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ASSESSING INCOME INEQUALITY IN GEORGIA AND ITS POTENTIAL IMPLICATIONS FOR MONETARY POLICY TRANSMISSION

ANA NIZHARADZE, DAVIT TUTBERIDZE

Abstract

This paper examines the dynamics of income inequality in Georgia and analyzes its potential implications for the effectiveness of monetary policy transmission. Drawing on household-level data from the Integrated Household Survey (IHS) published by the National Statistics Office of Georgia (GeoStat), the study estimates Gini coefficients for three income concepts over the period 2006–2024. The empirical findings reveal that, although income inequality has generally declined since its peak in 2010, it remains elevated. The analysis indicates that social transfers and non-cash agricultural income derived from own agricultural production have played a significant role in reducing income inequality.

Drawing on international theoretical and empirical literature, the paper explores the potential effects of income inequality on the principal channels of monetary policy transmission, including the interest rate, credit, asset price, balance sheet, and expectations channels. The analysis suggests that income inequality in Georgia may represent a structural constraint on the effectiveness of monetary policy transmission; however, direct empirical validation of this relationship requires further research.

Keywords: Income inequality, Gini coefficient, monetary policy transmission, heterogeneous agents, marginal propensity to consume.

Introduction

The collapse of the Soviet Union led to a sharp deterioration in living standards across post-Soviet states. In Georgia, from the early 1990s to 2000, almost all socio-economic indicators reached critical levels, with poverty deepening and inequality rising (Yemtsov, 2001). In response, Georgian governments implemented a range of structural reforms and policy measures aimed at restoring macroeconomic stability. As outlined by Godar et al. (2018), since gaining independence, the governments of Georgia pursued neoliberal economic policies, including massive deregulation, trade and financial liberalization, flat personal income taxation, and large-scale privatization of public assets. The underlying rationale of these policies was to reduce the state's role in the economy and establish an efficient market environment that would facilitate the attraction of foreign direct investment (FDI) and sustainable economic growth. An additional objective was to address the high unemployment and extreme poverty that followed the collapse of the Soviet Union.

The results of these economic reforms were reflected in favorable international assessments of the business environment. Georgia ranked 9th among 190 economies in the World Bank's Doing Business 2018 report and further improved its position to 7th place globally in the 2020 edition (World Bank, 2020; World Bank, 2018). In the latest World Bank's

Business Ready (B-READY) 2024 report, which replaced the Doing Business ranking, Georgia was placed among the top three economies out of the 50 countries assessed, reflecting continued progress in business regulation and operational efficiency (World Bank, 2024). Furthermore, reforms contributed to sustained economic growth, with real GDP in Georgia expanding approximately 6% on average annually between 2004 and 2025 (World Bank, 2026). This occurred despite numerous shocks, including the 2008 global financial crisis, the Russia-Georgia war, the COVID-19 pandemic, and the Russia-Ukraine war. Nevertheless, the reforms failed to deliver an equitable distribution of the benefits of economic growth across broad segments of society.

According to GeoStat (2025), the official unemployment rate in 2025 amounted to 13.9%. However, several studies argue that actual labor market slack is significantly higher once accounting for underemployment. Since a significant share of Georgia's labor force is concentrated in precarious jobs and low-productivity agriculture, the high rate of self-employment may conceal the true extent of underemployment and unemployment (Kakulia et al., 2016). Moreover, despite a declining trend in recent years, income inequality remains high. In particular, the Gini coefficient for total consumption expenditure stood at 0.36 in 2024 (GeoStat, 2024). The persistence of high inequality in Georgia is reflected in both significant urban-rural income disparities, with urban incomes exceeding rural incomes 1.8 times (Iashvili, 2020), and substantial income concentration, with the richest 10% of the population earning 16 times more than the poorest 10% (Kontselidze, 2016).

While a moderate degree of inequality is often regarded as an inherent feature of market economies that can encourage effort, innovation, human capital accumulation, and productivity growth, excessive inequality can become economically and socially damaging. As global evidence suggests, income inequality has not declined in recent decades; rather, it has continued to rise (Cingano, 2014). Although some degree of income differentiation creates incentives that are necessary for economic development, a high concentration of wealth and income can limit opportunities for economic advancement and social mobility, creating a "vicious circle of poverty" that is difficult to overcome. In this regard, excessive income inequality not only increases poverty levels, but also negatively affects various broader aspects of social and economic development. The World Inequality Report (2026) states that "Inequality has long been one of the fundamental features of the global economy, however by 2025, it had reached a level that demands urgent attention". Such concerns are not new. Nobel Prize-winning economist Joseph Stiglitz warned as early as 2012 that income inequality indicators had reached "dangerous levels", comparable to those observed during the Great Depression (Stiglitz, 2012).

Beyond its social implications, income inequality carries important macroeconomic consequences. A fundamental assumption underlying conventional monetary transmission mechanisms is a homogeneity across economic agents, whereby households and firms are expected to respond to monetary impulses in broadly similar ways (Woodford, 2003; Mishkin, 1996). However, high income and wealth inequality amplifies the heterogeneity of economic agents, leading to differences in consumption behavior, balance sheet positions, credit access, and marginal propensities to consume (MPCs) (Auclert, 2019; Coibion et al., 2017). As a result, the aggregate response of the economy increasingly reflects the combined effects of heterogeneous economic agents' diverse microeconomic reactions rather than the behavior of a single representative agent.

To address this limitation, Heterogeneous Agent New Keynesian (HANK) models have been developed, allowing macroeconomic analysis to account for differences in economic agents' characteristics and behavioral responses (Kaplan et al., 2018). These models often incorporate the potential weakening of and delays in the effectiveness of monetary policy transmission. For instance, when a larger share of income is concentrated among wealthier households with lower marginal propensities to consume, changes in interest rates generate smaller aggregate demand responses (Carroll et al., 2017; Kaplan and Violante, 2014). At the same time, financially constrained households may remain largely insensitive to policy easing due to limited access to credit markets (Brunnermeier and Sannikov, 2014). Consequently, elevated inequality may weaken both the effectiveness and predictability of monetary policy transmission mechanisms through both consumption and financial channels (ECB, 2018; Coibion et al., 2017).

A recent paper by the Bank for International Settlements (BIS), "How can central banks take account of differences across households and firms for monetary policy?" (BIS, 2025), shows that the monetary policy transmission mechanism is relatively less effective in economies with high income inequality, while it operates more effectively in economies with lower income concentration. The BIS study emphasizes that income distribution is one of the determining factors of the effectiveness of central bank decisions. Motivated by these findings, this paper assesses the level and dynamics of income inequality in Georgia and subsequently analyzes the principal channels through which inequality may influence the effectiveness of the National Bank of Georgia's monetary policy transmission mechanism.

Literature Review

The relationship between income inequality and monetary policy has attracted increasing attention in recent years, as advances in heterogeneous-agent macroeconomics have challenged the representative-agent paradigm traditionally employed in monetary economics. A growing body of research concludes that the distribution of income, wealth, and financial resources across households is not merely an outcome of economic processes but also an important determinant of monetary policy transmission. In particular, differences in marginal propensities to consume, liquidity constraints, debt positions, and asset holdings generate heterogeneous responses to monetary policy shocks, thereby influencing the strength of the consumption, credit, and balance-sheet channels (Auclert, 2019; Kaplan et al., 2018).

The recent literature on Heterogeneous Agent New Keynesian (HANK) models further emphasizes the role of household heterogeneity in the monetary policy transmission mechanism, particularly in shaping aggregate demand and inflation dynamics (Auclert et al., 2025). HANK models demonstrate that monetary policy operates not only through the intertemporal substitution channel but also through redistributive effects and heterogeneous financial positions across households (Auclert, 2019; Kaplan et al., 2018). In this setting, the aggregate consumption response to monetary policy depends critically on which households are affected by changes in interest rates and liquidity conditions, and to what extent.

Empirical evidence suggests that higher inequality weakens the effectiveness of monetary policy transmission by increasing the share of aggregate income held by high-income households with lower marginal propensities to consume, reducing the sensitivity of aggregate consumption to changes in interest rates. Evidence from central bank research suggests that economies with more equal income distributions exhibit stronger and more immediate consumption responses to monetary shocks (ECB, 2018), while financial frictions and household heterogeneity attenuate the pass-through of policy rates to aggregate demand (BIS, 2020). These findings suggest that the aggregate response is largely shaped by heterogeneity across households in terms of marginal propensities to consume and liquidity constraints. Accordingly, high inequality undermines the implicit homogeneity assumption embedded in representative-agent frameworks, leading to weaker, heterogeneous, and state-dependent monetary policy transmission mechanisms.

Building on these theoretical foundations, an expanding body of empirical literature investigates the impact of inequality on monetary policy effectiveness across households, regions, and countries. A large number of studies find that higher inequality and tighter financial constraints tend to weaken the monetary policy transmission mechanism (Zvereva, 2025; Chang and Schorfheide, 2024; Luetticke, 2021). At the same time, a related strand of the literature examines the reverse causal relationship, namely how monetary policy itself affects the distribution of income and wealth through the labor-market, inflation, and asset-price channels. However, the existing empirical evidence regarding the magnitude and direction of these effects remains inconclusive (Creel and El Herradi, 2024; Andersen et al., 2023; Amberg et al., 2022; Bernanke 2015).

Empirical research on income inequality in Georgia remains relatively limited. Iashvili (2020) analyzes income inequality in Georgia from the rural-urban perspective, with a particular emphasis on the impact of government redistribution. The study uses data from GeoStat's Integrated Household Survey (IHS) and the Standardized World Income Inequality Database (SWIID) Gini index. The author finds that the disparity between the urban and rural areas is significant with the urban population's income exceeding that of the rural population by 1.8 times. Meanwhile, social transfers, including pensions, family allowances, and stipends have partially reduced income inequality, the redistribution effect of fiscal policy over the decade covered by the study is estimated to have reduced the Gini coefficient by approximately 0.10 points. The author concludes that while this cumulative effect of absolute redistribution in Georgia is higher than in developing countries or emerging markets, the government needs to further improve the effectiveness of government redistribution policies.

The paper by Kakulia et al., (2017) provides a comprehensive analysis of poverty and income inequality in Georgia using data from the IHS for the period 2009–2016. The authors employ both time-series and panel-data approaches to examine the dynamics of poverty, chronic poverty, and income inequality, utilizing indicators such as the Gini and decile coefficients. Their findings indicate a moderate decline in income inequality in Georgia; particularly, the Gini coefficient of total income per capita decreased from 0.4318 in 2009 to 0.3996 in 2016. Despite this improvement, the authors argue that inequality remains a significant socioeconomic challenge and, using linear regression analysis, identify a strong positive correlation between income inequality and poverty. Furthermore, the study assesses the impact of government redistributive policies through a comparison of Gini coefficients calculated with and without pensions and social transfers. Although redistribution reduces income inequality, the analysis suggests that chronic poverty and unequal income distribution remain structural challenges in Georgia, underscoring the need for targeted policies to foster inclusive growth.

Kontselidze (2016) analyzes the relationship between economic growth and income inequality in Georgia, with particular reference to the Kuznets inverted-U hypothesis. Drawing on the data from World Bank and GeoStat, the author examines trends in income distribution, gross domestic product, gross national income, and the Gini coefficient. The study finds that, despite relatively sustained economic growth in Georgia since 2010 and a partial reduction in inequality, income disparities remained substantial. Particularly, during the period, the richest 10% of the population was earning approximately 16 times the income of the poorest 10%. The study finds that reducing inequality is an important prerequisite for achieving sustainable economic growth, while the Georgian experience is partly consistent with the theoretical predictions of the Kuznets curve.

Godar et al., (2018) provide a fiscal policy-oriented analysis of income distribution and the tax system in Georgia. The authors highlight that the post-Soviet flat income tax regime has contributed to persistently high inequality while limiting the fiscal capacity for development-oriented public spending. They situate Georgia's tax architecture in the context of the broad neoliberal reforms implemented since the early 21st century, arguing that proportional taxation, combined with weak redistribution mechanisms, failed to translate strong economic growth into inclusive welfare gains. The authors also analyze the potential effects of a progressive personal income tax regime, which, in their assessment, could reduce disposable income inequality and simultaneously generate additional public revenues to support human capital development and productive investment. Thus, tax reform is positioned not only as a redistributive tool but also as an instrument for fostering shared prosperity in Georgia.

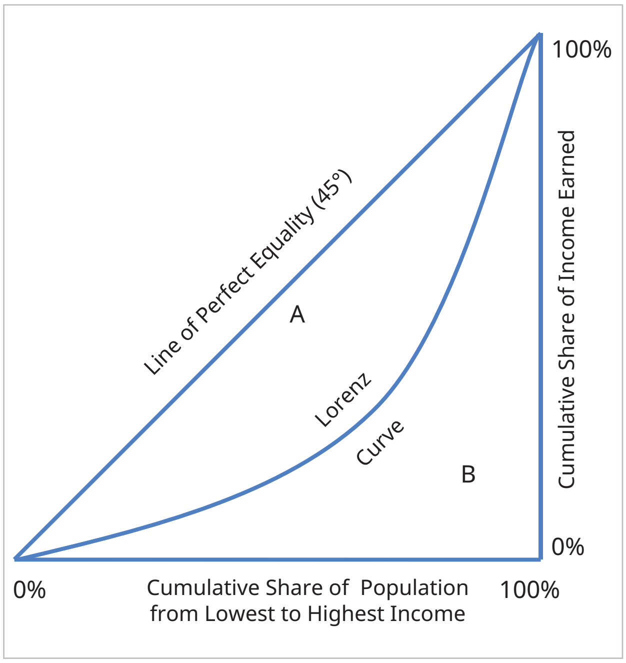
Methodology and Data

The empirical analysis draws on household-level microdata from the Integrated Household Survey (IHS), published annually by the National Statistics Office of Georgia (GeoStat). The IHS (which was renamed the Household Income and Expenditure Survey in 2017) is the primary source of household income and consumption expenditure data in Georgia. The survey is based on a random sampling methodology, ensuring sample representativeness and the comparability of results. Estimation of key indicators accounts for standard errors. The monthly sample size satisfies robustness requirements, and the methodology employed conforms to international standards.

While the IHS data represent an important source for measuring inequality, the literature identifies certain shortcomings. In particular, high-income households tend to avoid participating in surveys, which may lead to a systematic downward bias in measured inequality indicators (Atkinson et al., 2011).

Income inequality is measured using the Gini coefficient, developed by Italian statistician Corrado Gini (1912), which remains one of the most widely used single-summary measures of distributional inequality in economics. The Gini coefficient reflects the deviation of income distribution from the line of perfect equality and takes values between 0 and 1, where 0 indicates perfect equality and 1 indicates maximum inequality. In practice, such extreme values are rarely observed. Accordingly, the higher the Gini coefficient, the greater the concentration of income between high- and low-income groups in the population (Sitthiyot and Holasut, 2020).

Figure 1. Measuring the Concentration of Wealth



Source: Lorenz (1905).

Mathematically, the Gini coefficient is defined based on the Lorenz curve, introduced by Max Lorenz (1905). The curve illustrates the cumulative share of population income (Y-axis) corresponding to the bottom x% of the population (X-axis) (see Figure 1). The Lorenz curve lies below the 45-degree line of perfect equality (y=x). The further it deviates from this line, the higher the level of income inequality and consequently, the greater the Gini coefficient.

The Gini coefficient is defined as the ratio of the area between the line of perfect equality and the Lorenz curve (A) to the total area under the line of perfect equality (A + B).

$$Gini = \frac{A}{A+B}$$

Since

$$A + B = 0.5,\ Gini = 2A = 1 - 2B$$

If the population size is large, the distribution of income can be expressed as a continuous probability density function *f(x)*. The corresponding cumulative distribution function is defined as $\int_0^x f(t)dt,$ and under the conditions of a finite and positive mean value μ, the Lorenz curve *L(F)* can be expressed as a parametric function in the following form:

$$L(F) = \frac{1}{\mu}\int_0^{F(x)} F^{-1}(t)dt \tag{1}$$

where

$$\mu = \int_0^1 F^{-1}(t)dt$$

The value of B can be found through the integration:

$$B = \int_0^1 L(F)dF$$

Exploiting the definition of Gini index, as one minus twice the area B between Lorenz curve and perfect inequality, Gini index can be expressed as follows:

$$G = 1 - 2\int_0^1 L(F)dF \tag{2}$$

By substituting the expression for L(F) given in Equation (1) into Equation (2), it follows that:

$$G = \frac{2}{\mu}\int_0^{\infty} xF(x)dF(x) - 1 \tag{3}$$

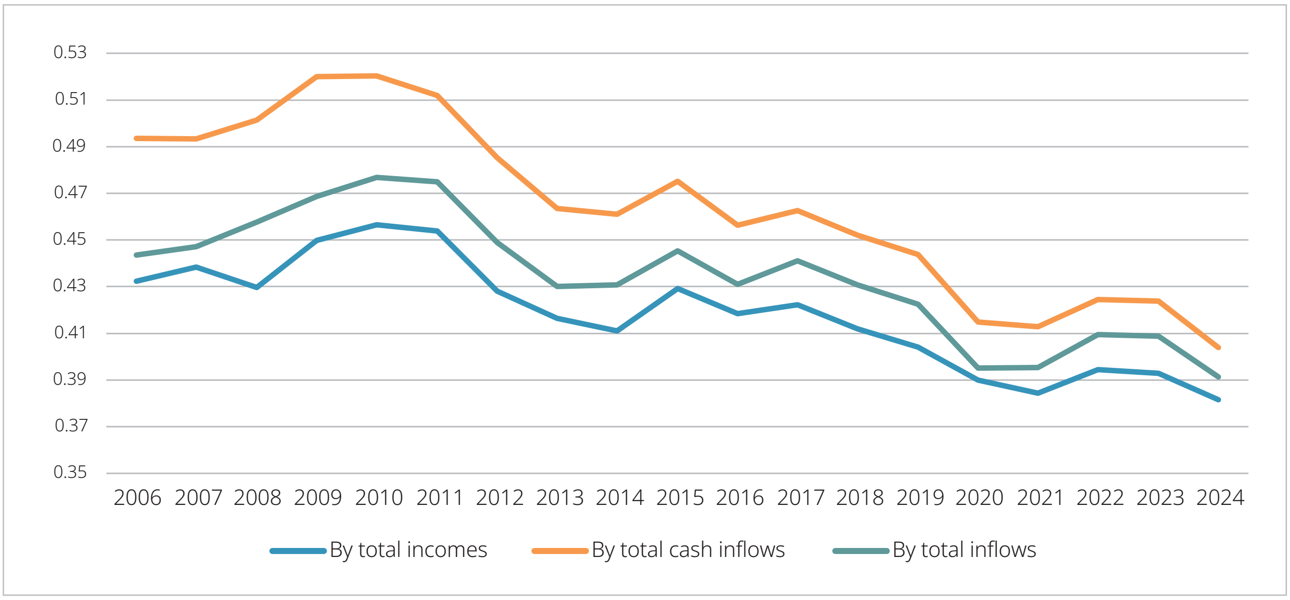
Since population income distributions are generally observed through sample data, the Gini coefficient is estimated using the empirical cumulative distribution function *(F)* derived from a random sample of (n-size) income observations. In this respect, the sample Gini index can be stated as:

$$\hat{G} = \frac{1}{\hat{\mu}}\int_0^{\infty} xd(\hat{F}\,(x))^2 - 1 = \frac{2\sum_{i=0}^{n} X_{i:n}\,(i - \frac{1}{2})}{n\sum_{i=1}^{n} X_i} - 1$$

Assessment of Income Inequality in Georgia

The empirical analysis reveals several important trends in the evolution of inequality in Georgia. One of the most notable patterns is the sharp increase in inequality between 2006 and 2010 across all Gini coefficients (see Figure 2). This deterioration likely reflected the combined effects of the 2008 global financial crisis and the Russia–Georgia war, both of which negatively affected employment, investment, and household incomes. Following 2010, inequality generally had a decreasing tendency, although progress was uneven across indicators and time periods. Specifically, a temporary increase in inequality was observed during 2014–2017 and again in 2022. The 2014–2017 period is likely associated with a slowdown in global and regional economic growth, including a recession in Georgia's main trading partner countries, which reduced employment opportunities and remittance inflows, and disproportionately affected low-income households (World Bank, 2018; UNICEF, 2018). Whereas the increase observed in 2022–2023 may reflect the uneven distribution of the post-pandemic economic recovery, as well as migration flows related to the Russia–Ukraine war and associated inflationary pressures (IMF, 2024).

Figure 2. Gini Coefficients Estimated for Georgia



Source: GeoStat; authors' calculations.

The analysis demonstrates significant variation in the level of inequality depending on the income measure used. In 2024, the Gini coefficient by total incomes stood at 0.382, compared to 0.404 for total cash inflows and 0.391 for total inflows. Among the reviewed measures, total cash inflows appear to have been distributed most unequally.

A structural comparison of these indicators allows for several important conclusions. In particular, the difference between the Gini coefficients for total cash inflows (0.404) and total inflows (0.391) indicates that non-cash income, such as the consumption of agricultural products from own production, estimated at current prices, serves as an important equalizing factor. This finding is consistent with the results reported by Kakulia et al., (2017), who similarly identify own production in rural households as a distributional buffer, despite the relatively low productivity associated with agricultural self-employment.

At the same time, the level of inequality measured by total inflows (0.391) exceeds that recorded for total income (0.382), suggesting that income from selling property, as well as access to loans and savings, plays a significant role in amplifying inequality. This result likely reflects the relatively limited access to assets and formal credit among lower-income households.

Channels through which increased inequality could weaken the effectiveness of monetary policy transmission

The effectiveness of monetary policy depends on the extent to which changes in the policy rate are transmitted to the economy through the interest rate, credit, asset price, exchange rate and other channels (Mishkin, 1996; Bernanke and Gertler, 1995). Traditionally, monetary policy is modeled within a "representative agent" framework that assumes a sufficient degree of homogeneity across households and firms such that economic agents respond to monetary impulses in a broadly uniform manner (Galı́, 2008).

High inequality in income and wealth undermine this premise in a structurally significant way. When economic resources are highly concentrated, the aggregate response to monetary policy reflects an aggregation of distinct micro-level reactions, as different income groups exhibit systematically different marginal propensities to consume, credit constraints, and exposure to financial market volatility.

As a result, monetary policy signals may be attenuated or transmitted with delays, thereby weakening the effectiveness and predictability of monetary policy transmission (Auclert, 2019; Coibion et al., 2017). This subsection analyzes the principal mechanisms through which elevated inequality may impair the effectiveness of monetary policy transmission by acting as a structural exogenous constraint on the transmission process.

An important mechanism through which inequality affects the transmission of monetary policy is heterogeneity in the marginal propensities to consume (MPCs) across income groups. Lower-income households typically exhibit higher MPCs, allocating a larger share of additional disposable income to consumption rather than saving. By contrast, higher-income households are characterized by substantially lower MPCs (Carroll et al., 2017; Kaplan and Violante, 2014). Accordingly, when income is concentrated in the upper quantiles of the distribution, aggregate consumption responds less strongly to a given change in interest rates, thereby weakening the demand channel of monetary policy (BIS, 2025; Eggertsson and Krugman, 2012). Under such conditions, expansionary monetary policy may generate a weaker increase in consumption, while the impact of contractionary policy on aggregate demand and inflation may also be diminished.

Kaplan et al. (2018) formalize this mechanism in a HANK model and demonstrate that indirect general-equilibrium effects operating through the labor income channel dominate the transmission of monetary shocks. Moreover, the strength of these effects depends significantly on the structure of the income distribution. Their findings imply that, in economies characterized by high levels of inequality, central banks often require larger and more prolonged changes in interest rates to achieve an equivalent degree of stabilization, thereby increasing the risks of financial instability and asset price corrections (Auclert, 2019).

The heterogeneity in MPCs, although most directly relevant to the consumption channel, also substantially determines the transmission of monetary policy through the asset price and balance sheet channels. Expansionary monetary policy typically raises the prices of financial and real assets (including equities, real estate, and fixed-income securities) both by lowering the discount rate and through portfolio rebalancing effects (Bernanke et al., 2004). Rising asset prices can stimulate economic activity through the wealth effect, whereby households increase consumption in response to perceived improvements in their balance-sheet positions. However, the magnitude of this effect depends significantly on the distribution of asset ownership across households (Saez and Zucman, 2016).

In economies where asset ownership is more broadly dispersed, a larger share of households benefit from balance-sheet gains and increase consumption accordingly. By contrast, when wealth is concentrated among high-income groups, which are characterized by relatively low MPCs, the impact of rising assets prices on aggregate demand is weaker. Consequently, any additional increase in asset prices generates a smaller stimulating effect on economic activity (Bivens, 2015). Bivens (2015) argues that this distributional channel partly explains why post-2008 quantitative easing programs in the United States and Europe generated substantial increases in asset prices, yet failed to deliver a proportionate recovery in consumer spending and real output.

The effectiveness of the credit channel in monetary policy transmission depends on the extent to which households and businesses can access formal credit and have the ability to adjust their borrowing in response to changes in financing conditions (Kumhof et al., 2015; Bernanke and Gertler, 1995). In more equal economies, access to finance tends to be more broadly distributed across income groups, enabling a larger share of agents to respond to the easing or tightening of monetary policy.

In contrast, in more unequal economies, although expansionary policy aims to stimulate economic activity, low-income and financially constrained households often face limited access to formal credit due to insufficient collateral, unstable income, or weak credit histories, consistent with the informational asymmetries present in credit markets (Rajan, 2010; Greenwald et al., 1984). As a result, even when the central bank lowers the policy rate, these households may remain unable to increase borrowing and, consequently, expand consumption. This weakens the effectiveness of monetary easing, since it is precisely those households with the highest MPCs—and therefore those most likely to translate cheaper credit into immediate demand expansion—that are often the most financially constrained (Auclert, 2019; Kaplan and Violante, 2014; Rajan, 2010; Greenwald et al., 1984). By contrast, high-income households generally face fewer credit constraints and have broader access to alternative sources of financing, which makes their consumption decisions less sensitive to marginal changes in borrowing costs (Cloyne et al., 2020). Thus, high income and wealth inequality weakens the credit channel by increasing the share of financially constrained agents in the economy and may require the central bank to implement larger policy rate adjustments in order to achieve a given macroeconomic objective.

Conclusion

In summary, the structure of income distribution is not merely a social concern but also a macroeconomic factor with important implications for the effectiveness of monetary policy transmission. The empirical analysis of IHS microdata for the period 2006-2024 reveals that, while inequality indicators have generally improved since their peak in 2010, income and wealth disparities remain relatively elevated. This may influence household consumption behavior, credit access, asset ownership, and inflation expectations. These structural differences generate heterogeneous responses to monetary policy impulses, thereby weakening several key transmission channels through which the National Bank of Georgia's monetary policy framework operates.

The mechanisms discussed above collectively suggest that a more equal distribution of income and wealth materially strengthens the effectiveness of monetary policy transmission and enhances the central bank's capacity to achieve its mandate. Lower inequality tends to raise the aggregate marginal propensity to consume, strengthening the response of aggregate demand to a given policy rate adjustment. This enables central banks to achieve inflation and output objectives with less aggressive policy intervention. Furthermore, broader financial inclusion strengthens the credit channel by expanding the share of households and firms that can respond meaningfully to changes in borrowing conditions. More widely distributed asset ownership also amplifies the transmission of monetary policy through wealth and asset price channels, reducing the likelihood that policy-induced asset price appreciation is concentrated among low-MPC households with weaker consumption responses. In addition, lower inequality reduces the share of financially constrained households that are structurally less responsive to interest rate changes, thereby widening the segment of the economy through which monetary policy propagates.

The aforementioned findings do not imply that monetary policy is ineffective in Georgia, nor that inequality is the only structural constraint on the monetary transmission mechanism. Rather, they suggest that monetary policy operates within important distributional and structural frictions that should be explicitly acknowledged within the National Bank of Georgia's analytical framework.

Continued progress in reducing income inequality, broadening financial inclusion, and advancing de-dollarization enhances the responsiveness of households and firms to monetary policy signals. At the same time, the continuous development of the analytical toolkit, including the Dynamic Stochastic General Equilibrium (DSGE) model for Georgia developed by Arevadze et al. (2024), constitutes an important step toward modeling structural frictions characteristic of the Georgian economy. Overall, the processes described above strengthen the consumption, credit, asset price, and expectations channels of transmission, enabling monetary policy to more effectively achieve its primary objective of price stability.

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KEY FACTORS OF THE CURRENT ACCOUNT BALANCE IN GEORGIA: DYNAMICS AND STRUCTURAL CHANGES

VAKHTANG PKHAKADZE, LIA DZEBISAURI

Abstract

This paper examines the dynamics of Georgia's current account, its key determinants, and the structural changes that took place between 2005 and 2025. The study finds that Georgia's current account structure has undergone a significant transformation over the past 21 years. The services balance, particularly travel, transport, and, more recently, computer services, has become a key factor in reducing the current account deficit.

The findings indicate that, despite its recent narrowing, the current account deficit remained broadly sustainable throughout the period under review. This outcome was largely attributable to the persistently large deficit in the trade balance of goods and the consistently negative primary income balance.

Keywords: Balance of payments, current account deficit, trade in goods, services, tourism, travel, computer services, export, import, primary income, secondary income, transfer, remittances, statistics.

Introduction

Global fragmentation and economic polarization, which are increasingly dividing the world economy into geopolitical blocs, regional economic spheres, and alternative trade and financial systems, are significantly reshaping cross-border trade flows. The rerouting of trade routes, the reorganization of supply chains, and the redistribution of energy resources and strategic goods create opportunities for Georgia to strengthen its role in the Middle Corridor and enhance its transit function. At the same time, structural shifts in the global economy, the geographical redistribution of remittances, changes in tourism dynamics, the impact of sanctions on financial flows, as well as Georgia's dependence on imported energy and rising energy import costs, exert a substantial influence on the current account of the balance of payments.

The current account is one of the most important indicators of a country's external economic position. It reflects the relationship between the domestic economy and the rest of the world, providing valuable information on macroeconomic equilibrium and the balance between national savings and investment. Its dynamics and structure have a significant bearing on economic growth, financial stability, and an economy's vulnerability to external shocks.

Historically, the current account deficit has been one of Georgia's key macroeconomic challenges. Its magnitude and underlying determinants have varied across different stages of the country's economic development, reflecting both domestic economic processes and global developments. The deficit in trade in goods, together with the primary income balance, has been the principal driver of the negative current account balance, while the services balance and current transfers have acted as mitigating factors.

Over the past two decades, Georgia's external sector has undergone a significant structural transformation, including the growth of services exports, the expansion of tourism, and the increasing role of remittances. These developments have partially reduced the current account deficit and altered its composition, although the issue of sustainability remains an important challenge.

The purpose of this study is to assess the dynamics of the main factors shaping Georgia's current account balance and its structural transformation over a twenty-year period. The analysis is based on time-series data, enabling the identification of both long-term trends and period-specific developments. Georgia compiles its balance of payments statistics in accordance with the sixth edition of the International Monetary Fund's Balance of Payments and International Investment Position Manual (BPM6). The indicators used in this study and their analysis are based on this methodological framework.

Literature Review

The existing literature on the dynamics of the current account and its determining factors covers several theoretical and empirical directions. In economic theory, the current account is typically considered as the macroeconomic expression of the difference between savings and investment (Obstfeld and Rogoff, 1994). In models of small open economies, a current account deficit is often perceived as an accompanying phenomenon of high investment activity and economic growth (Mankiw, 2008).

In the academic literature, great attention is paid to the analysis of the sustainability of the current account deficit and its determining macroeconomic factors. Calderón, Chong, and Loayza (2000), using the example of developing countries, show that current account dynamics are significantly influenced by economic growth, fiscal policy, terms of trade, capital flows, and external shocks. The authors particularly highlight the role of financial liberalization and the international mobility of capital.

Chinn and Prasad (2003) identify fiscal balances, financial development, trade openness, and demographic factors as key medium-term determinants of the current account balance. The authors note that in developing economies, current account dynamics are significantly dependent on both domestic savings and the international movement of capital.

Edwards (2004) notes that, for developing economies, current account deficits may initially reflect a natural consequence of economic growth and substantial capital inflows. However, their prolonged persistence may lead to heightened external vulnerability. Similarly, Milesi-Ferretti and Razin (1996) analyze current account sustainability through the lens of the interaction between external debt, capital flows, and economic growth.

Ca'Zorzi, Chudik, and Dieppe (2012) pay special attention to the impact of global financial integration and global savings imbalances. According to the authors, significant disruptions in the current account balance are often formed as a result of changes in both domestic structural factors and the global financial environment.

International studies also indicate that small open and transitional economies are particularly sensitive to external economic and financial shocks (IMF, 2023). In such countries, the dynamics of the current account are significantly influenced by export structure, import dependence, exchange rate fluctuations, foreign direct investment (FDI), remittances, and the development of the services sector.

In the context of the Georgian economy, much of the existing research is focused on individual components of the current account: trade in goods, travel, remittances, and foreign direct investment (IMF, 2025; NBG, 2025). However, the historical dynamics of the current account are relatively less studied in the context of structural transformation, especially during the period of 2005-2025, which encompasses periods of high economic growth as well as the global financial crisis, the COVID-19 pandemic, and various geopolitical changes.

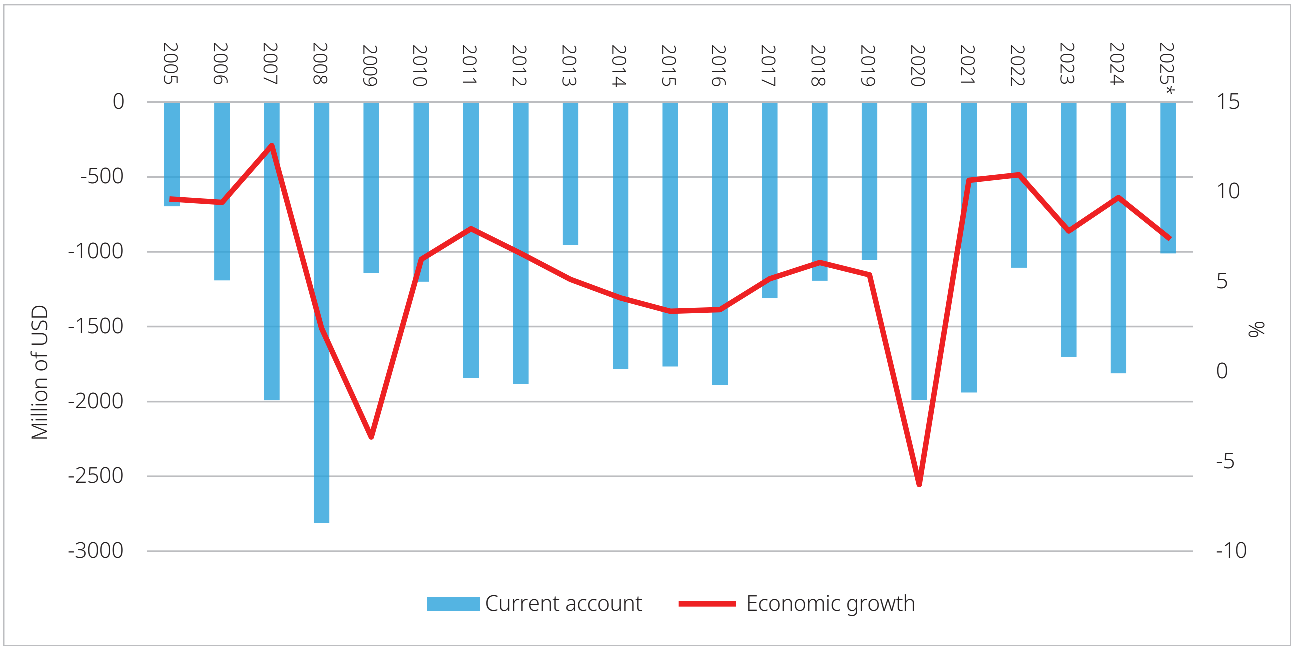
The present paper aims to analyze the key determining factors of Georgia's current account balance from a historical and structural perspective, based on the evaluation of current account components, economic transformation, and changes in the external sector.

Current Account Dynamics in Georgia: Historical Context

The current account balance is a key indicator of a country's external economic sustainability, and its ratio to GDP measures the scale of external imbalances and the economy's reliance on foreign financing. This analysis examines periods of rapid economic growth and intensive capital inflows, alongside major disruptions, such as the global financial crisis, the pandemic, and regional geopolitical shocks, that have significantly reshaped Georgia's external sector.

Between 2005 and 2025, Georgia's economic growth and its current account deficit shared a direct relationship: rapid expansion typically widened the deficit, whereas economic shocks and slowdowns caused it to narrow (see Figure 1).

Figure 1. Current Account and Economic Growth in Georgia, 2005–2025



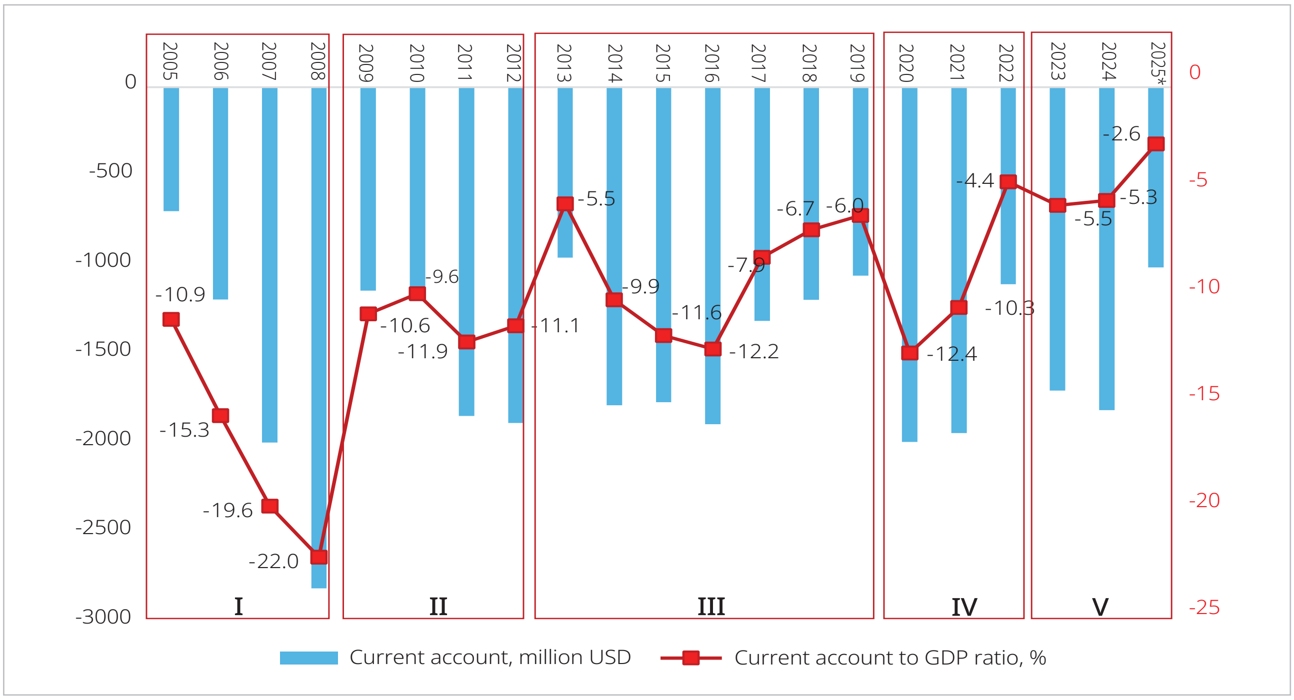
Source: The National Bank of Georgia.

** Preliminary data.*

This trend was particularly pronounced in 2007, when the economy recorded its highest historical growth rate of 12.6 percent, while the current account deficit reached USD 2.0 billion. The deficit hit a historic peak in 2008, reaching approximately 22.0 percent of GDP (see Figure 2). Subsequently, during the global financial crisis, the pandemic, and regional geopolitical shocks, the downturn in economic activity drove a decline in imports, leading to a temporary improvement in the current account deficit. Moreover, between 2021 and 2025, fueled by post-pandemic economic recovery and surging service exports, particularly in travel and the ICT sector, the current account deficit-to-GDP ratio narrowed to a historic low of -2.6 percent.

Figure 2 illustrates the dynamics of Georgia's current account balance and its ratio to the country's GDP. While the current account deficit in 2025 increased by 45.3 percent compared to 2005, the fluctuations during this period were much more dramatic than this overall difference suggests. In this context, the trajectory of Georgia's current account from 2005 to 2025 can be divided into five clearly defined phases: 2005-2008, 2009-2012, 2013-2019, 2020-2022, and 2023-2025.

Figure 2. Current Account Dynamics for Georgia, 2005–2025



Source: The National Bank of Georgia.
** Preliminary data.*

Figure 3 highlights the extremes of economic expansion and contraction for each phase. During the analyzed period, the highest growth rate was recorded at 12.6 percent in 2007, while the largest contraction was recorded in 2020 during the pandemic, at -6.3 percent. Each phase was shaped by different economic and geopolitical situations, which will be examined in greater detail throughout the analysis.

Figure 3. Economic Growth in Georgia, 2005–2025

Source: The National Bank of Georgia.
** Preliminary data.*

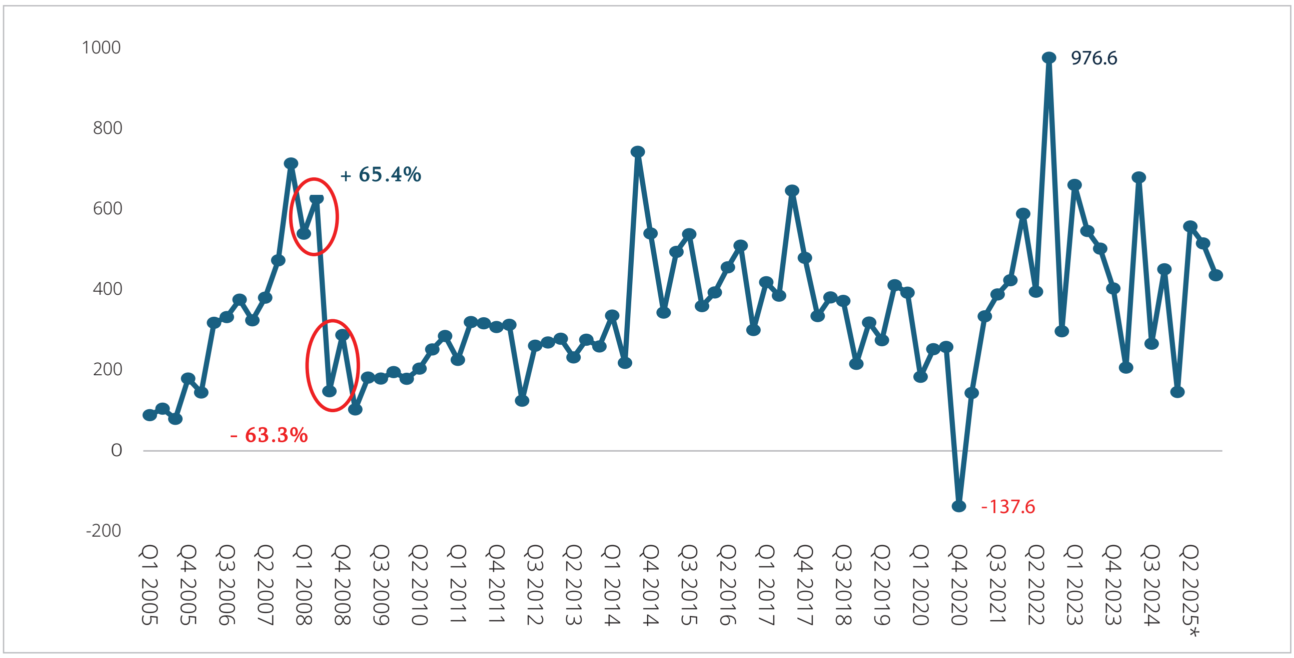
Phase I – High Current Account Deficit and Rapid Economic Growth (2005-2008)

The years 2005-2008 can be considered a period of high current account deficits and rapid economic growth. In 2005-2007, the average real GDP growth rate amounted to 10.5 percent. An exception was 2008, when the annual economic growth rate stood at 2.4 percent. This reflected the negative impact of the August war on economic growth, which naturally became more noticeable in the third and fourth quarters of 2008. The 11.0 percent and 8.4 percent growth rates recorded in the first and second quarters of 2008 were followed by declines of 5.6 percent and 1.0 percent in the third and fourth quarters.

The years 2005-2008 were characterized by large-scale infrastructure projects and active inflows of foreign capital. The economic dynamics of Georgia during this period were largely determined by major infrastructure projects such as the construction of the Baku-Tbilisi-Ceyhan oil pipeline and the East-West highway. These projects facilitated increased foreign direct investment, strengthened the country's transit function and, consequently, increased transit revenues, modernized road infrastructure, expanded the services sector, boosted service exports, established the country as a regional logistics hub, and, generally increased the significance of the external sector within the national economy. However, this process was accompanied by a rise in import demand, leading to a widening of the current account deficit.

Between 2005 and 2008, foreign direct investment in Georgia amounted to USD 5.1 billion, almost three times the total recorded during 1997-2004. Furthermore, as a result of the Russia-Georgia war of 2008, the 65.4 percent growth in foreign direct investment recorded in the first half of that year, compared to the corresponding period of the previous year, was followed by a 63.3 percent decline in the second half of the year (see Figure 4).

Figure 4. Foreign Direct Investment (Liabilities, Million USD)



Source: The National Bank of Georgia.

** Preliminary data.*

Against the backdrop of high economic activity, growing domestic demand, and large-scale infrastructure projects during 2005-2008, external trade expanded significantly. During this period, exports of goods grew by an average of 19.3 percent, while imports grew by 33.4 percent. The considerably faster growth in imports was mainly driven by increased demand for investment and consumer goods, the import of energy resources, and the inflow of industrial supplies and capital goods required for the implementation of infrastructure projects. During this phase, the highest average growth was observed in the import of industrial supplies (47.9 percent) and capital goods (41.0 percent).

The growth of exports during the same period was supported by increased demand in international markets for metallurgical products, ferroalloys, and motor cars; however, the volume and degree of diversification of exports still lagged significantly behind the corresponding parameters of imports.

The export dynamics of wine, mineral waters, and agricultural products of Georgian origin during this period were heavily negatively impacted by the embargo imposed by Russia in 2006 (lifted in 2013). Specifically, exports of Georgian wine decreased by 49.5 percent in 2006 compared to the previous year. This further deepened the negative balance of foreign trade in goods.

Compared with exports, the faster growth of imports also reflected the high import dependence of the country's economy and the characteristics of the economic growth model prevailing at the time, which was based on external financing, foreign direct investment, and the rapid expansion of domestic consumption.

As a result, the current account deficit deepened significantly, reaching a historic high of 22.0 percent of GDP in 2008, which was largely driven by the high negative balance in trade in goods.

Phase II – Post-August War and Global Financial Crisis Correction (2009-2012)

Alongside the 2008 Russia-Georgia war, the global financial crisis had a significant impact on the external sector of Georgia's economy. In 2009, economic activity slowed sharply, with real GDP declining by 3.7 percent. Against this backdrop, imports fell by 31.4 percent, which was accompanied by a 59.4 percent reduction in the current account deficit, to USD 1.1 billion. However, in subsequent years, as the economy recovered, import growth accelerated once again, averaging 24.1 percent in 2010-2012.

Remittances and service exports, especially the tourism sector, played an essential role in improving the current account balance during this period. At the same time, external vulnerability remained high, as the average economic growth of 6.9 percent in 2010-2012 was still largely driven by external financing and capital inflows.

Phase III – Relative Stabilization and the Growing Role of the Services Sector (2013-2019)

From 2013, the current account deficit moved onto a relatively stable trajectory. During this period, the deficit fluctuated within a range of 9-12 percent of GDP. Although the deficit in trade in goods remained the principal negative component of the current account, the contribution of service exports increased significantly, especially in the areas of travel, transport, and other services. Notably, in the third quarter of 2018, Georgia recorded a current account surplus of USD 9.6 million.

Between 2013 and 2019, the external sector of the economy became increasingly diversified, income from travel increased, and the quality of current account financing improved. The average annual growth of travel income during this period amounted to 11.7 percent and reached a total of USD 16.7 billion.

In 2013-2019, significant growth was observed in both the export and import of transport services. In

2019, compared with 2012, the export of transport services increased by 18.0 percent, while imports increased by 58.6 percent.

During the same period, foreign direct investment remained an important source of current account financing. Between 2013 and 2019, foreign direct investment in Georgia amounted to USD 10.9 billion, exceeding the cumulative total of the previous 16 years (1997-2012) by 2.4 percent.

Phase IV – The COVID-19 Pandemic Shock (2020-2022)

Between 2020 and 2022, the Georgian economy and its external sector experienced an unprecedented shock resulting from the COVID-19 pandemic, which had a profound impact on current account dynamics. In 2020, against the backdrop of the virtual standstill of tourism and the decline in global economic activity, the Georgian economy entered a deep recession, while the current account deficit widened substantially and reached 12.4 percent of GDP, one of the highest levels of the last decade. The main reason for the growth of the deficit was the sharp decline in the services balance, especially income from travel. In 2020, compared to the previous year, the number of international visitors to Georgia decreased by 82.7 percent.

In the fourth quarter of 2020, total foreign direct investment recorded a negative value for the first time, amounting to USD -137.6 million, which was mainly driven by the paralysis of the hotel sector during the pandemic. In contrast, the third quarter of 2022 marked a historic peak in FDI (liabilities), which reached USD 976.6 million.

At the same time, a 14.0 percent decline in imports and the relatively stable performance of remittances, which grew by 20.5 percent year-on-year in 2020, partially alleviated pressure on the external sector. From 2021, alongside the gradual reopening of the economy and the recovery of global demand, the Georgian economy rapidly returned to double-digit growth.

The 6.3 percent decline in 2020 was followed by growth of 10.6 percent and 11.0 percent in 2021 and 2022, respectively, accompanied by a reduction in the current account deficit to USD 1.1 billion. Particularly significant developments were recorded in 2022 when, against the recovery of the tourism sector (with the number of visitors increasing almost fourfold compared to 2020), the growth in computer service exports, and a sharp increase in remittances, the current account deficit declined to a historically low level. Moreover, in the third quarter of 2022, the current account temporarily recorded a surplus, amounting to USD 337.1 million. In addition, the improvement in current account dynamics was facilitated by regional geopolitical developments, most notably the increase in migration and financial inflows following the outbreak of the Russia-Ukraine war, which were reflected in both service exports and secondary income inflows.

Phase V – Post-Pandemic Recovery and Historically Low Deficit (2023-2025)

From 2023, the dynamics of Georgia's current account balance improved significantly. The growth in service exports, especially travel and ICT services, as well as the increase in remittances and external inflows, reduced the current account deficit to a historic low of USD 1.0 billion, which amounted to approximately 2.6 percent of GDP. It is noteworthy that in the third quarter of 2025, the current account again recorded a surplus and equaled USD 398.0 million.

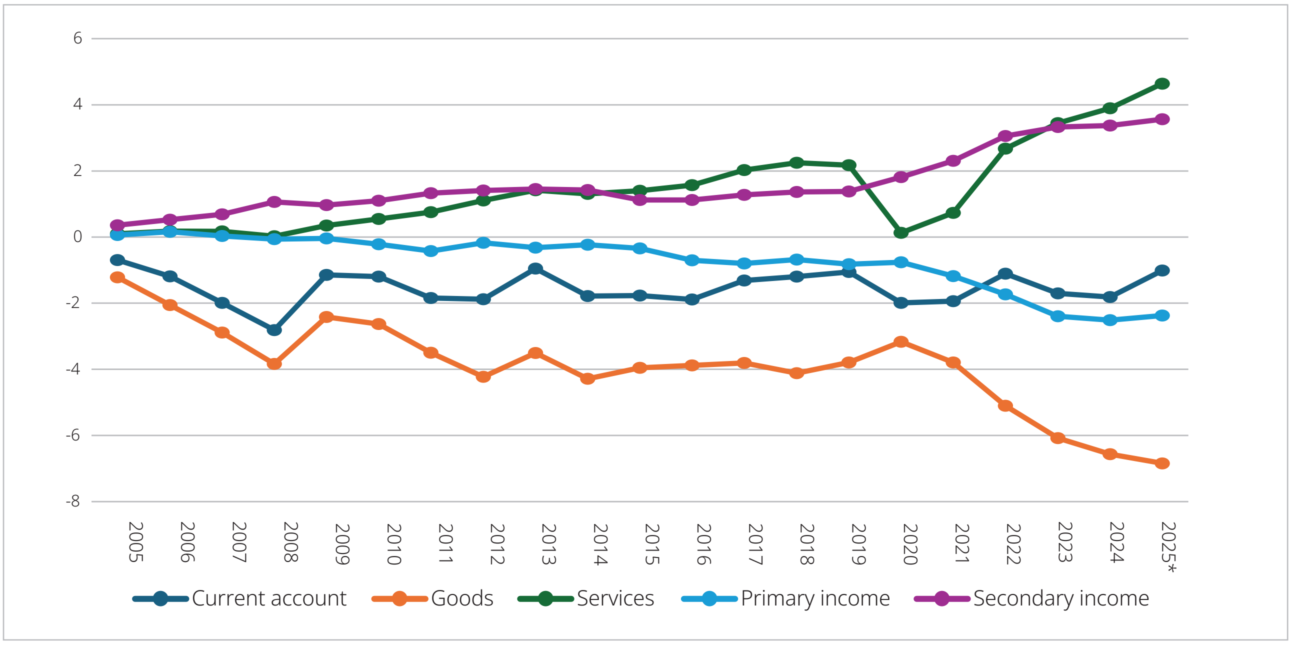
During this period, the services balance acquired particular importance, exceeding USD 3.0 billion in 2023. Its average annual growth over the three years amounted to 16.1 percent, and it reached a historic high of USD 4.6 billion in 2025. This significantly offset the traditionally high deficit in trade in goods. However, in 2025, the deficit increased again, reaching a historic high of USD 6.8 billion.

Thus, the dynamics of Georgia's current account balance between 2005 and 2025 reflect the transformation of the country's economy from a model of high external deficit and import dependence to a relatively more diversified and services-oriented economy. Although the deficit in trade in goods remains a significant challenge, the growth of service exports, the development of tourism, and the diversification of external inflows in recent years have improved the sustainability of the external sector.

Structural Transformation of the Current Account

In this section, we examine the structural dynamics of the current account and its individual components. The current account comprises four main components: trade in goods, services, primary income, and secondary income. The interaction of these components determines the overall result of the country's balance of payments (see Figure 5).

Figure 5. Georgia's Current Account, 2005–2025 (Billion USD)



Source: The National Bank of Georgia.
** Preliminary data.*

Balance of Trade in Goods

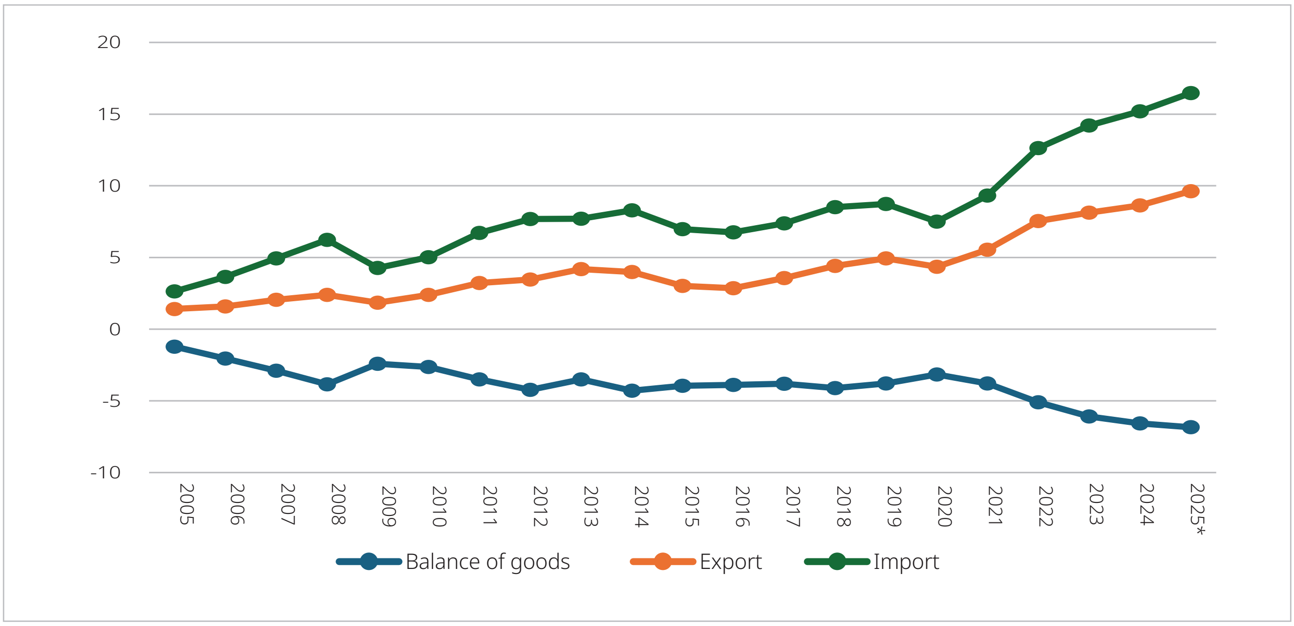
The growth rates of goods exports and imports are among the key determinants of current account dynamics, as they have a direct impact on the external trade balance.

For small open economies such as Georgia, this dependence acquires special significance, as economic growth is often associated with import-intensive consumption and investments. At the same time, export diversification and improvements in international competitiveness constitute important prerequisites for the sustainability of the current account.

Between 2005 and 2025, trade in goods remained the largest and consistently negative component of Georgia's current account. In the Georgian economy, imports have consistently exceeded exports (see Figure 6), reflecting the limited capacity of domestic production and its relatively narrow export base, as well as strong domestic demand for imported energy resources, consumer goods, and investment goods.

The diversification of exports led to some improvement in 2017-2019; however, the 2020 pandemic once again exacerbated the high deficit in trade in goods. During the period analyzed, the highest annual growth rate of goods exports was recorded in 2022, when it amounted to 36.0 percent. During the same period, imports grew at a slightly lower rate of 35.5 percent, which reduced the current account deficit by 43.0 percent compared to the previous year. In recent years, a partial improvement in goods exports has been observed; however, the trade deficit remains the principal constraint on the current account. In 2025, the trade in goods deficit reached USD 6.8 billion.

Figure 6. Balance of Goods in the Current account, 2005–2025 (Billion USD)



Source: The National Bank of Georgia.

** Preliminary data.*

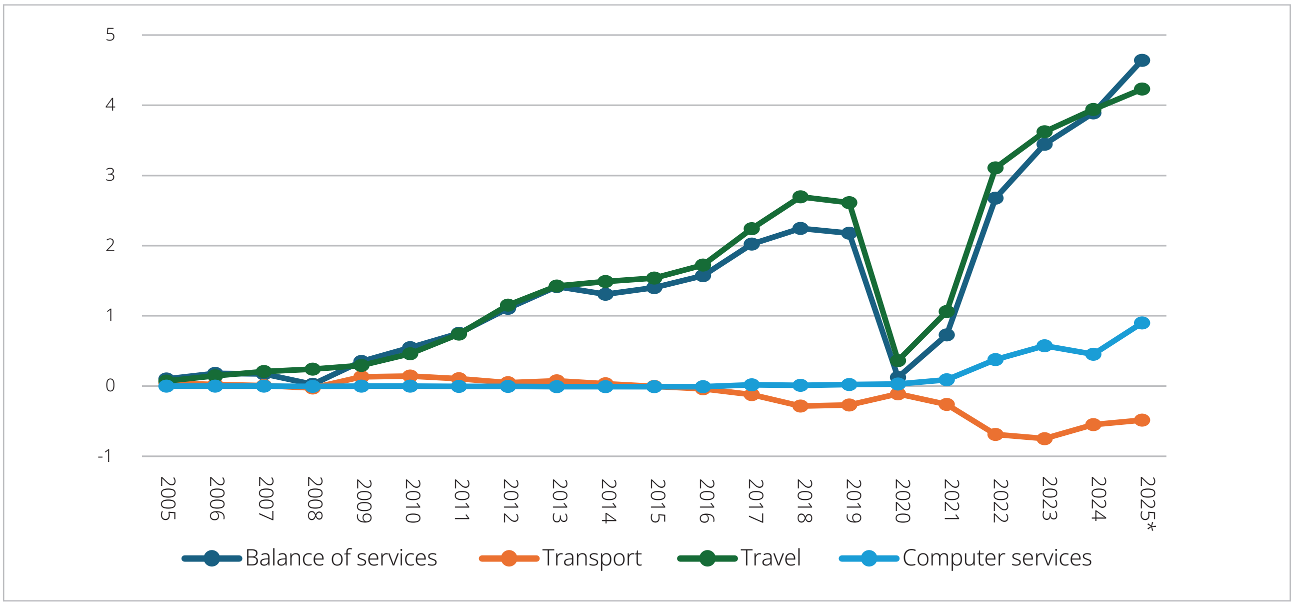
Services Balance

Between 2005 and 2025, the services balance emerged as one of the most significant and fastest-growing components of the current account. While service exports were relatively modest in the mid-2000s, the role of tourism, transport, and, later, computer services increased markedly in subsequent years (see Figure 7). The services balance significantly offset the chronic deficit in trade in goods and reduced the overall current account deficit.

As Figure 7 shows, the travel component remained the largest and only consistently positive contributor to the services balance throughout the entire period analyzed. Particularly rapid growth was recorded between 2010 and 2019, driven by the increase in the number of international visitors, the development of tourism infrastructure, the liberalization of air transport, and the growing popularity of Georgia as a tourist destination.

The gradual liberalization of Georgia's aviation market and the simplification of market access for international airlines had a significant impact on the development of the tourism sector. This process was also facilitated by the signing of the Common Aviation Area Agreement with the European Union in 2010, which aimed at the gradual integration of Georgia's aviation sector with the European aviation market, as well as by the increase in direct international flights and the entry of low-cost airlines, such as Wizz Air and Ryanair, into the Georgian market. As a result, between 2010 and 2012, the flow of international visitors increased by an average of 47.9

Figure 7. Services Balance, 2005–2025 (Billion USD)

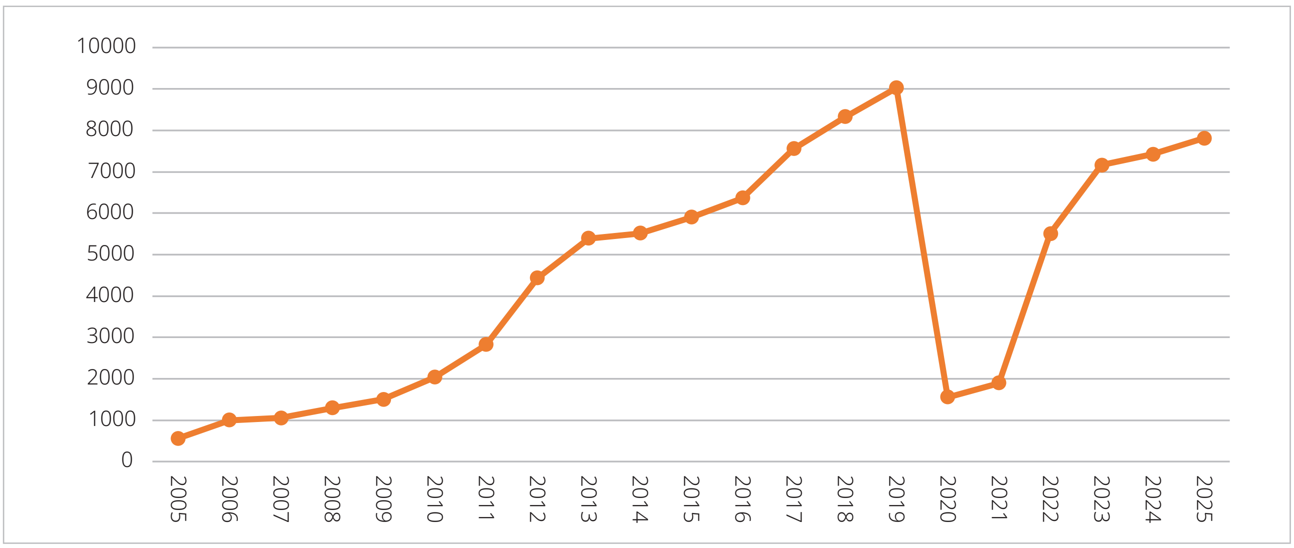


Source: The National Bank of Georgia.
** Preliminary data.*

percent. In 2019, the number of international visitors reached a historic peak of 9.0 million (see Figure 8), becoming one of the key factors behind the growth of service exports and the improvement of the current account balance.

In 2020, the COVID-19 pandemic caused a sharp decline in travel income, which also had a significant negative impact on the services balance. The number of international visitors decreased by 82.7 percent, although a rapid recovery began in 2021. Between 2022 and 2025, the number of international visitors grew by an average of 13.0 percent. Consequently, travel income increased once again, reaching USD 4.2 billion in 2025. This growth was facilitated by regional migration processes, increased international mobility, and the recovery of the services sector.

Figure 8. International Visitors, 2005–2025 (Thousands)



Source: The National Bank of Georgia.

The dynamics of transport services were significantly dependent on Georgia's transit function and regional trade flows. Between 2005 and 2025, the main drivers of growth in this sector were the development of regional transit corridors, the utilization of oil and gas pipelines, the increase in freight turnover, and the expansion of logistics infrastructure. At the same time, the transport services component of the services balance exhibited relatively high volatility, reflecting its strong dependence on global trade, energy markets, and regional geopolitical processes. During the COVID-19 pandemic, transport services declined considerably; however, they recovered in subsequent years alongside the growth of regional freight flows and logistics activity.

Computer services grew particularly rapidly after 2018 and emerged as one of the most dynamic components of Georgia's services exports. Initially, the growth of computer service exports reflected the gradual development of the ICT sector and the improvement of digital infrastructure. However, a turning point occurred in 2020. The increased demand for digital services during and after the pandemic significantly strengthened the role of this sector. Nevertheless, the biggest impetus came from the geopolitical shock of 2022. The Russia-Ukraine war positioned Georgia as a relatively stable and attractive business destination within the region, leading to the large-scale relocation of international IT companies and specialists from Russia, Ukraine, and Belarus.

This process temporarily turned the country into a regional digital hub, where growth dynamics were driven more by global labor mobility and the relocation of service outsourcing than solely by the expansion of domestic technological capabilities. Nevertheless, the information technology sector became one of the fastest-growing sectors in the Georgian economy, with computer service exports increasing from USD 67.9 million in 2020 to USD 1.0 billion in 2025.

One of the main advantages of computer services is that they are less dependent on physical imports, generate high value added, and are relatively resilient to external shocks. Therefore, in recent years, this segment has become one of the most promising components of service exports.

Overall, between 2005 and 2025, Georgia's services balance transitioned from a tourism-dependent model to a more diversified structure, in which the role of digital services has become increasingly important. This trend is important for the country's external sustainability, as service exports have emerged as one of the key factors contributing to reducing the current account deficit.

Primary Income

The primary income balance reflects the structural characteristics of an economy in which the country serves as a recipient of foreign capital. It comprises compensation of employees, investment income, and other primary income.

Since 2008, the primary income balance has remained a persistently negative component for Georgia's current account (see Figure 9). This reflects the fact that foreign direct investments in the economy significantly exceeds investments abroad. Between 2005 and 2025, the primary income deficit was mainly stable and was largely associated with the high share of foreign capital in the economy.

Along with the growth of foreign direct investment, the income received by investors also increased over time, which was reflected in the widening of the primary income deficit. Furthermore, interest payments on external debt played an important role, increasing particularly during periods of global crises and the expansion of fiscal support measures.

Figure 9. Primary Income Balance in Georgia, 2005–2025 (Million USD)

Source: The National Bank of Georgia.
** Preliminary data.*

Although the compensation of employees component has a partially positive influence on the primary income balance, as Figure 9 shows, its contribution has remained relatively limited. As a result, the primary income deficit in Georgia represents one of the major determinants of the chronically negative current account balance (after trade in goods) and reflects the country's dependence on foreign capital and external financing.

Secondary Income

Between 2005 and 2025, Georgia's secondary income balance represented one of the most stable and positive components of the current account. Structurally, it includes general government sector transfers, as well as transfers of financial and non-financial corporations, households, and non-profit institutions serving households. Throughout the period analyzed, its principal source was personal transfers, commonly referred to as remittances, which consist of funds transferred by Georgian citizens employed abroad to their families in Georgia. These flows directly increase household income, stimulate domestic consumption, and help mitigate the current account deficit. Remittances played a particularly important role during periods of crisis, including the 2008-2009 global financial crisis, during the COVID-19 pandemic, and in the post-pandemic recovery period.

Secondary income grew particularly rapidly between 2005 and 2013, alongside rising emigration and the development of international remittance systems. Between 2014 and 2016, however, remittance inflows declined against the backdrop of the economic slowdown and the depreciation of the Russian ruble. In this period, Russia accounted for 42.1 percent of Georgia's total remittance inflows and outflows, but this share fell to 34.2 percent by 2016, while overall remittance inflows were 21.9 percent lower in 2016 than in 2013. In subsequent years, supported by geographical diversification, particularly through growing inflows from EU countries, the US, and Israel, remittances exhibited relatively stable dynamics.

Despite the 2020 pandemic, the secondary income balance remained resilient. After 2022, amid geopolitical shocks, increased migration, and capital movement, the volume of transfers increased sharply. It is noteworthy that money transfers from Russia saw a particular increase during this period, making an important contribution in financing the current account.

Overall, the positive balance of secondary income significantly offset the chronic deficit in trade in goods and primary income, and between 2005 and 2025, it emerged as one of the main pillars supporting the external sustainability of the Georgian economy. Overall, between 2005 and 2025, the current account deficit was largely characterized by sustainability, although its funding sources and composition changed. While the current account balance in the earlier years was primarily shaped by the rapid growth of imports, in later years the roles of service exports and remittances increased substantially. Furthermore, an improvement in current account dynamics was observed in 2023-2025, driven by export growth, the strengthening of the services sector, and the economy's partial adaptation to external shocks.

Conclusion

The dynamics of Georgia's current account between 2005 and 2025 clearly reflect the key characteristics of the country's external sector development and the main trends associated with its integration into the global economy. Throughout the period, the current account remained predominantly in deficit, although its magnitude, composition, and sources of financing changed considerably over time. The analysis shows that the current account deficit was primarily driven by the persistently large deficit in trade in goods, reflecting the economy's high dependence on imports and its relatively limited export base.

At the same time, the study demonstrates that Georgia's external sector has undergone a significant structural transformation over the past 21 years. The services balance, particularly travel, transport, and, more recently, computer services, emerged as a key factor in reducing the current account deficit. The rapid development of tourism infrastructure, the liberalization of air transport, and the increase in international visitor arrivals contributed substantially to the expansion of service exports. In the post-pandemic period, the rapid growth of the ICT sector and digital services further diversified the services balance. Particularly noteworthy was the sharp increase in computer services exports after 2022, which was partly associated with regional geopolitical developments and the relocation of a portion of the international IT workforce to Georgia. The study also confirms that the primary income balance remained consistently negative throughout the period under review, reflecting Georgia's reliance on foreign capital and external financial resources. Profit repatriation associated with foreign direct investment and interest payments on external debt continued to be important contributors to the current account deficit. By contrast, the secondary income balance, particularly remittance inflows, represented one of the most stable supporting components of the current account and played a significant role during both crisis and post-crisis periods.

The analysis further indicates that current account dynamics in Georgia were closely linked to economic growth cycles. Periods of strong economic growth were generally accompanied by a widening current account deficit, reflecting increased domestic demand, investment, and imports. Conversely, periods marked by the global financial crisis, the COVID-19 pandemic, and other external shocks were associated with temporary current account adjustments as economic activity weakened. The post-pandemic recovery period was particularly significant, as strong growth in services exports, travel, remittance inflows, and the ICT sector contributed to reducing the current account deficit to historically low levels. Overall, Georgia's external sector underwent substantial structural transformation between 2005 and 2025. Although the large deficit in trade in goods remains a significant challenge, the strengthening of the services sector, the diversification of external inflows, and the development of the digital economy have materially improved the sustainability of the current account. Nevertheless, ensuring the long-term sustainability of the external sector will continue to require export diversification, the development of high-value-added industries, and the gradual reduction of import dependence.

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CRYPTOCURRENCIES AND THE CHALLENGES OF FINANCIAL GLOBALIZATION: THE TRANSFORMATION OF INDIVIDUAL MONETARY CHOICE

ZURAB ABRAMISHVILI

Abstract
The structural problems of the global financial system—including inequality driven by the uneven distribution of monetary resources, inflation, high transaction costs, and the weakening of individual monetary choice—are fueling growing interest in cryptocurrencies as an alternative and supplementary financial mechanism.

This paper examines the extent to which cryptocurrencies can serve as a response to these challenges, while also considering the new risks they generate. Against this backdrop, the emergence of cryptocurrencies is reshaping the relationship between the state and individuals.

Particular attention is devoted to analyzing the clash of monetary interests between the state and the public. This conflict is examined within a strategic game framework, highlighting the tension between the state's objective of maintaining monetary control and individuals' efforts to protect their savings.
The functioning of cryptocurrencies is explored in the context of their primary flaw—price volatility. Using Bitcoin as a case study, the paper explores how volatility ultimately dictates the stability and scalability of its application.

Furthermore, the paper assesses the use of Bitcoin by economic agents as an additional instrument to safeguard savings in high-inflation environments.

Keywords: Cryptocurrency, Bitcoin, inflation, volatility, individual monetary choice, financial instruments, financial globalization, decentralized finance, programmable money, smart contracts, protection of savings.

Introduction

In the context of contemporary financial globalization, the functions of money and the institutional frameworks governing them are undergoing a significant transformation. The development of digital payments, tokenized assets, stablecoins, decentralized finance, and programmable settlements have increasingly turned money into a technologically organized infrastructure, where trust, transfer of ownership, settlement, and contract execution increasingly rely on programmatic rules. Recent literature characterizes this process as a structural transformation of the monetary system associated with tokenized deposits, central bank digital currencies (CBDCs), unified ledgers, and programmable financial infrastructure (BIS, 2022; BIS, 2023a; BIS, 2025a).

Moreover, in recent years, inflationary pressures and exchange rate depreciation have become pronounced in numerous developing economies. The cases of Argentina and Türkiye are particularly notable, where high inflation and the devaluation of national currencies have eroded the real purchasing power of savings held in fiat currencies (IMF, 2023; World Bank, 2024).

The costs associated with international transactions also remain a significant problem. For instance, the average commission on transfers made by migrants ranges between 6–10%, placing a particularly heavy burden on low-income countries (World Bank, 2023b). This environment increases interest in alternative financial forms that transcend the boundaries of traditional monetary institutions.

Interest in cryptocurrencies tends to increase especially when the cost of remaining within traditional monetary channels rises. Such an environment may emerge under conditions of high inflation, national currency devaluation, capital controls, high costs of international transfers, limited access to banking infrastructure, or declining institutional trust (World Bank, 2023b; BIS, 2023b; BIS, 2025b). In this scenario, cryptocurrencies generate demand not through directly reducing inequality, but by serving as an additional monetary choice in an environment where using the fiat system becomes more expensive, less predictable, or less accessible for individuals.

Furthermore, blockchain technology is utilized in the financial sector to increase transaction transparency and reduce operational costs (Catalini and Gans, 2020).

Programmable money and smart contracts represent important building blocks in the evolution of digital financial systems. For instance, within the Ethereum network, smart contracts enable the automatic execution of financial transactions once predefined conditions are satisfied. This mechanism can reduce traditional counterparty risk by limiting reliance on intermediaries and reducing dependence on the subsequent actions or commitments of the parties involved. However, the risk does not disappear; rather, it changes form. Risks associated with coding errors, cybersecurity, systemic resilience, legal enforcement, and regulatory interpretation become more significant. Accordingly, smart contracts should be viewed not as a universal risk-reduction mechanism but as an instrument that partially replaces counterparty risk with technological and legal risks (Ghose, 2025).

However, this transformation is not straightforward. The cryptocurrency market is characterized by high volatility. Particular attention is drawn to the connection between this volatility and Bitcoin's "halving"—the periodic reduction of mining rewards by half, which occurs in approximately four-year cycles. However, this should not be viewed as the defining factor of the volatility structure. Rather, it is one of the factors related to the supply cycle that interacts with other market conditions and typically shapes the extreme boundaries of volatility rather than the overall pattern of Bitcoin's volatile behavior itself. In addition, network bandwidth constraints, including the relatively low speed of Bitcoin transactions, remain one of the principal challenges to scalability (Croman et al., 2016).

In this context, the issue of monetary choice acquires particular relevance. In high-inflation environments, such as those observed in countries like Venezuela and Argentina, there has been an increasing shift among the population towards inflation-resistant assets, including cryptocurrencies and stablecoins, driven by their ease of digital access (Chainalysis, 2024a).

This trend indicates a partial redistribution of monetary control between the state and economic agents, which can be analyzed within the framework of strategic interaction in game theory.

An analysis of these developments demonstrates that, in the context of increasing financial globalization, a comprehensive assessment of cryptocurrencies, programmable money, and monetary choice is essential—one that accounts for both their transformative potential and the risks they introduce. Under certain conditions, crypto-assets can expand individual monetary choice by providing alternative mechanisms for value transfer and reducing dependence on traditional financial intermediaries. At the same time, they pose substantial challenges related to price volatility, liquidity, cybersecurity, regulatory uncertainty, consumer protection, and broader financial stability. Therefore, this paper examines crypto-assets as an emerging monetary instrument that creates new opportunities while remaining subject to considerable risks and continuing institutional development.

Global Financial Challenges

One of the major challenges facing the global financial system is the high cost and prolonged processing time of international transfers. Modern cross-border payments typically pass through multiple intermediaries, which increases both transaction costs and delays. This issue is particularly acute for small-value remittances, where commission fees often consume a substantial portion of the transferred funds. In this context, decentralized financial networks present a viable alternative, offering the potential to reduce the number of intermediaries and streamline payment execution (Catalini and Gans, 2020).

Another major challenge is limited access to financial services. Within the traditional financial system, the ability to open an account, receive payments, or access credit often depends on the availability of banking infrastructure, formal identification documents, and an established financial history. These requirements can exclude vulnerable and low-income groups from fully participating in economic activity. According to World Bank data, a significant share of the global adult population remains without access to formal banking services, limiting their ability to engage in financial and economic transactions (World Bank, 2021). In this regard, blockchain-based wallets and open financial networks may reduce entry barriers, expand access to financial services, and contribute to greater financial inclusion (Prasad, 2021).

The complexity of international settlements is also a significant problem, especially for small- and medium-sized businesses. Payments in foreign currencies often require additional time, pre-approvals, and the participation of multiple institutions. This means that capital is temporarily frozen, while operational costs for the business increase. Digital assets and tokenized settlement models create an opportunity to partially reduce the scale of this problem, as payment confirmation and final settlement can be executed within a unified digital infrastructure, including through the use of smart contracts (Catalini and Gans, 2020).

Another challenge is related to the protection of savings from high inflation and exchange rate fluctuations. When the purchasing power of a national currency drops rapidly, economic agents attempt to preserve their real incomes and savings by utilizing alternative assets (Rogoff, 2016; Prasad, 2021). For example, against the backdrop of high inflation in Argentina, the use of US dollar-pegged digital assets has increased as a relatively stable store of value and means of payment (Chainalysis, 2024b). Such cases demonstrate that decentralized financial instruments become particularly attractive when traditional monetary channels are less predictable for everyday economic decisions.

Another weakness in financial relations is counterparty risk—the possibility that one party to a transaction may be unable or unwilling to fulfill its obligations. In traditional financial markets, this problem is mitigated through intermediaries, legal contracts, and oversight, which increase costs and slow down the execution process. The use of smart contracts offers an alternative approach: when predefined conditions are met, transactions are executed automatically. This reduces uncertainty and is particularly effective for standardized operations (Prasad, 2021).

Thus, many of the challenges facing the modern financial system—including the high cost of international transfers, barriers to accessing financial services, complexities in cross-border settlement, difficulties in preserving savings under inflationary conditions, and counterparty risk—are closely linked to the structural characteristics of the existing financial architecture. Decentralized finance does not provide a universal solution to these challenges; nevertheless, the mechanisms built upon its foundations can, in certain cases, contribute to reducing transaction costs, expanding access to financial services, and enhancing operational flexibility.

Challenges of Cryptocurrencies

The proliferation of cryptocurrencies in the financial system creates risks that are associated not only with technological infrastructure but also with financial stability, legal enforceability, consumer protection, and the effectiveness of monetary policy. The main challenges include platform risk, cybersecurity, the potential for money laundering and terrorist financing, sanctions evasion, trade in illegal goods, regulatory arbitrage, and monetary fragmentation (FSB, 2023a; IMF-FSB, 2023; IOSCO, 2023).

Platform Risk: Although cryptocurrencies are based on decentralized infrastructure, a large portion of users store assets and conduct operations through centralized exchanges, wallets, payment providers, and other intermediaries. This creates risks related to asset mismanagement, opaque reserve practices, insolvency, conflicts of interest, and restricted access to user assets (IOSCO, 2023; FSB, 2023a).

Cybersecurity: Access to assets in the crypto-ecosystem depends on private keys, wallets, smart contracts, blockchain bridges, centralized platforms, and the user's digital behavior. Cyberattacks can occur not only at the protocol level but also at the application, platform, and end-user device levels. Furthermore, the irreversibility of transactions makes asset recovery extremely difficult and often impossible (IOSCO, 2023; FSB, 2023a).

Risk of Money Laundering and Terrorist Financing: The cross-border nature, pseudonymity, and intermediary-free transfer capabilities of crypto-assets attract illicit financial flows, including those intended for sanctions evasion, moving ransomware proceeds, or transferring undeclared capital. Although transactions on public blockchains are technically traceable, the identification of transacting parties becomes more difficult when mixers, privacy coins, unregulated platforms, and peer-to-peer channels are used (FATF, 2021; IMF-FSB, 2023).

Use of Crypto-Assets in the Trade of Illegal Goods and Services: This includes the trade of drugs, weapons, forged documents, malware, or other illicit products. Such activities are especially prevalent in channels where identification requirements are weak and payments are executed rapidly across jurisdictions (FATF, 2021; IMF-FSB, 2023).

Regulatory Arbitrage: A crypto-asset service provider may be formally registered in one jurisdiction, serve users in another country, and have assets moving within a global network. This reduces the effectiveness of national oversight and creates an environment where market participants opt for less stringent regulatory spaces (FSB, 2023a; IOSCO, 2023; IMF-FSB, 2023).

Reliability of Stablecoins: Stablecoins are often perceived as a relatively stable part of the crypto-ecosystem; however, their resilience depends on the quality of reserves, liquidity, redemption rights, issuer transparency, and legal status. If a stablecoin becomes widely used for payments or savings, a disruption affecting its operation could rapidly escalate into a broader crisis of confidence and liquidity (FSB, 2023b; CPMI-IOSCO, 2022; IMF-FSB, 2023).

Monetary Fragmentation: If a significant portion of payments and savings shifts to private stablecoins, foreign digital currencies, or unregulated crypto-assets, the role of the national currency may weaken in both its settlement and store-of-value functions. This is particularly concerning for small open economies, where the risk of dollarization is already high (IMF-FSB, 2023; FSB, 2023b).

Incompatibility of Digital Financial Networks: If banks, fintech companies, crypto-asset service providers, stablecoins, and tokenized assets develop in isolation from one another, the financial system may become fragmented across multiple incompatible infrastructures. This increases costs for users and makes risk detection exceedingly difficult for supervisors (BIS, 2023; BIS, 2025b; FSB, 2023a).

Thus, the challenges associated with cryptocurrencies should not be viewed merely as isolated technical or legal issues (FSB, 2023a; IMF-FSB, 2023; BIS, 2023b). Rather, they demonstrate that, in the context of an increasingly digital financial system, the traditional mandate of the central bank may need to be expanded to include a coordinating role across monetary networks. The essence of this function is for the central bank to facilitate the coexistence of diverse digital and traditional monetary channels in such a way that ensures innovation does not evolve into systemic vulnerability and that regulation does not become a barrier to technological development.

The Importance and Effect of Programmable Money

Programmable money is a form of digital money whose movement and utilization are governed by predefined rules that are automatically executed through programming code. Payments are executed only when specific conditions, which are fixed in advance within smart contracts, are satisfied. Smart contracts are programs hosted on a blockchain that facilitate the automatic execution of agreed-upon rules without the need for intermediaries. A transaction is initiated by a user on the network, after which the smart contract verifies the fulfillment of the conditions, and only upon successful verification are the funds transferred to the respective party.

The use of programmable money is particularly evident in supply chains. For example, in international trade, the movement of cargo is often associated with payment delays, as funds are transferred only after the necessary documentation has been processed. With programmable payments, it is possible to "lock" funds and automatically transfer them to the supplier as soon as logistical conditions are satisfied—for instance, when a warehouse system confirms receipt of the cargo. Such a mechanism reduces disputes and accelerates settlement processes (Catalini and Gans, 2020).

The use of programmable money is even more evident in real estate transactions. By using a smart contract, it is possible to deposit a buyer's funds so that the money is automatically transferred to the seller only when property registration is completed. This shortens settlement times and mitigates the trust problem, as the execution of the transaction depends on the fulfillment of predefined conditions and not on individual trust (Prasad, 2021).

In the case of international transfers, small exporting companies can benefit from the conditional execution of payments, whereby funds are released only after an invoice or delivery has been verified. This mechanism reduces the time required to execute the transaction and lowers the need for temporary liquidity (Catalini and Gans, 2020).

Another important development is the emergence of micro-investments, which are often restricted in the traditional financial system due to minimum thresholds, transaction fees, and administrative costs. Through the use of programmable money, assets can be fractionalized, enabling small investments. This is particularly important for low-income groups, as it reduces capital requirements and increases financial inclusion (Prasad, 2021).

Programmable money also creates an opportunity for targeted financial payments. For example, social assistance can be issued in such a way that the funds may only be used for defined purposes (such as education or medication), which increases the efficiency of resource utilization.

In the banking sector, similar approaches are reflected in the use of tokenized deposits, whereby deposits are represented in digital form, and their transfer can follow programmatic rules. For example, corporate payments can be executed so that each transaction automatically verifies compliance requirements and applicable limits. This reduces operational risks and simplifies the control process (Prasad, 2021).

Thus, the primary effects of programmable money are reflected in the automation of transactions, the reduction of execution time, the partial mitigation of the trust problem, and the reduction of administrative costs. Moreover, the possibilities for micro-investments and targeted payments demonstrate that programmable money is not only a technological innovation but also a new way of organizing the financial system.

The Strategic Game of Monetary Choice with a Three-Part Distribution of Savings

Monetary choice can be modeled as a strategic game involving the allocation of real savings between fiat and hedged systems. In practice, individuals do not fully abandon the fiat system; instead, they distribute their savings into three directions. Let the following notations be introduced:

a — the share of savings maintained in fiat currency;
b — the share allocated to classic hedged assets, such as stocks, bonds, gold, or foreign currency;
c — the share allocated to crypto-assets and stablecoins.

Since a, b, and c denote the shares of existing savings, we have: $a + b + c = 1$

where: $a \geq 0$, $b \geq 0$, $c \geq 0$.

In this model, the fiat system is represented by a, while the hedged system is represented by (b + c). Consequently, an increase in a implies a decrease in (b + c), and vice versa. The fiat and hedged systems are substitutes for each other in the allocation of savings. Within the hedged system, however, b and c are both complements and substitutes, since both reduce dependence on fiat savings, but the economic agent still makes a choice between classic assets and crypto-assets.

The state chooses between two strategies:
S — a credible low-inflation policy;
D — a discretionary or less credible policy.
The population chooses between two typical distributions of savings:
F — a fiat-dominated distribution, where $a \geq b + c$;
H — a hedge-dominated distribution,
where $b + c > a$.

This choice does not imply a complete transition from fiat to crypto. In both cases, the simultaneous existence of a, b, and c is possible; the difference lies in their proportions.

The F and H regimes represent two typical states of a continuous distribution of savings. Their separation is merely an analytical simplification, while the real intensity is determined by the size of their respective shares.

The main macroeconomic conditions of the model are:

$\tau S > \tau D$
$\pi S < \pi D$
$\mu S < \mu D$

where τ denotes trust in the monetary regime, π the current inflation rate, and μ expected long-term monetary dilution, defined as the anticipated pressure on the purchasing power of fiat savings arising from the growth of the broad money supply, including M2.

In the model, D does not denote a deliberate increase in inflation by an independent central bank. It signifies a less credible monetary-fiscal regime where fiscal needs, seigniorage incentives, or long-term monetary dilution increase the real loss of fiat savings.

Let A denote the preferential utility per unit of fiat savings: $A = L\tau + i - \pi - \mu$

where $L\tau$ represents the utility of liquidity and trust in the fiat currency; i denotes the interest income received on fiat savings; π represents the current or short-term inflationary loss expressed through the price increase effect; and μ captures the expectation of long-term monetary dilution.

Let B denote the preferential utility per unit of a classic hedged asset: $B = y + \omega\mu - k$

where y is the expected return on classic assets, including the combined effect of stocks, bonds, dividends, coupons, and capital growth; $\omega\mu$ denotes that classic assets partially protect savings from long-term monetary dilution; and k is the cost of entry, storage, conversion, and liquidity for classic assets.

Let C denote the preferential utility per unit of a crypto-asset: $C = g + x + \lambda\mu - z$

where g is the utility driven by expectations of crypto-asset price growth; x is the technological, network, fractional, cross-border, and self-custody utility of the crypto-asset; $\lambda\mu$ denotes the additional attractiveness of the crypto-asset against the backdrop of long-term monetary dilution; and z represents the volatility, regulatory, infrastructural, and technological risk of the crypto-asset.

Furthermore: $\lambda \geq \omega$

This condition shows that long-term monetary dilution does not affect hedged assets equally. Typically, for a crypto-asset, λ may exceed the average ω of classic assets, although ω depends on the internal structure of b. Classic assets partially protect savings from fiat dilution, whereas in the case of a crypto-asset, this effect can be stronger due to limited supply, global accessibility, and decentralized ownership. However, this does not mean that a crypto-asset is always the dominant choice, as it may be accompanied by a high value of z, reflecting high volatility and regulatory or infrastructural risks.

The preferential utility of the population will take the following form:

$P = Aa + Bb + Cc$

And in expanded form:

$P = a(L\tau + i - \pi - \mu) + b(y + \omega\mu - k) + c(g + x + \lambda\mu - z)$

This formula shows that the attractiveness of fiat savings increases with higher levels of trust and greater interest income, while it decreases with the rise of inflation and long-term monetary dilution. The attractiveness of classic assets depends on their expected returns, their ability to protect against monetary dilution, and their costs. The attractiveness of crypto-assets, on the other hand, depends on price appreciation expectations, technological and network advantages, the digital-scarcity premium in the presence of long-term fiat dilution, and the risks inherent in holding such assets.

The utility of the state will take the following form:

$G = q\tau + s(\pi + \mu)a - r(\pi + \mu)(1 - \tau) - u(b + c) - v{*}c$

where $q\tau$ is the institutional benefit of credibility; $s(\pi + \mu)$ a is the short-term benefit of seigniorage or discretionary policy dependent on savings remaining within the fiat system; $r(\pi + \mu)(1 - \tau)$ represents the reputational cost of inflation, monetary dilution, and loss of trust; $u(b + c)$ denotes the weakening of monetary control and the transmission mechanism caused by the shift into the hedged system; and $v * c$ captures the specific effect of crypto-assets and stablecoins, as they facilitate a faster, more digital, more fractionalized, and more cross-border exit from the fiat system.

The strategic matrix will take the following form:

Table 1. Strategic Model of Savings Distribution

State \ Population	F: Fiat-dominated distribution	H: Hedged-asset-dominated distribution
S: Credible low-inflation policy	G = qτS + s(πS + μS)aF - r(πS + μS)(1 - τS) - u(bF + cF)- v*cF; P = AS*aF + BS*bF + CS*cF;	G = qτS + s(πS + μS)aH - r(πS + μS)(1 - τS) - u(bH + cH)- v*cH; P = AS*aH + BS*bH + CS*cH;
D: Discretionary/less credible policy	G = qτD + s(πD + μD)aF - r(πD + μD)(1 - τD) - u(bF + cF)- v*cF*; P = AD*aF + BD*bF + CD*cF	G = qτD + s(πD + μD)aH - r(πD + μD)(1 - τD) - u(bH + cH)- v*cH; P = AD*aH + BD*bH + CD*cH

whereas:
$AS = L\tau S + i - \pi S - \mu S$
$BS = y + \omega\mu S - k$
$CS = g + x + \lambda\mu S - z$
$AD = L\tau D + i - \pi D - \mu D$
$BD = y + \omega\mu D - k$
$CD = g + x + \lambda\mu D - z$

For the fiat-dominated distribution, we have:
$aF \geq bF + cF$
$aF + bF + cF = 1$

For the hedged-asset-dominated distribution, we have:
$bH + cH > aH$
$aH + bH + cH = 1$

The population shifts from a fiat-dominated distribution to a hedge-dominated distribution if:
$P(H) \geq P(F)$.

Under a credible policy, this condition is recorded as follows:
$AS*aH + BS*bH + CS*cH \geq AS*aF + BS*bF + CS*cF$

Under a discretionary or less credible policy:
$AD*aH + BD*bH + CD*cH \geq AD*aF + BD*bF + CD*cF$

This condition shows that shifting to the hedged system becomes rational when the combined preferential utility of classic and crypto-assets exceeds the combined effect of the liquidity, trust, and interest benefits of fiat savings.

Within the hedged system, the share of crypto-assets increases at the expense of classic assets if:
$C \geq B$ i.e.: $g + x + \lambda\mu - z \geq y + \omega\mu - k$; or simplified:
$g + x - z \geq y - k - (\lambda - \omega)\mu$.

This condition shows that the share of crypto-assets within the hedged system increases when expectations of crypto price growth, technological and network benefits, and the digital scarcity effect generated by the long-term growth of the money supply exceeds the returns of classic assets, after accounting for their respective costs and risks.

Whereas a fiat-dominated distribution is more likely when: $A \geq B$ and $A \geq C$;
i.e.: $L\tau + i - \pi - \mu \geq y + \omega\mu - k$; and $L\tau + i - \pi - \mu \geq g + x + \lambda\mu - z$.

This outcome is more likely when trust in the monetary regime is high, inflation is low, interest income on fiat savings is sufficient, and the net benefit of switching to hedged assets fails to cover the associated costs and risks.

The state will opt for a credible low-inflation policy if: $G(S) \geq G(D)$. In the given distribution conditions, the condition can be expressed as follows:

$$q\tau S + s(\pi S + \mu S)a - r(\pi S + \mu S)(1 - \tau S) - u(b + c) - v*c \geq q\tau D + s(\pi D + \mu D)a - r(\pi D + \mu D)(1 - \tau D) - u(b + c) - v*c$$

Hence, the condition for selecting the credible policy is:
$q(\tau S - \tau D) + r[(\pi D + \mu D)(1 - \tau D) - (\pi S + \mu S)(1 - \tau S)] \geq s[(\pi D + \mu D) - (\pi S + \mu S)]a$

This condition shows that a credible policy is rational when the institutional benefit obtained from maintaining trust and avoiding reputational costs exceeds the short-term benefit of a discretionary policy. Moreover, the benefit of a discretionary policy depends on a, that is, the share of savings remaining within the fiat system. As a decrease and b + c increases, the benefit of the discretionary policy weakens further.

The novelty of crypto-assets in this model is not that they have created the opportunity to exit the fiat system. Gold, foreign currencies, stocks, and bonds have historically served a similar function. Rather, the distinctive role of crypto-assets lies in the fact that they increase the attractiveness of c through three channels: expectations of price growth, technological and network accessibility, and digital scarcity against the backdrop of long-term fiat dilution. Therefore, c can increase even when current inflation is low, provided that economic agents expect an appreciation of crypto-asset or anticipate the long-term monetary dilution of the fiat system.

In the model, the distribution of savings among fiat, classic hedged, and crypto-asset channels is not a one-time decision. It represents a repeated process in which the monetary and fiscal regime influences trust, current inflation, and expectations of long-term monetary dilution. In turn, a decrease in the share of savings remaining in the fiat system affects the subsequent incentives of the state, as it diminishes the fiat base, reduces the benefits derived from seigniorage, and weakens the effectiveness of the monetary policy transmission mechanism.

A shift away from fiat savings does not damage monetary policy in general but weakens its specific operational mechanisms. In particular, the interest rate channel becomes less effective because, if a portion of the population's savings no longer responds to domestic interest rates, the effectiveness of monetary policy transmission decreases. The bank deposits and lending channel also weakens, since a reduction in fiat deposits diminishes banks' liquid resources and restricts lending opportunities. The exchange rate channel also comes under pressure, as shifting to foreign or digital assets intensifies competition against the national currency and reduces demand for it.

Thus, the model illustrates the interdependent mechanism between monetary credibility and the distribution of savings. A decline in monetary credibility and the deterioration of the real utility of fiat savings reduce the attractiveness of remaining within the fiat system and increase the share of hedged assets. Within the group of hedged assets, the share of crypto-assets may increase when their price, technological, cross-border usability, and scarcity-related benefits outweigh both their inherent risks and the net benefit of classic hedged assets.

In the model, the (S, F) combination, which corresponds to a credible, low-inflation policy and a savings distribution dominated by fiat assets, can be considered a Pareto-optimal state. In this state, the state maintains effective monetary policy transmission mechanisms, while the population receives the benefits of the fiat currency's liquidity and credibility. This outcome is conditional and is achieved only when, under a credible policy, the net benefit of remaining in the fiat system is not inferior to the net benefit of shifting to hedged assets.

The Nash equilibrium is determined by the players' best responses. (S, F) constitutes a Nash equilibrium if a fiat-dominated distribution is preferable for the population compared to shifting to hedged assets, and if, for the state, maintaining a credible policy is more profitable than switching to a less credible regime.

In a short-term, single-stage environment, a Nash equilibrium of the (D, H) type is also possible. This occurs when, under a less credible regime, the net benefit for the population of redistributing towards hedged assets exceeds the benefit of remaining in the fiat system, and for the state, the short-term payoff of a discretionary policy still outweighs the benefit of restoring credibility. However, such an equilibrium is fragile in the long run, because an increase in the share of hedged assets shrinks the fiat base, weakens monetary policy transmission mechanisms, and reduces the future benefits derived from the discretionary policy.

The Stackelberg equilibrium depends on which player acts as the leader. If the state is the leader and pre-commits to a credible monetary policy, the population's best response may be a fiat-dominated savings distribution (F), resulting in the (S, F) outcome. In this case, a credible policy increases the net benefit of remaining in the fiat system and reduces the incentive to redistribute toward hedged assets.

However, if the population or the market acts as the leader and the share of hedged assets (H) increases beforehand, the shrinking of the fiat base reduces the potential benefit of a discretionary policy for the state. Consequently, the state's best response may become choosing a credible policy, leading to the (S, H) outcome. Thus, in the model, the possibility of shifting to hedged assets acts as a disciplining mechanism: the threat of an exit from the fiat system increases the state's incentive to maintain a credible monetary-fiscal policy regime.

Potential Expansion of Portfolio Choice in Georgia

The adoption of crypto-assets by economic agents can be viewed as an expansion of the portfolio choice space. For a small open economy such as Georgia, this issue is particularly significant, as the structure of savings is shaped not only by expected returns but also by inflation expectations, exchange rate dynamics, interest rates, access to financial instruments, and the level of public trust in the fiat system.

To illustrate this point, we can consider the example of Georgia's accumulative pension system. Operating since 2019, the mandatory accumulative model within the pension system involves a regular distribution of approximately 6% of an employee's income into individual pension accounts (consisting of equal 2% contributions from the employee, the employer, and the state). This represents a standard instrument for ensuring long-term financial stability.

The pension system is not built on the principle of expected profit maximization. Its goal is long-term, risk-adjusted, and diversified accumulation, where special importance is attached to capital preservation, regulatory compliance, liquidity, transparency, and the protection of participants' interests. Bitcoin's historically high returns have been accompanied by the risks of high volatility, deep drawdowns, regulatory uncertainty, and market cyclicality. Consequently, comparing Bitcoin to pension savings is appropriate only as an illustration of the fact that the economic agent's choice space has expanded, and not as a recommendation that a high-risk crypto-asset should replace the institutional model of long-term pension accumulation.

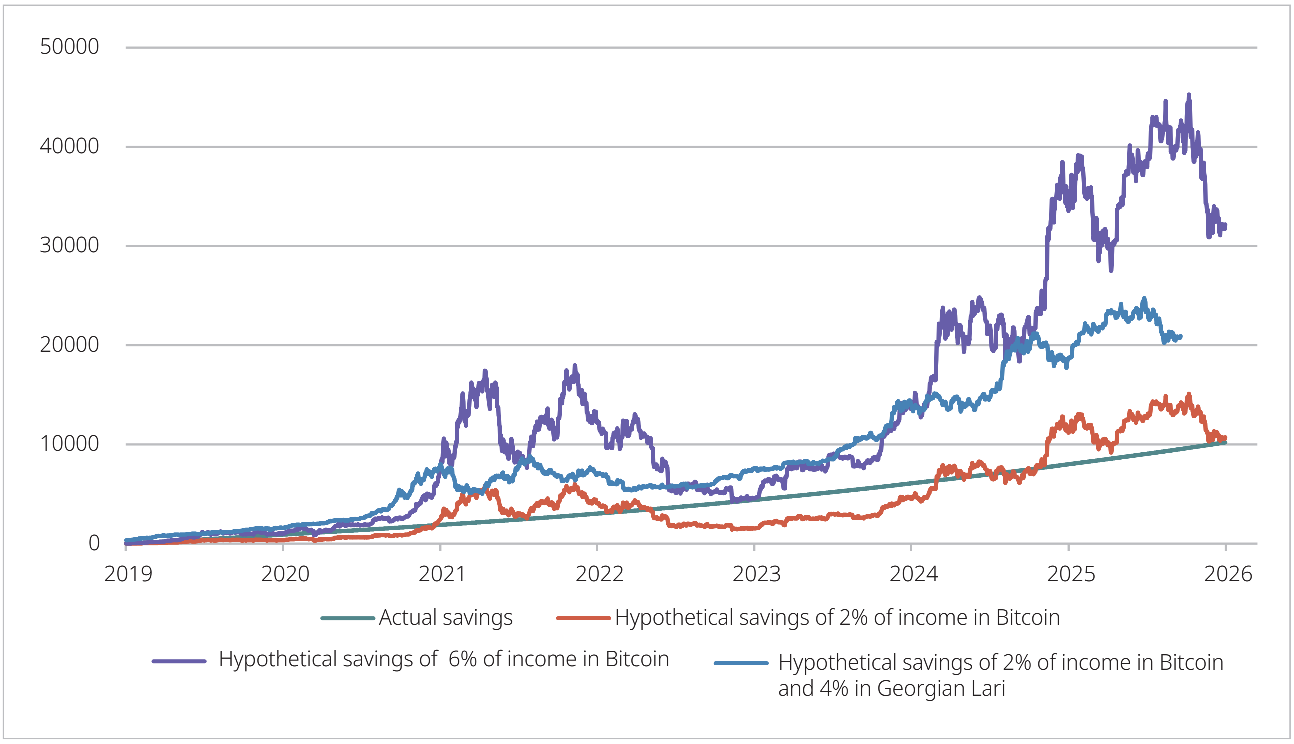
From this perspective, the Bitcoin example illustrates not an alternative to the pension system, but rather a different risk-return profile. Therefore, for an economic agent, Bitcoin might serve as an additional investment instrument or means of portfolio diversification, but it can hardly be regarded as a perfect substitute for traditional savings and pension accumulation instruments.

An analysis of alternative saving scenarios yields the following results. If we assume that the same volume of contributions had been regularly invested in Bitcoin since 2019, the value of the accumulated portfolio under 2025 prices would have been significantly higher. According to the calculations performed, the value of such savings would be approximately three times greater than the result of traditional accumulation over the same period.

It is important to note that, if the same methodology were applied over the same period, another high-growth asset—such as the stock of an individual technology company—could also have generated strong returns. Therefore, Bitcoin's superior performance during a particular period should not be interpreted as evidence of its general investment superiority or as a justification for replacing pension systems. Rather, it demonstrates an expansion of choice. It illustrates that a technologically accessible, globally tradable, and fractionally purchasable asset can transform even small, regular contributions into an alternative accumulation mechanism. This highlights one of the distinctive features of crypto-assets: they provide individuals with access to an asset class that either did not previously exist or was not available in a comparable form. This does not imply the elimination of traditional savings channels; instead, it reflects the increasing diversity of options available to economic agents.

A useful interpretation of this result is that assets such as Bitcoin provide economic agents with an additional option when forming long-term savings. The emergence of digital assets has expanded the range of portfolio choices available to individuals. Economic agents can now compare not only fiat savings and bank deposits but also foreign currency, real estate, stocks, bonds, gold, stablecoins, and crypto-assets against each other.

Figure 1. Average Pension Savings of a Georgian Citizen (GEL)



Source: Author's calculations.

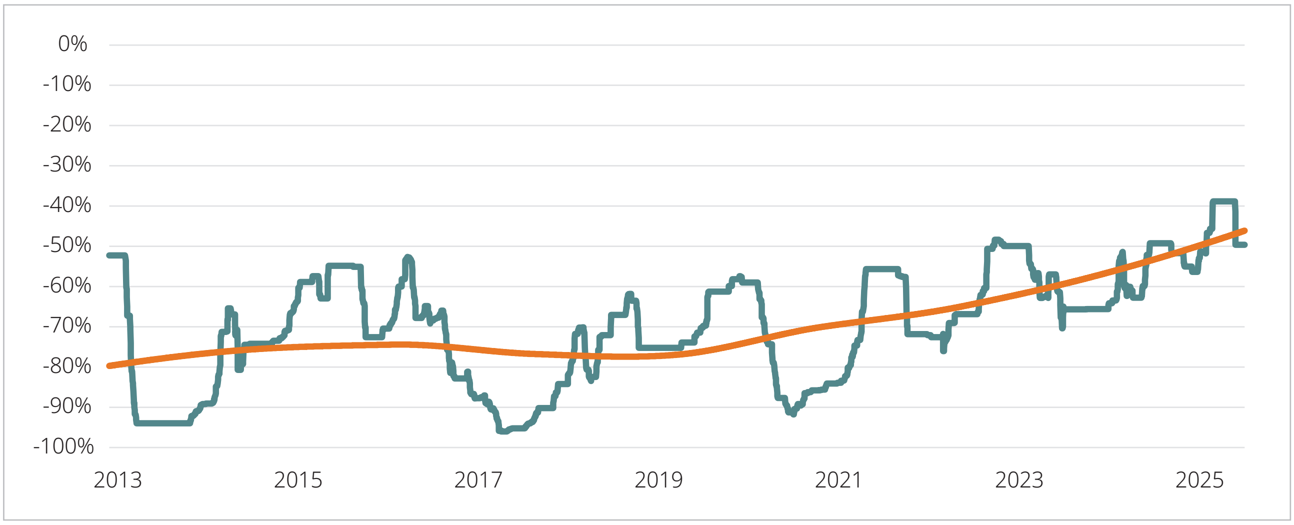
The Structure of Bitcoin's Price Volatility

Figures 2 and 3 below illustrate different but interconnected aspects of Bitcoin's risk. Figure 2 depicts Bitcoin's price drop from its annual maximum, while Figure 3 shows the relationship between market capitalization and volatility. Taking together, these support an important conclusion: Bitcoin indeed remains a risky asset, but its risk structure is identifiable and modelable, while the intensity of the risk appears to be moderating over time.

The dynamics of the drop from the annual maximum show that the Bitcoin market no longer repeats the extreme behavior characteristic of its early cycles on the same scale. The data clearly show that in the early phases, post-peak declines reached over approximately 80%, whereas in subsequent cycles, the maximum drop gradually decreased. This does not mean the risk has disappeared. It would be more accurate to say that the market has transitioned from a regime characterized by deep, systemic corrections to one marked by more limited and comparably milder corrections.

What is particularly important here is not only the depth of the drop but also its structure. In early cycles, the drop was more chaotic and prolonged, whereas in subsequent periods, the drops, despite their severity, are better subjected to cyclical logic. In other words, Bitcoin's risk remains high, but it is more "priced in" by the market and less resembles a completely uncontrollable event. This precisely constitutes the significant difference between high volatility and true unpredictability.

Figure 2. Bitcoin Price Drop from the Annual High



Source: Author's calculations.

$$\frac{\mathrm{P}_{\min(t;t+364)} - \mathrm{P}_{\max\,(t;t+364)}}{\mathrm{P}_{\max\,(t;t+364)}} * 100$$

$P_{min\ (t;t+364)}$ – minimal price of the period

$P_{max\ (t;t+364)}$ – maximum price of the period

Figure 3 illustrates the structural foundation of this transformation. As capitalization increases, volatility tends to decline, and this relationship is clearly reflected in the data. During the early period, when Bitcoin's market capitalization remained below several billion US dollars, the volatility indicator was considerably higher; for instance, the January 2015 value exceeded 418%, while at the December 2018 minimum it reached 511%. In subsequent market cycles, as capitalization grew to hundreds of billions and later surpassed one trillion US dollars, the same indicator declined substantially: in November 2022, it was approximately 317%, and by February 2026, with capitalization already exceeding one trillion dollars, it had fallen to around 98.5%.

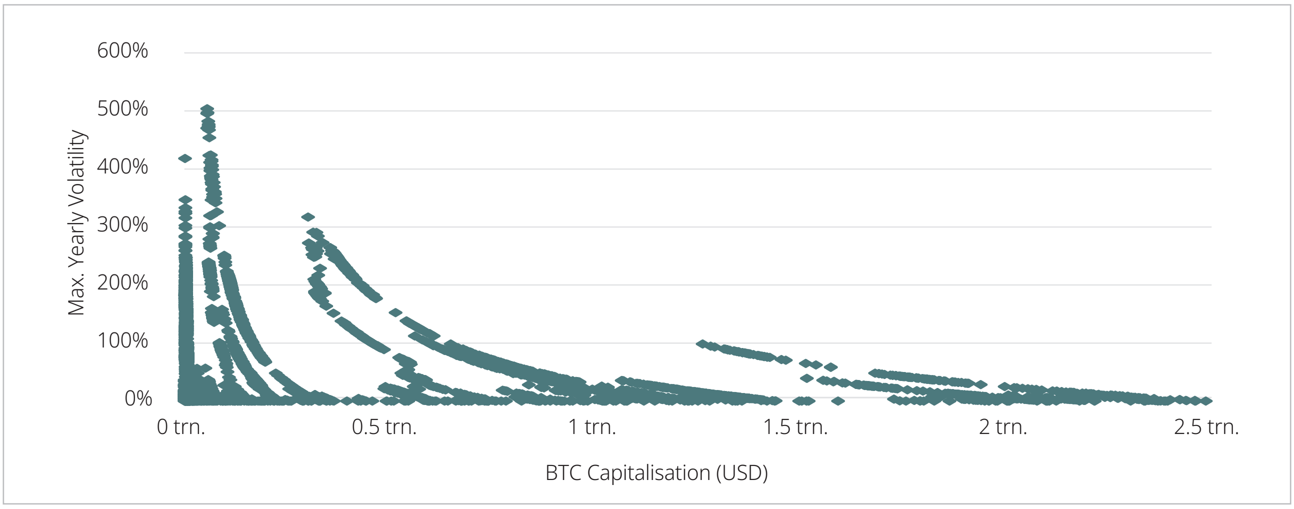
This reflects a classic principle of financial markets: as an asset becomes larger in size, its price becomes increasingly difficult to move with the same speed and magnitude.

$$\frac{P_{max(1;365)} - P_t}{P_t} * 100$$

$P_{max\ (1;365)}$ – maximum price of the period

P_t – current daily price

Figure 3. Relationship Between Bitcoin Price Volatility and Capitalization



Source: Author's calculations.

Note: Unlike Figure 2, price volatility in this case is calculated on an aggregate basis, considering both upward and downward deviations. This distinction arises from the fact that, theoretically, price increases have no upper limit, whereas price declines are constrained by a maximum loss of 100%.

Furthermore, the increase in capitalization does not eliminate risk; rather, it transforms its nature. In smaller markets, prices react more easily to a lack of liquidity, a narrow circle of participants, and panic-driven behavior. In larger markets, by contrast, the asset becomes deeper, more liquid, and less vulnerable to one-off shocks. As a result, Bitcoin's volatility is gradually transitioning from the regime of an early experimental asset to that of a larger-scale, institutionally grown asset. This transformation is important not only from an investment perspective but also for the analysis of monetary choice.

However, this relationship should not be interpreted as implying that capitalization independently and mechanically determines Bitcoin's volatility. Market capitalization itself is the result of broader economic processes. Instead, the relationship may be conceptualized as one in which capitalization establishes the upper extreme limit of volatility, which is important for long-term structural analysis. The space below this upper extreme boundary is the range within which volatility is determined by other short-term factors, such as demand structure, the number and type of market participants, liquidity depth, institutional investor participation, the regulatory environment, the development of trading infrastructure, and general macro-financial conditions. Consequently, the observed relationship between capitalization and volatility should be read as one of the indicators of market maturation, and not as the sole determining cause of volatility.

This is precisely where the connection with a high-inflation environment emerges. When an individual compares two risks—on the one hand, the predictable devaluation of the national currency, and on the other, the volatility of Bitcoin—what becomes decisive for them is not the absolute stability of the asset, but which risk is more acceptable and comprehensible. If the national currency systematically loses purchasing power, then high, yet shrinking and cyclically recognizable volatility might be perceived as an even more rational choice for a risk-inclined population. From this perspective, the attractiveness of Bitcoin in a highly inflationary environment cannot be explained solely by ideological considerations. Rather, it arises from the comparison of two imperfect alternatives: one involving an almost guaranteed loss in the long run, and the other involving high losses that, over time, become describable and potentially recoverable.

Thus, the joint analysis of the figures presented above demonstrates two complementary trends: first, the scale of Bitcoin's price drops has gradually been compressing over time; second, along with market growth, the intensity of volatility has also decreased. It is at the intersection of these two processes that Bitcoin's potential monetary significance becomes apparent. An asset that was previously perceived as extremely unstable and almost useless for savings is gradually evolving into an instrument whose risk remains high but has become less chaotic and more structured. This helps explain why Bitcoin may become an attractive option in economic environments where the central problem is no longer generating income, but rather the preservation of value.

Conclusion

Cryptocurrencies represent one possible answer to some of the structural problems facing the global financial system. Their development broadens the monetary choices of economic agents and gradually changes the traditional forms of monetary interaction between the state and individuals. As a result, a more competitive monetary environment is formed, where fiat money, classical hedging assets, and crypto-assets coexist in parallel.

However, the proliferation of crypto-assets does not lead to the disappearance of risks; on the contrary, risks take on new forms and encompass challenges related to platforms, cybersecurity, regulations, consumer protection, stablecoin reliability, and monetary fragmentation. Accordingly, the development of crypto-assets should not be viewed as a full replacement for the traditional monetary system, but rather as a competitive and complementary component of it.

Under these conditions, the role of the central bank is no longer limited solely to the issuance of money and ensuring price stability. In the era of digital financial networks, it may also assume the role of a coordinator, facilitating the coexistence of financial innovations, private digital money, and public monetary infrastructure in such a way that technological progress does not generate new systemic vulnerabilities or threaten financial and monetary stability.

In this context, a strategic interaction is formed between the goals of monetary policy and the portfolio choices of economic agents. The state strives to maintain monetary and financial stability, while economic agents utilize an increasingly broad spectrum of financial instruments to protect the real value of their savings. As a result, the resilience of the monetary system becomes increasingly dependent not only on formal policy instruments, but also on its credibility and competitiveness relative to alternative forms of savings.

At the same time, alongside the growth of the crypto-asset market and the development of its infrastructure, certain market inefficiencies—including extreme price volatility—may decrease, and market liquidity may increase. Under such conditions, crypto-assets could become a more attractive alternative, particularly in an economic environment characterized by high inflation, expectations of monetary debasement, or a deficit of trust in fiat institutions.

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FROM TRADITIONAL BANKING TO DIGITAL ECOSYSTEMS: THE SUPER APP PHENOMENON AND PERMISSIBLE BANKING ACTIVITIES

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Abstract

Based on an analysis of international practice, this paper examines the phenomenon of super apps, their main types, functional capabilities, development trends, and their impact on the transformation of the banking sector.

The paper analyzes operational and strategic models that are being widely adopted across the banking sector in response to the demands of the modern competitive environment. Furthermore, it explores how country-specific factors and the scope of permissible banking activities shape the formation of these models. In this context, the article also considers the implications of the growing super app trend for the Georgian banking sector.

Keywords: Permissible banking activities, super application, super app, Banking as a Service (BaaS), Bank as a Platform (BaaP), Application Programming Interface (API), digital ecosystem, one-stop-shop principle.

Introduction

In response to ongoing digitalization trends and the resulting changes in consumer behavior, the global economy is undergoing a digital transformation. The digitalization of services is significantly reshaping market structures and traditional business models (Feyen et al., 2021).

The sharp increase in mobile application usage during the COVID-19 pandemic significantly elevated the role of delivering financial services through digital channels and accelerated the digital development of banking services (Deloitte, 2022a). Concurrently, the progress of financial technology, along with creating new opportunities for the banking sector, gave rise to new players in the financial services market in the form of fintech companies and contributed to the strengthening of competition.

In parallel with receiving services through digital channels, the simplicity, speed, and efficiency of such services became increasingly important for consumers, including the ability to access various services within a single space. Following these trends, a new type of business model emerged—the super application or "super app."

Alongside the development of fast payments and platform integration capabilities, the expansion of fintech companies and super apps was given a significant boost by the rapid evolution of open banking and digital financial services, including embedded finance, as well as the large-scale use of application programming interfaces (APIs) and other technological solutions (Huy et al., 2026). Moreover, the implementation of open banking standards forced the banking sector to open its closed information architecture to other market participants, resulting in reduced information asymmetry and further intensified competition (Zachariadis and Ozcan, 2017).

Against the background of such market changes, competition expanded beyond the scope of the traditional banking sector, and both financial and non-financial companies have begun to compete with one another (Diaz and Andrea, 2021).

In response to these trends, some banks chose to pursue the so-called neobank model, which is entirely based on digital services, while traditional banks, within the limits of their existing resources, began to review and, in some cases, modernize their business models.

Within the framework of business model modernization, banks have moved toward creating digital ecosystems—whether through developing the "Bank as a Platform" model, integrating banking services into third-party platforms within the "Banking as a Service" model, or creating financial or non-financial super apps at the group level. In analyzing these developments, it becomes particularly important to take into account each country's context and regulatory framework, especially the scope of permissible banking activities and its related regulations.

It is noteworthy that the existing academic literature has widely discussed the technical characteristics, advantages, and associated risks of open banking, embedded finance, and super apps (World Bank, 2022). Furthermore, numerous studies have reviewed the significance of each of these directions, their impact on both the economy and on competition, as well as their role in the transformation of the financial services market (Feyen, 2021).

In addition, social and marketing aspects related to super apps have been actively discussed (Haselwander and Weiss, 2025), including the use of big data accumulated on platforms, both for the purpose of offering tailored, personalized services to consumers and in the context of potential risks of restricting competition through market power concentration, product tying, and bundling (World Bank, 2022).

However, in-depth analyses of the super app phenomenon from a regulatory framework perspective are relatively less common. Moreover, within the Georgian academic space, the impact of the global super app trend on the development of the Georgian banking sector has not been studied through the prism of the Georgian context and the legal framework of permissible activities for commercial banks.

The Super App Phenomenon and International Trends

The term "super app" was first introduced in 2010 (Festini and Roth, 2021). Consequently, the super app concept is a relatively new phenomenon and represents one of the major technological breakthroughs that emerged based on both a desire to reduce friction for users and the growing demand for digital convenience (Deloitte, 2024). These platforms have significantly altered market dynamics and competitive structures, particularly in regions where the widespread use of mobile devices and the large-scale adoption of platforms facilitate the development of integrated digital services (Hasselwander, 2026).

At its core, a super app is a multi-functional platform that consolidates a diverse range of services and focuses on providing services tailored to the daily needs of consumers within a single space, operating under a "single umbrella" principle (Diaz and Andrea, 2021). Such an application reduces the need to use multiple independent applications and ensures the seamless acquisition of various types of services without switching to other platforms (Hasselwander, 2026).

Generally, designating a digital platform as a super app does not depend on its market power, dominant position, or on the type and quality of the services provided. It is primarily driven by the diversity of integrated services (Steinberg et al., 2022). Within this approach, depending on the specific nature of the activity, several main types of super apps can thus be identified: financial, non-financial, and aggregator (Deloitte, 2024).

A financial super app focuses on consolidating various types of financial products and services within a single platform, including banking, payment, investment, insurance, and other financial services.

A non-financial super app primarily serves to integrate non-financial products and services. Such services may include communication, e-commerce, transportation services, travel, so-called lifestyle services, and others. Furthermore, to create a seamless user experience through embedded finance, it often provides certain financial services, particularly payment services. However, even if a non-financial super app includes certain financial functions, that does not automatically transform it into a financial super app.

The third type, the aggregator super app, refers to a platform that functions as an intermediary and more easily connecting users with various service providers from a single space.

The origin of the super app concept stemmed from China and Southeast Asia (Okassova, 2025). These platforms soon expanded to Africa and Central America—regions where a more liberal regulatory environment existed compared to Europe and the United States. The case of China is particularly noteworthy, where, given the specifics of its regulatory framework, American technology giants (gatekeeper companies) had less opportunity to hinder the development of super apps (Deloitte, 2022b).

The most famous examples of super apps in Asia are Tencent Holdings' WeChat and Ant Group's Alipay. WeChat was created in 2011 as a platform for communication and social interaction, though its functionality later expanded significantly. Through mini-programs ("an app within an app") and diverse integrations, the platform began offering both financial and non-financial services. Alipay's development trajectory, unlike WeChat, was initially focused on payment services and digital wallet functionality, after which it gradually evolved into a multi-functional ecosystem (Deloitte, 2024).

Similar to WeChat and Alipay, super apps typically rely on a single core product/service during their initial stages of development, around which various proprietary and third-party products/services are subsequently consolidated, ultimately leading to the formation of a broad digital ecosystem (Schreieck et al., 2024). These examples demonstrate that the success of the super app business model heavily relies on the effectiveness of the growth and development strategies deployed by digital platforms (Hasselwander, 2024).

Although super apps acknowledge the importance of partnerships with third parties for future growth (Diaz and Andrea, 2021), in practice, some of them tend toward forming a closed or largely interconnected ecosystem of companies. The cases of WeChat and Alipay are particularly interesting in this regard, as a network of interconnected companies formed around both platforms, including in the area of financial service delivery (KPMG, 2019).

The convenience created by integrating various services into a multi-functional digital environment, along with user interface optimization and personalized offerings, contributed to the rapid growth of the super app audience. This trend, in turn, created certain competitive pressure on traditional banking business models, as a segment of consumers began a partial migration from banks' own digital channels to super app ecosystems in the process of obtaining specific services (Diaz and Andrea, 2021).

Moreover, because of high levels of user interaction, super apps gained access to large volumes of data. As a result, a significant informational resource became concentrated in their hands, making it possible to offer personalized products and services better tailored to consumer behavior and needs. Additionally, this contributed to increased operational efficiency and more effective execution of targeted marketing campaigns (Deloitte, 2024). For instance, Ant Group created its own creditworthiness assessment model based on consumer data (Roa et al., 2021). Technology companies built upon data of such a scale and with a multi-million user base are typically referred to as "BigTech" companies (World Bank, 2022).

Digital payments are one of the key elements of super app success since, on one hand, they facilitate the introduction of new services, and on the other hand, they ensure user retention within the super app ecosystem. For example, the WeChat platform has approximately 1.2 billion monthly active users (Blakey, 2024) and features thousands of available mini-programs. The company does not charge partners a fee for hosting on the platform, yet WeChat Pay plays a significant role in transactions executed within the mini-programs (Deloitte, 2022b).

The Asian experience shows that the super app business model has become fundamentally established in the region, which has also contributed to the emergence of additional risks. Particularly noteworthy are the risks of concentrating large volumes of data and market power in the hands of a few platforms, potential conflicts of interest resulting from product tying and bundling, as well as over-reliance on a single platform (Papikyan, 2025). In view of this, regulators in the region began to pursue a gradual regulation of super app activities, including in the direction of competition policy and data security (Zeng and Kim, 2025).

As for the digital transformation of the banking sector in Europe, reforms implemented within the framework of the European digital strategy, particularly the steps taken toward open banking and open finance based on the PSD2[1] directive, generated a new wave of digital transformation in Europe. Consequently, competition increased significantly, and new opportunities emerged for fintech companies, including in terms of the opening of informational boundaries and providing regulated access to consumer data.

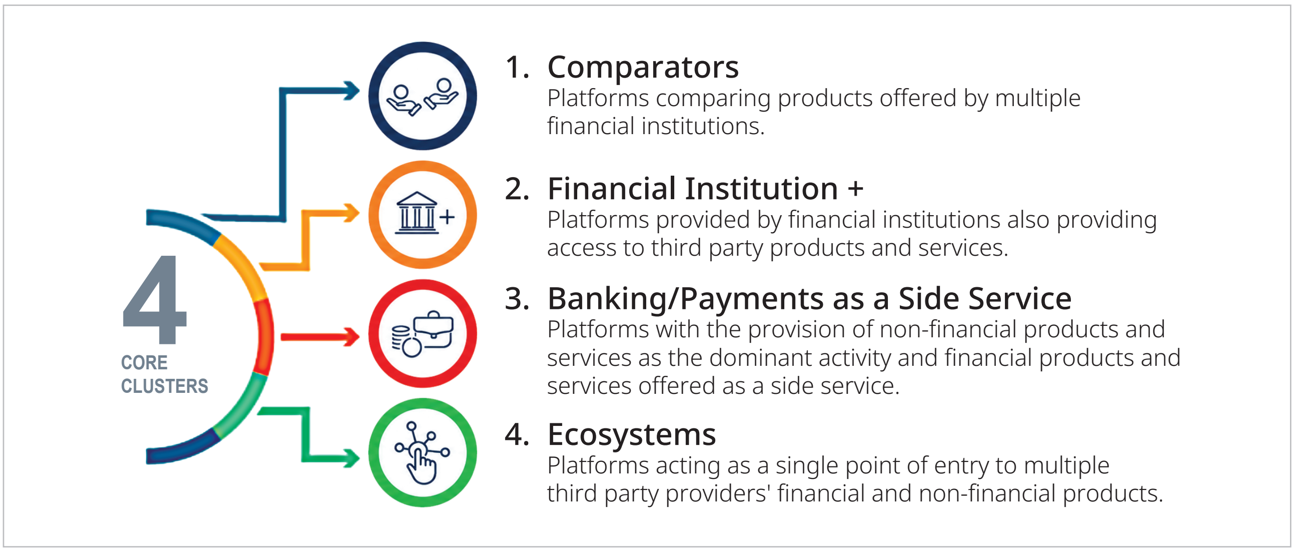
According to the assessment of the European Banking Authority (EBA), digital transformation has had a significant impact on the financial services delivery market, especially regarding the development of platform-based business models. One of the major outcomes of this process is considered to be the sharp acceleration of digital transformation in the payment sector. Financial institutions are increasingly active in developing or deploying third-party technological solutions to simplify access to financial products and services for consumers.

Within this process, the rapid growth in the use of digital platforms that function as intermediaries between consumers and financial institutions has been particularly visible. A further deepening of this trend is expected, driven, on one hand, by the desire to meet growing consumer demand, and on the other hand, by the drive to reduce operational costs.

In addition, the EBA distinguishes various types of digital platforms into separate categories to describe the possible formats of financial services delivery (EBA, 2021b). However, for the purposes of this paper, this classification can be viewed in a more generalized context.

1. Directive (EU) 2015/2366 of the European Parliament and of the Council of 25 November 2015 on payment services in the internal market, amending Directives 2002/65/EC, 2009/110/EC and 2013/36/EU and Regulation (EU) No 1093/2010, and repealing Directive 2007/64/EC.

Figure 1. Main Clusters of Digital Platforms



Source: EBA (2021b).

Admittedly, in Europe—compared to Asia—under the conditions of a much clearer and stricter sectoral regulatory framework (including GDPR[2], DMA[3], competition law, and others), the emergence of a super app of an Asian scale and influence is less likely; however, a clear trend toward the super app business model is also observed in Europe (Vezzoso, 2024).

Under the conditions of increasing competition in the financial services delivery market and digital transformation, several key operational and strategic approaches have emerged within the banking sector. In the process of transitioning from traditional banking services to the formation of digital ecosystems, banks often utilize one or several models simultaneously. Considering global practice, including the experience in Europe, several main models can be identified:

1. Bank as a Platform (BaaP)—the development of a bank's digital platform into a multi-functional application, within which both banking and various third-party services are integrated;
2. Banking as a Service (BaaS)—the embedding of banking products and services into third-party platforms, which facilitates the delivery of financial services to a broader circle of consumers;
3. Formation of a multi-functional ecosystem within the banking group—the development of an application by a banking group that consolidates various financial and non-financial services. Examples of this approach in Europe include the ecosystems developed by the Revolut, KBC, N26, and OTP banking groups.

Furthermore, when selecting operational and strategic development models, particular importance is attached to the individual context and regulatory approaches of each country, especially the scope of permissible banking activities and the competitive environment.

2. Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation).
3. Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on contestable and fair markets in the digital sector and amending Directives (EU) 2019/1937 and (EU) 2020/1828 (Digital Markets Act).

The Scope of Permissible Banking Activities

Given the highly regulated nature of the banking sector, the operational and strategic development models defined for the purpose of adapting to the demands of the modern digital economy must fall within the framework of permissible banking activities.

The starting point for defining the scope of permissible banking activities is the banking license itself, the models of which may fundamentally differ across countries. Considering that within the framework of the Association Agreement "between the European Union and the European Atomic Energy Community and their Member States, of the one part, and Georgia, of the other part," Georgia is actively striving to align its national legislation in the banking sphere with relevant European standards. For the purposes of this paper, it is thus more relevant to focus precisely on the EU regulatory framework than on reviewing the regulatory models of various countries.

Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions (CRD) does not directly define the permissible banking activities of credit institutions (commercial banks, for the purposes of this paper). However, Annex I of the directive lists a range of activities that may be subject to mutual recognition by EU Member States. This is possible if the commercial bank's license provides for the execution of the respective activity and so long as that activity is permitted by the national legislation of the country performing the recognition. Consequently, at the EU level, this list can be used as a general benchmark for permissible banking activities.

Approaches in EU Member States vary according to both the types of banking licenses and the activities permitted within their scope. Universal, specialized, or restricted activity licensing models are found in different countries. However, even in the presence of universal licensing, practice may differ in terms of permissible activities.

In countries where a universal licensing regime operates, the banking license typically covers all permissible activities defined by legislation. In contrast, in jurisdictions where a universal licensing model does not exist, the license is issued on an activity-by-activity basis (EBA, 2021a). In such cases, the initial license may require an extension if the licensed bank wishes to engage in an additional activity—for instance, offering investment services or performing other financial operations—and the initial license does not include said activity (ECB, 2019). Such differentiation in licensing directly defines the scope of banks' activities and, consequently, exerts a significant influence on their operational models and development strategies.

Taking into account these points and the essence of super apps, it is noteworthy that both financial and non-financial (mixed) super apps often face challenges in complying with various regulatory frameworks—whether this relates to the delivery of banking, investment, payment, insurance products and services, or other related activities. In such cases, a practical solution is to partner with entities holding the appropriate license or to obtain the right to conduct the specific activity. Furthermore, it is important to note that under existing regulatory approaches, it is generally impossible in practice for a single legal entity to conduct all activities—specialization and functional segregation are essential for efficiency (Papikyan, 2025). Given these circumstances and the scope of permissible activities, a number of entities recognized an opportunity for developing super apps at the banking group level. Examples of such a strategic model already exist in Europe, whereby platforms are created at the group level rather than directly at the bank level. As a result, under such frameworks, the user receives both non-banking services (such as hotel bookings) and classical banking and other financial services within a single application. Moreover, in practice, the entities providing specific products or services and their responsibilities are clearly segregated (Revolut, 2026; KBC Brussels, 2026). For example, banking products integrated into the application are offered to the consumer by a bank within the group operating under its own banking license and embedded into the third-party platform, while other types of services are provided by other entities authorized for the respective activity. Additionally, it should be noted that such a model is characterized by the integration of services from companies within a single group, which may require further research and assessment in terms of conflicts of interest, interdependence risks, and potential impact on market competition.

While the aforementioned strategic model is directed toward the consolidation of services within a banking group, an alternative model of digital transformation—"Banking as a Service" (BaaS)—is based on the opposite, relying on a decentralized approach. In this case, banks attempt to expand traditional operational boundaries using the BaaS concept, as a result of which the scope of permissible banking activities becomes even more flexible.

BaaS has emerged as one of the major transformative forces in the financial sector and substantially alters the logic of delivering financial services to consumers (Bansal, 2024). It refers to banks offering banking services to consumers through non-banking intermediaries—such as fintech and BigTech companies (BIS, 2024)—which is primarily executed on the basis of API integrations.

The BaaS model enables non-financial institutions to integrate banking services into their own platforms by utilizing the technological infrastructure of licensed banks. However, this opportunity is not only significant for non-banking intermediaries, but for the banks themselves. Such partnerships allow banks to increase their consumer base, diversify revenue streams, and reduce operational costs. At the same time, such a model also represents a challenge for banks, as it requires adaptation to a new technological environment and the development of technical provisioning capabilities for integrations (Bansal, 2024).

Prominent examples of this model are often considered to be N26, Starling Bank, Revolut, and Monzo, which, prior to obtaining banking licenses, offered banking products to consumers on their digital platforms precisely by use of the BaaS model (PwC, 2024).

In view of the above, it can be said that BaaS serves two primary purposes. On one hand, it enables companies that do not hold the relevant license to offer banking products and services to consumers on their platforms based on a partnership with a licensed bank; on the other hand, it provides banks with access to a broader circle of consumers through alternative digital channels (WhiteSight, 2023).

Consequently, the BaaS model has contributed to the diversification of fintech companies and has reduced market entry costs (Mdluli et al., 2022). Simultaneously, it has simplified consumer access to banking services, which contributes to the strengthening of competition and ultimately results in both a wider choice and increased accessibility to banking services for the consumer (Bansal, 2024).

According to existing forecasts, the global compound annual growth rate of the BaaS market until 2030 will be around 15–16% and, by this period, the revenues generated by the sector will reach EUR 75–85 billion (Mdluli et al., 2022).

One of the alternative ways to compete with BigTech companies is for banks to transform their own digital platforms into multi-functional ecosystems, i.e., developing the "Bank as a Platform" (BaaP) model, which is deservedly called a "beyond banking" approach (Resano, 2021). In this case, the bank's digital channel itself becomes a platform through which the bank consolidates various products and services to offer consumers a wider spectrum of services. Consequently, the bank allows third-party partners to utilize its platform. This model is sometimes referred to as platform banking (Unit21, 2026).

The goal of this approach is to both retain existing consumers and increase their number by offering diverse services, whether delivered by the bank itself or products/services offered on the basis of third-party partner API integrations. Although this format can to some extent be considered a continuation of the development of ecosystem banking, it is noteworthy that within the BaaP model, the bank itself transforms to a certain degree into a quasi-BigTech company.

In the prism of the super app concept, it is necessary to distinguish between two different approaches within the BaaP model: first, the case where a bank creates a financial super app on its own platform within the scope of permissible banking activities; and second, where a bank attempts to integrate such non-banking products and services into its platform that it cannot deliver directly itself since they fall outside the scope of permissible banking activities.

Even in the latter case, despite the fact that a specific non-banking service is provided to the consumer by a third party and the bank formally acts only as an intermediary, the bank's platform remains the main interface—the so-called "front bank." As a result, in the user's perception, the respective services are still associated with the banking institution, since it is the bank that provides the digital environment, its security, and operational resilience.

It should be noted that at the global level, the possibility of implementing a "beyond banking" strategy heavily depends on the regulatory framework of permissible banking activities and, consequently, on the regulator's vision regarding how permissible a bank's involvement is in the process of delivering non-financial/non-banking products and services. In jurisdictions where the principle of strict separation of banking and non-financial activities operates, banks are only allowed to offer consumers such services that perform a concomitant or ancillary function to their core financial products and services (Resano, 2021).

Given the established principle of separating banking and non-banking activities, the development of the "beyond banking" model creates both a legal and a socio-economic dilemma. The existence of a clear boundary between non-financial and banking activities represents one of the fundamental principles of banking regulation, the purpose of which is to reduce various risks to protect both the economic system and the bank and its depositors directly.

In parallel with the platformization trend, the United States maintains a model based on the structural separation of banking and commercial activities; while Europe, despite supporting the universal banking model, still does not grant banks the opportunity to engage in non-financial activities (Resano, 2021). Consequently, under existing regulatory restrictions, the BaaP model has been less developed in the direction of integrating non-banking services into banks' platforms.

The Impact of Super App Development Trends on the Georgian Banking Sector

In parallel with these broader trends of digital transformation and platformization, the dynamics of interest and development in this direction are also clearly outlined in the Georgian reality, where their growth is still primarily shaped by the national regulatory context and the legislative scope of permissible banking activities.

As of 2025, according to the calculations of the National Bank of Georgia, the ratio of commercial bank assets to the country's Gross Domestic Product stands at 102.7% (NBG, 2025). Unlike global trends, the banking sector in Georgia maintains a leading position in terms of both financial and technological capabilities and holds a significant competitive advantage over fintech companies or other new players that are developing at a relatively slower pace in the market. Added to this is high consumer loyalty, which is substantially driven by the quality of the user experience offered by banks. Furthermore, it should be taken into account that the Georgian banking sector is characterized by high concentration, and the digital services and platforms banks offer to consumers are considered one of their main competitive advantages.

The legislative framework operating in Georgia is based on the so-called universal banking license model, which covers a relatively broad spectrum of activities, including those related to permissible banking activities. The list of permissible activities defined by a banking license largely corresponds to the activities provided for in Annex I of the CRD Directive. However, it should be noted that, despite the broad nature of the concept of a "universal license," the scope of permissible banking activities remains clearly bounded.

Presently, a gradual implementation of the BaaS model by commercial banks can clearly be observed in Georgia. In addition, taking into account the aforementioned characteristics of super apps, it can be said that the digital platforms of some Georgian commercial banks already represent a functional analogue of a super app.

Admittedly, under the current legal framework, banks cannot directly offer non-financial/non-banking services on their platforms that fall outside the scope of permissible banking activities—such as purchasing airline or cinema tickets, hotel bookings, e-commerce services, and others; however, banks have long been offering consumers services that significantly go beyond traditional banking activities (of taking deposits and lending). Examples of this include investment modules integrated into banks' digital platforms, which may be provided directly by the bank or accessible based on third-party integration. Also noteworthy are insurance products offered to consumers, which banks provide within the framework of rendering intermediary services in the financial market.

Furthermore, within the scope of permissible banking activities, banks provide consumers with a diverse range of services tailored to their daily needs, including the payment of utility bills and traffic fines, the purchase of parking permits, mobile balance top-ups, and the replenishment of accounts required for various services, among other similar services. For comparison, it is interesting that, in relation to banks like Revolut, KBC, and OTP banks, international sources often classify these and similar activities under the category of non-financial or non-banking services.

Consequently, under current conditions, Georgian commercial banks are already represented in the financial services market with quite developed digital ecosystems, diverse products, and services. In some cases, this has been supplemented by the multi-faceted development of banking group and partnership relations among constituent companies.

Grounding the development of the BaaP model within the scope of permissible banking activities acquires essential importance, both in terms of compliance with the regulatory framework and the maintenance of a competitive environment in the market. If this does not occur, the offering of services by commercial banks that lie beyond the scope of permissible banking activities, and, consequently, the increase of the market power of those banks, may pose an unjustified threat to the development of other players in both financial and non-financial services markets, and may further increase the existing concentration in the banking sector.

In this regard, it is noteworthy that, unlike in Europe, where fintech and BigTech companies actively compete with traditional banking business models, in Georgia, the banking sector itself represents one of the leading forces of financial and technological development. Moreover, Georgian banks have long been part of the process of transformation from traditional banking to models based on digital ecosystems, and they do not face the type of competitive challenges observed in European markets.

Conclusion

Global digital transformation, including the development of digital banking services and shifts in consumer preferences, has exerted a significant influence on market behavior and the evolution of the financial sector.

The trends of economic platformization, as well as their impact on the transformation of traditional banking business models, are becoming increasingly obvious and visible. In the new digital era, the super app business model has emerged as one of the major benchmarks for strategic development. By consolidating a diverse range of services into a single platform, such ecosystems set new standards in digital experience, personalized services, and digital consumer engagement. Under the conditions of the platformization trend, rising consumer expectations, and intensified competition, banks are actively striving toward the development of their own digital ecosystems.

At the global level, in response to the super app phenomenon, three main operational and strategic directions for the development of the traditional banking model have emerged. The first is related to the active implementation of Banking as a Service (BaaS); the second, to the development of the Bank as a Platform (BaaP) model; and the third, to the formation of super apps within banking groups. These processes are significantly influenced by regional context, consumer preferences, market structure, and differences within regulatory frameworks, which define both the expansion possibilities of digital platforms and the volume and nature of the services they integrate. The Georgian banking sector has followed these global trends and, taking into account the country's context and permissible banking activities, these have already been reflected in the operational and strategic models of banks.

Although digital transformation is accompanied by significant positive economic effects, it requires a complex and balanced approach from regulators in terms of financial stability, market integrity, the competitive environment, the efficiency of business models, data protection, and the protection of consumer interests. In this process, particular importance should be attached to the economic, institutional, and legal context of each country.

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CREDIT DERIVATIVES AND SECURITIZATION: MULTI-NAME CREDIT INSTRUMENTS

LEVAN SURGULADZE

Abstract

This article analyzes multi-name credit derivatives, in particular basket and portfolio default swaps. Dependence among the underlying instruments is modeled through asset correlation within a Gaussian copula framework, while correlated times to default are generated by Monte Carlo simulation. The resulting outputs are used to assess the distribution of portfolio losses, the allocation of risk across tranches, and to evaluate fair spreads. The paper also discusses the relevance of this framework for the development of Georgia's financial market and securitization instruments.

Keywords: credit derivatives, multi-name credit instruments, spread, correlation, loss distribution, tranches, portfolio credit risk, portfolio credit default swap, Georgia.

Introduction

Credit derivatives allow market participants to isolate, transfer, and trade the credit risk associated with underlying credit instruments. In the case of single-name instruments, credit default swaps provide a means of hedging the default risk of an individual borrower or underlying credit instrument, as well as the risk of deterioration in its credit quality. In the case of multi-name structures, the analysis extends beyond the credit risk profile of an individual underlying credit instrument to encompass the risk profile of the entire portfolio. This substantially broadens the modeling problem: the value of a basket or portfolio default swap depends not only on the default probabilities, spreads, recovery rates, and maturities of the individual underlying instruments included in the portfolio, but also on the correlation structure governing their joint default behavior.

The development of multi-name credit derivatives was closely linked to the rapid growth of markets for trading credit risk and structured finance products. Basket default swaps, portfolio default swaps, and instruments based on tranched portfolios made it possible to evaluate and transfer not only the risk of an individual underlying credit instrument, but also the credit risk of different tranches of a portfolio. First-to-default, second-to-default, and higher-order default swaps transfer risk according to the sequence of defaults within a basket, while instruments that transfer tranche risk allocate risk according to the distribution of possible cumulative portfolio losses relative to the boundaries of the relevant tranche. The valuation of such instruments therefore requires a modeling framework for correlated default events and for the resulting distribution of possible portfolio losses.

An important advance in the modeling of multi-name credit risk is associated with the use of copula functions. These functions make it possible to construct a joint default distribution on the basis of individual default distributions and the correlations among the underlying credit instruments. The use of the Gaussian copula in credit portfolio modeling, as introduced by Li (2000), became the standard approach in both market practice and the academic literature. The general theory of reduced-form credit risk modeling and single-name default calibration is discussed in detail in Duffie and Singleton (2003), Lando (2004), and Schönbucher (2003). Broader overviews of credit derivatives and structured credit products are provided in O'Kane (2008), Bluhm, Overbeck, and Wagner (2010), and Gregory (2010). At the same time, the limitations of Gaussian copula models—in particular, the relatively thin tails of the implied distribution and the resulting potential errors in modeling the credit portfolio loss distributions—have been widely discussed in the literature. Accordingly, the Gaussian copula should be regarded as a transparent and practical benchmark framework whose predictive capacity is limited in relation to rare but large-loss scenarios.

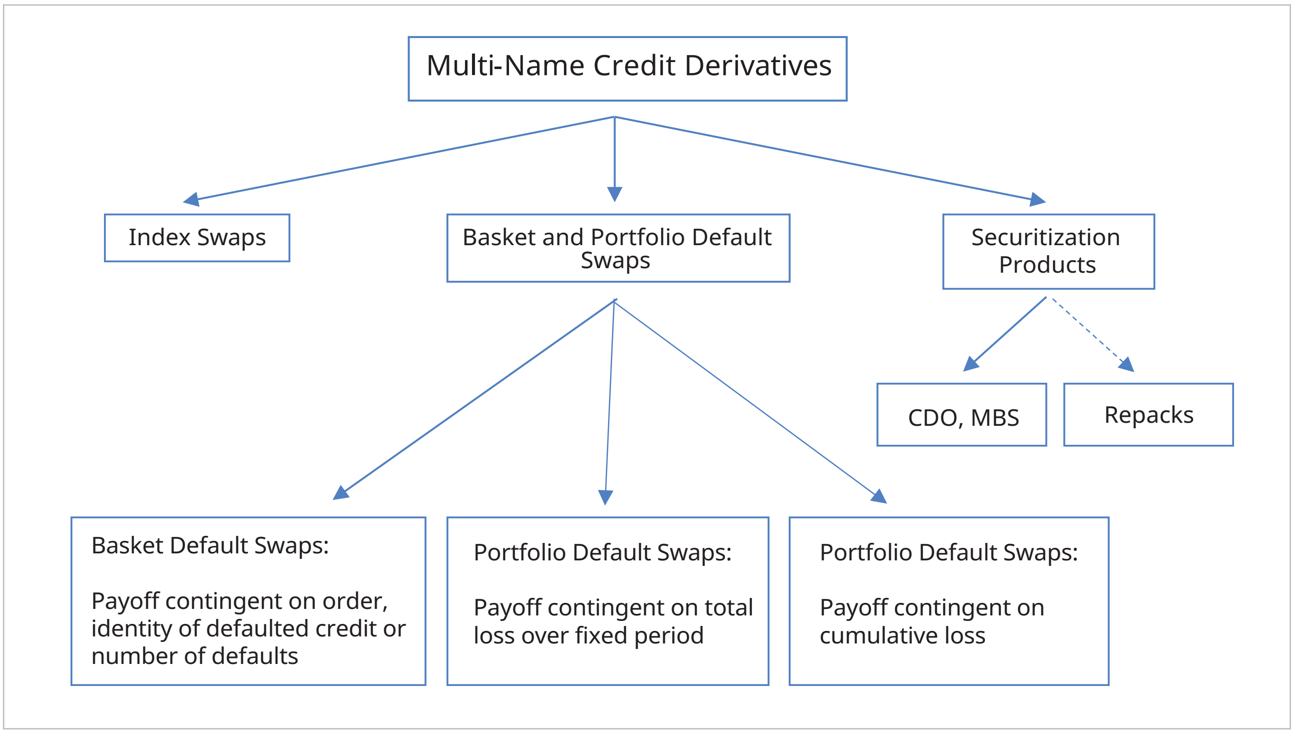
Building on this model, the present article develops a compact methodological framework for the valuation of multi-name credit default swaps. Individual default distributions are obtained on the basis of standard reduced-form calibration procedures used for single-name instruments. For the approach applied in this study, see Surguladze (2026), and for standard theoretical references, see Duffie and Singleton (2003), Schönbucher (2003), and Lando (2004). The paper extends the author's earlier work on single-name credit instruments (Surguladze, 2026) to the modeling of correlated defaults, portfolio loss distributions, and the valuation of multi-name credit default swaps.

The article discusses the main types of multi-name credit instruments, including index swaps, basket default swaps, and portfolio default swaps. The valuation framework is based on individual distributions of times to default, the asset correlation matrix, the Gaussian copula construction, and Monte Carlo simulation of correlated times to default. The resulting loss distribution is used to evaluate expected loss, standard deviation, Value at Risk (VaR), and Expected Shortfall, as well as to value Nth-to-default basket instruments and determine the fair spreads of default swaps written on portfolio tranches. The numerical results show that asset correlation is one of the main determinants of portfolio credit risk. An increase in asset correlation reduces the fair spread of the equity, or first-loss tranche, increases the spreads of the senior and super-senior tranches, and has a relatively limited effect on the valuation of the mezzanine tranche. The results also indicate that even very high asset correlation does not make tranches identical in a heterogeneous portfolio, because differences among the underlying instruments—in spreads, recovery rates, and default probabilities—preserve the hierarchical structure of loss allocation.

Main Types of Multi-Name Credit Instruments

Multi-name credit derivatives can be divided into three broad categories: index swaps, basket and portfolio default swaps, and securitization products. The present article mainly focuses on index swaps and on basket and portfolio default swaps.

Figure 1. Classification of Multi-Name Credit Derivative Products



Source: Author's illustration.
Note: CDO — collateralized debt obligation; MBS — mortgage-backed security.

A common feature of these instruments is that they provide exposure to the credit risk of a group or portfolio of underlying credit instruments. Index swaps do this through the total return or performance of a credit index. Basket and portfolio default swaps, by contrast, allow the credit risk of the underlying portfolio to be structured in different ways, including by reference to the order of defaults, the cumulative level of portfolio losses, or specific portfolio tranches.

An index swap is designed to take a position in relation to the credit and market risks of a broad group of credit instruments. It can be viewed as a multi-name analogue of the total return swap discussed in Surguladze (2026). In a typical index swap transaction, the buyer receives the total return of the underlying credit index, including both coupon income and gains or losses arising from changes in the index price, and in exchange pays the seller a base floating interest rate plus a fixed spread.

As with all multi-name credit derivatives, the payoff of a basket default swap is determined by the default profile of a portfolio of underlying credit-risky assets. A credit event occurs as a result of the default of a specified combination of the underlying reference names included in the portfolio. Contractual terms may vary. For example, the payment obligation may be triggered when a pre-specified cumulative number of defaults is reached, while the amount of the payoff may be fixed or may depend on the losses generated by the defaulted asset or assets.

The present article considers the most widely used structures of basket default swaps. In an Nth-to-default basket swap, the payment obligation arises when the Nth default occurs in the basket, that is, when at least N defaults have been recorded in the portfolio in total. In market practice, the most common structures are first-to-default, second-to-default, and higher-order default swaps. The specific payoff mechanism and amount may differ depending on the contractual terms.

In a first-to-default swap, the payment obligation is triggered by the first default of any underlying asset in the basket. In the standard case, the payoff corresponds to the notional amount less the recovery amount, adjusted for accrued premium, although contractual terms may vary. The seller of a first-to-default swap receives a premium in exchange for assuming first-loss risk; as a result, the spread received is often substantially higher than the spread obtained either by directly holding the underlying asset or by selling a single-name credit default swap (CDS) on that asset. This reflects the fact that the probability of a credit event occurring in the basket is significantly higher than the default probability of any individual name included in the portfolio. For investors with a relatively lower risk appetite, a second-to-default swap may be more attractive, since the payment obligation is activated only upon the occurrence of the second default in the basket. Higher-order default swaps are constructed analogously.

The value and fair spread of basket default swaps are determined by the credit quality of the underlying assets included in the basket and by their correlation, that is, by the degree of dependence among them. The analysis below focuses on how the valuation of basket and portfolio default swaps changes as asset correlation changes.

A portfolio default swap is written on a portfolio of credit instruments. Its payoff depends on the level of cumulative loss of the underlying portfolio, as defined by the contract. In some contracts, the payoff may also depend on the total loss realized over a pre-specified period. As in the case of basket default swaps, contractual terms may differ: payments may be made on pre-specified dates, at the end of contractually specified periods, or progressively as losses occur.

The main difference from basket default swaps is that, in a portfolio default swap, the payoff depends on the amount of the portfolio loss or its percentage level, rather than on the order or number of defaults.

In the following sections, this idea is developed using the example of default swaps written on portfolio tranches, in which the payoff is linked to a pre-specified layer, or tranche, of cumulative portfolio losses.[1]

Portfolio Credit Risk and Correlation Structure

Credit Portfolio and Correlation Matrix

Before turning to the modeling and valuation methodology, this subsection defines the underlying portfolio of assets with correlated credit risk, together with the relevant notation and parameters. Consider a portfolio consisting of n underlying credit assets, distributed across m industry groups:

$$B_1,\dots B_{n_1}, B_{n_1+1},\dots, B_{n_2} B_{n_2+1},\dots, B_{n_3},\dots,\dots, B_{n_{m-1}+1},\dots, B_{n_m}, \qquad \sum_{i=1}^{m} n_i = n$$

The assets included in the portfolio are characterized by notionals $N_1, \dots, N_n$, maturities $T_1, \dots, T_n$, recovery rates $R_1, \dots, R_n$ and observed flat spread term structures, that is, spreads assumed to be constant over maturity $s_1, \dots, s_n$.

The dependence structure among credits is introduced through asset correlations. We assume that all pairs of assets within a given industry group have identical correlation. Accordingly, within-industry asset correlations are summarized by the following m-dimensional vector:

1. Overviews of multi-name credit derivatives are provided, for example, in Bowler and Tierney (2000), O'Kane (2001), and J. P. Morgan (1999), as well as in Arvanitis and Gregory (2001) and Schönbucher (2000).

$$(\rho_1,\ldots,\rho_m)$$

Correlations between assets belonging to different industry groups are summarized by the m×m matrix:

$$(\rho_{ij})_{m\times m}$$

This structure, together with the assumption of homogeneous within-industry correlation, substantially reduces the number of input parameters. Using the m-dimensional vector of within-industry correlations and the m ×m matrix of cross-industry correlations, we construct the following n×n asset correlation matrix:

$$\Omega = (\rho_{kl})_{n\times n} \tag{1}$$

The diagonal elements satisfy $\rho_{kk}=1$. If two assets belong to the same industry group g, then $\rho_{kl}=\rho_g$. If two assets belong to different industry groups g and h, then $\rho_{kl}=\rho_{gh}$. This grouped structure significantly reduces the number of correlation parameters while preserving the main dependence structure relevant for valuation.

The spread term structures, recovery rates, and maturities of the underlying assets determine the default probability profile of each individual asset. These individual default profiles, together with the asset correlation matrix **Ω** defined in equation (1), determine the default probability profile of the portfolio.

Joint Default Probability Distribution via Copula Functions

The joint default probability distribution is modeled using n-dimensional Gaussian copula functions, in accordance with the standard approach used in the literature (Li, 2000).

For each asset in the underlying credit portfolio, let τ_i denote the random variable representing the time to default. Accordingly, for a portfolio consisting of n credit assets, the vector of times to default is

$$(\tau_1, \tau_2 \ldots,\tau_n) \tag{2}$$

For each asset, the marginal distribution of time to default is

$$P_t^{(i)} = \text{Probability } [\tau_i<t] \tag{3}$$

These marginal default distributions are obtained using standard single-name reduced-form calibration procedures.[2] The correlation structure is represented by the n×n correlation matrix **Ω** given in equation (1).

In the portfolio context, our objective is to construct a joint distribution of times to default that is consistent with the known marginal default distributions and the correlation structure. In general, the uniqueness of the solution to this problem cannot be established. By contrast, if the joint distribution is given, then the marginal distributions and the correlation structure are uniquely determined from it.

Copula functions provide a convenient way to construct such a joint distribution. The joint distribution of times to default may be written in terms of an n-dimensional copula function as follows:

$$\text{Probability}[\tau_1 < t_1, \tau_2 < t_2, \ldots, \tau_n < t_n] = P(t_1, t_2, \ldots, t_n, \Omega) = C(P_{t_1}^{(1)}, P_{t_2}^{(2)}, \ldots, P_{t_n}^{(n)}, \Omega) \tag{4}$$

By construction, the copula representation reproduces the marginal distributions $P_{t_1}^{(1)}, P_{t_2}^{(2)}, \ldots, P_{t_n}^{(n)}$. For example, to recover the marginal distribution of asset i, one keeps the corresponding time argument for i unchanged and lets all the other time arguments tend to infinity. As a result, the restrictions on the times to default of the remaining assets no longer matter, since Probability $(\tau_j \le \infty)=1$. In equa-

2. See, for example, Duffie and Singleton (2003), Schönbucher (2003), and, for the specific approach used here, Surguladze (2026).

tion (4), all copula arguments except one therefore become equal to 1, yielding the corresponding marginal distribution of time to default for the individual credit.

The choice of copula function is not unique. In the present paper, we use the multivariate Gaussian copula, which, despite its well-known limitations, remains a standard benchmark model in both industry practice and the academic literature (Li, 2000; Schönbucher, 2003). One of its important limitations is its inability to adequately capture tail risk, which means that the model may fail to reflect the likelihood of rare but large joint-loss scenarios. Alternatively, one may use a t-copula, which better reflects severe scenarios in which several credit instruments default or incur large losses simultaneously (Schönbucher, 2003; O'Kane, 2008).

Within the Gaussian copula framework, the joint distribution of times to default can be written as follows:

$$P(t_1, t_2, \dots, t_n, \Omega) = C(P_{t_1}^{(1)}, P_{t_2}^{(2)}, \dots, P_{t_n}^{(n)}, \Omega) = \Phi_n(\Phi^{-1}(P_t^{(1)}), \dots, \Phi^{-1}(P_t^{(n)})) \tag{5}$$

where Φ_n denotes the n-dimensional standard normal cumulative distribution function with correlation matrix Ω, and Φ^{-1} denotes the inverse of the one-dimensional standard normal cumulative distribution function.

Monte Carlo Simulation of Correlated Times-to-Default

There is the following one-to-one correspondence between the marginal default probabilities $P_t^{(i)}$ and the corresponding default thresholds x_i:

$$x_i = \Phi^{-1}(P_t^{(i)}) \tag{6}$$

Default occurs whenever the normal random variable X_i falls below its threshold, that is, whenever $X_i \le x_i$. To simulate correlated times to default, we use the following relationship:

$$\tau_i = P_i^{-1}[\Phi[X_i]] \tag{7}$$

Here, X_i denotes a correlated standard normal variable, while the dependence structure across assets is described by the correlation matrix Ω. To obtain the vector of correlated normal random variables ($X_1, \dots X_n$), we first simulate a vector of independent standard normal random variables ($Y_1, \dots Y_n$) and then apply the Cholesky decomposition of the asset correlation matrix (see, for example, Golub and Van Loan, 2013):

$$(X_1, \dots, X_n) = (Y_1, \dots, Y_n) \times W \tag{8}$$

where W is a matrix satisfying the condition:
$W^T \times W = \Omega$.

The next step is to determine the functional form of $P_i^{-1}[\cdot]$. Under the approximation of a flat spread term structure, or equivalently a flat term structure of default hazard rates, we obtain (Surguladze, 2026):

$$P_i^{-1}[\cdot] = -\frac{1}{h_i} \times Log\left[1 - [\cdot]\right] \tag{9}$$

Since the default hazard rate is not directly observable in the market, whereas CDS spreads are observable, it is convenient to use a spread-based expression (Surguladze, 2026):

$$P_i^{-1}[\cdot] = \frac{1}{Log\left[\frac{1-\frac{s_i/2}{1-R_i}}{1+\frac{s_i/2}{1-R_i}}\right]} \times Log\left[1 - [\cdot]\right] \tag{10}$$

The advantage of equation (10), compared with equation (9), is that it directly incorporates the calibration step: for each asset, directly observable CDS spreads and assumed recovery rates can be used.

Accordingly, for a portfolio of n assets, the Monte Carlo procedure for simulating times to default can be summarized as follows:

1. Simulate a vector of independent standard normal random variables ($Y_1,... Y_n$).
2. Using the Cholesky decomposition, transform the vector ($Y_1,... Y_n$) into the vector of correlated standard normal random variables ($X_1,... X_n$) (see equation (8)).
3. For each asset, calculate the time to default τ_i using equations (10) and (7).

As a result, we obtain the (M+1)×n matrix τ of simulated times to default, where M denotes the number of Monte Carlo scenarios:

$$\tau = \begin{bmatrix} B_1, & B_2, & \cdots & B_n \\ \tau_{1,1}, & \tau_{1,2}, & \cdots & \tau_{1,n} \\ \vdots & \vdots & \cdots & \vdots \\ \tau_{M,1}, & \tau_{M,2}, & \cdots & \tau_{M,n} \end{bmatrix} \tag{11}$$

The first row corresponds to the names of the underlying credit instruments. Each subsequent row corresponds to one Monte Carlo scenario and shows the simulated times to default for all assets included in the portfolio. For example, $\tau_{1,1}$ denotes the simulated time to default of credit B_1 in the first simulated scenario; more generally, $\tau_{i,j}$ denotes the simulated time to default of credit B_j in scenario i.

This matrix contains the information needed to define the simulated default profile of the underlying credit portfolio and can be used to value basket and portfolio default swaps across a wide range of contractual payoff specifications.

Statistical Characteristics of Portfolio Losses

The full distribution of times to default for a portfolio of correlated credits generally cannot be described in closed form. In practice, Monte Carlo simulation provides a flexible and efficient tool for studying the portfolio default profile and the statistical characteristics of the resulting losses. In this subsection, we define the portfolio loss variable and present selected statistical characteristics that are computed from the simulated matrix of times to default.

As noted above, the matrix of times to default obtained in the previous subsection, equation (11), essentially contains the full information about the default profile of the underlying basket. This matrix can be used to define and compute useful statistical characteristics.

First, consider the cumulative portfolio loss over a given time horizon, expressed as a percentage of total portfolio notional. The first few moments of the loss distribution can be obtained from the simulated matrix of times to default. For example, for a given time horizon t, the expected cumulative loss is computed as follows:

$$E\left[\text{Cumulative loss}\right]_t = \frac{1}{M} \times \sum_{i=1}^{M} \frac{\sum_{j=1}^{\text{Defaulted Assets}_i} (1-R_j) N_j}{\sum_{j=1}^{\text{All Assets}} N_j} \tag{12}$$

where M is the number of Monte Carlo scenarios. The inner sum calculates, for each scenario i, the credit losses of the underlying assets that have defaulted before the given horizon t. The term structure of expected cumulative loss is obtained by applying the same calculation across all relevant time horizons.

As a first numerical illustration, consider a simplified 100-name portfolio used solely to demonstrate the portfolio loss distribution and summary loss statistics. The portfolio is divided into three credit-quality groups: low-risk, medium-risk, and high-risk. This numerical example remains compact while reflecting the economic differences among different credit-quality levels. All underlying instruments are assigned identical notionals and a common seven-year horizon. We assume that the pairwise asset correlation is identical for all instruments and equals 30%. The initial data are summarized in Table 1.

Table 1. Initial Data for a 100-Name Credit Portfolio

Risk category	Number of credits	Notional of each credit	Spread (bp)	Recovery rate (%)	Maturity (years)
Low risk	30	10,000,000	100	50	7
Medium risk	40	10,000,000	200	40	7
High risk	30	10,000,000	350	30	7

For each Monte Carlo scenario, correlated times to default are simulated using the Gaussian copula methodology described above. For the seven-year horizon, the cumulative portfolio loss is computed according to equation (12), where t=7. Thus, the loss assigned to a defaulted instrument is equal to its economic credit loss N_i (1-R_i).

The loss distribution is estimated using 10,000,000 simulated Monte Carlo scenarios. Since the unconditional distribution contains many zero-loss scenarios, Figure 2 presents the portfolio loss distribution excluding scenarios with zero loss. The corresponding numerical results are summarized in Table 2.

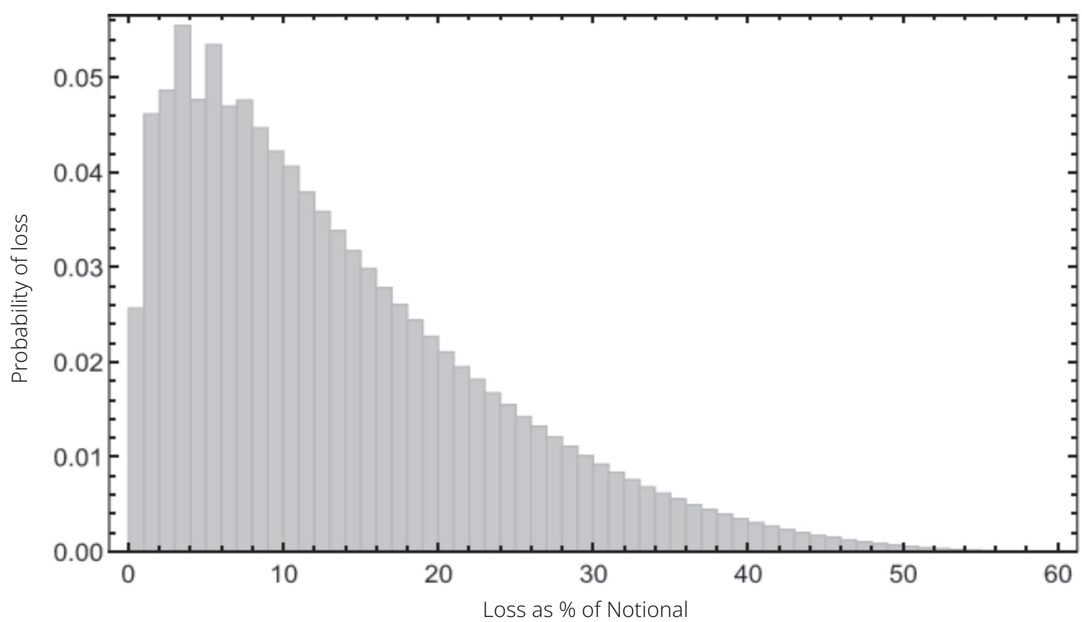
Table 2. Portfolio Loss Statistics, 100-Name Portfolio, 7-Year Horizon

Expected loss	Standard deviation	VaR 95%	VaR 99%	Expected Shortfall 95%	Expected Shortfall 99%
13.15%	10.16%	33.4%	43.3%	39.3%	47.1%

Source: Author's calculations.

Value at Risk (VaR) and Expected Shortfall are computed directly from the simulated loss distribution. VaR at a given confidence level is the loss threshold to the left of which the specified percentage of the total area under the loss distribution lies. For example, for the 95% VaR, this area is 95%, while the remaining 5% of the area to the right of VaR corresponds to scenarios in which losses exceed VaR. The 99% VaR is defined analogously, as the threshold to the left of which 99% of the distribution area lies. Expected Shortfall is computed as the average of simulated losses beyond the corresponding VaR threshold. All statistical characteristics are expressed as percentages of the total portfolio notional. The results are rounded for ease of presentation.

Figure 2. Loss Distribution of a 100-Name Credit Portfolio



Source: Author's calculations.

Valuation of an Nth-to-Default Swap by Monte Carlo Simulation

This subsection describes the valuation of an Nth-to-default swap on a basket using the Monte Carlo method and the matrix of simulated times to default presented in equation (11). We consider two approaches. The first approach uses the simulated Nth time to default to construct the term structure of cumulative Nth-default probabilities. This approach is simple and computationally efficient but is particularly convenient when the underlying credits included in the basket have identical notionals and recovery rates. The second approach values the contract directly in each Monte Carlo scenario and represents a more flexible and recommended valuation method.

From the matrix of simulated times to default in equation (11), the times to default are sorted in increasing order in each Monte Carlo scenario. The Nth time to default is then selected for each scenario. This gives the following simulated sample of Nth times to default:

$$\tau^{(N)} = \begin{pmatrix} \tau_1^{(N)} \\ \vdots \\ \tau_M^{(N)} \end{pmatrix} \tag{13}$$

The cumulative probability that the Nth default occurs by time t is estimated by the following simple count:

$$P_t^{(N)} = \frac{\text{COUNT}_{i=1}^{M}[\tau_i^{(N)} \le t]}{M} \qquad t = 1,2,\ldots T \tag{14}$$

The present value of an Nth-to-default swap can be computed using the resulting term structure of probabilities. If $p_i^N = P_i^N - P_{i-1}^N$, then the valuation expression is given in equation (15), and the corresponding fair spread is obtained from equation (16):

$$PV_{CDS}^{N^{th}-to-Default} = Notional \times \sum_{i=1}^{T} df_i \times \left[p_i^{(N)} \times (1 - R - \frac{S}{2}) - (1 - \sum_{j=1}^{i} p_j^{(N)}) \times S \right] \tag{15}$$

where S is the annual premium. Setting the right-hand side of equation (15) equal to zero and solving for $S \equiv s_{fair}^{(N)}$, we obtain:

$$s_{fair}^{(N)} = 2(1-R)\left[1 + 2\frac{\sum_{i=1}^{T_n} df_i (1 - \sum_{j=1}^{i} p_j^{(N)})}{\sum_{i=1}^{T_n} df_i p_i^{(N)}} \right]^{-1} \tag{16}$$

Equations (15)–(16) provide compact valuation expressions for cases in which the payoff of an Nth-to-default swap can be expressed through the term structure of Nth-default probabilities. This includes homogeneous baskets or contracts where a fixed payoff is specified upon the occurrence of the Nth default. In such cases, it is not necessary to know exactly which instrument became the Nth defaulted name. However, if the payoff of the default swap depends on the actual loss of the Nth defaulted credit, then in each simulated scenario it is necessary to identify that credit, including its corresponding notional and recovery rate. In this case, a scenario-based simulation method is required.

The scenario-based simulation method also starts with the matrix of simulated times to default given in equation (11). From this matrix, one can obtain all the information needed to determine the payoff specified by the contract in each scenario. Below, for the basic case of an Nth-to-default swap, we identify in each scenario the Nth defaulted credit, together with its notional, recovery rate, and time to the Nth default.

$$\tau^{(N)} = \begin{bmatrix} B_1 & Notional_1 & R_1 & \tau_1^{(N)} \\ \vdots & \vdots & \vdots & \vdots \\ B_j & Notional_j & R_j & \tau_j^{(N)} \\ \vdots & \vdots & \vdots & \vdots \\ B_M & Notional_M & R_M & \tau_M^{(N)} \end{bmatrix} \quad (17)$$

In the matrix above, the subscripts denote a specific scenario, or simulation, and not the identity of the asset. For example, in a given scenario, the entry B_j in the matrix denotes the credit that became the Nth defaulted name; this credit may be any of the credits B_1,... B_n included in the portfolio.

It should be noted that equation (17) represents a compact form of scenario information for a basket Nth-to-default swap where the payoff is linked directly to the Nth defaulted credit. If the contractual payoff depended not only on the Nth default, but on all credits defaulted from the first through the Nth default, then each simulated scenario would need to identify all such credits, including their times to default, notionals, and recovery rates.

For a basket Nth-to-default swap, the cash flows in a simulated scenario depend on whether the Nth default occurs before the contractual maturity. If, in scenario j the simulated time to the Nth default $\tau_j^{(N)}$ exceeds the contractual maturity T, no contingent payment is made and the cash flows are limited to premium payments. If $\tau_j^{(N)} < T$, the cash flows include accrued premiums and the payment corresponding to the actual loss of the Nth defaulted credit. The average value of discounted cash flows across all scenarios gives the present value of the contract:

$$PV^{(\mathrm{N^{th}-to-default\ CDS})} = \frac{1}{M}\sum_{j=1}^{M}\Bigg\{\Theta\left(T-\tau_j^{(N)}\right) \times \Bigg(df_{[1+\tau_j^{(k)}]}\left[Notional_j\left(1-R_j\right) - Notional \times S\left(\tau_j^{(N)} - [\tau_j^{(N)}]\right)\right] - Notional \times S\sum_{t=1}^{[\tau_j^{(k)}]} df_t\Bigg) - \left[1-\Theta(T-\tau_j^{(N)})\right] Notional \times S\sum_{t=1}^{T} df_t\Bigg\} \quad (18)$$

where M is the number of simulations, S is the annual premium, and df_t is the risk-free discount factor corresponding to time *t*. $Notional_j$ and R_j denote the notional and recovery rate of the Nth defaulted asset in scenario *j*. *Notional* denotes the contractual notional of the default swap, on the basis of which the premium is paid, and it does not necessarily have to coincide with the notional of any underlying asset. $\Theta(x)$ is the theta function, which equals 1 for non-negative arguments and 0 otherwise. $[\tau_j^{(N)}]$ denotes the integer part of $\tau_j^{(N)}$, that is, the number of full years.

It should be noted that the accrued-premium term

$$S\left(\tau_j^{(N)} - [\tau_j^{(N)}]\right)$$

may be approximated by the first-order approximation s/2, or a higher-order correction may be used (Surguladze, 2026).

The fair spread of the contract is computed by setting the average present value in equation (18) equal to zero and solving for S. This means finding the premium at which the average values of the discounted cash flows from the contingent payment and the premium leg are equal.

Valuation of a First-to-Default Swap — Closed-Form Solution

Although the present paper mainly relies on Monte Carlo simulation, for small baskets a first-to-default swap can also be valued in closed form. Consider a basket consisting of n underlying credits, with common contractual notional Notional, recovery rate R, spread term structures s_i, $i=1,2,\ldots,n$ and asset correlation matrix $\boldsymbol{\Omega}$. For a T-year first-to-default CDS with annual premium *S*, the present value can be written as follows:

$$PV^{(\text{1st-to-default CDS})} = Notional \times \sum_{t=1}^{T} df_t \left[\left(Q_{t-1}^{1\cap 2\cap\ldots\cap n} - Q_t^{1\cap 2\cap\ldots\cap n} \right) \times \left(1 - R - \frac{S}{2} \right) - Q_t^{1\cap 2\cap\ldots\cap n} \times S \right] \tag{19}$$

where $Q_t^{1\cap 2\cap\ldots\cap n}$ denotes the probability that all credits included in the basket survive until time *t*. This probability can be expressed as:

$$Q_t^{1\cap 2\cap\ldots\cap n} = 1 + \sum_{k=1}^{n} (-1)^k \sum_{1\le j_1<\cdots<j_k\le n} P_t^{(j_1)\cap(j_2)\cap\cdots\cap(j_k)} \tag{20}$$

where

$$P_t^{(j_1)\cap(j_2)\cap\ldots\cap(j_k)} = \Phi_k\left[\Phi^{-1}\left(P_t^{(j_1)}\right),\ldots,\Phi^{-1}\left(P_t^{(j_k)}\right),\Omega_{j_1,\cdots j_k}\right] \tag{21}$$

Here, $\boldsymbol{\Omega}_{j1,\ldots jk}$ is the corresponding k×k submatrix of the correlation matrix Ω, and $\boldsymbol{\Phi}_k$ is the k-dimensional cumulative normal distribution function. The corresponding integral is evaluated numerically. Equations (19)–(21) provide a practical closed-form representation for small baskets, while for large baskets the combinatorics quickly becomes complex and the Monte Carlo approach is more convenient.

In the limiting case of zero pairwise asset correlation, the survival probability factorizes:

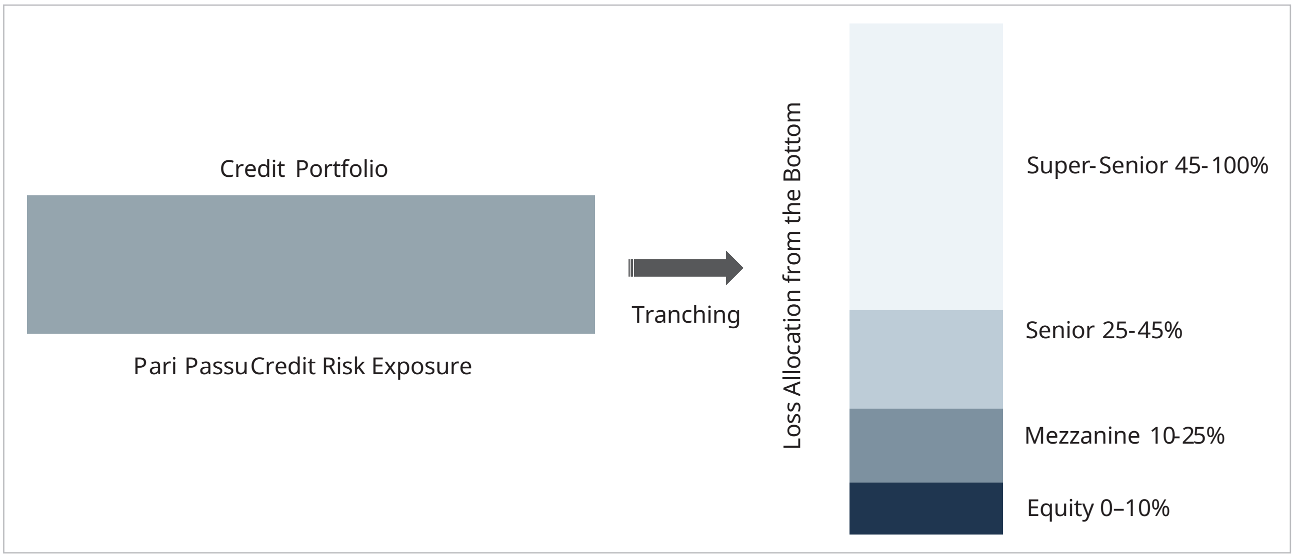
$$Q_t^{1\cap 2\cap\ldots\cap n} = \prod_{i=1}^{n}\left(1 - P_t^{(i)}\right)$$

This case provides useful intuition: when correlations are low, the probability of a first default reflects the probability that at least one of several largely independent credits defaults. As a result, other things being equal, the fair premium of a first-to-default swap is higher under low correlation. As correlation approaches one, credits display more joint behavior, and the first-to-default swap increasingly resembles a credit default swap written on the riskiest credit in the basket.

Valuation of a Portfolio Default Swap

Before considering the tranches of a credit portfolio, it is useful to distinguish between a portfolio in which the risk of credit losses is distributed across the total notional amount on a pari passu basis and a tranched portfolio, in which the same credit-loss risk is allocated across different tranches according to a pre-specified priority rule. Loss allocation starts from the lower tranches, while higher, senior tranches are affected only after the lower tranches have been exhausted. Figure 3 illustrates the transition from a pari passu allocation of credit risk to a tranched allocation, where the darker color symbolically represents a higher level of risk.

Figure 3. Conceptual Illustration of Portfolio Tranching



Source: Author's illustration.

A portfolio default swap written on a tranche transfers the risk of possible credit losses that may be allocated to that tranche under the contract.

Let a denote the lower boundary of the tranche and d the upper boundary, where a and d are expressed as percentages of the total portfolio amount and $0 \leq a < d$. The tranche may be affected by portfolio losses that exceed a and are below d. Accordingly, the maximum loss of the tranche is equal to its "thickness," (d-a).

Let L_t denote the cumulative portfolio loss at time t, expressed either in monetary units or as a percentage of the total portfolio notional. Let Z_t denote the cumulative loss of the given tranche at time t. Then:

$$Z_t = \min\{\max[L_t - a, 0], d - a\} \quad (22)$$

Thus, $Z_t=0$, as long as $L_t \leq a$. If $a < L_t < d$, the tranche has not yet been fully exhausted, while if $L_t \geq d$, the tranche is fully exhausted and $Z_t = d-a$. The change in the loss allocated to the tranche over the period from t-1 to t is:

$$\Delta Z_t = Z_t - Z_{t-1} \quad (23)$$

The valuation of a portfolio default swap written on a tranche by Monte Carlo simulation is straightforward. For each simulated scenario, times to default are generated using the Gaussian copula methodology described above; the cumulative portfolio loss is then computed over the relevant time horizon, while the cumulative loss allocated to the corresponding tranche is determined by equation (22). The discounted cash flows of the contingent payment and premium leg of the tranche portfolio default swap are then averaged across simulated scenarios.

For a fixed-notional premium structure, the present value of the contingent payment leg of a portfolio default swap is obtained by discounting the incremental losses of the tranche over time intervals, summing them, and averaging across simulated scenarios:

$$PV_{\text{prot}} = Notional \times \frac{1}{M}\sum_{j=1}^{M}\sum_{t=1}^{T} df_t \Delta Z_t^j \quad (24)$$

where M is the number of Monte Carlo scenarios, df_t is the risk-free discount factor corresponding to payment date t, and ΔZ_t^j is the incremental loss on the given tranche in scenario j over the period ending at time t.

The premium is paid on the contractual notional until either contractual maturity or the exhaustion of the tranche, whichever occurs first. Let $\overline{T}_j$ denote the final premium payment date in scenario j. Then:

$$PV_{\text{prem}} = S \times Notional \times \frac{1}{M}\sum_{j=1}^{M}\sum_{t=1}^{\bar{T}_j} df_t \quad (25)$$

where S is the annual premium rate and Notional is the contractual notional. The fair spread is the value of S that equates the present value of premium payments to the present value of the contingent payment.

In the numerical illustration, we use a heterogeneous 100-name portfolio with five exposure groups, as shown in Table 3. This structure is compact, but it captures heterogeneity in notionals, spreads, and recovery rates.

Table 3. Initial Assumptions and Data for the 100-Name Portfolio

Exposure group	Number of credit names	Notional per name (mn)	Flat spread term structure (bp)	Recovery rate (%)
Low risk A	20	5.0	80	45
Low risk B	20	7.5	120	45
Medium risk A	20	7.5	200	40
Medium risk B	20	10.0	300	40
High risk	20	10.0	500	35
Total	100	800	—	—

The maturity of the portfolio default swap written on the tranche is T=7 years. For simplicity, we assume that all assets in the underlying portfolio shown in Table 3 also have a maturity of seven years and that losses are measured over the same seven-year horizon.

Pairwise asset correlation is uniform across the entire portfolio and takes the following values:

$$\rho = 0\%, 15\%, 30\%, 45\%, 60\%, 75\%, 85\%, 90\%, 95\%, 98\%, 99\%.$$

The tranche structure is shown in Table 4 (see also Figure 3).

Table 4. Tranche Structure of the 100-Name Portfolio

Tranche	Lower tranche boundary	Upper tranche boundary	Tranche thickness
Equity / first-loss	0%	10%	10%
Mezzanine	10%	25%	15%
Senior	25%	45%	20%
Super-senior	45%	100%	55%

Discount factors are calculated on the basis of the nominal U.S. Treasury yield curve observed on 8 May 2026, using linear interpolation for intermediate maturities. The vector of discount factors used in the numerical illustration is:

$$\{df_1, \cdots df_7\} = \{0.9639, 0.9263, 0.8911, 0.8558, 0.8211, 0.7855, 0.7503\}$$

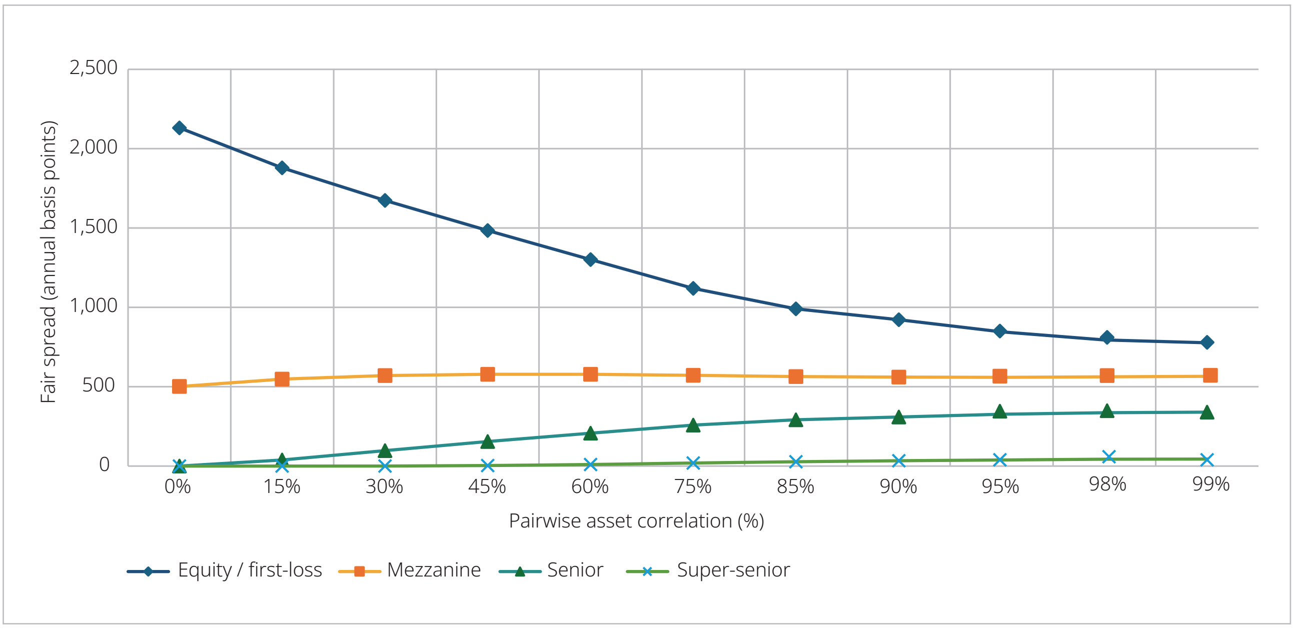
Table 5. Fair Spreads of Tranches for Different Values of Asset Correlation

CORRELATION	EQUITY / FIRST-LOSS SPREAD		MEZZANINE		SENIOR		SUPER-SENIOR	
	spread	std. error	spread	std. error	spread	std. error	spread	std. error
0.00	2,131.4	0.18	501.2	0.08	0.0	0.00	0.0	0.00
0.15	1,879.3	0.31	548.3	0.17	38.0	0.04	0.0	0.00
0.30	1,674.4	0.37	569.6	0.21	97.4	0.09	0.8	0.00
0.45	1,485.0	0.41	578.4	0.26	154.7	0.12	3.9	0.01
0.60	1,301.5	0.31	578.0	0.22	208.0	0.13	9.9	0.01
0.75	1,119.1	0.33	571.4	0.24	258.7	0.17	19.4	0.02
0.85	990.8	0.34	564.1	0.27	292.2	0.17	28.1	0.03
0.90	921.7	0.34	560.5	0.27	309.1	0.20	33.2	0.03
0.95	846.4	0.36	559.8	0.28	326.1	0.20	39.1	0.03
0.98	795.4	0.36	563.1	0.29	336.0	0.20	43.0	0.04
0.99	776.9	0.35	565.4	0.28	339.8	0.22	44.2	0.04

Source: Author's calculations.

Note: "Spread" denotes the fair spread of the tranche; "std. error" denotes the Monte Carlo standard error.

Figure 4. Dependence of Tranche Fair Spreads on Pairwise Asset Correlation



Source: Author's calculations.

Fair spreads and Monte Carlo standard errors are presented in annual basis points. The results are based on 10,000,000 Monte Carlo simulations for each correlation value, divided into 100 independent simulation blocks. The program code, calculations, and graphs were prepared in Wolfram Mathematica (2019).

The results show that asset correlation has a substantial effect on the potential losses and fair spreads of the tranches. The fair spread of the equity, or first-loss, tranche decreases monotonically as pairwise asset correlation increases, because higher correlation reduces the frequency of diversified moderate-loss scenarios, which are the main source of expected loss for this tranche.

By contrast, the spreads of the senior and super-senior tranches increase with correlation. High correlation makes clustered defaults more likely and increases the probability that cumulative portfolio losses will reach the upper tranches of the capital structure. In this numerical example, the spread of the senior tranche increases from approximately zero under zero correlation to 339.8 basis points under 99% correlation, while the spread of the super-senior tranche increases from approximately zero to 44.2 basis points.

The mezzanine tranche is exposed only to a limited band of intermediate losses—in this example, between 10% and 25% of total portfolio notional. An initial increase in correlation brings portfolio losses into this range more frequently, which increases the fair spread of the mezzanine tranche. However, once losses exceed the 25% upper boundary, additional large losses affect the senior and super-senior tranches more than the mezzanine tranche. For this reason, the spread of the mezzanine tranche initially increases and then becomes relatively stable at high levels of correlation.

The effect of high correlation also clarifies an important modeling issue. The relevant parameter here is asset correlation, which is used in the Gaussian copula framework, rather than default-event correlation, which depends on the time horizon and on the individual default probabilities of the credits.

Pairwise asset correlation being close to one does not mean that default events are perfectly correlated and, consequently, that all defaults occur simultaneously. In a heterogeneous portfolio, differences in spreads, recovery rates, and individual default probabilities preserve the priority structure of loss allocation. As a result, tranche fair spreads remain different even under very high asset correlation.

The case $\rho=1$ is a singular limit: the equicorrelation matrix becomes singular, and the standard representation of the Gaussian copula contains terms that are problematic for integration, for example, $1/\sqrt{1-\rho^2}$. Accordingly, this case is not included in the numerical calculations. It can, however, be analyzed using a one-factor Gaussian copula model.

Concluding Remarks in the Georgian Context

Multi-name credit instruments are not yet standard products in Georgia's financial markets. Nevertheless, the analytical framework developed in this paper is important for several reasons.

First, Georgian commercial banks, institutional investors, pension funds, and regulators increasingly need portfolio-level models to measure credit concentration, correlated defaults, and extreme risks located in the tails of loss distributions. Even in the absence of an active domestic market for the relevant derivatives, these approaches are essential for credit portfolio stress testing, efficient capital allocation, and the structuring and valuation of future securitization products.

Second, the results of the study show that portfolio credit risk cannot be explained solely by the credit quality of individual borrowers. Correlation, a measure of borrowers' joint behavior, is critical when assessing the risk of large and unpredictable losses in the tails of the loss distribution. Two portfolios with identical individual expected losses may differ sharply in terms of their extreme-loss profiles if the pairwise correlations within those portfolios differ. This is especially relevant for emerging and relatively small financial systems such as Georgia, where exposures are often concentrated in specific sectors, currencies, or groups of connected borrowers. In such an environment, incorporating correlation is not merely a technical detail; it can materially alter the loss distribution and the overall assessment of portfolio credit risk.

Third, the illustration of tranched losses clearly shows how the same underlying portfolio can be transformed into instruments with different risk profiles. The equity, or first-loss, tranche absorbs portfolio losses first and therefore requires the highest fair spread. Senior and super-senior tranches benefit from the subordination of lower tranches, but their spreads react strongly to increases in asset correlation. This confirms that a higher position in the hierarchy alone does not determine the safety of a tranche; the risk profile is shaped jointly by tranche boundaries, recovery rates, and correlation, a measure of joint behavior among credits. For regulators and investors, this is an important reminder that stress testing should include not only shocks to default probabilities, but also the possible increase in correlation among credit exposures during periods of crisis.

The results of the analysis of correlation dependence are particularly important from a risk management perspective. They show that correlation reallocates risk within a tranched capital structure, while for an untranched portfolio it determines the shape of the loss distribution and, to a significant extent, its main parameters. As correlation increases, diversified moderate losses become less frequent, while clustered-default scenarios become more likely.

For Georgia, these lessons are relevant even before the corresponding markets are fully developed. The development of such a market may begin not with trading in traditional instruments on a secondary market, but with the creation of practical instruments for the securitization of credit portfolios and relatively predictable project-related cash flows, as well as with the execution of the corresponding transactions. Accordingly, the first preparatory step is analytical and methodological in nature and includes modeling correlated defaults, estimating the distribution of portfolio losses, and understanding and measuring the allocation of risk across different structures. These tools can support more effective management and control of credit risk, the formation of risk profiles that are understandable to investors, and the development of the relevant market.

The paper developed a basic analytical framework for modeling portfolio credit risk, tranching that risk, and valuing it using the Gaussian copula and Monte Carlo simulation. The Gaussian-copula-based approach provides a transparent and practical benchmark model, although it cannot fully capture the extreme risks associated with heavy tails in the distribution. Accordingly, future extensions of the research may include the incorporation of non-flat spread term structures, stochastic recovery rates, and copulas with heavy tails, including the t-copula. Such extensions are particularly important for the more accurate analysis and pricing of collateralized debt obligations (CDOs) and other securitization instruments.

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