	(0.05)	(0.22)	(0.13)
Adjusted R^2	0.04	-0.00	0.22	0.16	0.01	-0.03
N	48	48	48	48	48	48

Notes: Table 2a shows the association between weekly changes in bank trading profits and the market return for each of the markets and changes in the risk-free rate. The market return is specific to each of the markets (by column) and described in Section 3.1. Table 2b shows the same association for the absolute value of weekly changes. Table 2c shows the same association for the tail market returns (10% largest changes in market returns). Standard errors are robust.

Table 3: Weekly Changes in Trading Profits and Volume

(a) By Market

	Δ Profits					
	Cmdty	Credit	Equity	FX	MBS	Rates
Δ Securities Volume	0.047	0.973***	0.585***	-0.165	0.772*	0.491
	(0.164)	(0.285)	(0.163)	(0.209)	(0.424)	(0.392)
Δ Derivatives Volume	0.943*	0.373	-0.050	1.439***	0.061	0.215
	(0.561)	(0.265)	(0.071)	(0.415)	(0.134)	(0.376)
Adjusted R^2	0.02	0.14	0.15	0.13	0.02	0.01
N	142	142	142	142	142	142

(b) Aggregate

	Δ Profits		Δ Sec Vol	Δ Der Vol
	(1)	(2)	(3)	(4)
Δ Credit Volume	0.809***		0.321***	0.355***
	(0.107)		(0.044)	(0.089)
Δ Securities Volume		0.656**		
		(0.288)		
Δ Derivatives Volume		0.311		
		(0.212)		
Adjusted R^2	0.24	0.13	0.32	0.16
N	481	142	142	142

Notes: Table 3a shows the association between weekly percent changes in bank trading profits and weekly percent changes in trading volume with customers by asset market. We have two measures of customer trading volume: (i) securities trading volume and (ii) derivatives trading volume. For these volume measures, we have a shorter sample from January 2021 to September 2023. We extend the sample of our analysis using a proxy for bank trading volume with customers: trading volume in the secondary bond market. In weekly changes, secondary bond market volume is strongly correlated with bank securities trading with customers (57 percent) and bank derivatives trading with customers (41 percent) for their overlapping sample. Table 3b shows the association between weekly changes in bank trading profits and secondary bond market volume volume. Standard errors are robust.

Table 4: Sharpe Ratios Summary Statistics

(a) By Level of Aggregation

	Bank	Bank-Market	Desk Weighted	Desk
Mean	15.94	9.37	8.08	3.89
Range	4.47	2.60	3.89	2.09

(b) By Market

	Cmdty	Credit	Equity	FX	MBS	Rates	Oth
Mean	4.40	8.58	14.85	9.88	4.98	7.43	2.81
Range	3.03	4.40	5.26	12.26	4.40	0.79	5.77

Notes: Table 4a shows the mean ratio of the dollar Sharpe ratio at the bank level, size weighted market and desk level, and the equal weighted desk level, as well as the range of the dollar Sharpe ratio computed as the difference between the maximum and the minimum of it. Table 4b shows the mean ratio of average annualized trading profits divided by the standard deviation of trading profits (dollar Sharpe ratio) at the bank level and bank by market level of aggregation, as well as the range of it computed as the difference between the maximum and the minimum of it.

Table 5: Trading Profits per Trader

	Weekly Trading Profits				
	(1)	(2)	(3)	(4)	(5)
Number of Traders	0.375***	0.341***	0.281***	0.248**	0.250**
	(0.057)	(0.055)	(0.054)	(0.076)	(0.076)
Bank FE	N	Y	Y	Y	Y
Market FE	N	Y	Y	Y	Y
Time FE	N	N	Y	Y	Y
Market × Time FE	N	N	N	Y	Y
Bank × Time FE	N	N	N	N	Y
Adjusted R^2	0.41	0.53	0.61	0.67	0.63
N	3,330	3,330	3,330	3,330	3,330

Notes: Table 5 shows the association between trading profits and number of traders, where each observation is bank by asset market at the monthly frequency from January 2014 to September 2023. One additional trader is associated with a 0.25 million dollar increase in weekly trading profits or 13 million dollars per year (column 5). Standard errors are clustered by time and by market.

Table 6: Bank Trading Desk Sharpe Ratios

	Sharpe Ratio				
	(1)	(2)	(3)	(4)	(5)
Range of Bank FE	2.341***	2.082***	2.162***	2.292***	1.171***
	(0.558)	(0.413)	(0.423)	(0.430)	(0.411)
Customer Trading Vol		1.735***	1.671***	1.625***	1.052***
		(0.160)	(0.162)	(0.167)	(0.229)
Number of Traders		0.480***	0.454***	-0.058	0.322
		(0.147)	(0.150)	(0.526)	(0.521)
Profit Corr		1.720***	1.678***	1.493**	1.565***
		(0.599)	(0.570)	(0.565)	(0.520)
Bank FE	N	Y	Y	Y	Y
Sample FE	N	N	Y	Y	Y
Market FE	N	N	N	Y	Y
Submarket FE	N	N	N	N	Y
Adjusted R^2	0.05	0.34	0.35	0.37	0.49
N	556	546	546	546	542

Notes: Table 6 shows the cross-sectional differences in trading desk Sharpe ratios across banks, while controlling for trading desk characteristics. Across all specifications, the range of bank fixed effects is economically large and statistically significant. Customer trading volume and the number of traders are standardized such that 1 unit is a standard deviation of their natural log. Column 2 shows that a 1 standard deviation increase in the customer trading volume (number of traders) of a trading desk is associated with a 1.74 (0.48) increase in its Sharpe ratio. Profit Corr is the correlation of the trading desk's profit to that of the bank holding company. Increasing a trading desk's correlation from 0 to 1 with that of the bank holding company's trading profits is associated with an increase in the desk's Sharpe ratio of 1.72. Columns 2 to 5 have progressively more granular fixed effects. Standard errors are clustered by submarket.

Table 7: Bank Trading Desk Profit-VaR Ratio

	Profit-VaR Ratio				
	(1)	(2)	(3)	(4)	(5)
Diff Bank FE	0.611**	0.629**	0.702***	0.768***	0.482**
	(0.258)	(0.246)	(0.233)	(0.255)	(0.198)
Customer Trading Vol		0.351***	0.290***	0.226**	0.291**
		(0.081)	(0.092)	(0.095)	(0.121)
Number of Traders		0.259***	0.256***	0.188	0.556***
		(0.073)	(0.070)	(0.324)	(0.184)
Profit Corr		0.358	0.417	0.330	0.441*
		(0.283)	(0.274)	(0.270)	(0.238)
Bank FE	N	Y	Y	Y	Y
Sample FE	N	N	Y	Y	Y
Market FE	N	N	N	Y	Y
Submarket FE	N	N	N	N	Y
Adjusted R^2	0.03	0.14	0.15	0.18	0.58
N	415	405	405	405	399

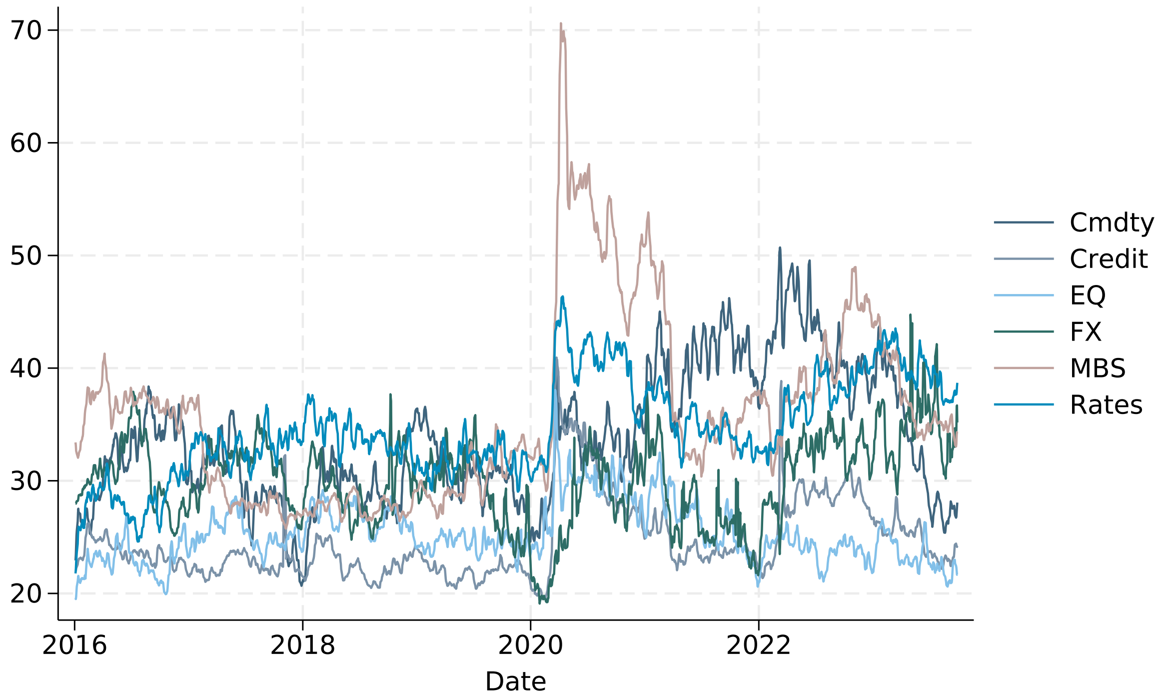
Notes: Table 7 shows the cross-sectional differences in trading desk profit-VaR ratios across banks, while controlling for trading desk characteristics. Across all specifications, the range of bank fixed effects is economically large and statistically significant (the average profit-VaR ratio is 0.88). Customer trading volume and the number of traders are standardized such that 1 unit is a standard deviation of their natural log. Column 2 shows that a 1 standard deviation increase in the customer trading volume (number of traders) of a trading desk is associated with a 0.35 (0.26) increase in its profit-VaR ratio. Profit Corr is the correlation of the trading desk's profit to that of the bank holding company. Increasing a trading desk's correlation from 0 to 1 with that of the bank holding company's trading profits is associated with an increase in the desk's profit-VaR ratio of 0.36. Columns 2 to 5 have progressively more granular fixed effects. Standard errors are clustered by submarket.

Online Appendix: Not For Publication

This appendix includes several sections of supplemental information. Appendices A and B present additional figures and tables, respectively, Appendix C contains definitions of all the variables used in the paper.

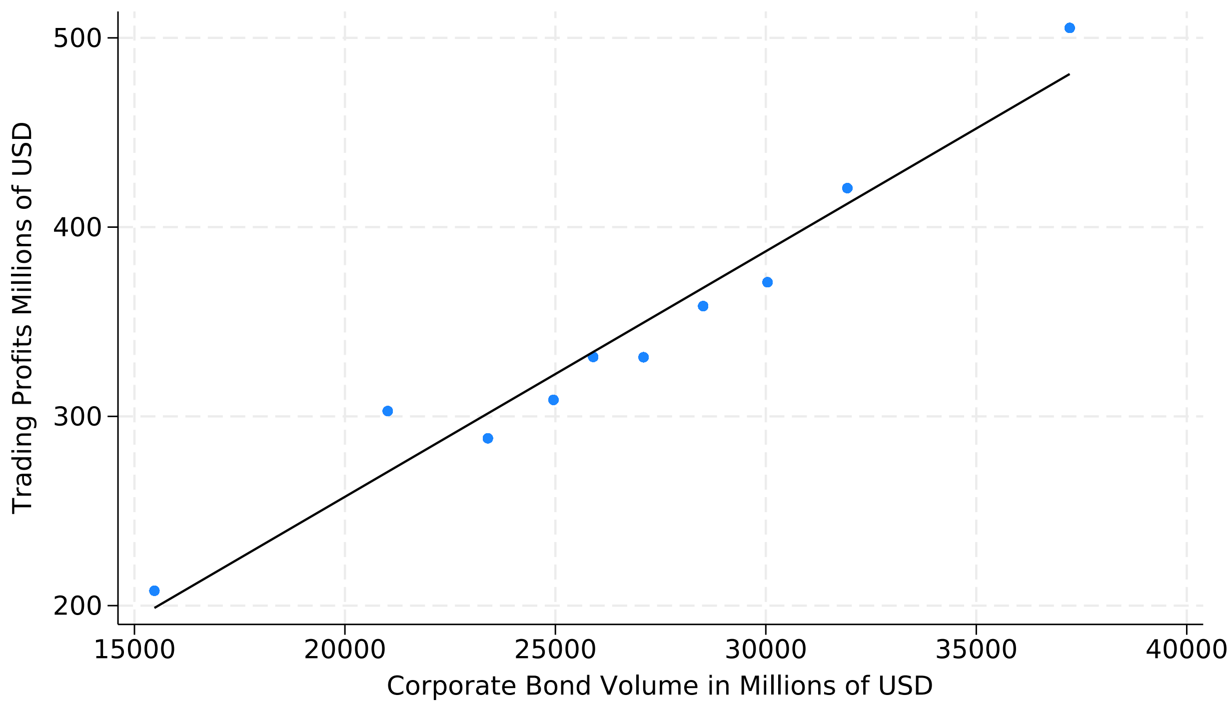
A Appendix Figures

Figure A.1: VaR Utilization by Market over Time



Notes : Figure A.1 shows the average VaR utilization across trading desks by asset market over time.

Figure A.2: Trading Profits and Volume in Levels



Notes : Figure A.2 shows the association between the weekly average level of bank trading profits and secondary market dollar trading volume in corporate bonds. Each point is a decile of average levels of corporate bond volume and the average level of trading profits for this decile.

B Appendix Tables

Table B.1: Weekly Levels of Bank Trading Profits by Desk and Market Returns

Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
Market Ret	0.17	0.00	-0.05*	0.08**	0.18	0.09*
	(0.11)	(0.04)	(0.03)	(0.03)	(0.13)	(0.05)
RF Rate	0.04	-0.05***	-0.03**	0.04***	-0.08**	0.01
	(0.03)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)
Adjusted R^2	0.02	0.02	0.02	0.03	0.03	0.01
N	481	481	481	481	481	481

Absolute Value of Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
|Market Ret|	0.53***	0.09*	0.10**	0.20***	-0.07	0.15*
	(0.16)	(0.04)	(0.04)	(0.05)	(0.22)	(0.08)
RF Rate	0.05	-0.05***	-0.03**	0.04***	-0.07*	0.00
	(0.03)	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)
Adjusted R^2	0.09	0.04	0.03	0.07	0.01	0.02
N	481	481	481	481	481	481

Tail Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
Market Ret	0.16	-0.01	-0.07**	0.17***	0.23	0.01
	(0.19)	(0.04)	(0.04)	(0.04)	(0.20)	(0.09)
RF Rate	-0.03	0.14**	-0.05	0.20***	-0.35***	-0.07
	(0.13)	(0.06)	(0.04)	(0.06)	(0.10)	(0.11)
Adjusted R^2	-0.00	0.06	0.13	0.27	0.09	-0.03
N	48	48	48	48	48	48

Notes: Table 2 shows similar tables to that Table B.1 but for levels of trading profits by market.

Table B.2: Weekly Changes to Aggregate Bank Trading Profits and Market Returns

Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
Δ Market Ret	0.06*	0.01	0.02	0.08**	-0.01	0.03
	(0.03)	(0.08)	(0.04)	(0.04)	(0.05)	(0.04)
Δ RF Rate	0.01	0.01	0.01	-0.00	0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Adjusted R^2	0.01	-0.00	-0.00	0.01	-0.00	-0.00
N	481	481	481	481	481	481

Absolute Value of Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
|Δ Market Ret|	0.04	0.15***	0.12***	0.08*	0.14**	0.10**
	(0.03)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)
|Δ RF Rate|	0.00	-0.03	-0.02	-0.00	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adjusted R^2	-0.00	0.07	0.03	0.01	0.04	0.01
N	481	481	481	481	481	481

Tail Market Returns

	Cmdty	Credit	Equity	FX	MBS	Rates
Δ Market Ret	0.04	-0.00	-0.02	0.12**	-0.03	-0.02
	(0.05)	(0.09)	(0.06)	(0.05)	(0.08)	(0.08)
Δ RF Rate	-0.01	0.01	-0.04	-0.06	0.08	0.05
	(0.08)	(0.05)	(0.06)	(0.04)	(0.09)	(0.07)
Adjusted R^2	-0.02	-0.04	-0.04	0.08	-0.03	-0.03
N	48	48	48	48	48	48

Notes: Table B.2 shows similar tables to that Table 2 but for weekly changes in total bank trading profits.

C Classification of Trading Desks

For our sample of 5 banks, we have trading desks that have names and descriptions.

We group the trading desks into the following asset markets: commodities, foreign exchange, mortgage-backed securities, credit, equities, rates, and other. Within each asset market, we form sub-groups of trading desks. For each of the sub-groups, we list criteria in decreasing specificity and each trading desk belongs only to one sub-group. The final sub-group is a residual category called "Trading" that includes all trading desks that do not belong to a more specific sub-group.

For trading desks that describe activities in multiple asset markets, we choose the primary asset market. The primary asset market is the asset market best reflected in the name of the trading desk. If no asset market is in the name of the trading desk, then we use the first market described in the description.

For trading desks without any asset market referenced in their name, we use information in the description to identify the asset market. We use the same criteria applied to the name for the description.

For trading desks with "legacy", "winding down", "unwind", "runoff", "Heritage" or "worthless" in their name or description, we classify these in the other asset market with the subcategory of "legacy".

For the criteria, we use but do not explicitly list all the various spellings or abbreviations of the phrase. For example, a criterion for being a trading desk in the commodity market is having "commodity" in the name, which includes "commodities" and "commod".

Subgroups that are geographically specialized include North America (NA), Europe Middle East and Africa (EMEA), Asia Pacific (APAC), and Latin America (LATAM). We form subgroups by geography if at least 2 banks report trading desks with geographic specialization.

- NA includes geographic references to North America, Canada, and United States.
- EMEA includes geographic references to Europe, Middle East, and Africa.

- APAC includes geographic references to Asia and the Pacific.
- LATAM includes geographic references to Latin America.

Criteria for each trading desk: I classify each trading desk and subgroup iteratively in the order that they are listed below:

The commodities trading desks include those that have "commodity" in their name or list a specific commodity, such as "Gas", "Metals", and "Oil" in their name. Within the commodity asset market, we have the following sub-groups and identifying phrases:

- Hedging – In the name of the trading desk, there is "CVA" (credit valuation adjustment), "XVA" (X value adjustment), "Funding", "Management", "RMH" (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.
- EMEA Gas – In the name of the trading desk, there is "Gas" and there is a geographic reference to EMEA.
- NA Gas - In the name of the trading desk, there is "Gas" and there is a geographic reference to NA.
- Gas – In the name of the trading desk, there is "Gas".
- Metals – In the name of the trading desk, there is "Metals"
- Oil – In the name of the trading desk, there is "Oil"
- Trading – The residual category which broadly encompasses market making activities for this asset category.

The FX trading desks include those that have "currency" or "Foreign Exchange" (FX) in their name. Within the FX asset market, we have the following sub-groups and identifying phrases:

- Hedging– In the name of the trading desk, there is “CVA” (credit valuation adjustment), “XVA” (X value adjustment), “Funding”, “Management”, “RMH” (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.
- APAC FX - In the name or the description of the trading desk, there is a geographic reference to APAC.
- EMEA FX – In the name or the description of the trading desk, there is a geographic reference to EMEA.
- LATAM FX – In the name or the description of the trading desk, there is a geographic reference to LATAM.
- NA FX – In the name or the description of the trading desk, there is a geographic reference to NA.
- Prime Brokerage – In the name of the trading desk, there is “Prime Brokerage”.
- Options – In the name of the trading desk, there is “Options” and not “Spot”.
- Spot – In the name of the trading desk, there is “Spot” and not “Options”.
- Trading – The residual category which broadly encompasses market making activities for this asset category.

The MBS trading desks include those that have “mortgage”, “MBS” (mortgage-backed security), “Agency”, “CRE” (commercial real estate), “residential”, in their name. Within the MBS asset market, we have the following sub-groups and identifying phrases:

- Hedging– In the name of the trading desk, there is “CVA” (credit valuation adjustment), “XVA” (X value adjustment), “Funding”, “Management”, “RMH” (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.

- Agency RMBS Underwriting – In the name of the trading desk, there is “Agency”, (“RMBS” or “residential”) and one of the following terms in the name or description of the trading desk “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”. If both agency and non-agency RMBS are underwritten by the trading desk or it does not specify, classify it as agency because the agency market is much larger.

- Agency RMBS – In the name of the trading desk, there is “Agency” and (“RMBS” or “residential”). If both agency and non-agency RMBS are traded by the trading desk or it does not specify, classify it as agency because the agency market is much larger.

- Non-Agency RMBS Underwriting – In the name of the trading desk, there is “Non-Agency”, (“RMBS” or “residential”), and one of the following terms in the name or description of the trading desk “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- Non-Agency RMBS – In the name of the trading desk, there is “Non-Agency” and (“RMBS” or “residential”).

- Agency CMBS Underwriting – In the name of the trading desk, there is “Agency”, (“CMBS” or “commercial”) and one of the following terms in the name or description of the trading desk “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”. If both agency and non-agency CMBS are underwritten by the trading desk or it does not specify, classify it as agency because the agency market is much larger.

- Agency CMBS – In the name of the trading desk, there is “Agency” and (“CMBS” or “commercial”). If both agency and non-agency RMBS are traded by the trading desk or it does not specify, classify it as agency because the agency market is much larger.

- Non-Agency CMBS Underwriting – In the name of the trading desk, there is “Non-

Agency”, (“CMBS” or “commercial”), and one of the following terms in the name or description of the trading desk “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- Non-Agency CMBS – In the name of the trading desk, there is “Non-Agency” and (“CMBS” or “commercial”).

- Underwriting- In the name or description of the trading desk, there is “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- Non-Agency Trading - The residual category which broadly encompasses market making activities for this asset category with the term “Non-Agency”, “ABS”, “CLO”, “CDO”

- Trading - The residual category which broadly encompasses market making activities for this asset category.

The Rates trading desks include those that have “Rates”, “Gov”, “Inflation, “Treasury”, “IRP” (Interest Rate Products), or “Liquid Products” in their name. Within the rates asset market, we have the following sub-groups and identifying phrases:

- Hedging - In the name of the trading desk, there is “CVA” (credit valuation adjustment), “XVA” (X value adjustment), “Funding”, “Management”, “RMH” (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.

- APAC Non-Linear – In the name or the description of the trading desk, there is (“Non-linear” or “Structured”) and there is a geographic reference to APAC.

- EMEA Non-Linear – In the name or the description of the trading desk, there is (“Non-linear” or “Structured”) and there is a geographic reference to EMEA.

- LATAM Non-Linear – In the name or the description of the trading desk, there is (“Non-linear” or “Structured”) and there is a geographic reference to LATAM.

- NA Non-Linear – In the name or the description of the trading desk, there is ("Non-linear" or "Structured") and there is a geographic reference to NA.

- Non-Linear- In the name or the description of the trading desk, there is "Non-linear" or "Structured".

- APAC Rates – In the name or the description of the trading desk, there is a geographic reference to APAC.

- EMEA Rates – In the name or the description of the trading desk, there is a geographic reference to EMEA.

- LATAM Rates – In the name or the description of the trading desk, there is a geographic reference to LATAM. 13. NA Rates – In the name or the description of the trading desk, there is a geographic reference to NA.

- Trading- The residual category which broadly encompasses market making activities for this asset category.

The Credit trading desks include those that have "Credit", "Yield", "HY, "Investment Grade" (IG), "Debt", "CDS", "Bonds", "Notes", "Fixed Income", "Loans", "Syndicate", "ABS", "CLO", "Money Market", or "Convertible" in their name. Within the credit asset market, we have the following sub-groups and identifying phrases:

- Hedging - In the name of the trading desk, there is "CVA" (credit valuation adjustment), "XVA" (X value adjustment), "Funding", "Management", "RMH" (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.

- Short-term Underwriting- In the name of the trading desk, there is ("short term", "PF" (public finance), or "money markets") and one of the following terms "Origination", "Primary", "Syndicate", "Underwriting", "Securitization", or "Warehouse".

- Short-term - In the name or description of the trading desk, there is “short term” “PF” (public finance), or “money markets”.
- High Yield Underwriting - In the name or description of the trading desk, there is “High Yield” or “Not Investment Grade” (NIG) and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.
- High Yield APAC - In the name or description of the trading desk, there is “High Yield” or “Not Investment Grade” (NIG) and a geographic reference to APAC.
- High Yield EMEA - In the name or description of the trading desk, there is “High Yield” or “Not Investment Grade” (NIG) and a geographic reference to EMEA.
- High Yield NA - In the name or description of the trading desk, there is “High Yield” or “Not Investment Grade” (NIG) and a geographic reference to NA.
- High Yield - In the name or description of the trading desk, there is “High Yield” or “Not Investment Grade” (NIG).
- Distressed - In the name or description of the trading desk, there is “Distressed”.
- Investment Grade Underwriting- In the name or description of the trading desk, there is “Investment Grade” and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.
- Investment Grade APAC - In the name or description of the trading desk, there is “Investment Grade” and a geographic reference to APAC.
- Investment Grade EMEA - In the name or description of the trading desk, there is “Investment Grade” and a geographic reference to EMEA.
- Investment Grade NA - In the name or description of the trading desk, there is “Investment Grade” and a geographic reference to NA.

- Investment Grade - In the name or description of the trading desk, there is “Investment Grade”.
- APAC Credit – In the name or description of the trading desk, there is a geographic reference to APAC.
- EMEA Credit – In the name or description of the trading desk, there is a geographic reference to EMEA.
- LATM Credit – In the name or description of the trading desk, there is a geographic reference to LATAM.
- NA Credit – In the name or description of the trading desk, there is a geographic reference to NA.
- Structured Credit- In the name of the trading desk, there is “Structured”.
- CDS - In the name or description of the trading desk, there is “CDS”.
- ABS - In the name or description of the trading desk, there is “ABS” or “ABF”.
- CLO - In the name or description of the trading desk, there is “CLO”.
- Funding- In the name or description of the trading desk, there is “Funding” or “Financing”.
- Underwriting – In the name or description of the trading desk, there is “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.
- Trading- The residual category which broadly encompasses market making activities for this asset category.

The Equity trading desks include those that have “Equity”, “ECM” (Equity Capital Market), “EDG” (Equity Derivatives Group), “ADR” in their name. Within the equity asset market, we have the following sub-groups and identifying phrases:

- Hedging - In the name of the trading desk, there is “CVA” (credit valuation adjustment), “XVA” (X value adjustment), “Funding”, “Management”, “RMH” (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.

- APAC Underwriting – In the name or description of the trading desk, there is a geographic reference to APAC and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- EMEA Underwriting – In the name or description of the trading desk, there is a geographic reference to EMEA and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- LATM Underwriting – In the name or description of the trading desk, there is a geographic reference to LATAM and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- NA Underwriting – In the name or description of the trading desk, there is a geographic reference to NA and one of the following terms “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- Underwriting – In the name or description of the trading desk, there is “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.

- Derivatives APAC - In the name or description of the trading desk, there is (“Derivatives” or “Options”) and a geographic reference to APAC.

- Derivatives EMEA - In the name or description of the trading desk, there is (“Derivatives” or “Options”) and a geographic reference to EMEA.

- Derivatives NA - In the name or description of the trading desk, there is (“Derivatives” or “Options”) and a geographic reference to NA.

- Derivatives - In the name or description of the trading desk, there is “Derivatives” or “Options”.

- Prime Brokerage – In the name or description of the trading desk, there is “Prime Brokerage”.

- APAC Equity – In the name or description of the trading desk, there is a geographic reference to APAC.

- EMEA Equity – In the name or description of the trading desk, there is a geographic reference to EMEA.

- LATM Equity – In the name or description of the trading desk, there is a geographic reference to LATAM.

- NA Equity– In the name or description of the trading desk, there is a geographic reference to NA.

- Trading – The residual category which broadly encompasses market making activities for this asset category.

The Other trading desks are the residual trading desks that could not be classified into any of the above asset markets. Within the other asset market, we have the following sub-groups and identifying phrases:

- Legacy– In the name or description of the trading desk, there is “legacy”, “winding down”, “runoff”, or “worthless”.

- Hedging - In the name of the trading desk, there is “CVA” (credit valuation adjustment), “XVA” (X value adjustment), “Funding”, “Management”, “RMH” (risk-mitigating-hedging) or in the description, the emphasis is on hedging and risk management but not market making.

- Derivatives– In the name or description of the trading desk, there is “Derivatives”.
- Underwriting - In the name or description of the trading desk, there is “Origination”, “Primary”, “Syndicate”, “Underwriting”, “Securitization”, or “Warehouse”.
- Funding– In the name or description of the trading desk, there is “Funding” or “Collateral”.

There are a small number of manually assigned desks that do not fit the pattern mentioned above, and we describe them in an internal federal reserve document.

D Classification of Traders from their LinkedIn Profiles

For our sample of 5 banks, we have the LinkedIn profile information of their employees from Revelio Labs. We start with all of the LinkedIn users that has ever listed one of the 5 banks as an employer. We identify traders as LinkedIn users that have the word “trader” or “trading” in one of their employment positions with one of our 5 banks.

We restrict our sample to match that of our data on bank trading desks. The employment position needs to have an end date after January 2014. We restrict to employment locations of the United States or United Kingdom, where nearly all of the traders of the large U.S. dealer banks work. Finally, we also exclude very short term employment that lasts for 3-months or less, which excludes summer internship programs. We further exclude employment positions that are related to support staff, temporary work, commercial banking, wealth management, and relationship management.

With these filters, we have 10,350 LinkedIn users and we classify each of their trading jobs at our 5 banks by asset market. **The commodities trading jobs** are those that have the following in their title:

- "agriculture", " ag ", "bulks", "bullion", "commod", "corn", "crude", "distillate", "dry bulk", "energy", "gas", "metal", "natural", "oil", "power", "softs", "soybeans", "steel", "wheat".

The credit trading jobs are those that have the following in their title:

- “abs”, “bond”, “cdo”, “cds”, “clo”, “corporate”, “credit”, “distressed”, “ficc”, "fixed income", "hy ", "ig ", "investment grade", “junk”, “loan”, “securitized”, “senior”, “structured”, “yield”

The equity trading jobs are those that have the following in their title:

- "algo", "delta", "electronic trading", "equities", "equity", "etf", "funds", "mutual", "prime", "shares", "single name", "stock"

The FX trading jobs are those that have the following in their title:

- "currenc", "emerging", "foreign exchange", "forex", "fx", "g10", "macro", "xccy"

The MBS trading jobs are those that have the following in their title:

- “mbs”, “mortgage”, “cmo”

The rates trading jobs are those that have the following in their title:

- “agency”, “egb”, “inflation”, “interest rate”, “ir " , “irp”, “irs”, “money”, “rates”, “repo”, “swap”, “treasu”,

Conditional on not being able to classify a trader by title, we classify traders by their description using the same methodology as above. Finally, for traders that have the phrase "sales and trading" in their title and no other classification information, we classify these as equity traders. For all other unclassified traders, we attribute them to the other category.