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Impact of the Volcker Rule on the Trading Revenue of Largest U.S. Trading Firms During the COVID-19 Crisis Period

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Abstract

Using a novel data collection, we examine the impact of the Volcker Rule on trading revenue of the 21 largest U.S. trading firms during the 100 day stress period centered on the COVID-19 financial crisis. We find that despite the market volatility, trading profits were consistent with volume-driven fees, commissions, and widening of the bid-ask spread. This work adds to the growing body of evidence that a consequence of the Volcker Rule on firm revenue associated with trading is increased financial stability and decreased risk exposure to market shocks.

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1 Introduction

In the aftermath of the 2007-2009 global financial crisis (GFC), the United States Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act . The legislation clarifies and amends rules surrounding the implementation of section 13 of the 1956 Bank Holding Company Act¹. In particular, section 619 of the Dodd-Frank act, colloquially known as the Volcker Rule, prohibits firms from engaging in proprietary trading of securities, derivatives, commodity futures, and options of those instruments. The regulation was designed to increase the stability of the financial system by mitigating the potential risks posed by depository institutions who might otherwise take large proprietary positions.

The 2020 financial crisis resulting from the worldwide outbreak of the COVID-19 novel coronavirus provided the first opportunity to investigate the impacts of post-GFC reforms on the financial system under an actual stress scenario. Several recent works have done so. Duncan et al. (2022) asses the bank regulatory framework using the COVID-19 crisis as a real-world stress test, emphasizing the role of capital and liquidity requirements. Abboud et al. (2021) describe the actions regulators took to exempt backtesting exceptions from increasing market risk capital requirements and potentially avoiding procyclical regulatory impacts during the crisis period.

Falato, Iercosan, and Zikes (2021) provide evidence that U.S. banks with large trading exposures to market risk took measures to curtail it following the implementation of the Volcker Rule. Abboud et al. (2021), and Duncan et al. (2022) show that transaction volume (in dollar terms) increased during the COVID crisis, leading to increased trading profits. These works both provide evidence that the trading profits were driven by market making activities rather than (or despite) gains or losses driven by directional movement against trading positions.

In this short note we seek to provide additional evidence that the Volcker Rule has had the effect of mitigating systemic risk to the banking system by ensuring that

 $^{^1124}$ Stat. 1376 - Dodd-Frank Wall Street Reform and Consumer Protection Act

trading firms are realizing profits via market making activities rather than engaging in proprietary trading. To do this, we examine a novel collection of trading data provided by 21 of the largest trading firms in the world. The H1 2020 data spans approximately 100 trading days surrounding the crisis period. Using several statistical methodologies, we directly compare reported Actual and Hypothetical P&L of these entities.

We find that despite a significant increase in market volatility, firms' trading books continued to not only make regular profit during the crisis period, but actually became more profitable. Our analysis provides additional evidence that firm trading profitability is consistent with fees, commissions, and the widening of the bid-ask spread associated with market making activities.

2 Background

We examine daily market and firm trading activity during 1H 2020, with a particular focus on March 2020, the height of the crisis period. Figure 1 displays the normalized 1-day change in SPX and VIX for the period in question, according to $\phi(x) = \frac{x-\mu}{\sigma}$.

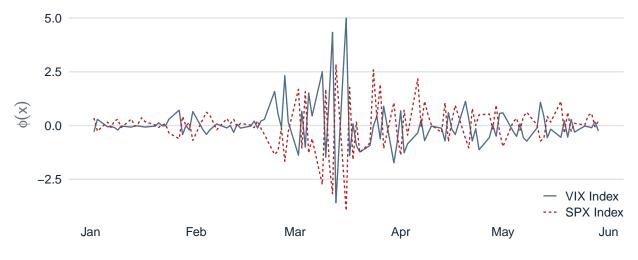


Figure 1: Normalized $\Delta S\&P$ and ΔVIX Indices

Both market condition measures highlight the significant elevation in volatility during the crisis period.

In addition to elevated volatility, increased trading volume both during and immedi-

ately following the crisis period was observed. We examine the total normalized volume and mean normalized spread of the constituents of the S&P 500 single name stocks, given by $vol_{tot,t} = \frac{\sum vol_{i,t}}{max(vol_{tot})}$ and $spread_t = \frac{\sum (ask_{t,i} - bid_{t,i})/price_{t,i}}{n}$ for *n* firms. Figure 2 displays the resulting time-series.

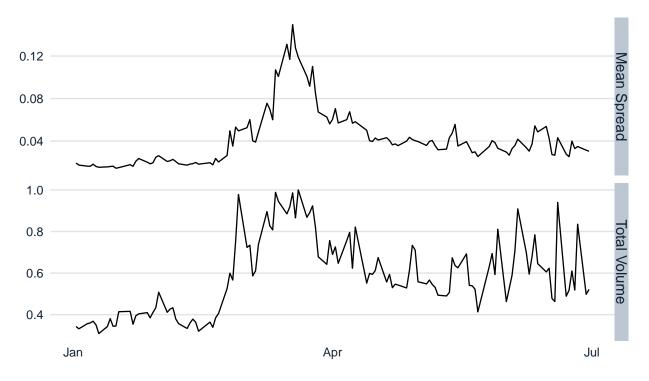


Figure 2: Normlized S&P 500 Spread and Volume

The mean normalized bid-ask spread in stock price across the S&P 500 constituents peaks dramatically during the crisis period before quickly returning to levels slightly elevated relative to the pre-crisis period. This is consistent with the ΔVIX and ΔSPX indices presented in figure 1. Total trading volume peaks dramatically directly prior to the highest normalized spread, then remains consistently high throughout the crisis period. Total trading volume peaks directly prior to the highest normalized spread, then remains consistently high throughout the crisis period. Total volume remains elevated with increased variability directly after the crisis period

As part of regulatory filings related to the Volcker data collection², each firm subject

²Firms subject to the Volcker rule reporting requirements are a subset of the firms subject to the Market Risk Rule. While this data set is therefore slightly different than the set that is the general focus of this paper, we considered it to be generally illustrative of trading firm behavior.

to the reporting requirement provides, among other measures, 30-, 60-, and 90-day trailing sums of customer and non-customer facing transactions. Figure 3 presents the normalized mean of the trailing 30-day sum of customer-facing transactions³ across firms subject to the rule. This data mirrors the publicly available total trading volume of S&P 500 stocks as shown in figure 2

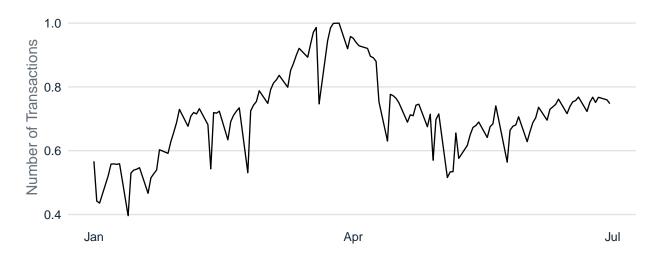


Figure 3: Mean Customer Transactions Among Volcker Firms, Trailing 30 Day Sum

3 Data

We examine daily P&L and VaR from the trading book of 21 of the largest trading firms in the world from January 2020 through June 2020. Trading book P&L data was provided by each firm, aggregated at the Bank Holding Company (BHC) level, to include all covered trading positions under the Basel III standards⁴. Definitions of Hypothetical P&L and Actual P&L are given below. For confidentiality reasons, all charts and figures presented in this paper are aggregated according to globally systemic banks (GSIBs) and non-GSIBs⁵. In general, these aggregations accurately capture the

³Market making related activities are defined in 12 CFR § 248.4(b)(2). Definitions of client, customers, and counterparties are given in 12 CFR § 248.4(b)(3). Together, these definitions show that increases in customer-facing transactions as a response to increases in near-term reasonably expected demands are indicative of increased market making activity, permitted under the Volcker rule.

⁴Section 205, part C

 $^{^{5}}$ We consider GSIBs to be the 10 largest trading firms by trading assets and liabilities during the time period of this study. Non-GSIBs are the remaining large trading firms within our sample, subject to the

dynamics observed at the individual firm level.

Hypothetical P&L

Profit and Loss due to the change in the value of covered trading positions that would have occurred if the end-of-previous day covered trading positions remained unchanged.

Actual P&L

Profit and Loss due to daily trading activity for covered trading positions including intraday trading, net interest income, time effects, fees, commissions, and the bid-ask spread.

Figure 4 displays aggregated daily Actual P&L minus Hypothetical P&L, by firm group. For confidentiality purposes, and to facilitate direct comparison, the resulting P&L difference is scaled by σ_i for each firm group, *i*. The data shown is then the standardized aggregated profit and loss due to intraday trading, net interest income, time effects, fees, commissions, and the bid-ask spread from market making activity.

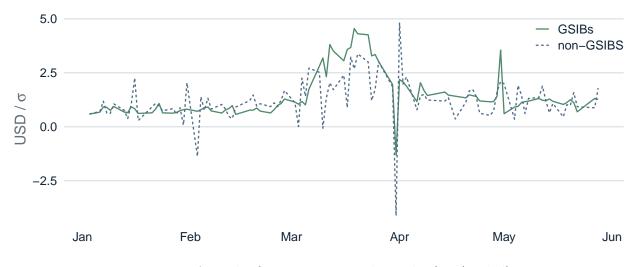


Figure 4: Actual P&L minus Hypothetical P&L (scaled)

As can be seen, profit for both GSIBs and non-GSIBs mirrors increases in trading volume as shown in Figures 2 and 3.

Market Risk Rule

4 Methodologies

Our primary focus is to understand how reported Hypothetical P&L relates to reported Actual P&L, with an emphasis on how these metrics conform to the Volcker Rule. Broadly speaking, all MRR firms must comply with some of the Volcker rule requirements such as prohibition of proprietary trading; however, only the firms which have the largest trading activity must report Volcker metrics.

We expect the Hypothetical P&L of each firm's Trading Book to be approximately risk-neutral. Hypothetical P&L is expected to be driven purely by changes to underlying risk factors related to trading positions. Actual P&L is driven by Hypothetical P&L and the net interest income, time effects, fees, commissions, the bid-ask spread, and intraday trading to facilitate bank clients' trading needs. We utilize the various methodologies presented in this section to examine the consistency of these expectations.

As previously noted, regulatory data is aggregated to ensure the confidentiality of each individual firm. Where relevant, firm group data for i firms in each firm group is aggregated according to:

$$P\&L_{tot,t} = \sum P\&L_{i,t} \tag{1}$$

$$VaR_{tot,t} = \sqrt{\sum \sum \sigma_{i,t}^2 + \sigma_{j,t}^2 + \rho_{ij}\sigma_i\sigma_j} \quad for \quad i \neq j$$
⁽²⁾

Where,

 $\sigma_{i,t} = |VaR_{i,t}|$ and,

 ρ_{ij} is the static pearson correlation of $P\&L_{ij}$

4.1 Correlation Between Hypothetical and Actual P&L

Because Hypothetical P&L is expected to be Actual P&L with fees and commissions removed, a high correlation between the two series is expected. Fees and commissions scale with volume and market conditions, in addition to a number of other idiosyncratic factors. As a result, perfect correlation is not expected, particularly across volatile periods marked by widely fluctuating market demands.

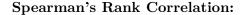
We estimate correlation three ways:

Pearson Correlation:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 (y_i - \bar{y})^2}}$$

Kendall Rank Correlation:

$$\tau = \frac{2}{n(n-1)} \sum_{i < j} sgn(x_i - x_j) sgn(y_i - y_j)$$



$$\rho = 1 - \frac{cov(R(X), R(Y))}{\sigma_{R(X)}\sigma_{R(Y)}}$$

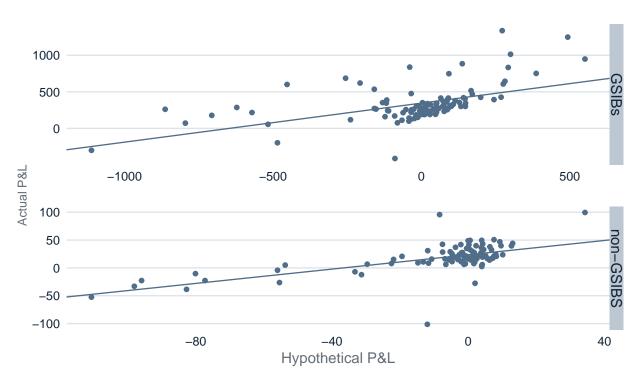


Figure 5: Actual vs Hypothetical P&L (USD Millions)

Figure 5 displays a scatter plot of Actual P&L versus Hypothetical P&L. Table 1 displays the correlation measures between the two P&L types. The correlations are positive, as expected. Variance in the volatility over the observation period and increased customer demand drive differences in fees and commissions collected for market making activities. The result of these daily fluctuations cause the correlations to deviate from 1.

| | pearson | kendall | spearman |
|-----------|---------|---------|----------|
| GSIBs | 0.53 | 0.45 | 0.57 |
| non-GSIBS | 0.63 | 0.38 | 0.53 |

Table 1: P&L Correlation

While the correlation between Actual and Hypothetical P&L is similar across groups, figure 5 highlights the difference in profitability across firm groups. Throughout the crisis period, the aggregated GSIB Trading Book lost money on only 3 trading days. The aggregated non-GSIB Trading Book Actual P&L values show a number of losses over the same period.

The discrepancy in the number of days with aggregated losses can be explained by differences in the volume of market making activity between GSIB and non-GSIB firms. Market making activities of the GSIBs increased sufficiently enough to offset any losses from incidental positions that were taken. While non-GSIBs did see increases in trading volume relative to their baseline, it was not always sufficient to offset large losses.

4.2 Moments

A profitable trading book will have an Actual P&L mean that is significantly shifted to the right of the corresponding Hypothetical P&L mean (which should itself be approximately zero). Fluctuations in market volume and volatility may cause slight changes in the standard deviation, skew, and kurtosis; however, these moments should be relatively similar between the two reported P&L measures.

| | Actual P&L | | | Hypothetical P&L | | | | |
|----------------------------|------------|----------|----------|------------------|--------|----------|----------|-----------|
| | μ | σ | γ | β_2 | μ | σ | γ | β_2 |
| GSIBs | 336.13 | 65387.76 | 1.18 | 6.85 | -17.46 | 63653.06 | -1.73 | 7.77 |
| $\operatorname{non-GSIBS}$ | 18.06 | 649.58 | -0.93 | 8.70 | -8.50 | 632.65 | -2.43 | 8.70 |

Table 2: Moments of P&L Distributions

Table 2 compares the moments of the Actual and Hypothetical P&L distributions across firm groups. It is expected that a well hedged portfolio will be market neutral and therefore have a mean Hypothetical P&L of zero. Perfectly hedged portfolios are theoretical constructs. It is therefore expected that firms will have some exposure to market risk factor movement, even within the strictest regulatory environment.

Because the observation window centers around the COVID-19 crisis period, some average loss is expected. Importantly, μ_{GSIBs} is on the order of approximately 0, relative to the magnitude of the daily trading P&L of the largest firms in the world. Equally as important, Actual P&L mean values are positive across firm groups, even during the height of the crisis. In particular, GSIB firms continued to earn an average daily profit of \$336 Million despite the volatile market conditions.

As can be seen, the second moment of the distribution for both Actual and Hypothetical P&Ls across firm groups are approximately equal. The slight increase in variance in Actual versus Hypothetical P&L can be explained by increases in fees, commissions, bid-ask spreads, and customer-facilitated transactions associated with variable trading volume over the observed 100 day trading period.

The skew of the GSIB Actual P&L distribution further suggests that the period of increased volume during the crisis led to increased profits. This contrasts with the Hypothetical P&L, which suggests that the heavy tails are relative to the realized losses in the trading positions themselves. The slight leftward shift in the non-GSIB Actual P&L is unexpected. The relatively large single day loss at the end of March is the likely driver of this behavior.

The relatively high values of $\beta 2$ across all P&L types are expected, as the observed

heavy tails are stylized facts of crisis periods.

4.3 Kernel Density Estimation

The probability density function (PDF) of aggregated Actual and Hypothetical P&L series are estimated using a standard kernel density estimator (KDE):

$$\hat{f}_x(x_0) = \frac{1}{N\lambda} \sum_{i=1}^{N} K_\lambda(x_0, x_1)$$
(3)

The probability densities are then compared directly to understand the daily probability estimate of P&L. It is expected that for a well-hedged trading book, the PDF of Hypothetical P&L will be symmetric about mean 0. The corresponding Actual P&L pdf for a profitable trading book should display a right-ward shift with a similar overall shape.

This behavior is indicative of profits due to fees and commissions rather than speculative positions commonly associated with proprietary trading and increased risk. Drastic shifts in the overall shape of the PDF may be indications that the firm is taking on additional balance sheet items not driven by customer-facing transactions.

It should be noted that while the shape is expected to be similar, some deviations are reasonable, particularly across a time period punctuated by large fluctuations in trading volume.

Figure 6 compares KDEs of Hypothetical P&L and Actual P&L aggregated by firm group. In general, Actual P&L PDF estimates display the expected rightward shift from the associated Hypothetical P&L estimates. The shapes for each group are approximately the same. Actual P&L density estimates display a slightly larger approximate standard deviation, with lower density estimates about the mean. This is driven by the variance in fees and commissions collected during the period of changing volatility and volume. No appreciable deviations are apparent that would suggest risk associated with large-scale proprietary trading among firms.

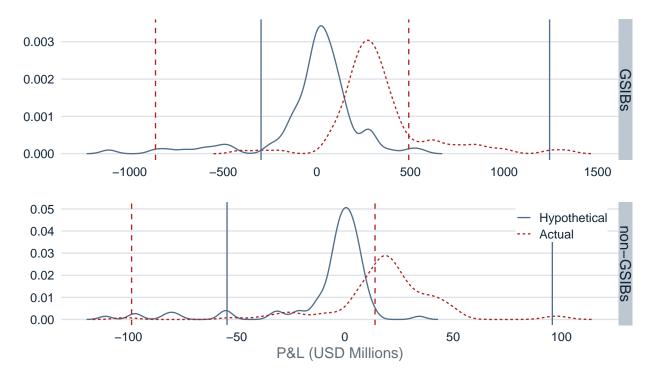


Figure 6: Comparison of Kernel Density Estimates

4.4 Regressing VaR on P&L

Value-at-Risk (VaR) is estimated one day ahead at the $\alpha = 0.01$ threshold at the BHC level for each firm subject to the Market Risk Rule. Firms estimate VaR_{99} subject to models approved by the Federal Reserve Board of Governors, consistent with the rule.

Here we regress $|VaR_{99}|$ on |P&L|:

 $|P\&L| = \alpha + \beta VaR_{99}$

In the case of a well-balanced portfolio, the slope of the regression on Hypothetical P&L is expected to be positive, with an intercept close to zero. Slight positive deviations should be driven by the risk-free rate of return. A negative slope is indicative of poor model performance, poor pricing, or some combination of both.

This regression extends the concept discussed under kernel density estimation to the relationship between VaR and P&L. A similar regression of VaR against the Actual P&L is expected to result in a positive slope with a positive y-intercept due to the inclusion of fees and commissions.

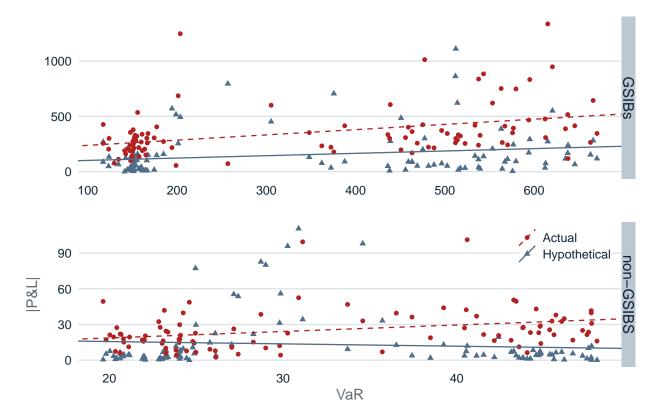


Figure 7: Regression of VaR on P&L (USD Millions)

| | Actual P&L | | | | Hypothetical P&L | | | |
|----------|------------|------------|---------|-------------|------------------|------------|---------|-------------|
| | Estimate | Std. Error | t value | $\Pr(> t)$ | Estimate | Std. Error | t value | $\Pr(> t)$ |
| GSI | Bs | | | | | | | |
| α | 190.50 | 42.76 | 4.46 | 0.0000 | 79.87 | 39.67 | 2.01 | 0.0467 |
| β | 0.47 | 0.11 | 4.38 | 0.0000 | 0.21 | 0.10 | 2.13 | 0.0355 |
| non- | GSIBs | | | | | | | |
| α | 7.84 | 5.90 | 1.33 | 0.1873 | 19.59 | 7.87 | 2.49 | 0.0146 |
| β | 0.54 | 0.17 | 3.13 | 0.0024 | -0.20 | 0.23 | -0.84 | 0.4029 |

 Table 3: Regression Coefficients

 Table 4: Regression Fit

| | Act | tual P&L | Hypothetical P&L | | |
|-----------|--------|-------------------------|------------------|-------------------------|--|
| | R^2 | Adjusted \mathbb{R}^2 | R^2 | Adjusted \mathbb{R}^2 | |
| GSIBs | 0.1595 | 0.1512 | 0.0430 | 0.0336 | |
| non-GSIBs | 0.0932 | 0.0837 | 0.0074 | -0.0031 | |

Figure 7 compares the regression of VaR_{99} on Hypothetical and Actual P&L. The associated regression parameters are given in table 3, with the model fit parameters given in table 4. For both firm groups, the slope of the regression is positive and statistically significant for Actual P&L.

Behavior of the slope for Hypothetical P&L varies across the firm groups, though the regression line is always below the corresponding Actual P&L regression. The discrepancy in expected behavior ($\beta_{Hyp} = 0$) for non-GSIB Hypothetical P&L is not statistically significant.

5 Conclusion

During the height of the COVID-19 financial crisis, trading volume and volatility were significantly elevated. Evidence for this can be seen in the increases in volume and normalized bid-ask spread in the equities market, as well as by significant increases in customer facing transactions in the regulatory Volcker data. During this time, the Hypothetical and Actual trading book P&L reported at the BHC level saw large increases in volatility across firms. The difference between Actual P&L and Hypothetical P&L, representing trading book profits, increased dramatically during the crisis period.

There are several possible explanations for the observed profitability of large trading firms during the crisis period. The real economy and the financial markets deviated drastically from each other. That is, the worldwide economic shutdowns had significant negative impacts on main street that did not spillover appreciably to the capital markets. A reasonable argument can be made that the roll out of the diverse main street facilities and the decisive action taken by the Federal Reserve helped to ensure investors maintained confidence in the capital markets despite the turmoil in the real economy.

Another possible explanation for the sustained profitability of trading books was driven by the realized fees and commissions associated with the increased trading volume facilitating customer transactions and market making activities. While the existence of some proprietary trading cannot be ruled out, evidence presented within this note suggests that if speculative trading did occur, it was obfuscated by the increase in profitability attributed to the aforementioned profit sources.

The Volcker rule was designed to prevent firms from engaging in proprietary trading while allowing them to engage in market making activities. These two activities can often be difficult to distinguish from one another. However, evidence from the COVID-19 crisis suggests that firms continued to facilitate markets but did not suffer large losses due to positioning or trading as principals while exposed to large market shocks. That is, the Volcker rule may have had a positive impact on the relatively risk-neutral positions taken by firms in order to avoid the appearance of proprietary trading.

We choose not to take a position on any of the possible explanations, but rather leave to the motivated reader a number of avenues for further research in this area.

15

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