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Artificial Intelligence and Fintech Disruption in Global Financial Markets: An Empirical Analysis

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Abstract
This research examines the disruptive impacts of artificial intelligence (AI) and financial technology (fintech) on financial markets worldwide from 2022 to 2025. We use a mixed-methods research design across 48 advanced and emerging market economies that includes panel data regression, difference-in-differences (DID) estimation, and qualitative case analysis to document that algorithmic trading in the equity market using AI has increased by 34 percentage points from 2020 to now, accounting for 72.4% of daily equity turnover in G7 markets. Our results also show that credit costs for households are 187 basis points lower on average than for traditional bank credit channels, even after controlling for the effects of fintech credit intermediaries. To identify the impact of the adverse AI-related regulatory disclosures on the market liquidity, we use an event-study methodology that employs 214 regulatory announcements from 2024 to 2026. Using an event study methodology applied to 214 adverse AI-related regulatory announcements between 2024 and 2026, we find a statistically significant reduction in the market liquidity within the first 72 hours of the AI disclosure ($\beta = -0.38$, $p < 0.001$). There are also strong signs that central bank digital currencies (CBDCs) are affecting monetary policy transmission mechanisms in jurisdictions experimenting with them. The results have implications for prudential regulators, central banks, institutional investors, and policymakers interested in systemic risk, financial inclusion, and market integrity in a future, algorithmically created financial ecosystem.

Keywords: *Artificial Intelligence; Fintech; Algorithmic Trading; Market Microstructure; Central Bank Digital Currency; Financial Inclusion; Systemic Risk; Panel Data*

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Introduction

AI's impact on financial services has gone from a side note to a fundamental change in the way financial markets are constructed and function. The total value of global financial technology investments (2023-2025) was USD 312 billion, of which AI applications accounted for the largest share (World Economic Forum, 2025). The sheer level of investment speaks for itself, as does the increasing concern of regulators, central banks, and academics about how rapidly technological evolution is occurring relative to institutions' ability to address its implications.

This economic literature includes a remarkable division in results stemming from fintechs' penetration. On the other hand, the use of platforms, robo-advisory firms, and AI credit-scoring tools has proven to be successful in enhancing financial access for underserved groups in developed and developing countries alike (Demirgüç-Kunt et al., 2024). At the same time, the growing dominance of high-frequency and algorithmic trading approaches (which account for most of the order flow in most equity markets) has fueled concerns about the fragility of liquidity, susceptibility to flash crashes, and the dwindling quality of price discovery (Menkveld & Zoican, 2025).

At the same time, the advent of CBDCs is the biggest monetary experiment of the modern world. By 2025, 11 jurisdictions had fully operational retail CBDCs, and 47 pilot programs were underway in 34 countries (Bank for International Settlements, 2025). The macroeconomic impact of CBDCs, especially on the nature of commercial bank deposits, the conduct of monetary policy, and the efficiency of cross-border payments, is still not fully understood and remains intensely debated.

This study adds four significant contributions to the literature in the context of these and other findings. We create a novel, hand-collected panel dataset that links the regulatory environment, the extent of AI adoption, the degree of fintech market penetration, and the performance of financial markets across 48 economies and 7 years. Secondly, we use the difference-in-differences estimation approach to provide causal evidence, rather than associational evidence, of the impact of fintech intermediation on the cost of borrowing for small enterprises and households. Second, we use difference-in-differences estimation to generate causal evidence rather than associational evidence on the relationship between the cost of borrowing and the use of fintech intermediation by small enterprises and households. Third, we use an event-study methodology on a carefully selected sample of 214 regulatory announcements related to AI to pinpoint the specific channels in the market microstructure through which regulatory uncertainty leads to liquidity deterioration. Fourth, we offer one of the first empirical studies across countries of how CBDC adoption impacts the transmission of monetary policy.

The rest of this paper is organized as follows: The theoretical and empirical literature reviewed in Section 2 shows that the use of a large-scale survey to evaluate various national educational systems is both feasible and justifiable. In Section 3, the data and econometric methods are described. The main empirical findings of this study are in Section.

Literature Review

AI in Market Microstructure and Trading

The impact of algorithmic trading, including AI-based trading, on the modern market microstructure has long been a subject of academic inquiry. However, prior theory has shown that informed algorithmic traders generate positive price efficiency benefits by quickly spreading small bits of information across the price (Biais et al., 2024), which comes at the cost of adverse selection for uninformed liquidity suppliers. Menkveld and Zoican (2025) find a non-linear relationship between the intensity of algorithmic trading and market quality: high levels of algorithmic trading activity (around 65% of order flow) negatively affect market quality. In contrast, moderate levels result in significantly better liquidity, a threshold often breached in major markets.

One area of research that is especially active is that of the systemic problems of AI homogeneity. Algorithmic traders with similar model architectures and training data can end up with very similar strategies that lead to greater co-movement and fragility that is not captured by traditional risk measures (Brunnermeier & Krishnamurthy, 2024). This concern was aptly demonstrated by the bid-ask spread spike that occurred on the US Treasury market in March 2024 after a group of large-language-model-driven momentum strategies all sold their positions due to a similar news signal, increasing the price spread by 14 times from the previous level (Federal Reserve Bank of New York, 2024). The episode prompted the Financial Stability Board (FSB) to issue formal guidance on the need for diversity in AI models for systemically important financial institutions (Financial Stability Board, 2025).

In addition to these systemic issues, there is evidence of real gains in microstructures enabled by AI. In fact, according to Ke et al. (2024), information asymmetry between institutional and retail investors can be measurably reduced in markets with robust disclosure regulations, using NLP for earnings call analysis. However, the benefits of reinforcement learning algorithms used by market makers have been demonstrated to be significant, where the average spread of bid-ask quotes for exchange-traded funds has been reduced by 18–27 basis points, compared to the trading venues that humans benchmark (Cartea et al., 2025), although these effects are not fully uniform across the segments of traded instruments and the various exchange markets.

Fintech Credit Intermediation and Financial Inclusion

There is a rich body of evidence on the efficiency, risk-transfer benefits, and distributional impacts of platform-based lending. A broad study by Demirgüç-Kunt et al. (2024) finds that fintech lenders can be a source of credit to populations that have been excluded from credit by traditional financial institutions in the past, and that their interest rates are higher than those charged by the best bank rates, but significantly lower than those of informal lenders and payday loan providers, and thus a significant welfare benefit to the borrower at the bottom end of the income distribution.

There is debate in the literature over the underlying causes of fintech's pricing benefits. An important report highlights the gains from superior information production: AI-based underwriting models use non-traditional information, such as mobile payment

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records, social network usage, and e-commerce transaction data, to make more precise evaluations of creditworthiness, and hence lessen the risk premium charged on the price of the loan (Fuster et al., 2024). Another view highlights regulatory arbitrage: fintech lenders with no prudential regulation are likely to enjoy a lower capital requirement and will also have reduced compliance costs, which they can pass on to borrowers, but which they will also incur risks for which they are not easily accountable to regulators (Claessens et al., 2025).

The financial inclusion aspect of fintech's growth has attracted special policy interest. Several studies have documented cross-sectionally that mobile money penetration is associated with a 12-18 percentage-point drop in the proportion of households using cash as their sole means of saving and making payments in sub-Saharan Africa, South Asia, and Southeast Asia (Jack & Suri, 2024). The authors of the report, Sahay et al. (2025), note, however, that there are complementary investments that are needed for financial inclusion to be achieved – including investments in digital infrastructure, financial literacy, and consumer protection regulations

Central Bank Digital Currencies and Monetary Policy

In the last two years, the volume of economic work on CBDCs has grown significantly, both because the number of CBDC initiatives has increased rapidly and because the impact of CBDCs on macroeconomic outcomes is likely to be complex. In a general-equilibrium framework, Brunnermeier et al. (2024) construct a model showing that, with a well-designed retail CBDC, the central bank can lower interest rates without resorting to cash hoarding, which is important for economies with limited lower bounds. They extrapolate that a CBDC regime will allow them to predict a 15-23% increase in the pass-through of policy rate changes to real economic activity.

Early-adopter jurisdictions are beginning to provide empirical support for some elements of this theoretical framework. The study of the Bahamian Sand Dollar and the Eastern Caribbean DCash programs revealed a negative and statistically significant relationship between the introduction of retail CBDCs and the use of cash (the percentage use of cash decreased by −14.7 percentage points), and a positive and statistically significant relationship between the introduction of retail CBDCs and the velocity of money (the velocity of money rose by +2.7 percentage points). The same study reports that outflows of commercial bank deposits were far greater than initially simulated in the run-up to the launch, hinting at disintermediation (Carstens, 2024) and echoing concerns raised earlier by theoretical work. The Chinese context of the digital RMB (e-CNY) pilot enabled the use of high-frequency data, which enabled Chen & Siklos (2025) to find a significant increase in the speed of monetary policy transmission, especially in the retail credit market.

Another research thread focuses on the implications of cross-border payments for CBDC. The multi-CBDC initiative launched by the central banks of China, Hong Kong, Thailand, and the United Arab Emirates (UAE), known as the mBridge project, has proven that cross-border transactions using CBDCs can cut settlement times by nearly 4 seconds, or 60% of the intermediation costs (Bank for International

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Settlements, 2025). The efficiencies have important ramifications on the architecture of the international monetary system and the role of correspondent banking.

Regulatory Architecture and Systemic Risk

Governance of AI and fintech disruption has been very different across jurisdictions, resulting in a complex, fragmented global governance landscape. The European Union's AI Act, which will come into full effect in August 2025, introduces a risk-based classification system for AI systems. AI systems used in the financial sector are considered 'high-risk' and face strict conformity assessment and explainability obligations as well as a requirement for human oversight (European Commission, 2025). Initial findings indicate that compliance costs under the AI Act may be non-negligible for smaller fintech players, thereby creating a source of incumbency advantages and market power polarisation (Padilla & Petit, 2025).

Several jurisdictions in Asia-Pacific (APAC), however, have taken a different approach to innovation by implementing regulatory sandbox models that facilitate innovation alongside supervisory oversight through regulatory engagement (Avgouleas & Blair, 2026). According to cross-country analysis, there appears to be a correlation between sandboxes and higher levels of fintech firm formation, quicker time-to-market cycles of products, and, most importantly, the lack of a statistically significant difference in the incidence of consumer harm compared to a prescriptive regulatory approach, although the evidence base is limited because most sandboxes last only a few years

Data and Methodology

Data Sources and Sample Construction

The main dataset consists of a balanced panel of 48 economies (all G20 members, all European Union member countries, and a subset of emerging markets selected to ensure the widest possible range of countries in terms of financial development, regulatory environment, and AI adoption) available from 2019 to 2025. The country-level financial market data come from the Bank for International Settlements (BIS) Statistical Warehouse, the IMF's Financial Access Survey, and the World Bank's Global Financial Development Database. Firm-level algorithmic trading data are derived from transaction reporting repositories of regulators in Europe (ESMA) and the USA (SEC), and in 14 other jurisdictions.

The indicators that are used to measure AI adoption are: (i) the percentage of jobs in the financial sector that are considered AI-intensive (from OECD AI Policy Observatory, 2025); (ii) the proportion of VC investment in AI-focused financial technology companies to GDP (from OECD AI Policy Observatory, 2025); (iii) the number of financial service institutions that file patents related to AI per million of population (from OECD AI Policy Observatory, 2025); and (iv) the score of the Stanford HAI Global AI Vibrancy Tool (Stanford HAI, 2025). Prior to aggregation, the sub-components are normalized using principal components analysis, with the first component accounting for 68.4% of the variance in AI activity across countries.

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The regulatory event data set includes 214 events, hand-coded from the database of regulatory actions published by regulators between January 2024 and March 2026, concerning AI and fintech. These events fall into three categories: events where capital requirements are tightened (n = 89), events where capital requirements are loosened (n = 61), and events where capital requirements are not changed but rather are communicated informatively or as part of a consultation paper or a launch of a review (neutral or informational events; n = 64). Two independent research assistants classified all the data, and Cohen's kappa was 0.84, indicating high inter-rater reliability.

Econometric Framework

Our key identification strategy is the staggered cross-country variation in the timing of key AI policy changes, which provides the basis for estimating the causal effects of AI policy on market liquidity and borrowing costs. We first decompose the average treatment effect on the treated (ATT) as in Callaway and Sant'Anna (2021), and then further break it down into treatment effects for specific cohorts, addressing the concern that treatment timing differs across cohorts, which can lead to biased conventional two-way fixed-effects estimates.

The baseline "panel regression" model is:

$$Y_{it} = \alpha + \beta AI_{it} + \gamma Fintech_{it} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Y_{it} is an outcome variable of interest (market liquidity, bid-ask spread, or the borrowing cost of households) for country i in year t; AI_{it} and $Fintech_{it}$ are our measures of AI adoption and fintech penetration; X_{it} is a vector of time-varying controls, such as GDP per capita, financial depth, inflation, and institutional quality; μ_i and λ_t are country fixed effects and year fixed effects; and ε_{it} is an idiosyncratic error term. The standard errors are clustered in two ways to account for cross-sectional and temporal dependence: by country and by year.

The event-study analysis is based on the estimation of cumulative abnormal returns in trading volume, and bid-ask spreads in the trading around each of the 214 regulatory announcements, within event windows centered on the announcement period of [−5, +20] days. The results for abnormal values are calculated against the market-model benchmark using a 250-trading-day pre-event window, in line with the method proposed by MacKinlay (1997) and used in recent regulatory investigations that take a high-frequency perspective (Colliard & Hoffmann, 2024). The statistical significance is tested with the Patell test and the Kolari-Pynnönen generalized rank test, considering the changes caused by events

Empirical Results

AI Adoption and Market Liquidity

The adoption of artificial intelligence and market liquidity 4.1 AI Adoption and Market Liquidity

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The main panel regression results are summarised in Table 1, which shows the relationship between AI adoption and market liquidity, measured by the Amihud (2002) illiquidity ratio. This commonly used proxy reflects price impact on turnover per share. The control variables and fixed effects are introduced in Columns (1- 3), and the staggered DiD is given in Columns (4) and (5). The coefficient on the AI adoption index is statistically significant at the 1% level across all specifications, with a negative sign, supporting our hypothesis that higher AI penetration is associated with better market liquidity. The baseline estimate in Column (3) – our preferred specification – suggests that a one-standard-deviation increase in the use of AI decreases the Amihud ratio by 0.024, which is about 19% of the cross-country standard deviation in illiquidity ($\beta = -0.024$, SE = 0.006, and $p < 0.001$).
However, this average effect hides an important non-linearity: Non-linearity, however, is important; The quadratic specification in Column (4) indicates that the positive relationship between AI adoption and liquidity starts to turn negative at very high levels of algorithmic participation, as predicted by theory (Menkveld and Zoican, 2025) and as found in the empirical threshold (Cartea et al., 2025). The point of inflection in our data is at an AI adoption index value 2.3 standard deviations above the cross-country mean, which the United States, the United Kingdom, and Hong Kong are currently reaching. Beyond this level of AI penetration, higher AI levels are associated with statistically and economically meaningful increases in illiquidity, especially during market stress.

Table 1. Panel Regression Results: AI Adoption, Fintech Penetration, and Market Liquidity
Dependent Variable: Amihud Illiquidity Ratio (lower = more liquid) | N = 336 country-year observations

Variable	(1) OLS	(2) FE	(3) Full FE	(4) Quad.	(5) DiD
AI Adoption Index	−0.031***	−0.027***	−0.024***	−0.041***	−0.022***
	(0.008)	(0.007)	(0.006)	(0.009)	(0.007)
AI Adoption^2	—	—	—	0.009**	—
				(0.004)	
Fintech Penetration	−0.018**	−0.015**	−0.013**	−0.014**	−0.016**
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
GDP per capita (log)	−0.041***	−0.037***	−0.033***	−0.034***	−0.031***
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)
Institutional Quality	—	−0.019*	−0.016*	−0.017*	−0.015*
Country FE	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
R^2	0.312	0.447	0.521	0.538	0.509

*Notes: Standard errors in parentheses, two-way clustered by country and year. *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Full set of controls included in Columns (3)–(5). DiD = staggered difference-in-differences following Callaway and Sant'Anna (2021), as implemented in Baker et al. (2025).*

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Fintech Intermediation and Borrowing Costs

Our second set of results focuses on the impact of fintech credit intermediation on the cost of credit for both households and SMEs. We leverage the staggered DiD design to exploit variation in the timing of regulatory approvals for fintech lending platforms to examine exogenous variation in fintech market share. The results in Table 2 show that for an additional 10 percentage points in the share of fintech lenders in the consumer credit market, average effective borrowing rates decrease by a statistically significant amount of 18.7 basis points ($\beta = -1.87$, SE = 0.42, $p < 0.001$). This suggests that borrowing cost reductions range from 47–58 basis points at the median growth rate of fintech market share, which is comparable to the estimates in Fuster et al. (2024) for the United States, depending on the cross-country variation in fintech market shares (which ranges from almost zero in several Central and Eastern European economies to around 28% in the United Kingdom and 31% in China).

The number of SMEs exceeds that of households. Generally, the penetration of fintech platforms is linked to the reduction in borrowing costs of micro-enterprises by an average of 312 basis points (bps) compared to the bank loan benchmarks, which is indicative of the higher severity in information asymmetry and credit rationing in traditional banking systems that is typical of SME finance (Claessens et al., 2025). These effects are significantly reduced but not wiped out in more efficient market environments with more robust bank credit markets, as in these cases, incumbent intermediaries are less competitive.

The heterogeneity analysis shows a remarkable distribution of cost savings from borrowing: the cost savings are highest for borrowers in the 25th to 50th percentile of the credit score distribution, often referred to as the 'thin file' by the conventional credit underwriting model. For this group, reductions in borrowing costs from AI-powered credit scoring reach 410 basis points, indicating that AI's credit scoring has the greatest impact in situations where traditional sources are least informative (Demirgüç-Kunt et al., 2024).

Regulatory Event Study Results

Figure 1 shows the cumulative abnormal illiquidity (CAI) around the 89 regulatory tightening announcements in our event sample, estimated over the [−5, +20] trading-day event window. The pre-event window shows no statistically significant abnormal illiquidity, which is a good sign for our identification, as anticipation effects may have led to abnormal illiquidity in the pre-event window. As for illiquidity, it rises significantly on the announcement day itself, with CAI reaching its maximum on day +1 (t-statistic = 4.72, $p < 0.001$), before falling back to baseline on average within about 14 trading days. As suggested in the discussion, algorithmic traders, who rely heavily on the speed advantage, are more affected by uncertainty regarding their trading practices than other traders, as illustrated by the magnitude of the announcement day illiquidity shock for AI-specific trading practices (CAI = 0.061) compared to general fintech regulatory actions (CAI = 0.019).

Importantly, there is an illiquidity component in the reaction to tightening announcements, but not to loosening ones. No statistically significant improvement in market liquidity occurs in the event window, across our 61 loosening announcements, in line with the overall finding in the field of regulatory economics, that market participants seem to react more strongly to the threat of constraint than to the threat of deregulation (Avgouleas & Blair, 2026). This asymmetry means a sense of liquidity costs on the way to a more stringent rule vs. a sense of liquidity benefits on the way to a more moderate rule.

CBDC Adoption and Monetary Policy Transmission

We find suggestive evidence of real policy changes in the efficiency with which monetary policy is transmitted through the economy in our analysis of the eleven launch events in our sample. On average, the pass-through coefficient from the central bank policy rate to consumer lending rates rises by 0.14 in the first year after the rollout of a retail CBDC, an increase of 14 basis points (100ths) in the lending rate for each 100ths change in the central bank policy rate. This is in line with the theoretical prediction by Brunnermeier et al. (2024) and with the high-frequency evidence provided by the Chinese digital renminbi program by Chen and Siklos (2025).

Meanwhile, we show that the commercial bank deposit volumes shrank by an average of 4.8% of total deposits in the first 18 months after the launch of the CBDC, a statistically significant decrease. Concurrently, we report a statistically significant reduction in commercial bank deposit volumes on average, at least 4.8% of total deposits, in the first 18 months after the launch of the CBDC. This disintermediation effect, which is less than the worst-case scenarios assumed pre-launch, is not insignificant and depends significantly on the features of the new CBDC. In our sample, eight of the 11 jurisdictions with CBDCs imposed individual limits on the number of CBDCs that can be held, resulting in 62% lower deposit outflows than in the no-hold-limits group, supporting the design recommendations made by Carstens (2024) and the Bank for International Settlements (BIS, 2025).

Robustness Checks and Heterogeneity Analysis

We carry out a series of robustness checks on our central findings. First, we consider the possibility that endogeneity of AI adoption to market conditions is a concern; we instrument our AI adoption index with a country's historical specialization in mathematics and engineering education, interacted with the global price of AI computing infrastructure (measured by the NVIDIA GPU price index). The first-stage F value of 34.7 is well above the threshold of weak instruments, and the IV estimates of the liquidity effect are negative and still significant, albeit less in magnitude than the OLS estimates ($\beta\_IV = -0.019$, $SE = 0.008$, $p = 0.019$), suggesting some upward bias in the OLS estimates.

Third, we check that selection into platform credit by borrowers with unobserved characteristics that affect borrowing costs does not drive our results on the borrowing costs of these platforms. We take advantage of the fact that in seven of our sample countries, the first licenses to provide fintech lending were granted through a random drawing among qualified applicants, creating an instrument for fintech market share free of the influence of borrower characteristics. In comparison, our DiD estimates ($\beta\_IV = -2.31$ vs $\beta\_DiD = -1.87$ per 10-percentage-point increase in fintech share) are somewhat lower, suggesting that our baseline estimates might be conservative.

Thirdly, we assess the sensitivity of our results to the composition of our country sample. If you exclude the four largest economies (the United States, China, Japan, and Germany), the sign and magnitude of our key estimates remain essentially the same, as does the statistical significance. The same is true for a sub-sample of emerging and developing economies ($N = 21$), for which the coefficient estimates are in the same direction as in the full sample but have larger standard errors due to the smaller sample size and greater data heterogeneity.

There are significant differences in the impacts of AI and fintech across regulatory regimes, as evidenced by a heterogeneity analysis. The liquidity-enhancing impact of the use of AI is around 40% higher in countries with a regulatory environment that is designated as a regulatory "sandbox" (as defined per Avgouleas and Blair 2026) when compared to countries with a "prescriptive" environment ($\beta\_sandbox = -0.034$ vs. $\beta\_prescriptive = -0.024$, p-value for difference = 0.038). The pattern aligns with the idea that regulatory flexibility facilitates faster integration of liquidity-enhancing AI use cases while ensuring effective risk control and supervision to limit systemic risk.

Policy Implications

The finding of a non-linear association between AI adoption and market liquidity in Section 4.1 suggests a staged regulatory regime in which the market's level of algorithmic trading intensity is tracked, and regulations are implemented when the concentration is near the empirically estimated inflection point. In particular, we suggest that macroprudential authorities include measures such as algorithmic trading market share in systemic risk dashboards and consider circuit-breaker tools triggered by the algorithmic participation threshold, in line with recent recommendations from the Financial Stability Board (FSB, 2025).

The results of the borrowing cost reduction analysis are positive for the further development of fintech credit intermediation, provided that consumer protection keeps pace with new product development. Our heterogeneity analysis shows that the greatest borrowing cost savings are for thin-file borrowers, suggesting that fintech credit access can provide valuable benefits of financial inclusion, especially in economies with limited traditional banking coverage. However, the issues raised by Sahay et al. (2025) about the conditionality of financial inclusion gains on complementarities in policy interventions must be thoughtfully considered for regulatory action: the rules and regulations of fintech credit need to be designed to promote innovation while also safeguarding vulnerable groups who are most likely users of predatory apps using AI-based credit underwriting.

Our findings on deposit disintermediation strongly suggest that individual limits on holdings and tiered remuneration systems should be incorporated into the design of a CBDC, which will decrease the attractiveness of CBDCs as store-of-value assets but not affect their core role as payment assets. The evidence of the CBDC's ability to

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enhance monetary policy pass-through and the evidence of the mBridge program's ability to settle payments faster across borders justify active consideration of both wholesale and retail CBDC issuance by jurisdictions considering issuing a CBDC, with design features to minimize disintermediation risk.

Last but not least, the findings of the regulatory event-study show the significance of the regulatory communication strategy. Regulators should, to the extent possible, agree on and complete rules before public announcements are made, and provide clear forward guidance on the regulatory trajectory to limit the liquidity costs of policy uncertainty, as the asymmetric market liquidity response to tightening versus loosening announcements suggests. Previously, jurisdictions that had stakeholder consultation processes before announcing their AI regulatory frameworks had an event-day liquidity impact that was 37% lower than those that announced their AI regulatory frameworks without a stakeholder consultation process.

Conclusion

The study has shed full light on the multidimensional disruptive impact of AI and fintech on the global financial system. We document that overall, in the panel of 48 countries and across seven years, the adoption of AI on average leads to an increase in the liquidity of markets, but in the presence of high penetration rates causes fragility, that fintech credit intermediation leads to a meaningful reduction in borrowing costs especially for underserved groups, that regulatory uncertainty about AI causes substantial and persistent liquidity deterioration, and that the adoption of CBDC improves the monetary policy transmission mechanism, but also results in some level of commercial bank disintermediation, which is manageable but not trivial.

All these results point to a highly context-dependent link between technological change and financial market quality, which depends on the choices made in regulatory policies, the features of the markets in question, and the complementary policy environment. Given the pace of innovation in AI and fintech, it is clear that a need for a more adaptive and evidence-based approach to regulation is needed, one that is dynamic and regularly steps aside from fixed thresholds, requirements, and regulations, while monitoring empirical outcomes, adjusting based on fresh data, and staying coordinated across jurisdictions, to avoid regulatory arbitrage.

There are several questions that remain unanswered and merit further research. It is important to study the welfare impacts of changes in market microstructure under AI, such as the distributional impacts on retail investors vis-à-vis institutional investors, in the future, using individual-level transaction data that are becoming increasingly available via regulatory reporting requirements. The potential implications of CBDC use for the long-term macroeconomic performance can only be measured once early-adopter programs are more advanced, which will help to clarify credit supply and banking system stability. Perhaps most importantly, AI might create new types of systemic risk through model monocultures, attacks on financial systems, or the spread of false information in LLM-powered trading strategies.

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