ERASMUS UNIVERSITY ROTTERDAM
Rotterdam School of Management

Master Thesis

FINANCE & INVESTMENTS

The Diversification Dilemma: a Study of Diversification and Asset Similarity Effects on CIS Banking Risk & Performance

AUTHOR
Samir SABITLI
557678ss

COACH
Wolf WAGNER, PROF.DR

CO-READER
Michele PELLI, PHD.

Keywords: Diversification, Banking Performance, Income Diversity, CIS, Asset Similarity
JEL Codes: C58, C01

Date Current Version: June 12, 2025

Acknowledgment

I would like to acknowledge the indispensable contributions of Afron Smith, Jonathan Rietveld, and Dazhong Wu in the creation of the `pydynpd` module for Python, enabling our analysis to take shape. The library can be found on the pydynpd GitHub Page.

Abstract

This paper investigates the effects of income and asset diversification on the performance and risk profiles of banks in the CIS using individual bank-level data spanning 2010 to 2024. We consider robust panel regression methods and incorporate the Generalized Method of Moments (GMM) framework with dynamic panels. Past research and theories suggest that diversification affects banking performance through intermediate mechanisms, such as motivating economic agents to have certain behaviours or through how banking behaviour is shaped by market power. We also consider more conceptual mechanisms, such as systemic asset similarities across banks as a consequence of diversification. As highlighted by the CIS-specific context introduced by Sharipova (2015) and CIS-focused empirical studies such as Djalilov et al. (2016), it is crucial to account for macroeconomic, bank-level, regulatory and/or governance, and market power measures to obtain more robust and relevant results. Ultimately, our results indicate that income or asset diversity lacks a significant effect on risk or performance. This result is observed when splitting banks by ownership or assessing the asset similarity channel of effect. Interestingly, CIS managers' incentives appear to prevent agency conflict, rather than create it, disputing Acharya (2006). This is seen from the significance of the central banking authority, external macroeconomic shocks, and persistence in influencing performance. Interestingly, these results could indicate that CIS banks approach diversification and risk differently than their Western counterparts. With some evidence of developmental difference (Sharipova, 2015), we recommend further investigation into the factors driving managerial decision-making across the CIS and its variance between ownership structure.

Contents

List of Figures

List of Tables

1 Introduction

In the wake of rapid global financial integration and liberalisation, banks under market economies have eagerly leveraged their increased freedom to explore new, novel means of diversification as a means to improve their financial returns (Kim et al., 2020). The rapid and arguably unmitigated proliferation of diversification strategies is believed to expose banks to excessive risk and instability (C.-F. Lee & Su, 2012). Managing this elusive source of risk is one of the objectives of central banks (Javid Nabiyev et al., 2016). Consequently, understanding the dynamics of diversification is crucial to good financial oversight. However, numerous parts of the world feature notably different market conditions, particularly those that have transitioned from the Soviet closed-market economies. Hence, we raise the question of how diversification affects the CIS – the collection of states that have gained independence from the Soviet Union – particularly, their financial sector.

Following the Soviet collapse, these Republics underwent swift and drastic reform, dismantling the remaining mono-banking system, undergoing rapid privatisation, and reducing state influence over market forces such as interest rates (Sharipova, 2015). In the first round of reforms, a two-tier banking system was introduced, creating central banks and dividing formerly state-controlled institutions that functioned as agents of the state to stimulate competition. Crucially, the second round aimed to establish a system of financial intermediation, creating a framework through which banks could play a pivotal role in creating investment and economic activity, more akin to the mechanisms driving economic growth in other more developed market economies. Additionally, the lack of developed capital markets makes CIS banks uniquely positioned as the main drivers of the financial sector, allowing systemic faults to propagate throughout the economy more readily. Risk management, especially considering the salience of diversification, is therefore more consequential for these Republics. As a result of weak regulatory and legal frameworks, insufficient expertise, public trust, and other factors, Djalilov et al. (2016) and Sharipova (2015) show that the Republics require ongoing reform, as this process is still incomplete. Considering the importance of the financial sector in the development of these Republics, bank risk and performance can systemically affect the allocation of national financial resources (Sufian & Habibullah, 2009). Furthermore, research indicates that greater banking profitability can improve the resilience of the financial sector to negative shocks (Athanasoglou et al., 2008), making its research crucial to inform policy on future economic development of the CIS.

Prior research on this issue is disappointingly sparse. Some literature assesses CIS banking sectors, omitting a diversification-related focus. Broader literature on diversification effects on banks also remains indeterminate (Zhou, 2014). Recent studies investigate diversification from either the lens of portfolio effects akin to Modern Portfolio Theory (MPT), or an incentive-based premise, focusing on agency theories (Lepetit et al., 2008). Some European studies, such as Baele et al. (2007) and Chiorazzo (2008) find that diversification of revenue enhances both profitability and risk dimensions. Numerous others corroborate these results for other geographies, such as North America (Elsas et al., 2010). Lepetit et al. (2008) reject these conclusions, arguing instead that three factors point to the costliness of diversification. First, information and switching costs make it more difficult to transition away from lending as a line of business, whereas other, more diversified income sources may not have such a barrier, increasing income volatility. Further, other income streams can increase operational leverage since they may require additional expenditure on personnel, for example. The authors suggest that lending has a comparatively lower marginal cost. Third, the lack of regulation on capital reserve requirements for non-lending activities can increase volatility since banks may be incentivised to increase financial leverage beyond the levels of more lending-oriented banks. Other types of studies, such as the statistical modelling conducted by Wagner (2010) indicate that asset similarity, particularly in less open economies with fewer diversification opportunities, is another primary channel through which diversification can propagate risks.

This study aims to analyse the effects of diversification on the profitability and risk of banks across 11 CIS Republics using published financial indicators aggregated on Orbis BankFocus between 2010-2024. In doing so, we extend existing literature by including both income and asset diversity, improving the breadth of the investigation. We evaluate their effects on numerous indicators of profitability, several types of banking-related risk, degree of foreign control, and market power. We further contribute to wider literature by incorporating the innovations of Tasca et al. (2014) and Wagner (2010), explicitly accounting for an asset similarity effect. As Djalilov et al. (Djalilov & Piesse, 2016) highlight, CIS economies vary in development and depth. As such, we split our analysis based on the Republics' level of development, as defined by Sharipova (2015). Following similar papers, we base our econometric setup on leveraging the dynamic nature of our panel data. To do so, the general method of moments (GMM) framework is used to reduce threats of endogeneity and improve our ability to make valid statistical inferences.

Following necessary transformations to the BankFocus dataset, ultimately, we do not find evidence for a significant diversification effect. Instead, we find that performance is significantly persistent, supporting Berger et al. (2000). Moreover, the importance of market power in explaining banks' net interest margins alongside the significance of macroeconomic indicators cannot support Acharya (2006), suggesting that agency conflicts may be minimal, with incentives being dictated by a wider interest in stability. Moreover, bank ownership or asset similarity does not appear to be relevant in determining risk or performance. The structural limitations of CIS financial institutions, per Sharipova (2015), likely do not conform to the assumptions commonly made in Literature (Diamond, 1984). Notwithstanding, limited data availability and quality from Orbis BankFocus contribute towards the invariance of our regressors.

Generally, the System-GMM specification is robust to its diagnostics, both statistical and methodological. We have validated our instruments through Hansen J-tests and confirmed the presence of second-order autocorrelation, exclusive of an AR(1) effect. The use of numerous yet different indicators of profitability and risk ensures that results are robust to different accounting treatments and components of banking risk.

In the following sections, we first craft a conceptual framework by describing the main classes of theories that are considered important in governing critical economic mechanisms. Then, we introduce the unique context of the CIS, their Soviet legacy, and highlight more contemporary indicators to bridge the contextual gap. We subsequently perform a literature review, showcasing important findings relating to income and asset diversification and how they interact with the conceptual framework we have built. Importantly, we then introduce studies focusing on the CIS to observe special empirical considerations other other studies are less informative about. This framework is then leveraged to craft hypotheses of our expectations, culminating in the overview of how our data and methodology provide a methodological basis for testing these hypotheses. Following that, we discuss our results from a methodological and empirical perspective, incorporating prior discussions on the unique circumstances surrounding the CIS and how they may contribute towards our findings.

2 Theoretical Framework

2.1 Empirical Overview

The empirical debate on the effects of diversification on banks' performance and risk dimensions remains inconclusive. Arguably, literature focuses mostly on statistical evaluation of these relationships rather than a theory-based approach due to the extraordinary difficulties in practically assessing these concepts (Laeven & Levine, 2007).

Some studies find that diversification is broadly beneficial. Baele et al. (2007) assess the market value of European banks and decompose risk, finding a positive relationship between the degree of diversification. They argue that stock markets can anticipate the potential for diversification to enhance profitability. They also find a non-linear relationship for the combined idiosyncratic and systematic risk components, arguing that diversification can lower idiosyncratic risk, reducing the probability of default. In this regard, we relate these findings to Gambacorta et al. (2014), who, studying around 100 international banks, show that diversification correlates with profitability non-linearly. In spite of the result, Baele et al. (2007) confirm that banks relying on non-interest income tend to exhibit greater market beta and systematic risk. Chiorazzo (2008) shows that Italian banks exhibit greater risk-adjusted returns when they diversify their income streams. While this effect is greater for larger banks, they experience diminishing returns to diversification. Positive returns to diversifying may also hold for other geographies; Elsas et al. (2010) find similar results for a large number of banks from the U.S., Canada, Australia, Germany, Italy, Spain, France, and Switzerland. These results challenge Laeven et al. (2007), arguing against a 'conglomerate discount', where market participants reduce their market valuations of more diversified firms, anticipating agency conflicts. Crucially, Elsas et al. (2010) show that the range of results found in literature may be a consequence of the way they measure diversification; the aggregate measures they use can create confounding effects, distorting more granular effects. To this end, they disaggregate their measures, making their results comparatively robust.

Other studies present a less favourable diversification effect. Lepetit et al. (2008) investigate a range of European banks across 1996-2002, finding that expansion through non-interest income such as commission and fees presents greater insolvency risk compared to banks which mainly supply credit. The results from Baele et al. (2007) do, to a degree, corroborate this finding for Europe. Similarly to others, the authors observe a size effect, showing that smaller banks can experience lower asset and default risk, especially through trading activities. As Radojičić and Marinković (2023) highlight, studies focus largely on developed economies. To this end, Wang and Lin (2021) investigate 14 emerging economies of South East Asia and demonstrate that diversification clearly improves banks' risk profiles, but not necessarily for commercial banks of developed economies of the region.

Further, a growing sector of literature expands common associative econometric tools to instead study connectedness. Tasca et al. (2014) expand on Merton's (1974) model, investigating the joint default probability of leverage and diversification. Importantly, they show that even in the presence of strict diversification benefits, diversification can increase systemic risk through increasing correlations between bank portfolios. Raffestin (2014) create a generalised diversification model by combining general empirical insights. Their model combines contagion models depicting the channels through which systemic risks are created, statistical analyses, the likes of Wagner (2010), where the statistical properties of various diversification scenarios are compared, and finally, network analysis, where the econometric problem is bounded. Ultimately, the model demonstrates that while individuals experience less risk, diversification creates common asset holdings among investors, creating connections through which systemic risks can rapidly propagate.

2.2 Theoretical Foundations

Similar to literature, the theoretical foundations of diversification are widely debated. Prevailing theories differ not only in their expected outcome but also in the channel of effect. The initial models of diversification can be seen as contagion models, based on agency, information, and financial intermediation theory, as classified by Raffestin (2014). As conceptualised by Winton (1995), the traditional view formalised by Diamond (1984) argues that diversification is beneficial to the extent that it enables banks to acquire information about firms and the wider market. By supplying credit, they acquire proprietary information which they can use to better facilitate other financial services. This new information, in turn, enhances banks' loan portfolios, ultimately creating economies of scope that boost market valuation. However, as Acharya (2006) highlights, the traditional view predates agency theories; a more contemporary perspective is that as a firm grows larger and more complex, it experiences greater agency conflicts resulting from practical difficulties in aligning differing stakeholder incentives. According to Jensen and Meckling (1976), even if diversification is known to be value-destroying, the firm can still willingly diversify if the marginal private benefits of diversification to its controlling agents exceed the loss in firm value. Acharya (2006) evaluates this theory empirically concerning the traditional view, finding that firms experience diseconomies of diversification when they expand into industries where they lack experience or face high competition. When the probability of insolvency is high, agents are less incentivised to monitor their credit portfolio. Consequently, in the presence of high risk, improvements to monitoring benefit the bank's creditors comparatively more than the bank, which bears the cost of additional monitoring. Diversification necessitates greater monitoring, as maintaining credit portfolio quality is relatively more difficult in the presence of high competition and an unfamiliar operating environment. It follows that diversification reduces monitoring incentives, worsens asset quality, and increases insolvency risk. Acharya (2006) places a particular emphasis on the competition channel as a significant factor; when entering new, highly competitive markets, banks face a smaller pool of available clients, prohibiting efficient information acquisition, which reduces their ability to screen borrowers. This ultimately leads to the provision of credit to low-quality borrowers, giving way to the 'winner's curse' (Marquez, 2002). Further, Acharya (2006) argue that the left-skewed nature of debt return distribution means that deviations can change the probability of default non-linearly. Their analysis yields a significant U-shape effect, reinforcing the notion of weakening monitoring incentives. Another prominent agency theory pertains to moral hazard arising from agents' risk-shifting behaviour. If agents undertake diversification despite their increased riskiness, they may be stimulating instability to induce a bank failure to receive government bailouts (Acharya et al., 2006; Dijkman, 2010; Yang et al., 2020). This may be more evident in the presence of high market power concentration, where there is greater reliance and interdependence between the financial sector and the wider economy; in such cases, a bailout is more probable.

Statistical analysis models commonly argue that increasing correlation or similarity between banking assets drives risk. Wagner (2010) presents a model demonstrating that while in isolation diversification expands the asset base of a bank, reducing the likelihood of failure, however, full diversification crucially leads to banks holding an approximately similar portfolio of assets, increasing correlations such that they are ultimately exposed to the same systemic risks. This means that a shock within the system can propagate to all banks, causing joint systemic bank failure. In line with this premise, Lee et al. (2020) investigate the risk implications of diversification with relation to asset correlations for 1008 banks across 53 countries. They utilise pairwise correlations between the market and individual ROA of banks to assess asset similarity. They find that diversification indeed increases systemic risk, and notably, that excluding highly asset-correlated banks makes this effect insignificant, supporting Wagner (2010). Considering the breadth and robustness of the study, this suggests that asset similarity could be important in explaining bank portfolio risk.

2.3 Contextual Implications for the CIS

Research on the CIS has several important differences from its more developed counterparts that warrant consideration for a rigorous research design.

A core historical feature of many CIS economies has been their bank-centric financial intermediation. Following the collapse of the Soviet regime and their subsidisation of the Republics, the CIS nations' economic developments diverged, contingent on the different state of their real sectors (Barisitz, 2008). Underpinning any future developments was the lingering underdevelopment of capital markets and institutional infrastructure across the CIS (Berglof & Bolton, 2002). Studying indicators of financial intermediation, Sharipova (2015) finds that even the most developed CIS Republics lag behind developed economies. Even within the CIS, we observe significant divergence; across the 11 countries, for Assets/GDP, Credits/GDP, Deposits/GDP, and Capital/GDP, Sharipova (2015, p. 40) implies standard deviations of 21.4%, 14.4%, 14.6%, and 7.1% in 2014, respectively, suggesting substantial heterogeneity in development. The most consequential limiting factors in this underdevelopment pertain to insufficient domestic funds, poor regulation and supervision, and inadequate professional bank management.

Further, the size and consolidation of CIS banking sectors are informative of their market structure. Between the years of the Global Financial Crisis (GFC), we observe a reduction in the number of CIS banks, decreasing by 74 and 56 across 2009 and 2010, respectively. This decline continued, reaching a decline of 194 banks (-13.8%) in 2014 relative to 2009. Despite this, Sharipova (2015) reports that the share of the total assets of the three largest banks, known as the concentration ratio, has decreased 13.3% between 2005-2013. Interestingly, this suggests that the consolidation process has not involved significant mergers and acquisitions activity among large banks, but that this is likely untrue for smaller institutions.

Unlike their developed counterparts, CIS banks vary substantially in ownership structure. In terms of foreign assets, between 2009 and 2014, foreign ownership ranged from an average of 20.36% for Belarus to 75.09% for Armenia (Sharipova, 2015, p. 46). Similarly, Ukraine and Belarus accounted for over 70% of CIS-based foreign investments (Sharipova, 2015, p. 59). In Republics such as Armenia, the attraction of foreign capital can be seen as a shrewd strategy to overcome limited domestic banking resources and develop financial intermediation, whereas in Tajikistan and Kyrgyzstan, it is a consequence of weak institutions (Sharipova, 2015). Berger et al. (2000) propose two hypotheses to explain the dynamics of foreign and domestically-owned banks. The global advantage hypothesis posits that foreign banks can be more efficient due to their greater managerial skills, experience with good institutional governance, and access to tools to analyse and process information. Additionally, being relatively larger, they possess economies of scale and scope. These factors enable them to offer services unavailable to domestic banks and provide a framework to develop superior tools for managing risk in the face of diversification. The general form of this hypothesis considers these advantages strong enough to overcome limitations in all operating countries, whereas the limited form only prescribes advantages in countries with more favourable operating conditions. The home field advantage hypothesis argues the converse, stating that domestic banks' greater experience and knowledge of their own markets, particularly with language, culture, currency, regulatory/supervisory structures, and country-specific factors (Berger, DeYoung, et al., 2000; Sharipova, 2015). Evaluating these hypotheses empirically, Berger (2007) finds that home field advantage holds for developed economies, and global advantage for less developed economies. Styrin (2005) investigated the phenomena in Russia, finding greater efficiency for non-Russian banks, however, other CIS countries have not been analysed in the literature.

2.4 Conclusion

Developing a theoretical and conceptual framework inclusive of relevant CIS context enables us to discuss theoretical and distant empirical insights with respect to the idiosyncrasies of the region.

The traditional view of diversification posits a positive relationship with performance and risk reduction, based on the advantages that banks gain as they grow, gather information, and develop the expertise to improve their financial services (Diamond, 1984; Winton, 1995). However, the pursuit of diversification may bring marginal private benefits to agents, incentivising strategies that reduce overall bank value through agency conflicts (Jensen & Meckling, 1976). These conflicts can become particularly acute when diversification extends into unfamiliar markets, worsening monitoring incentives, reducing loan portfolio quality, and increasing moral hazard (Acharya et al., 2006). Empirical evidence supports this, as Chiorazzo (2008) finds diminishing returns to diversification depending on bank size, indicating potential diseconomies of scale. Similarly, Laeven et al. (2007) highlight a 'conglomerate discount', where market participants anticipate agency problems and penalise diversified banks through lower valuations. However, in the context of CIS Republics, Sharipova (2015) emphasises that poor financial intermediation, weak capital markets, low investor participation, and insufficient managerial expertise undermine these traditional valuation mechanisms. In such environments, the fundamental channels through which diversification is theorized to enhance bank stability, namely, (1) the ability to acquire high-quality proprietary information about borrowers and markets, (2) the effective use of this information to monitor and manage new business lines, and (3) external market discipline through transparent valuations are systematically impaired. Specifically, weak information environments reduce the benefits of scale by making it harder to differentiate between good and bad clients, resulting in riskier credit portfolios even as banks diversify. Poor monitoring capabilities exacerbate adverse selection and moral hazard risks, as banks lack the operational expertise to manage diversified activities efficiently. Finally, thin and underdeveloped capital markets limit external oversight, allowing poorly managed diversification strategies to persist unchecked. Consequently, diversification in the CIS context is more likely to worsen bank risk and performance, particularly in less developed Republics where these institutional deficiencies are most severe. These contextual differences motivate the hypothesis that:

$\mathbf{H}_1^a$: **Greater income and asset diversification negatively affects bank performance and stability, especially in less developed CIS countries.**

Driven by regional integration patterns and historical legacies, foreign bank ownership assumes particular importance in the context of CIS economies, differing fundamentally from dynamics observed in more developed financial systems. In the CIS, foreign ownership is disproportionately concentrated among more developed Republics and is often directed toward host markets characterised by weak institutional frameworks, fragile regulatory enforcement, and underdeveloped financial infrastructures (Sharipova, 2015). This ownership pattern aligns closely with the limited form of the global advantage hypothesis proposed by Berger et al. (2000), which posits that foreign banks enjoy efficiency advantages — such as superior risk management capabilities, better corporate governance practices, and access to advanced financial technologies — particularly when entering markets with relatively low barriers to informational acquisition and weaker competitive pressures. In the CIS, foreign banks are likely to attain relatively greater performance when diversifying into other non-credit markets, not simply because of operational scale, but because of the stark deficiencies in local managerial expertise, governance standards, and risk assessment practices. In particular, Sharipova (2015) highlights a lack of professional experience as one of the most significant barriers to banking development. Assuming this relative advantage by foreign banks, diversification disproportionally benefits them in two ways; one, by directing resources more efficiently they can, per Acharya (2006), obtain a higher amount, and quality of, proprietary information, lowering the costs of credit monitoring, reducing overall risk.

Two, their greater managerial experience can facilitate improved strategic decision-making, allowing foreign banks to diversify into non-interest income more successfully than their domestic counterparts, enhancing profitability. By transferring knowledge, imposing stronger internal controls, and introducing more sophisticated financial products, foreign banks may partially substitute for the institutional weaknesses of their host environments, giving support to the general form of the theory by Berger et al. (2000). However, these advantages are unlikely to be uniform; their impact may be attenuated in more developed CIS Republics, where local banks already exhibit relatively better governance and operational efficiency. Consequently, we hypothesise that:

$\mathbf{H}_2^a$: **Foreign bank ownership improves risk and performance outcomes, with stronger effects in less developed CIS countries.**

The statistical model developed by Wagner (2010), along with the generalised diversification framework proposed by Raffestin (2014), demonstrates that asset similarity and systemic network propagation are critical mechanisms through which diversification can paradoxically increase, rather than reduce, banking sector risk. This nuance has been relatively underexplored in empirical literature; however, Lee et al. (2020) provide robust evidence that asset similarity materially influences the extent to which diversification affects bank performance, with higher portfolio correlations significantly amplifying systemic vulnerabilities. In the context of the CIS, this channel is likely to be particularly salient. The combination of limited risk management expertise, underdeveloped financial markets, and a narrow range of viable lending opportunities constrains banks' ability to diversify meaningfully across uncorrelated assets. As a result, even efforts at diversification may lead banks to accumulate highly similar portfolios, reinforcing systemic exposure rather than mitigating it. Consequently, diversification and asset similarity are not opposing, but co-occurring phenomena that jointly exacerbate systemic risk (2010). The structural lack of deep capital markets and limited access to non-traditional assets further entrench this pattern, leaving banks more interconnected and vulnerable to sector-wide downturns. Consequently, we hypothesise that:

$\mathbf{H}_3^a$: **Higher asset similarity worsens the risk and performance outcomes as a conflating factor of diversification, particularly in less developed CIS countries.**

3 Data

This study utilises annual financial statement data for individual banks from the Orbis BankFocus database across 2010-2024. We define the CIS to include Azerbaijan, Armenia, Georgia, Ukraine, Belarus, Moldova, the Russian Federation, Belarus, Kazakhstan, Kyrgyzstan, Uzbekistan, and Tajikistan. We exclude Turkmenistan since their banks are simply agents of the central bank and have no significant role in financial intermediation (Sharipova, 2015). As of 2025, Georgia has exited the CIS organisation, however, its past membership makes its inclusion warranted. Initially, the sample contained 147,767 unbalanced panel observations across 623 individual banks of the 11 Republics. As outlined in the variables' description of Table 1, we first select the appropriate levels of financial consolidation to ensure no duplicate data. Similar to other literature such as Hu et al. (2022), we include banks with either complete or incomplete consolidation, C_1, U_1, and partial consolidation, either C_2 or U_2, depending on which code contained the greatest number of valid observations. We include commercial banks only to avoid influence from non-retail activities. The preliminarily validated dataset contains 64,723 observations from 497 individual banks. However, subsequent data validation steps eliminated banks with few valid observations, yielding a smaller observation pool.

3.0.1 Dependent Variables

Generally, literature favours Return on Assets, *ROA*, as the optimal measure of banking profitability (Acharya et al., 2006). The ability for a bank to generate ROA directly reflects its competency in leveraging its resources to enhance profitability (Djalilov & Piesse, 2016). Researchers typically assess ROA together with Return on Equity (ROE), however, we exclude ROE since it omits the effects of leverage, which is especially pertinent when investigating banking performance (Flamini et al., 2009). ROA is known to be biased by the presence of performance-affecting assets off the balance sheet; however, Djalilov et al. (2016) argue that this is unlikely for transition countries such as the CIS Republics. We improve the measure by taking average assets, computed as the average balance of total assets between fiscal years, which reflects banks' asset bases more accurately and is more stable over time (Korytowski, 2018). To counteract biases from low-quality financial reporting and increase robustness, we measure performance through other dimensions as well; Net Interest Margin, *NIM*, measures performance relative to the bank's interest rate policies and quality of its loan portfolio (Radojičić & Marinković, 2023). Interest is computed from average interest-earning assets to reduce year-to-year volatility and be more representative. The Cost-to-Income ratio, *EFF*, evaluates the bank's operational efficiency (Radojičić & Marinković, 2023).

Tables 2, and A1 alongside A2 in the Appendix suggest that across the entire sample, less developed Republics have lower median ROA, lower levels of interest margin, and notably better mean efficiency ratios. Interestingly, their standard deviations for these performance measures tend to be lower as well. When the data is split according to domestic ownership, the performance figures for less developed and more developed Republics show instances of greater similarity, particularly for domestically-owned banks. Similar to the entire sample, less developed Republics within these ownership categories generally exhibit lower volatility in performance measures. Notably, there are significantly fewer observations for CIS-owned foreign banks compared to non-CIS-owned foreign banks, suggesting that non-CIS-owned foreign banks are more prevalent across the region. In more developed Republics, non-CIS foreign banks achieve significantly greater mean ROA and improved mean efficiency ratios, alongside a somewhat lower mean interest margin when compared to CIS-owned foreign banks. This could suggest that their performance arises significantly from cost efficiencies. For less developed Republics, non-CIS foreign banks also achieve higher mean ROA and improved mean efficiency ratios compared to CIS-owned foreign banks; however, in contrast to more developed Republics, they exhibit a higher mean interest margin. Though generally, non-CIS foreign banks tend to be more volatile across their performance measures in both less and more developed Republics.

Following Djalilov et al. (2016), we enhance the robustness of the study by proxying risk through a range of factors rather than a single measure, as commonly done in literature. *Credit Risk* has a clear link to the probability of bank default (Varotto, 2011). This is measured as the ratio of loan loss provisions to the gross loans issued to customers. Further, *Capital Risk*, measured by a ratio of equity to total assets, is crucial in assessing regulatory conditions; a highly capitalised bank is less likely to engage in risky behaviour, in part due to improved risk management arising from the bank's size (Laeven & Levine, 2007). Additionally, large amounts of capital are a safety net in the event of financial distress (Athanasoglou et al., 2008), lowering risk. Holding capital can be seen as an inexpensive way of signalling stability, which may be pertinent in less developed regulatory environments. Extending Djalilov et al. (2016), we include *Credit Risk*, computed as loan loss provisions divided by gross loans issued to customers. This directly assesses the quality of loan portfolios since greater loss provisions are associated with uncertainty about customer default (Radojičić & Marinković, 2023).

Literature widely utilises Z-Score as a proxy for stability (Berger et al., 2009). Measured as the ratio of buffer capital and profitability to the dispersion in profitability, it combines the aforementioned insights by evaluating the rate at which profit destruction depletes capital reserves (Boyd & De Nicoló, 2005). Thus, a higher value corresponds to greater fiscal capacity, indicating higher stability. Our sample contains numerous valid, yet highly skewed Z-Scores resulting from extremely low *ROA* values. We correct for this by logarithmically transforming it, per Clark et al. (2018).

Counter to performance measures, descriptive statistics indicate that less developed Republics have proportionally fewer median liquid assets across the whole sample, less median capital, and notably less median credit risk. More developed Republics deviate more greatly in the standard deviations of these risk measures, however. When observing domestically-owned banks, similar trends in median risk levels are noted, where less developed Republics show fewer median liquid assets, less median capital, and less median credit risk compared to more developed domestically-owned banks; regarding volatility, more developed domestically-owned banks exhibit greater standard deviations for capital and credit risk, but a lower standard deviation for liquidity risk. Though, in terms of foreign ownership, median risk characteristics between CIS and non-CIS based banks present some differences, particularly in more developed Republics where median credit risk is notably lower for CIS-owned banks, and median capital risk is higher for CIS-owned banks in both less and more developed Republics; however, Non-CIS owned banks consistently demonstrate greater volatility across liquidity, capital, and credit risk measures in both less and more developed Republics.

3.0.2 Independent Variables

Diversification is one of the main effects under study. Prominent studies such as Acharya (2006) rely on the Hirschman Herfindahl Index (HHI), which measures the exposure of a variable to its constituents' sum of squares. Diversification is mainly viewed through income diversity. We measure this through ID^{HHI}, classifying total interest and non-interest incomes as a portion of operating revenue as the components of an HHI measure. This captures the effects of diversifying from traditional lending activities into non-interest revenue sources. Observations corresponding to negative operating revenues or income components are excluded as they would bias the analysis erroneously. Taking revenue as the denominator increases our statistical power by elevating the number of viable observations since fewer result in negative values. To standardise it with the rest of our measures, the range is between -50 and 50, where -50 denotes a complete non-interest portfolio and 50 denotes a full interest-based one. Since HHI is inherently non-directional, we include the non-income composition as a separate variable, indicating the direction. Moreover, we follow Nguyen et al. (2015) and avoid excluding banks with negative non-interest income by giving it a value of zero instead, implying 100% interest income. Doing so is viable assuming that negative non-interest income resulted in higher revenue from net interest income. Notwithstanding, Laeven et al. (2007) suggest that traditional lending activities can give rise to other income types, such as fees or commissions, overestimating the contribution of interest, and that the difficulty in accurately measuring non-interest income necessitates asset-based measures of diversification. Similar to ID^{HHI}, AD^{HHI} uses HHI, taking loans and other earning assets as components of total assets. To indicate direction, we show loans' composition of total assets. It follows that AD^{HHI} tends to -50 as assets are more diversified.

Evaluating the asset similarity channel of diversification presents an operationalisation challenge. We draw inspiration from Lee et al. (2020), who measured similarity based on individual banks' relation to an equally-weighted market average. While their approach focused on ROA, reasoning that similar banks should earn a similar ROA to that of the market, we, following Fricke (2016), deviate by instead comparing the composition of asset portfolios directly. Typically, measures such as Euclidean distance of cosine similarity are used to evaluate similarity; however, we opt for Shannon Entropy. Based on information theory, we treat loan and non-loan asset shares as discrete probability distributions, which are then normalised to obtain a pseudo-concentration measure. This method offers significantly greater insights since a holistic comparison across entire distributions is more sensitive to small changes compared to point measures; this is especially pertinent considering the highly concentrated nature of asset diversity (Figure A2). Moreover, by considering the information content of income and asset porfolios, we treat changes in these portfolios as signals to financial stakeholders, which is closer to traditional notions of market efficiency (Markowitz, 1952; Shannon, 1948). The paper by Almog and Shmueli (2019) supports this rationale, arguing that studying community sizes within financial networks yields significantly more meaningful measures of connectedness than simpler scalar metrics. In this sense, entropy similarity, formulated in Table 1, offers a richer perspective on asset similarity.

In addition to similarity, we further categorise banks according to the development of their operating country and their ownership status. Sharipova (2015) highlights that the Republics' development levels have strong implications for banks' operating environments. For instance, more developed Republics tend to have better-established retail banking and subsequently, a greater pool of viable customers. This directly implicates the quality of information banks can gather and reap scope economies from. We construct a binary index classifying each Republic as being 'More Developed' or 'Less Developed' according to Sharipova's (2015) development indicators. Their research similarly finds ownership to be a material factor in bank efficiency. However, since BankFocus provides incomplete data, it was only possible to reliably classify banks by domestic, non-domestic, CIS-based, and non-CIS-based foreign ownership through binary indicators. To uncover ownership status, we used the 'Global Ultimate Owner' designation by BankFocus. Berger et al. (2000), through their two advantage hypotheses, specify further, showing that foreign ownership can interact with competitive forces to jointly impact foreign banks' success in new markets. However, literature finds that Competition may also be consequential in isolation (Lepetit et al., 2008). Researchers consistently rely on HHI to operationalise competition, alongside the Lerner Index (Berger, Bonime, et al., 2000). Both Djalilov et al. (2016) and Dietrich and Wanzenried (2011) conceptually demonstrate that competition can be reliably operationalised to evaluate the various competition hypotheses. The rigorous data requirements of the Lerner Index are unsuitable for CIS data, however, the World Bank publishes market concentration ratios, measuring the combined market share of the three largest banks. As individual banks' market shares are unavailable, this overall ratio is used to proxy *Concentration*.

Preliminary data analysis indicates that less developed Republics have more concentrated income streams, dominated by interest income. For domestically-owned banks, income streams in less developed Republics are also more concentrated compared to those in more developed Republics. Regarding asset diversification, while banks overall may show varied levels, when considering specific segments, more developed Republics exhibit notable differences in asset concentration by ownership, with non-domestically owned banks being significantly less concentrated in loans than domestically-owned ones. Less developed domestic banks, in turn, are more concentrated towards lending-based assets compared to their non-domestic counterparts in less developed Republics or domestic banks in more developed ones. Interestingly, while both types of foreign ownership generally indicate greater asset diversity compared to domestic banks, the difference in this asset diversity for foreign banks when comparing less developed Republics to more developed Republics is not consistently greater than the difference observed for domestic banks. Diversification opportunities may be more readily available in more developed nations for foreign entities, as foreign banks in more developed Republics tend to have slightly lower mean loan asset share than their counterparts. Generally, market concentration is high across Republics, though it is notably higher in less developed Republics than in more developed ones. When considering entropy similarity provided across all data, the sample shows a mean of 0.14 and a minimum of 0.00, suggesting that banks are generally undiversified. The box plots in Figure A2 depict individual distributions, demonstrating that similarity tends to be highly concentrated around zero. Thus, there is relatively low variance within the measure.

3.0.3 Control Variables

While evaluating the core effects, it is crucial to account for other significant variables to reduce model bias. Many studies show that bank size, measured through their total assets, has structural implications. For example, Baele et al. (2007) and Acharya (2006) show that bank scale can either lower idiosyncratic risk and volatility or increase them when diversifying through entry into new markets. The extreme dispersion in total assets across the dataset necessitates instead taking its logarithm (Radojičić & Marinković, 2023). Broad macroeconomic conditions are measured through *GDP Growth* and *Inflation*. Changes in macroeconomic performance is directly linked to bank profitability and risk of insolvency (Beck & Levine, 2004). Javid et al. (2016), interestingly, show that macroeconomic conditions can be the sole drivers of bank stability, specifically within the CIS as well. Inflation is noted as a particularly consequential "precursor", as it responds more quickly and rapidly to perceptions of risk. Further, the authors find that indicators of governance can exacerbate risk by, unconventionally, incentivising more accurate financial reporting, particularly negative results. Alongside Sharipova's (2015) evidence of systemic regulatory shortcomings in the region, it is evident that regulatory indicators can contribute greatly to our overall results. Importantly, Clark et al. (2018) differentiate the regulatory environment from the supervisory, suggesting that greater powers for the latter can in fact worsen banking risk, unlike improvements to regulatory environments, which have clear benefits. We capture these dynamics through Garriage's (2016) Weighted Central Bank Independence Index, *CBI*, examining four components of central banking: its chief executive officer's characteristics, its de facto role in policy formulation, its objectives, and limitations to public lending, ranging 0-1, from lowest independence to highest. These factors are pertinent for the CIS, as their power can, de facto, vary de jure. To avoid multicollinearity or noise, we only selected *Peace & Stability* and *Rule of Law*, which evaluate distinct, yet important aspects of governance.

Descriptive analysis based on the provided tables suggests that while median GDP growth, 3.20% across the whole sample, and inflation 7.58%, across the Republics might appear within certain bounds, they exhibit considerable variation, as indicated by their standard deviations, 4.48% and 9.17%, respectively, and wide ranges, pointing to periods of significant instability. These observations may align with events such as the COVID pandemic and earlier episodes in the 2010s, such as the aftermath of the 2008 financial crisis and regional instabilities. Regarding bank size, its logarithmic transformation in the tables shows a substantial range from 8.29 to 17.15, and a standard deviation of 1.71, which indeed implies extreme variance in actual bank sizes across the Republics, clearly indicating size effects; these variations may also be indicative of scale and/or scope economies, given that they are coupled with relative improvements in cost efficiency or the bottom-line.

Concerning two nations of two different levels of 'high' development, the U.S. and Poland, we observe a median Peace and Stability index of 0.39 and 0.56, and Rule of Law index of 1.56 and 0.56, respectively. Relative to these metrics, the CIS Republics are jointly significantly less politically stable and have worse rule of law. The disparity is very high, even compared to Poland, a former Eastern Bloc state. In terms of central bank independence, the U.S. hovers around 0.5, whereas Poland is rated approximately 0.9. Better-developed Republics have significantly greater independence than less developed counterparts; however, at its highest, the former exceeds the U.S. However, central bank independence cannot be conflated with its efficacy. These institutions may have greater autonomy; however, if they are functionally limited, their independence has less impact on economic development.

Table 1: Data | Variable Descriptions and Construction

Variable	Description and Special Procedures or Treatments to Reduce Noise
DEPENDENT VARIABLES | Performance Measures	
ROA	Return on average assets as computed by BankFocus. ROA = $\frac{\text{Net Income}}{\text{Average Total Assets}}$. Due to the presence of erroneous outliers, we winsorize the entire sample by 95%.
NIM	Net interest margin computed as NIM = $\frac{\text{Net Interest Revenue}}{\text{Average Earning Assets}}$. Due to the presence of erroneous outliers, we winsorize the entire sample by [5%, 90%]
EFF	Cost efficiency, defined as cost-to-income ratio, as computed by BankFocus. EFF = $\frac{\text{Total Operating Expenses}}{\text{Operating Income}}$. Numerous observations held values that are implausibly high. As such, we winsorize by 90%. We also restrict the lower bound to zero since the ratio cannot be negative.
DEPENDENT VARIABLES | Performance Measures	
Liquidity Risk	Measure of the ratio of liquid assets to total assets. A higher ratio is indicative of greater liquidity and lower overall default risk due to the greater relative availability of liquid assets. This measure was computed manually. The domain was restricted to 0-100 to combat present data errors, since liquid assets cannot comprise more than the total asset base.
Capital Risk	Measure of the regulatory conditions based on the bank's degree of capitalization. A lower value can represent lower efficiency due to increased funding costs arising from higher risk associated with greater leverage. The ratio is provided directly by BankFocus and is calculated as: Capital Risk = $\frac{\text{Total Equity}}{Total\ Assets}$. We restrict the range to 0-100 and remove erroneous data.
Credit Risk	Measure of loan loss reserves over total loans, indicating the riskiness of the loans and capturing the quality of bank assets. BankFocus defines it as an indication of how much of the total portfolio has been provided for, but not charged off. Expressed as a percentage of total loans. We remove all values below zero since it is not plausible for a bank to have negative loan balances under typical circumstances.
log Z	Z-Score indicates the rate at which bank profitability would decrease before the bank's capital resources are fully depleted. Higher values indicate greater stability and lower overall risk as it suggests a larger financial safety net. Z Score = $\frac{\text{ROA+ETA}}{\sigma(\text{ROA})}$ where ROA is the return on average assets, ETA is the ratio of equity to total assets, and σ(ROA) is the standard deviation of ROA. There were several observations that deviated signifcantly from the median, however, they remain valid observations. Consequently, we took the logarithmn to account for this skewness.
INDEPENDENT VARIABLES | Diversification Measures	
ID^{HHI}	Income diversification is computed as the Herfindahl Index of Interest and Non-interest portions of Operating Revenue, as such: $\text{ID}^{\text{HHI}} = \sum_{k=1}^{K} 1 - \left[\left(\frac{\text{Non Interest Revenue}_{t,k}}{\text{Operating Revenue}_{t,k}}\right)^2 + \left(\frac{\text{Total Interest Revenue}_{t,k}}{\text{Operating Revenue}_{t,k}}\right)^2\right] \cdot 100$, where $\{t,k\}$ represent the specific year and bank belonging to the particular observation. We excluded a bank if its operating revenue was found to be negative or if the portion of interest or non-interest revenue was found to be outside of the [0,100] percentage range.
AD^{HHI}	Asset diversification is computed as the Herfindahl Index of total (interest) Earning Assets and Non (interest) Earning Assets, as such: $\text{AD}^{\text{HHI}} = \sum_{k=1}^{K} 1 - \left[\left(\frac{\text{Customer Loans}_{t,k}}{\text{Total Assets}_{t,k}}\right)^2 + \left(\frac{\text{Other Earning Assets}_{t,k}}{\text{Total Assets}_{t,k}}\right)^2\right] \cdot 100$, where $\{t,k\}$ represent the specific year and bank belonging to the particular observation. We excluded a bank if its Loans or Other-Earning Assets as a portion of Total Assets was found to be outside of the [0,100] percentage range.
INDEPENDENT VARIABLES | Similarity Measures	
Entropy Similarity	Entropy is traditionally a measure of informational uncertainty, however, they are useful as a proxy for asset similarity as two assets' co-movements can be captured in a nuanced way by the measure. First, we add an extremely small non-zero value to each observation as to prevent data loss from the subsequent logarithmic transformation. Then, we apply Shannon Entropy as such: $H(X) = -\sum_x p(x)\log_2 p(x)$, where x is each observation for two asset classes, Loan Share and Non-Loan Share, representing the amount of interest-based assets as a portion of total assets. Then, we normalize the entropy to [0,1] through $\frac{H(X)}{\log(N)}$, where N is the number of asset classes, in this case, two. Then, we obtain a similarity index by finding asset concentration: $\text{SIM}^{\text{Entropy}} = 1 - H(X)^{\text{Normalized}}$. Finally, to ensure that all variables are scaled the same way, we multiply the final measure by 100.
INDEPENDENT VARIABLES | CIS Republics' Development	
Development	Dummy variable that takes value of 1 when the Republic is considered 'More Developed' and 0 if it is 'Less Developed'. The classifications are taken according to the analysis of Sharipova (2015).'More Developed' Republics include: Russian Federation, Kazakhstan, Belarus, and Ukraine. 'Less Developed' Republics include: Azerbaijan, Armenia, Georgia, Moldova, Uzbekistan, Tajikistan} and Kyrgyzstan.
INDEPENDENT VARIABLES | Market Power Measure	
Concentration	Measure of the assets of the three largest banks as a share of total commercial banking assets, compiled by the World Bank and originating from BankScope and Orbis.
INDEPENDENT VARIABLES | Bank Ownership Measures	
Domestic Control	Dummy variable that takes value of 1 when the bank is owned domestically and zero if the owner is non-domestic. This was classified according to Orbis's Global Ultimate Owner indicator. When there was no indicator of the Global Ultimate Owner, per BankFocus, we assumed that the bank was Domestic.
CIS Foreign Control	Dummy variable that takes a value of 1 when the bank is owned by an entity outside of the Republic and the owner is from of the CIS and zero if the owner is foreign and from outside of the CIS.
CONTROL VARIABLES | Macroeconomic Indicators	
GDP Growth	Defined as the growth in the real Gross Domestic Product based on constant prices and domestic currency. We made no transformations to the data since these figures did not appear to be faulty.
Inflation	Defined as the change in the Consumer Price Index at the end of the period. Belarus had one extreme observation, however, we do not consider this a data error.
CONTROL VARIABLES | Bank Level Control	
log Size	Defined as the logarithmn of total bank assets. Log transformation reduces the distortive effect of outliers, which is necessary since our dataset contains banks of varying sizes.
CONTROL VARIABLES | Regulatory and Supervisory	
Peace & Stability	Measures perceptions of the likelihood of political instability and/or politically inspired violence, including terrorism. We make no alterations to the data since these indicators are constructed correctly with no apparent error.
Rule of Law	Compound measure which includes several indicators measuring the extent to which have confidence in and abides by societal rules. These perceptions include crime, effectiveness and predictability of the judiciary and enforceability of contracts. In aggregate, these measure the success of a society in developing a fair and predictable rules-based environment.
CBI	A weighted index measuring Central Banking Independence through the Cukierman, Webb, and Neyapti (1992) criteria. Weights: Chief Executive Officer 20%, Objectives 15%, Policy Formulation 15%, Limitations on Lending to the Government 5%. Ranges from 0 to 1, with 1 representing the greatest degree of Central Banking Freedom.

Note. This table depicts each variable used in subsequent modelling steps. Alongside the names and basic descriptions of each variable, where relevant, we present the specific expressions that describe their formulation more precisely. Certain variables contained noise that can reduce the efficacy of our models. Therefore, a series of transformations was undertaken to combat this issue. Where conducted, the precise data cleaning or validation steps are described in full. Furthermore, sources are provided to clarify the origins of our data.

Table 2: Data | Descriptive Statistics | Split by Development

	Performance Measures			Risk Measures				Diversity Measures				Mkt.	Sim.	Macro Factors		Bank Controls	Regulatory Environment		
Statistics	**ROA**	**NIM**	**EFF**	**Liquidity Risk**	**Capital Risk**	**Credit Risk**	log **Z**	$\mathbf{ID}^{\mathrm{HHI}}$	NII/OR	$\mathbf{AD}^{\mathrm{HHI}}$	$Loans/TA$	**Conc.**	**Entropy Similarity**	**GDP Growth**	**Inflation**	log **Size**	**Peace & Stability**	**ROL**	**CBI**
All Data																			
Obs.	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388	1,388
Mean	1.66	7.34	62.30	31.27	20.93	8.85	2.37	0.41	38.31	0.41	0.56	69.44	0.14	1.86	9.45	12.64	-0.74	-0.65	0.63
Median	1.54	6.40	59.75	28.07	16.04	5.51	2.53	0.44	35.96	0.45	0.59	69.76	0.07	3.20	7.58	12.59	-0.53	-0.73	0.69
Std. Dev.	2.12	4.13	19.71	17.43	15.05	10.39	0.99	0.10	18.13	0.11	0.20	13.80	0.18	4.48	9.17	1.71	0.68	0.35	0.18
Minimum	-3.79	2.21	34.02	0.14	2.53	0.00	-1.53	0.00	0.00	0.00	0.00	34.94	0.00	-9.77	-1.37	8.20	-2.02	-1.45	0.22
Maximum	6.06	24.12	101.44	94.17	95.91	97.44	4.79	0.50	97.55	0.50	0.98	100.00	0.98	13.90	108.69	17.15	0.35	0.34	0.85
Less Developed Republics | All Data																			
Obs.	623	623	623	623	623	623	623	623	623	623	623	623	623	623	623	623	623	623	623
Mean	1.58	6.62	61.40	29.23	19.76	6.26	2.61	0.39	32.42	0.42	0.58	77.43	0.13	3.51	6.42	12.79	-0.48	-0.52	0.66
Median	1.53	5.81	59.20	26.44	16.05	4.11	2.69	0.41	29.88	0.45	0.61	73.45	0.07	4.34	5.18	12.79	-0.44	-0.54	0.67
Std. Dev.	1.82	3.37	18.44	16.19	12.65	6.64	0.86	0.11	15.87	0.10	0.19	10.30	0.16	4.33	5.16	1.38	0.22	0.46	0.13
Minimum	-3.79	2.21	34.02	3.01	2.75	0.39	-1.28	0.03	1.60	0.05	0.03	54.74	0.00	-8.30	-1.37	8.72	-0.91	-1.45	0.50
Maximum	6.06	24.12	101.44	94.17	95.91	46.60	4.76	0.50	95.45	0.50	0.97	100.00	0.83	13.90	18.78	16.28	0.15	0.34	0.85
More Developed Republics | All Data																			
Obs.	765	765	765	765	765	765	765	765	765	765	765	765	765	765	765	765	765	765	765
Mean	1.72	7.92	63.03	32.93	21.88	10.95	2.18	0.42	43.11	0.40	0.54	62.94	0.16	0.51	11.91	12.52	-0.96	-0.75	0.61
Median	1.54	6.86	60.09	29.62	15.98	7.60	2.32	0.45	40.60	0.45	0.58	62.43	0.08	2.44	9.78	12.20	-1.13	-0.76	0.77
Std. Dev.	2.34	4.58	20.68	18.22	16.71	12.26	1.05	0.09	18.44	0.11	0.22	12.85	0.20	4.13	10.84	1.93	0.83	0.15	0.20
Minimum	-3.79	2.21	34.02	0.14	2.53	0.00	-1.53	0.00	0.00	0.00	0.00	34.94	0.00	-9.77	-0.20	8.20	-2.02	-1.12	0.22
Maximum	6.06	24.12	101.44	93.39	93.93	97.44	4.79	0.50	97.55	0.50	0.98	93.36	0.98	7.50	108.69	17.15	0.35	-0.47	0.77

Note. This table shows data for all variables aggregated across 2010-2024 from individual CIS Republics, on an individual bank level. The data originates from Orbis BankFocus. The data shown includes 1) the cleaned and validated dataset, 2) data filtered by less developed CIS Republics, and 3) More Developed Republics. From the raw dataset, we exclude all central banks, data corresponding to repeated consolidation codes, and any observation that is deemed implausible. Alongside $\mathbf{ID}^{\mathrm{HHI}}$ and $\mathbf{AD}^{\mathrm{HHI}}$, we present data for Net Interest Income as a portion of Operating Revenue and Total Earning Assets as a portion of Total Assets to indicate the direction of the Herfindahl Index value. In computing $\mathbf{ID}^{\mathrm{HHI}}$, we exclude banks with negative operating revenue or non-interest incomes as these make the observation less informative or misleading. For $\mathbf{AD}^{\mathrm{HHI}}$, we exclude banks with negative asset values or when the asset comprises more than 100% of total assets. In isolation, it is not clear which type of income or asset the Herfindahl Index is skewed towards. Additionally, we eliminate any individual banks with more than a missing observation as to ensure the consistency of upcoming dynamic panel regressions, which are vulnerable to small samples within groups.

4 Methodology

4.1 Statistical Framework

We adopt an empirical framework that best takes advantage of the structure and variance within our data. Traditional static panel models assume that the idiosyncratic error is uncorrelated over time, namely, $\mathbb{E}(X_{i,t}|\varepsilon_{i,t} = 0)$. However, this is unlikely in reality. Market power can be directly influenced by any of our risk measures (Clark et al., 2018). The bank, for example, may pursue risky diversification strategies in anticipation of greater returns, causing an endogeneity problem. These biases disqualify the use of static Ordinary Least Squares (OLS) estimators. Certain dynamic panel models, however, account for these temporal differences and resulting bias by including lagged dependent variables and fixed individual effects to control for unobserved heterogeneity among banks, which can be another source of significant persistence (Tilburg University, n.d.). Our core dynamic panel model can be shown to be:

$$\begin{aligned} Y_{i,t} = \alpha &+ \beta' \mathbf{Y}_{i,t-1} + \beta_{\text{ID}} \text{ID}_{i,t}^{\text{HHI}} + \beta_{\text{AD}} \text{AD}_{i,t}^{\text{HHI}} + \beta_{\text{SIM}} \text{SIM}_{i,t}^{\text{Entropy}} + \beta_{\text{DEV}} \text{DEV}_{i,t} \\ &+ \beta_{\text{DOM}} \text{DOM}_{i,t} + \beta_{\text{FOR}} \text{FOR}_{i,t} + \gamma' \mathbf{X}_{i,t} + \eta' \mathbf{Z}_{i,t} \\ &+ \mu_i + \lambda_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $Y_{i,t}$ is a chosen performance metric representing a function of $\mathbf{Y}_{i,t-1}$, the vector of its own one-period-lag, $\text{ID}_{i,t}^{\text{HHI}}$ and $\text{AD}_{i,t}^{\text{HHI}}$, income and asset diversification measures, $\text{SIM}_{i,t}^{\text{Entropy}}$, entropy similarity across individual banking asset types, $\text{DEV}_{i,t}$ is a dummy variable with value 1 if the bank originates from a more developed CIS Republic, and zero otherwise, $\text{DOM}_{i,t}$ and $\text{FOR}_{i,t}$ are dummy variables denoting whether the bank is domestically-owned, and if not, whether the foreign owner originates from the CIS or abroad, respectively, $\mathbf{X}_{i,t}$, a vector of control variables defined previously, $\mathbf{Z}_{i,t}$, a vector of interaction terms to test specific aspects of each hypothesis, μ_i, representing individual bank fixed effects to absorb unobserved time-invariant heterogeneity, λ_t, a vector of time-series dummy variables to control for time-varying unobserved heterogeneity, and an idiosyncratic error term $\epsilon_{i,t}$, which is independent and identically-distributed with a constant variance and mean of zero.

However, according to Nickell (1981), basic dynamic panel models introduce sufficient endogeneity to make Fixed Effects or Random Effects estimators biased and inconsistent. These issues are exacerbated when there is high persistence and short time length, which, unfortunately, cannot be alleviated by increasing sample size. Studies such as Berger et al. (2000) show that bank profitability likely persists over time following its dependence on macroeconomic factors, which themselves are serially-correlated. In tandem with practice and literature, we counter these concerns through the Generalized Method of Moments (GMM) regressions first formulated by Blundell and Bond (1998). The first variant of GMM is Difference-GMM, which transforms regressors by first-differencing, eliminating the fixed effect. Further, the endogenous lagged dependent variable is instrumented with its past observations. However, if the sample is finite and time period is short, as in our case, then the instrumentation by Difference-GMM weakens, causing the estimator to be inconsistent and biased. The development of the System-GMM variant, however, improves instrumentation efficiency substantially by introducing a greater number of moment conditions. Following Clark et al. (2018), we use the two-step estimation, which is advantageous since its weighting matrix allows for heteroskedasticity and autocorrelation in the error terms, making it asymptotically more efficient. However, two-step results in a severe downward bias in standard errors with small samples, overestimating test statistics. To account for this, we adopt Windmeijer's correction (2005), making statistical inferences more accurate. System-GMM is commonly applicable for dynamic panel applications due to its ability to conduct orthogonal transformations, which preserve significantly more observations than would otherwise be lost to first-differencing in the second step. Further, a common pitfall with GMM involves overfitting resulting from too many instruments, invalidating the Hansen J-test. To avoid weakening our instrumentation, we collapse our instruments, reducing their overall count.

4.2 Model Validation and Robustness Tests

While System-GMM appears to be a better fit for our dataset, we validate the method by following the rule of thumb outlined by Bond (2001). First, for each hypothesis, we estimate dynamic Fixed Effects models. Then, each resulting estimator ϕ_i is considered to be an approximation of the true lower-bound estimate. If the Difference-GMM estimators are consistently lower than ϕ_i, it is considered to be downward biased, resulting from weak instrumentation. In this case, the System-GMM is instead utilised. Subsequently, we consult the exhaustive guide created by Roodman (2009) to evaluate the validity of our GMM specifications. The first criterion is the Hansen J-test for over-identification, which determines the validity of models' instrumentation (Hansen et al., 2008). Given a failure to reject its null hypothesis at 5%, we found support for our selection of instruments. Further, considering that the GMM framework aims to reduce endogeneity arising from persistence, it follows that we test for its presence. The lag structure of GMM is found to be well-specified if we fail to reject the null hypothesis of the Arellano-Bond test for second-order autocorrelation. Specifically, it suggests that the error term of the first-differenced instruments has no remaining persistence and that the moment conditions are correct. In addition to the AR(2) test, we conduct AR(1) tests to determine whether the first-differencing action under GMM is necessary. Having validated our models, we subsequently assess individual estimators' significance through their z-statistic.

4.3 Evaluation of Hypotheses

The main hypotheses are evaluated by restricting Expression 1. Per H_1^a, we determine whether an overall diversification effect exists per development level. To evaluate the validity of a System-GMM specification, we construct a Fixed-Effects specification and subsequently, a Difference-GMM specification, comparing their results. These restricted models omit $\mathrm{SIM}_{i,t}^{\mathrm{Entropy}}$, $\mathrm{DOM}_{i,t}$, $\mathrm{FOR}_{i,t}$, $\mathbf{Z}_{i,t}$, alongside λ_t as to not introduce high complexity initially. Given that the results justify a System-GMM specification, we then construct a restricted variant of System-GMM, including λ_t over the Difference-GMM variant. Following this, a second permutation is estimated, including the interaction terms

$$\mathbf{Z}_{i,t}^{\mathrm{H}_1} = \begin{cases} \mathrm{ID}_{i,t}^{\mathrm{HHI}} \times \mathrm{DEV}_{i,t}, & \eta_1, \\ \mathrm{AD}_{i,t}^{\mathrm{HHI}} \times \mathrm{DEV}_{i,t}, & \eta_2. \end{cases} \tag{2}$$

If diversification, on average, negatively affects risk and performance, then we expect that the estimated coefficients $\hat{\beta}_{\mathrm{ID}} < 0$ and $\hat{\beta}_{\mathrm{AD}} < 0$, statistically significant. If this effect is worse for less developed Republics, then we require that the dummy variable $\mathrm{DEV}_{i,t} = 0$. If we find that $\hat{\beta}_{\mathrm{DEV}} \neq 0$, then it would suggest that more developed Republics have a non-zero effect on performance, compared to less developed counterparts. If the interactions $\hat{\eta}_1 \neq 0$ or $\hat{\eta}_2 \neq 0$, it would indicate that relative to less developed Republics, shifting from non-interest income to interest-based income has a non-zero effect on performance.

Assessing Hypothesis 2, we examine the effects arising from ownership. To do so, we repeat the construction of validation models under Hypothesis 1 with the addition of $\mathrm{DOM}_{i,t}$ and $\mathrm{FOR}_{i,t}$. Similarly, the restricted System-GMM model adds λ_t, but the interaction variant instead includes the interactions

$$\mathbf{Z}_{i,t}^{\mathrm{H}_2} = \begin{cases} \mathrm{ID}_{i,t}^{\mathrm{HHI}} \times \mathrm{DOM}_{i,t}, & \eta_1, \\ \mathrm{AD}_{i,t}^{\mathrm{HHI}} \times \mathrm{DOM}_{i,t}, & \eta_2, \\ \mathrm{ID}_{i,t}^{\mathrm{HHI}} \times \mathrm{FOR}_{i,t}, & \eta_3, \\ \mathrm{AD}_{i,t}^{\mathrm{HHI}} \times \mathrm{FOR}_{i,t}, & \eta_4. \end{cases} \tag{3}$$

If we find that the reference category $\hat{\beta}_{\mathrm{DOM}=0} > 0$, then it would indicate that, relative to domestic ownership, foreign banks on average perform more highly, ceteris paribus. We specify the effect further by assessing $\hat{\beta}_{\mathrm{FOR}}$. If the estimate is shown to be significant and different from zero, then CIS-based foreign banks perform, on average, better than their non-CIS foreign counterparts. The extent to which these effects are contingent on diversification measures is dictated by the interaction terms specified above. Given that $\hat{\eta}' \neq 0$, then, each respective ownership indicator, relative to their reference category, the effect is dependent on the bank's level of diversification. To determine whether significant variation exists across development levels, given that they are significant individually, we determine the difference $\hat{\beta}_{\mathrm{DEV}}^{\mathrm{H2}} - \hat{\beta}_{\mathrm{DEV}}^{\mathrm{H1}}$. This suggests whether the addition of ownership changes the marginal explanatory power of development, indicating if performance is better understood contingent on ownership.

Finally, H_3^a evaluates the asset similarity channel of effects. Model validation begins with the restricted Fixed-Effects and Difference-GMM models under Hypothesis 1 with the addition of $\mathrm{SIM}_{i,t}^{\mathrm{Entropy}}$. As before, the restricted System-GMM specification adds time dummies, then, the interactions specific to entropy similarity, namely,

$$\mathbf{Z}_{i,t}^{\mathrm{H}_3} = \begin{cases} \mathrm{ID}_{i,t}^{\mathrm{HHI}} \times \mathrm{SIM}_{i,t}^{\mathrm{Entropy}}, & \eta_1, \\ \mathrm{AD}_{i,t}^{\mathrm{HHI}} \times \mathrm{SIM}_{i,t}^{\mathrm{Entropy}}, & \eta_2. \end{cases} \tag{4}$$

Given $\hat{\beta}_{\mathrm{SIM}} \neq 0$, we would conclude that entropy similarity has a marginal non-zero effect on performance. Depending on the difference $\hat{\beta}_{\mathrm{ID}}^{\mathrm{H3}} - \hat{\beta}_{\mathrm{ID}}^{\mathrm{H1}}$ and $\hat{\beta}_{\mathrm{AD}}^{\mathrm{H3}} - \hat{\beta}_{\mathrm{AD}}^{\mathrm{H1}}$, we can determine whether the addition of similarity influences the explanatory power and significance of diversification measures. In other words, demonstrates whether they jointly explain variations in performance. If the interaction terms are found to be significant and non-zero, then this reveals whether the two kinds of measures can explain each other sufficiently as marginal effects. Further, given their significance, by assessing the difference $\hat{\beta}^{\mathrm{H3}}_{\mathrm{DEV}} - \hat{\beta}^{\mathrm{H1}}_{\mathrm{DEV}}$, we can determine if the asset similarity channel offers sufficient explanatory power to improve our overall ability to make inferences on performance.

5 Results and Discussion

Having outlined the general methodology, we now evaluate the hypotheses empirically. First, following Roodman (2009), a series of Random Effects and two-step Difference-GMM dynamic panel models are estimated and compared to obtain evidence that System-GMM is better able to account for observed endogeneity. Upon passing these diagnostics, we interpret the GMM models to first determine the overall impact of income and asset diversity on risk and performance metrics. Then, bank ownership status is added to determine whether foreign banks have a relative performance advantage and how they affect the initial diversification association established. In addition, we can assess how asset similarity interacts with diversification measures to assess its role within the diversification mechanism. Moreover, by estimating both marginal and interaction terms, particularly significant joint impacts can be highlighted if any exist. Given the results' validity, throughout this section, we will highlight their consistency across our diverse range of dependent variables as a test of robustness.

5.1 Preliminary Model Validation

Before interpreting the final results of each hypothesis, we must ensure that endogeneity across our observed banking metrics is accounted for. Across Tables 3, 4, and 5, we observe that lagged dependent variables are highly significant for the Random Effects models, supporting the assertion of Berger et. al. (2000) that performance metrics tend to exhibit persistence. However, per Nickell (1981), Random Effects models are biased in such cases. The subsequent two-step Difference-GMM model attempts to correct for this error, however, model diagnostics heavily indicate that these models, too, are invalid. Notably, across all hypotheses, we observe significant Hansen J-statistics, which results in a rejection of its null hypothesis, indicating that the instrument specification is invalid. This weak instrumentation suggests that solely taking first differences across endogenous variables is insufficient. Rather, it may be necessary to take lags of differences and increase instrumentation efficiency, as System-GMM does. Further, per the rule of thumb by Bond (2001), a System-GMM regression is favoured over Difference-GMM if the estimated coefficients of the latter are below those of their Random Effects equivalents. Across our target variables and hypotheses, these coefficients are consistently lower, which gives further evidence of model misspecification. Therefore, we present two-step System-GMM models with collapsed instruments, preventing overfitting and increasing instrumentation efficiency. We discuss the diagnostics of these subsequent models in the following subsections.

5.2 General Diversification Impacts on Performance

First, we evaluate the general impacts of diversification measures on performance metrics under Hypothesis 1, controlling for relevant confounding effects.

The first set of System-GMM regressions includes the main predictors, alongside their respective sets of control variables, excluding interaction effects. Based on the standard set of diagnostics for System-GMM presented by Bond (2001) and Roodman (2009), these regressions appear more valid than their predecessors. Excluding the liquidity risk model, the null hypothesis of the Hansen J-tests cannot be rejected at 5%, indicating that the GMM instruments are likely to be specified correctly. This is aided by the substantial reduction in instruments from 51 to 28 due to instrument collapsing, which is important since the J-test approaches $p = 1$ as the number of instruments grows to $I = N$. Further, the endogenous lags of performance metrics are instrumented correctly if we exhibit an insignificant second-order autocorrelation. Under Table 3, AR(1) is universally significant, which is expected since we have evidence of persistence. For the remaining valid models, AR(2) tests yield insignificant statistics, suggesting that the remaining persistence is accounted for.

The endogenous instruments for dependent variables' lags are highly significant, with a percentage increase in lagged ROA, efficiency ratio, capital, credit, and stability risk being associated with a respective 0.42%, 0.58%, 0.76%, 0.61%, and 0.48% increase in the current metric. While all metrics aside from NIM are highly significant, they do not appear to be economically significant, as their overall magnitude is relatively inconsequential. The fact that the lagged effects are partially carried over suggests that there may exist a mean reversion among the CIS Banks since we have controlled for external macroeconomic shocks. These results broadly support Berger et. al. (2000), who find strong evidence for a persistence effect among financial institutions, however, unlike the U.S. context, the insignificance or low magnitude of institutional factors such as banking concentration, GDP, or inflation suggest that persistence in the CIS is driven by localized shocks. These shocks result in low, non-durable rents, providing evidence for relatively lagged development of institutional and market structures. Per Sharipova (2015), this is an important driver of banking dynamics across the CIS.

The institutional implications of small localised persistence across banks link directly to the sharp divergence observed in our estimates for diversification measures. We find that only asset diversification exhibited significance, and solely for the stability model. However, its interpretation is subject to scrutiny; a single point change in concentration is associated with over 1000% increase in Z-score, which strongly indicates that asset diversity is extremely low within the sample, as a small change has an unrealistic impact on bank stability. These findings imply that, whether measured from an asset or income perspective, diversification generally has no meaningful impact on banks' risk or performance across the CIS. These results oppose the traditional view proposed by Diamond (1984), suggesting that diversification is unlikely to lead to increased capabilities in information acquisition and efficiencies gained by pooling depositing and lending activities. This is further supported by the insignificance of the size effect, implying that economies of scale or scope do not drive this effect. The efficiency gains prescribed by Diamond (1984) require a well-established capacity to undertake information processing activities, which is known to be underdeveloped owing to the lack of professional management experience across the CIS (Berglof & Bolton, 2002; Sharipova, 2015).

Further, the results oppose Acharya (2006), suggesting a fundamentally different agency conflict dynamic may drive CIS banks' diversification strategies. In contrast, CIS managers may face greater credit monitoring incentives despite banks' substantially greater degree of overall market concentration. Since credit risk is driven mainly by macroeconomic factors, localised bank-level shocks likely do not drive the quality of their asset portfolios. This suggests relatively high monitoring incentives as credit quality responds positively to external factors. Considering the significance of market concentration in determining net interest margin, we instead find that bank managers exploit their market power to charge higher fees and spreads rather than engaging in moral hazard that would deteriorate credit quality. Further, a unit improvement in the Central Bank Independence Index significantly improves net interest margin, increasing it by 11.74%. The positive response to greater central banking authority indicates that managers' credit monitoring incentives are linked more strongly to national macroeconomic objectives. This notion also supports Sharipova's (2015) assertion that central banking supervision is a limiting factor in CIS economic development as we observe a positive relationship.

Interestingly, while our diversity measures present no significant effects on most metrics, bank size itself presents a more nuanced discussion regarding CIS banks. The System-GMM estimations indicate that larger CIS banks are associated with significantly lower capital risk, with a coefficient of -1.355, implying stronger capitalisation levels. However, this enhanced capitalisation does not translate into improved overall stability. Notably, larger bank size is linked to significantly lower Z-scores with a coefficient of -0.096. The contrast between larger, yet more capitalised banks resonates with the nuanced arguments presented by Chiorazzo et al. (2008), who posit that bank size acts as a significant channel through which the effects and the limitations of diversification strategies become clear. Specifically, their research on Italian banks identified diminishing returns to scale, suggesting that greater size benefits diversification only to an extent. They argue that the increased complexities within banks' inner management alongside their operations lead to diseconomies of scale. While the CIS banking landscape is inherently distinct from that of Italy, the lower observed stability of larger CIS banks, despite their stronger capital positions, aligns with this framework of size-induced diseconomies. Arguably, the relatively lower technical and risk management experience within the CIS can amplify these inefficiencies, increasing the rate of diminishing returns (Sharipova, 2015). These observations also cohere with concerns raised by Stiroh and Rumble (2006) regarding the "dark side of diversification," where bank size and organisational structure can themselves become sources of amplified risk. Despite the insignificance of our diversity measures, bank size may represent the overall net negative effects arising from growing scale. Consequently, the challenge faced by larger CIS banks may not be strictly related to expansion into new markets, but rather to developing the expertise and experience necessary to overcome systemic inefficiencies. As we cannot find evidence for a meaningful, significant negative or non-zero effect of diversification on performance, we cannot support the first hypothesis.

Moreover, more developed CIS Republics are associated with a 2.79% improvement in net interest margin relative to less developed Republics, which is significant at 1%, however, other risk or performance metrics have no significant impact. These results are most closely related to Djalilov et. al. (2016). The insignificance of development level across our metrics supports the authors' findings that, relative to early transition countries, greater capitalisation has an insignificant effect on profitability. In their paper, this finding was attributed to more stable financial conditions, which enable greater business opportunities and provide more flexibility in resolving acute financial distress. As demonstrated by Sharipova, (2015), while the developmental divergence across CIS Republics is significant, their collective divergence from more developed non-CIS nations is even greater. Alongside this, considering that our sample of more developed banks exhibits, on average, greater variance than their counterparts, it follows that less developed banks may have insufficient meaningful variation to lead to a statistically significant variation across developmental levels. Further, the authors find that CIS Republics exhibit a significant negative relationship between increased credit risk and bank profitability. Their study relates this to the increasing competency of higher developed Republics in risk mitigation, which is consistent with the association established initially. Considering the greater frequency of highly-skilled managers, it follows that over time, they can develop sufficient risk management protocols to provide the fiscal space needed to improve margins. In the presence of these effects, the insignificance of diversification measures indicates CIS managers' preference for growth within the lending spaces they already dominate rather than inorganic expansion elsewhere. Ultimately, we maintain our inability to support the first hypothesis.

Notwithstanding, we posit that the insignificance among our diversity measures reflects a broader inconsistency in the measurement of diversification in literature. Elsas et. al. (2010) present a robust framework for evaluating diversification, highlighting that the lack of granularity in these measures conceals its indirect effects. First, the authors challenge Laeven and Levine (2007), advocating against classifying income into interest vs non-interest components. Arguably, this binary classification is unrepresentative as different revenue sources have differing risk-return and covariance characteristics. Further, the authors make a distinction between revenue, asset, and activity diversification, which supports our addition of the asset channel. They demonstrate that each factor is imperfectly correlated with the rest, which biases estimated coefficients if studies aim to test a general diversification effect. These arguments give credence to methodologies such as Acharya (2006), demonstrating that greater dimensionality through industrial or geographic expansion can present more reliable results. However, CIS institutions and market environments do not follow the ideal prescribed by the authors. Namely, unfair competitive dynamics, accounting inconsistencies, underdeveloped regulatory frameworks alongside other factors (Sharipova, 2015) can limit the additional explanatory power further granularity would present.

While not our primary objective, a discussion of time dummies reveals important unobserved time variation. Their inclusion does not weaken our System-GMM instrumentation however instead, improves model robustness by absorbing unobserved macroeconomic or policy-related shocks that would otherwise be omitted. We observe several significant dummies, mostly negatively impacting performance across numerous metrics, which validates their inclusion in the models and suggests that individual CIS bank performances are susceptible to external shocks. This provides further evidence that wider national policy may strongly influence managers, combating the moral hazard or adverse selection described by Acharya (2006).

To assess the interdependence of diversification measures with Republics' developmental levels, we add interaction terms to the previous System-GMM regression. Table 6 indicates that the NIM and liquidity risk-based model has significant J-test values, suggesting weak instrumentation. These models are subsequently excluded from discussions.

In contrast to the non-interaction model, interacting diversity measures yield a significant negative total effect of $-14.36\% + 12.93\% = -1.43\%$ on ROA for a more developed Republic. However, a less developed Republic is associated with a 12.93% improvement from a unit difference. Therefore, in relative terms, a greater level of development reduces ROA. These results indicate that pooling all the Republics dilutes the true impact of income diversity, giving credence to the current model specification. However, since we cannot establish a baseline diversification effect, we cannot broadly support the notion of a development effect on diversification, per Hypothesis 1. Notwithstanding, these findings are generally consistent with the extensive study of CIS banking dynamics by Sharipova (2015). Notably, the author finds that over time, less developed Republics tend to exhibit proportionally greater growth levels since their markets and customer bases are comparatively less saturated than more developed Republics. Additionally, this saturation forces larger Russian and Kazakh banks to expand elsewhere for growth. As the author argues, the costs associated with this growth require greater risk tolerance and incur relatively more losses, increasing the variance in ROA.

Table 3: Results | Modeling Validity for Hypothesis 1

	RANDOM EFFECTS MODEL UNRESTRICTED MODEL							Avg. β Diff.	TWO-STEP DIFFERENCE GMM RESTRICTED MODEL WITH CONTROLS							TWO-STEP SYSTEM GMM RESTRICTED MODEL WITH CONTROLS						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	Δ_β	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables																						
L1 ROA	0.55***	-	-	-	-	-	-	0.21	0.34***	-	-	-	-	-	-	0.41***	-	-	-	-	-	-
L1 NIM	-	0.19***	-	-	-	-	-	0.15	-	0.04	-	-	-	-	-	-	0.07	-	-	-	-	-
L1 EFF	-	-	0.67***	-	-	-	-	0.42	-	-	0.25**	-	-	-	-	-	-	0.59***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.82***	-	-	-	0.47	-	-	-	0.35***	-	-	-	-	-	-	0.79***	-	-	-
L1 Capital Risk	-	-	-	-	0.78***	-	-	0.33	-	-	-	-	0.45***	-	-	-	-	-	-	0.73***	-	-
L1 Credit Risk	-	-	-	-	-	0.71***	-	-0.04	-	-	-	-	-	0.75***	-	-	-	-	-	-	0.67**	-
L1 log Z	-	-	-	-	-	-	0.91***	0.61	-	-	-	-	-	-	0.30**	-	-	-	-	-	-	0.42**
ID^{HHI}	-0.37	-4.85***	8.35**	-0.54	-5.66***	-2.49	0.05	12.65	5.52	-14.07***	-66.20***	17.44	-30.04	-6.17	-0.56	1.01	-12.32	17.85	27.20	-15.22	0.95	-0.93
AD^{HHI}	0.88**	-2.19**	1.12	1.84	-2.90*	-3.73**	0.18**	-7.06	-2.58	-10.03**	31.30	41.15**	-4.98	-9.01	-1.20	-0.37	-5.28	1.15	-57.44***	-10.95	-4.65	-0.53
Development	0.50***	1.63***	-0.79	3.51***	0.07	0.24	-0.03	0.73	0.00**	0.00	0.00***	0.00***	0.00	0.00	0.00***	0.57	2.79***	-0.90	1.30	-0.65	-0.74	-0.16
Concentration	0.01**	0.03***	0.02	0.06**	-0.05**	-0.03	0.00	-0.02	0.02**	0.00	0.03	0.03	0.06	0.02	0.00	-0.04	0.22***	0.42	0.11	0.04	-0.13	0.01
Entropy Similarity	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
log Size	0.05*	-0.47***	-1.99***	0.23	-1.29***	-0.07	-0.02***	1.00	0.29	-1.90***	-4.17*	5.01**	-7.46***	-1.93*	-0.41***	-0.09	0.04	-1.38	0.64	-1.36**	-0.25	-0.10**
Peace & Stability	0.00	-0.01	-3.49***	0.58	0.24	-0.43	-0.02	-1.19	-0.04	0.36	3.80	2.46	-0.73	-0.59	-0.04	2.06**	-3.45*	-15.43**	-5.76	-4.13	0.71	-0.28*
ROL	-0.03	-1.22**	-0.79	-2.77**	2.21***	0.23	0.09**	-0.19	-0.41	2.49**	-5.50	-2.83	5.49*	-0.45	0.24	0.31	-4.97***	-5.55	1.69	4.92**	2.36	0.53*
CBI	0.26	2.67**	-9.47***	5.41*	-5.59***	-0.82	-0.23**	9.91	-17.67	14.80	-98.45	1.73	15.60	4.92	1.94	0.36	11.74***	0.62	-1.13	-18.12***	-7.71	-1.62**
Domestic Ownership	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CIS Foreign Ownership	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Exogenous (IV) Variables																						
GDP Growth	0.05***	0.09***	0.22**	-0.19**	0.14***	-0.11**	0.01***	0.03	0.05***	0.02	0.07	-0.07	0.04	-0.14***	0.01***	0.05***	0.00	0.03	-0.16	0.08	-0.12**	0.01***
Inflation	0.00	0.00	-0.20***	-0.12***	0.02	0.04*	0.00	0.00	-0.01	0.00	-0.24***	0.06	-0.13***	0.07	-0.01***	0.04**	-0.05	-0.42***	-0.34***	-0.02	0.00	0.00
Constant	-1.53**	8.55***	45.17***	-7.06	31.77***	7.66**	0.56***	-	-	-	-	-	-	-	-	5.66	-15.86	-3.38	1.87	44.76**	23.70*	3.94**
Number of Instruments	-	-	-	-	-	-	-	-	51	51	51	51	51	51	51	26	26	26	26	26	26	26
Number of Observations	1,388	1,388	1,388	1,388	1,388	1,388	1,388	-	948	948	948	948	948	948	948	948	948	948	948	948	948	948
Number of Groups	-	-	-	-	-	-	-	-	199	199	199	199	199	199	199	199	199	199	199	199	199	199
F-Statistic	73.34***	41.52***	204.64***	247.92***	558.21***	194.05***	853.79***	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
R^2	0.37	0.27	0.62	0.66	0.83	0.61	0.87	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hansen J-Test	-	-	-	-	-	-	-	-	44.25	61.36**	52.17*	58.88**	64.60***	58.36**	75.14***	6.94	9.60*	2.95	13.39**	9.16*	9.38*	6.20
Hansen J-Test p value	-	-	-	-	-	-	-	-	0.30	0.02	0.09	0.03	0.01	0.03	0.00	0.22	0.09	0.71	0.02	0.10	0.09	0.29
AR(1) Test (1^{st} Difference)	-	-	-	-	-	-	-	-	-4.44***	-1.74*	-3.65***	-2.86***	-2.84***	-2.35**	-3.18***	-5.47***	-1.97**	-7.00***	-6.17***	-3.69***	-2.42**	-3.14***
AR(2) Test (1^{st} Difference)	-	-	-	-	-	-	-	-	-0.07	-2.63***	-0.57	0.53	-0.39	0.58	1.08	-0.69	-0.52	-0.36	2.00**	-0.18	0.60	0.60

Note. The table presents modelling results pertaining to the first hypothesis, as specified in the methodology section. In accordance, we estimate three models to evaluate the validity of our desired System-GMM specification. These include a Random-Effects and then a Difference-GMM specification across our risk and performance indicators. We compare the coefficients between the Random-Effects and Difference-GMM estimators to evaluate the necessity of a System-GMM specification. Alongside this, the Hansen-J test for over-identification and AR(2) test for autocorrelation indicate whether the instrumentation and lag structure of the GMM models were specified correctly. The third model is a System-GMM specification with the addition of time dummy variables to remove unobserved time-varying heterogeneity. To provide more context for the validity of the specifications, the number of groups, total observation, and instrument counts are presented.
The asterisks denote significance levels as follows: $p \leq 0.1: *$, $p \leq 0.05: **$, and $p \leq 0.01: ***$.

5.3 Evaluation of Bank Ownership in Diversification Effects

Supplementing the previous analysis, we assess bank ownership structure to determine the nature of its influence on the dynamics of diversification.

The construction of the initial System-GMM model appears to exhibit overfitting, as across the ROA, NIM, efficiency ratio, capital, and stability models, the Hansen J-tests are highly insignificant, reaching around $p \approx 0.90$. According to Roodman (2009), p-values above around $p \approx 0.5$ should be treated with increased suspicion. While the instrument count is relatively low, they are unlikely to contribute to a meaningful reduction in endogeneity. Therefore, we interpret the liquidity and credit risk models. The addition of ownership interactions with diversification measure conceptually enables a direct assessment of whether a significant direct relationship may exist. These additional regressors introduce more instruments, weakening them, as seen in Table 6. The liquidity and credit models remain interpretable, however, the stability model now shows healthier instrumentation as the J-test can no longer be rejected.

Consistent with the general diversification effect baseline model, we observe statistically significant, yet economically insignificant estimations of lagged endogenous performance. This consistency is highly suggestive that this effect is robust to differing model specifications, though its inherent endogeneity makes GMM are more suitable forum for its discussion.

Relative to foreign banks, domestic banks do not appear to exhibit any significant differences across performance metrics. Considering the relative insignificance of domestic versus foreign ownership in both the restricted and interaction models, it follows that further examining non-domestic banks originally from a CIS nation does not yield exceptionally different results. Ultimately, these results, alongside overfitting concerns, for both the restricted and interaction models, do not lend support to Hypothesis 2. These banks, compared to non-domestic banks originating outside of the CIS, do not perform significantly differently. Further, the constant is insignificant for all models, suggesting that no combination of the reference categories of ownership indicators is masking any meaningful effects either. Interestingly, these results generally contrast with those of Sharipova's (2015) research. The author finds that state-owned banks have significantly greater technical and cost efficiency compared to private banks. While we do not analyse state banks directly, the arguments are highly relevant nonetheless; state banks have disproportional advantages in their involvement in government projects, as they serve to further state developmental interests. This results in a comparatively higher level of productive output. Further, resulting from the Republics' Soviet legacies, such banks tend to be trusted more, meaning that they have wider and cheaper access to human and capital resources, giving them cost advantages. The asymmetry of these advantages can eliminate the theoretical advantages that foreign CIS banks can hold under the limited form global hypothesis (Berger, DeYoung, et al., 2000). Foreign banks' comparative advantages, such as a more robust risk framework, greater managerial experience, or otherwise, may be insufficient concerning the endogenous influence of state-owned banks. In addition to their cost and investment opportunities, Rajan (1992) argues that such asymmetries can be exacerbated by endogenous switching costs borne by customers, which is especially salient in the CIS due to the relatively small customer pool (Berglof & Bolton, 2002). If such high informational disparities prevail, then the degree of informational processing or acquisition expertise required by commercial banks would be sufficiently great that they would be unable to grow their respective clientele, effectively placing a ceiling on their performance. These dynamics can offer a powerful explanation for the insignificant performance metrics observed, demonstrating that there is a lack of meaningful variation both within and across the metrics. Further reinforcing the lack of evidence for an effect, the interactions yield sufficient evidence to reject the premise that ownership changes the strength of diversification effects. Combining this with the previous finding that CIS managers are unlikely to have a strong competition-oriented focus, this can justify banks' focus on extracting greater value from customers due to higher spreads and fees rather than diversification strategies aimed at expanding into new markets.

In assessing CIS-owned foreign banks relative to non-CIS owners, Sharipova (2015) find a strong and significant positive relationship with ROA, which our results do not corroborate. Justifying the result, the paper points to the fact that Russian and Kazakh banks are among the largest and most developed, combined with their greater technical efficiency, in explaining their success in other CIS markets. Our discrepancy can be explained by the fact that our sample originates from self-reported financial indicators; given that Russian and Kazakh banks constitute the greatest portion of the sample, it follows that the models assess their impact on too few non-developed banks, yielding an insignificant result.

However, our results cannot meaningfully validate the author's finding that foreign banks are less efficient, challenging the global advantage theory. Interestingly, they argue that foreign banks have greater difficulty in processing local market information, giving them a comparative disadvantage. The weak instrumentation of the efficiency ratio model is suggestive of high overfitting, caused possibly by highly collinear relationships or the classification of most variables as endogenous. Notwithstanding, this is a result in itself; the fact that neither diversification measures nor ownership indicators can offer meaningfully different explained variation individually suggests that our sample of CIS banks may operate more homogeneously, or the presence of other unaccounted unobserved systemic factors. The apparent asymmetries in competitive dynamics, managerial incentives, and macroeconomic priorities may overcome more technical or theoretical considerations that the more technocratic management frameworks in Western economies appear to emphasise.

Table 4: Results | Modeling Validity for Hypothesis 2

	RANDOM EFFECTS MODEL UNRESTRICTED MODEL							Avg. β Diff.	TWO-STEP DIFFERENCE GMM RESTRICTED MODEL WITH CONTROLS							TWO-STEP SYSTEM GMM RESTRICTED MODEL WITH CONTROLS						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	Δ_β	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables																						
L1 ROA	0.54***	-	-	-	-	-	-	0.24	0.30***	-	-	-	-	-	-	0.35***	-	-	-	-	-	-
L1 NIM	-	0.19***	-	-	-	-	-	0.18	-	0.01	-	-	-	-	-	-	0.26	-	-	-	-	-
L1 EFF	-	-	0.67***	-	-	-	-	0.37	-	-	0.30***	-	-	-	-	-	-	0.55***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.82***	-	-	-	0.48	-	-	-	0.34***	-	-	-	-	-	-	0.70***	-	-	-
L1 Capital Risk	-	-	-	-	0.78***	-	-	0.33	-	-	-	-	0.45***	-	-	-	-	-	-	0.63***	-	-
L1 Credit Risk	-	-	-	-	-	0.71***	-	-0.01	-	-	-	-	-	0.72***	-	-	-	-	-	-	0.78***	-
L1 log Z	-	-	-	-	-	-	0.91***	0.62	-	-	-	-	-	-	0.29**	-	-	-	-	-	-	0.36**
ID^{HHI}	-0.40	-4.90***	8.15**	-0.22	-5.79***	-2.64	0.05	7.94	3.37	-9.36*	-47.47**	17.32	-22.40	-2.27	-0.55	-3.46	15.52	8.30	18.91	-29.17	-4.49	-1.37
AD^{HHI}	0.91**	-2.14**	0.98	1.92	-2.90*	-3.87**	0.18**	-6.61	-2.03	-5.60	20.15	36.87**	-5.98	-1.07	-0.99*	-6.94	9.53	-12.24	-44.06	17.97	-2.21	0.15
Development	0.53***	1.67***	-0.75	3.43***	0.12	0.26	-0.03	0.75	-0.00***	0.00***	0.00***	0.00	0.00***	0.00**	0.00	0.68	1.93	0.48	2.06	0.84	-1.02	-0.08
Concentration	0.01**	0.03***	0.02	0.06*	-0.05**	-0.02	0.00	-0.02	0.02**	0.00	0.00	0.06	0.07**	0.03	0.00	-0.03	0.24	0.52	0.27	0.16	-0.11	0.01
Entropy Similarity	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
log Size	0.05*	-0.48***	-1.98***	0.22	-1.31***	-0.05	-0.02***	0.84	0.23	-2.15***	-3.87**	6.31***	-7.41***	-2.16**	-0.41***	-0.19	0.28	-1.67	1.21	-1.15	-0.32	-0.14**
Peace & Stability	0.01	0.00	-3.44***	0.50	0.26	-0.40	-0.02	-1.02	0.00	0.36	2.92	2.00	-0.86	-0.33	-0.03	0.79	-1.22	-18.01**	-6.83	0.65	-0.77	0.01
ROL	0.01	-1.09**	-0.50	-3.20**	2.36***	0.41	0.10**	-0.39	-0.29	2.43**	-4.80	-2.01	6.05*	-0.76	0.23	4.97	-22.47	-1.70	2.47	-18.56	7.08	-0.21
CBI	0.18	2.41**	-9.34***	5.34*	-5.78***	-0.67	-0.24**	5.84	-20.21	26.77**	-46.48	-36.62	7.27	18.74	1.54	-9.59	53.61	-11.64	5.86	36.16	-17.47	-0.46
Domestic Ownership	-0.07	-0.14	1.04	-1.18*	0.05	0.79**	-0.01	0.07	0.00	0.00***	-0.00***	-0.00***	0.00***	0.00	0.00	0.46	-13.72	-7.78	17.38	-7.76	4.49	-1.19
CIS Foreign Ownership	-0.45**	-1.20**	0.45	0.11	-0.76	0.64	-0.02	-0.18	-0.00**	0.00	0.00	0.00	-0.00***	0.00	0.00	-13.08	37.38	-35.35	19.32	57.31	-6.74	-0.46
Exogenous (IV) Variables																						
GDP Growth	0.05***	0.09***	0.22**	-0.19**	0.14***	-0.11**	0.01***	0.03	0.05***	0.03**	0.11	-0.10*	0.05	-0.12***	0.01***	0.09**	-0.16	0.05	-0.14	-0.10	-0.10	0.01
Inflation	0.00	0.00	-0.20***	-0.12***	0.02	0.04*	0.00	0.00	-0.01	-0.01	-0.21**	0.05	-0.12***	0.06	-0.01***	0.02	-0.04	-0.46***	-0.34	0.04	0.00	0.00
Constant	-1.33*	9.07***	44.44***	-6.18	32.43***	6.92**	0.57***	-	-	-	-	-	-	-	-	19.87	-68.73	19.99	-31.85	-14.56	29.24	4.33
Number of Instruments	-	-	-	-	-	-	-	-	69	69	69	69	69	69	69	30	30	30	30	30	30	30
Number of Observations	1,388	1,388	1,388	1,388	1,388	1,388	1,388	-	948	948	948	948	948	948	948	948	948	948	948	948	948	948
Number of Groups	-	-	-	-	-	-	-	-	199	199	199	199	199	199	199	199	199	199	199	199	199	199
F-Statistic	62.68***	35.87***	173.31***	210.41***	469.00***	164.74***	721.54***	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
R^2	0.37	0.27	0.62	0.67	0.83	0.61	0.87	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hansen J-Test	-	-	-	-	-	-	-	-	57.72	80.09**	76.68**	69.61*	79.14**	69.56*	85.01***	2.66	2.67	2.90	10.59	1.37	10.30	2.94
Hansen J-Test p value	-	-	-	-	-	-	-	-	0.41	0.02	0.03	0.10	0.02	0.11	0.01	0.91	0.91	0.89	0.16	0.99	0.17	0.89
AR(1) Test (1st Difference)	-	-	-	-	-	-	-	-	-4.19***	-0.70	-4.09***	-2.92***	-2.82***	-2.31**	-3.18***	-4.97***	-1.28	-5.12***	-4.75***	-3.47***	-2.58***	-3.00***
AR(2) Test (1st Difference)	-	-	-	-	-	-	-	-	-0.18	-2.67***	-0.36	0.57	-0.29	0.55	1.07	-1.13	-0.38	-0.50	1.84*	-0.45	0.58	0.48

Note. The table presents modelling results pertaining to the second hypothesis, as specified in the methodology section. In accordance, we estimate three models to evaluate the validity of our desired System-GMM specification. These include a Random-Effects and then a Difference-GMM specification across our risk and performance indicators. We compare the coefficients between the Random-Effects and Difference-GMM estimators to evaluate the necessity of a System-GMM specification. Alongside this, the Hansen-J test for over-identification and AR(2) test for autocorrelation indicate whether the instrumentation and lag structure of the GMM models were specified correctly. The third model is a System-GMM specification with the addition of time dummy variables to remove unobserved time-varying heterogeneity. To provide more context for the validity of the specifications, the number of groups, total observation, and instrument counts are presented.
The asterisks denote significance levels as follows: $p \leq 0.1 : *$, $p \leq 0.05 : **$, and $p \leq 0.01 : ***$.

5.4 Evaluation of Asset Similarity Channel of Effect

The examination of the asset similarity channel of diversification is notably different from the prior analysis, namely, rather than investigating the target regressor as a confounding effect, we wish to understand specifically the degree to which it replicates the diversification effects we expect. As implied by Wagner (2010), similarity can be seen as a different lens through which to view diversification effects.

The initial model with control variables appears to be the healthiest across our models. Disregarding the significant J-test arising from the liquidity model, the remaining models all show $p \leq 0.35$. Assessing the interaction model, we find that all models reject the Hansen J-test null hypothesis; however, since $p = 0.93$ for the efficiency ratio model, we conclude that its instrumentation is overfitting, preventing a reliable interpretation of its endogenous regressors.

Consistent with prior results, the endogenous lagged dependent variables across the models are almost identical to the model under Hypothesis 1, indicating that the persistence in performance is unaffected by the addition of a proxy for the diversification effect. However, in this case the NIM model does not show a significant lagged effect. Consequently, we add no further points to conclude the discussion on the endogenous persistence observed throughout the study.

The views presented by traditional portfolio theory argue for the benefits of diversification, granted that they are idiosyncratic and imperfectly correlated. Paradoxically, the works of Wagner (2010) and Raffestin (2014) challenge this notion, arguing that diversification strategies and asset portfolios converge, leading to correlated bank failures. Observing the restricted model, we find that a unit increase in entropy similarity, representing diversifying away from non-interest income, leads to a significant increase of 7.40% in bank stability. The result, however, is significant only for the stability metric. This challenges Hypothesis 3, suggesting that less diversity can worsen performance outcomes. Interestingly, its inclusion makes the asset diversity indicator significant, indicating that a higher asset concentration towards interest income leads to a 12.32% improvement in stability. Subscribing to the argument presented for Hypothesis 2, CIS managers' focus on their own core operational strengths in lending can be seen as a strategy to protect commercial banks' limited comparative advantages over other institutions (Rajan, 1992). Given this, it follows that if diversity measures and asset similarity are co-dependent, then neither would exhibit a meaningful performance improvement.

However, the interaction model is markedly different. Seemingly, the inclusion of entropy similarity introduces noise, making inferences unreliable. This is most likely the result of the very high and concentrated values of similarity across the banks, reducing the amount of meaningful variation that GMM can interpret. However, as entropy can capture relatively small changes in data, we find it reasonable to interpret its sign. We observe that entropy similarity has a significant negative association with liquidity risk, suggesting that banks with a more concentrated interest-based asset portfolio have lower liquidity bases. Naturally, the significant negative interaction of similarity with asset diversity suggests that lower liquidity is amplified, hinting that the two metrics may capture similar dynamics. Considering that more developed Republics have the same significant negative effect, we posit that this represents a deliberate choice by some banks to hedge asset concentration risk by controlling the scale of their operations. Doing so can take shape by decreasing the relative size of their loan portfolios. Given this, the phenomenon can be linked to the greater issue that underdeveloped CIS financial markets do not present many avenues for the acquisition of more diverse assets, limiting diversification opportunities (Sharipova, 2015). Despite our conceptual inferences, we cannot find evidence that asset similarity has a significant and consistent influence on risk and performance either by itself or through diversification measures indirectly. Therefore, we cannot reasonably lend support to Hypothesis 3.

Notwithstanding, it is imperative to highlight that we study diversification across individual banks, whereas the theory crafted by Wagner (2010) focuses on an aggregate-level effect across banks. Therefore, we study whether asset similarity can yield similar effects as diversification on an individual level, rather than directly evaluating the theory within the CIS context. Generally, while results could have interesting implications for banks' portfolio management, the insignificance of entropy similarity across our models fails to provide sufficient evidence to reliably conclude that it has a non-zero effect on performance. In the end, we fail to support the notion of either a joint or marginal effect of similarity on performance or diversification, per Hypothesis 3.

Table 5: Results | Modeling Validity for Hypothesis 3

	RANDOM EFFECTS MODEL UNRESTRICTED MODEL							Avg. β Diff.	TWO-STEP DIFFERENCE GMM RESTRICTED MODEL WITH CONTROLS							TWO-STEP SYSTEM GMM RESTRICTED MODEL WITH CONTROLS						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	Δ_β	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables																						
L1 ROA	0.55***	-	-	-	-	-	-	0.23	0.32***	-	-	-	-	-	-	0.42***	-	-	-	-	-	-
L1 NIM	-	0.19***	-	-	-	-	-	0.17	-	0.02	-	-	-	-	-	-	0.07	-	-	-	-	-
L1 EFF	-	-	0.67***	-	-	-	-	0.36	-	-	0.31***	-	-	-	-	-	-	0.58***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.81***	-	-	-	0.43	-	-	-	0.38***	-	-	-	-	-	-	0.79***	-	-	-
L1 Capital Risk	-	-	-	-	0.78***	-	-	0.40	-	-	-	-	0.38***	-	-	-	-	-	-	0.76***	-	-
L1 Credit Risk	-	-	-	-	-	0.71***	-	0.01	-	-	-	-	-	0.70***	-	-	-	-	-	-	0.61***	-
L1 log Z	-	-	-	-	-	-	0.91***	0.64	-	-	-	-	-	-	0.27**	-	-	-	-	-	-	0.48***
ID^{HHI}	-0.32	-4.95***	8.04**	-1.73	-5.76***	-2.42	0.05	4.61	5.15	-6.87	-39.05**	35.86**	-34.51	0.79	-0.75	1.67	-12.42	19.04	19.04	-7.97	1.34	-1.03
AD^{HHI}	-5.76	12.20	33.54	143.96***	11.59	-13.13	-0.22	-4.42	-16.13	-6.35	244.89	370.59**	-125.41	-249.04	-5.40	2.30	-108.53	-15.30	58.09	215.35	73.19	12.32**
Development	0.51***	1.62***	-0.82	3.38***	0.06	0.24	-0.03	0.71	0.00	0.00	0.00	0.00***	0.00	-0.00**	0.00	0.56	2.84***	-0.94	1.50	-0.87	-0.48	-0.16
Concentration	0.01**	0.03***	0.02	0.06**	-0.05**	-0.03	0.00	-0.01	0.01	0.00	0.02	0.01	0.06*	0.04	0.00	-0.04	0.24***	0.42	0.07	-0.06	-0.14	0.01
Entropy Similarity	-3.86	8.36	18.84	82.57***	8.41	-5.47	-0.23	1.11	-7.16	0.71	133.35	190.52*	-66.59	-147.61	-2.34	1.36	-60.73	-9.78	70.74	127.15	44.48	7.40**
log Size	0.05*	-0.46***	-1.95***	0.37**	-1.27***	-0.07	-0.02***	1.12	0.23	-1.93***	-3.12	5.45**	-8.73***	-2.63*	-0.43***	-0.09	0.04	-1.43	0.70	-1.36**	-0.21	-0.07**
Peace & Stability	0.01	-0.02	-3.52***	0.43	0.23	-0.42	-0.01	-0.72	-0.22	0.26	1.93	1.21	-0.54	-0.81	-0.06	1.92**	-4.30***	-15.33**	-4.13	-0.18	1.27	-0.19
ROL	-0.02	-1.24**	-0.86	-3.09**	2.17***	0.25	0.10**	-0.36	0.11	1.91*	-4.73	-5.58	7.55**	0.24	0.35*	0.29	-4.74***	-5.32	0.93	3.90	1.64	0.40*
CBI	0.24	2.73**	-9.35***	5.84**	-5.53***	-0.86	-0.23**	-7.04	-24.15*	23.85**	-29.17	-3.97	38.64	35.52	1.41	0.37	10.79***	0.23	0.14	-13.62*	-5.28	-1.27**
Domestic Ownership	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
CIS Foreign Ownership	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Exogenous (IV) Variables																						
GDP Growth	0.05***	0.09***	0.23**	-0.18**	0.14***	-0.11**	0.01***	0.02	0.06***	0.03**	0.13*	-0.06	0.04	-0.14***	0.01***	0.05***	-0.01	0.03	-0.16	0.11	-0.11**	0.01***
Inflation	0.00	0.01	-0.20***	-0.12***	0.02	0.04	0.00	0.00	-0.01	-0.01	-0.24***	0.05	-0.11***	0.06	-0.01***	0.04**	-0.07*	-0.42***	-0.32***	0.06	0.00	0.00
Constant	1.83	1.28	28.62	-78.76***	24.35**	12.41	0.76	-	-	-	-	-	-	-	-	3.64	34.35	6.00	-51.71	-64.69	-15.90	-2.89
Number of Instruments	-	-	-	-	-	-	-	-	60	60	60	60	60	60	60	28	28	28	28	28	28	28
Number of Observations	1,388	1,388	1,388	1,388	1,388	1,388	1,388	-	948	948	948	948	948	948	948	948	948	948	948	948	948	948
Number of Groups	-	-	-	-	-	-	-	-	199	199	199	199	199	199	199	199	199	199	199	199	199	199
F-Statistic	67.41***	38.20***	187.63***	232.55***	513.13***	177.79***	782.16***	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
R^2	0.37	0.27	0.62	0.67	0.83	0.61	0.87	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hansen J-Test	-	-	-	-	-	-	-	-	62.19*	79.77***	68.89**	64.00*	81.83***	64.54**	86.46***	7.52	9.27	2.96	13.95**	8.72	9.55	6.65
Hansen J-Test p value	-	-	-	-	-	-	-	-	0.08	0.00	0.03	0.06	0.00	0.06	0.00	0.28	0.16	0.81	0.03	0.19	0.15	0.35
AR(1) Test (1st Difference)	-	-	-	-	-	-	-	-	-4.16***	-0.96	-4.49***	-3.00***	-2.78***	-2.58***	-2.93***	-5.38***	-2.56***	-6.96***	-6.01***	-3.69***	-2.14**	-3.73***
AR(2) Test (1st Difference)	-	-	-	-	-	-	-	-	-0.23	-2.62***	-0.23	0.65	-0.70	0.52	0.63	-0.56	-0.52	-0.37	2.10**	0.19	0.59	1.19

Note. The table presents modelling results pertaining to the third hypothesis, as specified in the methodology section. In accordance, we estimate three models to evaluate the validity of our desired System-GMM specification. These include a Random-Effects and then a Difference-GMM specification across our risk and performance indicators. We compare the coefficients between the Random-Effects and Difference-GMM estimators to evaluate the necessity of a System-GMM specification. Alongside this, the Hansen-J test for over-identification and AR(2) test for autocorrelation indicate whether the instrumentation and lag structure of the GMM models were specified correctly. The third model is a System-GMM specification with the addition of time dummy variables to remove unobserved time-varying heterogeneity. To provide more context for the validity of the specifications, the number of groups, total observation, and instrument counts are presented.
The asterisks denote significance levels as follows: $p \leq 0.1 : *$, $p \leq 0.05 : **$, and $p \leq 0.01 : ***$.

Table 6: Results | Unrestricted System GMM Model | All Hypotheses

	TWO-STEP SYSTEM GMM MODEL HYPOTHESIS 1						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables							
L1 ROA	0.45***	-	-	-	-	-	-
L1 NIM	-	0.07	-	-	-	-	-
L1 EFF	-	-	0.58***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.70***	-	-	-
L1 Capital Risk	-	-	-	-	0.71***	-	-
L1 Credit Risk	-	-	-	-	-	0.64**	-
L1 log Z	-	-	-	-	-	-	0.42**
ID^{HHI}	12.93**	-4.50	42.12	95.37	-33.55	-11.76	-0.02
AD^{HHI}	-7.53	-16.95	-16.21	-117.90*	15.58	26.37	-2.37
Development	2.70	-2.50	2.47	-4.34	-1.90	10.92	-1.31
Concentration	-0.07*	0.23**	0.34	-0.08	0.07	-0.11	0.01
Entropy Similarity	-	-	-	-	-	-	-
log Size	-0.19	-0.01	-1.66	0.03	-1.46***	-0.14	-0.11**
Peace & Stability	2.40**	-3.85*	-14.32**	-3.75	-4.16	0.89	-0.24
ROL	1.73	-4.11	-2.36	10.08	2.69	-0.46	0.68
CBI	-1.31	11.66**	-3.14	-10.29	-16.05**	-4.57	-1.62**
Domestic Ownership	-	-	-	-	-	-	-
CIS Foreign Ownership	-	-	-	-	-	-	-
Interaction Terms							
ID^{HHI} × Development	-14.36**	0.59	-28.33	-94.55	21.52	10.52	-0.19
AD^{HHI} × Development	8.30	11.75	18.19	103.50	-16.80	-37.40	2.94
ID^{HHI} × Domestic	-	-	-	-	-	-	-
AD^{HHI} × Domestic	-	-	-	-	-	-	-
ID^{HHI} × CIS Foreign	-	-	-	-	-	-	-
AD^{HHI} × CIS Foreign	-	-	-	-	-	-	-
ID^{HHI} × Entropy Similarity	-	-	-	-	-	-	-
AD^{HHI} × Entropy Similarity	-	-	-	-	-	-	-
Exogenous (IV) Variables							
GDP Growth	0.05**	0.01	0.03	-0.18	0.09	-0.14**	0.01**
Inflation	0.05**	-0.06	-0.39**	-0.32**	-0.01	0.01	0.00
Constant	9.65	-13.73	9.56	39.28	38.05	8.56	4.89*
Number of Instruments	28	28	28	28	28	28	28
Number of Observations	948	948	948	948	948	948	948
Number of Groups	199	199	199	199	199	199	199
Hansen J-Test	3.80	10.84**	2.68	13.24**	8.83	8.86	6.58
Hansen J-Test p value	0.58	0.05	0.75	0.02	0.12	0.11	0.25
AR(1) Test (1st Difference)	-5.71***	-1.68*	-7.07***	-5.86***	-3.75***	-2.10**	-3.09***
AR(2) Test (1st Difference)	-1.47	-0.59	-0.33	2.02**	-0.15	0.57	0.60

	TWO-STEP SYSTEM GMM MODEL HYPOTHESIS 2						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables							
L1 ROA	0.40***	-	-	-	-	-	-
L1 NIM	-	0.21	-	-	-	-	-
L1 EFF	-	-	0.60***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.69***	-	-	-
L1 Capital Risk	-	-	-	-	0.64***	-	-
L1 Credit Risk	-	-	-	-	-	0.69***	-
L1 log Z	-	-	-	-	-	-	0.41**
ID^{HHI}	4.27	26.99	55.65	91.58	-60.87	25.66	0.17
AD^{HHI}	-18.43	72.78	-101.08	-123.66	-36.08	41.06	-2.88
Development	0.25	3.34**	-2.05	1.55	-0.19	-0.24	-0.21
Concentration	-0.04	0.19	0.45	0.09	0.18	-0.18	0.01
Entropy Similarity	-	-	-	-	-	-	-
log Size	-0.10	-0.01	-1.30	0.41	-1.30**	-0.55	-0.10**
Peace & Stability	1.93*	-4.14*	-16.72**	-3.34	-8.46*	1.91	-0.35
ROL	0.29	-2.60	-2.79	-1.25	5.64**	4.61	0.70**
CBI	-0.16	8.92	-0.77	6.01	-20.60***	-9.68	-1.76**
Domestic Ownership	-11.31	72.33	-24.51	-15.81	-20.40	39.31	-0.56
CIS Foreign Ownership	-1.87	63.87	-79.14	-28.53	-49.94	11.72	-1.98
Interaction Terms							
ID^{HHI} × Development	-	-	-	-	-	-	-
AD^{HHI} × Development	-	-	-	-	-	-	-
ID^{HHI} × Domestic	1.36	-63.00	-48.34	-97.67	37.61	-35.13	-0.86
AD^{HHI} × Domestic	24.27	-105.78	109.98	130.25	18.26	-57.30	2.50
ID^{HHI} × CIS Foreign	-9.19	-40.77	14.67	-68.44	75.56	-10.31	1.12
AD^{HHI} × CIS Foreign	11.08	-107.26	178.71	134.34	47.10	-23.24	3.55
ID^{HHI} × Entropy Similarity	-	-	-	-	-	-	-
AD^{HHI} × Entropy Similarity	-	-	-	-	-	-	-
Exogenous (IV) Variables							
GDP Growth	0.06***	-0.05	0.11	-0.14	0.09	-0.14**	0.02***
Inflation	0.03	-0.04	-0.43**	-0.30**	-0.11	0.06	0.00
Constant	12.93	-62.94	23.56	8.77	63.45	4.04	4.57*
Number of Instruments	34	34	34	34	34	34	34
Number of Observations	948	948	948	948	948	948	948
Number of Groups	199	199	199	199	199	199	199
Hansen J-Test	4.28	3.78	1.90	12.81*	6.50	11.32	7.03
Hansen J-Test p value	0.75	0.80	0.97	0.08	0.48	0.13	0.43
AR(1) Test (1st Difference)	-5.27***	-1.46	-6.94***	-5.39***	-4.40***	-2.68***	-3.05***
AR(2) Test (1st Difference)	-1.23	-1.04	-0.35	1.77*	-0.52	0.32	0.42

	TWO-STEP SYSTEM GMM MODEL HYPOTHESIS 3						
	ROA	NIM	EFF	Liquidity Risk	Capital Risk	Credit Risk	log Z
Endogenous Variables							
L1 ROA	0.41***	-	-	-	-	-	-
L1 NIM	-	0.05	-	-	-	-	-
L1 EFF	-	-	0.56***	-	-	-	-
L1 Liquidity Risk	-	-	-	0.56***	-	-	-
L1 Capital Risk	-	-	-	-	0.83***	-	-
L1 Credit Risk	-	-	-	-	-	0.66***	-
L1 log Z	-	-	-	-	-	-	0.64***
ID^{HHI}	-6.94	-1.78	-9.16	-3.72	-9.28	5.67	-2.02
AD^{HHI}	-148.10	-881.52	-1776.85	-5854.91**	1006.17	1460.06	28.93
Development	0.88*	2.29	0.14	3.38*	-1.14	-1.07	-0.03
Concentration	-0.02	0.19**	0.44*	0.00	-0.03	-0.16	0.01
Entropy Similarity	-87.95	-434.46	-987.48	-3105.78**	532.38	764.64	12.50
log Size	-0.06	0.06	-1.53	0.46	-1.07	-0.41	-0.06
Peace & Stability	1.80**	-3.51*	-14.86**	0.24	-1.53	1.53	-0.14
ROL	-0.03	-3.70	-5.86	0.00	3.42	1.91	0.16
CBI	0.23	9.59*	1.15	3.07	-14.17*	-6.82	-0.82
Domestic Ownership	-	-	-	-	-	-	-
CIS Foreign Ownership	-	-	-	-	-	-	-
Interaction Terms							
ID^{HHI} × Development	-	-	-	-	-	-	-
AD^{HHI} × Development	-	-	-	-	-	-	-
ID^{HHI} × Domestic	-	-	-	-	-	-	-
AD^{HHI} × Domestic	-	-	-	-	-	-	-
ID^{HHI} × CIS Foreign	-	-	-	-	-	-	-
AD^{HHI} × CIS Foreign	-	-	-	-	-	-	-
ID^{HHI} × Entropy Similarity	20.33	-56.00	126.30	99.80	-11.61	6.45	5.74
AD^{HHI} × Entropy Similarity	-53.18	-371.22	-712.50	-2417.23**	404.44	601.84	12.10
Exogenous (IV) Variables							
GDP Growth	0.05**	0.03	0.06	-0.14	0.06	-0.16**	0.01*
Inflation	0.04**	-0.03	-0.39***	-0.14	0.01	-0.01	0.00
Constant	81.02	422.92	899.97	2939.41**	-468.43	-707.80	-11.95
Number of Instruments	30	30	30	30	30	30	30
Number of Observations	948	948	948	948	948	948	948
Number of Groups	199	199	199	199	199	199	199
Hansen J-Test	6.82	9.79	1.85	8.48	9.52	7.71	5.51
Hansen J-Test p value	0.34	0.13	0.93	0.21	0.15	0.26	0.48
AR(1) Test (1st Difference)	-4.16***	-1.07	-6.61***	-4.14***	-3.86***	-2.65***	-2.67***
AR(2) Test (1st Difference)	-0.65	0.01	-0.32	1.79*	-0.18	0.34	-0.06

Note. The table presents modelling results from the interaction terms across the System-GMM models and hypotheses. Alongside these results, the Hansen-J test for over-identification and AR(2) test for autocorrelation indicate whether the instrumentation and lag structure of the GMM models were specified correctly. The asterisks denote significance levels as follows: $p \leq 0.1: *$, $p \leq 0.05: **$, and $p \leq 0.01: ***$.

6 Conclusion

6.1 Implications for the Research Problem

The aim of this study was to evaluate the extent to which diversification and its potential proxy, asset similarity, affected risk and performance across individual banks of the Commonwealth of Independent Nations. Motivated by past empirical findings, relevant salient facts, theory, and the unique context of the CIS, we formulate hypotheses to investigate specific aspects of the research problem. In concluding, we classify our results into distinct themes.

First, we assess the claim that greater income or asset diversity harms performance, which we believe to be worse for more developed Republics. Generally, we found insufficient evidence to support a systemic effect of asset or income diversification on performance. From the traditional perspective on diversification, Diamond (1984) argues that informational advantages gained through the pooling of banking activities result in greater performance. However, the insignificance of the size effect alongside either income or asset diversity cannot support this premise. Further, Diamond (1984) stresses the importance of sufficient proficiency in processing information, which appears unlikely considering the historically lagged development of technical expertise among our banks (Berglöf, E. & Ronald, G., 2007). Our results cannot support the agency theory perspective of Acharya (2006) either. In contrast, we argue that CIS managers face greater credit monitoring incentives than Acharya (2006) assumes. Notably, the significance of GDP and inflation alongside central banking supervision power in improving credit risk demonstrates that agents' behaviour is influenced by broader macroeconomic trends. Further, greater market concentration leads to an increase in net income margins, suggesting that managers are more likely to use their position to charge higher spreads and fees rather than engaging in morally-hazardous diversification. Moreover, we observe divergences in terms of how CIS banks scale with size. Chiorazzo et. al. (2008), studying Italian banks, describe diminishing benefits to diversification arising from growing bank operational complexities. Paradoxically, while we do not observe a notable diversification effect, we find that greater bank size enhances their capitalisation, however, at the expense of stability. Broadly, this is suggestive of diseconomies of scale, possibly due to the relatively higher complexities associated with operating larger banks in this region, which, considering that diversification is considered a proxy for expansion, would support Chiorazzo et. al.'s (2008) general conclusions regarding diminishing returns to scale. In this sense, the result is supportive of Stiroh and Rumble (2006) as well.

However, studying the effect more closely, we were unable to find evidence that developmental level is an important factor in determining diversification effects. Interestingly, a relatively small, significantly negative effect is shown for the ROA model, suggesting that more developed Republics could have disproportionately worse returns to diversification. While the result is not indicative of a broader trend, it could suggest that more latent effects may be concealed by the linear model specification.

Notwithstanding, other factors reveal other notable effects. Across all models and hypotheses, we observe significant persistence for first-order lags, implying that endogenous past performance has a strong impact on current levels. Notably, the effects' magnitudes were diminishing, providing some evidence of possible mean reversion. Discussing Berger et. al. (2000), the authors suggest that institutional and 'durable' rents likely drive U.S. banks' persistence; however, Sharipova's (2015) assessment of CIS financial sectors demonstrates the weakness of CIS financial intermediation. Therefore, we instead argue that such shocks are indicative of non-durable local rents. Diverging from the interaction effect, we find limited evidence for more developed Republics having higher net interest margins compared to their counterparts. However, we dispute this evidence based on Djalilov et. al. (2016) and Sharipova (2015). The former study found differences in performance between early and late transition countries, determining that CIS countries do not exhibit significantly better capitalisation. The authors attribute this to the relatively limited investment opportunities and financial headroom their banks inherited. Sharipova (2015) clarifies, arguing that while the developmental divergence between CIS Republics is high, it is significantly higher compared to the Eastern Bloc. Combined with the high confidence interval observed, both papers' arguments are reasonably applicable.

Further, we assess the effects of foreign bank ownership in improving performance outcomes, which we believe to be stronger for more developed Republics. Ultimately, we are unable to establish either a consistent effect of ownership on diversification or performance. Then, considering past models' results, it follows that the interaction of ownership with diversity measures fails to yield significant results as well. We posit that unfair market conditions contextualise this effect. Studying the effects of private versus state banks, Sharipova (2015) reveals that the comparatively greater trust in state banks over private institutions lowers their human and capital costs, enabling a higher technical and cost efficiency. Further, their close relationship with the State provides more lucrative investment opportunities, creating an unfair market environment. Consequently, other domestic and foreign private banks have comparatively smaller customer pools, limiting their growth. Crucially, Rajan's (1992) argument that the high endogenous switching costs borne by customers are especially salient, as per Acharya (2006) and Diamond (1984), implies state banks' significant control over proprietary information limits other banks' economies of scope. We emphasise these dynamics to argue that in Republics with state intervention in banking, all other banks are inherently disadvantaged to the extent that their performance has little meaningful variation concerning the regressors studied. We believe that this is partly responsible for the consistent insignificance and unreliability of our estimations, even though most System-GMM models pass our validation process. We elaborate further in the following subsection.

Finally, to determine the degree to which diversification can be proxied or supplemented by asset similarity, we evaluate how entropy similarity affects risk and performance. We hypothesised that this effect is stronger across less developed Republics. In the end, we cannot reliably support the hypothesis, following both the insignificant entropy similarity estimates in the restricted and interaction models. Notwithstanding, it was found that interacting similarity with asset diversity yielded a significant decrease in liquidity, which could suggest a deliberate choice by certain banks to hedge against their highly concentrated loan portfolios by lowering their relative exposure to riskier liquid assets. This mechanism could result from underdeveloped financial markets, which limit banks' options for ways to diversify into other liquid assets (Sharipova, 2015). However, the inconsistency and unrealistic nature of these effects demand caution in their interpretation. Overall, in our effort to understand whether asset similarity has a similar channel of effect as diversification, we fail to find a notable effect across individual banks. Notwithstanding, we cannot relate these findings to Wagner (2010), as the author instead theorises for an aggregate, rather than an individual firm effect.

6.2 Limitations and Robustness of the Study

This investigation reveals important insights regarding dynamic panel modelling. First, we stress the importance of a comprehensive framework to evaluate the desired model specification. Namely, following Roodman (2009) and Bond (2001), we successfully motivated our choice of the System-GMM, highlighting that Random-Effects estimators succumb to the Nickell bias (Nickell, 1981), making estimates biased and inconsistent. Under GMM, we demonstrated that across all hypotheses and models, while Difference-GMM was able to account for persistence correctly, its instrumentation was severely inefficient, yielding weak instruments. Rather, the validity of the majority of restricted System-GMM specifications in its instrumentation and lag structure justified its use in evaluating our hypotheses.

Further, we highlight that our measures of diversification may be inherently flawed, according to Elsas et. al. (2010). Specifically, the authors demonstrate that the choice of two asset categories can mask the true effect, as other asset classes have their own set of characteristics that make them imperfectly correlated with performance. Further, while studying asset diversity is an improvement over only considering revenue, diversification can have different effects for other aspects, for instance, expansion into new industries. Therefore, by assessing diversification through greater scope and granularity, they argue that estimators' precision can be greatly improved. While this data is generally unavailable for the CIS, Sharipova (2015) demonstrates that local data brokers improve data quality substantially over Orbis BankFocus.

Notwithstanding, certain models indicated data issues, undermining our robustness measures. For instance, the restricted NIM and liquidity risk System-GMM models under Hypothesis 1, although improved over Difference-GMM, were still found to have weak instrumentation. Conversely, under the restricted model of Hypothesis 3, we observed severe instrument overfitting for the capital risk and stability models. These inconsistencies in diagnostics suggest that our endogenous variables likely had low meaningful variation across individual banks. To mitigate this issue, we would either require significantly more restrictive data cleaning steps to remove the influence of all outliers or to aggregate banks such that each panel group observation is more robust to data issues. The former would drastically reduce the number of observations and possibly induce bias from selective data removal, and the latter could harm model performance by removing useful variation. Rather, we find that a Machine Learning framework can be substantially more robust than traditional regression models studied in Finance. To overcome the limitations and restrictive assumptions of parametric regression models, we would opt for the non-parametric Decision Tree framework, incorporating ensemble techniques, preferably, Boosting. Under this, the XGBoost model would be chosen for its sequential error-correction algorithm, which would prevent the overfitting we observed under GMM. Then, we would undertake hyperparameter tuning through a Grid or Bayesian Search to ensure that our set of model learners accommodates the salient features of our data. Having obtained a tuned XGBoost specification, we would perform stratified cross-validation to ensure that the model is stable and performs sufficiently well.

6.3 Further Research

This study presents a premise that is relatively unexplored in Literature, especially within the domain of Banking. Throughout the process, we uncovered other, similarly consequential, areas of study. In expanding the premise, we recommend investigating the non-linear 'U-Shaped' diversification effect observed by Acharya (2006). Evaluating Hypothesis 1, our finding that income diversity had a significant interaction with ROA could suggest that latent, non-linear relationships may exist in our data. This could reveal an atypical mechanism through which CIS banks undertake diversification. Further, in Table A2, it was shown that non-CIS foreign banks exhibited greater volatility than their CIS counterparts, which could present important operational differences between these kinds of banks. More specifically, understanding the factors driving this observation can uncover specific risk exposures such banks face relative to others, and evaluate their resilience to instabilities faced in the region.

References

Acharya, V. V., Hasan, I., & Saunders, A. (2006). Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios*. *The Journal of Business*, *79*(3), 1355–1412. https://doi.org/10.1086/500679

Almog, A., & Shmueli, E. (2019). Structural Entropy: Monitoring Correlation-Based Networks Over Time With Application To Financial Markets. *Scientific Reports*, *9*(1), 10832. https://doi.org/10.1038/s41598-019-47210-8

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability [Publisher: Elsevier]. *Journal of international financial Markets, Institutions and Money*, *18*(2), 121–136.

Baele, L., De Jonghe, O., & Vander Vennet, R. (2007). Does the stock market value bank diversification? *Journal of Banking & Finance*, *31*(7), 1999–2023. https://doi.org/10.1016/j.jbankfin.2006.08.003

Barisitz, S. (2008). Banking Transformation (1989 - 2006) in Central and Eastern Europe - with Special Reference to Balkans. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4165386

Beck, T., & Levine, R. (2004). Stock markets, banks, and growth: Panel evidence. *Journal of Banking & Finance*, *28*(3), 423–442. https://doi.org/10.1016/S0378-4266(02)00408-9

Berger, A. N. (2007). International Comparisons of Banking Efficiency. *Financial Markets, Institutions & Instruments*, *16*(3), 119–144. https://doi.org/10.1111/j.1468-0416.2007.00121.x

Berger, A. N., Bonime, S. D., Covitz, D. M., & Hancock, D. (2000). Why are bank profits so persistent? The roles of product market competition, informational opacity, and regional/macroeconomic shocks. *Journal of Banking & Finance*, *24*(7), 1203–1235. https://doi.org/10.1016/S0378-4266(99)00124-7

Berger, A. N., DeYoung, R., Genay, H., & Udell, G. F. (2000). Globalization of Financial Institutions: Evidence from Cross-Border Banking Performance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.203509

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank Competition and Financial Stability. *Journal of Financial Services Research*, *35*(2), 99–118. https://doi.org/10.1007/s10693-008-0050-7

Berglof, E., & Bolton, P. (2002). The Great Divide and Beyond: Financial Architecture in Transition. *Journal of Economic Perspectives*, *16*(1), 77–100. https://doi.org/10.1257/0895330027120

Berglöf, E. & Ronald, G. (2007). *The economics of Transition: The fifth Nobel symposium in economics*. Palgrave Macmillan.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bond, S., Hoeffler, A., & Temple, J. (2001, September). *GMM Estimation of Empirical Growth Models* (tech. rep.) (Issue: 2001-W21). Economics Group, Nuffield College, University of Oxford. https://EconPapers.repec.org/RePEc:nuf:econwp:0121

Boyd, J. H., & De Nicoló, G. (2005). The Theory of Bank Risk Taking and Competition Revisited [Publisher: [American Finance Association, Wiley]]. *The Journal of Finance*, *60*(3), 1329–1343. Retrieved February 10, 2025, from http://www.jstor.org/stable/3694928

Chiorazzo, V., Milani, C., & Salvini, F. (2008). Income Diversification and Bank Performance: Evidence from Italian Banks. *Journal of Financial Services Research*, *33*(3), 181–203. https://doi.org/10.1007/s10693-008-0029-4

Clark, E., Radić, N., & Sharipova, A. (2018). Bank competition and stability in the CIS markets. *Journal of International Financial Markets, Institutions and Money*, *54*, 190–203. https://doi.org/10.1016/j.intfin.2017.12.005

Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies*, *51*(3), 393. https://doi.org/10.2307/2297430

Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money*, *21*(3), 307–327. https://doi.org/10.1016/j.intfin.2010.11.002

Dijkman, M. (2010, June). *A Framework For Assessing Systemic Risk*. The World Bank. https://doi.org/10.1596/1813-9450-5282

Djalilov, K., & Piesse, J. (2016). Determinants of bank profitability in transition countries: What matters most? *Research in International Business and Finance*, *38*, 69–82. https://doi.org/10.1016/j.ribaf.2016.03.015

Elsas, R., Hackethal, A., & Holzhäuser, M. (2010). The anatomy of bank diversification. *Journal of Banking & Finance*, *34*(6), 1274–1287. https://doi.org/10.1016/j.jbankfin.2009.11.024

Flamini, V., McDonald, C. A., & Schumacher, L. B. (2009). The determinants of commercial bank profitability in Sub-Saharan Africa [Publisher: IMF working paper].

Fricke, D. (2016). Has the banking system become more homogeneous? Evidence from banks' loan portfolios. *Economics Letters*, *142*, 45–48. https://doi.org/10.1016/j.econlet.2016.02.024

Gambacorta, L., Scatigna, M., & Yang, J. (2014). Diversification and bank profitability: A nonlinear approach. *Applied Economics Letters*, *21*(6), 438–441. https://doi.org/10.1080/13504851.2013.866196

Garriga, A. C. (2016). Central Bank Independence in the World: A New Data Set. *International Interactions*, *42*(5), 849–868. https://doi.org/10.1080/03050629.2016.1188813

Hansen, C., Hausman, J., & Newey, W. (2008). Estimation With Many Instrumental Variables. *Journal of Business & Economic Statistics*, *26*(4), 398–422. https://doi.org/10.1198/073500108000000024

Hu, B., Schclarek, A., Xu, J., & Yan, J. (2022). Long-term finance provision: National development banks vs commercial banks. *World Development*, *158*, 105973. https://doi.org/10.1016/j.worlddev.2022.105973

Javid Nabiyev, Kanan Musayev, & Leyla Yusifzade. (2016). Banking Competition and Financial Stability: Evidence from CIS. *Central Bank of Azerbaijan*, (72167). https://mpra.ub.uni-muenchen.de/72167/1/MPRA_paper_72167.pdf

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Kim, H., Batten, J. A., & Ryu, D. (2020). Financial crisis, bank diversification, and financial stability: OECD countries. *International Review of Economics & Finance*, *65*, 94–104. https://doi.org/10.1016/j.iref.2019.08.009

Korytowski, M. (2018). Banks' profitability determinants in post-crisis European Union [Publisher: Society for the Study of Business and Finance]. *International Journal of Finance & Banking Studies*, *7*(1), 1–12.

Laeven, L., & Levine, R. (2007). Is there a diversification discount in financial conglomerates? *Journal of Financial Economics*, *85*(2), 331–367. https://doi.org/10.1016/j.jfineco.2005.06.001

Lee, C.-F., & Su, J.-B. (2012). Alternative statistical distributions for estimating value-at-risk: Theory and evidence. *Review of Quantitative Finance and Accounting*, *39*(3), 309–331. https://doi.org/10.1007/s11156-011-0256-x

Lee, C.-C., Chen, P.-F., & Zeng, J.-H. (2020). Bank Income Diversification, Asset Correlation and Systemic Risk. *South African Journal of Economics*, *88*(1), 71–89. https://doi.org/10.1111/saje.12235

Lepetit, L., Nys, E., Rous, P., & Tarazi, A. (2008). Bank income structure and risk: An empirical analysis of European banks. *Journal of Banking & Finance*, *32*(8), 1452–1467. https://doi.org/10.1016/j.jbankfin.2007.12.002

Markowitz, H. (1952). PORTFOLIO SELECTION*. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Marquez, R. (2002). Competition, Adverse Selection, and Information Dispersion in the Banking Industry: Table 1. *Review of Financial Studies*, *15*(3), 901–926. https://doi.org/10.1093/rfs/15.3.901

Merton, R. C. (1974). ON THE PRICING OF CORPORATE DEBT: THE RISK STRUCTURE OF INTEREST RATES*. *The Journal of Finance*, *29*(2), 449–470. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Nguyen, T. C., & Vo, D. V. (2015). Risk and income diversification in the Vietnamese banking system [Publisher: Scientific Press International Limited]. *Journal of Applied Finance and banking*, *5*(1), 93.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, *49*(6), 1417. https://doi.org/10.2307/1911408

Radojičić, J., & Marinković, S. (2023). Impact of Income and Assets Diversification on Bank Performance in Serbia. *Economic Themes*, *61*(2), 197–214. https://doi.org/10.2478/ethemes-2023-0010

Raffestin, L. (2014). Diversification and systemic risk. *Journal of Banking & Finance*, *46*, 85–106. https://doi.org/10.1016/j.jbankfin.2014.05.014

Rajan, R. G. (1992). Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt [Publisher: [American Finance Association, Wiley]]. *The Journal of Finance*, *47*(4), 1367–1400. https://doi.org/10.2307/2328944

Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal: Promoting communications on statistics and Stata*, *9*(1), 86–136. https://doi.org/10.1177/1536867X0900900106

Shannon, C. E. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sharipova, A. (2015, October). *Essays on Banking Sector Performance in the CISs* [PhD thesis]. Middlesex University, Business School [Backup Publisher: Middlesex University].

Stiroh, K. J., & Rumble, A. (2006). The dark side of diversification: The case of US financial holding companies. *Journal of Banking & Finance*, *30*(8), 2131–2161. https://doi.org/10.1016/j.jbankfin.2005.04.030

Styrin, K. (2005). *What explains differences in efficiency across Russian banks?* (Tech. rep.). EERC Research Network, Russia and CIS.

Sufian, F., & Habibullah, M. S. (2009). DETERMINANTS OF BANK PROFITABILITY IN A DEVELOPING ECONOMY: EMPIRICAL EVIDENCE FROM BANGLADESH. *Journal of Business Economics and Management*, *10*(3), 207–217. https://doi.org/10.3846/1611-1699.2009.10.207-217

Tasca, P., Mavrodiev, P., & Schweitzer, F. (2014). Quantifying the impact of leveraging and diversification on systemic risk. *Journal of Financial Stability*, *15*, 43–52. https://doi.org/10.1016/j.jfs.2014.08.006

Tilburg University. (n.d.). Dynamic Panel Data Estimation with System-GMM. https://tilburgsciencehub.com/topics/analyze/causal-inference/panel-data/system-gmm/

Varotto, S. (2011). Liquidity risk, credit risk, market risk and bank capital (U. R. Mittoo, Ed.) [Publisher: Emerald Group Publishing Limited]. *International Journal of Managerial Finance*, *7*(2), 134–152. https://doi.org/10.1108/17439131111122139

Wagner, W. (2010). Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, *19*(3), 373–386. https://doi.org/10.1016/j.jfi.2009.07.002

Wang, C., & Lin, Y. (2021). Income diversification and bank risk in Asia Pacific. *The North American Journal of Economics and Finance*, *57*, 101448. https://doi.org/10.1016/j.najef.2021.101448

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

Winton, A. (1995). Delegated Monitoring and Bank Structure in a Finite Economy. *Journal of Financial Intermediation*, *4*(2), 158–187. https://doi.org/10.1006/jfin.1995.1008

Yang, H.-F., Liu, C.-L., & Yeutien Chou, R. (2020). Bank diversification and systemic risk. *The Quarterly Review of Economics and Finance*, *77*, 311–326. https://doi.org/10.1016/j.qref.2019.11.003

Zhou, K. (2014). The Effect of Income Diversification on Bank Risk: Evidence from China. *Emerging Markets Finance and Trade*, *50*(sup3), 201–213. https://doi.org/10.2753/REE1540-496X5003S312

Table A1: Data | Descriptive Statistics | Split by Development and Domestic Ownership

	Performance Measures			Risk Measures				Diversity Measures				Mkt.	Sim.	Macro Factors		Bank Controls	Regulatory Environment		
Statistics	**ROA**	**NIM**	**EFF**	**Liquidity Risk**	**Capital Risk**	**Credit Risk**	log **Z**	$\mathbf{ID}^{\mathrm{HHI}}$	*NII/OR*	$\mathbf{AD}^{\mathrm{HHI}}$	*Loans/TA*	**Conc.**	**Entropy Similarity**	**GDP Growth**	**Inflation**	log **Size**	**Peace & Stability**	**ROL**	**CBI**
Less Developed Republics | Domestically-Owned Banks																			
Obs.	343	343	343	343	343	343	343	343	343	343	343	343	343	343	343	343	343	343	343
Mean	1.60	7.03	62.64	29.71	19.21	6.22	2.48	0.39	34.46	0.41	0.61	75.27	0.15	3.40	7.47	12.82	-0.52	-0.70	0.61
Median	1.44	6.14	61.23	26.78	15.81	4.43	2.52	0.42	32.53	0.44	0.63	72.63	0.08	4.39	7.58	12.81	-0.47	-0.72	0.53
Std. Dev.	1.94	4.01	18.97	17.22	13.00	6.03	0.94	0.11	17.39	0.11	0.19	9.64	0.18	4.06	5.36	1.46	0.23	0.40	0.11
Minimum	-3.79	2.21	34.02	4.09	4.85	0.39	-1.28	0.03	1.60	0.05	0.03	54.74	0.00	-8.30	-1.17	8.72	-0.88	-1.45	0.50
Maximum	6.06	24.12	101.44	94.17	95.91	43.02	4.76	0.50	95.45	0.50	0.97	100.00	0.83	13.90	18.78	16.28	0.15	0.34	0.85
More Developed Republics | Domestically-Owned Banks																			
Obs.	489	489	489	489	489	489	489	489	489	489	489	489	489	489	489	489	489	489	489
Mean	1.58	7.69	65.12	29.55	23.48	11.93	2.26	0.43	46.21	0.41	0.55	61.84	0.14	0.47	12.12	12.31	-1.05	-0.75	0.64
Median	1.23	6.67	63.58	27.27	17.10	8.42	2.41	0.46	45.23	0.45	0.58	59.16	0.07	2.44	9.78	11.84	-1.16	-0.76	0.77
Std. Dev.	2.24	4.41	19.85	15.64	18.55	12.69	1.10	0.08	18.09	0.11	0.20	12.62	0.18	4.25	10.89	2.03	0.81	0.14	0.19
Minimum	-3.79	2.21	34.02	0.14	2.53	0.00	-1.14	0.04	1.88	0.00	0.00	34.94	0.00	-9.77	-0.20	8.69	-2.02	-1.12	0.22
Maximum	6.06	24.12	101.44	85.84	93.93	97.44	4.79	0.50	97.55	0.50	0.98	93.36	0.98	7.50	108.69	17.15	0.35	-0.47	0.77
Less Developed Republics | Non-Domestically-Owned Banks																			
Obs.	280	280	280	280	280	280	280	280	280	280	280	280	280	280	280	280	280	280	280
Mean	1.57	6.12	59.89	28.65	20.43	6.32	2.77	0.38	29.91	0.43	0.55	80.07	0.10	3.66	5.14	12.76	-0.44	-0.30	0.73
Median	1.65	5.70	57.78	26.34	16.79	3.75	2.83	0.41	28.31	0.46	0.59	83.37	0.06	4.20	3.70	12.75	-0.42	-0.32	0.80
Std. Dev.	1.66	2.29	17.69	14.84	12.19	7.34	0.71	0.10	13.39	0.08	0.18	10.48	0.13	4.64	4.59	1.27	0.20	0.43	0.11
Minimum	-3.79	2.21	34.02	3.01	2.75	0.44	-0.89	0.05	2.71	0.06	0.04	58.12	0.00	-8.30	-1.37	9.74	-0.91	-1.14	0.50
Maximum	6.06	15.89	101.44	81.03	81.69	46.60	4.50	0.50	81.24	0.50	0.97	100.00	0.80	13.90	18.78	15.86	0.15	0.34	0.85
More Developed Republics | Non-Domestically-Owned Banks																			
Obs.	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276	276
Mean	1.95	8.33	59.33	38.92	19.04	9.21	2.03	0.41	37.63	0.39	0.53	64.88	0.18	0.58	11.55	12.89	-0.79	-0.76	0.56
Median	2.04	7.24	54.33	34.53	15.77	5.65	2.18	0.44	34.25	0.43	0.60	66.16	0.10	2.36	9.78	13.11	-0.75	-0.76	0.56
Std. Dev.	2.49	4.84	21.61	20.78	12.33	11.26	0.93	0.10	17.80	0.12	0.24	13.05	0.22	3.94	10.76	1.66	0.84	0.17	0.22
Minimum	-3.79	2.21	34.02	5.44	3.52	0.01	-1.53	0.00	0.00	0.01	0.00	34.94	0.00	-9.77	-0.20	8.20	-2.02	-1.12	0.22
Maximum	6.06	24.12	101.44	93.39	90.45	90.82	3.66	0.50	92.54	0.50	0.97	89.05	0.97	7.50	108.69	16.09	0.35	-0.47	0.77

Note. This table shows data for all variables aggregated across 2010-2024 from individual CIS Republics, on an individual bank level. The data originates from Orbis BankFocus. The data shown includes 1) Data by Domestic ownership across Less developed Republics, 2) Data by Domestic Ownership and More developed Republics, 3) Data by Non-domestic ownership and Less developed Republics, and finally, 4) Data by Non-domestic ownership and More developed Republics. From the raw dataset, we exclude all central banks, data corresponding to repeated consolidation codes, and any observation that is deemed implausible. Alongside $\mathbf{ID}^{\mathrm{HHI}}$ and $\mathbf{AD}^{\mathrm{HHI}}$, we present data for Net Interest Income as a portion of Operating Revenue and Total Earning Assets as a portion of Total Assets to indicate the direction of the Herfindahl Index value. In computing $\mathbf{ID}^{\mathrm{HHI}}$, we exclude banks with negative operating revenue or non-interest incomes as these make the observation less informative or misleading. For $\mathbf{AD}^{\mathrm{HHI}}$, we exclude banks with negative asset values or when the asset comprises more than 100% of total assets. In isolation, it is not clear which type of income or asset the Herfindahl Index is skewed towards. Additionally, we eliminate any individual banks with more than a missing observation as to ensure the consistency of upcoming dynamic panel regressions, which are vulnerable to small samples within groups.

Table A2: Data | Descriptive Statistics | Split by Development and Foreign Ownership

	Performance Measures			Risk Measures				Diversity Measures				Mkt.	Sim.	Macro Factors		Bank Controls	Regulatory Environment		
Statistics	**ROA**	**NIM**	**EFF**	**Liquidity Risk**	**Capital Risk**	**Credit Risk**	log **Z**	$\mathbf{ID}^{\mathrm{HHI}}$	NII/OR	$\mathbf{AD}^{\mathrm{HHI}}$	$Loans/TA$	**Conc.**	**Entropy Similarity**	**GDP Growth**	**Inflation**	log **Size**	**Peace & Stability**	**ROL**	**CBI**
All Data																			
Less Developed Republics | CIS-Owned Foreign Banks																			
Obs.	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46	46
Mean	1.24	5.74	63.78	20.80	19.76	3.32	2.65	0.35	25.56	0.43	0.63	81.46	0.11	3.79	4.01	12.36	-0.46	-0.10	0.78
Median	1.32	5.41	62.40	21.76	18.06	2.67	2.64	0.40	28.17	0.46	0.64	83.71	0.06	4.70	2.41	12.60	-0.43	-0.13	0.80
Std. Dev.	0.96	1.58	13.10	11.00	6.66	2.35	0.63	0.12	11.49	0.08	0.13	11.04	0.14	4.57	4.22	0.79	0.17	0.30	0.08
Minimum	-1.77	2.74	44.04	3.01	11.10	0.48	0.41	0.09	4.88	0.06	0.33	62.55	0.00	-8.30	-1.37	10.67	-0.84	-0.70	0.53
Maximum	2.95	11.19	96.72	41.74	35.75	11.20	3.66	0.50	46.65	0.50	0.97	96.00	0.80	13.90	13.94	13.49	-0.16	0.34	0.85
More Developed Republics | CIS-Owned Foreign Banks																			
Obs.	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60
Mean	1.00	6.70	65.74	33.31	20.32	10.52	2.36	0.42	42.41	0.42	0.57	70.57	0.13	1.06	9.56	12.74	-0.40	-0.78	0.44
Median	1.14	6.78	64.77	32.90	14.73	7.51	2.67	0.45	37.53	0.45	0.63	72.47	0.07	2.36	8.40	13.15	-0.05	-0.82	0.26
Std. Dev.	1.95	3.11	18.61	16.18	15.31	10.52	0.89	0.10	18.54	0.09	0.19	10.87	0.17	3.06	6.00	1.65	0.75	0.19	0.21
Minimum	-3.79	2.21	34.02	7.90	6.91	0.86	-0.46	0.14	9.38	0.01	0.01	39.47	0.00	-9.77	4.05	9.41	-2.02	-1.12	0.26
Maximum	4.35	14.96	101.44	93.39	75.94	59.63	3.63	0.50	92.54	0.50	0.84	89.05	0.95	4.50	43.31	15.03	0.35	-0.47	0.77
Less Developed Republics | Non-CIS-Owned Foreign Banks																			
Obs.	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577
Mean	1.61	6.69	61.21	29.91	19.76	6.50	2.61	0.39	32.96	0.42	0.58	77.11	0.13	3.49	6.61	12.82	-0.48	-0.56	0.65
Median	1.57	5.87	58.97	26.95	15.91	4.26	2.69	0.41	30.38	0.45	0.60	73.45	0.07	4.34	6.07	12.81	-0.44	-0.61	0.60
Std. Dev.	1.87	3.47	18.80	16.35	13.01	6.82	0.87	0.10	16.05	0.10	0.19	10.18	0.16	4.32	5.18	1.41	0.22	0.45	0.12
Minimum	-3.79	2.21	34.02	4.09	2.75	0.39	-1.28	0.03	1.60	0.05	0.03	54.74	0.00	-8.30	-1.37	8.72	-0.91	-1.45	0.50
Maximum	6.06	24.12	101.44	94.17	95.91	46.60	4.76	0.50	95.45	0.50	0.97	100.00	0.83	13.90	18.78	16.28	0.15	0.34	0.85
More Developed Republics | Non-CIS-Owned Foreign Banks																			
Obs.	705	705	705	705	705	705	705	705	705	705	705	705	705	705	705	705	705	705	705
Mean	1.78	8.03	62.80	32.89	22.01	10.99	2.16	0.42	43.18	0.40	0.54	62.29	0.16	0.46	12.11	12.50	-1.00	-0.75	0.63
Median	1.60	6.89	59.90	29.23	16.39	7.60	2.28	0.45	40.78	0.45	0.58	59.16	0.08	2.44	9.78	12.11	-1.16	-0.76	0.77
Std. Dev.	2.36	4.67	20.84	18.39	16.83	12.40	1.06	0.09	18.44	0.11	0.22	12.80	0.20	4.21	11.13	1.95	0.82	0.14	0.20
Minimum	-3.79	2.21	34.02	0.14	2.53	0.00	-1.53	0.00	0.00	0.00	0.00	34.94	0.00	-9.77	-0.20	8.20	-2.02	-1.12	0.22
Maximum	6.06	24.12	101.44	91.39	93.93	97.44	4.79	0.50	97.55	0.50	0.98	93.36	0.98	7.50	108.69	17.15	0.35	-0.47	0.77

Note. This table shows data for all variables aggregated across 2010-2024 from individual CIS Republics, on an individual bank level. The data originates from Orbis BankFocus. The data shown includes 1) Data by CIS Foreign ownership across Less developed Republics, 2) Data by CIS Foreign Ownership and More developed Republics, 3) Data by Non-CIS Foreign ownership and Less developed Republics, and finally, 4) Data by Non-CIS Foreign ownership and More developed Republics. From the raw dataset, we exclude all central banks, data corresponding to repeated consolidation codes, and any observation that is deemed implausible. Alongside $\mathbf{ID}^{\mathrm{HHI}}$ and $\mathbf{AD}^{\mathrm{HHI}}$, we present data for Net Interest Income as a portion of Operating Revenue and Total Earning Assets as a portion of Total Assets to indicate the direction of the Herfindahl Index value. In computing $\mathbf{ID}^{\mathrm{HHI}}$, we exclude banks with negative operating revenue or non-interest incomes as these make the observation less informative or misleading. For $\mathbf{AD}^{\mathrm{HHI}}$, we exclude banks with negative asset values or when the asset comprises more than 100% of total assets. In isolation, it is not clear which type of income or asset the Herfindahl Index is skewed towards. Additionally, we eliminate any individual banks with more than a missing observation as to ensure the consistency of upcoming dynamic panel regressions, which are vulnerable to small samples within groups.

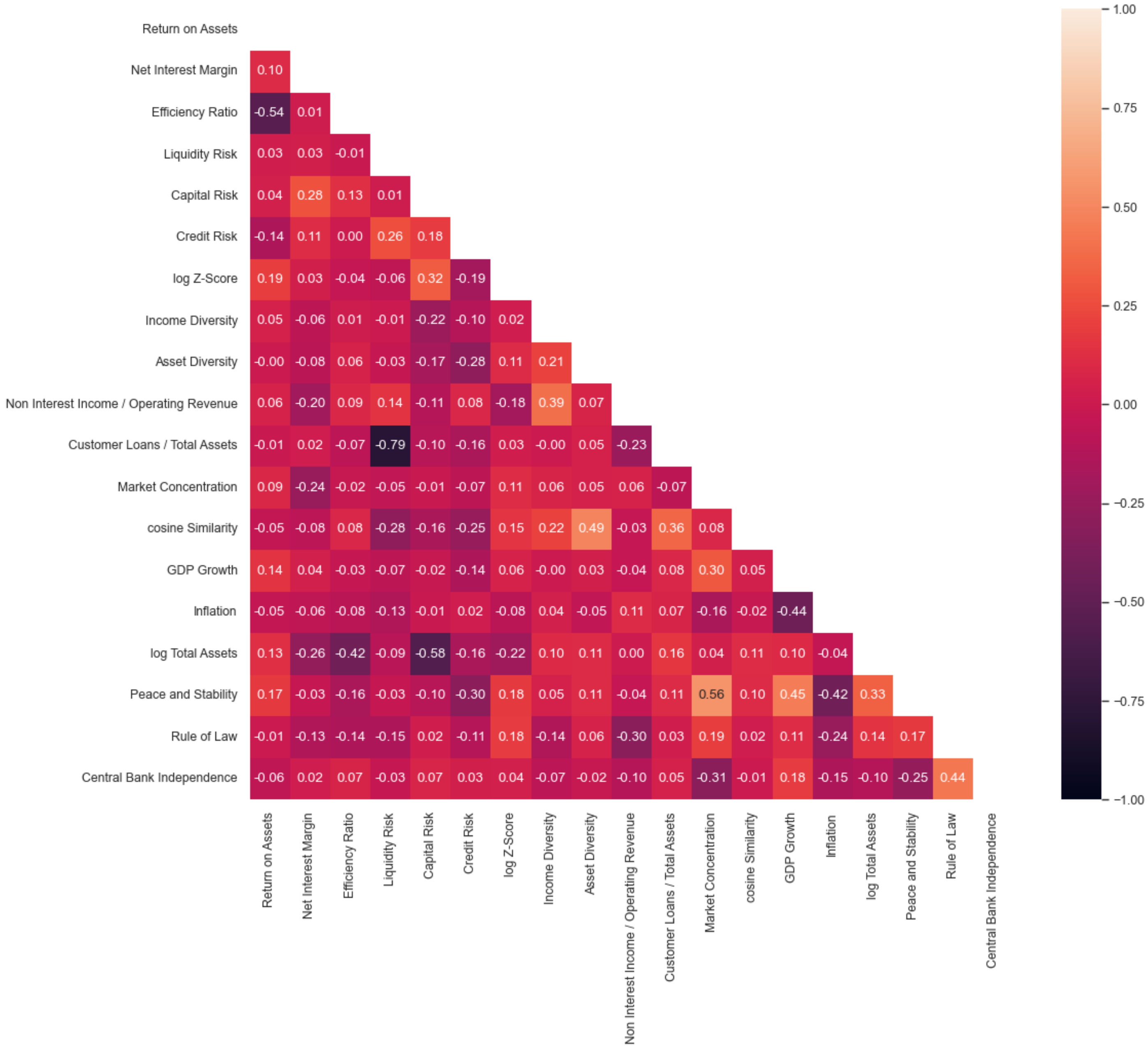

Figure A1: Appendix | Descriptives | Correlation Heatmap

Note. This figure presents correlations across the main series of variables used in the models throughout the study. By observing these metrics, we can determine the degree of multicollinearity that exists, possibly alerting us to the possibility of model misspecification. Broadly, these metrics are also useful in highlighting co-dependencies across the variables.

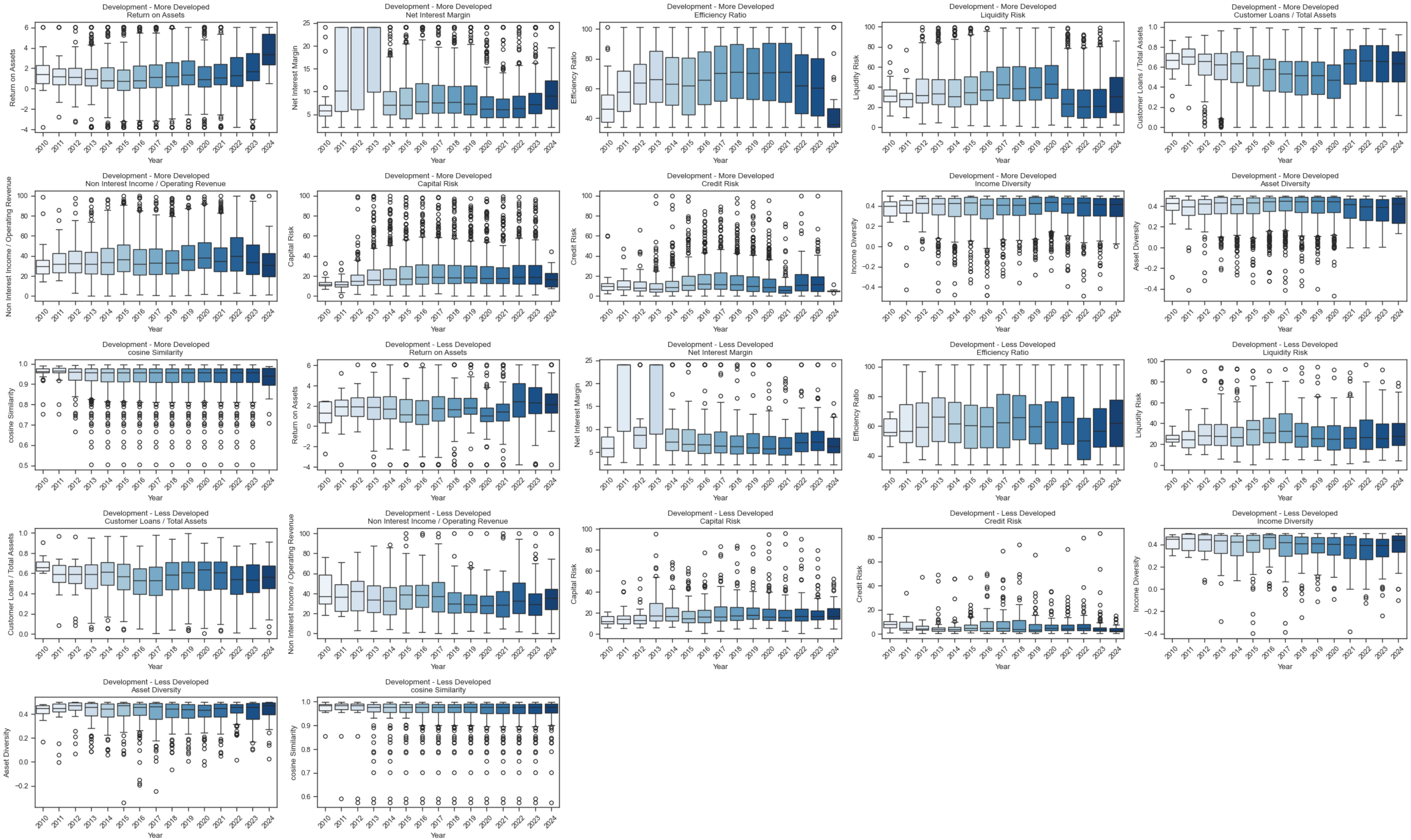

Figure A2: Appendix | Descriptives | Boxplots

Note. This figure presents a series of boxplots demonstrating the distributions of each variable relevant in the study over time. By observing these, we can be informed of the potential impacts of unexpected data features to the extent that they alter our conclusions or model validity.