UNIVERSITY OF TECHNOLOGY SYDNEY

Three Essays in Finance

by Zechu Liu

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Certificate

I, Zechu Liu, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the UTS Business School at the University of Technology Sydney. This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution. This research was supported by an Australian Government Research Training Program (RTP) Scholarship doi.org/10.82133/C42F-K220.

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Abstract

This dissertation comprises three essays that examine the consequences of financial frictions within the domains of macro-finance, asset pricing, and financial regulation. The first and second essays provide empirical analyses of the Bank of Japan's equity ETF purchase program, focusing on its operating mechanisms, impact on market volatility, and the extent to which it achieves its policy objectives. The third essay investigates how the incidence of consumer fraud is influenced by local cultural norms, and explores the underlying mechanisms driving this relationship.

The first essay examines the Bank of Japan's unprecedented program of equity exchange-traded fund (ETF) purchases – one of the largest equity market interventions by any central bank. This unconventional policy was intended to calm the stock market and bolster investor confidence. The BOJ's sustained presence as a top shareholder in its domestic equity market offers a unique opportunity to evaluate the long-run consequences of such direct market support. A causal evaluation reveals that while these large-scale interventions provide short-term support, they inadvertently amplify market volatility over time. This paradox illustrates how a well-intentioned policy tool designed to reduce risk can unexpectedly increase market fragility, challenging traditional notions of central bank neutrality and market efficiency.

Expanding on the theme of policy-driven influences, the second essay investigates the predictability and market impact of the BOJ's interventions. It shows that the central bank's equity purchases follow a transparent, data-driven pattern – often triggered by morning market losses – which makes these operations highly anticipated by investors. By developing a long-short trading strategy that exploits this predictability, the study demonstrates that traders can earn abnormal returns around intervention days, thereby influencing price dynamics. Further analysis reveals that the impact of these interventions is not uniform across firms: the effects are stronger for firms with larger market capitalization and lower liquidity, suggesting that the BOJ's policy provides disproportionate support to large and high-risk firms.

Shifting from institutional actions to societal factors, the third essay explores the role of social trust in shaping community-level vulnerability to consumer financial fraud across U.S. regions. Contrary to the notion that trust increases exposure to opportunistic behavior, the study finds that communities with higher levels of social trust experience lower incidences of fraud. This relationship appears to be mediated by the quality of local communication networks: high-trust communities tend to foster more effective information sharing and collective awareness, which enhances their resilience to fraudulent schemes.

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I would also like to thank my family for their support throughout this journey. I am especially grateful to my father, whose constant help and encouragement have meant a great deal to me. To my wife, thank you for your patience, love, and sacrifice during the years we spent apart across countries—your presence, even from afar, has been a source of strength. Lastly, I wish to express my heartfelt gratitude to my late mother. Though you are no longer with us, I hope to share this work with you in spirit. May you rest in peace.

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CHAPTER 1

Introduction

1.1. Literature Review on BOJ ETF Interventions

A growing body of literature is documenting the impact of unconventional monetary policy tools, particularly asset purchase programs, on various financial markets. Among these, the Bank of Japan (BOJ) offers a particularly salient case: It has implemented one of the most aggressive equity market interventions on the globe by purchasing index-linked exchange-traded funds(ETFs). These interventions provide a unique empirical framework to evaluate the effect of central bank operations on asset prices, investor behavior, and broader market dynamics.

1.1.1. Mechanism of BOJ intervention. In terms of the mechanism, various empirical studies consistently indicated that BOJ's interventions adopt contrarian strategy, often triggered by negative overnight or morning returns (Charoenwong et al., 2021; Hattori and Yoshida, 2023; Toshino, 2020). Such patterns suggest a reactive policy orientation aimed at mitigating short-term market stress. Empirical evidence indicates that interventions tend to occur after early-day declines averaging –1.45%, with associated volatility spikes of around 2%.

Furthermore, BOJ's interventions do not affect all stocks equally. Cross-sectional differences arise due to factors such as index weight, ETF allocation ratios, firm size, and liquidity. Harada and Okimoto (2021) measure the relative exposure of individual stocks to BOJ purchases and show that stocks more heavily affected by the BOJ—such as constituents of the Nikkei 225—experience significantly greater price impacts than non-Nikkei 225 stocks. Similarly, Charoenwong et al. (2021) find that firms with higher ETF ownership benefit more from BOJ purchases and are more likely to issue equity. The positive response is especially pronounced among small- and mid-cap stocks with limited liquidity, which are more sensitive to demand shocks and may exhibit stronger price reactions under constrained supply conditions.

These heterogeneous effects underscore the role of institutional design: since BOJ's operations are conducted via passive vehicles, the resulting flows are shaped by index methodology and weighting schemes. Consequently, firms that happen to be overrepresented in the Nikkei or

TOPIX indices benefit more, regardless of fundamentals. This raises concerns about capital misallocation and market segmentation, particularly when index composition diverges from the broader economic structure.

1.1.2. Price effect of BOJ intervention. A substantial body of literature confirms that the BOJ's equity purchases consistently lead to positive stock returns. Charoenwong et al. (2021) and find statistically significant increments in price, with estimated magnitudes ranging from 1.95 to 5.54 basis points per 10 billion yen purchased. Dang et al. (2021) draw similar conclusions in the Chinese context, where state-led interventions also induce both trading and announcement effects. Such price movements may not be necessarily driven by fundamentals, instead they may reflect mechanical or predictable price pressure, as discussed in several related studies on ETF flows and dividend reinvestment effects (Brown et al., 2021; Hartzmark and Solomon, 2022a; Pan and Zeng, 2017).

Notably, the price impact is not uniform across time. Harada and Okimoto (2021) highlighted that the effects were most pronounced during QQE3, when purchase intensity peaked, and weakened during QQE4 due to reduced allocations to Nikkei-linked products. Such evidence suggests that the market reacts to not only purchase amounts but also shifts in institutional preferences, product structures and perceived policy credibility. Such interventions are often justified as tools for market stabilisation; However, the limited effect sizes—despite trillions of yen in cumulative purchases—raise questions about marginal effectiveness, potential saturation effects and diminishing returns over time.

1.1.3. Policy effectiveness and broader theoretical implications. The literature presents a clear divergence on the role of central banks in responding to equity market fluctuations. The conventional view, rooted in inflation-targeting frameworks, argues that interventions should be avoided unless asset price movements have a substantial impact on inflation or real economic activity. Seminal contributions emphasise that monetary policy should focus on stabilising inflation and output gaps, warning of potential policy errors from misjudging asset price misalignments (Bernanke and Gertler, 2000, 2001; Cecchetti, 2000; Smets, 1997). In contrast, a more flexible strand contends that equity market interventions can be appropriate and effective without undermining the credibility of inflation-targeting regimes. Proponents argue that financial stability considerations can legitimately extend the scope of monetary policy (Bordo and Jeanne, 2002; Filardo, 2004; Friedman, 2004; Sellin, 2001), a view supported by policy practices such as

China's 'national team' purchases during market turbulence (Dang et al., 2021), the Hong Kong Monetary Authority's index futures operations during the Asian Financial Crisis (Jao, 2001), and Korea's creation of a market stabilisation fund. These contrasting perspectives underscore the need for further empirical evidence on the conditions under which equity market interventions achieve—or fail to achieve—their intended stabilisation objectives.

Still, the literature raises concerns that sustained central bank interventions may generate long-term distortions in capital allocation, investor incentives, and corporate governance norms (Charoenwong et al., 2021; Chen et al., 2019). Firms benefiting from price support may be more inclined to issue equity or pursue suboptimal investments, while passive investors may overlook deteriorating fundamentals, fostering moral hazard as markets come to expect central bank backstops regardless of underlying risk. Although the BOJ's asset purchases are intended to reduce risk premia and lower the cost of capital, evidence suggests ambiguous effects on market quality. Furthermore,Chen et al. (2019) document that large-scale BOJ ownership reduces liquidity by narrowing the free float, decreasing the number of shareholders, increasing ownership concentration and lowering turnover, ultimately impairing price discovery—particularly when holdings are concentrated in ETFs or when substantial portions of the market become passively held.

1.1.4. Contributions. This thesis makes several contributions to the literature on policy interventions, with a particular focus on the Bank of Japan's (BOJ) ETF purchase program. It advances existing knowledge by clarifying the temporal transmission of equity-market interventions, strengthening causal identification using complementary empirical designs, and providing new evidence on predictability, trading implications, and cross-sectional heterogeneity.

First, the thesis provides novel evidence on the dynamic and lagged effects of central bank equity purchases, as developed in the first essay. Whereas most prior studies emphasize contemporaneous or same-day responses to BOJ ETF purchases (Charoenwong et al., 2021; Harada and Okimoto, 2021; Takahashi and Yamada, 2021; Toshino, 2020), the first essay shows that the volatility response unfolds gradually and persists for several trading days after intervention. This delayed volatility pattern is consistent with a mechanism in which a central bank, acting as a non-profit-maximizing marginal buyer with imperfect information, alters investors' beliefs about the policy reaction function and intensifies strategic trading around intervention episodes. Such belief updating and coordination or friction effects can elevate short-run uncertainty and amplify price adjustments, manifesting as a higher conditional variance rather than a smoother price path. Importantly, this interpretation implies that short-run price support and elevated volatility are not mutually exclusive: they may coexist because they reflect different objects, horizons, and underlying shocks.

To sharpen the interpretation of these dynamics, the thesis links intervention-induced volatility changes to risk compensation by focusing on risk-adjusted performance measures, rather than relying on volatility movements alone. In the first essay, we supplement volatility-based evidence with a set of risk-adjusted metrics that evaluate whether the short-run price support associated with BOJ purchases is sufficient to compensate investors for the concomitant increase in risk. The results reveal a clear deterioration in risk-adjusted performance around intervention days, followed by a gradual normalization over subsequent trading days. This dynamic pattern implies that any immediate price support is not fully reflected in contemporaneous risk-adjusted outcomes, so the rise in short-run risk is not instantaneously offset by higher returns. Consequently, the stabilizing role of BOJ equity interventions appears limited when assessed through the lens of risk-adjusted performance and may be counterproductive over short horizons, reinforcing the broader argument that policy intentions and market reactions can diverge (Charoenwong et al., 2021; Chen et al., 2019).

Second, the first essay strengthens causal inference by adopting a triangulated empirical strategy. While much of the literature evaluates the BOJ's equity purchase program through asset returns or liquidity effects (Charoenwong et al., 2021; Chen et al., 2019; Katagiri et al., 2022), this thesis adopts a distinct perspective by focusing directly on volatility as a policy-relevant outcome. The analysis begins with a reduced-form OLS framework using a newly constructed policy intensity index. It then employs a Structural VAR model to capture dynamic interdependencies between interventions and market volatility, and finally applies a Fuzzy Regression Discontinuity Design that exploits a threshold-based intervention rule. Taken together, these complementary approaches mitigate key endogeneity concerns—such as omitted variables and reverse causality—and provide robust evidence on the stabilizing, or destabilizing, effects of central bank equity interventions.

Third, the thesis offers a critical policy evaluation by comparing the BOJ's stated objectives with observed market outcomes. Contrary to the aim of reducing market risk and stabilizing investor sentiment, the results show that interventions are associated with higher volatility and increased risk compensation pressures. These findings raise concerns about unintended consequences of large-scale asset purchases and contribute to the broader debate on whether and how monetary authorities should respond to asset-price fluctuations (Bernanke and Gertler, 2000, 2001; Rigobon and Sack, 2003).

Finally, the second essay develops a real-time prediction framework that speaks directly to monetary policy transparency and market efficiency. While existing studies document that BOJ interventions follow relatively transparent rules and respond to observable market conditions (Fukui and Yagasaki, 2023; Hattori and Yoshida, 2023; Nangle and Yates, 2017), they generally do not test real-time predictability using publicly available information. The second essay fills this gap by estimating a logit model that forecasts intervention days with high accuracy over a multi-year sample, providing systematic evidence on how data-driven monetary policies operate in practice. Building on this predictability, the essay shows that investors can construct implementable portfolios that earn abnormal returns by exploiting predictable intervention patterns, even in a transparent policy environment. This finding extends the literature on non-fundamental price pressure induced by large flows (Coval and Stafford, 2007; Dyakov and Verbeek, 2013; Hartzmark and Solomon, 2022b; Lou, 2012) by demonstrating that flow-driven distortions can remain economically meaningful despite public disclosure and broad anticipatability. It therefore challenges the strong-form implication of the efficient market hypothesis that public information should be fully and instantaneously incorporated into prices.

In addition, the second essay provides new evidence on cross-sectional heterogeneity in the effects of BOJ interventions along risk and liquidity dimensions. Using portfolio decompositions and cross-sectional regressions, it shows that BOJ purchases disproportionately affect illiquid and high-risk stocks, consistent with the view that equity purchases can operate as a form of downside insurance and shape the distribution of price impact across securities (Katagiri et al., 2022). Together, the two essays offer a coherent account of how predictable, rules-based central bank equity interventions transmit to asset prices through both risk dynamics and mechanical flow channels, and why these effects can persist beyond the intervention day.

1.2. Literature review on social trust and consumer fraud

Social trust plays a complex and multifaceted role in shaping individual exposure to consumer fraud. Existing literature provides competing theoretical mechanisms and a growing body of empirical evidence to understand this relationship. This section reviews the literature along three dimensions: (1) the dual behavioral effects of trust, (2) the interaction between social norms and formal regulation, and (3) the amplification of trust-related risks in digital financial environments.

1.2.1. Behavioral mechanisms: The dual role of trust in fraud exposure. Social trust exerts both protective and detrimental effects on individuals' vulnerability to fraud. High-trust individuals are generally more receptive to new information and unfamiliar actors, which increases their exposure to deceptive financial offers (Falcone and Castelfranchi, 2001; Zhou, 2014). At the same time, they tend to exhibit adaptive learning, recognizing fraud more quickly and taking action to mitigate losses. In contrast, low-trust individuals show greater initial skepticism, which reduces their probability of being deceived at the outset (Zhou and Tian, 2010). However, once defrauded, they are less likely to report or react promptly, often leading to more severe financial harm (Benartzi and Thaler, 1999).

These behavioral patterns are consistent with evidence from the corporate fraud literature. Hertzberg (2005) and Wang et al. (2010) argue that high-trust environments may enable opportunistic behavior by reducing oversight and increasing the effectiveness of deception. These findings underscore the idea that while trust facilitates cooperation and reduces transaction costs, it can also lower vigilance, thereby creating opportunities for exploitation.

1.2.2. Trust, informal norms, and institutional enforcement. Beyond individual behavior, trust also shapes how communities interact with regulatory frameworks. Hayes et al. (2021) show that residents in high-trust U.S. states file fewer complaints to the Consumer Financial Protection Bureau (CFPB) relative to those in low-trust states, even when controlling for the incidence of abusive financial practices. This suggests that generalized trust may substitute for formal enforcement by reducing the perceived need for redress. Interestingly, after the CFPB's establishment, banks in low-trust regions responded more aggressively by lowering fees—possibly in anticipation of heightened regulatory scrutiny due to more vigilant consumer behavior.

These findings highlight the complementarity and potential substitution between informal norms and institutional design. When trust is high, individuals may underutilize formal protections, potentially allowing malfeasance to go unchecked. Conversely, distrust may lead to higher demand for institutional safeguards, inducing firms to preemptively adjust their behavior. This duality underscores the importance of aligning consumer protection policies with local cultural contexts.

1.2.3. Digitalization, trust, and the erosion of traditional safeguards. The rise of digital finance introduces new challenges to trust-based interactions. Traditional trust cues such as face-to-face communication, reputation within local networks, and physical proximity have become less salient in online environments. As Phua et al. (2025) and Hayes et al. (2021) emphasize, the closure of physical bank branches and the migration to digital services—especially among older consumers—have increased reliance on generalized trust in opaque online settings. This shift has heightened fraud vulnerability, particularly for consumers less familiar with digital tools.

Wei and Zhang (2020) and Shao and Wang (2021) also demonstrate how trust levels shape portfolio behavior. Low-trust investors exhibit local bias, allocating capital to familiar or geographically proximate firms to mitigate perceived governance risk. High-trust individuals, in contrast, are more likely to diversify and explore unfamiliar investment opportunities—enhancing long-term returns but also increasing exposure to fraud and misinformation in the absence of traditional safeguards.

These dynamics are further complicated by rising concerns over data privacy and online deception. Lappeman et al. (2022) argue that as digital platforms become the dominant channel for financial interactions, the erosion of verifiable trust cues may fundamentally alter how individuals assess risk and credibility. In this context, trust shifts from being a relationship-based expectation to a more generalized and potentially unreliable heuristic.

1.2.4. Contributions. In the third essay, we mainly introduce social trust as a core explanatory factor in understanding consumer fraud incidence. While the literature has primarily emphasized financial, institutional, or regulatory explanations—linking fraud patterns to business cycles, investor sophistication, and enforcement mechanisms (Povel et al., 2007; Wang et al., 2010)—relatively little attention has been given to cultural and social determinants, particularly local trust norms. The third essay constructs a panel dataset covering U.S. states from 2011 to 2022 and examine the relationship between social trust and fraud complaints. Our results show that higher local trust levels are consistently associated with fewer consumer fraud incidents. By highlighting this behavioral and institutional mechanism, we offer a cultural lens that complements traditional economic explanations of fraud dynamics (Amiram et al., 2018).

Another contribution of the third essay is that it demonstrates that social trust remains a potent behavioral defense against fraud, even in a highly digitized and tightly regulated environment. Existing policy discussions often focus on technological advancement and regulatory tightening as primary fraud prevention tools (Wei and Zhang, 2020; Shao and Wang, 2021; Phua et al., 2025). These approaches may overlook underlying cultural drivers of vulnerability. Our analysis shows that trust enhances informal enforcement and lowers victimization risk through stronger social cohesion. This finding has direct policy implications: it supports incorporating trust-building measures—such as community watch programs, neighborhood engagement, and culturally tailored outreach (Lappeman et al., 2022)—into fraud mitigation strategies. By embedding cultural norms into economic policy design, we broaden the available toolkit for addressing the global rise in consumer fraud.

1.3. Thesis outline

The remainder of this thesis is organized into three main chapters covering three studies, as listed below:

- Chapter 2: Assessing Bank of Japan purchase of equity ETFs: Has it achieved its policy objectives?
- Chapter 3: Data-driven monetary policy: Evidence from the Bank of Japan's equity purchase program
- Chapter 4: Social trust and consumer fraud

Chapter 5 concludes the thesis by synthesizing the main findings, discussing their broader implications, and outlining potential directions for future research.

CHAPTER 2

Assessing Bank of Japan purchase of equity ETFs: Has it achieved its policy objectives?

2.1. Introduction

Bank of Japan has implemented one of the largest equity market interventions in modern financial history. This policy aimed to reduce market risk premia and lower the cost of capital for Japanese listed firms (BOJ, 2010, 2013a; Charoenwong et al., 2021). Since 2013, BOJ has spent over 27 trillion yen for purchasing index-linked ETFs tied to TOPIX and Nikkei indices. Its equity holdings now exceed 7% of total market capitalisation on the Tokyo Stock Exchange and 80% of ETF assets[1]. BOJ's scale of asset accumulation and persistent equity presence set it apart from all other central banks. Such large-scale purchase and long-term commitment raises the first research question of the thesis: Has BOJ achieved its policy objective of reducing market risk premium?

The central motivation of this study arises from the ongoing divergence in the academic literature regarding central banks' response to stock market fluctuations. Traditional monetary theory, which is grounded in inflation-targeting frameworks, generally maintains that central banks should not intervene in equity markets unless such fluctuations have a substantial impact on inflation or real economic activity. Foundational contributions by Bernanke and Gertler (2000, 2001); Cecchetti (2000) contended that monetary policy should be directed exclusively toward stabilising inflation and output gaps, and caution should be observed against responding directly to asset price volatility. In a similar vein, Smets (1997) emphasised the risk of policy errors arising from misjudging asset price misalignments. Consistent with this perspective, major central banks in advanced economies, including the Federal Reserve, the Bank of England, and the European Central Bank, operate under inflation-targeting regimes that do not include asset price stabilisation as an explicit policy objective.

[1]Numbers from Bloomberg https://www.bloomberg.com/news/articles/2024-03-13/japan-etfs-what-will-the-boj-do-with-its-475-billion-hoard

Meanwhile, a parallel strand of research adopts a more flexible view on the role of central banks in responding to asset market fluctuations, arguing that such interventions can be both appropriate and effective. For instance, Bordo and Jeanne (2002); Filardo (2004); Sellin (2001) suggested that monetary responses to stock market shocks do not necessarily undermine the credibility of inflation-targeting frameworks. Friedman (2004) further argued that concerns over financial stability, including equity market interventions, may legitimately fall within the broader scope of monetary policy objectives. This academic perspective has gained theoretical support and has been reflected in policy practice. Several governments and monetary authorities have engaged in equity-related interventions during episodes of financial stress. A few notable examples include China's 'national team' purchases of equities during market turbulence (Dang et al., 2021), the Hong Kong Monetary Authority's index futures operations during the Asian Financial Crisis (Jao, 2001), and Korea's establishment of a market stabilisation fund.[2] These cases illustrate that both in theory and in practice, equity market interventions have been viewed as a viable component of broader financial and monetary policy responses.

BOJ provides a unique empirical opportunity to address the following long-standing debate in monetary economics: Can central bank interventions in equity markets generate lasting policy effects? BOJ's ETF purchase program was the focus for three main reasons. First, unlike most major central banks in advanced economies, such as the Federal Reserve, the Bank of England and the European Central Bank—which operate under inflation-targeting regimes that preclude direct asset price stabilisation, BOJ has conducted regular and sustained equity market operations for over a decade. This long intervention horizon and policy-driven implementation creates a rare setting for observing the effects of persistent stock market interventions. Second, in contrast to the episodic and reactive interventions observed in economies such as mainland China, Hong Kong and South Korea, BOJ's ETF purchases are long-term, policy-driven and embedded in its broader monetary strategy rather than designed as crisis response measures. Third, the scale of BOJ's intervention is historically unprecedented. Over the past decade, it has allocated hundreds of billions of U.S. dollars towards ETF purchases, making it the world's largest institutional investor in domestic equities. Therefore, this study begins by evaluating whether BOJ's large-scale equity market interventions have successfully achieved their stated policy objectives. In doing so, it not only assesses the effectiveness of BOJ's program but also provides empirical

[2] See Bank of Korea website `https://www.bok.or.kr/eng/main/contents.do?menuNo=400110`

evidence to inform the broader debate over whether central banks should respond to unexpected equity market shocks.

To examine whether BOJ's ETF purchases affect the market risk premium, we follow the ICAPM model by Merton (1973) and investigate BOJ intervention's impact on market volatility.[3] This model links expected risk premium to the ex ante return variance, scaled by a constant risk aversion factor. We assume that risk aversion remains stable over short periods, as suggested by Guiso et al. (2018), who showed that it changes slowly through four main channels. Hence, we treat changes in daily market volatility as a proxy for changes in the market risk premium. If BOJ's intervention affects volatility, it also indirectly affects the risk premium through this channel. We construct market volatility from 5-minute intra-day TOPIX returns, which capture short-term investor uncertainty. This high-frequency measure helps us better reflect the market's immediate response to BOJ's actions.

In contrast to existing studies that primarily examine the contemporaneous effects of BOJ interventions (Charoenwong et al., 2021; Hattori and Yoshida, 2023; Nangle and Yates, 2017; Toshino, 2020), the analysis of this study focus on BOJ's lagged impact on financial markets, because the analysis reveals that the impact of BOJ interventions is not likely to be fully absorbed within the same trading day. We find that the scale of BOJ's intervention orders often exceed what can be executed by brokers within a single session. To assess the relative magnitude of these interventions, we compare BOJ's purchase volumes in TOPIX-linked ETFs with the total trading value of the TOPIX index. As shown in Figure 2.1.1, we construct an intervention ratio using both full-day and afternoon-session trading value as denominators. The ratio is smoothed using a 10-day moving average to mitigate the impact of extreme values. The latter is particularly relevant given that BOJ interventions are typically implemented in the afternoon following earlier losses, as documented by Harada and Okimoto (2021). Our estimates show that, on average, BOJ purchases account for 1.34% of daily trading volume and 2.53% of afternoon-session volume—ratios that steadily increased, reaching nearly 3.8% and 7%, respectively, by 2019. This growing market footprint suggests that the effects of BOJ interventions may unfold gradually and persist over time. Accordingly, we extend the existing literature by examining not only contemporaneous responses but also the lagged effects of interventions on market volatility. Capturing these

[3] Merton (1973) established a positive relationship between market risk premium and return volatility under the intertemporal CAPM framework: $\text{MRP}_t = A \cdot \sigma_t^2$, where A is the coefficient of relative risk aversion and σ_t^2 is the conditional variance.

delayed dynamics is essential to fully understand BOJ's influence on risk pricing and broader market behavior.

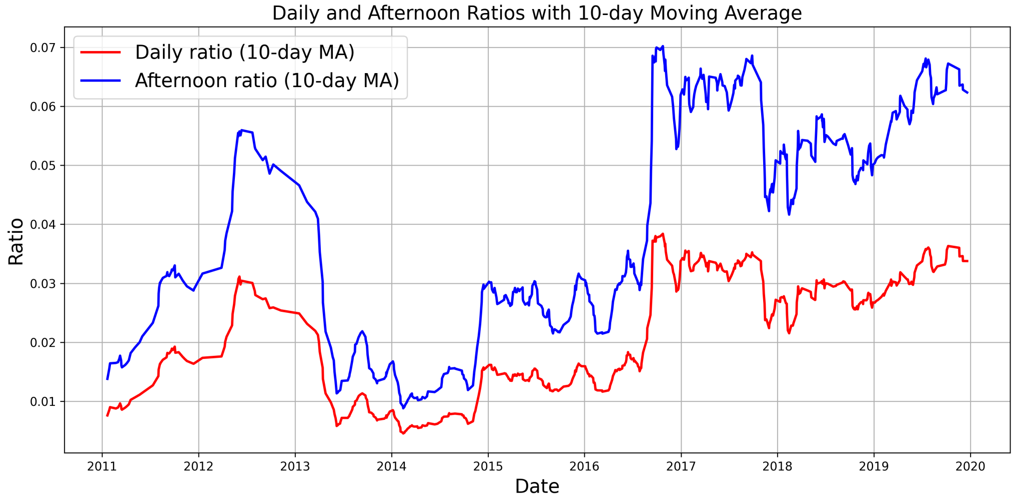

FIGURE 2.1.1. The ratio between the ETF intervention amount and daily and afternoon trading values on intervention days. The ratio is smoothed using a 10-day moving average to mitigate the impact of extreme values.

Motivated by this observation, we investigate the dynamic and lagged effects of BOJ interventions on market volatility and employ a baseline reduced-form OLS framework that relates intervention activity to subsequent changes in volatility. We construct a policy intensity index that measures the number of intervention days within a rolling five-day window preceding each trading day. This index captures the cumulative intervention pressure over time and serves as a proxy for BOJ's market presence. By regressing realised volatility on this intensity measure, we test whether repeated interventions generate delayed effects on market sentiment and uncertainty. The regression results show that BOJ intervention in the past five trading days is significantly associated with higher intra-day volatility, suggesting a lagged effect of policy actions. Furthermore, same-day intervention also predicts increased volatility, reflecting BOJ's reactive behavior during periods of heightened market stress.

The policy intensity variable captures the frequency of BOJ interventions over the preceding five trading days and helps reduce concerns about reverse causality. However, the OLS specification remains vulnerable to endogeneity issues, most notably omitted variable bias. Specifically, the model may fail to account for unobservable or hard-to-quantify factors such as market sentiment or structural shifts in trading behavior that influence both interventions and market volatility.

To address these concerns and strengthen causal inference, we employ a structural vector autoregression (SVAR) framework. The SVAR leverages exogenous variation and the dynamic ordering of variables to trace the effects of structural shocks to BOJ interventions via impulse response functions. The model incorporates lagged values of returns, interventions, volatility and ETF share creation, thereby capturing their joint temporal evolution. This structure allows for isolating policy-driven shocks and evaluating their causal effects. It also exploits the high-frequency nature of volatility responses and the timing regularities in BOJ intervention decisions. This approach provides a more credible identification strategy than standard regression techniques.

The SVAR results indicate that shocks to BOJ interventions induce an immediate and statistically significant increase in both ETF share creation and market volatility. These dynamic responses yield two key insights. First, the delayed yet pronounced increase in ETF share creation suggests that BOJ interventions set operational mechanisms. Market dealers gradually assemble the required ETF shares over subsequent periods. This finding is consistent with evidence reported in Brown et al. (2021) and Pan and Zeng (2017). Second, the persistent elevation in market volatility following intervention shocks implies that the effects of such interventions are not merely contemporaneous, but extend beyond the intervention day. This temporal persistence indicates that while BOJ interventions activate institutional channels designed to support market liquidity, they may simultaneously introduce short-term uncertainty that may potentially undermine the interventions' intended stabilising objectives.

While the SVAR framework addresses key endogeneity concerns by leveraging exogenous timing and lag structures, it relies on the assumption that policy shocks are unanticipated innovations. However, BOJ's equity market interventions are not purely random; they are partially predictable based on observable market conditions such as lagged returns and volatility. Such predictability may violate the SVAR's orthogonality assumption and potentially bias the estimated impulse responses. To reinforce the credibility of our identification strategy, we complement the SVAR analysis with a fuzzy regression discontinuity design (fuzzy RDD) that explicitly accounts for BOJ's implicit intervention rule. Specifically, the probability of intervention rises sharply when the morning market return falls below an estimated threshold, -0.5% (Chung, 2020). By using this threshold-crossing indicator as an instrument for actual intervention, we estimate the local average treatment effect of BOJ purchases on subsequent volatility. This quasi-experimental design exploits policy discontinuities in a narrow window around the threshold, under the assumption that other factors evolve smoothly.

Rather than relying on a distinct control asset, the identification strategy exploits a comparison between days just below the intervention threshold, when the likelihood of intervention is higher, and days just above the threshold, when intervention is less likely. This localised comparison forms the foundation for causal identification. Although an ideal regression discontinuity design would incorporate cross-sectional variation in treatment exposure, the time-series approach employed in this study remains methodologically sound and informative. The results from the fuzzy RDD indicate that BOJ interventions are associated with a statistically significant increase in volatility on the second and third trading days, as well as over the cumulative T+1 to T+3 window. These findings offer additional evidence of a lagged volatility effect, potentially reflecting market participants' perception of interventions as indicators of underlying market stress or as disruptions to the price discovery process.

These findings also reveal a misalignment between BOJ's equity market interventions and its stated objective of stabilising financial markets. Instead of mitigating uncertainty, the evidence indicates that such interventions are followed by a sustained increase in market volatility over subsequent trading days. Elevated market volatility translates into a higher market risk premium, suggesting that BOJ has not succeeded in achieving its goal of reducing perceived market risk (Merton, 1973). This pattern further implies that large-scale asset purchases may inadvertently signal underlying market fragility or interfere with normal price discovery processes, thereby heightening short-term risk perceptions[4]. These outcomes are consistent with the concerns expressed by Bernanke and Gertler (2000, 2001), who caution that monetary interventions targeting asset prices may yield unintended consequences, including distorted risk signals, mispricing, and diminished policy credibility. Hence, the results underscore the need for careful assessment of both the transmission mechanisms and potential side effects associated with unconventional monetary policy instruments.

The remaining sections of the essay are structured as follows: Section 2.2 provides a literature review on BOJ's related research, including price impact and timing of BOJ's purchase. Section 2.3 describes the data and the methodology we use throughout the essay. Section 2.4

[4]Because BOJ interventions in our sample are purchases (i.e., with a downside-protection motive), an increase in total volatility could in principle be driven by upside deviations rather than greater downside risk. To address this, we complement volatility evidence with a downside-focused risk-adjusted measure: the Sortino ratio (MAR = 0, consistent with Japan's near-zero risk-free environment in 2014–2019). The Sortino ratio is below its annual average on the intervention day and the following two days, then rises above average from day 3 (peaking around day 4) before gradually reverting. This pattern indicates a lagged improvement in downside-risk-adjusted performance and is consistent with—rather than contradictory to—our main finding that interventions are associated with elevated short-horizon risk.

discusses the findings on the impact of BOJ's ETF purchase mechanism we find and volatility impact from BOJ's purchase. Section 2.5 presents robustness tests using Nikkei 225 index and ETF data. Section 2.6 concludes and discusses policy implications.

2.2. Institutional background and literature review

Bank of Japan has conducted one of the most extensive and unique equity market interventions among major central banks by purchasing index-linked ETFs as part of its unconventional monetary policy framework. A growing body of literature seeks to understand the timing, price impact, and other consequences of these interventions along with their broader implications for market efficiency and monetary transmission.

2.2.1. BOJ equity purchase program. BOJ started its unconventional monetary policy of purchasing exchange-traded funds (ETFs) associated with equity indexes at the end of 2010. Initially, BOJ described the equity ETF purchase program as a temporary measure to encourage a decrease in longer-term interest rates and various risk premiums and further enhance monetary easing BOJ (2010). Therefore, the annual purchase budget in index-linked ETF was only 0.45 trillion Japanese yen in 2010, and the amount gradually increased to 1.5 trillion yen during the following three years. To fight against the low inflation condition, the governor of BOJ, Haruhiko Kuroda, announced a very aggressive expansionary monetary policy named 'Quantitative and qualitative Easing (QQE)' BOJ (2013a,b). As one of the instruments added in QQE monetary policy, the annual budget of the equity ETF purchase program quickly increased to 3 trillion yen in 2014 and the amount even further doubled in 2016, to 6 trillion yen with a purchase of 70 billion yen per intervention day at the end of 2019.

Furthermore, while the mechanism of BOJ's equity ETF intervention differs operationally from the conventional non-fundamental shocks discussed in previous literature, the two are interrelated. Brown et al. (2021); Pan and Zeng (2017) show that non-fundamental shocks in the stock and ETF market lead to temporary deviations between ETF prices and their net asset values (NAVs), which are then arbitraged away by authorised participants (AP) through share creation or redemption processes. This arbitrage activity links price pressure in the ETF market to underlying equity prices via demand transmission. Although BOJ has not explicitly disclosed whether it purchases ETF shares directly or acquires underlying stocks that are later converted into ETF shares, available information indicates that Sumitomo Mitsui Trust Bank (SMTB), acting as the designated agent bank, is responsible for executing BOJ's ETF-related transactions[5]. It is understood that SMTB transmits purchase instructions to affiliated securities firms, which then place orders in the market. While this process differs from the conventional arbitrage-driven mechanism involving authorised participants, BOJ's repeated and predictable interventions can still generate price pressures that resemble non-fundamental demand shocks. By consistently creating upward pressure on selected equities, such operations can influence ETF NAVs in a way that mimics the effects observed in ETF arbitrage literature. Therefore, despite the lack of a typical arbitrage loop, BOJ's ETF purchase mechanism remains inter-related with broader market pricing dynamics.

2.2.2. Existing literature related to BOJ purchase program. Several studies have examined BOJ's decision-making mechanism in determining the time when the equity market is likely to be intervened. Charoenwong et al. (2021); Hattori and Yoshida (2023); Nangle and Yates (2017); Toshino (2020) provide consistent evidence that BOJ tends to conduct purchases near the end of the trading day, particularly following significantly negative overnight or morning returns. This recurring pattern suggests a reactive, rather than pre-emptive, policy stance aimed at mitigating intra-day market stress. Our study confirms and reinforces this stylised fact, offering additional empirical validation for BOJ's intervention timing and its potential anchoring role in daily market sentiment. Specifically, we find that on intervention days, intra-day volatility tends to increase by approximately 2%, and the combined overnight and morning session returns average around –1.45%, indicating that BOJ's operations are often triggered by substantial early-day losses and heightened uncertainty.

The empirical literature provides mixed evidence on the price impact of BOJ's ETF purchases. Charoenwong et al. (2021) and Harada and Okimoto (2021) document statistically significant effects. For instance, Charoenwong et al. (2021) estimates that a 10% increase in BOJ's daily purchase volume raises returns on targeted stocks by 0.2 basis points relative to untargeted stocks. Similarly, Harada and Okimoto (2021) find that a 10 billion yen intervention increases stock prices by 1.95 to 5.54 basis points, depending on the period examined. These magnitudes appear to be limited given the scale of intervention, with BOJ holding over 75% of Japan's ETF market and committing trillions of yen to asset purchases.

[5] `https://www.boj.or.jp/en/mopo/measures/mkt_ope/ope_t/index.htm#p01`

Furthermore, BOJ's interventions may influence not only price levels but also the volatility and liquidity of the underlying assets. Charoenwong et al. (2021) examine these broader market effects and report that BOJ's ETF purchases reduce market liquidity, perhaps due to investor crowding and impaired price discovery. Their study also highlights announcement effects from major policy changes in 2014 and 2016, which produced short-term abnormal returns but were later offset by longer-term deterioration in trading efficiency. Chen et al. (2019) add that BOJ's stock purchases may disproportionately affect illiquid stocks, exacerbating fragility in less resilient market segments. In contrast, our essay focuses on the lagged consequences of day-to-day interventions for volatility profiles, not on discrete announcement shocks or policy revisions. Notably, we find that BOJ interventions are associated with a subsequent rise in market volatility, suggesting that such actions, while intended to stabilise prices, may also reflect or reinforce deteriorating market conditions and investor uncertainty.

However, a growing body of research highlights how non-fundamental price pressures—arising from mechanical, predictable or policy-driven order flows—can lead to persistent distortions in asset prices. Coval and Stafford (2007) and Lou (2012) show that predictable but uninformed trades, such as those associated with index inclusion, rebalancing, or institutional mandates, can generate substantial price impacts and cause asset prices to deviate from fundamentals.

In the context of ETFs, Brown et al. (2021) and Pan and Zeng (2017) demonstrate that non-informational shocks can trigger temporary deviations between ETF share prices and their net asset values (NAVs), which are typically corrected through arbitrage by authorised participants (APs) via the share creation and redemption mechanism. This process not only restores price alignment but also transmits demand shocks from the ETF market to the underlying equity market. More broadly, Hartzmark and Solomon (2022b) show that even fully anticipated flows—such as dividend payments—can create abnormal returns through slow-moving capital and price pressure. Our empirical findings are also consistent with Ben-David et al. (2018), who show that ETFs can amplify non-fundamental volatility, particularly when institutional ownership—such as BOJ's holdings of index-linked ETF shares—is elevated.

These insights have been extended to government-related flows as well. For instance, Dang et al. (2021) document that interventions by China's 'national team' of state-affiliated financial institutions produce measurable trading and announcement effects in equity markets, despite limited transparency regarding intervention timing. Their findings underscore that even policy-driven flows, when predictable and large in scale, can shape market dynamics in ways similar to mechanical or passive flows.

Our study contributes to the growing literature in this field by explicitly modeling the dynamic responses of returns and volatility to BOJ interventions. Whereas Charoenwong et al. (2021); Chen et al. (2019); Harada and Okimoto (2021) center on immediate market reactions; However, in this study, it is explored whether these interventions produce persistent volatility changes in subsequent days. Our approach is motivated by the hypothesis that central bank asset purchases—particularly those that are predictable and large in scale—may exert lagged effects as market participants gradually absorb the new price signals or rebalance portfolios in response.

Finally, our findings contribute to the broader debate on the effectiveness of unconventional monetary policy in stabilising equity markets. One strand of literature, grounded in traditional inflation-targeting frameworks, maintains that central bank intervention in response to unexpected equity market shocks is largely ineffective and potentially distortionary (Bernanke et al., 1999; Bernanke and Gertler, 2001; Rigobon and Sack, 2003). These studies argue that asset prices are inherently volatile and that attempts to offset transitory fluctuations may fail to deliver lasting stability, while risking misallocation of resources and policy credibility losses. In contrast, a parallel body of research adopts a more flexible view, suggesting that equity market interventions can be both appropriate and effective under certain conditions. For instance, Bordo and Jeanne (2002); Filardo (2004); Sellin (2001) contend that monetary responses to stock market shocks do not necessarily undermine the credibility of inflation-targeting regimes. Friedman (2004) further argues that safeguarding financial stability, including through targeted equity market measures, can legitimately fall within the broader remit of monetary policy. This divergence in perspectives underscores the need for empirical evidence on the conditions under which such interventions achieve their intended objectives.

Our results align more closely with the former view, as we find that sustained central bank interventions in equity markets can have unintended adverse effects—most notably, by increasing market volatility—thereby undermining their intended stabilisation objectives. Leveraging the Bank of Japan's large-scale and long-running equity ETF purchase program as a unique empirical setting, we are able to examine this issue in a context where interventions are frequent, sizeable, and highly transparent. This setting allows us to provide rare, data-driven evidence on the long-term market consequences of equity-specific monetary policy actions, offering empirical support for the cautionary stance articulated by Bernanke and Gertler (2001) and extending the debate with new insights from an unconventional policy environment.

2.3. Data and Methodology

2.3.1. Data. The sample period for this study is from 1 January 2011 to 31 December 2019. Note that during BOJ's monthly monetary policy meeting in October 2010, it decided to launch the unconventional monetary program known as BOJ ETF purchase program. As only two purchases were made from October 2010 to December 2010, they are ignored. The sample period ends on December 30, 2019 to intentionally avoid the impact of COVID-19 and associated financial market movements. Furthermore, shortly after the initial shock of the COVID pandemic, BOJ lowered its frequency of purchases. From 2011 to 2019, BOJ intervened in roughly 20–30% of total trading days on average. However, BOJ only intervened less than 10 times during 2022. Thus, these policy changes in recent years may impair the quality of empirical conclusions.

Our study utilises equity market and policy data to examine the impact of Bank of Japan's equity ETF purchases. Data on BOJ's daily intervention decisions are collected from its official website.[6] On each trading day, BOJ publishes a file indicating whether it intervened in the equity market and the corresponding purchase amount for each index-linked ETF. A null value indicates no intervention on that particular day. The file is typically updated between 4:00 p.m. and 5:00 p.m. Japan Standard Time, approximately 1 to 2 hours after the close of the Japanese equity market. As a result, investors receive information on BOJ's interventions only after market closure, reinforcing the ex-post nature of the intervention signal.

In addition to the intervention records, BOJ's website provides policy documents outlining the general framework of its ETF purchase program, which includes annual budget allocations and target proportions for purchases across different equity indices (e.g., TOPIX, Nikkei 225, and Nikkei 400). However, the exact mechanisms behind BOJ's purchase decisions, such as intraday timing and trigger thresholds, are not disclosed in official documentation. Consequently, the assumptions regarding the timing and logic of BOJ purchases are based on empirical findings and established frameworks in the literature (Harada and Okimoto, 2021; Hattori and Yoshida, 2023; Katagiri et al., 2022).

[6]Data can be accessed at: `https://www3.boj.or.jp/market/en/menu_etf.htm`

TABLE 2.3.1. **Descriptive statistics of variables**

This table summarizes the descriptive statistics of the daily TOPIX index return by year from 2011 to 2019. Reported metrics include the mean, median, maximum, minimum, and standard deviation of daily returns, the number of observations (trading days), the total annual BOJ equity purchase amount (in billions of yen), and the number of BOJ intervention days. All return and volatility values are expressed in percentages.

Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Mean Return (%)	–0.07	0.08	0.19	0.05	0.05	0.01	0.08	–0.06	0.07
Median Return (%)	0.00	0.00	0.16	0.08	0.14	0.14	0.06	0.00	–0.06
Maximum Return (%)	6.26	2.65	5.74	4.28	6.25	8.06	2.38	4.86	2.83
Minimum Return (%)	–9.06	–2.61	–6.48	–4.75	–5.63	–7.43	–2.06	–4.63	–2.51
Std. Deviation (%)	1.40	0.98	1.58	1.18	1.26	1.66	0.68	1.13	0.84
Sample Size (Days)	245	248	245	244	244	245	247	245	241
BOJ Purchase (Billion ¥)	800	640	1095	1285	3069	4382	5607	6210	4088
BOJ Intervention Days	42	23	58	75	89	90	78	87	58

Market data are obtained from Bloomberg and it include daily time-series for ETF share prices, net asset values (NAV), and fund premiums for all ETFs linked to the TOPIX, Nikkei 225, and Nikkei 400 indices listed on the Tokyo Stock Exchange. We also collect daily figures for trading volume and shares outstanding of each TOPIX ETF. These data allow us to construct measures of market return and volatility, and to investigate potential liquidity effects and pricing deviations from NAVs. By combining BOJ intervention records with Japanese equity market data, we could study the dynamic effects of monetary policy operations on equity market behavior.

Table 2.3.1 provides summary statistics of BOJ's intervention, revealing a clear upward trend in the annual ETF purchase amounts and the number of intervention days until 2018, followed by a decline in 2019. Notably, BOJ intervention frequency tends to increase in years with higher market volatility, consistent with findings in the existing literature (Charoenwong et al., 2021; Toshino, 2020).

2.3.2. Methodology.

2.3.2.1. *Policy intensity measure and BOJ intervention on volatility.* To assess the lagged effects of Bank of Japan's equity market interventions, we use market volatility as the primary outcome variable. Volatility is widely recognised as a forward-looking and high-frequency measure of market uncertainty that reacts sensitively to policy signals. As emphasised byBekaert et al. (2013), financial market volatility co-moves closely with shifts in macroeconomic and policy conditions, making it a particularly suitable metric for evaluating the effectiveness of central bank interventions. In the case of BOJ, whose unconventional monetary policy has included large-scale purchases of equity-linked exchange-traded funds, one of the explicit policy goals has been to stabilise financial markets and compress risk premia (BOJ, 2013a,b). Thus, changes in volatility serve as a natural proxy for BOJ's influence on market sentiment.

$$\begin{aligned}\text{Volatility}_t = \alpha + \beta \cdot \text{Policy Intensity}_{t-1,t-5} + \gamma \cdot \text{Intervention}_t \\ + \theta \cdot \text{Controls} + \text{Year Fixed Effect} + \varepsilon_t \end{aligned} \tag{2.3.1}$$

Given BOJ's substantial presence in the equity market that account for a significant share of daily ETF trading volume, we hypothesize that its intervention may not be fully concentrated on a single trading day, but rather distributed across several days. To capture this dynamic effect, we construct a policy intensity index, defined as the number of days within a five-day rolling window prior to a given trading day in which BOJ was active in the market. This measure reflects the cumulative intervention pressure over the recent past. In Equation 2.3.1, the dependent variable is the intra-day volatility of the Japanese TOPIX index on day t. The main explanatory variable is policy intensity. The intervention variable indicates whether Bank of Japan intervened on day t. This variable is primarily included to control for the contemporaneous impact on day t, as the Bank of Japan typically intervenes in the stock market when there is a decline during the morning session. Thus, adding the intervention dummy for the day effectively controls for volatility driven by market factors on day t. Other control variables include the log of daily transaction value, the number of share creations of TOPIX index-linked ETFs, the yen-dollar exchange rate, lagged daily volatility, and lagged returns. If BOJ interventions indeed generate lagged effects, then higher values of the policy intensity index should be associated with increased volatility on the current trading day. This prediction is consistent with the argument that central bank intervention can amplify trading activity and information flow, thereby contributing to elevated short-term volatility (Naik et al., 2018).

2.3.2.2. *Structural vector autoregression and impulse response.* A key empirical challenge in estimating the impact of central bank interventions on market volatility is the presence of endogeneity, including omitted variable bias and reverse causality. For instance, volatility may influence the likelihood of intervention, and unobserved market conditions may drive both. As a result, estimates from standard OLS regressions are likely to suffer from biased and inconsistent coefficients.

To address these identification concerns, we adopt a structural vector auto-Regression framework that offers two key advantages. First, by incorporating lagged values of all endogenous variables, the SVAR mitigates reverse causality and captures dynamic feedback effects between policy actions and market responses. Second, by imposing structure on the contemporaneous relationships among variables, the SVAR allows for isolating exogenous policy shocks and tracing their causal effects through impulse response functions. Importantly, the IRFs reflect the lagged effect of BOJ's intervention, due to the model's recursive structure.

The SVAR includes the following four endogenous variables: TOPIX index return (Ret_t), a dummy variable for BOJ ETF purchase activity (BOJ_t), realised market volatility (Vol_t), constructed from 5-minute intra-day returns and TOPIX index-link ETFs' net share creation. We include seven lags in the system, selected based on the Akaike Information Criterion, ensuring adequate control for short-term dynamics.

The structural form of the SVAR is specified as follows:

$$Ay_t = \tau_0 + \sum_{i=1}^{7} \tau_i y_{t-i} + B\epsilon_t \tag{2.3.2}$$

where:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix}, \quad y_t = \begin{bmatrix} Ret_t \\ BOJ_t \\ Vol_t \\ Creation_t \end{bmatrix}, \quad \tau_0 = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix}$$

$$\tau_i = \begin{bmatrix} \gamma_{11,i} & \gamma_{12,i} & \gamma_{13,i} & \gamma_{14,i} \\ \gamma_{21,i} & \gamma_{22,i} & \gamma_{23,i} & \gamma_{24,i} \\ \gamma_{31,i} & \gamma_{32,i} & \gamma_{33,i} & \gamma_{34,i} \\ \gamma_{41,i} & \gamma_{42,i} & \gamma_{43,i} & \gamma_{44,i} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 \\ 0 & 0 & b_{33} & 0 \\ 0 & 0 & 0 & b_{44} \end{bmatrix}, \quad \epsilon_t = \begin{bmatrix} \epsilon_{ret,t} \\ \epsilon_{boj,t} \\ \epsilon_{vol,t} \\ \epsilon_{creation,t} \end{bmatrix}$$

The identification strategy is informed by institutional characteristics of BOJ intervention. Specifically, ETF purchases are conducted in the afternoon session and are triggered by morning price declines, which justifies allowing stock returns to contemporaneously influence BOJ purchases while assuming that BOJ actions do not contemporaneously affect returns. However, Volatility is permitted to respond contemporaneously to both returns and BOJ purchases, reflecting the market's fast adjustment to new information.

The diagonality of matrix B reflects the assumption that structural shocks are orthogonal, a standard identifying restriction in SVAR models.

$$B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix}$$

Impulse response functions derived from the SVAR reflect the temporal dynamics of realised volatility following an exogenous shock to BOJ intervention activity. These IRFs provide insight into how volatility—and by extension, investor uncertainty—evolves in response to policy shocks, helping assess the effectiveness of equity market interventions as a monetary policy tool.

2.3.2.3. *Regression discontinuity design of BOJ intervention.* Although structural vector autoregressive models are designed to address endogeneity by capturing dynamic interactions among endogenous variables, they rest on strong identification assumptions, particularly the exogeneity of structural shocks (Sims, 1980), posing a limitation in BOJ's context of market interventions, which are not purely exogenous shocks but are systematically triggered by observed market conditions, especially large negative returns during the morning trading session (Blanchard and Quah, 1988). Consequently, even SVAR estimates may be biased if the identification strategy fails to fully isolate policy-induced variation from other confounding factors. Such bias may arise due to omitted variables that jointly affect intervention decisions and volatility, or from reverse causality.

To address this challenge, we adopt a fuzzy regression discontinuity design, which is well-suited for empirical settings where treatment is not randomly assigned but where the probability of treatment exhibits a discontinuous change around a known threshold (Cattaneo et al., 2024). In the case of BOJ intervention, although the decision to intervene is not deterministic, the likelihood increases sharply once the morning return breaches a specific cutoff, reflecting an implicit, rule-based policy response. Fuzzy RDD exploits this quasi-experimental variation by using the threshold-crossing indicator as an instrumental variable for actual intervention. This approach helps isolate exogenous variation in treatment intensity, thereby offering a more credible estimate of the causal effect of BOJ intervention on subsequent market volatility. Compared to conventional approaches such as OLS or SVAR, which require stronger assumptions about the exogeneity of treatment assignment, the fuzzy RDD framework provides a more robust identification strategy in this context.

Our identification strategy relies on the assumption that, within a narrow window around the threshold, observations are as good as randomly assigned to different levels of treatment intensity (Chung, 2020; Fukui and Yagasaki, 2023). Specifically, we define a binary instrument Z_i that takes the value of one if the morning return falls below the policy-relevant threshold, and 0 otherwise. This instrument captures an implicit intervention rule followed by BOJ and is thus highly predictive of the actual intervention variable D_i. Simultaneously, since Z_i is mechanically determined by a narrow range of morning returns, it is plausibly unrelated to unobserved determinants of post-market volatility, aside from its influence through intervention itself.

To implement the Fuzzy RDD, we estimate a two-stage least squares (2SLS) model as follows:

$$\text{First stage:} \quad D_i = \alpha_0 + \alpha_1 Z_i + \alpha_2 \text{running}_i + \boldsymbol{\alpha_3}' \mathbf{X}_i + \epsilon_i \tag{2.3.3}$$

$$\text{Second stage:} \quad Y_i = \beta_0 + \beta_1 \hat{D}_i + \beta_2 \text{running}_i + \boldsymbol{\beta_3}' \mathbf{X}_i + u_i \tag{2.3.4}$$

In the first stage (Equation 2.3.3), we regress the endogenous treatment variable D_i—an indicator of BOJ intervention—on the instrument Z_i, controlling for the running variable and a set of covariates $\mathbf{X}_i$ that include past returns, transaction volumes and lagged volatility. The predicted value $\hat{D}_i$ is then used in the second stage (Equation 2.3.4) to estimate its causal effect on the outcome variable Y_i, which denotes future market volatility (e.g., $\Delta\text{volatility}_{T1:T3}$). The coefficient β_1 thus represents the local average treatment effect (LATE) of BOJ intervention for the subpopulation of observations induced into treatment by crossing the threshold.

The instrument Z_i satisfies the two core conditions for instrument validity. First, the relevance condition holds, as the threshold-crossing variable Z_i is strongly correlated with D_i, consistent with BOJ's operational response to sharp morning losses. Second, the exclusion restriction is plausible: Z_i affects future volatility only through its impact on the intervention decision. While this condition is fundamentally untestable, its credibility remained unrefuted by including a rich set of controls and limiting the sample to observations near the threshold, where confounding variables are expected to vary smoothly. In this way, fuzzy RDD allows for credibly isolating the causal impact of BOJ interventions on market volatility in a setting where classical methods fall short due to endogeneity in policy assignment.

2.4. Empirical results

2.4.1. Policy intensity. Table 2.4.1 reports the OLS regression results for the determinants of intra-day volatility over a 5-hour window (2.5 hours of morning session and 2.5 hours of afternoon session). The key independent variable of interest, policy intensity, is defined as the number of BOJ's equity market interventions during the preceding five trading days, capturing the cumulative and potentially lagged impact of BOJ policy actions. In Column (2) to (4), we introduce the intervention dummy, capturing whether BOJ intervened on the current trading day. Columns (3) and (4) introduce additional control variables—market return, transaction value, ETF share creation and exchange rate—and lagged values of return and volatility to address potential endogeneity and persistence.

The results are consistent with Bekaert et al. (2013), which shows that central bank monetary policy has a significant impact on stock market volatility. The result also indicates the descriptive evidence that BOJ's interventions exhibit a lagged effect rather than an immediate impact. Specifically, the policy intensity variable that measures the number of BOJ interventions in the 5 trading days prior to the current day shows a strong and statistically significant positive relationship with intra-day volatility. A higher value of this variable implies more intensive recent intervention activity, and on average, each additional intervention day within the past 5 days is associated with a 6 bps increase in same-day volatility, suggesting that the impact of BOJ interventions is not fully absorbed on the intervention day itself but instead spills over and influences market behavior in subsequent sessions.

Moreover, the *Intervention* dummy is indicated positively and significantly associated with volatility, aligning with findings in the existing literature(Charoenwong et al., 2021; Harada and Okimoto, 2021; Hattori and Yoshida, 2023). This result reflects the fact that BOJ interventions are systematically triggered by sharp market downturns, particularly during the morning session, when volatility is already elevated. Hence, both the cumulative and contemporaneous measures of policy action point to the complexity of disentangling intervention effects from underlying

TABLE 2.4.1. **OLS regression for vol_5hour**

This table presents the results of OLS regressions examining the determinants of daily market volatility. The dependent variable, daily volatility, is measured using intra-day returns based on 5-minute index intervals. The key explanatory variable, *Policy Intensity*, captures the number of BOJ interventions over the preceding five trading days. The variable $Intervention_t$ is a dummy equal to one if BOJ conducted an equity purchase on day t, and is included to control for the contemporaneous effects of interventions. All regressions include year fixed effects to account for time-varying macroeconomic and institutional factors. Robust standard errors are reported in parentheses. Statistical significance is indicated at the *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ levels.

	(1)	(2)	(3)	(4)
Dependent variable	Volatility	Volatility	Volatility	Volatility
Policy intensity$_{t-1,t-5}$	0.0012***	0.0012***	0.0010***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
Intervention$_t$		0.0026***	0.0019***	0.0018***
		(0.0003)	(0.0003)	(0.0003)
Return			0.0066	0.0234***
			(0.0102)	(0.0096)
Transaction value			0.0048***	0.0041***
			(0.0002)	(0.0002)
ETF share creation			0.0000	0.0000
			(0.0000)	(0.0000)
Exchange rate			0.0035	0.0163
			(0.0190)	(0.0182)
Volatility$_{t-1}$				0.2366***
				(0.0189)
Returnt$_{t-1}$				–0.0475***
				(0.0081)
Year fixed effect	Y	Y	Y	Y
Adjusted R square	0.204	0.250	0.333	0.419

market conditions, underscoring the reactive and anticipatory nature of central bank behavior in equity markets.

2.4.2. Impulse response analysis from SVAR model. To address potential endogeneity concerns in baseline OLS estimation, especially the simultaneity between BOJ interventions and market volatility, we employ a vector auto-regressive framework to analyze the dynamic effects of BOJ interventions on market outcomes using impulse response functions. To capture the lagged effects of BOJ's intervention policy, we adopt a structural VAR with an A matrix, which allows for imposing economically meaningful restrictions on contemporaneous relationships and identifying structural shocks.

TABLE 2.4.2. **Granger Causality Test among Return, Volatility, and BOJ Intervention**

This table reports the results of the Granger causality tests among index return, market volatility, and BOJ intervention variables. The column labeled F-statistic presents the test statistic for rejecting the null hypothesis, and *Prob.* reports the associated p-value under the null of no Granger causality.

Null Hypothesis	F-statistic	Prob.
BOJ Dummy does not Granger Cause Index Return	1.0119	0.421
Index Return does not Granger Cause BOJ Dummy	1.8592	0.073
Volatility does not Granger Cause Index Return	2.4752	0.016
Index Return does not Granger Cause Volatility	9.2747	0.000
Volatility does not Granger Cause BOJ Dummy	0.6224	0.737
BOJ Dummy does not Granger Cause Volatility	3.0734	0.003

The identification strategy of A matrix relies on the causal ordering of variables within the SVAR system(Higham, 1990). Our model includes four key variables: TOPIX index return, BOJ intervention amount, market volatility, and ETF share creation. We posit the following causal sequence: First, BOJ's intervention decisions are systematically influenced by early morning price declines—interventions typically occur after sharp negative returns during the first trading session, as widely documented in the literature (e.g., Charoenwong et al. 2021). This implies that Return Granger-causes Intervention, but not the reverse, justifying the placement of returns before intervention in the SVAR ordering.

Second, we assume that BOJ interventions influence market volatility and ETF share creation, but not vice versa contemporaneously. BOJ's equity purchases are large and publicly observable, potentially altering risk perception and liquidity in the following trading hours. Importantly, ETF share creation—defined as the issuance of new ETF units by authorised participants—typically lags interventions by 2–3 days, as it requires time for market makers and APs to accumulate the underlying stocks and deliver them to the fund issuer. This delayed operational mechanism is consistent with the market microstructure and has also been supported by our Granger causality tests (see Table 2.4.2), which show that interventions Granger-cause volatility and share creation, while returns Granger-cause interventions.

Accordingly, our SVAR identification imposes a recursive causal order of:

$$\texttt{Return} \rightarrow \texttt{Intervention} \rightarrow \texttt{Volatility} \rightarrow \texttt{Share Creation}.$$

The impulse response analysis first focuses on the response of ETF share creation to a one-unit structural shock in BOJ's intervention policy. As shown in Figure 2.4.1, the blue IRF line rises sharply following the intervention shock, peaking around the fourth day, and remains elevated for several periods before gradually declining. This delayed but significant increase in ETF share creation provides strong evidence for the lagged market response to BOJ interventions, consistent with operational timelines of ETF market making. The observed pattern indicates that once BOJ intervenes, market dealers begin purchasing stocks in the underlying index and initiate share creation procedures shortly thereafter, which confirms that the intervention exerts not only an immediate psychological effect but also a concrete follow-up impact on ETF trading activity, highlighting its role in liquidity provision and fund flow adjustments. This finding is also consistent with the evidence reported by Brown et al. (2021) and Pan and Zeng (2017), who document non-fundamental market impacts resulting from ETF share creation and redemption activities carried out by authorised participants.

We next turn to the effect of intervention shocks on market volatility. Figure 2.4.2 presents the impulse response of daily realised volatility to the same intervention shock. The IRF reveals a pronounced and statistically significant rise in volatility immediately following the shock, with elevated levels persisting over the next several trading days. This finding suggests that BOJ's interventions, rather than calming the market, may induce higher short-term uncertainty. One possible explanation is that interventions serve as a signal of distress, reinforcing investor awareness of downside risks rather than mitigating them. Alternatively, large-scale equity purchases by the central bank could distort normal price discovery mechanisms, leading to temporary dislocations in risk assessment and contributing to higher realised volatility. The IRF curve begins with an approximate 2% increase in contemporaneous volatility, as consistent with our OLS regression results in Table 2.4.1 showing that volatility rises by an average of 2.1% on BOJ intervention days.

The observed persistence of elevated volatility across multiple trading horizons indicates that the effects of BOJ interventions are not confined to the intervention day but extend into subsequent sessions. This temporal spillover is particularly noteworthy given BOJ's aim to lower equity risk premia and enhance market stability. Theoretically, as demonstrated by French et al. (1987) and Merton (1980), expected excess returns increase with the conditional variance of returns. Accordingly, if interventions lead to higher volatility—and assuming that risk preferences remain constant—such actions could paradoxically raise the equity risk premium, thereby counteracting the central bank's stabilisation efforts. This interpretation is consistent with that

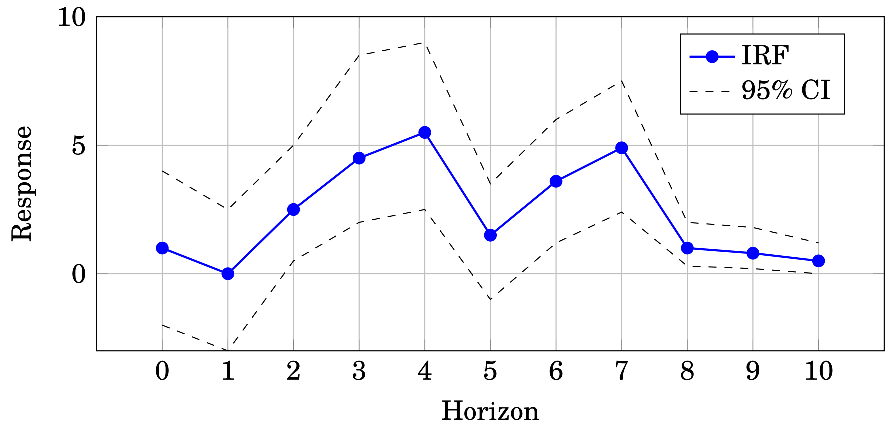

FIGURE 2.4.1. Impulse response of ETF share creation to a shock in intervention

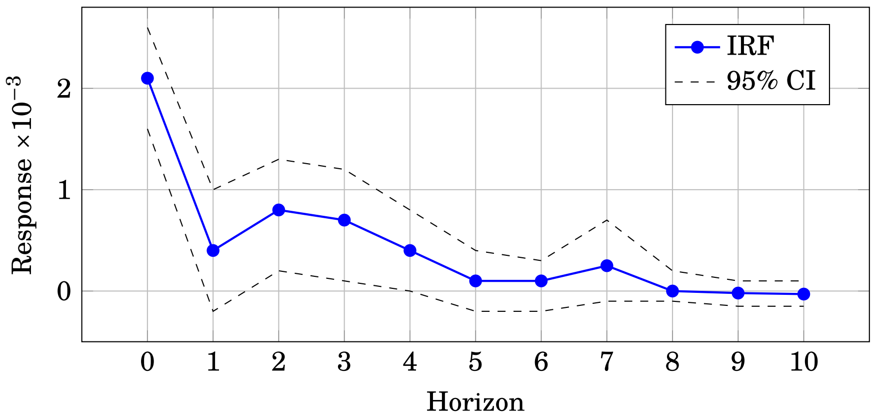

FIGURE 2.4.2. Impulse response of volatility to a shock in intervention

reached by Bernanke and Gertler (2001), who emphasised the central bank's reactive behavior in response to exogenous shocks to equity markets.

The SVAR analysis further reveals that BOJ interventions exert broad and lasting influences on both ETF market operations and overall volatility. The delayed surge in ETF share creation suggests frictions in the transmission mechanism, likely due to operational or institutional lags. Simultaneously, the uptick in market volatility encourages scrutiny over the unintended ramifications of large-scale asset purchases. These findings enrich our baseline OLS results by highlighting the dynamic adjustment processes and demonstrating the analytical advantages of structural identification in uncovering the channels through which policy shocks propagate.

2.4.3. Fuzzy RDD: Identifying the lagged effect of BOJ intervention. To address persistent endogeneity concerns, we adopt a Fuzzy RDD framework as a complementary identification strategy, given that the timing of BOJ's equity market interventions is not random. While

TABLE 2.4.3. **Fuzzy RDD estimates for volatility changes**

This table reports IV2SLS estimates from fuzzy regression discontinuity designs for the impact of ETF intervention (D) on changes in volatility over 1-day (Column1), 2-day (Column2), 3-day (Column3), and cumulative 3-day (Column4) horizons. Standard errors are reported below each coefficient. All regressions control for past returns, trading volume, market structure proxies, and lagged volatility. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Intervention_t	0.0006	0.0023***	0.0024***	0.0052***
	(0.0010)	(0.0010)	(0.0010)	(0.0020)
Morning return	−0.0770***	−0.0356	0.0053	−0.1089**
	(0.0210)	(0.0220)	(0.0220)	(0.0480)
Transaction value	0.0019***	0.0011***	0.0015***	0.0045***
	(0.0002)	(0.0003)	(0.0003)	(0.0005)
Share creation	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Exchange rate	−0.0308	−0.0487**	−0.0494**	−0.1272***
	(0.0200)	(0.0200)	(0.0210)	(0.0450)
R_{t-1}	−0.0701***	−0.0358***	−0.0546***	−0.1603***
	(0.0100)	(0.0110)	(0.0110)	(0.0230)
$\text{Intervention}_{t-1}$	−0.0005*	−0.0006*	−0.0006*	−0.0016**
	(0.0003)	(0.0003)	(0.0003)	(0.0010)
$\text{Transaction value}_{t-1}$	−0.0008***	−0.0004	−0.0010***	−0.0021***
	(0.0002)	(0.0003)	(0.0003)	(0.0010)
Volatility_{t-1}	0.4145***	0.3918***	0.3482***	1.1567***
	(0.0200)	(0.0210)	(0.0220)	(0.0460)
Year fixed effect	Y	Y	Y	Y
Adjusted R square	0.204	0.250	0.333	0.419

structural vector auto-regressive models account for dynamic feedback among variables, they rely on the assumption that structural shocks are exogenous. In the context of BOJ, this assumption is questionable, as interventions are systematically triggered by sharp declines in morning returns—typically below a threshold of -0.5% (Chung, 2020). Such endogenous policy timing risks introducing omitted variable bias and reverse causality, undermining causal inference in SVAR and OLS frameworks.

To overcome this limitation, we exploit the quasi-experimental variation generated by BOJ's implicit intervention rule. Specifically, fuzzy RDD was inplemented using a two-stage least squares (2SLS) approach, where the treatment variable D indicates actual intervention, and the instrument Z is a binary variable equal to 1 if the morning return falls below the policy threshold of

-0.5%. The running variable is the continuous morning return). This design isolates plausibly exogenous variation in interventions around the threshold, allowing for estimation of their causal, particularly lagged, effects on post-intervention volatility.

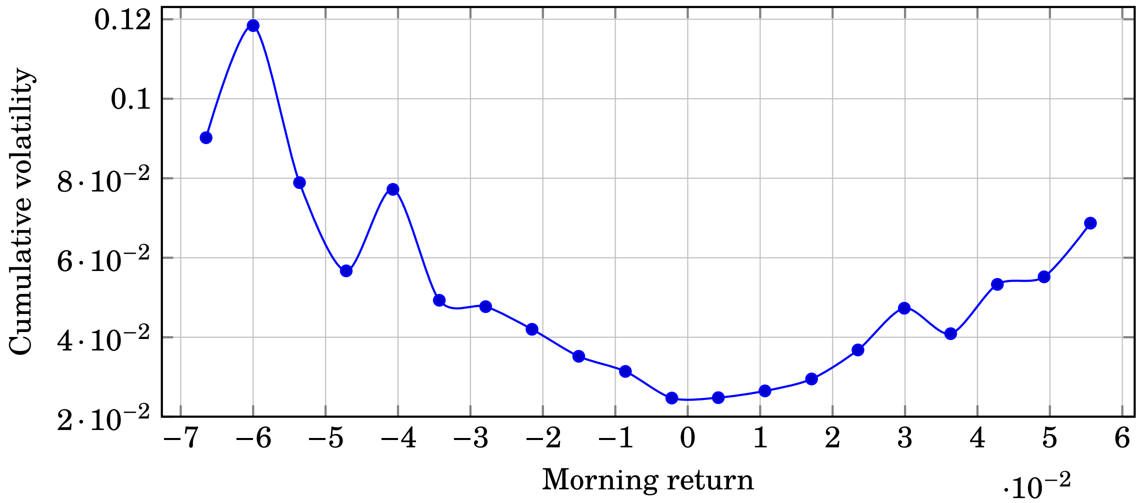

FIGURE 2.4.3. Fuzzy RDD binned means of cumulative volatility (T+1–T+3) by morning return

The outcome variables capture changes in realised volatility from day $T+1$ to $T+3$, as well as the cumulative change over this horizon. Table 2.4.3 reports the 2SLS estimates. The coefficient on the instrumented intervention variable is statistically insignificant at $T+1$, but becomes significantly positive at $T+2$ (0.0023, $p < 0.01$), $T+3$ (0.0024, $p < 0.01$), and over the cumulative $T+1$–$T+3$ window (0.0052, $p < 0.01$). These results support the existence of a lagged volatility effect: BOJ interventions do not immediately reduce volatility but instead exert influence over subsequent trading days, likely through delayed market reactions or gradual shifts in risk sentiment.

The running variable (morning return) also plays an important role. A more negative morning return is associated with a significant decrease in same-day volatility (-0.0770, $p < 0.01$), though this effect weakens at longer horizons and re-appears cumulatively (-0.1089, $p < 0.05$). This pattern suggests that sharp morning declines may temporarily suppress volatility, either by prompting BOJ intervention or by triggering other stabilizing mechanisms.

2.5. Robustness checks

Several robustness checks are considered to validate the robustness of the results regarding policy intensity measure. The analysis is first completed on a yearly basis over the sample period, and then heterogeneity by BOJ purchase exposure are investigated.

2.5.1. Disaggregated BOJ intervention dummies. To further validate the effectiveness of the policy intensity measure, we decompose it into BOJ's individual intervention dummies. In our earlier construction of the policy intensity measure, we counted the number of BOJ interventions in 5 trading days preceding each trading day and used this count as a proxy for the lagged effects of central bank interventions. Here, we replace the policy intensity measure with disaggregated BOJ intervention dummies as primary variable. By examining the impact of each dummy on the current day, we assess whether BOJ interventions have significant lagged effects on market volatility.

Table 2.5.1 reports whether BOJ intervention dummies from the 5 trading days prior to the current trading day have a significant impact on the volatility of the current day. The findings show that, regardless of whether the current day is a BOJ intervention day, interventions on preceding trading days significantly increase same-day volatility. This result remains robust even after controlling for several key covariates, including daily return, total transaction value, ETF creation amount, exchange rate, and the previous day's return and volatility.

These findings suggest that BOJ interventions exhibit significant lagged effects on market volatility with consistently positive effects, indicating that BOJ interventions tend to amplify volatility in subsequent trading days. There may be two underlying transmission channels. First, as evidenced by our SVAR analysis, index-linked ETF share creation typically rises significantly two to three days after the intervention, implying that BOJ's stock purchases may not be completed on the same day, but rather executed over the following days. However, BOJ interventions may also directly influence market sentiment and dynamics beyond the day of the intervention itself. This is reflected in the finding that interventions within the past 5 trading days consistently increase current-day volatility.

2.5.2. Alternative measure of policy intensity. To test the validity of the policy intensity measure, we further replaced the variable specification. In our baseline results, the policy intensity was defined as a dummy variable that only captured whether BOJ intervened, without

TABLE 2.5.1. **Disaggregated BOJ intervention OLS**

This table presents the results of OLS regressions investigating the determinants of daily stock market volatility. The dependent variable, daily volatility, is computed based on intra-day index returns using 5-minute intervals. The key explanatory variables include a series of dummy indicators, $Intervention_{t-1}$ to $Intervention_{t-5}$, which equal 1 if BOJ conducted equity market interventions on the corresponding prior trading day, and 0 otherwise. These variables are used to capture the lagged effects of BOJ interventions on market volatility. All regressions include year fixed effects, and robust standard errors are reported in parentheses. Statistical significance is denoted as follows: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Dependent variable	Volatility	Volatility	Volatility	Volatility
$\text{Intervention}_{t-1}$	0.0017***	0.0013***	0.0011***	0.0007*
	(0.000)	(0.000)	(0.000)	(0.004)
$\text{Intervention}_{t-2}$	0.0017***	0.0016***	0.0013***	0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Intervention}_{t-3}$	0.0012***	0.0011***	0.0009***	0.0007***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Intervention}_{t-4}$	0.0013***	0.0013***	0.0011***	0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Intervention}_{t-5}$	0.0008***	0.0007***	0.0005**	0.0004*
	(0.000)	(0.000)	(0.000)	(0.000)
Intervention_{t}		0.0025***	0.0019***	0.0018***
		(0.000)	(0.000)	(0.000)
Return			0.0068	0.0215**
			(0.010)	(0.010)
Transaction value			0.0048***	0.0041***
			(0.000)	(0.000)
ETF share creation			0.000	0.000
			(0.000)	(0.000)
Exchange rate			0.0026	0.0160
			(0.019)	(0.018)
Volatility_{t-1}				0.2520***
				(0.019)
Return_{t-1}				−0.0614***
				(0.009)
Year fixed effect	Y	Y	Y	Y
Adjusted R square	0.151	0.210	0.388	0.452

accounting for the amount of intervention. Therefore, we replaced the number of BOJ interventions over the past 5 trading days with the ratio of BOJ's total intervention amount to the total market trading volume over the same period.

TABLE 2.5.2. **Policy intensity measure by percentage of transaction value**

This table presents the results of OLS regressions examining the determinants of daily market volatility. The dependent variable, daily volatility, is measured using intra-day returns based on 5-minute index intervals. *Percentage of Transaction* is defined as the ratio of BOJ's total intervention amount over the past five trading days to the total market transaction value on the current day. The variable *Intervention$_t$* is a dummy equal to one if BOJ conducted an equity purchase on day t, and is included to control for the contemporaneous effects of interventions. All regressions include year fixed effects to account for time-varying macroeconomic and institutional factors. Robust standard errors are reported in parentheses. Statistical significance is indicated at the *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$ levels.

	(1)	(2)	(3)	(4)
Dependent variable	Volatility	Volatility	Volatility	Volatility
Percentage of Transaction	0.0263***	0.0223***	0.0217***	0.0126***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Intervention$_t$		0.0027***	0.0020***	0.0019***
		(0.0003)	(0.0003)	(0.0003)
Return			0.0108	0.0295***
			(0.0100)	(0.0090)
Transaction value			0.0050***	0.0042***
			(0.0002)	(0.0002)
ETF share creation			0.0000	0.0000
			(0.0000)	(0.0000)
Volatility$_{t-1}$				0.2562***
				(0.0190)
Return$_{t-1}$				–0.0533***
				(0.0080)
Year fixed effect	Y	Y	Y	Y
Adjusted R square	0.121	0.168	0.352	0.428

We did not use the raw amount of BOJ intervention because, although it seems intuitive that larger interventions would have a stronger market impact, both the total market capitalization of the TOPIX index and the average trading volume and value experienced substantial fluctuations over the sample period. To mitigate the confounding effects of changes in market size and liquidity, we constructed the variable as the ratio of intervention amount to daily trading volume.

Table 2.5.2 shows that replacing the number of BOJ interventions with the ratio of intervention amount to trading volume yields similarly significant results. Quantitatively, holding other variables constant, a 1% increase in the intervention-to-transaction ratio is associated with a 1.26% increase in market volatility on average. This suggests that the higher the proportion of equity purchases by BOJ relative to total market transactions over the past five trading days, the greater the volatility observed on the current trading day. This finding further confirms the validity of the policy intensity measure and provides additional evidence that BOJ interventions exert significant lagged effects on stock market volatility. Moreover, the result is consistent with our baseline findings, which indicate that the effects of BOJ interventions are not confined to the intervention day itself but persist over subsequent trading days.

2.6. Conclusion

This essay provides a comprehensive empirical assessment of Bank of Japan's equity market intervention through its ETF purchase program that stands as one of the most sustained and large-scale unconventional monetary policy actions in modern financial history. Motivated by the disconnect between established theoretical guidance—which generally warns against direct asset price targeting—and the increasing reliance of central banks on financial market interventions, we focus on evaluating whether BOJ's equity purchases have achieved their central objective, that it reducing market risk premia and lowering the cost of capital for listed firms. Using the intertemporal capital asset pricing model (ICAPM) as our theoretical foundation, we treat changes in market volatility as a proxy for shifts in the risk premium. Drawing on high-frequency intra-day data, we construct a volatility measure that captures short-term investor uncertainty and allows us to track the market's immediate response to BOJ interventions. Given the large size and regular frequency of BOJ's purchases, we hypothesise that the effects may extend beyond the intervention day itself. To capture both immediate and lagged effects, we employ a structural vector auto-regressive framework that explicitly separates contemporaneous interactions and endogenously treats the interplay among returns, intervention activity, and volatility.

Our empirical findings are striking. Across three methods, the results consistently show a persistent and statistically significant increase in market volatility following BOJ's ETF purchases, with no sign of reversal in the short term. Importantly, they challenge the assumption that such interventions effectively compress risk premia. According to the ICAPM framework and under the assumption of relatively stable risk aversion in the short run, rising volatility implies a higher ex ante risk premium. Thus, our evidence suggests that BOJ's large-scale equity purchases may have had the unintended effect of increasing the risk premium, in contrast to the policy's stated goal, encouraging deeper consideration of the long-term effectiveness and broader implications of persistent market interventions as a tool of monetary policy.

From a policy perspective, our findings offer several important insights. First, they highlight the limitations of relying on equity market purchases as a means of reducing funding costs for firms. While short-term price stabilisation may be achieved through central bank intervention, such actions may also introduce persistent uncertainty into market dynamics, elevating volatility and, consequently, the market risk premium. This unintended consequence underscores the trade-off between immediate market support and longer-term distortions in risk pricing. Second, our study underscores the need for greater caution and clearer exit strategies when central banks embark on unconventional market operations. Persistent and large-scale interventions can entrench expectations of official support, distort price signals, and lead to misallocations of capital. Moreover, once such programs become entrenched, unwinding them may involve additional volatility and credibility costs. Third, our results contribute to the broader debate on whether central banks should expand their mandates to include financial market stability more explicitly. While asset purchases can provide liquidity and calm markets in periods of stress, their regular use in normal times should be justified by robust evidence of long-term benefits. Our results suggest that although BOJ program has succeeded in scale and implementation, it may have fallen short of achieving its macro-financial objectives. Future research and policymaking should take the distinction between transitory and structural market effects seriously and evaluate unconventional monetary policy tools not only by their immediate price impact but also by their influence on underlying risk perceptions, investor behavior, and long-term financial conditions.

CHAPTER 3

Data-driven monetary policy:
Evidence from the Bank of Japan's equity purchase program

This chapter is based on the peer-reviewed journal publication (Liu et al., 2025).

3.1. Introduction

With the recent emergence of digitalization, central banks have increasingly adopted data-driven monetary policies (Powell, 2019; Lagarde, 2023). Such monetary policies refer to policy decision making by central banks based on the ever-growing pool of available economic data. These data sources aim to measure financial impacts and offer strategic solutions to overcome uncertainties associated with different economic conditions.[1] Measuring the consequences of data-driven monetary policies, however, is challenging due to the scarcity of real-time data (Orphanides, 2001; Orphanides and van Norden, 2002) and limited information exploitation (Bernanke and Boivin, 2003). To overcome these challenges, we examine the effects of data-driven monetary policies by exploiting the Bank of Japan's (BOJ) ETF purchase program.

The BOJ's ETF purchase program provides an ideal setting to study the effects of data-driven monetary policies for two reasons: first, the BOJ's equity purchase policy is highly mechanical. This suggests that the BOJ bases its policy decisions on financial market data rather than on subjective information. In fact, empirical studies reveal that the decision making of the BOJ intervention is closely related to the returns of the overnight and morning sessions (Nangle and Yates, 2017; Hattori and Yoshida, 2023; Harada and Okimoto, 2021; Fukui and Yagasaki, 2023). Second, the BOJ publishes monthly policy discussions and discloses daily intervention decisions at the end of each trading day.[2] As part of the Qualitative and Quantitative Easing monetary policy, the BOJ has been directly injecting capital into the equity market since late 2010 (BOJ,

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[1]For example, in response to the economic downturn during the COVID pandemic, the Federal Reserve purchased $500 billion in treasury bonds in March 2020. See https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm

[2]Data regarding these interventions can be accessed via the following link: https://www3.boj.or.jpmarketenmenu_etf.htm

2010, 2013a). Until the end of 2019, the BOJ has purchased more than 15 trillion yen in Japanese large-cap stocks. These frequent and large interventions motivate our investigation into their price impact on equity markets.

In theory, transparent information should be factored into the price of financial products (Timmermann and Granger, 2004). In other words, price movement derives not from trade itself but from information flow. Thus, the BOJ's frequent and large interventions in the stock market should have no impact on prices. However, recent studies (Coval and Stafford, 2007; Gabaix and Koijen, 2021; Hartzmark and Solomon, 2022a) challenge this idea by isolating price impact from market information. In that case, the BOJ's interventions may give rise to demand and supply imbalances, leading to temporary price dislocations in the stock market.

Moreover, because BOJ interventions are highly mechanical and predictable, they could also serve as a signal to synchronise the actions of market participants (Abreu and Brunnermeier, 2003). This signal has the potential to reduce the divergence of opinions in the market, which is a major cause of market uncertainty (Miller, 1977). Thus, even though the BOJ's interventions are highly transparent and predictable, they can generate price movements that are unrelated to fundamentals.

To exploit the predictability of BOJ's interventions, we use logit regressions to predict those interventions on a daily basis. Following Harada and Okimoto (2021), we assume that BOJ interventions begin in the afternoon session of the intervention days. To avoid any look-ahead bias, all the inputs in the prediction model are publicly available before the afternoon session on each trading day. We use 2011-2013 data as our training set for our logit prediction model. From the beginning of 2014, we start to use our trained model to predict the BOJ's intervention. To keep our model updated, we add the actual BOJ's action result into our sample and retrain our model after each trading day. In the six-year testing sample, we find that the model accurately predicts the likelihood of BOJ interventions for 1,272 of 1,466 trading days. The overall prediction accuracy rate is 86.77% with a sensitivity rate of 88.42% and a specificity rate of 85.97%. These patterns suggest that the timing of BOJ interventions is highly predictable.

We construct an independent double-sorted portfolio strategy to exploit the predictable nature of the BOJ interventions. The two sorting factors are the BOJ's purchase amount and a liquidity factor. Stocks are divided into five equal groups for each factor, which generates a 5×5 portfolio matrix. On each predicted intervention day, we go long (short) in stocks that are most (least) influenced by BOJ interventions if we predict that an intervention will occur. The long-short corner portfolio of this matrix indicates an average return of 10.48 basis points for each predicted BOJ intervention. This suggests a potential trading strategy: constructing a long-short portfolio during forecasted interventions and holding risk-free securities during nonintervention days. By doing so, investors in the Japanese equity market can achieve an average annual return of 10.58% relying solely on publicly available information[3]. Furthermore, we find that the BOJ's interventions have a larger price impact on less liquid stocks. In the portfolio matrix, we determine that less liquid stocks tend to generate a higher return during the predicted intervention days. Overall, our results suggest that the BOJ's interventions align with its objective to reduce risk premiums in equity markets and to manage economic uncertainties.

The profitability of our long-short strategy is robust to risk adjustment. Controlling for the Fama-French five factors with momentum factor, we find an abnormal return of 5.12 basis points per trading day, or 12.90% per year, from the long-short strategy. Negative loadings on the market and size factors suggest that our strategy is biased toward larger stocks with less market risk premium. Consequently, the results indicate that the BOJ interventions could have a significant price impact on the Japanese equity market.

Additionally, we examine whether BOJ interventions represent unexplained risk factors by performing Fama-Macbeth two-step regressions. Controlling for Fama-French factors and firm characteristics, we find that the BOJ's interventions continue to attract a positive premium in stocks. The BOJ has thus far not sold its holdings and acts as a significant source of demand for the exposed stocks. Therefore, we conjecture that strategies that lean against these price dislocations are likely to be risky, supporting a persistent "BOJ intervention" premium in exposed stocks.

To further support our findings, we perform several robustness tests. First, we assess the effectiveness of the doule-sorted portfolio by considering an alternative frequency for the average transaction value. Second, we change the prediction model from the logit model (in the baseline

[3]While we cannot replicate realised trading frictions due to data limitations, we provide conservative proxy estimates for Japan (2014–2019): round-trip bid–ask costs are about 2%, and stock-borrow costs for short positions are typically below 3% in a near-zero rate environment. These benchmarks are well covered by the strategy's economic magnitude (annualized excess return >13%). We therefore add a brief discussion of key cost components (spread, market impact, borrow constraints/fees) and a sensitivity check showing profitability remains under reasonable increases in assumed frictions; any arbitrage opportunities are interpreted as a byproduct of predictable intervention patterns and ETF trading/hedging mechanics rather than BOJ intent.

result) to other machine learning models, including random forest. We also conduct a prediction analysis on different subsamples of our dataset. These prediction models provide similar results to those of the logit model, which implies that key inputs – rather than the prediction model or the sample period used – contribute to the accuracy of the prediction results. Third, we evaluate the robustness of the long-short strategy by longing the BOJ affected index (TOPIX) and shorting the BOJ unaffected index (MOTHERS). The abnormal return is also significantly positive. Although this strategy is not feasible, it shows that BOJ interventions can potentially generate positive price pressure. Fourth, we examine the cross-sectional impact of BOJ interventions on indices not directly targeted, like JASDAQ, and demonstrate the limited BOJ impact on unaffected indices. Lastly, we assess potential macroeconomic impacts on BOJ interventions to control for the global economic and market performance on BOJ's decision making and our prediction model. After adding the high-frequency data Atlanta Fed GDPNow into the Fama-Macbeth regression model and incorporating the returns of international stock market indices into a logit prediction model, we find quantitatively similar results to our baseline findings.

This study contributes to the literature related to the BOJ purchase price pressure generated on intervention days (Charoenwong et al., 2021) and to the non-information-driven price pressure. There is empirical evidence that mutual fund and ETF flows could lead to underlying asset price changes (Ben-Rephael et al., 2011). These flows can be caused by mutual fund fire sales (Coval and Stafford, 2007; Lou, 2012) or by the creation and redemptions of ETF shares (Brown et al., 2021). Furthermore, these flows into mutual funds are potentially predictable (Dyakov and Verbeek, 2013). Dividend payments can also create price pressure on the stock level (Ogden, 1994; Berkman and Koch, 2017; Hartzmark and Solomon, 2022b). The price pressure of dividend reinvestment can also be predicted even several weeks before the payment date (Hartzmark and Solomon, 2022a). In particular, (Dang et al., 2021) find that the government's direct capital injection in the equity market could lead to both a trading effect and an announcement effect. In line with (Dyakov and Verbeek, 2013), we offer a prediction model anticipating the BOJ's intervention by using public information to design the model inputs.

This study also aims to shed light on the existence and impact of unconventional monetary policy. Unconventional monetary policy, especially direct capital injection into the equity market, has been controversial in recent decades. Studies such as Bernanke et al. (1999); Bernanke and Gertler (2001); Rigobon and Sack (2003) state that central banks are not effective in responding to shocks in the equity market. As a result, most central banks have not implemented monetary policy by directly injecting capital into the equity market in recent decades. Central banks are more concerned with expected inflation and changes in the yield curve. However, there are some central banks that have implemented an unconventional monetary policy by purchasing equities. In most cases, a price impact is observed (Charoenwong et al., 2021; Dang et al., 2021; Harada and Okimoto, 2021), although it has some side effects (Chen et al., 2019; Charoenwong et al., 2021). We demonstrate that BOJ interventions have a positive price impact on low-liquidity stocks, implying the efficacy of unconventional monetary policy in mitigating risk.

The remainder of the essay is structured as follows. Section 3.2 describes the data and methodology. Section 3.3 discusses the findings of the liquidity impact and the price impact in relation to BOJ's unconventional monetary policy. Robustness tests are presented in Section 3.4 and Section 3.5 concludes.

3.2. Data and methodology

3.2.1. Data. The sample period for this study is from 1 January 2011 to 31 December 2019. Note that during BOJ's monthly monetary policy meeting in October 2010, BOJ decided to launch the unconventional monetary program known as the BOJ ETF purchase program. As only two purchases were made from October 2010 to December 2010, we ignore them and start on January 1, 2011. The sample period ends on December 30, 2019 to intentionally avoid the impact of COVID-19 and associated financial market movements. Furthermore, shortly after the initial shock of the COVID pandemic, the BOJ lowered its frequency of purchases. From 2011 to 2019, the BOJ intervened in roughly 20–30% of total trading days on average. However, the BOJ only intervened less than 10 times during 2022. Thus, these policy changes in recent years may impair the quality of empirical conclusions.

We collect our data from several databases. BOJ daily intervention decisions are downloaded from its official website.[4] On the BOJ website, the updates on the intervention decision for each day and the purchase amount of each index-linked ETF are reported on each trading day. A null transaction in the spreadsheet means that there is no intervention on this trading day. The BOJ updates the file on a daily basis. Normally, the BOJ file is uploaded between 4:00 and 5:00 pm in the Japanese time zone, which is one to two hours after the closing of the Japanese equity

[4]Data can be found at the following link: https://www3.boj.or.jpmarketenmenu_etf.htm

market. Therefore, investors can only obtain information on any BOJ intervention after the market closes. Furthermore, the BOJ also discloses its ETF purchase program policy on its official website. The useful data in these documents include the annual budget of the ETF purchase program and the approximate purchase proportion in each index. However, the official BOJ documents do not disclose the purchase mechanism. Therefore, the timing of BOJ purchases and BOJ mechanisms assumed in our article are based on empirical evidence and rational assumptions from relevant literature such as Harada and Okimoto (2021); Katagiri et al. (2022); Hattori and Yoshida (2023).

Table 3.2.1 shows the descriptive statistics of the Japanese TOPIX index from 2011 to 2019. In addition to the financial performance of the TOPIX index, the table also contains features of the BOJ intervention during this nine-year period. As summarised in Table 3.2.1, in the early years of the BOJ's ETF purchase program, the annual budget for purchase is around 600–800 billion yen per year, and the purchase frequency is approximately 20–50 times per year (once a week or fortnight). The average purchase amount per intervention is around 10–30 billion yen. However, in 2013 the BOJ introduced an unconventional monetary policy, called Qualitative and Quantitative Easing (QQE) (BOJ, 2013a). As a result, the BOJ's equity ETF purchase program was merged with the large QQE program, and the annual purchase budget increased sharply from slightly more than one trillion yen to three trillion yen at the end of 2014. In addition, the frequency of purchases also increased rapidly, reaching 75–90 times per year. The annual purchase budget doubled in the middle of 2016, from three trillion yen to six trillion yen. However, instead of increasing the frequency of purchase, the BOJ increased the purchase amount per intervention from 35 billion yen to 70 billion yen.

From the Refinitiv Tick History (TRTH), we obtain 15–min intraday prices and transaction volumes of the TOPIX constituent stock (totaling 2045 component stocks). As there are no daily transaction value data disclosed in our database, we use the trading volume and stock price to approximate the daily transaction value of each stock. To estimate the daily transaction value of each stock, we use the last price of the stock times the trading volume of this stock within each 15–min interval and sum all intervals within each trading day. In Asian equity markets, there is normally a lunch break in the middle of the trading session. Thus, in the Japanese equity market, the whole trading session is split into four subsessions: overnight session (previous afternoon close to current morning open), morning session (morning open to morning close), lunch break session (morning close to afternoon open), and afternoon session (afternoon open to the

TABLE 3.2.1. **Descriptive statistics of variables**

The table shows the TOPIX index daily return's mean, median, max, min, daily volatility, number of observations, annual Bank of Japan (BOJ) purchase amount, and number of BOJ intervention day.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	–0.08%	0.07%	0.18%	0.04%	0.05%	0.01%	0.08%	–0.07%	0.06%
Median	–0.01%	0.03%	0.12%	0.08%	0.15%	0.05%	0.07%	–0.01%	0.04%
Maximum	6.64%	2.75%	5.21%	4.28%	6.40%	8.02%	2.36%	4.90%	2.81%
Minimum	–9.47%	–2.89%	–6.87%	–4.77%	–5.86%	–7.26%	–2.12%	–4.88%	–2.45%
Standard Deviation	1.42%	1.00%	1.51%	1.19%	1.27%	1.67%	0.68%	1.12%	0.82%
Sample size	245	248	245	244	244	245	247	245	241
Total BOJ Purchase (billion)	800	640	1095	1285	3069	4382	5607	6210	4088
Number of BOJ Days	42	23	58	75	89	90	78	87	58

afternoon close). We then compute the return of the overnight session (day t 9:00 am opening price divided by day $t-1$ 15:00 pm closing price), morning session (11:30 am closing price divided by 9:00 am opening price), lunch break session (12:30pm opening price divided by 11:30 am closing price), and afternoon session (15:00 pm closing price divided by 12:30 pm opening price), based on the TRTH intraday prices of each stock.

We also winsorise the return by the top 0.1% and the bottom 0.1%, because the TRTH intraday price of individual stock data does not adjust for any stock split, stock dividend, or reverse stock split. Therefore, in these cases, the return on the stock will be extremely large or small. To mitigate the outliers, we winsorise these outliers to the bottom 0.1% and the top 0.1% of 15-min intraday returns.

We gather daily weights of TOPIX index stocks from Bloomberg. As we assume that the BOJ's purchase will be placed in TOPIX index-linked ETFs, the TOPIX index weight of each individual stock can be the estimation of BOJ's purchase portion on each intervention day. Therefore, we collected daily weights of TOPIX constituent stock weights from January 1, 2011 to December 30, 2019.

3.2.2. Design of front-running strategy. To design a front-running strategy, we first study the returns obtained in different trading sessions: overnight, morning, lunch break, and afternoon sessions, on both intervention days and non-intervention days.

Table 3.2.2 shows the performance of the TOPIX index in these four sessions. Results are also classified into BOJ intervention day, non-BOJ intervention day, and full sample. In this table,

TABLE 3.2.2. **Four-session returns for BOJ days and non-BOJ days**

This table shows the overnight, morning, luch break and afternoon session performance on BOJ intervention days, non-BOJ intervention days, and in the full sample. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

Sessions	Overnight	Morning	Lunch break	Afternoon
BOJ days	−63.36***	−41.38***	0.31	4.81**
	(2.61)	(2.74)	(0.94)	(2.43)
Non-BOJ days	29.73***	13.09***	0.36	−1.53
	(1.54)	(1.25)	(0.43)	(1.20)
Full sample	4.60***	−1.62	0.35	0.18
	(1.59)	(1.28)	(0.41)	(1.06)

the returns on the BOJ days show that the overnight and morning session returns are significantly negative, while the afternoon session returns on BOJ days are significantly positive. This is probably because the BOJ tends to make intervention decisions based on how the Japanese stock market performs in the overnight and morning sessions and starts to undertake transactions in the afternoon session. It is well documented that the price pressure of the BOJ's purchase comes on the same day of that intervention, and the contemporaneous price impact is likely to come on the afternoon session (12:30 pm to 3:00 pm). Charoenwong et al. (2021) examine the intraday return difference between BOJ-affected stocks and non-BOJ-affected stocks. When the market performs poorly during these sessions, the BOJ is more likely to intervene to buy stocks and stabilise the equity market. Furthermore, Harada and Okimoto (2021) claim that BOJ purchases often begin during the afternoon session of the intervention day. This aligns with the findings in Table 3.2.2, where the afternoon session returns on BOJ days are significantly positive.

Although there is no official confirmation of the BOJ's buying process, these statistical findings suggest a probable pattern: if the BOJ observes that the overnight and morning sessions have performed poorly, it is likely to act to stabilise the Japanese market. This leads to purchases after the lunch break session, causing the afternoon session returns to become positive. Based on this mechanism, we assume that there is a potential front-running strategy to predict the BOJ's moves and profit from their purchases. Therefore, in Section 3.2.3 we determine the factors that are likely to trigger a BOJ intervention and build a model to predict the BOJ's actions before its actual purchases. Further, in Section 3.2.4 we create a long-short portfolio to derive the profits generated from predicting the BOJ's interventions.

3.2.3. Prediction model construction. To avoid look-ahead bias and make this strategy feasible, we use only publicly available information to predict the BOJ intervention in the afternoon session. This means that all the information collected should be no later than the end of the lunch break session. The first group of inputs that we consider are the overnight returns and the morning session returns, because they have been well discussed in several papers (Hattori and Yoshida, 2023; Harada and Okimoto, 2021; Katagiri et al., 2022). As discussed in Section 3.2.2, the returns in the overnight session and the morning session on BOJ days exhibit a significantly negative trend, whereas the returns in these sessions on non-BOJ days are positive. This discrepancy can be attributed to the fact that the BOJ is more inclined to make purchasing decisions when the performance of the overnight and morning sessions is unfavorable (Chen et al., 2019; Charoenwong et al., 2021). This implies that both the overnight return and the morning session return may contribute strongly to the predictive power when constructing the prediction model. Also, we add the lagged one-day return of the S&P 500 index to our model to capture the impact of worldwide equity market movements during the overnight session.

In addition to the overnight return, morning session return, and S&P 500 index lagged one-day return, we introduce the BOJ's annual purchase budget constraint to capture the impacts of that limit on the BOJ's market operations. The BOJ's monetary policy sets an upper limit on the annual purchase amount, which means that the total purchase amount within a year is unlikely to go beyond this target (although the total spending in 2018 exceeded the annual budget). Therefore, we introduce two factors to measure the impact of budget constraints on BOJ's purchase operation: hard limit and soft limit. The hard limit means that spending on ETF purchases has already exceeded its annual budget amount. In this case, BOJ officials are not likely to purchase shares aggressively due to budget constraints. This is likely to happen at the end of each year, as did occur in 2016 and 2018. After 1 January, the budget amount is refreshed. The soft limit means that spending on ETF purchases is faster than on a pro rata basis. For example, if the BOJ purchases ETF at high frequency at the beginning of the year, even though it does not reach the hard limit, it is still exceeding its expected year-to-date spend on a pro rata basis. Therefore, it is likely that the BOJ's spending will be lower for the rest of the year.

To quantify the impact of BOJ budget constraints on purchase operations, we first find several key dates on which the BOJ changes its annual budget amount. We then accumulate the BOJ's annual purchase amount yearly. The difference between the BOJ's annual budget amount on a specific date and the actual BOJ accumulated purchase value is the hard limit value (we use the % term here by dividing by the budget amount). The soft limit measure, on the other hand, is based on the remaining budget and the remaining days. We calculate the remaining budget proportion and remaining days (%) within each year and obtain the ratio of these two numbers minus one. For example, if the remaining budget is 80% and the remaining days are 60%, then we a ratio of 1.33, and the actual number we get is 0.33 by deducting 1. This ratio indicates that the remaining budget is probably sufficient for the remaining days of the year. If the number is below zero, that means that the money is being spent faster than on a pro-rata basis, and the BOJ is likely to reduce the frequency of purchase. However, it is worth noting that the impacts of hard limit and soft limit is not symmetrical. This is because the BOJ is likely to leave some budget untouched, but it is not likely that it would often exceed the budget constraint. Because of this lack of symmetry, we focus only on the negative side and set positive figures as zero. In addition, as there is an inclusion relation between the hard limit and soft limit, we set the soft limit to zero when the hard limit has been reached.

The logit model is shown below:

$$P_{Intervention=1} = \frac{1}{1+e^{-Z_t}},$$

$$\begin{aligned} Z_t = \alpha + \beta_1 \times Overnight\ return_t + \beta_2 \times Morning\ return_t \\ + \beta_3 \times S\&P500\ return_{t-1} + \beta_4 \times Hard\ Limit_{t-1} \\ + \beta_5 \times Soft\ Limit_{t-1} \end{aligned} \tag{3.2.1}$$

where $Overnight\ return_t$ refers to the overnight return on day t, $Morning\ return_t$ refers to the morning return at day t, $S\&P500\ return_{t-1}$refers to the SP500 index on day $t-1$, $Hard\ Limit_{t-1}$ refers to the hard limit of the previous trading day, and $Soft\ Limit_{t-1}$ refers to the soft limit.[5]

To avoid look-ahead bias and make our trading strategy feasible, we design a prediction strategy. First, we use the first three-year data as the initial training set to train the logit model and use

[5]There are potential concerns about an endogeneity issue between the morning session returns and the possibility of BOJ intervention in the morning session. In our prediction model, we have introduced five predicting factors, four of which are free from the endogeneity issue. In addition, the Shapley value indicates that the contribution power of the morning session return in the prediction model is around 25%, which means that the impact of any potential endogeneity would be modest. Furthermore, research has shown evidence that the poor performance of the equity market in the morning session triggers the BOJ intervention, including Nangle and Yates (2017); Hattori and Yoshida (2023); Fukui and Yagasaki (2023). There is empirical evidence that the price impact from BOJ's intervention begins in the afternoon session of the intervention day (Harada and Okimoto, 2021; Katagiri et al., 2022).

TABLE 3.2.3. **Logit model coefficients and predictions**

Panel A of the table shows the coefficients of five variables in logit prediction model. Panel B of the table shows the look-ahead-bias-free prediction result based on the logit model. Subsample 2014–2016 starts from November 4, 2014 when the BOJ tripled the annual budget of ETF purchase program from one trillion yen to three trillion yen, and subsample 2016–2019 starts from August 5, 2016, when the BOJ further doubled the annual budget from three trillion yen to six trillion yen. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

Panel A: logit Model Coefficients

	Coefficients	Standard Error	t-stat
Overnight return	–2.60	0.151	–17.17***
Morning return	–2.71	0.161	–16.82***
S&P 500 lag 1-day return	–0.02	0.010	–2.98***
Soft limit	–0.01	0.001	–8.10***
Hard limit	–0.31	0.101	–3.05***

Panel B: logit Model Predictions

Prediction	True	False	Accuracy
Full Sample	1272	194	86.77%
Subsample 2014–2016	358	69	83.84%
Subsample 2016–2019	724	110	86.81%

that model to predict the next trading day operation (intervention or not). Second, on each trading day, we can observe the actual results of any BOJ operation. We compare the prediction result and the actual result and record them in the table. Third, after each trading day, we add the actual result of this trading day to the training set and use the new training set to retrain the logit model. For example, if we are on day t (the sample starts from day zero), we have t samples in the training set. We use these samples to train the logit model and predict the BOJ operation at $t+1$ day. After the prediction, we add $t+1$ to the training set and retrain the model to predict BOJ operation $t+2$ days.

In this predicting strategy, we start to introduce dynamic Youden J statistics in each trading day to determine the threshold of the logit model, because the threshold default of 0.5 is not necessarily the default value. To find the optimal threshold, we use Youden's J statistics (Youden, 1950), which is the sensitivity rate plus the specificity rate minus one. Maximizing Youden's J statistic can give us the optimal threshold of the logit model. Before the prediction in each trading day, we calculate the optimal threshold using Youden's J statistics and fit the logit model with the latest optimal threshold. So, in our strategy, the threshold changes every day.

The prediction result and summary statistics for each sample period are shown in Table 3.2.3. The findings show that the model provides a very good accuracy ratio. The prediction accuracy (true prediction rate) is 88.26% for the full sample result, and the prediction model performs well in each subsample group. This indicates that the logit prediction model we construct in this section could effectively anticipate the BOJ's intervention in advance of its announcement after the market closes on each trading day. Furthermore, the inputs in the logit model are free of any look-ahead bias. In other words, all the information collected is publicly available in this logit model. We could claim that this prediction model makes it feasible for market participants to predict the BOJ's operation and potentially front-run. These highly accurate prediction results provide confidence to build a portfolio based on the front-running strategy.

3.2.4. Constructing the long-short portfolio. After the promising prediction results on BOJ interventions, we next identify the stocks that are most likely to be affected by a BOJ intervention. Here, we introduce two sorting factors when constructing our long-short portfolio: the dollar amount of the BOJ purchase of each TOPIX stock and the proportion of the amount of the BOJ purchase to the total daily trading value. We assume that the BOJ only purchases stocks in the TOPIX index based on the weights of stocks within the TOPIX. [6] Therefore, each stock's BOJ purchase dollar amount is calculated as

$$DA_{i,t} = BOJ_t \times w_{i,t}, \tag{3.2.2}$$

where BOJ_t represents the BOJ purchase amount on day t, and $w_{i,t}$ refers to the weight of stock i in TOPIX index on day t. The logic behind this is relatively simple: a higher purchase amount is likely to shift the demand curve towards the right and cause price pressure on stocks.

However, $DA_{i,t}$ may not be the perfect sorting factor because price pressure caused by interventions can be limited when there is sufficient market liquidity to absorb purchase orders. Therefore, we also introduce another sorting factor $RF_{i,t}$ calculated as the proportion of the BOJ purchase amount to the total daily trading value to represent the liquidity impact of the BOJ purchase. Thus,

$$RF_{i,t} = \frac{DA_{i,t}}{Trading\ Value_{i,t}} = BOJ_t \times \frac{w_{i,t}}{Trading\ Value_{i,t}}, \tag{3.2.3}$$

[6] Based on the BOJ's official documents, the BOJ's daily intervention is split into TOPIX, Nikkei225, and Nikkei400 index-linked ETFs. Due to the lack of weights of the Nikkei225 and Nikkei400 constituent stocks, we cannot proceed with the calculations like Charoenwong et al. (2021). However, as the BOJ's interventions are mostly allocated to the TOPIX index in later years, TOPIX constituent stock weights can be viewed as a good representation of weight allocation.

where, $Trading\ Value_{i,t}$ refers to the transaction value of the stock i on day t. It can also refer to the moving average of the trading value in the previous 5 trading days (one week period) and 22 trading days (one month period). Here $RF_{i,t}$ effectively captures the impact of liquidity and market depth. Although high DA may cause high price pressure, a high daily transaction value may indicate that the stock has strong liquidity and market depth. Accordingly, BOJ interventions can be quickly absorbed without a strong price impact.

However, if we use $DA_{i,t}$ and $RF_{i,t}$ to sort stocks on day t, there is a "look-ahead" issue because $w_{i,t}$ and $Trading\ Value_{i,t}$ can only be observed at the end of day t. Therefore, to make our trading strategy feasible, we must avoid look-ahead bias by using $DA_{i,t-1}$ and $RF_{i,t-1}$ to sort TOPIX stocks on day t. Another problem is that when day t or day $t-1$ is not a BOJ intervention day, BOJ_t or BOJ_{t-1} then becomes zero and both $DA_i, t-1$ and $RF_{i,t-1}$ turn zero for all stocks. To ignore this issue, we adjust the ranking factors as follows:

$$\widetilde{DA_{i,t}} = \frac{DA_{i,t}}{BOJ_t} = \frac{BOJ_t \times w_{i,t}}{BOJ_t} = w_{i,t}, \tag{3.2.4}$$

$$\widetilde{RF_{i,t}} = \frac{RF_{i,t}}{BOJ_t} = \frac{BOJ_t \times w_{i,t}}{BOJ_t \times Trading\ Value_{i,t}} = \frac{w_{i,t}}{Trading\ Value_{i,t}}. \tag{3.2.5}$$

We divide BOJ_t for both factors because BOJ_t is fixed for all stocks in the TOPIX index and when we do sorting for stocks, only $w_{i,t}$ and $\frac{w_{i,t}}{Trading\ Value_{i,t}}$ affect the sorting results. In this case, we could also sort when day t or day $t-1$ is not a BOJ day without being affected by the absence of the BOJ intervention dollar amount ($BOJ_t = 0$).

After computing $\widetilde{DA_{i,t}}$ and $\widetilde{RF_{i,t}}$, we use the TOPIX weight at day $t-1$ and each of the three ranking factors (1-day lagged, 5-day moving average, and 22-day moving average ranking factors) to construct double-sorted tables. On each trading day t, we sort the stocks by TOPIX weight $t-1$ and each of the three ranking factors one by one (results are shown separately) by quantiles. These two sorting processes are performed independently. This means that each group's number of stocks can be different - it is possible that some groups have more stocks, and some groups have less. For example, for group $(5,5)$ - that is, the highest ranking factor ratio and the highest TOPIX weight - contains approximately 50k stocks, while group $(1,1)$ may contain only 40k stocks. Using this double-sorting result, we calculate the mean, standard error, and $t-$stat for each group. Calculating the mean of each cell in this table means that we construct an equal weighted portfolio by purchasing all stocks within this cell with the same amount of money.

We add one more column (RF_LS) and one more raw (Weight_LS) to show the L-S portfolio result. The RF_LS is the long-short portfolio constructed by the long highest ranking factor and the short lowest ranking factor to realise the price impact generated by the liquidity issue. The Weight_LS is the Long-Short portfolio constructed by long highest TOPIX weight stocks and short lowest TOPIX weight stocks. As in our analysis, TOPIX weight is the representation of the dollar amount of the BOJ purchase, this long-short portfolio aims to capture the price pressure generated by the BOJ purchase. The intersection of RF_LS and Weight_LS (bottom right cell) is the corner portfolio of the long (DA5, RF5) and short (DA1, RF1) portfolio. This portfolio aims to capture both the BOJ purchase price pressure and the liquidity factor. Thus, the objective is to predict BOJ's behavior and invest in the days of predicted BOJ purchase at the closing time of the morning session to take advantage of the BOJ purchase in the afternoon session. Meanwhile, in the rest of the time (non-BOJ days shown by the model or the morning session during predicted BOJ days), we invest the portfolio in the Japanese 10−year government bond.

3.3. Empirical results

In this section, we present the findings of the long-short portfolio constructed based on our prediction model and the sorting method outlined in Section 3.2 to derive the potential profits from both the long leg and the short leg. Furthermore, we assess the performance of the long-short portfolio using the Fama-French five-factor model to calculate the abnormal return derived from our trading strategy. Fama-Macbeth two-step regression is introduced to test the BOJ's intervention as a risk factor and identify its impact on stock returns.

3.3.1. Long-short portfolio return. Table 3.3.1 presents a 5×5 matrix of portfolio return capturing the BOJ's impact from two fundamental dimensions of investment characteristics: stock weights in the TOPIX index and stock illiquidity. We investigate the returns of the portfolio matrix, which are generated by independently ranking the data based on these two factors and dividing them into quintiles. The vertical axis denotes the level of influence of the BOJ purchase amount on the portfolio. The top (bottom) row of the matrix indicates the average return of a portfolio constructed from stocks that are least (most) affected by the BOJ's intervention. The vertical axis illustrates decreasing stock liquidity from top to bottom, indicating the ease of buying or selling stocks without significantly affecting market prices. The far left (right) of the matrix represents the return of the portfolio with the least (highest) liquidity among all stocks,

TABLE 3.3.1. **Portfolios sorted by risk factor (RF) and dollar amount (DA)**

The table shows portfolio return results sorted by DA and RF (DA and RF are divided into five equal parts). DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. The bottom right portfolio is the corner portfolio obtained by longing (DA5, RF5) and shorting (DA1, RF1). *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

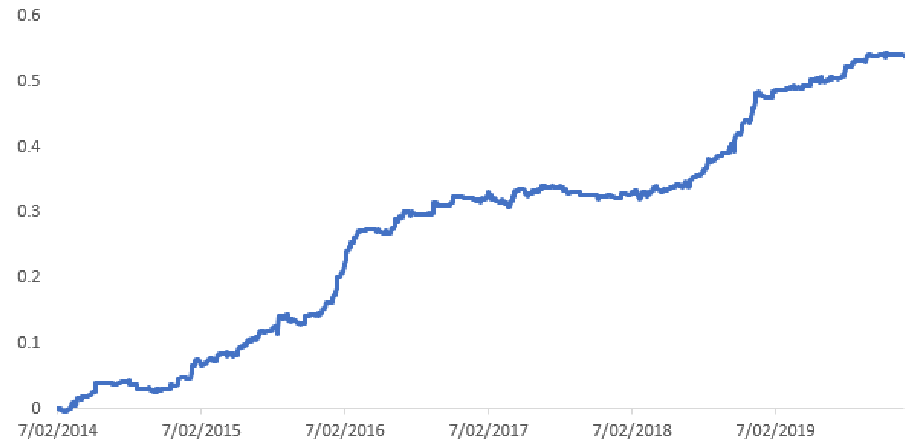
	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−5.92***	−8.45***	−8.59***	−7.64***	−2.83***	3.09***
	(0.62)	(0.54)	(0.53)	(0.61)	(0.73)	(0.95)
DA2	−2.58***	−5.13***	−5.61***	−3.97***	−0.56	2.03**
	(0.58)	(0.50)	(0.49)	(0.55)	(0.67)	(0.88)
DA3	−0.19	−1.51***	−2.13***	−0.05	0.99*	1.18
	(0.53)	(0.51)	(0.51)	(0.45)	(0.56)	(0.77)
DA4	1.24***	1.58***	1.64***	1.12**	6.29***	5.05***
	(0.45)	(0.47)	(0.48)	(0.46)	(0.44)	(0.63)
DA5	3.58***	3.34***	3.63***	5.10***	4.56***	0.97*
	(0.40)	(0.40)	(0.43)	(0.41)	(0.38)	(0.55)
DA5-DA1	9.51***	12.08***	12.22***	12.74***	7.39***	
	(0.74)	(0.73)	(0.72)	(0.73)	(0.75)	

according to our liquidity indicator. Therefore, each cell in the matrix represents the return associated with a specific combination of purchase amount and stock liquidity. The top left (bottom right) corner portfolio represents the least (most) affected stock portfolio return.

Table 3.3.1 reveals that the impact of BOJ interventions is uneven across stocks. More specifically, the impact of BOJ interventions is more pronounced on stocks with higher weights and less liquidity. Portfolios characterised by high intervention amounts (top to bottom) and less liquidity (left to right) tend to yield superior returns. In contrast, portfolios with low BOJ purchase amounts and higher stock liquidity exhibit lower returns.

Based on these results, we construct the long-short portfolio as follows. The long portfolio with the most affected position is (DA5, RF5), and the short portfolio with the least affected position is (DA1, RF1). The return of the corner portfolio is 10.48 basis points and is significantly below the 1% level. Taking into account that the number of intervention days per year is up to 90, the annual return generated based on this long-short strategy is as high as 11.97% per year. This result indicates a high potential for profit from such trading strategies. The accumulated portfolio return is shown in Figure 3.3.1. We perform the same analysis on the long-short strategy using the sorting factors of TOPIX weight and Amihud liquidity ratio to account for liquidity impact of the BOJ's intervention. The Amihud liquidity ratio provides quantitatively similar results that are presented in 3.5.

FIGURE 3.3.1. **Accumulated long-short portfolio return**
The figure shows the accumulated return generated from the long-short portfolio strategy from 2014 to 2019.



Furthermore, the long-leg and short-leg portfolio return patterns show that the trading strategy captures the price pressure from the BOJ interventions. The short-leg portfolio generates −5.92 basis points return for each BOJ intervention prediction. This result is consistent with the work of Gao et al. (2018) and (Zhang et al., 2019), which show that there is a strong momentum within a trading day. As the BOJ usually intervenes on trading days with poor performance in the overnight and morning sessions, poor performance in the overnight and morning sessions tends to incur a negative return in the afternoon session through the momentum effect. However, the long-leg portfolio shows a positive significant return result, suggesting that the BOJ's intervention could potentially overcome intraday momentum from the overnight and morning sessions and place strong and positive price pressure on affected stocks.

The long-short portfolio strategy strongly supports the hypothesis that BOJ's interventions could cause price pressure. Furthermore, the long-short portfolio is an extension of Harada and Okimoto (2021) opinion that the BOJ is likely to start an intervention in the afternoon session of the intervention day. The BOJ's intervention has a significant impact on the afternoon session of the Japanese equity market on intervention days, and by predicting the BOJ's intervention, we can potentially construct a feasible trading strategy to generate profits based on this feature. Similarly, the 5×5 portfolio matrix shows that the BOJ's intervention creates higher price pressure on less liquid stocks. The results shown in the $RF5-RF1$ column indicate long-short portfolio results by longing the least liquid stocks and shorting the most liquid stocks. Four of five long-short portfolios show positive significant returns, providing empirical evidence for the notion that the BOJ's intervention has higher positive impacts on high-risk stocks. As those interventions are likely to come when market performance is poor, BOJ's equity purchase works as a kind of "insurance" for market participants. Considering the BOJ's predictable mechanism and its downside-risk protection on high-risk stocks, the intervention can be treated as a signal to synchronise the market. The opinion convergence from synchronization can also reduce the level of market uncertainties (Miller, 1977).

3.3.2. Fama-Macbeth regression analysis. To further test the significance of BOJ's intervention in the afternoon session of the TOPIX index, we implement Fama-Macbeth regressions to test the consequences of BOJ's intervention as a pricing factor on stock returns.

For each of the stock listed in the sample, we run time series regressions between the afternoon returns of the stock and Fama-French five pricing factors, using a 30-day rolling window to calculate the estimated betas. After running time-series regressions, we obtain the estimated betas of all five Fama-French factors for each stock in the sample. Meanwhile, we add one more factor to the cross-sectional return, the "BOJ Dummy".[7] After running the regression between

[7]The BOJ dummy equals one when there is a BOJ intervention on that trading day and zero when the BOJ does not intervene on that trading day.

TABLE 3.3.2. **Fama-Macbeth cross-sectional regression**

The table shows the Fama-Macbeth two-step regression results. The first step of the Fama-Macbeth regression is running time series regressions for each individual stock against five Fama-French pricing factors. The second step of the Fama-Macbeth regression is running cross-sectional regressions between the afternoon session return of each individual stock and betas derived from step one of the regression with the BOJ dummy variable and control variables. The second-step regression result is shown in the table in %. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

risk factors	I	II	III
BOJ Dummy	0.038***	0.027***	0.027***
	(0.005)	(0.004)	(0.004)
MRP	−0.039	−0.009	−0.012
	(0.029)	(0.033)	(0.032)
SMB	−0.016	−0.014	−0.013
	(0.013)	(0.014)	(0.014)
HML	0.016	0.011	0.009
	(0.015)	(0.016)	(0.016)
RMV	−0.008	−0.006	−0.006
	(0.009)	(0.009)	(0.009)
CMA	0.012	0.004	0.005
	(0.009)	(0.009)	(0.009)
Ret 1-day lag$^{(1)}$		0.017***	0.018***
		(0.003)	(0.003)
Ret 22-day lag$^{(2)}$		0.012***	0.018***
		(0.000)	(0.001)
Vol 22-day lag$^{(3)}$		−0.003	−0.003
		(0.006)	(0.006)
Profit margin			−0.015**
			(0.006)
D/E ratio			0.002
			(0.002)
ROA			0.072***
			(0.014)
Growth rate			0.007
			(0.012)

(1): Lagged one-day individual stock afternoon-return
(2): Lagged 22-day accumulated individual stock afternoon-return
(3): Lagged 22-day volatility

asset returns and six loadings (and three control variables), we perform a time series analysis containing 1,450 trading days' risk premiums of six loading factors.

This analysis is presented in Table 3.3.2. The significant BOJ dummy variable suggests that BOJ interventions have an impact on the afternoon session returns of stocks in the TOPIX index. As we use a rolling 30-day window to generate beta loadings, there is no look-ahead bias. The Fama-Macbeth regression result indicates a feasible trading strategy by generating a return from the BOJ intervention factor. This suggests that market participants could generate excess returns by predicting the BOJ's intervention operations, as the BOJ can potentially influence stock market movements in the afternoon session.

3.3.3. Performance of long-short trading strategy. Driven by the significant and positive returns generated on BOJ's intervention days and the positive BOJ factor from the Fama-Macbeth model, we construct the trading strategy using the following steps. First, we construct a long-short portfolio at the beginning of the afternoon session of predicted BOJ intervention days and liquidate the portfolio at the end of the trading day. Second, for the rest of the trading days, we invest our capital in risk-free securities. Note that the predicted BOJ interventions are based on the results of the prediction model shown in Section 3.2.3.

We use the Fama-French three- and five-factor models with momentum factor, which include market excess return, SMB, HML, RMW, CMA, and MOM to assess the performance of our strategy based on the anticipated BOJ interventions. The results are reported in Table 3.3.3. We find that, in general, the abnormal returns based on the three- and five-factor pricing models are positive, including the long leg-only portfolio, the short-leg only portfolio, and the long-short portfolio. Specifically, the short leg (DA1,RF1) portfolio shows -2.90 basis points abnormal returns per each prediction, and the long leg (DA5, RF5) portfolio shows 1.17 basis points abnormal returns on average. Furthermore, the SMB loading for long (short) leg portfolio is -5.77 (7.26) basis points. These results comply with the feature of the long (short) leg portfolio because the long (short) leg portfolio contains the highest (lowest) market cap stocks in the TOPIX index. Therefore, the SMB loading for the long-short portfolio is -13.02 basis points and indicates that the portfolio is titled towards large stocks. All other factors, except MKT and SMB, are largely hedged out when using the long-short strategy.

These findings imply that it is possible to benefit from anticipating the BOJ's interventions in advance by using only publicly available information. In other words, the ex ante view used in the prediction model and the long-short portfolio provides a feasible trading strategy for market participants.

TABLE 3.3.3. **Abnormal returns from Fama-French model**

The table shows the classic Fama-French three and five factors with momentum on the long-short portfolio constructed in section 3.2.4. The long leg and short leg panels show the performance of long leg-only and short leg-only portfolio performances under these pricing model, while long short panel contains the performance of long-short portfolio under pricing models. Results are in basis points. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

Panel A: Fama-French three factors with momentum

	Alpha	MKT	SMB	HML	MOM	R^2
Long-only	1.18*	4.66***	–5.82***	–5.69***	0.97	0.052
	(0.71)	(1.26)	(2.16)	(1.75)	(1.89)	
Short-only	–4.01***	10.04***	7.78***	–3.44*	1.79	0.116
	(0.80)	(1.26)	(2.42)	(1.75)	(1.65)	
Long-short	5.19***	–5.38***	–13.60***	–2.25*	–0.82	0.102
	(0.61)	(0.74)	(1.91)	(1.24)	(0.93)	

Panel B: Fama-French five factors with momentum

	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
Long-only	1.17*	5.12***	–5.77***	–6.14***	1.53	4.50	0.92	0.054
	(0.68)	(1.28)	(2.18)	(2.57)	(4.69)	(3.40)	(1.86)	
Short-only	–3.91***	9.85***	7.74***	–3.99	–1.94	–1.23	1.79	0.116
	(0.79)	(1.28)	(2.43)	(2.47)	(4.58)	(3.58)	(1.66)	
Long-short	5.15***	–4.73***	–13.51***	–2.15	3.47	5.71**	–0.90	0.108
	(0.60)	(0.72)	(1.87)	(1.81)	(3.29)	(2.44)	(0.92)	

3.3.4. Three-index long-short portfolio. We incorporate three indices representing BOJ interventions into the analysis. According to BOJ disclosures, the bank intervenes by purchasing ETFs linked to three indices: the Nikkei 225, Nikkei 400, and TOPIX. Prior to 2014, BOJ interventions were limited to Nikkei 225 and TOPIX ETFs. However, following policy adjustments in 2014, the Nikkei 400 index was included in the intervention targets. In 2016 and again in 2018, the BOJ significantly increased its purchases of TOPIX-linked ETFs, with approximately 75%–80% of its holdings in TOPIX ETFs by the end of 2019. To estimate the BOJ's intervention across these indices more accurately, we use disclosed allocation ratios for the published portions and, for the undisclosed portions, rely on the market capitalization of the Nikkei 225, Nikkei 400, and TOPIX ETFs to assign the intervention amounts proportionally.

Following the methodology of Charoenwong et al. (2021), we calculate a weighted average of stock weights to test whether the long-short portfolio designed in the previous section continues

TABLE 3.3.4. **Double-sorted portfolios by three indices**

The table shows the portfolio return results sorted by absolute dollar amount (DA) and the liquidity-like risk factor (RF). The stocks are sorted by average weights (representing the Bank of Japan's [BOJ's] stock purchase dollar amount) of three indices, and the BOJ intervention days are predicted results from logit model. The liquidity-like risk factor is computed by the dollar amount divided by 22-day lagged average transaction value. In the table, DA and RF ratios are divided in five equal parts. DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−11.85***	−10.87***	−10.35***	−6.59***	−1.95***	9.90***
	(0.60)	(0.50)	(0.50)	(0.59)	(0.75)	(0.96)
DA2	−7.55***	−8.32***	−7.09***	−2.92***	3.21***	10.76***
	(0.56)	(0.48)	(0.48)	(0.54)	(0.67)	(0.73)
DA3	−3.86***	−3.98***	−3.62***	−0.47	3.82***	7.68***
	(0.53)	(0.50)	(0.50)	(0.51)	(0.57)	(0.78)
DA4	−0.93**	−1.36***	0.81*	2.15***	4.13***	5.06***
	(0.45)	(0.45)	(0.46)	(0.45)	(0.44)	(0.63)
DA5	2.46***	1.60***	3.52***	3.75***	4.88***	2.42
	(0.41)	(0.42)	(0.42)	(0.39)	(0.36)	(0.54)
DA5-DA1	14.31***	12.47***	13.87***	10.34***	6.83***	
	(0.73)	(0.65)	(0.65)	(0.71)	(0.83)	

to exhibit abnormal returns for these three indices.[8] Table 3.3.4 presents the portfolio return results sorted by absolute dollar amount (DA) and the liquidity-like RF for the weighted average holdings of each stock across the three indices. We find that by going long on the highest quintile (55) and short on the lowest quintile (11), we achieve a zero-cost corner portfolio with an average return of 16.73 basis points per trade. This indicates that the inclusion of weighted stocks from the three indices continues to yield similar results to those derived from using the TOPIX index alone in the baseline results.

We further test the portfolio strategy based on the three-index weighting method by using Fama-French multi-factor regressions to assess whether abnormal returns persist after controlling for different factor loadings. Table 3.3.5 lists the results of Fama-French regressions using TOPIX index weight only and the weighted average of the three indices' weights. We find that both methods yield similar results. Even after controlling for the five Fama-French pricing factors

[8]While Charoenwong et al. (2021) approach offers a more precise estimate of BOJ intervention in individual stocks, the lack of historical data on the weightings of Nikkei 225 components prevents us from accurately calculating the weighted averages. Consequently, we do not use these results as our baseline but rely on calculations based on the TOPIX index. However, the conclusions drawn from both approaches are highly consistent.

TABLE 3.3.5. **Fama-French regressions by TOPIX index only and by three indices**

The table presents the results of the classic Fama-French three- and five-factor regressions applied to the long-short portfolio constructed in section 3.2.4. The first two rows display the regression results using only the weights of TOPIX constituent stocks, while the last two rows show the results based on the weighted average method from Charoenwong et al. (2021), which incorporates the weights of three indices. The regression outcomes are expressed in basis points. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
TOPIX 3-factor	5.12***	–5.57***	–13.47***	–3.34***			–0.40	0.100
	(0.59)	(0.81)	(1.76)	(1.26)			(0.89)	
TOPIX 5-factor	5.12***	–5.17***	–13.45***	–4.37**	0.22	4.47**	–0.43	0.103
	(0.58)	(0.79)	(1.74)	(1.86)	(3.39)	(2.26)	(0.88)	
3-index 3-factor	5.19***	–5.38***	–13.60***	–2.25*			–0.82	0.102
	(0.61)	(0.74)	(1.91)	(1.24)			(0.93)	
3-index 5-factor	5.15***	–4.73***	–13.51***	–2.15	3.47	5.71**	–0.90	0.108
	(0.60)	(0.72)	(1.87)	(1.81)	(3.29)	(2.44)	(0.92)	

plus the momentum factor, the portfolios based on both the TOPIX index and the three-index weighted average generate abnormal returns exceeding 5 basis points per trading day. The similar performance of both portfolios is likely due to the substantial weight of BOJ purchases in TOPIX ETFs. Additionally, a significant portion of the BOJ's purchases target Nikkei 225 ETFs, whose constituents are the largest-cap stocks in the market. Under the three-index weighted average approach, these large-cap stocks receive a higher proportion of BOJ purchases, thereby boosting the portfolio's excess returns.

Furthermore, we apply a Fama-Macbeth regression to examine the premium associated with BOJ interventions as a factor loading in the three-index portfolio. The results are shown in Table 3.3.6 and indicate that the BOJ dummy variable significantly impacts stock returns, whether or not control variables are included. This result demonstrates that our findings remain valid under the methodology of Charoenwong et al. (2021).

3.4. Robustness tests

In this section, we perform several robustness tests to further support the validity of the results.

3.4.1. Alternative frequency of average transaction value. To test the effectiveness of the ranking factor model, or specifically the denominator of our RF ratio, we test alternative frequencies of the average transaction value. In the baseline analysis, we use the average of the 22-day lagged transaction value to capture the average trading value in the previous month. The

TABLE 3.3.6. **Fama-Macbeth cross-sectional regressions: Three indices**

The table shows the Fama-Macbeth two-step regression results. The first two columns contain the baseline results using TOPIX constituent stocks. Column 3–6 are regression results using Charoenwong et al. (2021)'s weighting method to compute the weighted average of three indices (TOPIX, Nikkei 225, and Nikkei 400), where columns 3 and 4 are baseline Fama-Macbeth results and columns 5-6 are Fama-Macbeth results with macro control. The Fama-French Japanese market pricing factors are downloaded from the Kenneth French Data Library. The fundamental factors are collected from the Refinitiv Workstation. The daily GDP control is from the Federal Reserve Bank of Atlanta. The regression results are shown in %. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

risk factors	I	II	III	IV	V	VI
BOJ Dummy	0.038***	0.027***	0.038***	0.027***	0.090**	0.0079**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.036)	(0.037)
MRP	–0.039	–0.012	–0.042	–0.014	–0.040	–0.014
	(0.029)	(0.032)	(0.030)	(0.032)	(0.029)	(0.032)
SMB	–0.016	–0.013	–0.015	–0.013	–0.015	–0.013
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
HML	0.016	0.009	0.014	0.009	0.016	0.009
	(0.015)	(0.016)	(0.009)	(0.016)	(0.015)	(0.016)
RMV	–0.008	–0.006	–0.009	–0.006	–0.009	–0.005
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
CMA	0.012	0.005	0.009	0.005	0.012	0.005
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)
Ret 1-day lag(1)		0.018***		0.018***		0.018***
		(0.003)		(0.003)		(0.003)
Ret 22-day lag(2)		0.011***		0.011***		0.011***
		(0.000)		(0.000)		(0.000)
Vol 22-day lag(3)		–0.003		–0.003		–0.003
		(0.006)		(0.006)		(0.006)
Profit margin		–0.015**		–0.015***		–0.015***
		(0.006)		(0.006)		(0.006)
D/E ratio		0.002		0.002		0.003
		(0.002)		(0.002)		(0.003)
ROA		0.072***		0.072***		0.072***
		(0.014)		(0.014)		(0.014)
Growth rate		0.007		0.007		0.007
		(0.012)		(0.012)		(0.012)
lagged GDP (4)					1.28	1.17
					(1.166)	(1.224)

(1): Lagged one-day individual stock afternoon-return
(2): Lagged 22-day accumulated individual stock afternoon-return
(3): Lagged 22-day volatility
(4): Lagged 1-day change of GDP growth rate

TABLE 3.4.1. **Portfolios sorted by dollar amount (DA) and 5-day risk factor (RF)**

The table shows the portfolio return results sorted by DA and RF with 5-day lagged average transaction value as denominator. In the table, DA and RF ratios are divided into five equal parts. DA1 means the stock group with lowest weights in the TOPIX index, and DA5 means the stock group with highest weights in the TOPIX index. Similarly, RF1 means the stock group with lowest RF ratio, and RF5 means the stock group with the highest RF ratio. RF5-RF1 is the portfolio that shorts RF1 and longs RF5, and DA5-DA1 is the portfolio that shorts DA1 and longs DA5. The bottom right portfolio is the corner portfolio by longing (DA5, RF5) and shorting (DA1, RF1). *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	RF1	RF2	RF3	RF4	RF5	RF5-RF1
DA1	−8.97***	−6.86***	−4.55***	−0.16	3.49	12.47***
	(0.33)	(0.52)	(0.81)	(1.49)	(4.39)	(2.35)
DA2	−7.11***	−5.07***	−1.52***	1.32	−4.27	2.84
	(0.39)	(0.41)	(0.54)	(0.88)	(2.61)	(1.69)
DA3	−4.39***	−1.76***	−0.29	0.88	−4.39***	−0.01
	(0.62)	(0.41)	(0.41)	(0.53)	(1.48)	(1.38)
DA4	−1.66	0.22	1.30***	1.49***	1.38**	3.04
	(1.65)	(0.59)	(0.36)	(0.31)	(0.58)	(1.92)
DA5	−6.38	2.15	3.34***	3.26***	4.00***	10.38
	(-)	(6.00)	(1.15)	(0.38)	(0.21)	(-)
DA5-DA1	2.59	9.01	7.89***	3.42***	0.50	
	(-)	(9.15)	(2.09)	(1.07)	(1.82)	

main benefit of using long-term average trading value is that it reduces short-term volatility and provides a more stable outcome.

We rerun the analysis using the average five-day lagged transaction value to capture a shorter frequency of the transaction value and determine whether the length of the transaction value has an impact on the results. The results of this analysis are summarised in Table 3.4.1 and are quantitatively similar to the baseline analysis. The corner portfolio generates 12.97 basis points return on average for each BOJ intervention compared to 10.48 basis points return from the baseline models. However, the average of the five-day lagged transaction value can be more volatile.[9]

3.4.2. Alternative prediction models and subsample tests. We further investigate the validity of our results by using an alternative prediction model (random forest model) and by performing the analysis over two sub-sample periods in our sample.

[9]Some of the cells in the 5×5 matrix do not contain enough samples. For example, the portfolio (DA5, RF1) contains only one sample, so $t-$statistics do not work. However, the 22-day RF results have no such issue. All cells of the 22-day RF results contain 30,000–50,000 samples in the 5×5 matrix, which implies that the results obtained from our baseline model are robust.

TABLE 3.4.2. **Logit model coefficients and predictions**

The table shows the coefficients of five variables in raddom forest prediction model. Subsample 2014–2016 starts from November 4, 2014 when the Bank of Japan (BOJ) tripled the annual budget of ETF purchase program from one trillion yen to three trillion yen, and subsample 2016–2019 starts from August 5, 2016, when the BOJ further doubled the annual budget from three trillion yen to six trillion yen.

Prediction	True	False	Accuracy
Full Sample	1265	201	86.29%
Subsample 2014–2016	375	52	87.82%
Subsample 2016–2019	717	117	85.97%

Apart from the logit model used in Section 3.2.3, we also consider other prediction models including random forest. Unlike the linear logit model, the random forest model is a nonlinear prediction model. Such model can capture more complex relationships than linear models, and thus may provide more robust results. The results of the random forest analysis are shown in Table 3.4.2 and reveal similar findings compared to the logit prediction analysis. The prediction accuracy rate is around 85%, and the performance in both sub sample periods is similar to the logit model. Therefore, linear and nonlinear models provide similar predictive performance.

Following the prediction results of the logit model in panel B of Table 3.2.3, Table 3.4.3 shows the abnormal returns of the long-short portfolio strategy from Fama-French regression using two subsamples; January 2014 to August 2016 and August 2016 to December 2019. This subdivision is justified by the significant increases in the BOJ budget for stock purchases, and in daily purchase amounts, starting in August 2016.[10] The logit model achieves consistently high prediction accuracy in the full sample (2014–2019) and the two subperiods (2014–2016 and 2016–2019). Similarly, the performance of the long-short portfolio strategy remains comparatively strong in the two subperiods and the full sample, with a lower alpha after 2016. This finding is consistent with the results in Harada and Okimoto (2021), who also demonstrate that the abnormal returns generated by BOJ interventions gradually decline over their sample period. Overall, despite the adjustments in BOJ policy during this time, the underlying mechanisms and their impact on the market remain relatively stable.

3.4.3. Alternative long-short strategies. To realise the abnormal return based on BOJ's purchase, we construct the long-short portfolio using long TOPIX, a BOJ-affected index, and

[10]The total annual budget was raised from three trillion yen to six trillion yen, and the daily purchase amount was increased from approximately 30 billion yen per day to 70 billion yen per day.

TABLE 3.4.3. **Fama-French multi-factor model in subsamples**

The table shows the Fama-French multi-factor regression results. The first two columns present the baseline results from full sample size (2014–2019). Columns 3–4 contain the results of the first subsample period from 2014 to 2016, and columns 5–6 contain the results of the second subsample period from 2016 to 2019. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	2014–2019		2014–2016		2016–2019	
	3-factor	5-factor	3-factor	5-factor	3-factor	5-factor
Alpha	5.12***	5.12***	5.99***	5.93***	4.26***	4.27***
	(0.59)	(0.58)	(0.94)	(0.70)	(0.71)	(0.71)
MRP	−5.57***	5.17***	−4.66***	−3.93***	−5.89***	−6.02***
	(0.81)	(0.79)	(1.11)	(0.60)	(1.24)	(1.17)
SMB	−13.47***	−13.45***	−9.21***	−9.14***	−18.48***	−18.56***
	(1.76)	(1.74)	(2.26)	(1.27)	(2.68)	(2.66)
HML	−3.34	−4.37**	−3.29	−3.74	−3.73**	−4.24*
	(1.26)	(1.86)	(2.01)	(3.15)	(1.65)	(2.52)
RMV		0.22		1.02		−1.81
		(3.39)		(0.97)		(4.61)
CMA		4.47**		7.77***		−0.88
		(2.26)		(3.00)		(3.33)
MOM	−0.40	−0.43	0.79	−0.86	−0.05	−0.04
	(0.89)	(0.88)	(1.29)	(0.88)	(1.16)	(1.18)

TABLE 3.4.4. **Fama-French multi-factor model from index level: TOPIX and MOTHERS indices**

The table shows the classic Fama-French three-, four- and five-factor evaluations on the long-short portfolio (the long BOJ-affected index [TOPIX] and the short BOJ-unaffected index [MOTHERS]). *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	Alpha	MKT	SMB	HML	RMW	CMA	R^2
3-factor	0.18***	0.01	−0.37***	0.35***			0.18
	(0.04)	(0.04)	(0.09)	(0.07)			
4-factor	0.17***	0.02	−0.35***	0.57***	0.48		0.20
	(0.04)	(0.03)	(0.08)	(0.11)	(0.18)		
5-factor	0.17***	0.01	−0.35***	0.61***	0.46***	−0.17	0.20
	(0.04)	(0.04)	(0.08)	(0.10)	(0.18)	(0.12)	

short MOTHERS, which is a Japanese start-up and small cap companies index that is not affected by BOJ interventions. To test the impact of BOJ interventions, we long the TOPIX index and short the MOTHERS index on BOJ intervention days. As the TOPIX index is the BOJ-affected index and MOTHERS is the unaffected index, if BOJ's purchase truly has a significant impact on index value, the risk-adjusted return of this long-short portfolio should be positive.

Table 3.4.4 presents the corresponding Fama-French five-factor analysis. Although it is not possible to trade the index, the results in Table 3.4.4 imply that the BOJ intervention has a significant positive impact on the value of the index and on stock prices involved in the affected index. After controlling for risk factors (the potential differences between the TOPIX index and the MOTHERS index in nature), risk-adjusted returns are significantly positive by longing the TOPIX index and shorting MOTHERS. The insignificant loading on MKT indicates that the market risk is mostly hedged out because both the long and short sides of the long-short portfolio are indices. The negative loading on SMB and positive loading on HML and RMW capture the major differences between TOPIX and MOTHERS: TOPIX contains large-cap, highly valued stocks with stable profitability, while MOTHERS contains small-cap start-ups that normally do not have stable cash flow. After controlling for these risk factors, the significant and positive results shown in Table 3.4.4 support the notion that BOJ interventions can have a significant price impact on stocks.

3.4.4. Cross-sectional impact on different indices. To explore the cross-sectional impact of BOJ interventions, we examine the impact on indices that are not directly targeted by the BOJ interventions, such as the JASDAQ index. We conduct a control experiment to compare the effects on TOPIX- and JASDAQ-constituent stocks in a long-short portfolio strategy. As the BOJ's intervention targets the Nikkei 225, Nikkei 400, and TOPIX, which encompass over 2,000 of Japan's largest stocks, small- and mid-cap indices like JASDAQ should theoretically remain unaffected.

We use intraday stock price data for JASDAQ constituents from 2014 to 2019 and compare the returns of TOPIX and JASDAQ constituents in four periods (overnight, morning, lunch break, and afternoon) in Table 3.4.5. On BOJ intervention days, both TOPIX and JASDAQ show significant negative returns in the overnight and morning sessions, suggesting that the BOJ's decisions are driven by these periods. However, unlike TOPIX, JASDAQ does not display positive returns in the afternoon session, probably due to its higher volatility. We further use market capitalization data for JASDAQ stocks to estimate constituent weightings and use intraday price and volume data to compute a liquidity-like RF for each stock. The performance of the TOPIX and JASDAQ portfolios, as captured by the Fama-French regression, is compared in Table 3.4.6. We find that the JASDAQ portfolios do not show significant excess returns, unlike the TOPIX portfolio, which generates excess returns of over 5 basis points. Thus, BOJ interventions predominantly

TABLE 3.4.5. **Four-session returns for BOJ days and non-BOJ days by TOPIX and JASDAQ**

This table presents the performance of TOPIX and JASDAQ constituent stocks across different trading sessions - overnight, morning, lunch break, and afternoon - on days with the Bank of Japan (BOJ) interventions (BOJ days), non-intervention days (non-BOJ days), and across the 2014–2019 entire sample period. The performance is measured in basis points. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

Index	Sessions	Overnight	Morning	Lunch break	Afternoon
	BOJ days	–63.36***	–41.38***	0.31	4.81**
		(2.61)	(2.74)	(0.94)	(2.43)
TOPIX	Non-BOJ days	29.73***	13.09***	0.36	–1.53
		(1.54)	(1.25)	(0.43)	(1.20)
	Full sample	4.60***	–1.62	0.35	0.18
		(1.59)	(1.28)	(0.41)	(1.06)
	BOJ days	–42.03***	–35.47***	–2.30	–2.59
		(4.73)	(8.30)	(1.60)	(6.44)
JASDAQ	Non-BOJ days	29.02***	21.59***	0.63**	–1.94
		(3.14)	(5.72)	(0.87)	(4.10)
	Full sample	4.59	2.89	–0.16	–2.11
		(2.91)	(4.79)	(0.80)	(3.49)

TABLE 3.4.6. **Fama-French results with TOPIX and JASDAQ constituent stocks**

The table shows the classic Fama-French three- and five-factor regressions on long-short portfolio constructed by the logit prediction model. The first two rows contain TOPIX-constituent stock results, while the last two rows contain JASDAQ-constituent stock results. The Fama-French Japanese market factor loadings are from the Kenneth French Data Library. The results are in basis points. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	Alpha	MKT	SMB	HML	RMW	CMA	MOM	R^2
TOPIX 3-factor	5.12***	–5.57***	–13.47***	–3.34***			–0.40	0.100
	(0.59)	(0.81)	(1.76)	(1.26)			(0.89)	
TOPIX 5-factor	5.12***	–5.17***	–13.45***	–4.37**	0.22	4.47**	–0.43	0.103
	(0.58)	(0.79)	(1.74)	(1.86)	(3.39)	(2.26)	(0.88)	
JASDAQ 3-factor	1.79	16.35	13.40	–40.01***			–0.48	0.090
	(0.76)	(10.50)	(19.56)	(15.38)			(8.76)	
JASDAQ 5-factor	0.78	12.45	6.21	–97.97***	–117.66***	7.83	–0.61	0.124
	(0.67)	(9.96)	(18.58)	(30.10)	(44.29)	(25.05)	(8.97)	

affect the three main indices, with limited impact on smaller, non-targeted indices such as the JASDAQ.

3.4.5. Macroeconomic impact on the BOJ's decision making. We add macroeconomic controls to demonstrate the robustness of our findings. Given that most macroeconomic indicators such as GDP, inflation, or unemployment rates, are released monthly or quarterly, they are not suitable for our daily long-short strategy. To address this, we choose the Atlanta Fed GDPNow as our control variable, as it is updated daily and provides real-time revisions to GDP estimates based on key economic data released throughout each day.[11] Thus, we include the lagged GDPNow growth rate to capture the impact of macroeconomic changes on BOJ intervention decisions. The results are shown in Table 3.4.7 and reveal that the significance of the BOJ dummy decreases from 1% to 5% after adding GDPNow as a control. However, the BOJ dummy remains significant overall, indicating that BOJ interventions continue to play a noteable role in Japanese stock returns, even after controlling for macroeconomic factors.

3.4.6. Global market performance and the BOJ's decision making. To address the potential impact of global market performance on the BOJ's decision making, we incorporate the return of the international stock market index as a proxy for global market performance into our logit prediction model. In the baseline model, we use the S&P 500 index to represent overnight stock market performance. To assess the influence of international factors, we replace the S&P 500 with six other major global indices: NASDAQ, Singapore SGX/STI30, Australia ASX200, Canada S&P/TSX, UK FTSE100, and China SH500. The precision of the prediction model and the excess returns from the trading strategy for these six indices are presented in Table 3.4.8. The results show no significant changes in the accuracy of the model prediction or the excess returns when replacing the S&P 500 with these other indices. This aligns with our expectations, as although international indices like the S&P 500 do reflect overnight global market trends, the overnight returns of the Japanese stock market are equally effective in capturing the impact of global market movements. Japanese investors may interpret overnight market information differently, and this local interpretation is more relevant to predict BOJ intervention.

[11]While GDPNow is updated about once or twice a week, it offers more frequent data than conventional quarterly GDP figures.

TABLE 3.4.7. Fama-Macbeth cross-sectional regression controlled by high-frequency GDP data

The table presents the results of the Fama-Macbeth two-step regressions. The first two columns display the baseline results based on TOPIX-constituent stocks, while the last two columns show the results incorporating macroeconomic controls. The BOJ Dummy variable is set to one on days when the logit prediction model indicates that the Bank of Japan is likely to intervene in the market and zero on days when the model suggests no intervention. The regression outcomes are expressed as percentages in the table. *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

risk factors	BL1	BL2	Robust1	Robust2
BOJ Dummy	0.038***	0.027***	0.090**	0.079**
	(0.005)	(0.004)	(0.036)	(0.037)
MRP	–0.039	–0.012	–0.039	–0.013
	(0.029)	(0.032)	(0.029)	(0.032)
SMB	–0.016	–0.013	–0.02	–0.013
	(0.013)	(0.014)	(1.204)	(0.013)
HML	0.016	0.009	0.016	0.009
	(0.015)	(0.016)	(0.015)	(0.016)
RMV	–0.008	–0.006	–0.009	–0.006
	(0.009)	(0.009)	(0.009)	(0.009)
CMA	0.012	0.005	0.012	0.005
	(0.009)	(0.009)	(0.008)	(0.009)
Ret 1-day lag(1)		0.018***		0.018***
		(0.003)		(0.003)
Ret 22-day lag(2)		0.011***		0.011***
		(0.000)		(0.000)
Vol 22-day lag(3)		–0.003		–0.003
		(0.006)		(0.006)
Profit margin		–0.015**		–0.015***
		(0.006)		(0.006)
D/E ratio		0.002		0.003
		(0.002)		(0.003)
ROA		0.072***		0.072***
		(0.014)		(0.014)
Growth rate		0.007		0.007
		(0.012)		(0.012)
lagged GDP (4)			1.276	1.180
			(1.094)	(0.964)

(1): Lagged one-day individual stock afternoon-return
(2): Lagged 22-day accumulated individual stock afternoon-return
(3): Lagged 22-day volatility
(4): Lagged one-day change of GDP growth rate

TABLE 3.4.8. **Logit model predictions**

The table contains the robustness check of using different global equity indices to replac the S&P 500 index in our baseline result. The alpha is the abnormal return generated from Fama-French five-factor with momentum regression, using TOPIX-only data and logit model for four fixed prediction factors (overnight TOPIX return, morning TOPIX return, hard budget limit, and soft budget limit) and one global index

Prediction	True	False	Accuracy	Alpha
S&P 500	1272	194	86.77%	5.12%
NASDAQ	1262	204	86.08%	5.10%
SG	1222	244	83.36%	4.89%
AU	1245	221	84.92%	4.95%
CA	1221	245	83.29%	4.80%
UK	1247	219	85.06%	4.92%
CN	1209	257	82.47%	4.51%

3.5. Conclusion

This essay investigates the economic consequences of data-driven monetary policies by drawing conclusions from the Bank of Japan's ETF purchase program. Although predicting central bank policy actions is challenging, we design a logit prediction model that achieves a prediction accuracy of 86.77%. Thus, based on the fact that BOJ interventions are based on data and publicly available information, they can be highly predictable. Furthermore, the implementation of a long-short trading strategy based on the model's predictions further challenges the efficient market hypothesis and identifies profitable strategies with an average return of 10.48 basis points per BOJ intervention. Thus, BOJ actions can generate significant price pressure in the Japanese equity market. Therefore, we provide empirical evidence that data-driven monetary policies could cause price pressure, despite being highly predictable.

This study assesses the consequences of unconventional monetary policy, particularly direct capital injections into the equity market. In contrast to some skepticism about the impact of such policies in responding to market shocks, the findings suggest that BOJ interventions have substantial price impacts (Charoenwong et al., 2021; Harada and Okimoto, 2021). Our results strongly support the view that BOJ interventions cause significant positive price pressure, especially in high-risk stocks. The downside protection works as "insurance" and helps market investors generate homogeneous expectations about stock prices, greatly reducing market uncertainties. In addition, non-fundamental price pressure is caused by exogenous forces, drawing parallels with studies on mutual fund and ETF flows, dividend payments, and government capital injections (Coval and Stafford, 2007; Dyakov and Verbeek, 2013; Hartzmark and Solomon, 2022a; Dang et al., 2023).

This study underscores the importance of data-driven policy-making in the central bank decision-making process and its potential implications for market participants. The insights drawn revealed in this study are valuable to central banks when adopting similar policies, as well as investors and analysts of financial markets.

TABLE 3.1.1. **Portfolio sorted by Amihud ratio & dollar amount (DA)**

The table shows the portfolio return results sorted by DA and Amihud liquidity ratio. In the table, DA and Amihud ratio are divided in five equal parts. DA1 means the stock group with lowest weights in TOPIX index and DA5 means the stock group with highest weights in TOPIX index. Similarly, Amihud1 means the stock group with lowest Amihud ratio and Amihud5 means the stock group with the highest Amihud ratio. Ami5-Ami1 is the portfolio that short Amihud1 and long Amihud5, and DA5-DA1 is the portfolio that short DA1 and long DA5. The bottom-right portfolio is the corner portfolio by longing (DA5,Amihud5) and shorting (DA1,Amihud1). *, **, and *** denote the 10%, 5%, and 1% level of signicance, respectively.

	ami1	ami2	ami3	ami4	ami5	ami5-ami1
DA1	−9.68***	−4.01***	0.60	0.01	7.36	17.04***
	(0.31)	(0.57)	(1.12)	(2.21)	(6.58)	(3.94)
DA2	−8.96***	−3.76***	−1.45***	−0.43	5.16**	14.12***
	(0.43)	(0.38)	(0.54)	(0.94)	(2.21)	(1.72)
DA3	−8.04***	−1.86***	−1.13***	−0.16	3.22***	11.27***
	(0.96)	(0.42)	(0.39)	(0.50)	(0.95)	(1.37)
DA4	−10.78***	0.48	0.72*	0.74**	2.81***	13.59***
	(3.86)	(0.71)	(0.38)	(0.33)	(0.42)	(3.82)
DA5	3.12	1.18	3.35***	2.55***	4.49***	1.37
	(7.03)	(1.74)	(0.59)	(0.33)	(0.23)	(7.66)
DA5-DA1	12.80	5.19*	2.75**	2.54**	−2.88	14.17***
	(10.28)	(2.99)	(1.27)	(1.30)	(2.96)	(0.39)

Appendix 3.1 Amihud liquidity ratio

To strengthen our results, we replace the ranking factor (RF) with the Amihud liquidity ratio and run the same long-short strategy. Table 3.1.1 presents this analysis and reveals results similar to the baseline model. The corner portfolio of long (DA5, Amihud5) and short (DA1, Amihud1) generates 14.17 basis points return on each Bank of Japan (BOJ) intervention day. This indicates that the BOJ intervention has a strong influence on both large stocks and less liquid stocks. In addition, the results of the Amihud liquidity ratio further demonstrate that our ranking factor ratio contains a liquidity-like feature.

CHAPTER 4

Social Trust and Consumer Fraud

4.1. Introduction

Fraud has emerged as an escalating global crisis with profound social and economic consequences. Recent estimates by the Global Anti-Scam Alliance (GASA) indicate that global scam-related losses reached an unprecedented one trillion U.S. dollars in 2024, underscoring the growing prevalence and sophistication of fraudulent activity worldwide. In the United States, the Federal Bureau of Investigation (FBI) reported fraud-related losses exceeding 50 billion dollars over the past five years. Meanwhile, the Federal Trade Commission (FTC) estimated that the broader societal costs of fraud may have surpassed 30 billion dollars in the same period. Despite increasing investments in fraud prevention, these staggering figures suggest that traditional deterrents may be insufficient and call for a deeper understanding of the structural and behavioral drivers of fraud at both national and local levels.

While most studies focus on financial or regulatory drivers of fraud (Povel et al., 2007; Wang et al., 2010), research rarely explores cultural factors contributing to it. Social trust is crucial to economic outcomes (Fukuyama, 1995; Knack and Keefer, 1997; Zak and Knack, 2001), and it shapes collective behavior and market integrity (Bjørnskov, 2007; Putnam, 2000). High-trust environments foster resilience and reduce transaction costs (Fukuyama, 1995), while low-trust settings may encourage deception and fraud (Judges et al., 2017). Therefore, this study addresses a critical and underexplored question: To what extent does local culture influence the incidence of consumer fraud?

However, this question is not easy to answer, as the influence of social trust on fraud and scam is multifaceted. On one hand, higher levels of social trust may promote integrated social norms within local communities, thereby reducing the likelihood of fraudulent behavior (Sliwka, 2007). On the other hand, individuals with greater trust may be more inclined to believe unfamiliar people or information, potentially increasing their susceptibility to scams (Hayes et al., 2021; Wang et al., 2010). This study aims to identify the effect of these opposing mechanisms. By empirically evaluating this relationship, our study seeks to bridge the gap between cultural theory and fraud prevention practice, offering meaningful implications for researchers and practitioners.

Through this study, we investigate the effect of social trust on consumer fraud using U.S. state- and region-level data from 2011 to 2022. Thereafter, trust levels are constructed from the General Social Survey (GSS), using state-level data for 2010 and division-level data. Consumer fraud is represented as US FTC consumer fraud complaint number at state level. In reduced-form OLS regressions, we find that a 1% increase in the trust index is associated with approximately 5.49 fewer complaints per state. This indicates that higher local trust levels help reduce the occurrence of consumer fraud. The findings support the hypothesis that cohesive social norms and interpersonal expectations can deter fraudulent activities.

However, a major empirical challenge in identifying the effect of trust on fraud lies in potential endogeneity. One primary concern is reverse causality. On one hand, high-trust communities often have better information sharing, which can reduce fraud driven by information asymmetry. On the other hand, higher levels of consumer fraud may significantly undermine local trust, especially when people feel unprotected. This two-way relationship creates feedback loops between fraud and trust. Another key concern is omitted variable bias. For example, both trust and fraud may be influenced by factors such as consumer sophistication, financial literacy, or digital access. These factors are often difficult to quantify—for instance, due to lack of concrete data to measure the sophistication level of a local community—which leads to omitted variable bias. These unobserved factors complicate causal inference and threaten identification.

To address these concerns, we implement a two-stage least squares (2SLS) instrumental variable (IV) approach based on Angrist and Imbens (1995). Our instrument is regional immigration inflows, which plausibly reduce local trust levels by increasing cultural and social diversity (Dinesen and Sønderskov, 2015; Putnam, 2007; Ziller, 2015). Importantly, immigration inflows are unlikely to be directly related to consumer fraud for several reasons. First, immigration decisions are primarily driven by regional economic conditions (Geis et al., 2013; Rabe and Taylor, 2012) and cultural ties (Dinesen and Sønderskov, 2015), rather than by patterns of online or consumer fraud. Second, U.S. immigrants generally exhibit high levels of education and employment, reducing the incentive or need to engage in criminal activity. Third, consumer fraud is typically perpetrated by trans-national criminal networks through remote communication channels, which need neither physical presence nor local integration. These factors suggest that immigration inflows affect consumer fraud only through their impact on social trust, making them a strong and credible instrument in our analysis. The IV results further demonstrate the impact of local trust on fraud. In the 2SLS model, we find that a one-percentage-point increase in the trust index is associated with approximately 184 fewer complaints per state. This result is consistent with the conclusion from the reduced-form OLS regression, indicating that even after addressing potential endogeneity issues, the negative relationship between local trust and fraud remains significant.

We further explore the potential transmission channel through which local trust affects fraud. Pearce (1974) suggested that the quality of communication is significantly higher among individuals with higher levels of trust compared to those with lower levels of trust. Based on this insight, we argue that communities with higher trust levels experience lesser amount of fraud, primarily due to higher-quality local community communication and information sharing. To test this hypothesis, we use the frequency of communication with neighbours reported by GSS respondents as a variable in our regression analysis. The results show that individuals who interact more frequently with their neighbours report fewer fraud complaints. This suggests that communication within the local community effectively reduces the risk of being scammed.

We also try to ensure that this transmission channel stems from local community communication rather than individual personality traits or social skills. We examine the frequency of communication with non-neighbour friends using GSS data. The results in this case are not significant, indicating that the transmission channel through which trust affects fraud primarily operates through communication within the local community. In communities with higher trust levels, there is more communication among neighbours, which effectively lowers the incidence of fraud in these communities, and vice versa.

The remainder of this essay is organised as follows: Section 4.2 reviews the related literature on social trust, economic crime, and fraud prevention. Section 4.4 presents the conceptual framework and empirical identification strategy. Section 4.3 describes the data sources, variable construction, and summary statistics. Section 4.5 reports the main empirical findings on the relationship between social trust and consumer fraud. Section 4.6 provides a series of robustness checks to validate the results.

4.2. Literature review

Social trust plays a complex and dual role in shaping individual behavior related to financial decision-making and fraud exposure. On the one hand, high-trust individuals are generally more receptive to new information and interpersonal interactions, which may make them more vulnerable to deception (Falcone and Castelfranchi, 2001; Zhou, 2014). However, they are also more adaptable, often adjusting their beliefs quickly and cutting losses once they recognise they have been scammed. On the other hand, low-trust individuals exhibit greater skepticism towards unfamiliar information, which may protect them from initial deception (Zhou and Tian, 2010). However, this skepticism often translates into emotional rigidity and slower reaction times once they do become victims, resulting in more prolonged exposure and greater financial losses (Benartzi and Thaler, 1999).

These patterns echo findings in the corporate fraud literature. Hertzberg (2005) and Wang et al. (2010) argue that trust can facilitate opportunistic behavior by reducing monitoring and increasing the effectiveness of deception. Managers and insiders may exploit a trusting environment to engage in fraudulent activities, relying on the assumption that stakeholders are less likely to question their actions. Similarly, Amiram et al. (2018) argues that firms located in high-trust regions are more prone to corporate misconduct due to lower perceived external scrutiny.

Trust also influences interactions between informal norms and formal regulatory mechanisms. Hayes et al. (2021) use U.S. state-level CFPB complaint data to examine how local trust culture influences consumer vigilance and institutional responses. They find that residents in high-trust states file fewer complaints against financial institutions than those in low-trust regions. Furthermore, following the establishment of the CFPB in 2011, banks in low-trust states reduced fees more significantly, perhaps due to the greater perceived threat of regulatory pressure. These findings highlight how trust can either complement or substitute formal enforcement, affecting both consumer behavior and firm strategy.

Beyond fraud and complaints, social trust is also linked to portfolio choice and investment patterns. Shao and Wang (2021) and Wei and Zhang (2020) show that low-trust investors exhibit strong local bias, allocating more capital to nearby or familiar firms due to concerns about governance or asymmetric information. In contrast, high-trust investors are more likely to diversify geographically and invest in unfamiliar assets. Our study supports this argument by showing that while high-trust investors are more open to external opportunities, this same openness also increases their vulnerability to fraud. Conversely, low-trust investors' preference for familiar options makes them less likely to be defrauded—but once targeted, their reluctance to admit mistakes or seek assistance results in greater losses.

Our findings are also consistent with those of Phua et al. (2025), who examine the implications of digitalisation for consumer trust and fraud exposure. They show that the closure of physical bank branches forces many investors—especially older ones—to transition to online banking, thus increasing their exposure to scams. In the past, high-trust individuals could rely on social cues and local community norms for reliable financial interactions. However, the rise of digital platforms has eroded these traditional mechanisms, exposing individuals to information sources that are more difficult to verify. Similar concerns are raised in studies on digital privacy and information asymmetry (Lappeman et al., 2022), which highlight how increased online interactions reduce the reliability of trust-based cues.

Our research contributes to this growing literature by shifting the focus from corporate fraud and consumer complaints to the incidence of consumer fraud itself. While Hayes et al. (2021) emphasise trust culture's influence on complaint behavior, our study examines how cultural traits such as generalised trust influence fraud victimisation rates. In doing so, we provide new empirical evidence on how informal norms affect individual outcomes in an increasingly digitised and decentralised environment.

4.3. Data

4.3.1. Trust level data. We construct *trust level index* using data from the *General Social Survey* (GSS) based on respondents' answers to the following question: *'Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?'* Responses fall into the following three categories: *'Can trust,' 'Can't be too careful,'* and *'Depends.'* Following the approach adopted in studies such as Wei and Zhang (2020), we use the percentage of respondents who answered *'Can trust'* as our measure of trust level.

For 2010, we obtained state-level trust data. However, for the period from 2011 to 2022, due to confidentiality restrictions, the GSS only provides region-level data, aggregating responses into the nine U.S. Census Bureau divisions (e.g., the Pacific division includes Alaska, California, Hawaii, Oregon, and Washington). Therefore, in our post-2010 analyses, we use division-level data for constructing the trust index.

In addition to trust levels, we extract other control variables from GSS, including respondents' income, education, and frequency of social interaction. Many of these responses are ordinally coded (e.g., education level: less than 6 years = 1, 6–9 years = 2, etc.), and we construct variables accordingly.

4.3.2. Consumer fraud data. Our consumer fraud data are obtained from the Federal Trade Commission (FTC) Sentinel database. Established in 2008, this reporting system enables consumers to file complaints regarding various types of fraud, particularly consumer fraud that occurs via phone or internet. Common categories include Imposter Scams, Mobile Services Fraud, and Foreign Money Offers and Counterfeit Check Scams. The fact that these scams typically do not involve face-to-face contact. This feature is also reflected in the payment method data. Over the past decade, fewer than 5% of reported cases involved cash or cash advance payments, indicating that more than 95% of victims paid using non-cash methods.

4.3.3. Demographic and socioeconomic controls. We obtain state-level demographic and socioeconomic data—including age distribution, gender composition, total population, and median income—for the period 2011–2022 from the U.S. Census Bureau. We also rely on the Census Bureau's geographic division classification to align the GSS region-level data with the FTC and Census datasets.[1]

4.3.4. Descriptive statistics. We summarise the main and control variables used in the Global Social Survey and the FTC Sentinel dataset, with their descriptive statistics presented in the Table 4.3.1. The GSS data is updated biennially. Due to the COVID-19 pandemic, data collection in 2020 was suspended, and the update was postponed to 2021. In the GSS dataset, each variable is constructed based on a specific survey question accompanied by a set of response options.

The main variable in Column **Trust** is based on the following question: *'Would you say that most people can be trusted or that you can't be too careful in dealing with people?'* Respondents are given the following three options: *'Can Trust'*, *'Can't be too careful'*, and *'Depends'*. In our state-level GSS dataset, the measure of trust level is the proportion of respondents selecting *'Can Trust'*. To maintain consistency between the baseline result and subsequent analyses, we use the proportion of respondents choosing *'Can Trust'* as the trust measure in all tests, even

[1]Division mapping data are available from the U.S. Census Bureau: `https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf`

TABLE 4.3.1. **Summary statistics of key variables from GSS and FTC sentinel datasets**

This table shows the descriptive statistics of Global Social Survey data and FTC sentinel data used in the essay from 2012 to 2022. The titles of the Panel A's last four columns are abbreviations from the GSS Code. Specifically, Norc refers to the size of the town or city where the respondent lives; Soc.Co indicates the frequency of communication with neighbours; Fr.Co represents the frequency of communication with non-neighborhood friends; and Rac.Liv reflects whether the respondent has neighbours of a different race.

Panel A: Summary Statistics of GSS Data

Year	Trust	Age	Income	Education	Gender	Norc[1]	Soc.Co[2]	Fr.Co[3]	Rac.Liv[4]
2012	0.32	48.67	10.86	13.48	1.43	4.03	4.68	3.99	1.29
2014	0.31	48.82	10.93	13.59	1.43	3.88	4.75	3.94	1.26
2016	0.32	48.44	10.97	13.70	1.46	3.92	4.76	4.02	1.25
2018	0.32	48.58	11.05	13.74	1.48	3.85	4.75	4.14	1.23
2021	0.25	53.28	11.33	14.92	1.46	3.89	5.25	4.53	1.18
2022	0.26	51.02	11.02	13.56	1.52	3.71	4.90	4.32	1.24

[1] GSS code: XNORCSIZ
[2] GSS code: SOCOMMUN
[3] GSS code: SOCFREND
[4] GSS code: RACLIVE

Panel B: Summary Statistics of FTC Sentinel Dataset

Year	Total Complaints	Amount	Per Complaint Loss
2012	17,727	23,767,706	1,340.74
2013	18,430	25,569,237	1,387.34
2014	24,627	26,569,951	1,078.88
2015	19,979	11,192,411	560.22
2016	20,702	11,738,570	567.02
2017	17,261	11,962,547	693.06
2018	21,112	20,489,557	970.54
2019	25,181	22,719,437	902.23
2020	32,982	47,024,907	1,425.76
2021	39,790	79,636,454	2,001.42
2022	33,860	124,514,844	3,677.32

though the values in the table are calculated from a national-level average, where *'Can Trust'* is coded as 1 and *'Can't be too careful'* as 2.

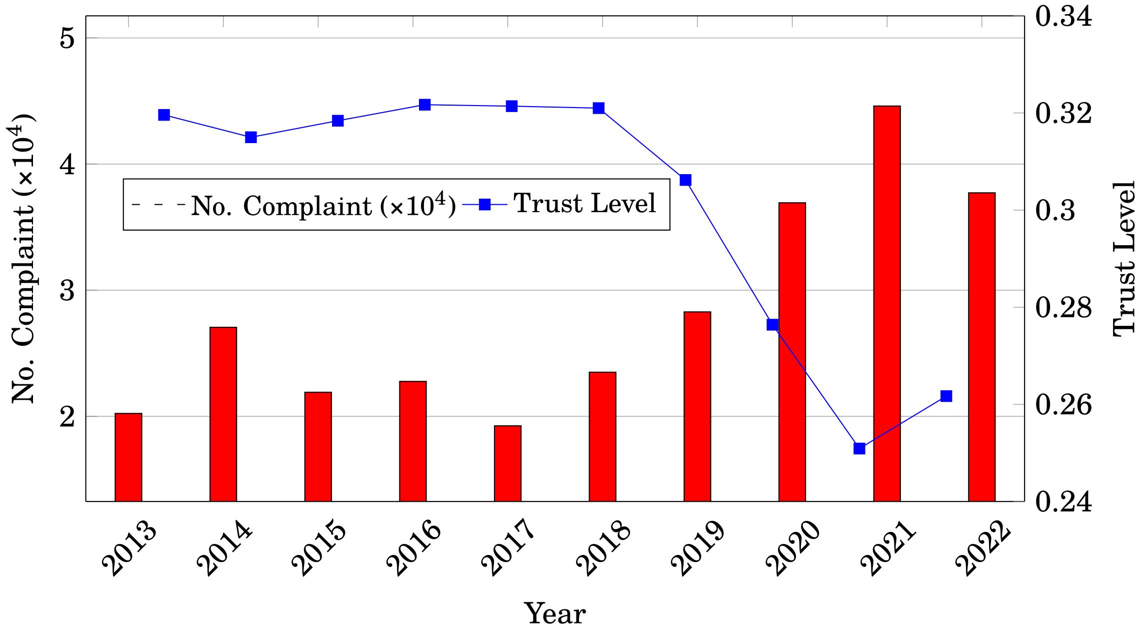
Column **Norc** corresponds to the following question *'What is the Norc size of the place?'* This variable includes 10 categories, with the first representing a very large city and the last representing open country. Column **Soc.Co** is based on the question *'How often do you spend a social evening with someone who lives in your neighborhood?'* There are 7 response options, where the first indicates 'almost daily' and the last indicates 'never.' As this order is counterintuitive, we reverse the coding in subsequent tests so that a higher value of SOCOMMUN reflects more frequent neighborhood communication. Column **Fr.Co** comes from the question *'How often do you spend a social evening with friends who live outside the neighborhood?'* Similarly, the 7 options range from 'almost daily' to 'never.' We also reverse the coding of this variable to ensure that higher values indicate more frequent interactions, following the same reasoning as above. Column **Rac.Liv** is derived from the question *'Are there any ('whites' for black respondents, 'blacks' for non-black respondents) living in this neighborhood now?'* There are two possible responses: *Yes* and *No*. This dummy variable reflects the level of diversity in the respondent's neighborhood. A lower value of **RACLIVE** indicates higher racial diversity, whereas a higher value suggests a more homogeneous population.

4.4. Methodology

4.4.1. Social trust and consumer fraud. Social trust has long been recognised as a fundamental factor shaping individual behavior in market and social environments. It influences how people interpret others' intentions, make decisions under uncertainty, and respond to potential threats. In the context of fraud, trust not only affects the likelihood of engagement in risky interactions but also governs how individuals perceive, detect, and respond to dishonest behavior.

Consumer fraud typically involves deception through interpersonal channels, such as impersonation scams, phishing messages, romance fraud, and fake customer service schemes. Unlike technical forms of cyberattack, these frauds exploit cognitive and emotional vulnerabilities, often relying on the target's willingness to trust a seemingly benign source. As such, fraud in this context is inherently relational, shaped by how individuals assess and respond to the trustworthiness of others in uncertain or unsolicited situations.

FIGURE 4.4.1. **Relationship between No. Complaint and Social Trust**
The figure shows the 2013–2022 US average trust level from Global Social Survey and number of consumer fraud complaints from FTC.



We hypothesise that trust level plays a crucial role in shaping responses to social fraud. Specifically, individuals with lower levels of trust tend to be more suspicious of others' intentions and are more sensitive to cues of deception, making them more likely to recognise fraudulent behavior and report it to the relevant authorities. Conversely, higher-trust individuals may overlook early signs of manipulation or assume benign intent, thus underreporting fraud even when they are affected. The relationship between the two can be visually reflected from the Figure 4.4.1. This has also been described in prior work such as Guiso et al. (2008) conceptualize trust as an investor's subjective belief in not being cheated, andHayes et al. (2021), who also argue that greater trust lowers consumers' awareness of potential bank misbehavior.

Unlike previous literature, our framework considers a alternative channel: communication. Individuals with high social trust are more willing to engage with others, exchange information, and discuss uncertain situations. This stronger tendency for communication creates informal warning networks, where trust-based interactions serve as a protective layer against fraud. As a result, although high-trust individuals may be less sensitive to fraudulent cues, their stronger reliance on social interaction may help them avoid or mitigate fraud, thereby reducing the need to report. This mechanism partly explains the empirical observation that fraud reporting rates are lower among individuals with higher trust, not necessarily because they are less affected, but because their losses are smaller due to earlier informal intervention.

This conceptual structure guides the empirical strategy of the essay. Subsequently, we investigate how cross-state variation in social trust relates to reported incidents of consumer fraud, using both aggregate complaint data and measures of trust from national surveys. The analysis focuses not only on overall complaint rates, but also on heterogeneity by communication intensity and risk perception, consistent with the aforementioned dual mechanisms described above.

4.4.2. Identification strategy. We also note that using reduced form OLS regression alone to assess the relationship between trust level and FTC consumer fraud complaints may introduce endogeneity issues. The most critical concern is potential reverse causality. For instance, a lower level of trust may make potential fraud victims more alert and more likely to report scams to the FTC. At the same time, a rise in fraud cases may worsen the public trust crisis, causing people to become more distrustful of others. To address such endogeneity issues, we adopt an instrumental variable identification strategy to isolate the endogenous component. Therefore, we use the number of new immigrants in each state as an instrument for trust level.

To demonstrate the validity of this instrumental variable, we first examined the relationship between immigration and local society. We then argued, from economic and cultural perspectives, as well as by considering the characteristics of U.S. immigrants and the current nature of consumer fraud, that there is no direct correlation between immigration and consumer fraud, further supporting the validity of the instrumental variable.

4.4.2.1. *Impact of immigration on local culture.* The relationship between immigration and local culture has been extensively discussed in the literature over the past few decades. A key argument is that the sub-cultures brought by new immigrants can impact the local population's culture, thereby negatively influencing local social trust. Such influence is mainly transmitted through the negative associations between local or degrees of ethnic/cultural diversity and trust (Dinesen and Sønderskov, 2015; Putnam, 2007; Ziller, 2015), and may also stem from economic and social issues caused by immigration (Abrego et al., 2017; Menjívar and Abrego, 2012). These theories demonstrate the substantial impact immigration has on local culture. Although the impact may be less significant in more open societies, it cannot be entirely eliminated (Ziller et al., 2019). As the size of immigrant populations grows, the economic and environmental impact of ethnic enclave cultures is further amplified (Grönqvist, 2006; Xie and Gough, 2011).

However, there is no direct or significant relationship between the number of immigrants and the number of FTC consumer fraud reports. Unlike local violent crime, consumer fraud is mostly conducted via the internet as a medium for communication and deception. The perpetrators and victims may never meet in person during the entire fraud process. Under this premise, we propose three arguments to demonstrate that the number of immigrants is not directly related to the number of fraud cases, and that the main transmission channel is the cultural impact of immigration, which in turn leads to changes in fraud occurrences.

4.4.2.2. *Immigration decision and local economy.* When foreign immigrants choose their destination, they typically consider the economic, cultural, and environmental conditions of their target region as the primary reference factors. From an economic perspective, immigrants tend to choose regions with stronger economic performance as their destination. Geis et al. (2013); Rabe and Taylor (2012) found that immigrants' decisions are primarily influenced by income levels and local unemployment rates. This indicates that economic factors play a significant role in migration decisions. In Table 4.4.1, we categorised the 50 U.S. states into three groups based on the proportion of immigrants in their populations. The first group consists of states of less than 5% of the immigrant population, the second group includes states with an immigrant share between 5% and 10%, and the third group includes states where immigrants account for more than 10%. We collected and calculated several economic indicators for these states, including total GDP, GDP per capita, median income, per capita income, and the percentage of the population with a bachelor's degree. The data show that states with a higher proportion of immigrants tend to perform better across these economic indicators. Hence, we can draw the following preliminary two-way conclusion: Immigrants tend to choose states with stronger economic performance, and these states, in turn, benefit from higher levels of immigration, further strengthening their economies.

This perspective was first proposed by Portes and Bach (1985) and is known as the Enclave Effect. Portes and Bach (1985) found that Cuban and Mexican immigrants in the United States often prefer to 'stick together', forming distinct immigrant communities, which in turn give rise to enclave economies and related sub-local cultures and create 'Enclave Economy'. This phenomenon remains relevant in today's society. For example, Chinatowns often attract large numbers of Chinese immigrants, and Europeans often choose suburbs with a high European presence. U.S. data show that states with higher immigrant populations tend to attract more immigrants,

TABLE 4.4.1. **States with different proportions of immigrations in the US**

The table presents the economic and educational characteristics of U.S. states with different proportions of immigrants. We divide the states into three groups based on the share of immigrants in the population: Column (1) includes states where immigrants make up less than 5% of the population; Column (2) includes states with an immigrant share between 5% and 10%; and Column (3) includes states where immigrants account for more than 10% of the population.

	(1)	**(2)**	**(3)**
Immigration	3.73%	7.34%	17.43%
Population	3,434,454	4,674,751	11,803,100
GDP (Billion)	189.09	285.45	889.19
GDP per capita	56,218	62,378	73,422
Income	36,807	39,113	43,030
PCPI	59,079	61,231	69,324
Education	0.61	0.63	0.64

especially those with a larger share of minority groups, which draw more same-ethnicity immigrants to settle there.

4.4.2.3. *Immigration decision and local culture.* From an cultural perspective, if a state has a higher concentration of a particular minority group, it tends to attract more new immigrants from that same group. According to data from the US Census Bureau, the largest source of US immigration—Latin America—has had the majority of its immigrants in the past decade settle in Florida and Texas. These two states together accounted for over half of all newly arrived Latin American immigrants. In 2010, the existing Latin American population represented approximately 27.4% and 39.8% of the total population in Florida and Texas, respectively, ranking as the largest minority group in both states. Similarly, in 2010, the Chinese population in the United States was around 3.8 million, with about half residing in California and New York. Between 2012 and 2022, the Chinese immigrant population increased by a total of 662,000, with California and New York remaining the top two destination states, together attracting more than half of the new Chinese immigrants. These facts indicate a strong pull effect of states with large existing Chinese communities on new immigrants, consistent with the ethnic enclave theory.

FIGURE 4.4.2. **Foreign-born population as a percentage of total state population: 2010**

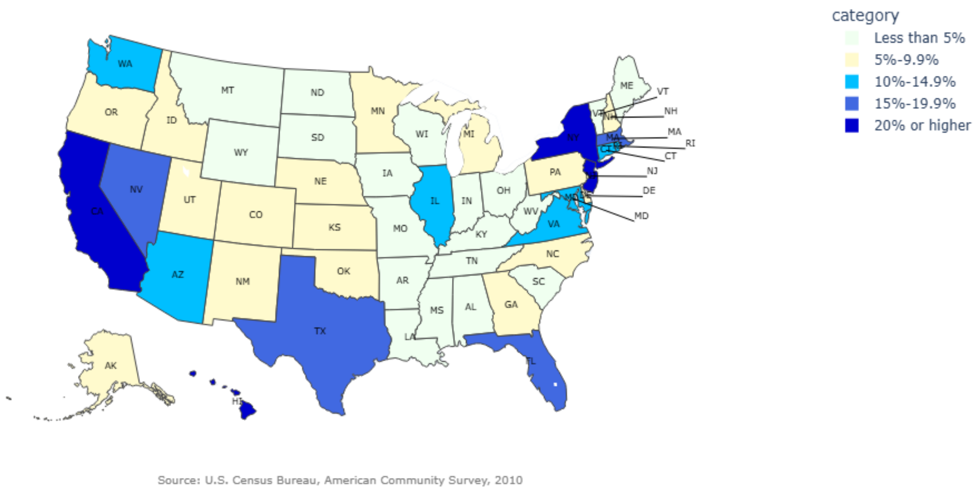
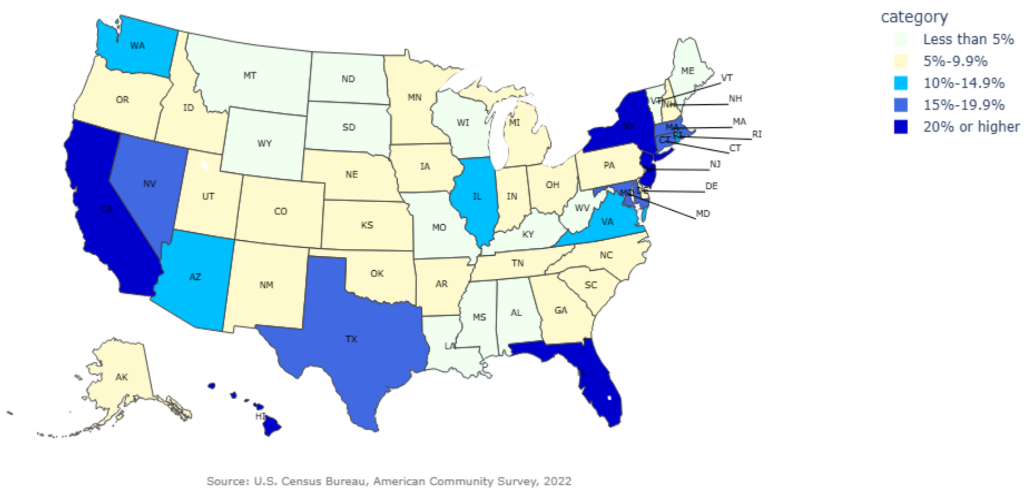


FIGURE 4.4.3. **Foreign-born population as a percentage of total state population: 2022**



Figures 4.4.2 and 4.4.3 show the distribution of immigrants in the United States in 2010 and 2022. As shown in the charts, apart from a few areas with relatively low numbers of immigrants that experienced some increase, the proportion of immigrants in most states has not

changed significantly. Since these figures present the number of first-generation immigrants only—excluding second-generation American immigrants—it suggests that new immigrants tend to consider the existing immigrant population in a destination when choosing where to settle. This may be influenced by local immigration policies or the appeal of immigrant communities and cultures. Table 4.4.2 also shows the race distribution of first-generation immigrants in terms of state from 2010 to 2023 and indicates that the proportion of immigrants in the U.S. has not changed much in recent decades, with the exception of tighter restrictions on Mexican immigration under the Trump administration. For other racial groups, the changes have been relatively minor. State-level data also show that, apart from a few states shifting from being predominantly White immigrant states to predominantly Hispanic due to a decline in White immigrant numbers, the largest racial group among immigrants in a given state a decade or so ago generally remains the largest today.

The table explains the transmission channel between immigration, social trust, and consumer fraud. When first-generation immigrants arrive in a new area, their unfamiliarity with local customs, rules, and culture naturally causes them to trust people from their own ethnic group more. Fraudsters within these ethnic groups may then exploit this cultural barrier to target newly arrived immigrants for scams. This view is consistent with that of Dinesen and Sønderskov (2015), who argue that language and cultural barriers make it difficult for new immigrants to trust local residents or obtain reliable information from them, thereby creating a favorable environment for fraud.

4.4.2.4. *Immigrants are less likely to get involved into fraud.* Apart from the immigration decision-making, newly arrived immigrants in the US may generally lack both the incentives and structural conditions that lead to criminal behaviour. This is largely attributable to the positive selection of immigrants—meaning the immigrant population tends to exhibit characteristics associated with higher socioeconomic status. Data from the U.S. Census Bureau show that immigrants outperform native citizens in several key areas: 78% of all U.S. immigrants had completed at least 12 years of education as of 2023, indicating broad access to formal schooling and employable skills. The unemployment rate among immigrants was 3.5%, lower than the 4.0% rate among natives, suggesting that most immigrant workers can secure jobs and have no economic necessity to engage in illicit activities.

TABLE 4.4.2. **Largest portion of immigration in each state in the US**

The table displays the dominant racial group and its corresponding percentage in each U.S. state for the years 2010, 2015, 2020, and 2023.

State	**2010**	%	**2015**	%	**2020**	%	**2023**	%
Alabama	White	38.50	Hispanic	37.49	Hispanic	35.56	Hispanic	38.75
Alaska	Asian	45.34	Asian	47.37	Asian	48.36	Asian	48.20
Arizona	Hispanic	45.24	White	43.24	Hispanic	41.57	Hispanic	41.91
Arkansas	Hispanic	47.08	Hispanic	43.82	Hispanic	43.64	Hispanic	44.22
California	Hispanic	41.25	Hispanic	39.13	Hispanic	38.24	Hispanic	39.04
Colorado	White	42.10	White	42.24	White	37.11	Hispanic	37.33
Connecticut	White	45.57	White	42.24	White	37.99	White	29.43
Delaware	White	33.93	White	32.11	White	29.50	Hispanic	27.70
D.C.	White	35.55	White	34.03	White	30.72	Hispanic	29.65
Florida	White	43.29	White	43.58	Hispanic	38.33	Hispanic	39.51
Georgia	Hispanic	36.75	Hispanic	32.51	Hispanic	30.06	Hispanic	31.62
Hawaii	Asian	73.44	Asian	74.18	Asian	73.29	Asian	73.01
Idaho	White	46.74	White	44.79	Hispanic	42.20	Hispanic	43.81
Illinois	White	39.76	White	40.73	White	36.65	Hispanic	34.64
Indiana	Hispanic	37.80	Hispanic	34.97	Hispanic	31.89	Hispanic	33.93
Iowa	White	34.91	White	35.08	White	29.68	Hispanic	29.77
Kansas	Hispanic	40.56	Hispanic	37.98	Hispanic	37.14	Hispanic	39.80
Kentucky	White	38.68	White	37.13	White	33.35	Hispanic	31.19
Louisiana	Hispanic	35.70	White	36.33	Hispanic	37.49	Hispanic	40.79
Maine	White	60.18	White	55.63	White	49.46	White	46.16
Maryland	White	27.87	Hispanic	26.77	Hispanic	27.23	Hispanic	29.80
Massachusetts	White	42.50	White	39.06	White	35.18	White	27.44
Michigan	White	51.02	White	49.82	White	46.53	White	40.72
Minnesota	Asian	30.27	Asian	31.36	Asian	31.04	Asian	30.23
Mississippi	Hispanic	38.39	Hispanic	37.12	Hispanic	35.55	Hispanic	37.66
Missouri	White	40.02	White	36.98	White	34.55	Asian	27.81
Montana	White	61.37	White	56.91	White	54.60	White	48.49
Nebraska	Hispanic	41.26	Hispanic	38.18	Hispanic	37.38	Hispanic	40.07
Nevada	Hispanic	40.28	Hispanic	41.40	Hispanic	41.43	Hispanic	41.29
New Hampshire	White	52.81	White	49.35	White	44.51	White	37.97
New Jersey	White	36.40	White	35.31	White	32.17	Hispanic	32.43
New Mexico	Hispanic	49.65	Hispanic	49.03	Hispanic	47.60	Hispanic	49.98
New York	White	32.39	White	30.52	White	28.03	Hispanic	28.38
North Carolina	Hispanic	44.35	Hispanic	39.18	Hispanic	36.20	Hispanic	38.59
North Dakota	White	47.55	White	36.77	Black	31.22	Black	31.54
Ohio	White	44.57	White	40.84	White	34.36	Asian	31.14
Oklahoma	Hispanic	42.66	Hispanic	41.59	Hispanic	39.94	Hispanic	41.07
Oregon	White	38.05	White	38.92	White	36.57	Hispanic	33.21
Pennsylvania	White	39.46	White	36.08	White	32.10	Asian	30.39
Rhode Island	White	38.31	White	37.96	White	35.84	Hispanic	36.74
South Carolina	White	41.92	White	41.56	White	37.17	Hispanic	37.01
South Dakota	White	35.46	White	31.66	White	27.65	Hispanic	24.78
Tennessee	White	38.72	White	38.07	White	36.90	Hispanic	36.75
Texas	Hispanic	48.15	Hispanic	44.43	Hispanic	43.03	Hispanic	43.52
Utah	Hispanic	42.56	Hispanic	43.03	Hispanic	43.09	Hispanic	44.26
Vermont	White	65.53	White	56.80	White	52.75	White	50.96
Virginia	White	32.45	White	32.59	Asian	29.96	Asian	29.86
Washington	White	35.66	White	34.98	Asian	35.17	Asian	36.15
West Virginia	White	42.55	White	40.80	White	37.40	White	33.97
Wyoming	White	44.49	White	42.93	White	43.51	Hispanic	41.10

Furthermore, disaggregated data reveal striking differences across ethnic groups. For instance, Asian immigrants had the highest educational attainment (91.7% with a high school diploma), the lowest unemployment rate (2.5%), and a remarkably low crime rate of just 0.65%. These statistics contradict prevailing stereotypes that associate certain Asian regions, particularly East and South Asia, with international fraud or transnational criminality. In fact, they underscore how structural integration—through employment, education, and institutional trust—acts as a strong deterrent against crime among immigrants.

Moreover, U.S. immigration policy itself creates a filtering mechanism that favors high-skilled, economically motivated individuals. Many immigrants enter through employment-based or family-based channels that require background checks, documentation of skills, and financial stability. Once settled, immigrants often face higher costs if convicted of crimes—including risk of deportation or ineligibility for naturalisation—which creates additional institutional disincentives for criminal behavior. Combined with cultural emphasis on social mobility and reputational concerns within tight-knit immigrant communities, these factors further lower the likelihood of immigrant involvement in criminal activities.

4.4.2.5. *Consumer fraud are largely involved by international scam organisations.* With the advancement of technology, consumer fraud is now more often carried out on a large scale by foreign criminal organizations rather than by local residents. Although comprehensive U.S.-specific data on the origin of fraud perpetrators remains limited, international evidence provides compelling indirect support for this claim. A report from the City of London Police reveals that over 70% of consumer fraud cases in the U.K. are either directly perpetrated by or traceable to foreign fraud organisations[2]. Given the U.K.'s status as one of the global hotspots for consumer fraud, such findings carry significant reference value for the U.S. context. This report underscores a key characteristic of modern consumer fraud that it is driven less by physical proximity and more by digital connectivity. Fraudsters can operate from virtually anywhere, leveraging telecommunication infrastructure, online platforms, and anonymous financial technologies to reach victims in the United States without ever setting foot on U.S. soil.

[2]Based on UK government's estimation, over 70% of fraud experienced by UK victims could have an international component. See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1154660/Fraud_Strategy_2023.pdf

This digitalisation of fraud implies that geographic presence—or the lack thereof—is largely irrelevant to the commission of these crimes. Consequently, fluctuations in the size of the immigrant population within the U.S. are unlikely to be causally linked to observed trends in consumer fraud. The vast majority of fraud campaigns can be, and often are, orchestrated from overseas, circumventing domestic law enforcement capacity through jurisdictional fragmentation, limited international cooperation, and the anonymity afforded by cross-border internet traffic.

Moreover, the logic of consumer fraud deviates fundamentally from that of traditional crimes like theft or violence. It does not require physical confrontation, territorial control, or localised logistical networks. Instead, it thrives in a virtual environment characterised by asymmetric information, fragmented regulatory enforcement, and low prosecution risk. These structural features make consumer fraud more akin to cybercrime or financial fraud than to street-level crime, and help explain why policy responses focused narrowly on immigrant crime risk may be misaligned with the nature of the threat.

4.5. Empirical Results

4.5.1. Reduced form analysis. We begin our analysis by examining the relationship between the number of complaints and the level of trust in the complainant's location. Similar to Hayes et al. (2021), we use the 2010 GSS (General Social Survey) state-level trust data to study how trust levels could affect the number of social fraud complaints at the state level. Our regression equation is as follows:

$$Complaint_{s,y} = \alpha + \beta \cdot \text{GSSTrust2010}_s + \gamma \cdot X_{s,y} + \varepsilon_{s,y} \tag{4.5.1}$$

Table 4.5.1 reports the regression results examining the relationship between local social trust and the incidence of consumer fraud across U.S. states from 2011 to 2022. The dependent variable is the annual number of consumer fraud complaints reported to the FTC at the state level, while the main explanatory variable is the state-level generalised social trust measured by the GSS in 2010—the last year in which such data are available at the state level. We adopt a reduced-form ordinary least squares specification and exploit the panel structure of the data by regressing the number of fraud cases on the 2010 trust levels across multiple years. This approach allows us to estimate the long-term influence of pre-determined social trust on fraud outcomes, while mitigating concerns of reverse causality or simultaneity bias.

TABLE 4.5.1. **GSS trust and consumer fraud**

This table presents the results of the relationship between state-level trust and the number of reported consumer fraud cases in the United States. The dependent variable is the number of state-level consumer fraud reports recorded by the FTC, and the explanatory variable is the GSS trust in 2010 at state level. The data cover the period from 2011 to 2022. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)
Dependent variable	Complaint	Complaint	Complaint
Trust2010	–33.71***	–10.47***	–5.49***
	(3.54)	(1.36)	(1.11)
Population (M)		3.93***	3.98***
		(0.45)	(0.47)
Age		1.92***	1.76***
		(0.35)	(0.26)
Gender		–188.67***	56.90**
		(40.32)	(26.64)
Education		–2.15**	–1.81**
		(1.00)	(0.91)
Income		0.0004***	0.0001
		(0.0001)	(0.001)
Year fixed effect	Y	N	Y
Adj R-Square	0.026	0.927	0.903

Across all model specifications, we find a consistently strong and statistically significant negative relationship between trust and fraud. Column (1) includes year fixed effects and shows that a one-percent increase in the trust index is associated with approximately 33.7 fewer fraud complaints. As expected, the magnitude of this coefficient decreases after introducing control variables in Columns (2) and (3); However, the relationship remains statistically significant at the 1% level throughout. In the fully specified model (Column 3), the effect size stabilizes at –5.49, indicating that a one-percent drop in trust is associated with 5.49 additional fraud complaints, which is consistent with main result of Hayes et al. (2021). The demographic and socioeconomic controls include total population, average age, gender composition, education level, and median income. Notably, the signs of the control variables are generally consistent with expectations. States with larger populations and higher average age tend to report more fraud cases, while higher education levels are associated with fewer complaints. The estimated coefficients on gender and income suggest that male population share and higher income may play nuanced roles in fraud exposure or reporting behavior.

It is also noteworthy that in this reduced-form specification, we include year fixed effects but not entity (state) fixed effects. This is because the key explanatory variable—social trust—is time-invariant across the panel, having been measured only in 2010 and including year would have absorbed all variation in the trust measure. However, as the key variable, GSS2010, is fixed throughout the sample period, we cannot add entity fixed effect because of multicollinearity issue. In subsequent analyses, we adopt division-level trust data, which vary over time and allow us to incorporate both entity and time fixed effects in a two-way fixed effects framework to control the potential omitted variable issue(Breuer and DeHaan, 2024).

4.5.2. Fama-Macbeth regression. To further strengthen our baseline result, we introduce the Fama-MacBeth two-stage regression approach from Fama and MacBeth (1973). This method is particularly well-suited for panel data that focus on estimating average cross-sectional relationships over time while accounting for time-series dependence in standard errors. The Fama-MacBeth regression results presented in Table 4.5.2 offer further evidence supporting the robustness of the relationship between social trust and consumer fraud. Specifically, the coefficients on both the time-invariant Trust2010 variable and the time-varying Trust variable remain consistently negative and statistically significant across model specifications, indicating that the observed inverse relationship is not sensitive to model choice or data frequency.

The Trust2010 variable, measured at the state level and used in Columns (1) and (2), serves as a baseline indicator of generalised trust across U.S. states prior to the observation window. Despite being a static measure, its significance across multiple years suggests that foundational cultural norms related to trust can exert persistent influence on fraud-related outcomes. The fact that this relationship holds even when controlling for demographic and economic variables—such as population size, age, gender composition, and income—underscores the explanatory power of deep-rooted cultural traits that are often slow to evolve.

Columns (3) and (4) in Table 4.5.2 introduce the annually updated Trust variable at the division level. The continued statistical significance of this measure further validates the main finding: Higher levels of social trust are associated with fewer consumer fraud complaints. The consistency of this result across both static and dynamic trust measures enhances our confidence that trust is not merely a proxy for omitted variables or cross-sectional noise. Instead, it appears to be a stable and meaningful determinant of fraud prevalence. Importantly, the Fama-MacBeth framework helps mitigate concerns about autocorrelation and unobserved time-specific shocks

TABLE 4.5.2. **Fama-Macbeth 2-stage regression**

This table reports the second stage results of Fama-MacBeth two-stage regressions examining the relationship between social trust and the number of consumer fraud complaints. Columns (1) and (2) use state-level trust measured in 2010 as the main independent variable, while Columns (3) and (4) use division-level average trust measured annually from 2011 to 2022. All regressions include year fixed effects and robust standard errors. The dependent variable is the number of complaints per 1,000 residents. Standard errors are computed using the time series of cross-sectional coefficient estimates. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)
Dependent variable	$\widehat{\text{Beta}}$	$\widehat{\text{Beta}}$	$\widehat{\text{Beta}}$	$\widehat{\text{Beta}}$
Trust2010 (,000)	−337.12***	−487.24***		
	(28.41)	(98.52)		
Trust (,000)			−512.44**	−165.63*
			(231.43)	(100.20)
Population (M)		0.003***		0.004***
		(0.000)		(0.000)
Age		1682.41***		−1073.95**
		(209.68)		(473.70)
Gender(,000)		57.85***		−230.80***
		(21.74)		(70.83)
Education		−213.27		−129.65*
		(135.21)		(67.41)
Income		0.03		3407.77*
		(0.02)		(2065.35)
Year fixed effect	Y	Y	Y	Y

by averaging coefficients across annual cross-sectional regressions (Pasquariello, 1999). The persistence of the trust and fraud relationship under this methodology suggests that the observed effect is not driven by isolated events or particular years but reflects a systematic pattern over time.

4.5.3. Identification strategy. While baseline OLS regressions reveal a strong negative association between generalised trust and the number of reported consumer fraud complaints, these results may be subject to endogeneity concerns, particularly reverse causality. For instance, a low-trust environment may make individuals more vigilant and thus more likely to report fraud incidents to the FTC. Conversely, an increase in fraud prevalence could deteriorate public trust by heightening social suspicion and reducing interpersonal confidence. Such bidirectional feedback may bias OLS estimates and obscure the true causal relationship between trust and fraud incidence.

To address these endogeneity problems, we adopt a two-stage least squares instrumental variable approach, as 2SLS IV method is effective in terms of eliminating these issues (Angrist and Imbens, 1995). The key to this identification strategy is isolating exogenous variation in social trust that is not affected by current fraud trends. Following a growing literature, we use the number of new immigrant arrivals in each region-year as an instrument for local trust levels. Recent studies (Dinesen and Sønderskov, 2015; Putnam, 2007; Ziller, 2015) have documented a robust negative relationship between immigration-induced ethnic diversity and generalised trust across western democracies. Immigration flows alter the social fabric of communities, often introducing linguistic, ethnic, and cultural heterogeneity that weakens shared norms and reduces social cohesion. This provides a plausible exogenous source of variation in trust.

At the same time, there is no direct theoretical or empirical reason to believe that immigration inflows are systematically related to consumer fraud reporting behavior, which has been discussed in Section 4.4. For example, FTC social fraud complaints typically concern consumer-facing schemes such as email phishing or romance scams—many of which originate internationally or online—rather than local crimes associated with physical safety or street-level violence. Official reports from the FBI and UK government indicate that over 70% of consumer fraud cases may have cross-border components. Therefore, while immigration plausibly influences trust, it does not directly affect the type of consumer fraud captured by the FTC, satisfying the exclusion restriction required for valid IV estimation.

We implement the following 2SLS model:

$$\text{Trust}_{r,y} = \pi_0 + \pi_1 \cdot \text{Immigration}_{r,y} + \delta' X_{r,y} + u_{r,y} \tag{4.5.2}$$

$$\text{Complaint}_{r,y} = \beta_0 + \beta_1 \cdot \widehat{\text{Trust}}_{r,y} + \lambda' X_{r,y} + \varepsilon_{r,y} \tag{4.5.3}$$

The first-stage equation estimates the relationship between immigration inflows and generalised trust levels, using division-level data from 2013 to 2022. The second-stage equation then estimates the effect of the predicted trust level on consumer fraud complaints. Control variables in both stages include average age, male population share, education level, population size, and median income at the division-year level.

TABLE 4.5.3. **Immigration IV 2SLS regressions**

This table report presents the results under IV (US immigration new arrivals) 2SLS regression result. The explanatory variables is the number of complaints from FTC, while the IV is the number of new immigrant arrivals (in million) from Census Bureau. All variables are division-level data from 2013-2022. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)
	1st stage	2nd stage
Dependent variable	Trust	Complaint
Immigration IV	−3.955***	
	(0.721)	
$\widehat{\text{Trust}}$		−184.12***
		(26.475)
Age	0.015*	6.328***
	(0.008)	(1.173)
Gender	1.825	823.26***
	(1.199)	(160.72)
Education	0.001	5.490***
	(0.015)	(1.919)
Population (M)	−0.013***	3.447***
	(0.003)	(0.209)
Income	0.068**	7.343
	(0.029)	(4.883)
Adj R-Square	0.453	0.9846
F stat (Weak IV test)	30.21	
F stat		522.20
No. Observation	108	108

Table 4.5.3 presents the 2SLS regression results. The first-stage regression confirms that immigration is a strong predictor of trust levels, with the coefficient significant at the 1% level. The first-stage F-statistic (Stock and Yogo, 2005) is 30.21, well above the conventional threshold of 10, rejecting concerns about weak instruments. In the second-stage regression, the fitted value, $\widehat{\text{Trust}}$, remains negatively associated with FTC fraud complaints and is also significant at the 1% level. Importantly, these results are qualitatively consistent with those from the OLS models, reinforcing the interpretation that the relationship is not driven by unobserved confounders or reverse causality. Furthermore, the adjusted R-squared of the second-stage model exceeds 0.98, indicating that trust—when instrumented—explains a substantial share of the variation in fraud complaints. This high explanatory power, in combination with a credible identification strategy, provides robust evidence that trust has a causal and economically meaningful effect on

the prevalence of consumer fraud, consistent with the findings of Oster (2019) regarding robustness to omitted variable bias.

4.5.4. Transmission channel. We further investigate the transmission channels between trust level and fraud. Consumer fraud, by nature, exploits information asymmetry to deceive victims (Ndofor et al., 2015). One of the most effective ways to address information asymmetry is through high-quality information sharing (Clarkson et al., 2007). Therefore, we use the frequency of communication among members within a local community as a potential transmission channel. Many studies have already shown a strong relationship between high levels of local community trust and interpersonal communication (Cheung et al., 2013; Mellinger, 1956; Pearce, 1974). Higher levels of trust within a community often imply more frequent communication among neighbours. At the same time, greater ethnic diversity within a community may reduce the quality of interactions among residents.

To test this channel, we rely on two communication frequency variables from the General Social Survey: SOCOMMUN and RACLIVE. The SOCOMMUN variable is based on the question: *'How often do you spend a social evening with someone who lives in your neighborhood?'* This variable directly reflects the respondent's frequency of interaction with other community members. More frequent interactions are expected to facilitate better information dissemination and reduce potential consumer fraud arising from information asymmetry. The second variable, *'Are there any ("whites" for Black respondents, "blacks" for non-Black respondents) living in this neighborhood now?'*, captures whether residents in the community belong to the same racial group. According to findings such as those by Lancee and Dronkers (2011), greater racial homogeneity within a community fosters communication among residents. This view is also consistent with the idea that immigration inflows may disrupt the local community culture.

Using these two variables, we regress them separately on the FTC's number of complaints. The results are presented in Table 4.5.4. As shown, both SOCOMMUN in Column (1) and RACLIVE in Column (2) are statistically significant at the 5% level. This suggests that more frequent communication among community members effectively reduces the likelihood of potential consumer fraud. Additionally, communities with greater racial homogeneity are also significantly associated with fewer fraud incidents, which is consistent with the findings of Lancee and Dronkers (2011). Both findings highlight the importance of information sharing within a community.

High-frequency and high-quality information sharing within communities can substantially mitigate the occurrence of consumer fraud.

At the same time, we acknowledge that information dissemination may not be confined to within the community—external information may also influence outcomes. To further test this idea, we employ a placebo test using another GSS variable: SOCFREND, based on the question: *'How often do you spend a social evening with friends who live outside the neighborhood?'* As a counterpart to SOCOMMUN, SOCFREND serves to isolate the information sharing pathway by restricting the domain of interaction to outside the community. Thus, SOCFREND is a well-suited placebo variable. The results are presented in Table 7, Column 3. We find that the placebo variable is statistically insignificant, with a t-statistic close to zero, while the t-statistic for SOCOMMUN exceeds 2.4. This indicates that the information sharing influencing consumer fraud primarily originates from interactions among members within the local community.

4.6. Robustness checks

4.6.1. Devision-level reduced form regression result. To further examine the relationship between trust level and consumer fraud, we use GSS division-level data to obtain annual trust levels and construct a new regression equation.

$$Complaint_{r,y} = \alpha + \beta \cdot \text{GSSTrust}_{r,y} + \gamma \cdot X_{r,y} + \varepsilon_{r,y}$$

where ....

In this new regression model, the dependent, independent, and control variables are all measured at the division-level. These divisions are based on the nine divisions defined by the U.S. Census Bureau. Although the FTC and Census Bureau provide data at the state level, we consider it a necessary part of our regression analysis at the divisional level to align with the publicly available GSS data.

The results indicate that even at the divisional level, a clear negative correlation between trust level and social fraud remained. To enhance the persuasiveness of the model results, we incorporate control variables, year fixed effects, and division fixed effects in Table 4.6.1. Year fixed effects effectively control for the influence of different time periods on the variables, while division fixed effects further eliminate regional differences that may affect the regression results. It

TABLE 4.5.4. **Communication channel regressions**

This table presents the potential communication channel between local trust and consumer fraud. Column (1) shows the effect of the within-community communication frequency variable SOCOMMUN on the FTC number of fraud complaints. In Column (2), the variable RACLIVE serves as an indicator of racial diversity within the community. Column (3) includes SOCFREND as a placebo variable, which measures the respondent's frequency of social interaction with friends outside the local community. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)
Dependent variable	Complaint	Complaint	Complaint
SOCOMMUN	–24.34**		
	(10.01)		
RACLIVE		–94.27**	
		(46.01)	
SOCFREND			1.84
			(9.24)
Age	5.06**	4.68**	4.48**
	(2.19)	(1.90)	(2.08)
Income	17.35	26.23	15.63
	(14.64)	(17.06)	(15.20)
Education	0.16	–6.10	–3.59
	(6.19)	(6.49)	(8.04)
Gender	68.48*	2.82	60.96
	(39.26)	(64.12)	(47.48)
Urbanization	–5.76	–5.16*	–7.75**
	(3.88)	(2.60)	(3.52)
Population(M)	4.22***	4.07***	4.21***
	(0.46)	(0.43)	(0.48)
Year fixed effect	Y	Y	Y
Division fixed effect	Y	Y	Y
Adj R-Square	0.909	0.907	0.804

is worth noting that regardless of whether control variables or fixed effects are included, the trust level remains significantly negatively correlated with the FTC number of complaints. The results from both regression models are consistent with the findings shown in Figure 1, which also indicates a clear negative correlation between trust level and the number of complaints. Specifically, a one-percent decrease in trust level is associated with 70,650 additional complaints on average. The discrepancy between the coefficients in the state-level and division-level models is due to two main factors. First, the GSS state-level trust data only covers 40 states, meaning each division on average includes data from 4 or 5 states. As a result, the total number of complaints at the divisional level is several times greater than that at the state level. Second,

Table 4.6.1. **GSS trust and consumer fraud**

This table presents the results of the relationship between division-level trust and the number of reported consumer fraud cases in the United States. The dependent variable is the number of division-level consumer fraud reports recorded by the FTC, and the explanatory variable is the GSS trust index at division level. The data cover the period from 2013 to 2022. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
	Complaint	Complaint	Complaint	Complaint	Complaint
Trust	−80.32***	−78.59***	−107.63***	−77.32***	−70.65**
	(31.98)	(12.98)	(26.83)	(20.77)	(30.30)
Age		−0.18	2.22	3.95**	−0.29
		(0.80)	(1.58)	(1.67)	(1.70)
Gender		−245.85***	1650.51***	498.22**	1684.6***
		(18.52)	(507.77)	(214.00)	(418.83)
Education		9.95***	5.82***	2.55**	−2.90
		(2.15)	(1.88)	(1.14)	(2.25)
Population (M)		3.47***	−1.63	3.79***	7.32*
		(0.45)	(4.99)	(0.48)	(4.50)
Income		1.56	3.07	3.60	4.89**
		(2.63)	(4.54)	(3.09)	(2.21)
Time fixed effect	Y	N	N	Y	Y
Division fixed effect	Y	N	Y	N	Y
Adj R-Square	0.173	0.957	0.723	0.916	0.238

the Figure 4.4.1 illustrating the relationship between trust level and complaints indicates that the negative correlation became stronger after 2017. Therefore, using 2010 trust data to explain complaint numbers in later years significantly underestimates the true coefficient.

4.7. Conclusion

In this essay, we have demonstrated that generalised social trust exerts a meaningful and causal influence on consumer fraud outcomes. Using U.S. state- and region-level data from 2011 to 2022, through reduced-form OLS, we show that higher trust is associated with substantially fewer reported fraud complaints. We then address endogeneity via a 2SLS design—instrumenting trust with immigration inflows—and confirm that exogenously higher trust levels lead to a marked reduction in complaint counts. Finally, by examining loss conditional on fraud exposure, we uncover a nuanced channel: Although more trusting individuals face greater financial harm once targeted, regions with stronger post-2020 consumer-protection policies experience a pronounced mitigation of this vulnerability.

These findings underscore the dual role of trust in the fraud ecosystem. On one hand, strong social capital deters fraud through enhanced informal communication networks and community surveillance; on the other, it can heighten individual susceptibility to deception in the absence of robust institutional safeguards. From a policy perspective, our results suggest that anti-fraud initiatives should combine efforts to cultivate social trust with targeted regulatory interventions—such as public education campaigns, reporting facilitation, and stricter enforcement—especially in high-trust communities. Future research can extend this framework to other forms of economic crime or explore the long-run effects of trust dynamics on digital fraud resilience.

Appendix 4.1 Local culture and probability of being scammed

To further explore the mechanism through which social trust influences the consequences of consumer fraud, we examine how trust levels affect the probability and severity of losses incurred following fraud incidents. In particular, we investigate whether individuals with higher trust are more likely to suffer financial losses once they become targets of fraud, potentially due to lower suspicion or reduced preventive behavior. We also examine the mitigating role of post-2020 legislative efforts to combat consumer fraud, which varied in intensity across regions.

To quantify the regional coverage of these legislative measures, we construct a population-weighted measure of policy impact for each U.S. Census Bureau-defined region. Based on the distribution of this measure, we divide the regions into two equally sized groups. Divisions in the top 50% are assigned a value of 1 for the years 2021 and 2022 (Post = 1), while those in the bottom 50% are assigned 0. We then estimate the following difference-in-differences (DID)-style regression model:

$$Y = \beta_0 + \beta_1 \cdot \text{Trust} + \beta_2 \cdot \text{Post} + \delta' X + \gamma_t + \mu_r + \varepsilon \tag{4.1.1}$$

where Y represents two distinct outcomes: (1) the probability of incurring a financial loss given that a fraud incident was reported, and (2) the average monetary loss per reported fraud case. Trust denotes the respondent-level trust index from the General Social Survey (GSS), where a higher value indicates lower trust. Control variables include age, gender, education level, income, urbanization status, and the number of reported fraud cases in each region. All regressions include year and region fixed effects to account for time trends and unobserved regional characteristics.

The regression results are presented in Table 4.1.1. Column (1) reveals that trust is positively associated with the likelihood of suffering losses in fraud cases. Specifically, a 1% increase in the Trust Index is associated with a 0.8% increase in the probability of incurring financial loss once fraud occurs, and the coefficient is statistically significant at the 1% level. This finding aligns with behavioral theories suggesting that individuals who exhibit higher levels of generalised trust may be more vulnerable to deception, less inclined to verify suspicious interactions, and more likely to fall victim to financial exploitation once targeted.

TABLE 4.1.1. **Potenial impact of fraud probability and loss incurred from trust index**

This table reports results from estimating the potenial impact of fraud probability and loss incurred in terms of trust level from different regions in the US. In equation (1), the dependent variable is the probability of loss incurred condition of fraud case reported, and in equation (2), the dependent variable is the average loss incurred per case reported.

	(1)	(2)
Trust index	−0.144***	−47.19***
	(0.036)	(13.09)
Post	−1.2258***	−0.9086*
	(0.018)	(0.506)
Age	−0.0612***	−215.16
	(0.0126)	(189.75)
Income	−0.1044	−11364.87***
	(0.09)	(1721.72)
Education	0.1674***	592.9
	(0.054)	(1315.27)
Gender	−0.3636	19286.19
	(0.522)	(12913.78)
Urbanization	−0.1314*	−715.66
	(0.072)	(1131.9)
No. Complaint(M)	0.7794	17281.88*
	(0.504)	(10074.35)
Year fixed effect	Y	Y
Region fixed effect	Y	Y
Adj R-Square	0.978	0.957

In addition, the coefficient on the Post dummy is also statistically significant and negative, indicating the effectiveness of consumer protection legislation. Regions with higher policy coverage (Post = 1) exhibit, on average, a 6.81% lower probability of loss following fraud incidents, relative to regions with weaker policy interventions. This suggests that targeted anti-fraud measures, such as public education campaigns and stricter enforcement mechanisms, can meaningfully reduce fraud-related harm, particularly in high-trust environments where individuals may be more susceptible.

While Column (2) confirms similar directional effects when using average monetary loss as the dependent variable, our primary emphasis is on the probability of loss (Column 1), as it directly captures behavioral vulnerability conditional on fraud exposure. Collectively, the high adjusted

R-squared values (0.978 and 0.957) suggest that the regression models account for nearly all observable variation, and that the results are unlikely to be driven by omitted variable bias.

CHAPTER 5

Conclusion and further directions for research

5.1. Conclusion

This thesis brings together three independent yet thematically inter-connected essays to examine the unintended consequences and behavioral implications of unconventional policies and social forces in modern financial systems. Through empirical investigation of Japan's equity market interventions and the role of social trust in fraud outcomes, it offers a unified narrative on how policies—whether monetary or regulatory—and informal institutions jointly shape financial behavior, risk perceptions, and welfare.

A central contribution of this thesis lies in its novel perspective on the limits of interventionist policies, particularly when they are predictable, large-scale, or grounded in behavioral assumptions. The first two essays focus on the Bank of Japan's ETF purchase program, one of the most sustained unconventional monetary policies in modern history. While central banks often justify such interventions as tools to stabilise markets or lower risk premia, the first essay reveals that BOJ's persistent equity purchases may have had the opposite effect—raising short-term market volatility and thus increasing the implied risk premium, contrary to the program's stated objectives. This finding challenges conventional wisdom in monetary policy literature and calls for a re-evaluation of the long-term effectiveness of financial market interventions.

The second essay further examines BOJ's interventions from a predictive and market-behavioral standpoint. By constructing a high-accuracy prediction model and demonstrating profitable trading strategies, the essay shows that even fully predictable, data-driven policies can cause non-fundamental price pressures. These results contest the efficient market hypothesis and suggest that the mere expectation of intervention can move prices, particularly in less liquid segments of the market. Together, the first two essays contribute to a growing literature questioning whether predictable monetary policy actions are truly neutral and whether central banks should weigh the behavioral consequences of their transparency and communication strategies more carefully.

The third essay shifts focus to the domain of consumer fraud, analyzing how generalized social trust affects fraudulent outcomes in the U.S. By addressing endogeneity through an instrumental variable strategy, the essay establishes a causal link between higher local trust and lower fraud incidence. It also reveals the following nuanced mechanism: While trust deters fraud at the community level, it may simultaneously increase individual vulnerability absent institutional safeguards. This insight expands the literature on trust from its traditional focus on economic growth and transaction costs to its role in shaping exposure to modern economic threats such as digital scams. The results have direct implications for policy design in fraud prevention, emphasising the need to balance social trust-building with regulatory enforcement.

Collectively, the three essays demonstrate the importance of moving beyond traditional models of rational behavior or frictionless markets. Instead, they highlight how predictability, perception, and informal norms can materially alter market outcomes. Methodologically, the dissertation leverages a range of empirical tools—from high-frequency financial data and structural VAR models to machine learning prediction and instrumental variable estimation—offering robust and interdisciplinary insights. The findings not only contribute to academic debates in monetary policy, behavioral finance, and institutional economics, but also offer timely guidance for policymakers navigating the complex trade-offs in designing effective and resilient financial systems.

5.2. Further direction of research

5.2.1. BOJ. Future research can explore the heterogeneous effects of BOJ interventions across firms and sectors with varying ownership structures, capital constraints, and industry characteristics. Such analysis would deepen the understanding of how intervention-induced volatility and risk repricing propagate through different segments of the corporate sector.

Alternatively, a potential research direction is to integrate richer measures of market expectations—such as survey-based sentiment indicators, option-implied volatility, or high-frequency trading data—and to conduct cross-country comparisons with similar programs implemented by other central banks. This would help identify the signaling and credibility channels of interventions, and assess the effect of institutional and market structures on their ultimate impact on financial stability.

Future research can also assess whether prediction-based trading strategies remain effective in other policy settings, such as central bank forward guidance or macroprudential measures, and examine how investor heterogeneity—particularly between algorithmic and retail traders—affects market reactions to predictable interventions.

Another direction is to expand the predictive framework by incorporating alternative machine learning methods and higher-frequency market data. Doing so would not only improve forecasting accuracy for intervention timing but also enable the development of real-time tools for evaluating the market impact of data-driven monetary policies.

5.2.2. Social Trust and Cconsumer fraud. The forth chapter shows that generalised social trust plays a significant role in reducing consumer fraud across U.S. states. Using a 2SLS approach that instruments trust with immigration inflows, the study establishes a causal link between higher trust and lower fraud complaints. The analysis also identifies the following mechanism: Trust promotes community communication, which acts as a deterrent. However, trusting individuals who are targeted still face greater financial losses, highlighting the dual nature of trust in the fraud ecosystem.

Future research can extend the trust–fraud framework to other forms of economic misconduct, such as phishing, identity theft, or crypto-related fraud, to test whether the protective role of trust operates consistently across different contexts. Such analysis would also help identify whether certain fraud types exploit trust more effectively than others.

Furthermore, future research can investigat how digital infrastructure and platform design shape the trust–fraud relationship, and how shocks to trust—arising from events like political scandals or large-scale data breaches—alter fraud vulnerability over time. This would provide deeper insight into how trust interacts with technological and institutional environments in influencing economic misconduct.

Bibliography

Abrego, L., Coleman, M., Martínez, D.E., Menjívar, C., Slack, J., 2017. Making immigrants into criminals: Legal processes of criminalization in the post-IIRIRA era. Journal on Migration and Human Security 5, 694–715.

Abreu, D., Brunnermeier, M.K., 2003. Bubbles and crashes. Econometrica 71, 173–204.

Amiram, D., Bozanic, Z., Cox, J.D., Dupont, Q., Karpoff, J.M., Sloan, R., 2018. Financial reporting fraud and other forms of misconduct: a multidisciplinary review of the literature. Review of Accounting Studies 23, 732–783.

Angrist, J.D., Imbens, G.W., 1995. Two-stage least squares estimation of average causal effects in models with variable treatment intensity. Journal of the American Statistical Association 90, 431–442.

Bekaert, G., Hoerova, M., Duca, M.L., 2013. Risk, uncertainty and monetary policy. Journal of Monetary Economics 60, 771–788.

Ben-David, I., Franzoni, F., Moussawi, R., 2018. Do ETFs increase volatility? The Journal of Finance 73, 2471–2535.

Ben-Rephael, A., Kandel, S., Wohl, A., 2011. The price pressure of aggregate mutual fund flows. Journal of Financial and Quantitative Analysis 46, 585–603.

Benartzi, S., Thaler, R.H., 1999. Risk aversion or myopia? Choices in repeated gambles and retirement investments. Management Science 45, 364–381.

Berkman, H., Koch, P.D., 2017. Drips and the dividend pay date effect. Journal of Financial and Quantitative Analysis 52, 1765–1795.

Bernanke, B.S., Boivin, J., 2003. Monetary policy in a data-rich environment. Journal of Monetary Economics 50, 525–546.

Bernanke, B.S., Gertler, M., 2000. Monetary policy and asset price volatility.

Bernanke, B.S., Gertler, M., 2001. Should central banks respond to movements in asset prices? American Economic Review 91, 253–257.

Bernanke, B.S., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. Handbook of Macroeconomics 1, 1341–1393.

Bjørnskov, C., 2007. Determinants of generalized trust: A cross-country comparison. Public Choice 130, 1–21.

Blanchard, O.J., Quah, D., 1988. The dynamic effects of aggregate demand and supply disturbances.

BOJ, 2010. Principal terms and conditions for the asset purchase program. Retrieved 25 August 2022, from $https://www.boj.or.jp/en/announcements/release\_2010/mok1010f.pdf$.

BOJ, 2013a. Introduction of the "quantitative and qualitative monetary easing. Retrieved 1 August 2022, from $https://www.boj.or.jp/en/announcements/release\_2013/k130404a.pdf$.

BOJ, 2013b. "quantitative and qualitative monetary easing (qqe) with yield curve control": New monetary policy framework for overcoming low inflation. Retrieved 25 August 2022, from $https://www.brookings.edu/wp-content/uploads/2016/09/1610-governor-kuroda\_brookings.pdf$.

Bordo, M.D., Jeanne, O., 2002. Boom-busts in asset prices, economic instability, and monetary policy. Technical Report. National Bureau of Economic Research Cambridge, Mass., USA.

Breuer, M., DeHaan, E., 2024. Using and interpreting fixed effects models. Journal of Accounting Research 62, 1183–1226.

Brown, D.C., Davies, S.W., Ringgenberg, M.C., 2021. ETF arbitrage, non-fundamental demand, and return predictability. Review of Finance 25, 937–972.

Cattaneo, M.D., Idrobo, N., Titiunik, R., 2024. A practical introduction to regression discontinuity designs: Extensions. Cambridge University Press.

Cecchetti, S.G., 2000. Asset prices and central bank policy. Centre for Economic Policy Research.

Charoenwong, B., Morck, R., Wiwattanakantang, Y., 2021. Bank of Japan equity purchases: The (non-) effects of extreme quantitative easing. Review of Finance 25, 713–743.

Chen, Z., Ito, K., Yamada, T., Zhang, B., 2019. Monetary policy through the stock market: Central bank purchase of equity index ETFs. Available at SSRN 3458250 .

Cheung, S.O., Yiu, T.W., Lam, M.C., 2013. Interweaving trust and communication with project performance. Journal of Construction Engineering and Management 139, 941–950.

Chung, J.C., 2020. The Bank of Japan's exchange-traded fund purchase program and its impact on daily stock market returns. The University of Tokyo, Tokyo , 1–9.

Clarkson, G., Jacobsen, T.E., Batcheller, A.L., 2007. Information asymmetry and information sharing. Government Information Quarterly 24, 827–839.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Dang, T.V., Li, W., Wang, Y., 2021. Managing China's stock markets: The economics of the national team. Available at SSRN 3546411 .

Dang, T.V., Li, W., Wang, Y., 2023. Government stock purchase undermines price informativeness: Evidence from China's "National Team". Journal of Financial and Quantitative Analysis , 1–61.

Dinesen, P.T., Sønderskov, K.M., 2015. Ethnic diversity and social trust: Evidence from the micro-context. American Sociological Review 80, 550–573.

Dyakov, T., Verbeek, M., 2013. Front-running of mutual fund fire-sales. Journal of Banking & Finance 37, 4931–4942.

Falcone, R., Castelfranchi, C., 2001. Social trust: A cognitive approach. Trust and Deception in Virtual Societies , 55–90.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Filardo, A.J., 2004. Monetary policy and asset price bubbles: calibrating the monetary policy trade-offs .

French, K.R., Schwert, G.W., Stambaugh, R.F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.

Friedman, B.M., 2004. Why the federal reserve should not adopt inflation targeting. International Finance 7.

Fukui, M., Yagasaki, M., 2023. The impact of central bank stock purchases: Evidence from discontinuities in policy rules. Available at SSRN 4365184 .

Fukuyama, F., 1995. Social capital and the global economy. Foreign Aff. 74, 89.

Gabaix, X., Koijen, R.S., 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. Technical Report. National Bureau of Economic Research.

Gao, L., Han, Y., Li, S.Z., Zhou, G., 2018. Market intraday momentum. Journal of Financial Economics 129, 394–414.

Geis, W., Uebelmesser, S., Werding, M., 2013. How do migrants choose their destination country? an analysis of institutional determinants. Review of International Economics 21, 825–840.

Grönqvist, H., 2006. Ethnic enclaves and the attainments of immigrant children. European Sociological Review 22, 369–382.

Guiso, L., Sapienza, P., Zingales, L., 2008. Trusting the stock market. the Journal of Finance 63, 2557–2600.

Guiso, L., Sapienza, P., Zingales, L., 2018. Time varying risk aversion. Journal of Financial Economics 128, 403–421.

Harada, K., Okimoto, T., 2021. The BOJ's ETF purchases and its effects on nikkei 225 stocks. International Review of Financial Analysis 77, 101826.

Hartzmark, S.M., Solomon, D.H., 2022a. Predictable price pressure. Technical Report. National Bureau of Economic Research.

Hartzmark, S.M., Solomon, D.H., 2022b. Reconsidering returns. The Review of Financial Studies 35, 343–393.

Hattori, T., Yoshida, J., 2023. The impact of Bank of Japan's exchange-traded fund purchases. Journal of Financial Stability 65, 101102.

Hayes, R.M., Jiang, F., Pan, Y., 2021. Voice of the customers: Local trust culture and consumer complaints to the CFPB. Journal of Accounting Research 59, 1077–1121.

Hertzberg, A., 2005. Managerial incentives, misreporting, and the timing of social learning: A theory of slow booms and rapid recessions. Unpublished Working Paper .

Higham, N.J., 1990. Analysis of the cholesky decomposition of a semi-definite matrix .

Jao, Y.C., 2001. The Asian financial crisis and the ordeal of Hong Kong. Bloomsbury Publishing USA.

Judges, R.A., Gallant, S.N., Yang, L., Lee, K., 2017. The role of cognition, personality, and trust in fraud victimization in older adults. Frontiers in Psychology 8, 588.

Katagiri, M., Takahashi, K., Shino, J., et al., 2022. Bank of Japan's ETF purchase program and equity risk premium: A CAPM interpretation. Technical Report. Bank for International Settlements.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? a cross-country investigation. The Quarterly Journal of Economics 112, 1251–1288.

Lagarde, C., 2023. Monetary policy statement - press conference. $https : //www.ecb.europa.eu/press/pressconf/2023/html/ecb.is230727 \quad e0a11feb2e.en.html$, Retrieved 05 Dec 2023.

Lancee, B., Dronkers, J., 2011. Ethnic, religious and economic diversity in dutch neighbourhoods: Explaining quality of contact with neighbours, trust in the neighbourhood and interethnic trust. Journal of Ethnic and Migration Studies 37, 597–618.

Lappeman, J., Marlie, S., Johnson, T., Poggenpoel, S., 2022. Trust and digital privacy: Willingness to disclose personal information to banking chatbot services. Journal of Financial Services Marketing 28, 337.

Liu, Z., Nikitopoulos, C.S., Phua, K., Wang, J., 2025. Data-driven monetary policy: Evidence from the bank of japan's equity purchase program. Pacific-Basin Finance Journal 90, 102615.

Lou, D., 2012. A flow-based explanation for return predictability. The Review of Financial Studies 25, 3457–3489.

Mellinger, G.D., 1956. Interpersonal trust as a factor in communication. The Journal of Abnormal and Social Psychology 52, 304.

Menjívar, C., Abrego, L., 2012. Legal violence: Immigration law and the lives of central american immigrants. American Journal of Sociology 117, 000–000.

Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica: Journal of the Econometric Society , 867–887.

Merton, R.C., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323–361.

Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. The Journal of Finance 32, 1151–1168.

Naik, P.K., Gupta, R., Padhi, P., 2018. The relationship between stock market volatility and trading volume: Evidence from south africa. The Journal of Developing Areas 52, 99–114.

Nangle, T., Yates, A., 2017. Quantifying the effect of the Bank of Japan's equity purchases. Retrieved July 2, 2018.

Ndofor, H.A., Wesley, C., Priem, R.L., 2015. Providing ceos with opportunities to cheat: The effects of complexity-based information asymmetries on financial reporting fraud. Journal of Management 41, 1774–1797.

Ogden, J.P., 1994. A dividend payment effect in stock returns. Financial Review 29, 345–369.

Orphanides, A., 2001. Monetary policy rules based on real-time data. American Economic Review 91, 964–985.

Orphanides, A., van Norden, S., 2002. The unreliability of output-gap estimates in real time. Review of Economics and Statistics 84, 569–583.

Oster, E., 2019. Unobservable selection and coefficient stability: Theory and evidence. Journal of Business & Economic Statistics 37, 187–204.

Pan, K., Zeng, Y., 2017. ETF arbitrage under liquidity mismatch. Available at SSRN 3723406 .

Pasquariello, P., 1999. The fama-macbeth approach revisited. New York University–Stern School of Business Working Paper .

Pearce, W.B., 1974. Trust in interpersonal communication .

Phua, K., Wei, C., Yu, G.Y., 2025. The digital economy and consumer fraud. Available at SSRN 5137239 .

Portes, A., Bach, R.L., 1985. Latin journey: Cuban and Mexican immigrants in the United States. Univ of California Press.

Povel, P., Singh, R., Winton, A., 2007. Booms, busts, and fraud. The Review of Financial Studies 20, 1219–1254.

Powell, J., 2019. Data-dependent monetary policy in an evolving economy. $https://www.federalreserve.gov/newsevents/speech/powell20191008a.htm$, Retrieved 05 Dec 2023.

Putnam, R.D., 2000. Bowling alone: The collapse and revival of american community. Simon Schuster .

Putnam, R.D., 2007. E pluribus unum: Diversity and community in the twenty-first century the 2006 johan skytte prize lecture. Scandinavian Political Studies 30, 137–174.

Rabe, B., Taylor, M.P., 2012. Differences in opportunities? wage, employment and house-price effects on migration. Oxford Bulletin of Economics and Statistics 74, 831–855.

Rigobon, R., Sack, B., 2003. Measuring the reaction of monetary policy to the stock market. The Quarterly Journal of Economics 118, 639–669.

Sellin, P., 2001. Monetary policy and the stock market: theory and empirical evidence. Journal of Economic Surveys 15, 491–541.

Shao, R., Wang, N., 2021. Trust and local bias of individual investors. Journal of Banking & Finance 133, 106273.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica: Journal of the Econometric Society , 1–48.

Sliwka, D., 2007. Trust as a signal of a social norm and the hidden costs of incentive schemes. American Economic Review 97, 999–1012.

Smets, F., 1997. Financial asset prices and monetary policy: theory and evidence .

Stock, J., Yogo, M., 2005. Asymptotic distributions of instrumental variables statistics with many instruments. Identification and Inference for Econometric Models: Essays in honor of Thomas Rothenberg 6, 109–120.

Takahashi, H., Yamada, K., 2021. When the Japanese stock market meets covid-19: Impact of ownership, China and US exposure, and esg channels. International Review of Financial Analysis 74, 101670.

Timmermann, A., Granger, C.W., 2004. Efficient market hypothesis and forecasting. International Journal of Forecasting 20, 15–27.

Toshino, M., 2020. How the BOJ has affected domestic equity markets by its ETF purchasing program .

Wang, T.Y., Winton, A., Yu, X., 2010. Corporate fraud and business conditions: Evidence from ipos. The Journal of Finance 65, 2255–2292.

Wei, C., Zhang, L., 2020. Trust and local bias. Journal of Financial and Quantitative Analysis 55, 2211–2245.

Xie, Y., Gough, M., 2011. Ethnic enclaves and the earnings of immigrants. Demography 48, 1293–1315.

Zak, P.J., Knack, S., 2001. Trust and growth. The Economic Journal 111, 295–321.

Zhang, Y., Ma, F., Zhu, B., 2019. Intraday momentum and stock return predictability: Evidence from China. Economic Modelling 76, 319–329.

Zhou, M., Tian, D., 2010. An integrated model of influential antecedents of online shopping initial trust: Empirical evidence in a low-trust environment. Journal of International Consumer Marketing 22, 147–167.

Zhou, T., 2014. An empirical examination of initial trust in mobile payment. Wireless Personal Communications 77, 1519–1531.

Ziller, C., 2015. Ethnic diversity, economic and cultural contexts, and social trust: Cross-sectional and longitudinal evidence from european regions, 2002–2010. Social Forces 93, 1211–1240.

Ziller, C., Wright, M., Hewstone, M., 2019. Immigration, social trust, and the moderating role of value contexts. Social Science Research 79, 115–126.