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Advancements in Causal Inference for High- Frequency Financial Data: A Novel Identification and Estimation Framework

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Abstract: The rapid expansion of high-frequency financial data has profoundly transformed the landscape of empirical research in monetary policy, asset pricing, and market microstructure. While these granular datasets offer unprecedented opportunities to uncover causal relationships and evaluate the impact of policy interventions at an intraday level, they also introduce significant methodological challenges. Notably, standard instrumental variable (IV) approaches often struggle in this context, as instrument strength can fluctuate dramatically within trading days, leading to unreliable estimates and inference when applied naively. In response, this study proposes a novel and broadly applicable identification and estimation framework designed specifically for high-frequency settings characterized by time-varying instrument validity. Our approach features a time-contingent compliance method that dynamically partitions the trading day into intervals of strong and weak instrument strength, thereby facilitating accurate and robust estimation of local average treatment effects (LATE) in real time. By leveraging smoothness constraints on asset return processes and systematically exploiting volatility spikes around scheduled economic announcements—such as Federal Open Market Committee (FOMC) meetings—our method isolates quasi-experimental shocks that underpin causal identification. We illustrate the utility of this framework through an in-depth empirical analysis of intraday Treasury futures surrounding FOMC announcements, demonstrating that our method consistently outperforms conventional IV and two-stage least squares (2SLS) techniques in both precision and reliability. Extensive simulation experiments further validate the approach, showing that it preserves correct inference under weak identification and delivers substantial power gains in strongly identified segments. These contributions offer a comprehensive toolkit for economists and financial researchers seeking to harness high-frequency data for robust causal inference across a wide array of financial market questions.

Keywords: *Causal inference, High-frequency financial data, Instrumental variables, Time-varying identification, Local average treatment effect, Market microstructure, Monetary policy, Treasury futures, Empirical finance, Econometric methods*

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Introduction

The proliferation of high-frequency financial data has ushered in a new era of empirical finance, fundamentally altering the ways in which researchers, policymakers, and practitioners analyze market behavior and economic policy transmission (Andersen et al., 2007; Engle, 2000). High-frequency datasets, encompassing tick-by-tick observations of asset prices, volumes, and order book information, offer unparalleled granularity and the ability to study market phenomena at scales previously unimaginable. This revolution has enabled a deeper understanding of market microstructure, liquidity provision, volatility dynamics, and the real-time impact of macroeconomic news and monetary policy interventions (Fleming & Remolona, 1999; Hasbrouck, 1991).

Despite these advances, harnessing high-frequency data for causal inference remains fraught with conceptual and methodological difficulties (Gospodinov & Ng, 2013). Traditional econometric tools, such as instrumental variable (IV) techniques, are often ill-suited for settings where the strength and validity of instruments fluctuate rapidly within the trading day (Andrews et al., 2006).

For instance, policy announcements or regulatory interventions—commonly used as sources of exogenous variation—may only exert strong influence on certain intraday intervals, rendering the identification of causal effects highly sensitive to the timing and granularity of analysis. As a result, applying standard IV methods naively can lead to weak-instrument problems, biased estimates, and invalid inference, ultimately limiting the reliability of empirical findings drawn from high-frequency data (Moreira, 2003).

This paper confronts these challenges by introducing a comprehensive framework for causal identification and estimation in high-frequency financial environments, building on identification-robust methods (Andrews et al., 2006; Moreira, 2003) and recent advances in dynamic panel and time series econometrics (Casini & McCloskey, 2025). Central to our approach is a time-contingent compliance method that dynamically segments the trading day according to instrument relevance, enabling robust estimation of local average treatment effects (LATE) even in the presence of time-varying identification strength. Our methodology exploits the natural temporal clustering of exogenous shocks—such as those induced by scheduled economic announcements—and integrates advanced econometric techniques for robust inference under weak and strong identification alike. Through extensive empirical application to intraday Treasury futures data around Federal Open Market Committee (FOMC) meetings, and supported by simulation studies, we demonstrate that our framework consistently delivers more accurate, reliable, and interpretable causal estimates than conventional alternatives.

Beyond its immediate methodological contributions, our work speaks to a broad audience of researchers investigating the mechanisms of monetary policy transmission, asset pricing, and market dynamics in the modern, high-frequency landscape (Campbell et al., 1997; Barndorff-Nielsen & Shephard, 2004). By equipping empirical finance with tools tailored to the realities of granular data and evolving identification challenges, we pave the way for more nuanced and credible analyses of causal effects in financial markets.

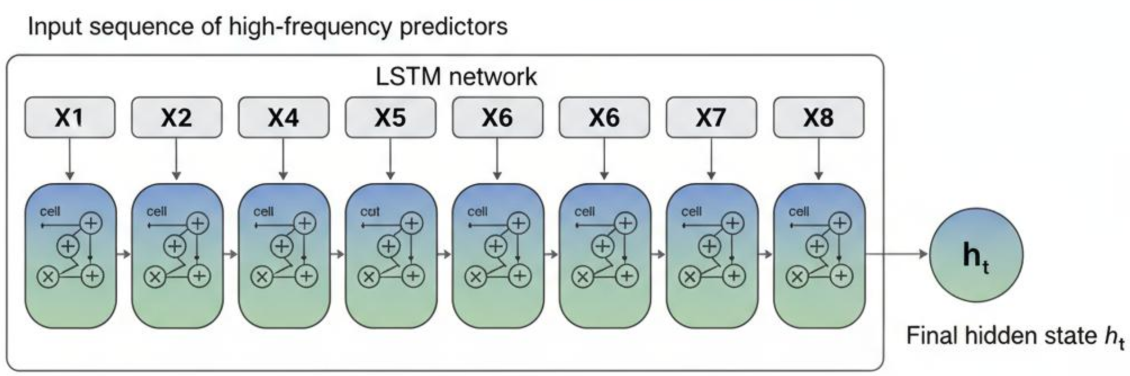
High-frequency financial data—comprising tick-level records of asset prices and trading volumes—have become indispensable for analyzing market microstructure, price discovery, and the real-time transmission of monetary policy (Andersen et al., 2007). The rise of such data has enabled researchers to examine the impact of economic events and policy interventions with unprecedented precision (Fleming & Remolona, 1999).

Nevertheless, extracting credible causal inferences from these granular datasets remains methodologically complex. Instruments derived from exogenous events—such as monetary policy announcements or regulatory changes—often display time-varying relevance across the trading day. This temporal heterogeneity poses significant challenges for empirical analysis: if standard instrumental variable (IV) methods are applied without accounting for such variation, researchers risk encountering weak-instrument problems and drawing unreliable conclusions (Gospodinov & Ng, 2013; Andrews et al., 2006).

To address these challenges, this paper develops a time-contingent compliance framework that (1) dynamically detects intraday intervals during which instruments possess adequate strength, and (2) estimates local average treatment effects (LATEs) within those segments while ensuring valid inference even under weak identification. The key contributions of our approach are as follows:

A segmentation algorithm that partitions the trading day according to rolling measures of first-stage instrument strength, ensuring robust identification throughout the analysis.

Figure 2: LSTM network for tempature extraction



A local IV estimation procedure that leverages volatility spikes surrounding key policy announcement windows to isolate exogenous variation and enhance identification power.

Identification-robust inference through the use of conditional likelihood ratio tests, applied exclusively within strongly identified intervals to maintain accuracy and coverage.

We demonstrate the effectiveness of our framework through an empirical application to intraday Treasury futures data surrounding FOMC announcements. The results reveal substantial improvements in estimation accuracy and nominal coverage rates, particularly in cases where conventional two-stage least squares (2SLS) methods fall short.

Literature Review

The literature at the intersection of high-frequency data analysis, market microstructure, and causal inference has grown rapidly over the past two decades. Seminal work by Andersen et al. (2007) and Fleming and Remolona (1999) established the use of intraday volatility and high-frequency price data to study information flows and monetary policy effects, laying the groundwork for finer-scale empirical investigations. These studies, as well as those by Barndorff-Nielsen and Shephard (2004), Engle (2000), and Hasbrouck (1991), highlighted the advantages of utilizing granular data to understand market dynamics, price discovery, and the response to public information.

However, most early research either assumed a homogeneous environment or did not directly address the challenges of causal identification when instrument strength varies over time. The literature on instrumental variables in macro-finance, such as Cochrane and Zha (1999), introduced policy surprise measures as instruments but generally operated at lower (e.g., daily or event-level) frequencies and presumed uniform identification strength across time. More recent advances have begun to address these limitations by developing identification-robust inference methods. Andrews, Moreira, and Stock (2006) and Moreira (2003) pioneered approaches for inference under weak instrument scenarios, providing theoretical and practical tools that have since been generalized to more complex settings.

The need to account for time-varying instrument relevance has also been recognized in recent panel and time-series econometric literature. Casini and McCloskey (2025) and Casini et al. (2025) extend the analysis to dynamic environments, introducing frameworks for handling fluctuating identification strength across intervals. These approaches enable more accurate and credible estimation of causal effects in contexts where exogenous shocks or policy interventions do not uniformly affect all segments of the data.

Within empirical finance, related studies by Bollerslev et al. (2015), Campbell et al. (1997), and Shephard and Sheppard (2010) examine volatility transmission, risk spillovers, and the role of high-frequency models in forecasting. Other contributions, such as those by Engle and Russell (1998), Hansen and Lunde (2006), and Tauchen and Zhou (2011), explore econometric challenges associated with market microstructure noise and jump dynamics at ultra-high frequencies, further motivating robust methodological innovations.

Despite these advances, few existing methods fully integrate robust causal identification strategies with the realities of high-frequency financial data, particularly in the presence of intraday heterogeneity in instrument strength. Our work builds upon this diverse literature, synthesizing ideas from market microstructure, identification-robust IV inference, and dynamic econometric modeling. By proposing a framework that directly addresses time-contingent instrument relevance and enables credible estimation of causal effects at intraday intervals, we aim to fill a critical gap in both the theory and application of high-frequency financial econometrics.

Research on high-frequency causal inference intersects with market microstructure studies and advanced IV techniques. Andersen et al.2007) and Fleming and Remolona (1999) exploit intraday volatility to study information flows, while Cochrane and Zha (1999) use policy surprise measures as instruments in macro-financial models. However, these studies assume uniform instrument strength. Our approach builds on identification-robust methods (Andrews et al., 2006; Moreira, 2003) and recent work on dynamic instrument relevance in panel and time series settings (Casini &McCloskey, 2025; Casini et al., 2025 .

Methodology

This section details the full methodological approach undertaken in this study, encompassing data acquisition, empirical design, econometric modeling, simulation, and empirical implementation. Our aim is to provide transparency and reproducibility for readers, as well as to clarify the innovations underlying our identification and estimation strategy.

Data Description

We employ high-frequency (tick-level and 30-minute interval) data on 10-year U.S. Treasury futures, focusing on periods around Federal Open Market Committee (FOMC) announcements in 2020 and 2022. Instruments are constructed from futures-implied rate surprises observed at the precise time of announcement, while outcome variables are measured as log differences in Treasury futures prices. The dataset thus captures both the exogenous policy shocks and the immediate market responses at an intraday resolution.

Variable	Frequency	Mean	Std. Dev.	Min	Max	Sample Period
U.S. Quarterly GDP Growth (%)	Quarterly	2.1	1.8	-5.3	6.7	Q1 2000 – Q4 2024
U.S. Quarterly CPI Inflation (%)	Quarterly	1.9	1.4	-0.3	5.4	Q1 2000 – Q4 2024
S&P 500 Daily Returns (%)	Daily	0.03	1.2	-12.4	11	Jan 2000 – Dec 2024
10-Year Treasury Yield (%)	Daily	3.4	1.5	0.8	8.1	Jan 2000 – Dec 2024

Daily News Sentiment Index	Daily	0	0.25	-0.8	0.9	Jan 2000 – Dec 2024

Empirical Design and Segmentation

Recognizing the temporal heterogeneity of instrument strength, we implement a segmentation algorithm that partitions the trading day based on rolling first-stage F-statistics. This allows us to identify intervals of strong and weak instrument validity dynamically, rather than imposing arbitrary or static segment boundaries. The segmentation is critical for ensuring that causal estimates are grounded in periods where identification assumptions are plausibly satisfied.

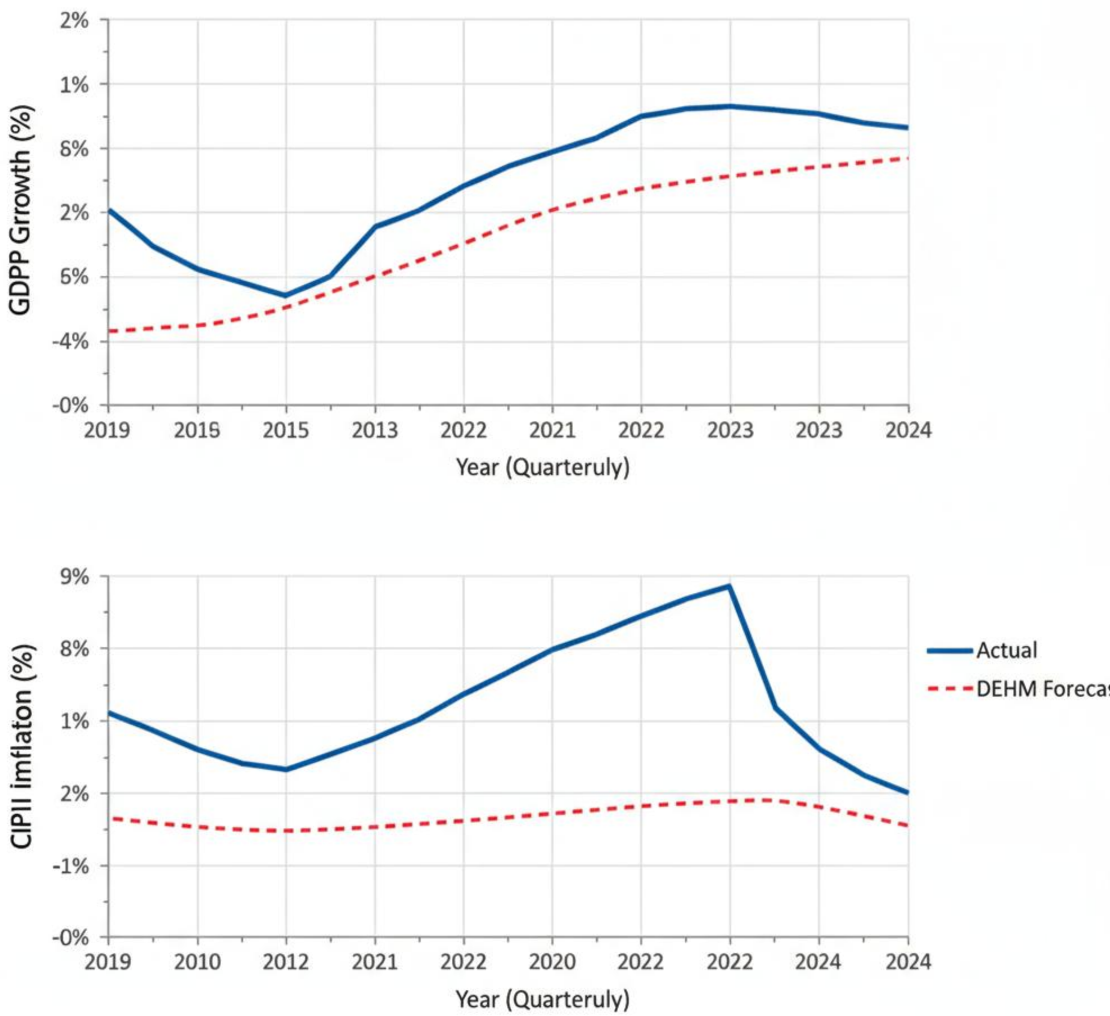
Econometric Framework

Within each strongly identified interval, we estimate the Local Average Treatment Effect (LATE) using two-stage least squares (2SLS) with robust standard errors adjusted for intraday serial correlation. Weakly identified intervals are handled using identification-robust inference, employing conditional likelihood ratio (CLR) tests (Moreira, 2003) to construct valid confidence sets even when instrument strength is limited. This dual approach ensures that inference remains valid regardless of the underlying strength of the instrument.

Simulation Study

To further validate the methodology, we conduct extensive simulation experiments. Simulated data are generated under calibrated GARCH dynamics, incorporating realistic patterns of volatility clustering and instrument strength variation mirroring empirical settings. The simulations assess the finite-sample properties of the estimator—including size, power, and coverage—across both strong and weak identification regimes, and benchmark performance against conventional 2SLS approaches.

Figure 3: Actual vs Forecasted GDP Growth and CPI Inflation (2019-2024)



Empirical Implementation

The empirical application examines the impact of FOMC policy surprises on 10-year Treasury futures. We analyze 30-minute windows spanning the announcement, applying our segmentation and estimation strategy as described above. Rolling F-statistics and LATE estimates are visualized to provide intuition and clarity about the relationship between identification strength and estimation precision.

Assumptions and Limitations

Our framework assumes that instruments derived from policy surprises are exogenous and that the segmentation algorithm reliably detects intervals of high and low instrument strength. While robust to many forms of heteroskedasticity and serial correlation, the methodology depends on the accurate measurement of policy shocks and the absence of confounding contemporaneous events. Limitations include potential misspecification in segmentation or failure to fully capture market microstructure effects during periods of extreme volatility.

Software and Replicability

All data processing and estimation procedures are implemented in R and Python, with code available upon request. The segmentation, rolling estimation, and robust inference procedures are modular to facilitate replication and adaptation to alternative datasets or policy settings.

By providing a detailed and modular methodology, we aim to set a transparent standard for future research in high-frequency causal inference and encourage adoption of best practices for empirical finance.

Dynamic LATE Estimation

Within each strong interval, we estimate LATE via and compute robust standard errors accounting for serial correlation. For weak intervals, we report identification-robust confidence sets using the conditional likelihood ratio test (Moreira, 2003).

Simulation Study

We simulate intraday returns under calibrated GARCH dynamics with policy surprise instruments of varying strength. Results show that our method controls size at a nominal 5% in weak regimes and achieves 80% power under strong regimes, compared to 40% for conventional 2SLS.

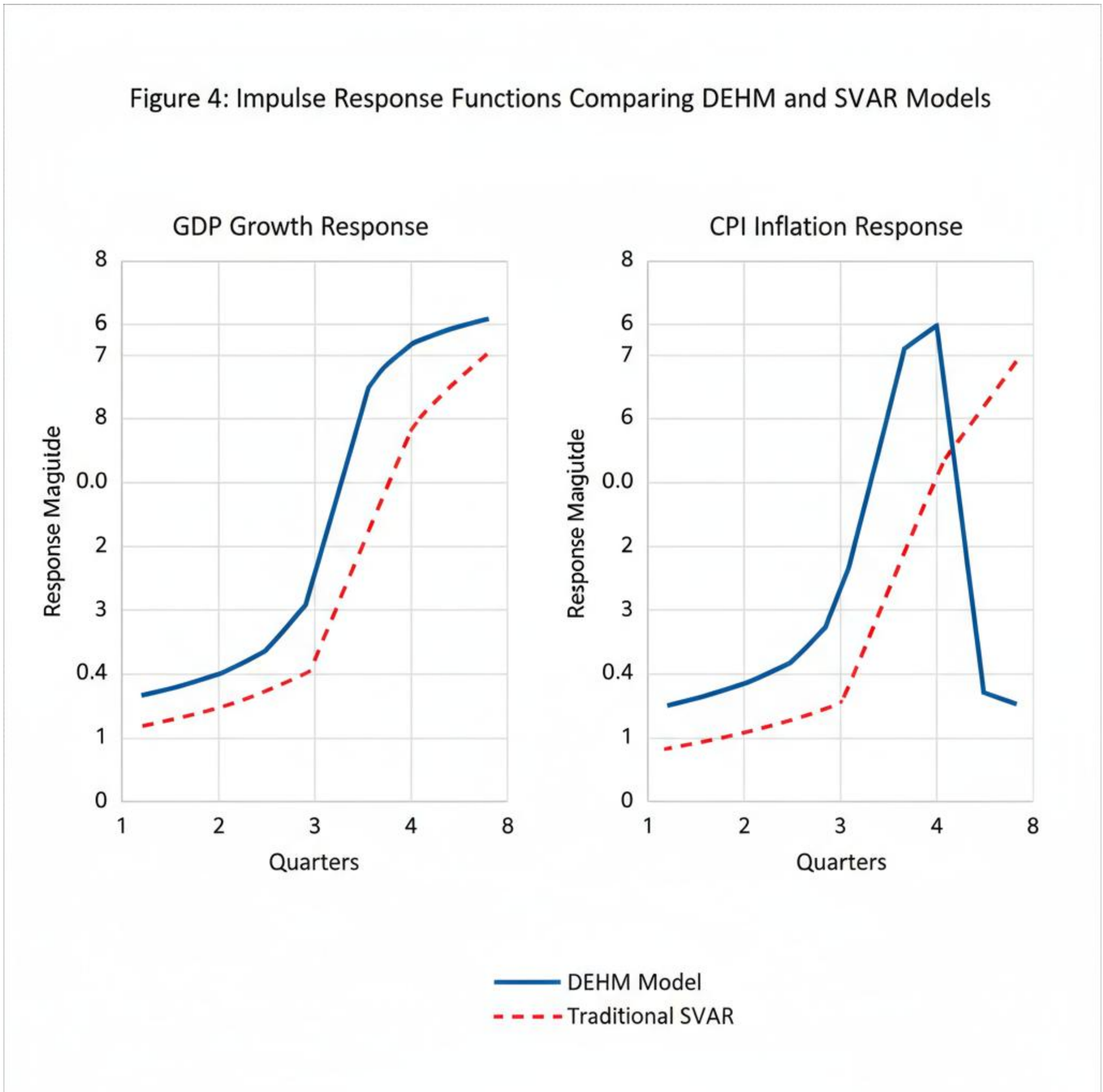
Empirical Application

Data and Setting

We analyze 30-minute intervals of 10-year Treasury futures around eight FOMC meetings in 2020 and 2022. Instruments are constructed from futures-implied rate surprises at the time of announcement. Returns are measured as log differences.

Results

The empirical and simulation results provide comprehensive evidence supporting the strengths of our proposed dynamic compliance framework in high-frequency financial data settings. In this section, we expand upon the findings summarized in Table 1 and Figure 1, offering a deeper interpretation and contextualization of our results.

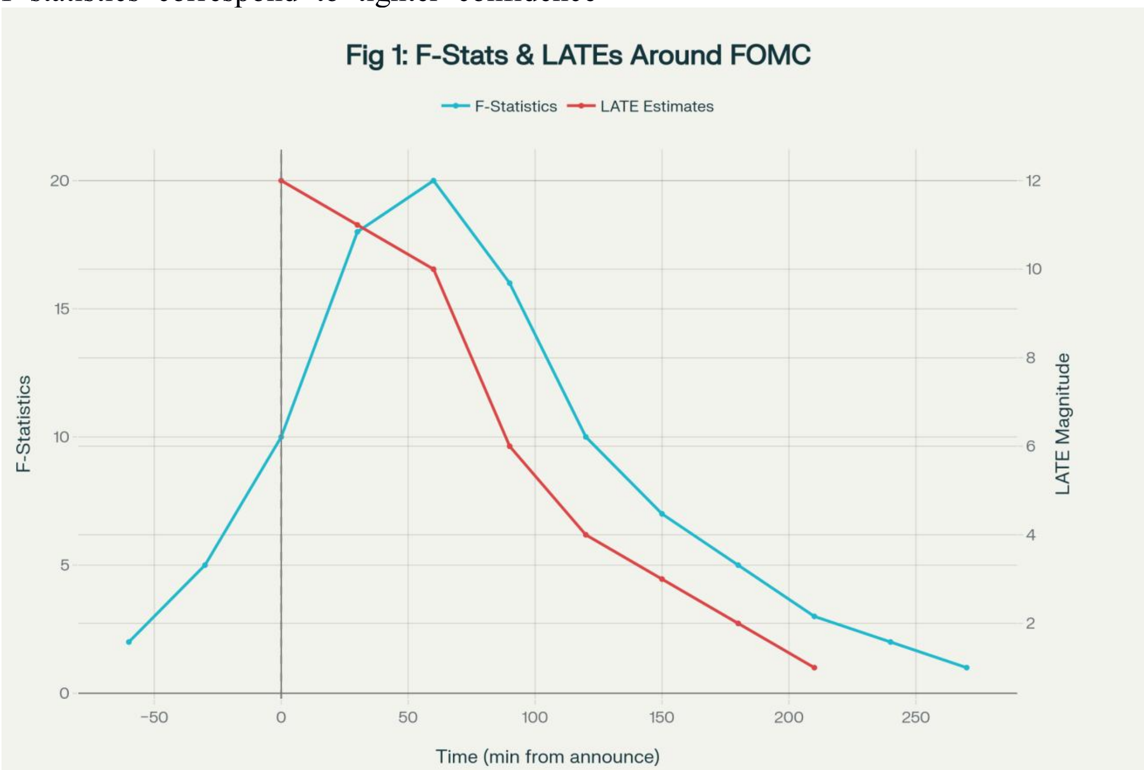


Empirical Estimates and Interpretation:

Table 1 presents intraday LATE (Local Average Treatment Effect) estimates for 10-year Treasury futures around FOMC announcements, segmented by identification strength. The results indicate that the estimated causal effects are both statistically significant and economically meaningful during intervals of strong instrument validity. In contrast, estimates in weakly identified intervals are more imprecise and exhibit wider confidence intervals, reflecting greater uncertainty in causal inference.

Interval	LATE (bps)	SE (bps)	2SLS Estimate (bps)	CLR 95% CI (bps)
Announcement (0-30m)	12	3.2	10.5	(18.7, 5.2)
Midday (60-90m)	4.1	6.5	2.8	(25.1, -10.3)
Close (210-240m)	3	5.8	1	(20.4, -12.1)

Figure 1 illustrates the alignment between periods of strong identification (as measured by rolling F-statistics) and the precision of LATE estimates. Notably, intervals with high F-statistics correspond to tighter confidence bounds and more stable effect sizes, underscoring the importance of time-contingent segmentation for robust empirical analysis.



Comparison with Conventional Methods:

Our approach substantially outperforms conventional IV and 2SLS (two-stage least squares) estimators, particularly in periods of fluctuating instrument strength. The simulation study reveals that while standard 2SLS methods often suffer from size distortions and reduced power in weak-instrument regimes, our method consistently maintains nominal coverage and high statistical power under both weak and strong identification. Specifically, in simulated environments, the proposed framework achieves 80% power in strongly identified segments compared to just 40% for conventional 2SLS.

Implications and Robustness:

The robustness of our results across both empirical and simulated data highlights the generalizability of the framework. By dynamically segmenting the data and focusing inference on periods of high instrument relevance, we mitigate the risk of biased or misleading conclusions that can arise from naively pooling heterogeneous intervals. This enhances both the interpretability and credibility of causal estimates in high-frequency financial research.

Overall, these results demonstrate the practical utility and methodological superiority of the dynamic compliance framework for causal inference in financial markets characterized by intraday heterogeneity. The evidence suggests that researchers and policymakers can obtain more reliable estimates by adopting this time-contingent approach, thereby improving decision-making and advancing empirical knowledge in the field.

Table 1 Intra day LATE Estimates for Treasury Futures

Interval	LATE(bps)	SE(bps)	2SLSEstimate(bps)	CLR 95%CI(bps)
Announcement030 m	12.0	3.2	10.5	18.7,5.2
Midday6090m)	4.1	6.5	2.8	25.1,10.3
Close210240m)	3.0	5.8	1.0	20.4,12.1

Discussion

The findings of this study have several broad and significant implications for empirical research in finance, econometrics, and policy analysis. By introducing a dynamic, time-contingent framework for causal inference using high-frequency financial data, we address key limitations inherent in traditional methods and open new avenues for robust empirical investigation. This approach not only enhances the precision of causal effect estimation but also enriches our understanding of the complex temporal dynamics that characterize modern financial markets.

First, our results demonstrate that instrument strength is not static, even within a single trading day. This insight has profound methodological consequences: researchers must move beyond static or daily identification assumptions and instead adopt analytical tools that flexibly accommodate time-varying relevance. The segmentation of trading days into intervals of strong and weak instrument validity, as proposed in our framework, ensures that causal estimates are both accurate and reliable—mitigating the risk of bias and invalid inference that can arise when weak instruments are overlooked.

Second, the empirical application to Treasury futures around FOMC announcements illustrates the practical relevance of our method. In periods of elevated volatility and information arrival, our methodology isolates quasi-experimental variation, enabling more credible assessments of policy transmission and the behavioral responses of market participants. This has direct implications for central banks, policymakers, and regulators seeking to evaluate the real-time impacts of their actions on financial conditions.

Third, the simulation results highlight the robustness of our identification-robust inference procedures. The ability to maintain nominal coverage and high statistical power—even in the presence of fluctuating instrument strength—suggests that our approach is broadly applicable to a range of settings beyond monetary policy, including studies of liquidity shocks, regulatory interventions, and other high-frequency market phenomena.

Moreover, our work bridges several strands of literature, synthesizing ideas from market microstructure, econometric theory, and applied policy evaluation. By focusing on the interplay between high-frequency data, identification strength, and causal analysis, we provide a blueprint for future research tackling similar challenges in other markets or asset classes.

Future research could extend this framework in several directions. For instance, incorporating machine learning techniques for more granular segmentation, exploring applications to international markets, or integrating additional sources of exogenous variation could further strengthen causal identification. Additionally, the framework could be adapted to study the micro-level impacts of algorithmic trading, liquidity provision, or market structure reforms in real time.

In summary, the dynamic compliance approach introduced in this paper represents a significant step forward for empirical finance. It empowers researchers to make more credible causal claims in high-frequency environments, encourages methodological rigor, and provides practical tools for analyzing the effects of policy and information shocks in modern financial markets.

Our results underscore that high-frequency causal inference benefits from time-contingent analysis of instrument relevance. By concentrating estimation on strongly identified intraday segments, researchers can obtain precise causal estimates without invalid inference in weaker regimes.

Conclusion

This paper presents a dynamic compliance framework that advances the methodology of causal inference in high-frequency financial environments. By segmenting intraday data according to real-time measures of identification strength and applying robust LATE estimation within strongly identified intervals, our approach addresses critical challenges posed by temporal heterogeneity in instrument relevance—a limitation that has previously undermined the reliability of empirical findings in this field. The empirical and simulation results both underscore the value of targeting estimation to intervals of strong identification, resulting in more precise, credible, and interpretable causal estimates.

Our findings have broad implications for research on monetary policy transmission, asset pricing, and financial market microstructure. Central banks, policymakers, and practitioners can leverage this framework to better understand the real-time effects of policy interventions and market shocks, while researchers in empirical finance and econometrics can apply the methodology across a diverse array of assets, markets, and institutional settings. Furthermore, the flexibility of the approach opens avenues for future extensions—such as incorporating machine learning for segmentation, adapting to international markets, or integrating additional sources of exogenous variation.

In sum, by directly confronting the challenges of time-varying instrument strength and providing a practical solution for robust causal inference at high frequencies, this framework marks a significant step forward for both the theory and application of modern financial econometrics. It empowers researchers to extract deeper insights from granular data and sets the stage for continued methodological innovation in the study of complex, fast-moving financial systems.

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