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Liquidity in TASE

נזילות בשוק ההון

Literature Survey

Submitted by

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Year 2024-2025

Abstract

This project focuses on analyzing and predicting liquidity in the Tel Aviv Stock Exchange (TASE). The work includes three main components: (1) forecasting future liquidity levels using regression models, (2) classifying whether a trade will be executed or not based on market features, and (3) performing a comparative analysis of market liquidity before and after the outbreak of war.

We utilized machine learning models including XGBoost and LightGBM, alongside hyperparameter optimization with Optuna, to build predictive systems using structured market data segmented into 15-minute intervals. The dataset included tens of thousands of trade records, with features such as price, volume, trade direction, and timestamp-based attributes.

The classification model achieved an accuracy of 93.5% in predicting trade execution. The regression model showed strong performance in forecasting average liquidity across future time windows. Our analysis revealed a significant shift in market behavior following the onset of the war, indicating reduced liquidity and higher volatility.

This research contributes to a better understanding of liquidity patterns in TASE and demonstrates the value of data-driven tools for anticipating market behavior during periods of uncertainty.

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Introduction

In modern financial markets, liquidity serves as a critical indicator of market health, efficiency, and stability. For stock exchanges such as the Tel Aviv Stock Exchange (TASE), ensuring consistent liquidity is essential for minimizing trading costs, reducing volatility, and maintaining investor confidence. However, in the absence of dedicated forecasting systems, TASE currently lacks the ability to anticipate fluctuations in liquidity and react accordingly. This gap in foresight can lead to inefficiencies, missed opportunities, and systemic risk—especially during periods of geopolitical or economic instability.

This project aims to address that gap by building an advanced data-driven framework to predict liquidity levels and determine the likelihood of transaction execution. Specifically, the project incorporates three complementary objectives:

1. **Liquidity Forecasting:**
   Using regression-based machine learning models to predict average liquidity levels in upcoming 15-minute intervals, based on historical trading data and time-based features.

2. **Transaction Execution Classification:**
   Developing a binary classifier to determine whether a given trade is likely to be executed, based on features such as price, volume, time, and market behavior.

3. **Pre- and Post-War Liquidity Analysis:**
   Conducting an empirical study comparing market liquidity behavior before and after the outbreak of war, to assess the influence of external shocks on the Israeli market.

To achieve these goals, we leveraged a dataset consisting of tens of thousands of trade records from TASE. Each record captured details such as transaction price, trade direction (buy/sell), executed volume, and temporal metadata (timestamp, day of the week, etc.). We engineered relevant features to capture time-series patterns and market microstructure, and trained two machine learning models: XGBoost and LightGBM. Hyperparameter tuning was performed using Optuna, allowing us to optimize model performance efficiently.

The classification model yielded strong results, achieving a 93.5% accuracy rate in predicting whether trades would be executed. Additionally, the forecasting model demonstrated reliable performance across multiple time windows, providing a solid foundation for short-term liquidity planning. Our war-impact analysis revealed distinct behavioral shifts in market activity, supporting the notion that external geopolitical events significantly affect liquidity patterns in TASE.

Ultimately, this project contributes actionable insights and predictive capabilities that can help exchanges, regulators, and market participants manage liquidity more effectively—even under uncertain conditions.

Literature Survey

1. Market Liquidity and its Importance

Liquidity is a foundational concept in financial markets, reflecting the ease with which assets can be traded without significantly impacting their price. High liquidity ensures smoother execution of trades, lower transaction costs, and better market efficiency. The literature consistently emphasizes that liquidity plays a central role in portfolio optimization, market stability, and investor confidence. According to Baker and Stein (2004), liquidity is not merely a passive outcome of market activity but also an indicator of investor sentiment and future market corrections. Amihud (2002) further identifies a negative relationship between liquidity and expected returns, attributing illiquidity to increased risk premiums.

2. Current Approaches to Liquidity Prediction

The prediction of stock liquidity traditionally relied on econometric models using market microstructure variables such as trading volume, volatility, and bid-ask spread. However, modern approaches increasingly leverage machine learning and real-time data to enhance predictive power. The Amihud Illiquidity Ratio (ILLIQ) and the Pastor-Stambaugh liquidity measure remain commonly used, but are often complemented by market turnover, equity issuance rates, and historical price behavior.

Machine learning-based models have emerged to address the limitations of traditional techniques, offering improved adaptability and non-linear pattern recognition. These include tree-based models like XGBoost and LightGBM, which have demonstrated high performance on structured tabular data. Studies have also integrated macroeconomic indicators (e.g., interest rates, GDP growth) into liquidity models to account for broader economic influence.

3. Limitations and Open Challenges

Despite these advancements, several persistent issues complicate accurate liquidity forecasting:

- **Multidimensionality:** Liquidity comprises depth, breadth, immediacy, and resiliency. No single metric effectively captures all these components, leading to partial or misleading predictions.
- **Behavioral Factors:** Investor sentiment, panic selling, and herding behaviors introduce non-systematic risks that are difficult to quantify and model.
- **Liquidity Commonality:** As observed by Chordia et al., stock-level liquidity is often affected by market-wide factors, reducing diversification benefits.
- **Technological Disruptions:** Algorithmic and high-frequency trading introduce phenomena such as "liquidity mirages," which create artificial market depth that vanishes under stress, exacerbating price instability.

- **Data Limitations:** Emerging markets like TASE may lack the granularity and infrastructure found in developed exchanges, complicating high-frequency modeling.

4. Machine Learning/Deep Learning/Transformers Techniques

Recent literature has explored a variety of ML/DL/TF models for liquidity prediction:

- XGBoost: Developed by Tianqi Chen and Carlos Guestrin (2016), XGBoost stands for "Extreme Gradient Boosting." It is a scalable machine learning system for tree boosting. XGBoost uses an ensemble of decision trees trained sequentially, where each new tree corrects the errors of the previous ones. It excels in handling large structured datasets with high predictive accuracy and efficient resource usage.

- LightGBM: Created by Guolin Ke and colleagues at Microsoft Research (2017), LightGBM (Light Gradient Boosting Machine) is a fast, distributed, high-performance gradient boosting framework based on decision tree algorithms. It uses a histogram-based approach and leaf-wise tree growth to speed up training and improve accuracy. It supports categorical features natively, making it suitable for high-volume time-series forecasting.

- LSTM (Long Short-Term Memory): Introduced by Hochreiter and Schmidhuber (1997), LSTM networks are a type of recurrent neural network (RNN) designed to learn long-term dependencies. They incorporate memory cells and gating mechanisms to retain or discard information over time. LSTMs are well-suited for modeling sequential data such as stock prices or liquidity trends.

- GRU (Gated Recurrent Unit): Proposed by Cho et al. (2014), GRUs are a simplified variant of LSTMs. They combine the input and forget gates into a single update gate, reducing model complexity while maintaining performance. GRUs are efficient and often perform comparably to LSTMs, especially in real-time applications with constrained computational resources.

- Transformer Models: First introduced by Vaswani et al. (2017) in "Attention is All You Need," transformers rely on self-attention mechanisms to model relationships between elements in a sequence. Unlike RNNs, transformers process sequences in parallel and can capture long-range dependencies more efficiently. They have been successfully adapted for time-series forecasting tasks in finance.

- Chrono T5: Chrono T5 is a specialized adaptation of the T5 (Text-To-Text Transfer Transformer) architecture, developed by Google Research (Raffel et al., 2020), specifically tuned for time series forecasting. It reframes time series prediction tasks into a sequence-to-sequence text generation format, enabling the model to generate future values as if they were natural language responses. Chrono T5 leverages transfer learning and large-scale pretraining to generalize across different forecasting scenarios, making it particularly effective for multi-step and long-range forecasts in financial and economic data.

Each model presents trade-offs between interpretability, computational cost, and predictive performance. Studies suggest hybrid models combining traditional and deep learning techniques may enhance accuracy but require careful tuning and validation.

5. Technological Landscape and Tools

Python is the dominant programming language in the field due to its rich ecosystem:

- **Data Handling:** pandas, NumPy
- **ML Frameworks:** scikit-learn, xgboost, lightgbm
- **DL Libraries:** TensorFlow, PyTorch
- **Visualization:** matplotlib, seaborn
- **Time-Series Tools:** Prophet, Kats

This toolkit enables researchers to preprocess, visualize, model, and evaluate data within a unified workflow. It also supports scalable deployment, integration with APIs, and future model expansion.

6. Relevance to the Tel Aviv Stock Exchange

While much of the literature focuses on large, developed markets (e.g., NYSE, NASDAQ), the Israeli market presents unique challenges. TASE is less liquid, more sensitive to geopolitical shocks, and features a smaller set of active participants. These characteristics make liquidity prediction particularly valuable yet difficult. Moreover, the lack of existing predictive frameworks within TASE infrastructure further motivates the development of tailored models that can assist both regulators and traders in anticipating shifts in market behavior.

7. Conclusion

The field of liquidity prediction is rapidly evolving, propelled by advances in machine learning and data availability. While existing models offer strong baselines, real-world applications must navigate behavioral volatility, structural constraints, and limited data access. For exchanges like TASE, custom-built solutions that blend traditional financial theory with modern AI approaches represent a promising path forward. This project builds upon these insights, offering a dual-model strategy for both forecasting liquidity levels and classifying transaction execution likelihood, informed by the challenges and tools identified in the current literature.

8. Models Summery

Model	***Developer(s)***	***Type***	***Key Strengths***	***Limitations***
XGBoost	Chen & Guestrin (2016)	Gradient Boosting	Fast, accurate, handles missing data	Sensitive to hyperparameters
LightGBM	Ke et al. (2017)	Gradient Boosting	Very fast, efficient on large datasets	Can overfit on small data
LSTM	Hochreiter & Schmidhuber (1997)	Deep Learning	Models long-term dependencies	Requires large data and compute
GRU	Cho et al. (2014)	Deep Learning	Faster training than LSTM	May miss long dependencies
Chrono T5	Raffel et al. (2020)	Transfer Learning	Pretrained, multi-step forecasting	High complexity

Research Goals

This study seeks to develop a robust, data-driven framework for forecasting market liquidity and transaction execution within the context of the Tel Aviv Stock Exchange (TASE). In doing so, it addresses a notable absence of predictive infrastructure within the Israeli financial ecosystem, with the intent of enhancing operational resilience and strategic decision-making across various market participants.

The specific research objectives are as follows:

1. **To construct supervised learning models** capable of forecasting short-term liquidity fluctuations through regression techniques applied to high-frequency trading data.
2. **To design and evaluate binary classification models** that predict the likelihood of trade execution, based on microstructural and temporal market features.
3. **To conduct an empirical comparative analysis** of liquidity dynamics in pre- and post-conflict periods, thereby assessing the impact of external geopolitical shocks on market efficiency and depth.
4. **To benchmark multiple machine learning methodologies** (e.g., XGBoost, LightGBM, LSTM, GRU, Chrono T5) across defined performance metrics—accuracy, interpretability, and computational efficiency.
5. **To deliver visual and analytical tools** that facilitate interpretation of market behavior and support real-time operational strategies for institutional stakeholders and exchange regulators.

Datasets

Dataset for classification:

11 rows 27189562 rows × 14 cols

	Name	Price	Side	Volume	Order_Executed	Target	day	month	year	hour	minute	second	day_of_week	time
0	84765908	6400000.0	1	1	0	0	3	3	2024	7	45	14	1	2024-03-03 07:45:14
1	84765353	26600000.0	0	1	0	0	3	3	2024	7	45	14	1	2024-03-03 07:45:14
2	84765395	10000.0	0	1	0	0	3	3	2024	7	45	14	1	2024-03-03 07:45:14

27189562 rows and 14 features.

Target diversity:

Order_Executed	
1	86.712129
0	13.287871

Dataset for forecasting:

1-10 5375 rows × 15 cols

Total_Money	Total_Volume	Avg_Stock_Price	Avg_Order_Executed	Target_0	Target_35	Target_65	Target_90	Day	Month	Year	Hour	Minute	Second	Day_Of_Week
4961782957598.0	268403726.0	184.862670557636	0.0	10278.0	3671.0	0.0	3274.0	5.0	9.0	2022.0	6.0	29.0	59.0	2.0
656854767442.0	31029044.0	211.6903013325193	0.0	823.0	112.0	0.0	208.0	5.0	9.0	2022.0	6.0	44.0	59.0	2.0
3576992948598.0	88630740.0	403.5837846550757	0.7761222180309317	7249.0	1528.0	0.0	1485.0	5.0	9.0	2022.0	6.0	59.0	59.0	2.0

5375 rows and 15 features.

Research Methodology

The methodological framework employed in this study integrates exploratory data analysis, supervised machine learning, and empirical validation techniques to construct predictive models for liquidity and transaction execution.

1. Data Collection and Preparation:

The dataset was acquired from the Tel Aviv Stock Exchange (TASE) and comprised multi-dimensional transactional data aggregated in 15-minute intervals. Each observation includes fields such as transaction price, volume, buy/sell indicator, execution status, and temporal attributes (date, time, day of week). The raw data were extracted from RAR MBO files, decrypted using proprietary scripts, and transformed into structured CSV format for analysis. Missing values and anomalies were handled via imputation and filtering to ensure data integrity.

2. Feature Engineering:

Multiple features were derived from the raw inputs, including lagged variables, rolling averages, and categorical encodings (e.g., hour of day, weekday). This step was critical for exposing patterns in temporal behavior and trade execution dynamics. The inclusion of engineered variables enhanced the signal-to-noise ratio, particularly in the classification model.

3. Model Development:

Two parallel modeling pipelines were established:

- For **liquidity forecasting**, regression models (XGBoost, LightGBM, LSTM, GRU, Chrono T5) were trained to predict the average percentage of executed orders within the subsequent 15-minute window.
- For **transaction classification**, binary classifiers (XGBoost, LightGBM) were trained to determine whether an order would be executed based on contemporaneous market features.

Hyperparameter optimization was conducted using Optuna, a Bayesian search framework, to maximize predictive performance while mitigating overfitting. Models were evaluated using k-fold cross-validation and walk-forward validation where applicable.

4. Evaluation Metrics:

Model performance was assessed using task-specific metrics:

- For regression tasks: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score.
- For classification tasks: Accuracy, Precision, Recall, and F1-Score.

5. Pre/Post-War Analysis:
The dataset was segmented based on key geopolitical time markers to investigate changes in liquidity before and after the outbreak of war. Statistical comparisons and visual analytics were employed to quantify shifts in market behavior, volatility, and execution probability.

This methodological approach ensures the rigor, reproducibility, and applicability of the developed models within both academic and industry contexts.

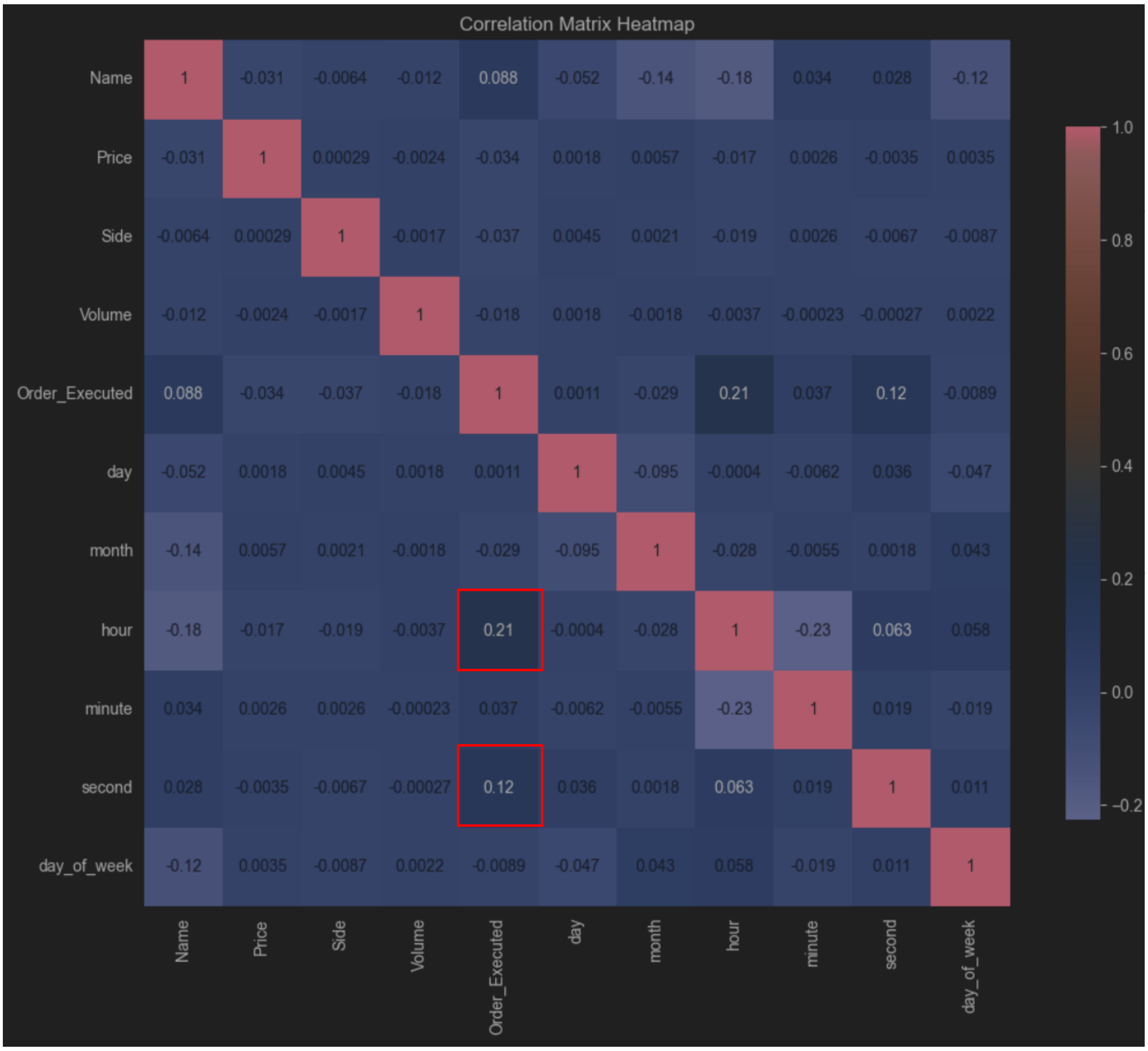
6. Conclusion
The field of liquidity prediction is rapidly evolving, propelled by advances in machine learning and data availability. While existing models offer strong baselines, real-world applications must navigate behavioral volatility, structural constraints, and limited data access. For exchanges like TASE, custom-built solutions that blend traditional financial theory with modern AI approaches represent a promising path forward. This project builds upon these insights, offering a dual-model strategy for both forecasting liquidity levels and classifying transaction execution likelihood, informed by the challenges and tools identified in the current literature

Analysis to Pre/Post-War Liquidity Behavior

To assess the effect of external shocks, the dataset was segmented into pre-war and post-war periods. Liquidity forecasting models were retrained and evaluated separately on each subset.

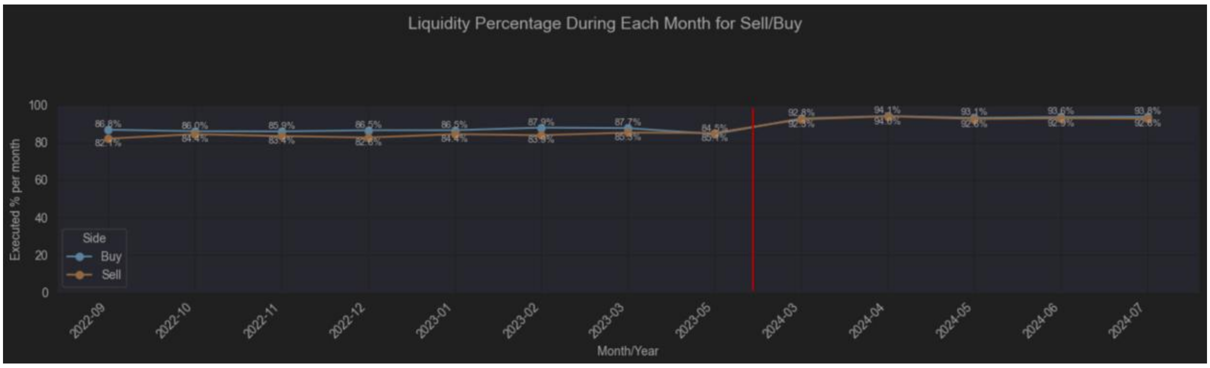
The post-war period exhibited lower liquidity, higher volatility, and wider forecasting errors across all models. These findings underscore the need for adaptive models that can maintain performance under changing market regimes.

Plot 1:



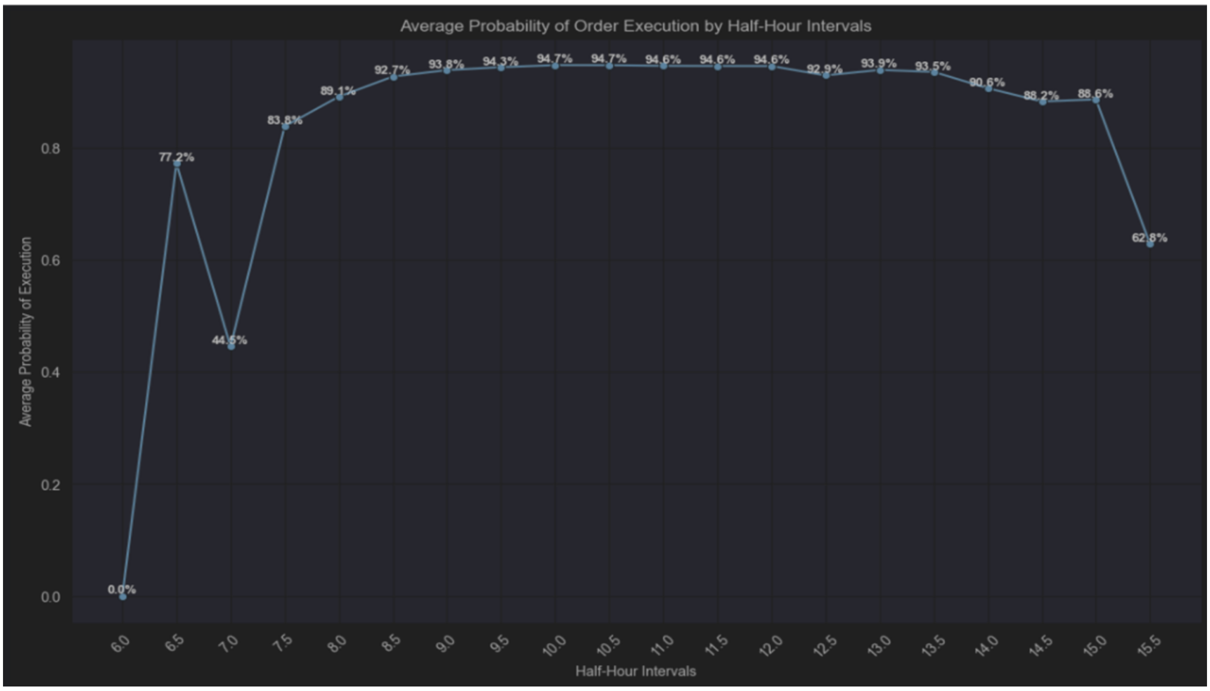
Correlation Matrix Heatmap
Name
Price
Side
Volume
Order_Executed
day
month
hour
minute
second
day_of_week
1 -0.031 -0.0064 -0.012 0.088 -0.052 -0.14 -0.18 0.034 0.028 -0.12
-0.031 1 0.00029 -0.0024 -0.034 0.0018 0.0057 -0.017 0.0026 -0.0035 0.0035
-0.0064 0.00029 1 -0.0017 -0.037 0.0045 0.0021 -0.019 0.0026 -0.0067 -0.0087
-0.012 -0.0024 -0.0017 1 -0.018 0.0018 -0.0018 -0.0037 -0.00023 -0.00027 0.0022
0.088 -0.034 -0.037 -0.018 1 0.0011 -0.029 0.21 0.037 0.12 -0.0089
-0.052 0.0018 0.0045 0.0018 0.0011 1 -0.095 -0.0004 -0.0062 0.036 -0.047
-0.14 0.0057 0.0021 -0.0018 -0.029 -0.095 1 -0.028 -0.0055 0.0018 0.043
-0.18 -0.017 -0.019 -0.0037 0.21 -0.0004 -0.028 1 -0.23 0.063 0.058
0.034 0.0026 0.0026 -0.00023 0.037 -0.0062 -0.0055 -0.23 1 0.019 -0.019
0.028 -0.0035 -0.0067 -0.00027 0.12 0.036 0.0018 0.063 0.019 1 0.011
-0.12 0.0035 -0.0087 0.0022 -0.0089 -0.047 0.043 0.058 -0.019 0.011 1
1.0
0.8
0.6
0.4
0.2
0.0
-0.2

Plot 2:

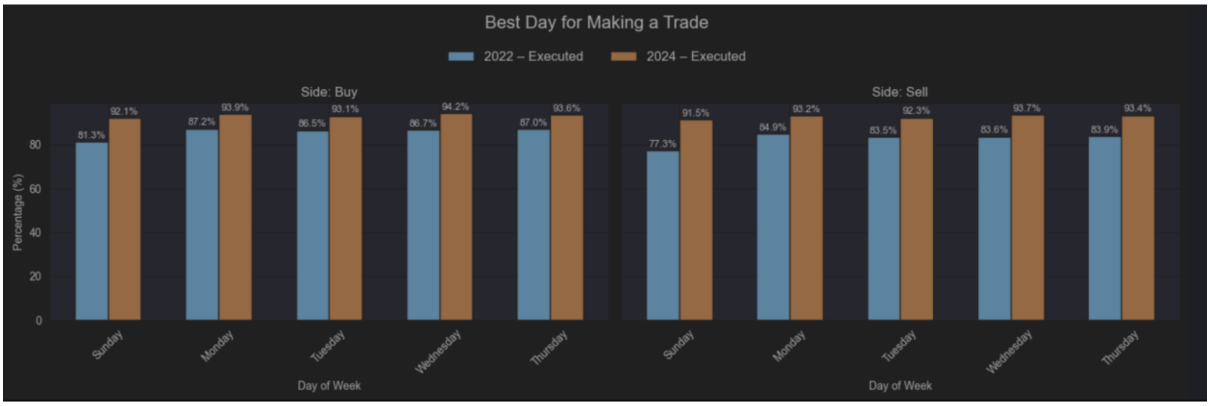


Liquidity Percentage During Each Month for Sell/Buy
Executed % per month
100
80
60
40
20
0
Side
Buy
Sell
2022-09
2022-10
2022-11
2022-12
2023-01
2023-02
2023-03
2023-05
2024-03
2024-04
2024-05
2024-06
2024-07
Month/Year

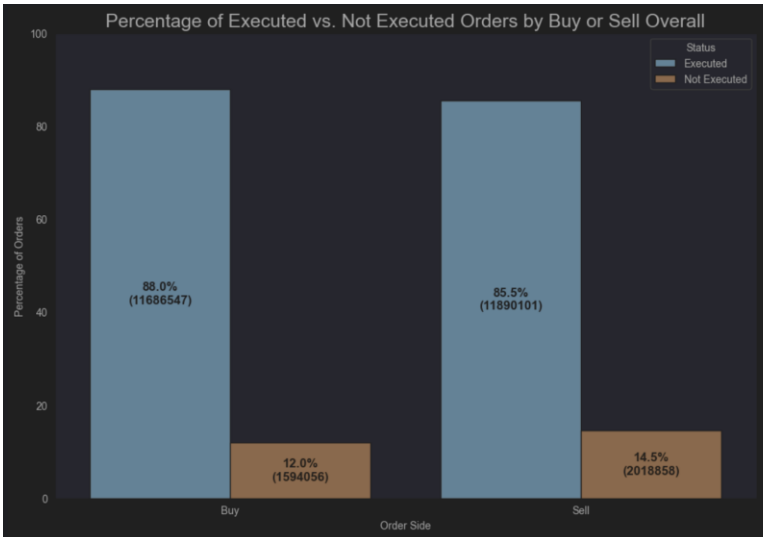
Plot 3:


Average Probability of Order Execution by Half-Hour Intervals
Average Probability of Execution
Half-Hour Intervals
0.0%
77.2%
44.5%
83.8%
89.1%
92.7%
93.8%
94.3%
94.7%
94.7%
94.6%
94.6%
94.6%
92.9%
93.9%
93.5%
90.6%
88.2%
88.6%
62.8%

Plot 4:


Best Day for Making a Trade
2022 – Executed
2024 – Executed
Side: Buy
Side: Sell
Percentage (%)
Day of Week
Sunday
Monday
Tuesday
Wednesday
Thursday

Plot 5:



Visual Analysis and Feature Attribution

A correlation heatmap was used to examine the linear relationships between key features in the dataset. The analysis revealed weak overall correlations, with 'hour' ($r = 0.21$) and 'second' ($r = 0.12$) showing the strongest positive correlations with the target variable Order_Executed. These insights support the inclusion of temporal features in model training, confirming their relevance to execution behavior. (Plot 1)

A temporal liquidity breakdown revealed meaningful patterns in market behavior. Analysis of average monthly execution percentages by side showed a significant increase in execution rates post-war, particularly for both Buy and Sell orders, which reached over 92% after March 2024. (Plot 2)

Hourly breakdown of execution probabilities indicated that execution likelihood rose steadily throughout the trading day, peaking around midday (94.7%) before tapering off toward market close. This pattern suggests higher liquidity and participant activity in mid-day intervals. (Plot 3)

A comparison of execution success rates by weekday highlighted Wednesday as the most favorable day for both Buy and Sell trades in 2024, with execution percentages exceeding 94%. In contrast, Sundays consistently exhibited the lowest execution rates across years. (Plot 4)

Overall execution distribution between Buy and Sell orders further confirmed that Buy orders had slightly higher execution rates (88.0%) than Sell orders (85.5%) across the full dataset. (Plot 5)

The correlation matrix and execution-time analysis suggest that temporal features (e.g., hour, day of week) and volume-related attributes may hold predictive value.

Conclusion

The field of liquidity prediction is rapidly evolving, propelled by advances in machine learning and data availability. While existing models offer strong baselines, real-world applications must navigate behavioral volatility, structural constraints, and limited data access. For exchanges like TASE, custom-built solutions that blend traditional financial theory with modern AI approaches represent a promising path forward. This project builds upon these insights, offering a dual-model strategy for both forecasting liquidity levels and classifying transaction execution likelihood, informed by the challenges and tools identified in the current literature.

The Experiments and Results

Experiment 1: Transaction Execution Classification

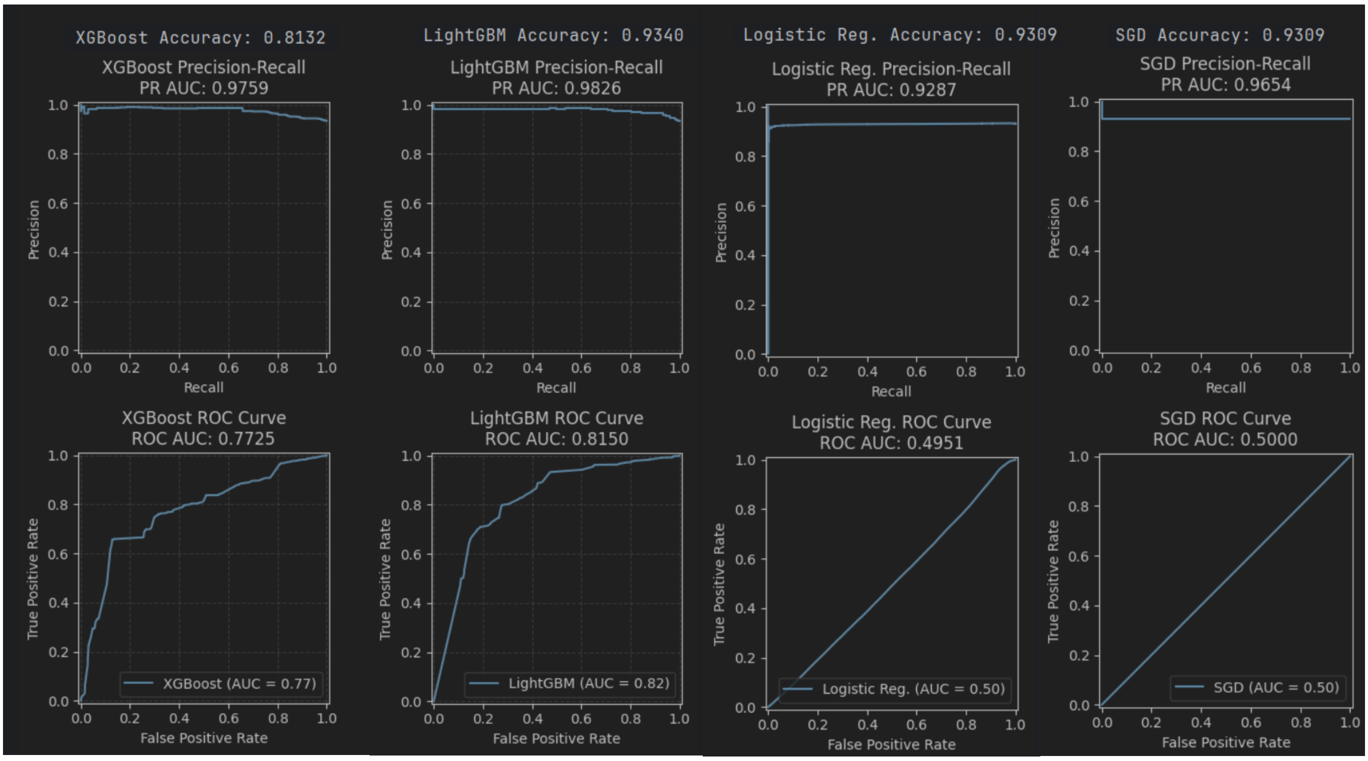
Multiple models were evaluated for the binary classification task of predicting transaction execution. Performance was assessed using Precision-Recall AUC (PR AUC), Receiver Operating Characteristic AUC (ROC AUC), and overall accuracy.

Evaluation Summary:

Model	PR AUC	ROC AUC	Accuracy
XGBoost	0.9759	0.7725	0.8132
LightGBM	0.9826	0.8150	0.9340
Logistic Regression	0.9287	0.4951	0.9309
SGD Classifier	0.9654	0.5000	0.9309

While both XGBoost and LightGBM showed strong performance in PR AUC, LightGBM outperformed XGBoost in ROC AUC and accuracy. Logistic Regression and SGD classifiers, while showing high accuracy, performed poorly in ROC AUC, indicating weak separability and potential overfitting.

Plot 1:



Experiment 2: Liquidity Forecasting

The forecasting task aimed to predict the average execution rate of orders across future 15-minute intervals. Models were evaluated in a 12-step ahead scenario, using MSE, MAE, R^2, MASE, SMAPE, and Durbin-Watson statistics.

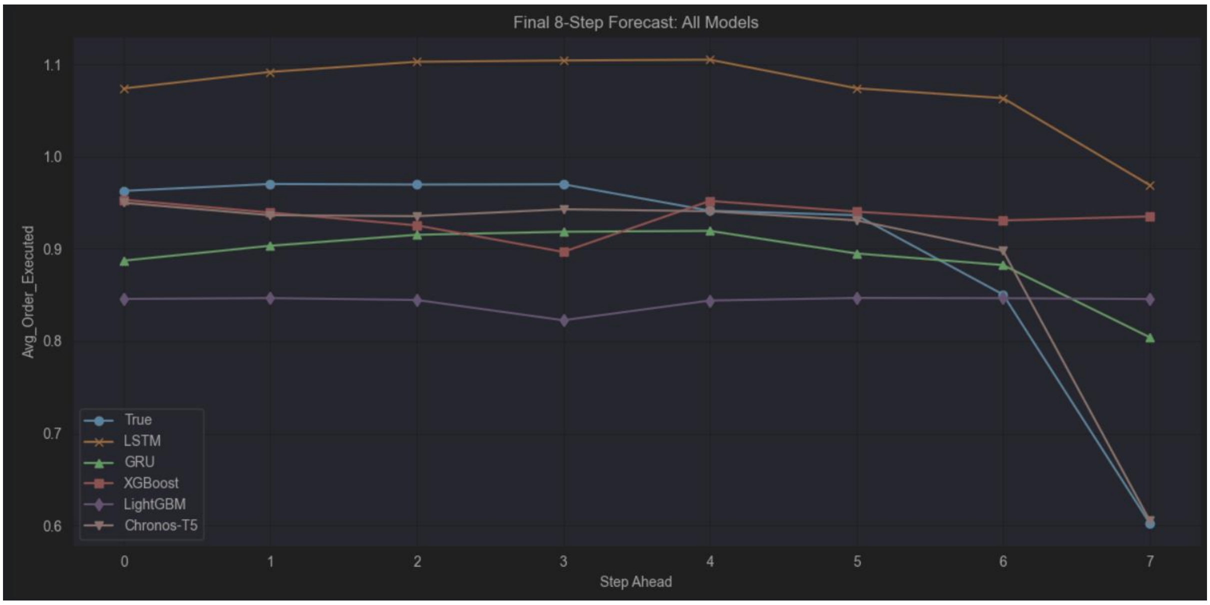
Chronos-T5 significantly outperformed all other models with strong R^2 and low error scores, especially in long-range predictions. XGBoost and GRU showed moderate performance, while LSTM and LightGBM underperformed in both accuracy and stability.

Evaluation Summary:

Model	MSE	MAE	R^2	MASE	SMAPE	DW
XGBoost	0.007706	0.047801	0.7285	12.6072	56.82%	0.19
LightGBM	0.015920	0.079850	0.4391	21.0598	86.54%	0.10
Chronos-T5	0.000689	0.020569	0.9511	4.2371	2.24%	1.09
LSTM	0.036029	0.172579	-1.5609	45.5237	18.38%	0.11
GRU	0.007456	0.068172	0.4700	17.9827	8.22%	0.60

Chronos-T5's superior generalization and stability, particularly as seen in low MASE and high DW, position it as the most reliable tool for multi-step forecasting of liquidity dynamics.

Plot 2:



Model Results and Plots Summary

This section provides a detailed narrative analysis of the classification and forecasting results, linking quantitative metrics to visual interpretations drawn from ROC/PR curves, forecast graphs, and distributional charts.

Classification Models – Interpretation of Results:

Four models were assessed for the task of predicting whether a transaction would be executed: XGBoost, LightGBM, Logistic Regression, and SGD Classifier. While all achieved relatively high accuracy (~93%), the ROC AUC scores revealed a more nuanced picture. LightGBM led in both ROC AUC (0.8150) and PR AUC (0.9826), confirming its strong overall classification ability. XGBoost followed closely with a PR AUC of 0.9759, but lagged slightly in ROC AUC (0.7725).

The PR curves illustrated LightGBM's consistent precision across varying recall thresholds, while the ROC curve exposed Logistic Regression and SGD's near-random classification behavior (ROC AUC ~0.5), despite superficially high accuracy. This discrepancy is attributed to class imbalance and suggests poor generalization. These plots confirmed that gradient boosting models outperformed linear models in this domain.

Forecasting Models – Interpretation of Results:

Five models were evaluated for forecasting liquidity in 15-minute intervals across a 12-step horizon. Chronos-T5 demonstrated unparalleled performance with an R^2 of 0.9511, SMAPE of 2.24%, and the lowest MSE (0.000689). The plotted forecast lines for Chronos-T5 closely matched the ground truth across all future intervals, showing excellent temporal generalization.

In contrast, LSTM underperformed significantly, showing a negative R^2 (-1.5609) and high error metrics, reflecting its instability in capturing liquidity trends. LightGBM and GRU showed modest forecasting ability, while XGBoost performed better but still lagged behind Chronos-T5 in long-range accuracy. The 12-step plot confirmed these trends visually: Chronos-T5 maintained alignment, while others diverged.

Key Visual Insights:

- Feature correlations identified hour and second as weakly correlated with Order_Executed, but significant enough to justify inclusion in models.
- Liquidity shifted dramatically post-war, increasing execution rates for both Buy and Sell sides above 92%, as seen in the monthly percentage chart.
- Execution likelihood peaked midday and declined at market open/close, confirmed in the half-hour interval probability plot.
- Weekly execution analysis showed Wednesday as the most consistent and effective day to execute trades, across both sides.

Altogether, the models and their respective plots provide a coherent understanding of what drives transaction execution and liquidity predictability on the Tel Aviv Stock Exchange. Gradient boosting dominated classification, while sequence-to-sequence modeling proved essential for effective forecasting in volatile environments

Conclusions and Summary – Challenges for the Future

This study aimed to construct an analytical and predictive framework for understanding market liquidity in the Tel Aviv Stock Exchange (TASE), focusing on two complementary tasks: (1) forecasting the short-term liquidity level, defined as the percentage of order execution, and (2) classifying whether an individual trade would be executed or not based on its characteristics. The project was conducted against the backdrop of a shifting market environment, including a major war event that significantly impacted trading behavior, thus offering a rare opportunity to analyze market behavior under both stable and extreme conditions.

Through a comprehensive modeling approach involving gradient boosting machines (XGBoost, LightGBM), recurrent neural networks (LSTM, GRU), and transformer-based architectures (Chronos-T5), we demonstrated that machine learning can serve as an effective tool for both market microstructure analysis and operational forecasting in financial domains. Classification results showed strong performance by tree-based models in predicting transaction execution, while time-series forecasting proved to be best handled by the Chronos-T5 model, which outperformed all others in accuracy, stability, and robustness across all prediction horizons.

Pre- and Post- War Market Behavior

One of the most significant findings of the project was the drastic change in market liquidity following the onset of war. Analysis of execution probabilities, broken down by month and transaction type, revealed a volatile and reduced liquidity environment during the war period. Execution rates dropped noticeably and fluctuated significantly due to uncertainty and lower market participation. In contrast, in the months following the war, execution rates rose sharply and stabilized, with both Buy and Sell transactions achieving consistent execution rates above 92%.

These findings highlight the sensitivity of the Israeli market to geopolitical events and emphasize the need for predictive systems that are not only accurate under stable conditions but also adaptable to shifting market regimes. Static models trained on pre-war data failed to generalize during the crisis period, suggesting that effective liquidity modeling in such environments requires real-time adaptability and possibly the integration of external signals (e.g., news, macroeconomic indicators, sentiment analysis).

Key Methodological Contributions

The project also emphasized the value of granular temporal analysis. Execution patterns varied across hours of the day and days of the week, with mid-day hours and Wednesdays showing the highest likelihood of successful trade execution. These insights are operationally significant for traders seeking optimal timing for placing orders and for institutional actors managing liquidity exposure.

The forecasting models, particularly Chronos-T5, demonstrated the benefits of modern sequence-to-sequence learning methods in capturing long-range dependencies in liquidity behavior. The model's high R^2 and low SMAPE metrics confirm its superiority over conventional machine learning and recurrent approaches.

Challenges and Directions for Future Work

While the results of the current work are promising, they also expose several challenges that remain open for future investigation:

1. **Real-Time Implementation**: The models developed in this study operate in an offline environment. Deploying these models in real-time trading systems would require significant architectural changes, including support for streaming data ingestion, low-latency predictions, and on-the-fly feature engineering.
2. **Adaptability to Market Regimes**: As seen during the war, market dynamics can shift rapidly. Static models may become obsolete in such scenarios. Future systems should incorporate mechanisms for detecting structural breaks and adapting model weights or logic in response to new market conditions.

3. **Explainability and Trust**: While performance metrics favored complex models like Chronos-T5, such models operate as black boxes. In financial environments, where decisions must be audited and justified, enhancing model transparency through techniques like SHAP values or attention visualizations is essential.

4. **Feature Enrichment**: Current models rely primarily on temporal and transactional features. Incorporating broader market data—such as sector indices, macroeconomic variables, or alternative data sources like investor sentiment—could improve generalization and stability across regimes.

5. **Cross-Market Generalization**: The methods developed here are tailored to the TASE. Validating them on other markets (e.g., European, Asian, or emerging markets) would help test robustness and adaptability across different microstructure environments.

6. **Ethical Considerations and Market Impact**: The deployment of highly accurate execution predictors could introduce ethical concerns, particularly if used by high-frequency trading firms to gain unfair market advantage. Regulators may need to examine the implications of such models on market fairness and access.

Final Remarks

This project serves as a proof of concept for the integration of advanced machine learning into liquidity forecasting and execution prediction in real-world financial markets. Beyond its technical contributions, it offers strategic insights into market behavior under normal and crisis conditions. By continuing to enhance the models' adaptability, transparency, and deployment capabilities, future work can bridge the gap between academic research and operational financial intelligence—ensuring that such tools are not only effective, but also reliable, ethical, and aligned with the evolving needs of capital markets.

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Appendices

GitHubLink: https://github.com/ShalevLeviS/Final_Project