

# INTRADAY MARKET IMPACT ANALYSIS:

Unraveling the Dynamics of Large Trades and Price Movements in Financial Markets

FIN-525: FINANCIAL BIG DATA

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## **ABSTRACT**

In the dynamic landscape of financial markets, this project revolving around the impact of intraday trading on the market delves into the intricate relationship between large trades and the resulting price movements on a minute-to-minute basis. This comprehensive investigation necessitates the meticulous analysis of detailed trade and quote data. The primary focus is on discerning patterns that characterize how the market absorbs substantial orders, the pivotal role of market liquidity in shaping these interactions, and the temporal aspects governing the stabilization of prices following significant trades. By unraveling these complexities, the analysis aims to contribute valuable insights into the resilience of financial markets and shed light on the associated costs of executing large positions.

The project's significance lies in its potential to enhance our understanding of market behavior, offering practitioners and analysts a nuanced perspective on the dynamics that govern large trades. Insights gleaned from this analysis could inform strategic decision-making, risk management strategies, and ultimately contribute to more informed and efficient trading practices in the ever-evolving realm of financial markets.

The code relevant to this project and subsequent analysis can be found publicly here:Intraday Market Impact Analysis Github 2024

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# Introduction

## 1.1 CONTEXT

In the ever-evolving landscape of financial markets, the ability to comprehend and navigate the intricacies of market dynamics is paramount. Investors, traders, and financial analysts are continually challenged by the complexities inherent in understanding how large trades influence market prices on an intraday basis. The execution of significant orders not only has immediate consequences for individual market participants but also plays a crucial role in shaping broader market trends. Recognizing the need for a more profound exploration into this phenomenon, this deep-dive analysis seeks to contextualize and dissect the multifaceted relationship between large trades and intraday price movements. This section lays the groundwork for our inquiry, highlighting the broader challenges and implications that underscore the importance of unraveling the dynamics of intraday market impact.

## 1.2 MOTIVATION

As financial markets become increasingly interconnected and responsive to a myriad of factors, the motivation behind this research stems from a critical recognition of the pivotal role played by large trades in shaping market outcomes. The execution of substantial orders has far-reaching implications, influencing not only immediate price movements but also the broader market sentiment and liquidity dynamics. This project is driven by the understanding that a nuanced exploration of the relationship between trade size and intraday price variations is essential for market participants seeking to optimize their strategies, manage risks effectively, and make informed decisions in real-time trading environments.

One crucial concept that plays a pivotal role in this context is the square root impact law. The SRIL, as explained in *A Bayesian theory of market impact* [Saddier and Marsili 2023], posits that the market impact of a trade is proportional to the square root of its size, according to:

$$\mathbb{E}[\Delta pt] \approx \pm C\sigma \sqrt{\frac{Q}{V}} + \dots \tag{1.1}$$

where  $\sigma$  and V respectively represent the volatility and the volume of transactions measured on the same time frame, C is a constant of order one, and the upper (lower) sign holds for a sequence of buy (sell) orders.

In simpler terms, as the size of a trade increases, the impact on market prices grows, but not in a linear fashion—rather, it follows a square root relationship. This phenomenon has profound implications for

trading strategies and risk management, shaping the decisions of market participants. As we delve into the analysis of market impact in subsequent chapters, understanding and applying the square root impact law will provide valuable insights into the nuanced dynamics of financial markets.

## 1.3 GOALS

This project is driven by a set of overarching goals designed to deepen our understanding of the quoted dynamics. The main aim and goals are as follows:

- 1. **Explore Order Book Dynamics:** Investigate the intricacies of bid and ask prices, quantities, and their temporal alignment within the order book.
- 2. **Quantify Market Impact:** Examine the impact of market orders on prices and quantify the relationship between trade size and resulting market impact.
- 3. **Analyze Trade Patterns:** Explore patterns in trade-related attributes, potentially including trade price, volume, time, and trade information, to gain insights into market transaction nuances.
- 4. **Empirically Verify the Square Root Law:** Endeavor to empirically verify the square root law's relationship between trade size and market impact, contributing to a nuanced comprehension of market behavior and potential applications in trading strategies.

By achieving these goals, our research aims to contribute meaningful insights that transcend the immediate implications of individual trades. We seek to provide a holistic understanding of market behavior, relating to the aforementioned SRIL, attempting to uncover insights and interpretations that help optimize strategies, manage risks effectively, and make informed decisions in the fast-paced realm of intraday trading.

# DATASET

The dataset under consideration is derived from trade information encompassing Canadian markets in the year 2016. The studied sample encompasses diverse market conditions, allowing for a robust analysis of how large trades impact prices on an intraday basis. It serves as a valuable foundation for unraveling the intricate relationship between trade execution and market movements. For the purpose of this analysis, we will focus on data from a single trading year to provide a focused exploration of the market impact dynamics, ensuring a detailed examination of the aforementioned relationship. By examining patterns, market resilience, and the temporal aspects of price stabilization within the context of Canadian trades in 2016, this analysis aims to contribute valuable insights into the unique dynamics of this specific market.

## 2.1 DATA CHARACTERISTICS

The dataset chosen for examination encapsulates key characteristics of Canadian trades throughout the year 2016. It is structured with the following:

- Trade Price: The execution price of the trade, which is central to assessing market impact.
- Trade Volume: The number of units traded, offering insights into the scale of transactions.
- Excel Time: The exact excel timestamp of each trade, allowing for the study of intraday patterns.
- Trade Category: Classification of trades, such as block trades or regular trades, providing context to the transaction.
- **Trade Information:** Metadata containing identifiers for buyers and sellers, which is pivotal for analyzing the market roles of participants.

One notable limitation of the dataset is the absence of individual trade sizes, which would have provided additional clarity on the market impact of specific trades. However, the trade volume metric serves as a reasonable proxy to assess the aggregate effect of market transactions.

## 2.2 PREPROCESSING

Prior to analysis, the dataset underwent several preprocessing steps to ensure data quality and usability. These included:

• **Conversion of Excel Time:** The Excel serial date numbers were converted into standard datetime objects for better interpretability and analysis.

• **Identification of Participants:** The trade information attribute was parsed to extract buyer and seller IDs, enabling the tracking of individual participant activity.

## 2.3 PROCESSING

Our processing pipeline is the following for each Ticker:

- Load and pre-process the data according to the previous part
- For each trading day, calculate the total traded volume and the daily volatility
- Identify daily meta-orders (i.e. successions of trades in that day) for each trader (buyer/seller)
- For each meta-order, calculate the total trader volume, the duration of the trade, as well as the price impact (assumed to be the price difference in absolute value of the first and last trade price)

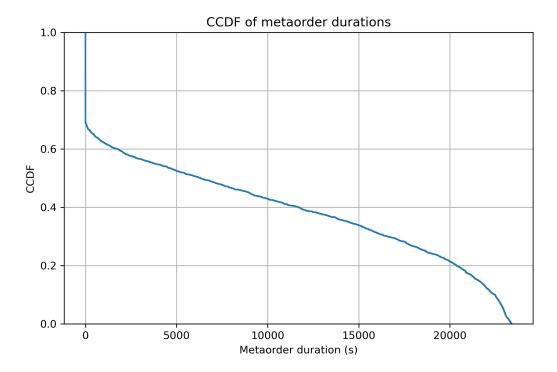
Given this information about each meta-order, we are now in measure to attempt reproducing the Square Root Impact Law.

## 2.4 DATA EXPLORATION

Prior to starting the Square Root Law's Empirical verification, we need to look at the data we have at hand.

#### META-ORDER DURATION

The following plot illustrates the CCDF of the duration of meta-orders.

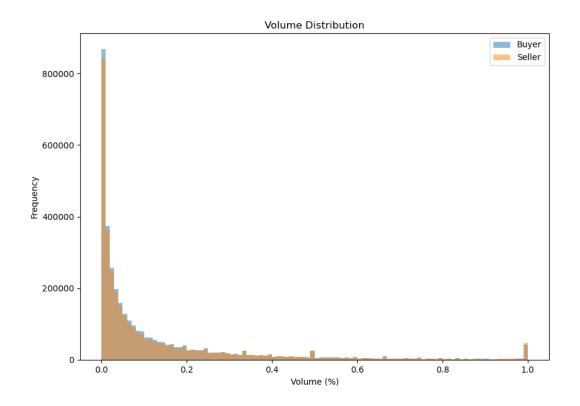


 $FIGURE \ 2.1 \\$  Meta-order duration Complimentary Cumulative Distribution Function

The plot indicates that a large proportion of meta-orders are executed in a very short time window. As  $\Delta_T$  increases, i.e. the time execution for the meta-order increases, and/or as the number of trades becomes larger and larger, we observe a more linear relationship between the price impact  $\Delta_P$  and the trade volume Q (Tóth et al. 2011).

#### META-ORDER DAILY VOLUME PERCENTAGE

The plot below shows the volume distribution as a percentage of the daily traded volume.



FIGURE~2.2 Meta-order trade volume (% of daily traded volume)

We can see that there are numerous days, where single participants trade a considerable amount of the asset. This would prove to be problematic since the price impact  $\Delta_P$  of such meta-orders tends to be linear (Tóth et al. 2011). This also has an intuitive explanation; for example, in a day where a single meta-order accounts for 90% of the total daily traded volume, the volatility of that particular day should not be very high, hence the Square Root Impact Law would not hold very well.

# **METHODS**

Once the dataset underwent preprocessing and a fundamental exploratory data analysis, our focus shifted towards the heart of the analysis. Projecting forward, we navigated through various methodologies to unravel market impact intricacies. Employing techniques such as quantile-based discretization, specifically the Q-Cuts method, we refined data segmentation. Binning strategies shed light on variable groupings, and time-series analyses brought temporal patterns into sharp focus. Our methodical journey encompasses these chosen methods, delivering a thorough investigation into the dataset.

## 3.1 QUANTILE-BASED DISCRETIZATION

Given the substantial volume of data points within the Canadian trades dataset, a direct analysis of each individual trade's market impact was computationally intensive and less informative due to the noisy nature of financial data. To address this, we employed quantile-based discretization, a technique that involves segmenting the continuous range of a variable into discrete intervals based on quantiles.

This method, also known as Q-Cuts, allowed us to downsample the dataset effectively. By dividing the data into quantiles, we ensured that each bin contained an equal number of observations, facilitating a more balanced representation of the data's distribution. Quantile-based discretization helps to mitigate the influence of outliers by distributing them evenly across bins.

#### 3.2 BINNING STRATEGIES

The binning strategy for trade volume involved discretizing the continuous *volume* variable into 150 quantile-based bins, ensuring an even distribution of data points per bin. This was achieved using the *volume\_bins* function, which:

- 1. Segmented the *volume* column into equal-frequency bins with the *pd.qcut* function.
- 2. Calculated the mean price impact for each bin to summarize the market impact data.
- 3. Assigned the midpoint of each bin's quantile range as a representative value.

This method facilitated a computationally efficient analysis, revealing clearer patterns by averaging out the noise of individual trades. The condensed dataset provided a refined lens to examine the square root law of market impact and proved essential in identifying nuanced market trends.

# **RESULTS**

This chapter elucidates the findings derived from the comprehensive analysis of the Canadian trades dataset for the year 2016. Following the preprocessing and binning of the data, several key insights emerged, shedding light on the intraday market impact of large trades.

## 4.1 MARKET IMPACT OF TRADE VOLUME

The application of quantile-based discretization to the trade volume revealed a nuanced relationship between the volume of trades and their corresponding price impacts. The binned data, representing the average price impact for discrete volume intervals, indicated a close match to the square root function.

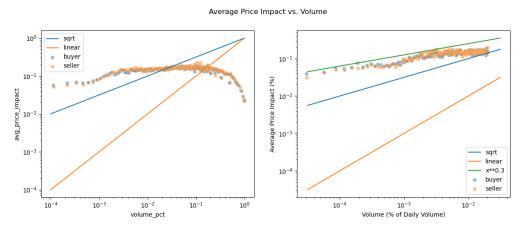


FIGURE 4.1

Plots comparing the relationship between the price impact and the volume of meta-orders. On the left, is the unfiltered data. On the right is a filtered version of the data where we set a threshold on the volume percentage of %10.

The above plot illustrates the dynamic between the Volume  $Q_T$  and the price impact  $\Delta_P$  of a meta-order. We can clearly see that for the unfiltered data, the law starts to hold very poorly once the volume percentage reaches the region of  $10^{-2}$  to  $10^{-1}$ . Beyond that, the law does not make much sense anymore. Once restrictions on the volume percentage are put in place however, the law seems to withhold with a  $\delta$  seeming to be in between 0.4 and 0.5 (a square root function). The  $\delta$  here indicates the exponent to which the the price impact is a function of, i.e. we assume the following  $\Delta_P \approx (Q/V)^{\delta}$  relationship.

# **DISCUSSION**

## 5.1 CHALLENGES ENCOUNTERED

Looking back at the work done throughout this project, we can note relative limitations that temper the conclusions drawn from our analysis. The methodological choices, notably the application of quantile-based discretization like Q-Cuts, binning strategies, and time-series analyses, have been instrumental in unraveling market impact dynamics. Nevertheless, the efficacy of these techniques is inherently tied to assumptions and the nature of the data. While steering clear of machine learning algorithms and complex statistical models, we employed straightforward yet insightful approaches. The assumptions upon which these methods rely for their effectiveness however may not perfectly align with real-world scenarios (expectations about the distribution of the data, relationships between variables, or assumptions about the stability of certain statistical properties over time). In light of these considerations, the insights gained from our analysis provide a solid foundation for future research and a nuanced understanding of market impact within the constraints of the chosen methodologies.

## 5.2 IMPLICATIONS FOR TRADING STRATEGIES

Our analysis, affirming the square root law of market impact, holds significant implications for the development and refinement of trading strategies. The elucidated relationship between trade size and market impact offers strategic insights for market participants, enabling them to fine-tune their trading approaches to minimize adverse price movements.

Incorporating the square root model into trade execution strategies allows for more effective management of trade sizes, reducing market impact costs and enhancing trade efficiency. This is particularly relevant in the design of algorithmic trading strategies, where understanding the nuanced interplay between order size and market dynamics is crucial. Traders can leverage this knowledge to segment large orders into optimally sized batches, mitigating the cumulative impact on the market and preserving trade profitability.

Moreover, the insights gained from our study extend to opportunistic trading scenarios. For instance, traders can anticipate the market impact of significant events, such as the re-balancing of leveraged ETFs, where trade volumes which are known in advance and likely market responses to the underlying can be estimated. This is because the daily volatility and the volume are easily implied or forecasted, thus allowing the use of the Square Root law to predict the price impact. By accurately predicting the extent of price changes due to such events, traders can position themselves to capitalize on the resultant market movements. This application underscores the potential for informed traders to not only mitigate their own market impact but also to exploit the predictable impacts of large trades in the market.

## 5.3 FUTURE RESEARCH DIRECTIONS AND SUGGESTED IMPROVEMENTS

Building on the foundation laid by our analysis, there are several promising directions for future research that can further elucidate the complexities of market impact. While this project harnessed relatively straightforward analytical tools to uncover insights from extensive datasets, the potential for integrating more sophisticated methodologies remains vast.

### 5.3.1 ADVANCED ANALYTICAL TECHNIQUES

Future studies could benefit from the application of machine learning algorithms to discern deeper patterns and dependencies not immediately apparent through conventional analysis. For instance:

- **Predictive Modeling:** Leveraging supervised learning techniques to forecast market movements based on historical trade data, potentially enhancing the predictability of market impact from large trades.
- **Anomaly Detection:** Utilizing unsupervised learning to identify unusual trading patterns, which could signal market manipulation, emerging market trends, or opportunities for arbitrage.
- Sentiment Analysis: Analyzing the sentiment in financial news and social media to gauge its influence on market dynamics, offering a more holistic view of the factors driving market impact.

#### 5.3.2 EXTENDED TIME-FRAME ANALYSIS

A significant extension of this work would involve broadening the analysis beyond intraday effects to encompass longer time-frames. By examining meta-orders and their market impact over extended periods, such as multiple days or weeks, we could gain insights into the persistence and decay of market impact over time. This could involve:

- **Sliding Window Approach:** Implementing a sliding window technique to analyze the market impact of trades over varying time windows, providing a dynamic view of how impact evolves and dissipates.
- Long-Term Trend Analysis: Investigating whether the patterns observed on an intraday basis hold true over longer periods, and how these patterns interact with broader market trends and cycles.

Such an extension would not only validate the robustness of the square root law over different time scales but also offer valuable insights into strategic trade execution and risk management over longer horizons.

In conclusion, the path forward for research in market impact analysis is both broad and deep, with ample opportunity to leverage cutting-edge analytical techniques and extend the temporal scope of analysis. These efforts promise to enrich our understanding of market dynamics, offering more nuanced strategies for navigating the financial markets.

# **CONCLUSION**

In conclusion, our exploratory journey into market impact analysis has yielded promising insights that align with the intricate dynamics of financial markets. The application of diverse and simple methods provided a nuanced understanding of order book dynamics, aligning with the subtle influence of the Square Root Impact Law mentioned in the introduction within the context of the chosen dataset on 2016 Canadian trades.

While our chosen methodologies deliberately steered clear of the complexity associated with machine learning algorithms, their simplicity proved instrumental in showcasing the potential of straightforward tools when applied to substantial datasets in a light and efficient manner. As we navigate the labyrinth of market impact, our research lays the groundwork for future investigations in the field. The inclusion of more sophisticated techniques could unveil deeper layers of complexity within market dynamics. Moreover, expanding the temporal scope and incorporating additional attributes might offer a more comprehensive understanding of the ever-evolving landscape of financial markets.

In essence, this study contributes not only to the understanding of market impact but also serves as a beacon, guiding future research endeavors towards unraveling the intricate dance between order flow and market response. The promising findings gleaned from our analysis underscore the continual evolution and refinement required in the pursuit of comprehending the complex fabric of financial markets.

# **BIBLIOGRAPHY**

- Intraday Market Impact Analysis Github (2024). https://github.com/Hamzezi/FBD-Projec
  t.git.
- Saddier, Louis and Matteo Marsili (2023). *A Bayesian theory of market impact*. arXiv: 2303.08867 [q-fin.TR].
- Tóth, B. et al. (Oct. 2011). 'Anomalous Price Impact and the Critical Nature of Liquidity in Financial Markets'. In: *Physical Review X* 1.2. ISSN: 2160-3308. DOI: 10.1103/physrevx.1.021006. URL: http://dx.doi.org/10.1103/PhysRevX.1.021006.
- Donier, Jonathan (2016). Square root law for price impact. https://www.imperial.ac.uk/media/imperial-college/research-centres-and-groups/cfm-imperial-institute-of-quantitative-finance/events/imperial-eth-2016/Jonathan-Donier-.pdf.