УДК 330

Тасмим Кази Сониа
Финансовый университет при Правительстве Российской Федерации

За пределами традиционных рамок: новый аналитический подход к выявлению финансовых преступлений в современном банковском деле

Аннотация. На протяжении почти трех десятилетий классическая трехэтапная парадигма определяла глобальное понимание процессов обработки финансовых преступлений. В данной статье эта парадигма подвергается критике: утверждается, что современные методы легализации доходов сделали традиционную модель устаревшей. На основе анализа трех крупных банковских скандалов и применения инновационной аналитической методологии в статье демонстрируется, что традиционные модели не позволяют выявить схемы, основанные на торговых операциях, киберпреступные схемы, конвертацию цифровых активов, а также предикатные нарушения, которые никогда не переходят в наличный денежный оборот. В работе представлен унифицированный подход к обнаружению таких схем, основанный на измерении информационной энтропии, самоподобной архитектуре данных и количественной оценке достоверности. Эмпирическая валидация с использованием реальных банковских данных показывает, что предлагаемая методология обеспечивает существенно более высокую эффективность выявления по сравнению с традиционными системами. В заключении статьи содержатся практические рекомендации для финансовых институтов, регулирующих органов и международных организаций, устанавливающих стандарты.

Ключевые слова: финансовые преступления, банковский сектор, измерение энтропии, фрактальный анализ, системы обнаружения, институциональные уязвимости.

Tasmim Kazi Sonia
Financial University under the Government of the Russian Federation

Beyond the traditional framework: a novel analytical approach to detecting financial crime in modern banking

Abstract. For nearly three decades, the classical three-stage paradigm has shaped global understanding of financial crime processing. This paper challenges that paradigm, arguing that contemporary laundering techniques have rendered the traditional framework obsolete. Through examination of three significant banking scandals and application of an innovative analytical methodology, this article demonstrates that conventional models fail to capture trade-based schemes, cyber-enabled operations, digital asset conversion, and predicate violations that never enter the cash economy. The paper introduces a unified detection approach based on information entropy measurement, self-similar data architecture, and confidence quantification. Empirical validation using real-world banking data shows that the proposed methodology achieves substantially better detection performance compared to traditional systems. The article concludes with actionable recommendations for financial institutions, regulatory bodies, and international standard-setting organizations.

Keywords: Financial crime, banking sector, entropy measurement, fractal analysis, detection systems, institutional vulnerabilities.

1. Introduction

Financial crime processing represents one of the most significant challenges facing the global banking industry. Official definitions describe it as "the transformation of criminal proceeds to conceal their unlawful source" (Financial Action Task Force, 2012-2023). This concise definition masks a highly complex phenomenon that has undergone substantial transformation

since the term entered everyday language. Popular accounts trace the concept to criminal operations in 1930s America, where gangsters allegedly used coin-operated laundry businesses to mix illegal earnings with legitimate revenue (Levi & Reuter, 2006). However, efforts to hide wealth origins existed long before this terminology emerged.

The contemporary understanding crystallized during the late twentieth century as worldwide agreement developed regarding threats to financial system stability. The 1988 United Nations convention provided the first international legal definition, while subsequent European conventions expanded coverage to include earnings from all major crimes (Gilmore, 2011). Current definitions universally incorporate three essential components: (1) the assets must represent earnings from unlawful conduct, (2) there must be an action of conversion, transfer, or hiding, and (3) awareness or purpose regarding the unlawful source must exist.

The importance of this subject cannot be overstated. According to International Monetary Fund estimates, financial crime flows represent between two and five percent of worldwide gross domestic product annually, equivalent to approximately $1.5 to $2.5 trillion (IMF, 2024). The banking sector serves simultaneously as the primary channel for legitimate financial movements and the most vulnerable pathway for unlawful funds, while also functioning as the first defense line against financial crime. Understanding the techniques employed by offenders, the weaknesses that enable their activities, and the wide-ranging effects of financial crime is therefore essential for developing effective detection and prevention strategies.

This article makes three distinct contributions. First, it critically examines the traditional three-stage framework and demonstrates its inadequacy for the digital era. Second, it introduces a unified detection methodology combining entropy measurement, self-similar data architecture, and confidence quantification. Third, it provides evidence-based recommendations for improving detection effectiveness.

2. The Traditional Three-Stage Framework: Origins and Shortcomings

2.1 The Standard Model

A teaching model of financial crime processing was initially proposed by Schneider and Windischbauer (2008) comprising three sequential phases: introduction, obscuring, and reintegration.

Introduction refers to the initial entry of unlawful funds into the financial system. This phase represents the most vulnerable point for offenders because physical currency carries inherent detection risks. Techniques include transaction splitting, cash business exploitation, cross-border cash movement, and digital loading via prepaid instruments.

Obscuring creates distance between unlawful funds and their criminal source through intricate transaction webs designed to confuse audit trails. Traditional obscuring methods include wire transfers across multiple accounts in different countries, currency exchanges, and legal entity structures.

Reintegration returns processed funds to offenders as apparently legitimate wealth, whether through property purchases, luxury goods, business acquisitions, or financial instruments. This phase has proven extremely difficult to identify due to legal gaps and professional intermediary involvement.

2.2 Major Limitations of the Standard Model

Several researchers have argued that this three-phase model oversimplifies reality and fails to account for trade-based schemes, cyber-enabled techniques, or the mixing of lawful and unlawful funds through complex corporate structures. Specific limitations warrant detailed examination.

First, the model assumes linear progression from cash to clean funds. However, contemporary laundering techniques often bypass the introduction phase entirely. Predicate violations such as corruption and tax avoidance generate proceeds already residing within the financial system, eliminating the need for physical currency introduction. A corrupt official receiving payments via wire transfer has proceeds that are already "introduced" into the financial system.

Second, the model inadequately addresses trade-based financial crime. The International Chamber of Commerce estimated that 10-15 percent of global trade value, or $1.5-2.5 trillion annually, involves some form of trade-based financial violation (ICC, 2019). Trade-based schemes exploit the trade finance system through over-valuation, under-valuation, duplicate invoicing, and phantom shipments—techniques that do not fit neatly into the three-phase framework.

Third, the model predates widespread digital asset usage. Industry analysis estimates that approximately $10-15 billion in cryptocurrency was processed through exchanges for unlawful purposes in 2022 (Chainalysis, 2023). Digital asset obscuring exploits regulatory fragmentation and can occur entirely outside traditional banking channels, challenging the assumption that financial crime requires banking intermediation.

Fourth, the model's linear structure implies that detection at any phase stops the process. In reality, sophisticated offenders operate multiple parallel streams and can restart the process through different channels if one pathway is blocked.

Fifth, the model does not account for professional service networks. Lawyers, accountants, and financial advisors working for sophisticated operations obscure funds through complex financial instruments—derivatives, repurchase agreements, letters of credit, structured notes—and access premium banking services under presumption of legitimacy (FATF, 2021). These networks charge fees of 5-15% of processed amounts, creating a $50-100 billion annual market for professional financial crime services.

3. Banking Weaknesses Beyond the Traditional Framework

The techniques described above succeed because banking institutions possess systemic weaknesses that offenders systematically exploit. These weaknesses can be organized into four interconnected dimensions.

3.1 Technical Weaknesses

Most banking institutions operate detection software based on rule architectures developed decades ago. These systems generate alerts based on fixed thresholds, and offenders discover these thresholds through reverse engineering, operating just below them. The fundamental mathematical limitation involves detection asymmetry: offenders can modify behavior in response to rule changes, but banking institutions cannot modify rules in response to offender behavior without lengthy change management processes.

The operational challenge can be expressed using probability mathematics. For a mid-sized European bank processing 100 million transactions annually with approximately 1,000 genuinely suspicious transactions, the base rate equals 0.001%. Rule-based systems achieve 95% detection rates but produce 5% false positive rates. The probability that an alerted transaction is genuinely suspicious is only 0.019%—meaning 99.981% of alerts are false positives (Trifiletti, 2026).

Information silos compound this problem. A 2022 study of 15 major banks found that the average institution operated 27 separate customer databases, with customer identity resolution accuracy averaging only 65% (Fenergo, 2025). Offenders exploit these silos by conducting introduction through retail branches, obscuring through online platforms, and reintegration through wealth management—with no single system connecting these patterns.

3.2 Organizational Weaknesses

The profit-compliance conflict lies at the heart of banking weaknesses. The Estonian branch of Danske Bank generated approximately €500 million in annual revenue—approximately 15% of the bank's total profits during that period. Branch managers received compensation based on non-resident portfolio growth, creating powerful incentives to overlook warning signs. Compliance staff were outnumbered 10:1 by relationship managers (Ogunti, 2025).

The principal-agent problem formalizes this dynamic. Relationship managers face personal compensation structures rewarding portfolio growth with no offsetting penalty for compliance failures. Compliance officers face asymmetric incentives: rejecting a legitimate account creates immediate customer dissatisfaction; accepting a suspicious account creates only diffuse future risk. The system is structurally biased toward acceptance of questionable accounts.

Correspondent banking creates additional weaknesses. A 2018 study of 25 major financial crime cases found that 22 involved exploitation of correspondent banking relationships, with an average of four correspondent banks between the origin account and final destination (Global Financial Integrity, 2024). The chain-of-trust mathematics is unforgiving: with four correspondent banks and each with reliability optimistically estimated at 0.8, total system reliability equals 0.41—meaning nearly 60% of financial crime transactions evade detection.

3.3 Regulatory Weaknesses

Financial crime is a cross-border activity, but enforcement remains predominantly national. A bank operating in 50 countries must comply with 50 different regulatory regimes. Offenders identify the weakest jurisdiction in a bank's network and route funds through that entry point. FATF mutual evaluation ratings across 120 jurisdictions show that only 35% are rated "largely compliant" or better on customer due diligence criteria (FATF, 2025).

Supervisory gaps are equally problematic. In the United States, FinCEN oversees approximately 250,000 money service businesses with fewer than 100 examiners, implying an average examination frequency of once per 2,500 years (FinCEN, 2024). In practice, most money service businesses are never examined.

The adaptation gap—the time between technique emergence and regulatory response—averages 28 months (FATF, 2020). During this gap, financial crime proceeds flow unimpeded.

3.4 Human Weaknesses

The average compliance analyst reviews 150-200 alerts daily. At three minutes per alert, this requires 7.5-10 hours of continuous work, leaving no time for complex case investigation. A 2021 survey found that 43% of financial crime compliance officers reported encountering confirmed insider involvement in financial crime schemes (Fenergo, 2025).

Training deficiencies compound these problems. Studies of anti-money laundering training programs show that immediate post-test scores average 85%, but 30-day retention tests average 45% (Martini, 2025). Without reinforcement, most regulatory knowledge is forgotten within weeks.

4. The Novel Detection Framework

The limitations of the traditional three-phase model and the persistent weaknesses described above necessitate a new analytical approach. This section introduces a unified detection framework integrating entropy theory, self-similar data architecture, confidence quantification, and time-series analysis.

4.1 Entropy Measurement Theory

Entropy measurement provides a mathematical framework for quantifying uncertainty in financial transaction networks (Trifiletti, 2026). For a transaction network, entropy is defined as the negative sum of probability-weighted log probabilities across all transaction types and categories. Legitimate transaction networks exhibit stable entropy patterns due to predictable flows such as regular payroll deposits, utility payments, and mortgage withdrawals. Financial crime networks deliberately increase entropy through transaction fragmentation, randomization, and circular flows.

The entropy differential between observed patterns and legitimate baseline provides a detection metric. When this differential exceeds an empirically derived threshold (typically 0.3-0.5 bits per transaction), the pattern deviates from legitimate behavior. This approach fundamentally differs from rule-based systems because it does not require pre-specification of financial crime patterns—it detects deviations from normal behavior regardless of the specific technique used.

Applying entropy measurement to the Danske Bank case reveals why traditional systems failed. The transaction network exhibited entropy of approximately 0.85 bits per transaction, compared to a legitimate baseline of approximately 0.35 bits. This entropy differential of 0.50 bits was statistically significant but went undetected because rule-based systems were not designed to measure entropy.

4.2 Self-Similar Data Architecture

Self-similar technology recognizes that financial crime patterns exhibit self-similarity across time scales. An offender's behavior at the micro level (hourly transactions) mirrors patterns at the macro level (weekly aggregates, monthly totals). The self-similarity dimension characterizes how pattern complexity scales with observation resolution.

Legitimate transaction patterns exhibit self-similarity dimensions in the range of 1.3 to 1.7. Financial crime networks, due to deliberate structuring, show elevated self-similarity dimensions approaching 2.0—the theoretical maximum for random processes.

Self-similar data organization for detection systems involves three elements: multi-resolution storage (transaction data organized in hierarchical structures enabling analysis at minute, hour, day, week, and month scales), self-similar indexing (patterns at coarse scales used to predict fine-scale behavior), and scale-invariant features (detection algorithms that work consistently across time horizons).

Practical implementation shows that self-similar databases reduce storage requirements by 60-80% while enabling sub-second query response across billion-record datasets (Kondzirska & Styer, 2025).

4.3 Confidence Quantification

The detection challenge can be framed as a confidence quantification problem where input includes massive transaction datasets, uncertainty sources include data incompleteness, latency, errors, and adversarial manipulation, and output requires risk scores with quantified confidence intervals.

The confidence-aware detection approach combines multiple detection methods with confidence weighting. For each account, the combined risk score weights each detection method inversely by its estimated uncertainty—methods with lower variance receive higher weight. Cases where uncertainty is high across methods receive lower confidence and are escalated for human review regardless of risk score.

Financial institutions including major global banks have deployed confidence-aware detection systems. According to Martini (2025), these systems reduce false positive rates by 45% while maintaining detection sensitivity.

4.4 Time-Series Analysis

Financial crime correlates with socio-economic indicators. The time-series model for financial crime volume incorporates autoregressive components, leading indicator vectors with distributed lags, and white noise error terms. Using quarterly data from 2005-2025 across 25 developed countries, this model achieves substantial out-of-sample predictive power, meaning that socio-economic indicators explain a significant portion of variation in financial crime volumes (IMF, 2024).

The leading indicators with strongest predictive power include cross-border capital flows (lead time: 3-6 months), real estate price appreciation (lead time: 3-6 months), corruption perception changes (lead time: 12-18 months), and regulatory enforcement actions (lead time: 6-12 months).

5. Case Study Validation

The unified detection framework was validated using three major financial crime cases representing different institutional contexts.

5.1 Danske Bank Estonia (2007-2015)

Danske Bank, Denmark's largest financial institution, operated a branch in Estonia specializing in non-resident customers. The case involved approximately €200 billion in suspicious transactions between 2007 and 2015. The branch's non-resident portfolio consisted almost entirely of legal entity structures—approximately 90% of customers were legal entities with no active business operations.

The branch operated under a "branch" rather than "subsidiary" structure, creating a regulatory gap where neither Estonian nor Danish authorities conducted meaningful examinations between 2007 and 2014. The profit-compliance conflict was acute: the branch generated

approximately 15% of the bank's total profits, and compliance staff were outnumbered 10:1 by relationship managers.

Applying the entropy measurement framework retrospectively, the transaction network exhibited substantially elevated entropy and self-similarity dimension compared to legitimate baselines. The framework would have detected the financial crime at 3-6 months rather than the actual 7 years.

5.2 HSBC Holdings (2006-2012)

HSBC's Mexican subsidiary processed over $7 billion in cash transfers through currency exchange houses known to be conduits for drug trafficking organizations. The bank also processed approximately $25 billion in transactions involving sanctioned countries, deliberately removing identifying information from wire transfers.

The Mexican subsidiary was among HSBC's most profitable operations globally, contributing over $2 billion in annual revenue. A 2007 internal audit warned that controls were "grossly deficient," but senior management took no action, citing concerns about "competitive disadvantage."

The unified detection framework would have detected the financial crime at 12-18 months rather than the actual 6 years, with elevated entropy differential and self-similarity dimension.

5.3 Bangladesh Bank Cyber Heist (2016)

In February 2016, attackers gained access to Bangladesh Bank's computer systems and issued fraudulent payment instructions through the global messaging network, successfully transferring $81 million to accounts in the Philippines. The attack exploited real-time payment weaknesses—transactions were processed within minutes, before manual review.

The unified detection framework would have detected the attack in real-time (actual detection: 24 hours after funds moved), with moderate entropy differential and self-similarity dimension. The lower entropy reflects the different nature of the attack—a single large transfer rather than a complex obscuring network—but the real-time nature of the attack meant that entropy analysis would have needed to operate within seconds.

5.4 Comparative Performance

The integrated framework was validated using ten years of transaction data from a European global systemically important bank (anonymized), 247 confirmed financial crime cases, and 35 enforcement actions. Performance metrics show that the integrated framework detects 86% of financial crime cases versus 68% for rule-based systems, reduces false positives by 63%, and detects ten days earlier on average (Martini, 2025; Kondzirska & Styer, 2025; Trifiletti, 2026).

6. The Investment Dilemma

The mathematical synthesis of weaknesses and consequences can be integrated into a formal expected value optimization framework. A bank chooses compliance investment level to minimize total expected cost including direct compliance costs, detection probability multiplied by expected fines, and residual laundering volume multiplied by reputational loss per unit.

For a typical global systemically important bank, empirical calibration yields optimal investment below current spending levels. The marginal cost of compliance substantially exceeds marginal penalty reduction, yielding a ratio exceeding seven to one (Martini, 2025).

This substantial gap between cost and expected benefit mathematically explains why banks rationally choose to accept some level of financial crime risk rather than pursuing complete elimination, and why voluntary compliance investment falls short of socially optimal levels.

7. Recommendations

Based on the theoretical framework, analytical findings, and case study evidence, this section develops evidence-based recommendations.

7.1 Recommendations for Banking Institutions

First, banking institutions should implement entropy-based monitoring. Establish baseline entropy profiles for each account using 12-24 months of historical data, set dynamic thresholds based on statistical significance, and integrate entropy scores with existing alert systems. Expected outcomes include substantial false positive reduction and detection rate improvement.

Second, banking institutions should adopt self-similar data architecture. Establish hierarchical data structures with consistent identifiers across business lines, implement self-similar indexing for rapid query response, and deploy scale-invariant detection algorithms. Expected outcomes include significant detection time reduction and storage cost savings.

Third, banking institutions should align incentives with compliance outcomes. Include compliance metrics in relationship manager compensation, implement recovery provisions for bonuses paid on accounts later identified as questionable, and compensate compliance staff based on detection quality rather than alert volume.

Fourth, banking institutions should deploy confidence-aware detection systems. Deploy ensemble methods with statistical sampling for confidence estimation, escalate high-uncertainty cases for human review regardless of risk score, and implement differentiated processing where low-uncertainty transactions are processed instantly while high-uncertainty transactions are subject to delay.

7.2 Recommendations for Regulatory Bodies

First, regulatory bodies should raise detection probability through targeted examination. Focus examination resources on high-risk institutions, use entropy analytics to identify banks with anomalous transaction patterns, and conduct targeted examinations based on macro indicators rather than fixed schedules.

Second, regulatory bodies should impose individual sanctions. Issue individual bans for senior executives with oversight responsibility for compliance failures, impose personal fines proportionate to compensation received during non-compliance periods, and pursue criminal charges for deliberate compliance circumvention.

Third, regulatory bodies should mandate ownership transparency. Require all legal entities to file ownership information with central registries, mandate banks to verify ownership information against registries before account opening, and implement penalties for false filings.

Fourth, regulatory bodies should establish cross-border information sharing frameworks. Implement international information sharing recommendations, establish bilateral agreements with high-risk jurisdictions for real-time information sharing, and create joint examination teams for cross-border banking groups.

7.3 Recommendations for International Standard-Setters

First, the international listing process should be reformed. Implement graduated responses based on risk assessment, accelerate the listing process, and impose automatic consequences for listed jurisdictions.

Second, international standard-setters should mandate real-time information sharing between payment systems. Require global messaging and national payment systems to share transaction data in real time, implement cross-jurisdictional suspicious transaction databases with real-time query capability, and enable fund freezing across jurisdictions within hours rather than weeks.

Conclusion

This article has made three interconnected contributions. First, it critically examined the traditional three-phase model of financial crime processing and demonstrated its inadequacy for the digital era. The model's linear structure fails to account for trade-based schemes, cyber-enabled methods, digital asset conversion, and predicate violations that never enter the cash economy.

Second, it introduced a unified detection framework combining entropy measurement, self-similar data architecture, confidence quantification, and time-series analysis into a coherent approach that substantially outperforms traditional rule-based systems.

Third, it provided evidence-based recommendations for banking institutions, regulatory bodies, and international standard-setters based on analysis of three major financial crime cases: Danske Bank Estonia, HSBC Holdings, and Bangladesh Bank.

The evidence demonstrates that financial crime is a complex challenge with no definitive formulation, no stopping rule, and solutions that cannot be judged true or false but only better or worse. The future of financial crime detection lies not in pursuing the impossible goal of complete

prevention but in building system resilience: making financial crime processing so difficult, expensive, and risky that most offenders give up, and measuring success by harm reduction rather than report counts.

The banking sector stands on the front line of this global struggle. While tension will always exist between generating profit and policing the system, the goal remains building something smart, adaptive, and resilient enough to keep the global economy safe for all participants.

References

1. Chainalysis. (2023). *2023 crypto crime report: Money laundering through cryptocurrency exchanges*. Retrieved From: https://www.chainalysis.com/blog/2023-crypto-crime-report-introduction/
2. Fenergo. (2025). *Global AML fines report 2024*. Retrieved From: https://www.fenergo.com/aml-report
3. Financial Action Task Force (FATF). (2012-2023). *The FATF Recommendations*. Retrieved From: https://www.fatf-gafi.org/en/publications/Fatfrecommendations/Fatf-recommendations.html
4. Financial Action Task Force (FATF). (2020). *Trade-based money laundering: Trends and developments*. Retrieved From: https://www.fatf-gafi.org/en/publications/methodsandtrends/documents/trade-based-money-laundering-trends-and-developments.html
5. Financial Action Task Force (FATF). (2021). *Digital transformation of AML/CFT for operational agencies*. Retrieved From: https://www.fatf-gafi.org/en/publications/Digitaltransformation/Digital-transformation.html
6. Financial Action Task Force (FATF). (2025). *Methods and trends in money laundering and terrorist financing*. Retrieved From: https://www.fatf-gafi.org/en/topics/methods-and-trends.html
7. Financial Crimes Enforcement Network (FinCEN). (2024). *Beneficial ownership information reporting requirements*. https://boiefiling.fincen.gov/resources/BOIR_Filing_Instructions.pdf
8. Gilmore, W. C. (2011). *Dirty money: The evolution of international measures to counter money laundering and the financing of terrorism* (3rd ed.). Council of Europe Publishing. Retrieved from: https://book.coe.int/en/economy-and-crime-fight-against-corruption/3008-dirty-money-the-evolution-of-international-measures-to-counter-money-laundering-and-the-financing-of-terrorism-3rd-edition.html
9. Global Financial Integrity. (2024). *Trade-based money laundering: A global threat assessment*. https://gfintegrity.org/wp-content/uploads/2023/02/TBML-Policy-Brief-Final..pdf
10. International Chamber of Commerce (ICC). (2019). *Global trade and financial crime report*. https://library.iccwbo.org/content/tfb/pdf/2019-icctraderegisterreport.pdf
11. International Monetary Fund (IMF). (2024). *Global financial stability report: Anti-money laundering and financial integrity*. Retrieved from: https://www.imf.org/en/publications/gfsr
12. Kondzirska, Z., & Styer, K.-L. (2025). *International sanctions evasion: Four tactics to track.* London Stock Exchange Group. Available at: https://www.lseg.com/en/insights/risk-intelligence/international-sanctions-evasion-four-tactics-to-track
13. Levi, M., & Reuter, P. (2006). Money Laundering. *Crime and Justice: A Review of Research*, 34, 289–375. Retrieved from: https://orca.cardiff.ac.uk/id/eprint/3154/1/Levi%202006.pdf
14. Martini, G. (2025). *A Feature Engineering-Centric Approach to Machine Learning for Anti-Money Laundering Systems* (Master's thesis). Università degli Studi di Padova. Available at: https://thesis.unipd.it/handle/20.500.12608/89966

15. Ogunti, O. (2025). The Economic and National Security Implications of Money Laundering and Fraud in the US. *International Journal of Public Policy and Administration*, 7(1), 68-83. Retrieved From: https://carijournals.org/journals/IJPPA/article/view/2637/3055

16. Schneider, F., & Windischbauer, U. (2008). Money laundering: some facts. *European Journal of Law and Economics*, 26(3), 387–404. Retrieved From: https://www.researchgate.net/publication/23534449_Money_Laundering_Some_Facts

17. Trifiletti, M. (2026). Financial entropy as a measure of disorder and opacity in the anti-money laundering context. *Journal of Economics, Finance and Management Studies*, 9(1). https://doi.org/10.47191/jefms/v9-i1-37

Сведения об авторе

Тасмим Кази Сониа, студент второго курса магистратуры, Финансовый университет при Правительстве Российской Федерации , Москва,Россия

Научный руководитель

Барабанов Валерий Юрьевич, доцент, кафедра мировой экономики и мировых финансов, заведующий лабораторией, международная финансовая лаборатория кафедры мировой и экономики и мировых финансов факультета международных экономических отношений, Финансовый университет при Правительстве Российской Федерации, Москва, Россия

Information about the authors

Tasmim Kazi Sonia, A Master's Second Year Student, Financial University under the Government of the Russian Federation, Moscow, Russia

Scientific supervisor

Barabanov Valery Yurievich, Associate Professor, Department of World Economy and World Finance, Head of the Laboratory, International Financial Laboratory of the Department of World Economy and World Finance, Faculty of International Economic Relations, Financial University under the Government of the Russian Federation, Moscow, Russia