ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

THE IMPACT OF BANK CREDIT UPTAKE ON INCOME INEQUALITY IN INFLATIONARY PERIODS: THE CASE OF TÜRKİYE

M.A. THESIS

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

ENFLASYONİST DÖNEMLERDE BANKA KREDİSİ KULLANIMININ GELİR EŞİTSİZLİĞİ ÜZERİNDEKİ ETKİSİ: TÜRKİYE ÖRNEĞİ

YÜKSEK LİSANS TEZİ

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To my beloved friend Muhammet Said Dağlıoğlu, who recently passed away at a young age,

FOREWORD

I would like to express my deepest gratitude to my advisor, Associate Professor Şerife Genç İleri, for her dedication and guidance throughout my master's thesis process, and for devoting her valuable time to me.

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Jan 2026 Ömer Faruk ERENBAŞ

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ABBREVIATIONS

NUTS-2	: Nomenclature of territorial units for statistics
OLS	: Ordinary Least Squares
GDP	: Gross Domestic Product
CBRT	: Central Bank of the Republic of Türkiye
FE	: Fixed Effect
GMM	: Generalized methods of moments
OECD	: Organization for Economic Co-operation and Development
BRICS	: Brazil, Russia, India, China and South Africa
RE	: Random Effect
VAR	: Vector Autoregressive
VECM	: Vector Error Correction Model
2SLS	: Two-stage Least Squares
BRSA	: Banking Regulation and Supervision Agency
CPI	: Consumer Price Index
SME	: Small and medium-sized enterprises

SYMBOLS

$\mathbf{X}_{\mathbf{it}}$	: Vector of control variables
$\boldsymbol{\delta}$	: Vector of coefficients of control variables
$\boldsymbol{\gamma_t}$	: Year fixed effects
$\boldsymbol{\varepsilon_{it}}$	: Error Term
$\boldsymbol{Y_{it}}$	: Outcome
$\boldsymbol{K}$	: Number of regions
$\boldsymbol{\alpha_i}$	: Regional fixed effects
$\boldsymbol{\rho}$	: Lagged coefficient of the dependent variable

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THE IMPACT OF BANK CREDIT UPTAKE ON INCOME INEQUALITY IN INFLATIONARY PERIODS: THE CASE OF TÜRKİYE

SUMMARY

This study analyzes the impact of regional credit utilization on income inequality during inflationary periods, using NUTS-2-level macroeconomic, financial, social welfare, and income distribution indicators for Türkiye covering the period 2014–2023. The study consists of two phases. In the first phase, I estimate a heterogeneous-effects pooled OLS model to examine whether the effect of inflation on income inequality varies across regions, and the results provide evidence of regional heterogeneity. In the second phase, I estimate panel fixed-effects models with interaction terms to examine how regional credit use relates to income inequality across pre-shock and post-shock periods, using 2020 as the reference year. I include credit-type shares and total deposits (as a percentage of GDP) and their interactions with the post-shock dummy. To illustrate different aspects of income inequality, I used the Gini coefficient, the P80/P20 ratio, and the total income shares received by different income groups as dependent variables; economic growth, the share of the trade deficit in GDP, years of education, population, and unemployment served as control variables. In continuation of the second part, I estimated dynamic models using the System GMM method by adding lags to the models established with the panel fixed effects method, and I compared the outputs obtained from the two methods. As for the results, both methods suggest that institutional credit usage increased income inequality in the post-shock period by increasing the share of the upper income group and decreasing the share of the middle-income group. On the other hand, the fact that the impact of personal financing loan and consumer credit card usage in the post-shock period was not found in the estimated outputs using the panel fixed effects method but was significant with the System GMM indicates that the credit variables are more suitable for a dynamic structure, thus supporting the use of the System GMM. While personal financing loans, similar to institutional loans, supported the upper class in the post-shock period, increasing the Gini and P80/P20 ratios (and thus income inequality), the effect of personal credit cards was the opposite. The fact that credit card usage, also in normal times, statistically significantly but inversely favored the upper income group demonstrates the modifying effect of the inflation shock. These findings are noteworthy because they show that the negative impacts of inflationary policies on income distribution can be mitigated through selective credit incentives.

ENFLASYONİST DÖNEMLERDE BANKA KREDİSİ KULLANIMININ GELİR EŞİTSİZLİĞİ ÜZERİNDEKİ ETKİSİ: TÜRKİYE ÖRNEĞİ

ÖZET

Tarih boyunca enflasyon, paranın satın alma gücünü ve tasarrufların reel değerini düşürmesi ve maliyet artışları yoluyla yaşam kalitesini azaltması nedeniyle ekonomik ve sosyal birçok soruna yol açmış ve ekonomik karar alıcılar tarafından önem verilen bir olgu olmuştur. Bununla birlikte, enflasyon toplumun tüm kesimlerini eşit derecede etkilememektedir. Gelirleri yalnızca ücret ve sosyal transferlere dayanan düşük gelir grupları, bu gelirlerin enflasyona paralel artmadığı durumlarda enflasyon baskısını daha yoğun hissetmekte; ücrete ek olarak kâr geliri elde eden üst gelir grupları ise enflasyona karşı kendilerini daha güçlü biçimde koruyabilmektedir. Ayrıca, gelirinin tamamını tüketime ayırmak zorunda kalan bireyler ile harcanabilir gelirinin bir kısmını tasarrufa yönlendirerek bundan kazanç sağlayan kesimler arasında da önemli farklılıklar bulunmaktadır. Bu nedenle enflasyonun dağılımsal etkileri olduğu göz ardı edilmemelidir. Kovid-19 pandemisiyle birlikte dünya ekonomilerinde üretim ve işgücü faaliyetleri önemli ölçüde daralmış ve birçok ülkede resesyona varan ekonomik küçülmeler yaşanmıştır. Pandemi sonrası dönemde hükümetler, ekonomik faaliyetleri pandemi öncesi seviyelere yaklaştırmak amacıyla düşük faiz politikaları ve kredi teşvikleri uygulamıştır. Türkiye gibi bazı ülkelerde bu politikaların görece uzun süre devam etmesi, enflasyon oranlarının hızla yükselmesine yol açmıştır. Enflasyondaki hızlı artışa paralel biçimde kredi kullanımının genişlemesi, borçlanma kanalının gelir dağılımı üzerindeki etkilerinin daha dikkatli biçimde incelenmesini gerekli kılmıştır. Mal ve hizmet fiyatlarının gelecekte daha yüksek olacağı ve kredi geri ödeme yükünün reel olarak azalacağı beklentisi, hem gerçek hem de tüzel kişileri enflasyonist dönemlerde borçlanma yoluyla tüketim ve yatırımlarını artırmaya yöneltmektedir. Bununla birlikte, farklı gelir gruplarının krediye erişim imkanları eşit değildir. Düşük gelir grupları finansal piyasalara erişimde çeşitli engellerle karşılaşmaktadır. Bankalar tarafından kredi kullanımında talep edilen gelir belgesi, kefalet, rehin, ipotek ve teminat mektubu gibi şartlar bu engellere örnek olarak verilebilir. Bu durum borçlanmanın gelir dağılımını bozduğu yönünde bir sonuca işaret etse de, etkinin ters yönde olduğunu savunan görüşler de bulunmaktadır. Bu görüş, borç veren kesimin çoğunlukla üst gelir grubundan oluşmasına ve borçların reel değerinin enflasyonist dönemde aşınmasına dayanan borçlu-alacaklı hipotezine dayanmaktadır. Dolayısıyla borçlanma kanalı üzerinden enflasyonun gelir eşitsizliği üzerindeki etkisinin yönü ve büyüklüğü farklılaşabilmektedir. Teorik ve ampirik literatürde borçlanmanın bu etkisine ilişkin birçok çalışma

bulunmakla birlikte, bölgesel heterojenlik nedeniyle farklı sonuçlara ulaşıldığı görülmektedir. Bu nedenle bölgelerin ekonomik, demografik ve finansal yapılarının farklılık gösterdiği ve bu farklılıkların elde edilecek sonuçları etkileyebileceği dikkate alınmalıdır. Türkiye özelinde de 26 NUTS-2 bölgesi arasında kredi kullanım yapısı bakımından önemli farklılıklar bulunmaktadır. Bazı bölgelerde tüzel kredi kullanımı baskınken, bazı bölgelerde tüketici kredileri ve bireysel kredi kartı kullanımı daha yaygındır. Bu yapısal farklılıklar, enflasyon ve borçlanma ilişkisinin gelir dağılımı üzerindeki etkisinin bölgesel düzeyde farklılaşabileceğine işaret etmektedir. Bu çalışma, 2014-2023 dönemini kapsayan Türkiye'ye ait 26 NUTS-2 bölgesine ilişkin makroekonomik, finansal, sosyal refah ve gelir dağılımı göstergelerini kullanarak, enflasyonist dönemlerde bölgesel kredi kullanımının gelir eşitsizliği üzerindeki etkisini analiz etmektedir. 2014-2023 dönemi, hem görece istikrarlı yılları hem de 2020 sonrası enflasyon şokunu içermesi bakımından karşılaştırmalı analiz yapılmasına imkân tanımaktadır. Çalışmanın temel araştırma sorusu, enflasyonist dönemlerde farklı kredi türlerinin bölgesel düzeyde gelir dağılımını iyileştirip iyileştirmediği ya da bozup bozmadığıdır. Çalışma iki aşamadan oluşmaktadır. İlk aşamada enflasyonun gelir eşitsizliğine etkisinin bölgesel olarak değişip değişmediğini anlamak amacıyla heterojen etkili havuzlanmış OLS yöntemiyle bir model kurulmuştur. Her bölge için oluşturulan kukla değişkenlerin enflasyon oranlarıyla çarpılarak bağımsız değişkenler olarak yer aldığı modelde yıl sabit etkileri kontrol edilmiş ve kümelenmiş standart hatalar kullanılmıştır. Elde edilen sonuçların Wald testiyle de desteklendiği model neticesinde bölgesel farklılıkların varlığı kanıtlanmıştır. İkinci aşamada, 2020 yılı referans alınarak şok öncesi ve şok sonrası dönemleri ayırt eden kukla değişkenler oluşturulmuş ve bölgesel kredi kullanımı ile gelir eşitsizliği arasındaki ilişki, etkileşim terimleri içeren panel sabit etkiler modelleriyle incelenmiştir. Oluşturulan modellerde kredi türlerinin ve toplam mevduatın GSYH'ye oranları ve bunların şok sonrası kuklası ile etkileşimleri bağımsız değişken olarak kullanılmıştır. Modellerde otokorelasyon ve heteroskedastisite sorunlarına karşı kümelenmiş sağlam (clustered robust) standart hatalar kullanılmış, Sargan-Hansen testi sonuçları sabit etkiler modelinin tercih edilmesini desteklemiştir. İkinci aşamanın devamında, gelir eşitsizliğinin süreklilik özelliği göstermesi ve modelde yer alan kredi değişkenlerinin potansiyel olarak endojen olabilmesi nedeniyle panel sabit etkiler çerçevesine gecikmeler eklenerek System GMM yöntemiyle dinamik modeller tahmin edilmiş ve iki yöntemden elde edilen sonuçlar karşılaştırılmıştır. Bulgular, her iki yöntemde de tüzel kredi kullanımının şok sonrası dönemde üst gelir grubunun payını artırıp orta gelir grubunun payını azaltarak gelir eşitsizliğini artırdığını göstermektedir. Buna karşılık, şok sonrası dönemde ihtiyaç kredileri ve tüketici kredi kartı kullanımının etkisinin panel sabit etkiler modellerinde görülmemesi ancak System GMM'de istatistiksel olarak anlamlı çıkması, kredi değişkenlerinin dinamik bir yapıda daha uygun biçimde yakalandığını ve System GMM kullanımını desteklediğini göstermektedir. Şok sonrası dönemde ihtiyaç kredileri, tüzel kredilere benzer şekilde Gini ve P80/P20 oranlarını artırarak üst gelir grubunu desteklerken, bireysel kredi kartlarının etkisi ise ters yöndedir. Kredi kartı kullanımının normal dönemde de istatistiksel olarak anlamlı biçimde fakat ters yönde üst gelir grubunu desteklemesi, enflasyon şokunun ilişkiyi değiştirdiğine işaret etmektedir. Bu bulgular, enflasyonla mücadelede kullanılan politikaların gelir dağılımı üzerindeki olumsuz etkilerinin seçici kredi teşvikleri yoluyla azaltılabileceğini göstermektedir. Düşük gelir grubunun bireysel kredi kartı gibi kısa vadeli borçlanma araçlarına erişiminin artırılması, alım güçlerini korumalarına katkı sağlayabilirken; tüzel kredi genişlemesinin seçili alanlara yönlendirilmesi, gelir dağılımı üzerindeki bozucu etkilerin sınırlandırılmasına yardımcı olabilir. Ayrıca, çalışmanın ilk aşamasında elde edilen bölgesel heterojenlik bulguları, politika tasarım süreçlerinde bölgesel farklılıkların dikkate alınmasının önemini ortaya koymaktadır.

1. INTRODUCTION

Inflation, which reduces the purchasing power of money and the real value of savings and decreases quality of life due to rising costs, leads to numerous economic and social problems and has been a significant concern for economic policymakers throughout history. On the other hand, it should not be overlooked that inflation has a distributional effect. This is because inflation does not affect all segments of society equally, as income sources differ. While the income of the low-income group consists of wages and government transfers, the high-income group earns profits in addition to wages by investing savings. Thus, when wages and transfers are not adjusted for inflation, low-income groups experience greater inflationary pressure. In addition, although the expectation that prices of goods and services will be higher in the future and that the burden of loan repayments will decrease over time pushes households and firms to increase their consumption and investment through borrowing during inflationary periods, low-income groups also face obstacles in accessing financial markets. Banks' requirements for income documentation, guarantees, pledges, mortgages, and letters of guarantee in loan applications constitute examples of these obstacles. This situation favors the upper-income group and further deteriorates income distribution. On the other hand, the fact that lenders are mostly high-income individuals and that the real value of debts erodes during inflationary periods redistributes wealth in favor of the lower-income group. In short, the effect of inflation on income inequality differs through the borrowing channel. Furthermore, although many studies in the theoretical and empirical literature examine this borrowing effect, different results are obtained due to regional heterogeneity. Therefore, studies need to consider the distinct characteristics of different regions and how these may affect the results.

The Covid-19 pandemic, with its lockdowns and travel restrictions, affected the workforce, production, and consumption in global economies, disrupted supply chains, and led to economic contractions in most countries. Governments sought to restore economic activity through low-interest-rate policies and credit support. Even though a similar pattern also emerged in Türkiye, negative real interest rates led to a rapid increase in inflation after 2020. Although inflation decreased somewhat by 2023 due to changes in monetary and fiscal policies, it has not returned to its 2020 level. Türkiye's inflation rates after 2014 are shown in Figure 1.1. Figures 1.2 and 1.3 respectively show the increase in income inequality and credit usage during the same period. The Gini coefficient, which had been fluctuating between 0.39 and 0.4 for an extended period, initially fell after the inflationary shock in 2020, but then, unlike previous years, it surpassed 0.4 and has continued its upward trend in 2022-2023. Total loans, whose annual growth rate did not exceed 25% between 2014 and 2019, grew by 33% and 36% in 2020 and 2021, respectively, and reached an annual growth rate of 55% in the last two years. Moreover, due to cultural, demographic, and economic differences among Türkiye's regions, credit usage habits and income inequality vary. While institutional loans are dominant across Türkiye, consumer credit usage is more prevalent in some regions. Regional differences exist even within consumer loan types. Differences in income inequality indicators, namely the Gini coefficient and the P80/P20 ratio, can be seen in Figures 2.1 and 2.2, respectively, in the second part, while differences in regional credit usage can be observed in Figures 2.3–2.8.

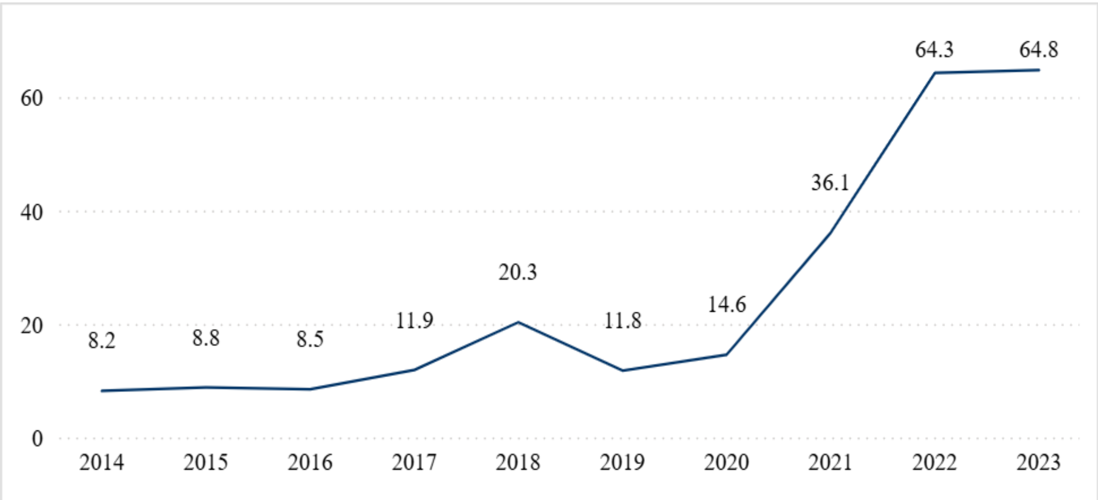

Figure 1.1 : Consumer Price Index.

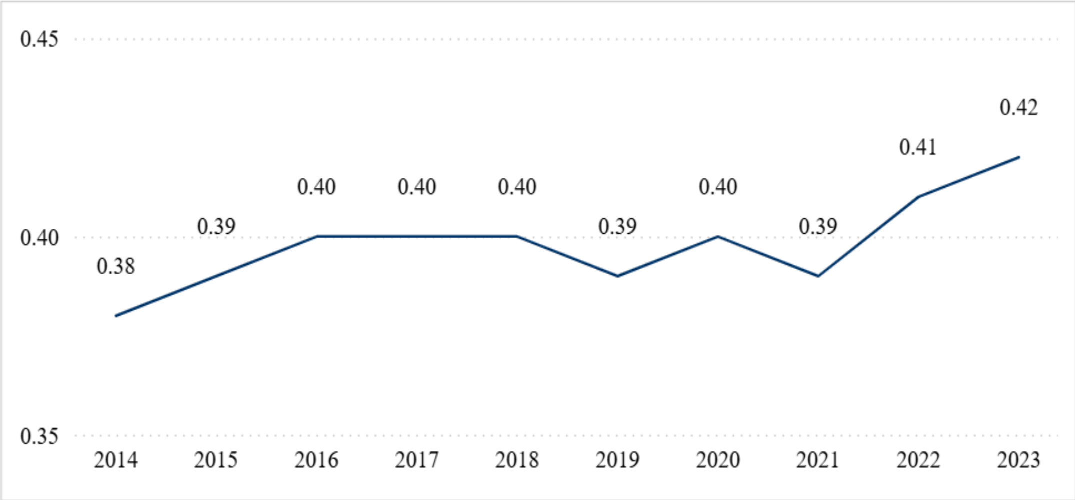

Figure 1.2 : Gini Coefficient.

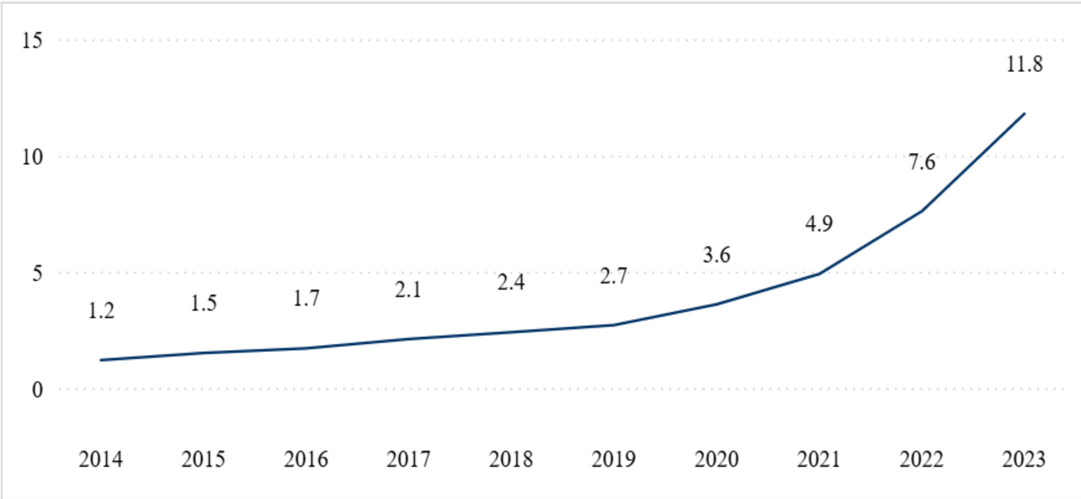

Figure 1.3 : Total Credits (Trillion TL).

This study analyzes whether the impact of inflation on income inequality varies across regional borrowing levels, using macroeconomic and financial indicators, as well as social welfare and distribution indicators, for 26 NUTS-2 regions in Türkiye between 2014 and 2023. The research question examines whether borrowing during inflationary periods improves or worsens income distribution. The study consists of two methodological parts. In the first part, I tested for regional differences in the impact of inflation on income inequality using a heterogeneous-effects pooled OLS method. In the second part, I constructed static models using panel fixed- effects and dynamic models using the system GMM method to compare the impact of bank-sourced borrowing on income inequality in the normal and post-inflation shock periods.

Based on the models applied in both parts of the study, I concluded that the impact of inflation on income inequality varies regionally, and that the use of different types of credit during normal and inflationary periods affects income inequality by increasing/decreasing the shares of different income groups. Overall, I found that the use of corporate and personal financing loans worsened income inequality in the post-shock period by reducing the share of the middle-income group and increasing the share of the upper-income group. On the other hand, it is important to note that the use of individual credit cards, which normally supports the upper-income group and worsens income distribution, transformed into a tool to correct income inequality in the post-shock period. Furthermore, the results of dynamic models estimated with System GMM are more comprehensive than those from the panel fixed-effects method, suggesting that the impact of a highly persistent variable such as income inequality can be better understood through dynamic models.

While there are studies in Türkiye that address the relationships between inflation and income inequality and between financial development and income inequality in general, studies that analyze credit types separately across NUTS-2 regions are very limited. This study is unique because it takes regional differences into account, focuses on a problem that remains relevant for Türkiye, and uses a different methodology (a comparative analysis using pooled OLS, panel fixed-effects, and system GMM methods) compared to studies in the literature. In this respect, the findings of this study may assist economic policymakers in implementing selective credit policies that consider regional differences and ensure a more equitable income distribution in the fight against inflation.

2. REGIONAL DIFFERENCES IN INEQUALITY AND LOAN USAGE

When examining the impact of bank-sourced borrowing on income inequality in inflationary periods, particularly in Türkiye, it is crucial to consider regional heterogeneity in economic structures, income distribution, and borrowing patterns. Western and coastal regions often differ from eastern and inland regions in terms of income and credit characteristics. Since inflation, one of the main variables of this study, is not available at the provincial or regional level, this section focuses on regional income inequality levels and borrowing habits to document regional differences.

Figures 2.1 and 2.2 show the P80/P20 ratio and the Gini coefficient at the NUTS-2 level in Türkiye. The figures are constructed using the quantile classification method based on frequency distribution. While many regions fall into similar categories under both indicators, some display different relative positions, reflecting that the P80/P20 ratio and the Gini coefficient capture different dimensions of inequality. For example, TR81 (Zonguldak, Karabük, Bartın) falls into a higher Gini bracket, whereas neighboring TR82 (Kastamonu, Çankırı, Sinop) records a higher P80/P20 ratio.

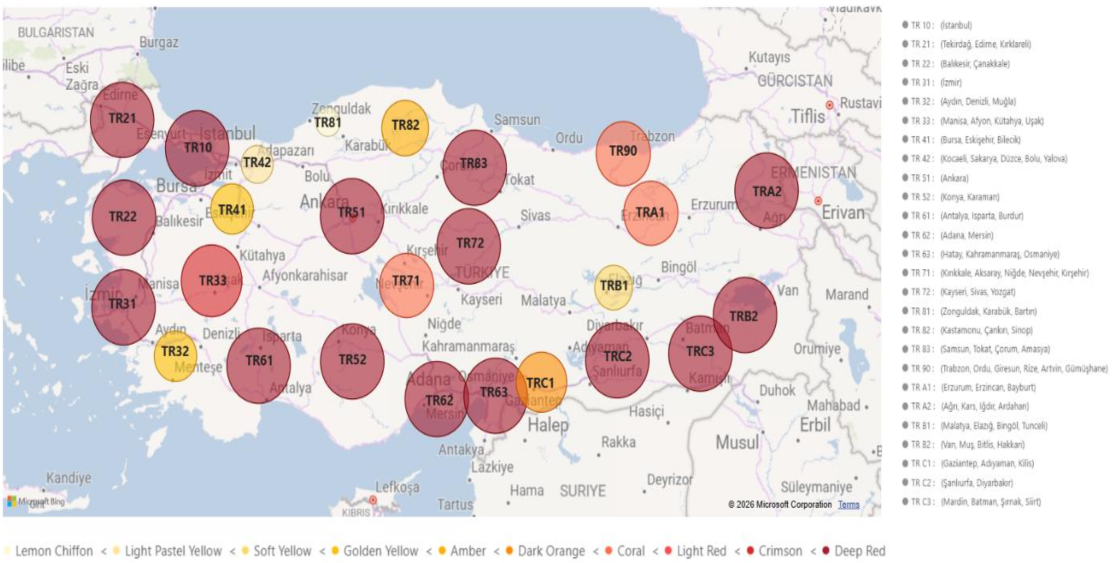

Figure 2.1 : Gini Coefficient by Region.

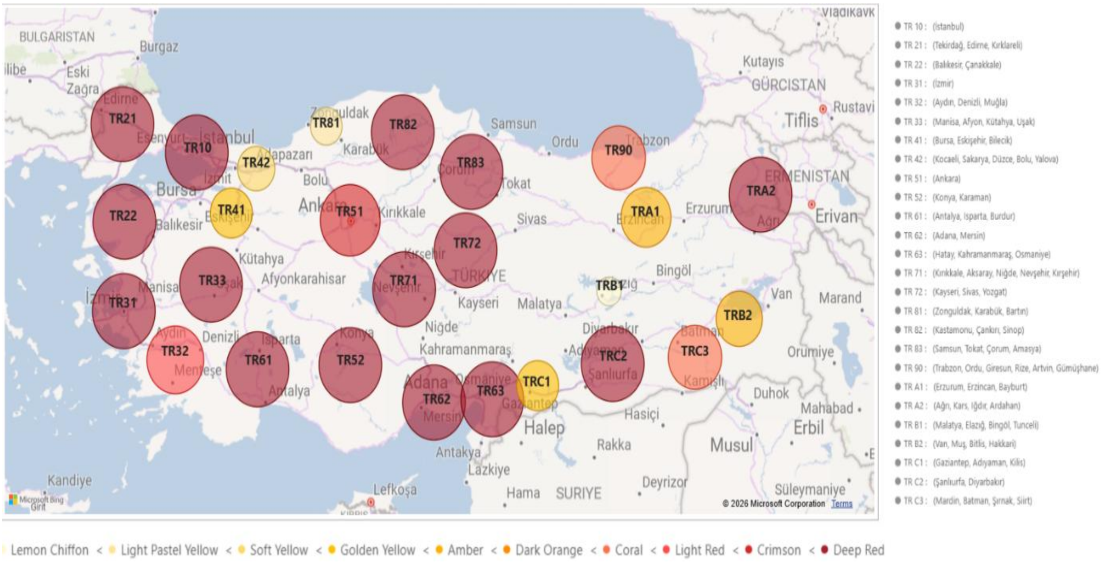

Figure 2.2 : P80/P20 Ratio by Region.

Borrowing patterns and habits also vary regionally in Türkiye. Although institutional loans constitute the majority of total loans in Türkiye (77% as of the end of 2023), personal loans are relatively more prevalent in some regions. Figure 2.3 shows personal credits and individual credit cards, and Figure 2.4 presents institutional loans regionally using the quantile classification method. A pattern broadly similar to that observed in income distribution indicators appears in these figures. In most coastal regions of Türkiye, such as TR31 (İzmir), TR32 (Aydın, Denizli, Muğla), TR61 (Antalya, Isparta, Burdur), TR62 (Adana, Mersin), TR63 (Hatay, Kahramanmaraş, Osmaniye), and TR90 (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane), both institutional and consumer loans have higher shares in GDP compared to many inland regions. In some regions, however, institutional loan ratios are relatively low while consumer loan intensity is high, or vice versa. For example, the TR10 region, which includes İstanbul, ranks highest in the ratio of institutional loans to GDP, while it ranks in the middle in the ratio of consumer loans to GDP.

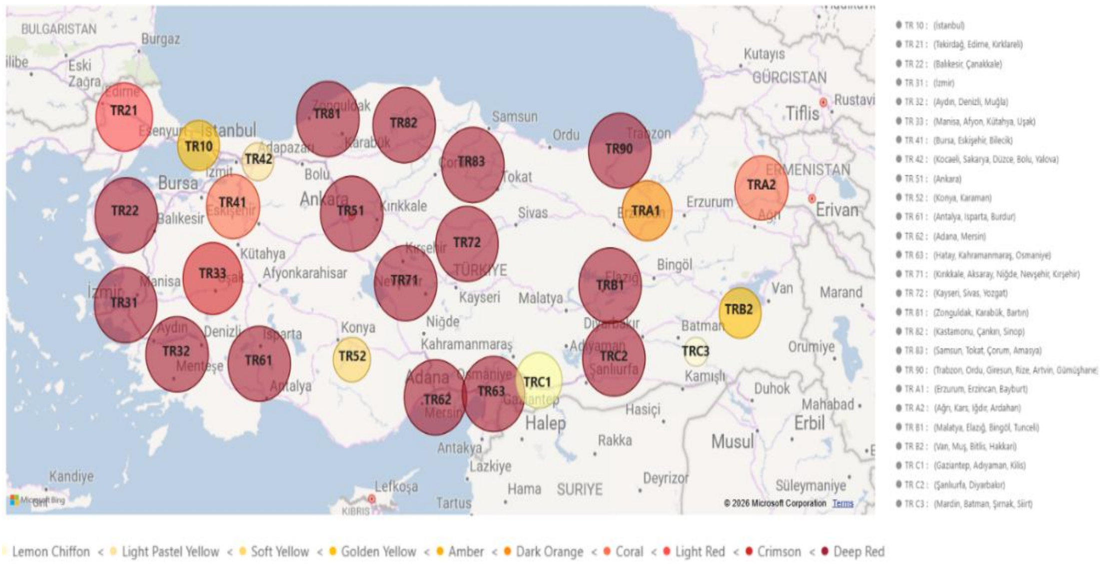

Figure 2.3 : Personal Credits and Consumer Credit Cards in GDP by Region.

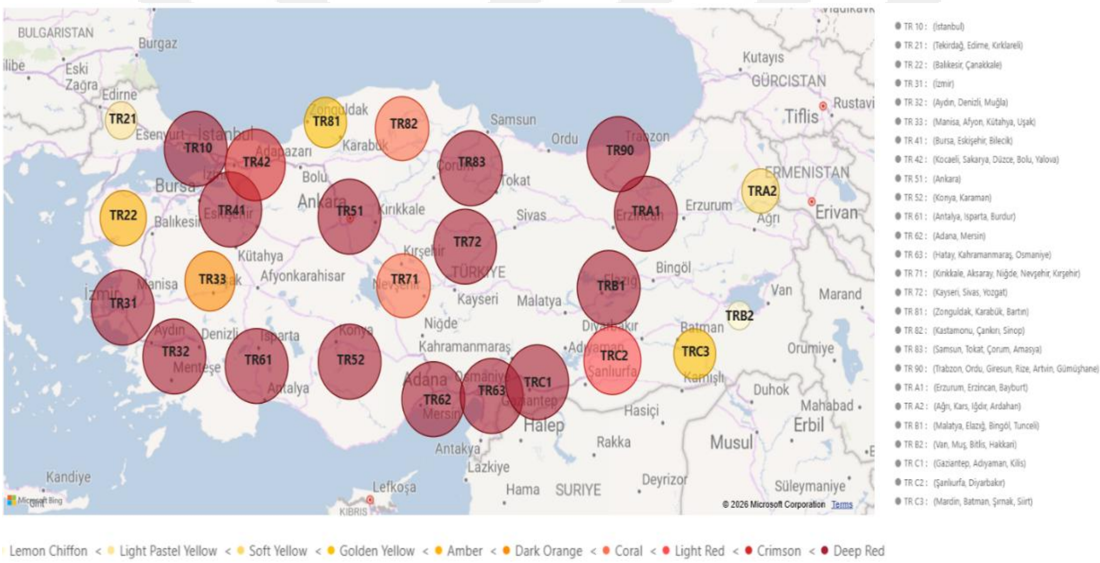

Figure 2.4 : Institutional Credits in GDP by Region.

The shares of housing loans, vehicle loans, personal financing loans, and personal credit cards — subcomponents of total consumer loans and individual credit cards — in GDP also vary regionally. Figure 2.5, which shows the share of housing loans in GDP, reveals that TR90 (Eastern Black Sea), TRA1 and TRA2 (Northeastern Anatolia), and TRB1 and TRB2 (Middle East Anatolia) have lower ratios compared to many western regions. Despite being part of the Southeastern Anatolia Region, TRC3 has the lowest ratio, in contrast to TRC1 and TRC2 within the same area. Figure 2.6, which presents the share of vehicle loans in GDP, shows that the Central Anatolia Region (TR71 and TR72) falls entirely into the low category, while low ratios are also observed in the eastern part of the Marmara Region, the western part of the Black Sea Region, and particularly in TR52 (Konya, Karaman).

Figures 2.7 and 2.8 illustrate the share of personal financing loans and personal credit card usage, respectively. In personal financing loans, TR10 (İstanbul), TR41, and TR42 (Eastern Marmara), as well as the Southeastern Anatolia Region (TRC1, TRC2, TRC3), exhibit relatively higher ratios. In personal credit card usage, similar to housing loans, many eastern regions, as well as parts of Eastern and Western Marmara and TR33 (Manisa, Afyon, Kütahya, Uşak), are positioned at the lower end of the distribution.

Overall, there is considerable geographical variation in the shares of different types of credit in GDP as well as in income inequality measures. While significant intra-regional differences persist, western and coastal regions often exhibit higher credit-to-GDP ratios and, in many cases, higher inequality indicators than eastern and inland regions. These patterns suggest that geographical heterogeneity is substantial and should be explicitly taken into account in the empirical analysis.

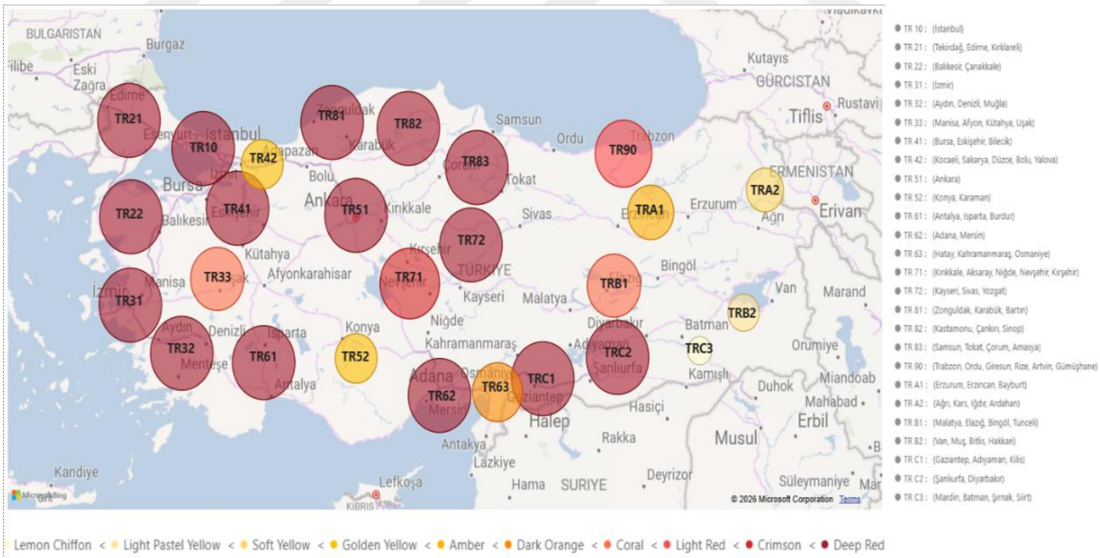

Figure 2.5 : Morgage Credits in GDP by Region.

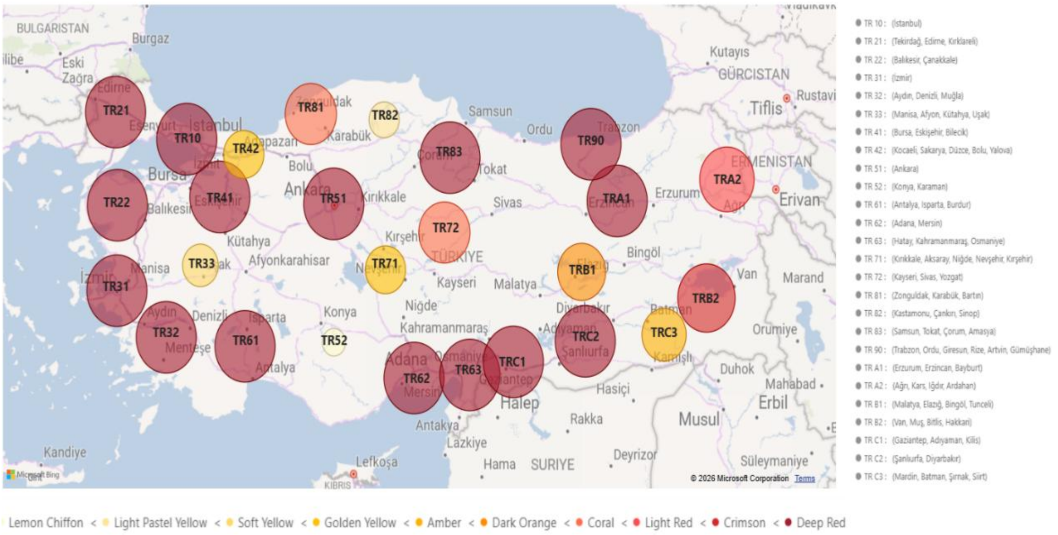

Figure 2.6 : Vehicle Credits in GDP by Region

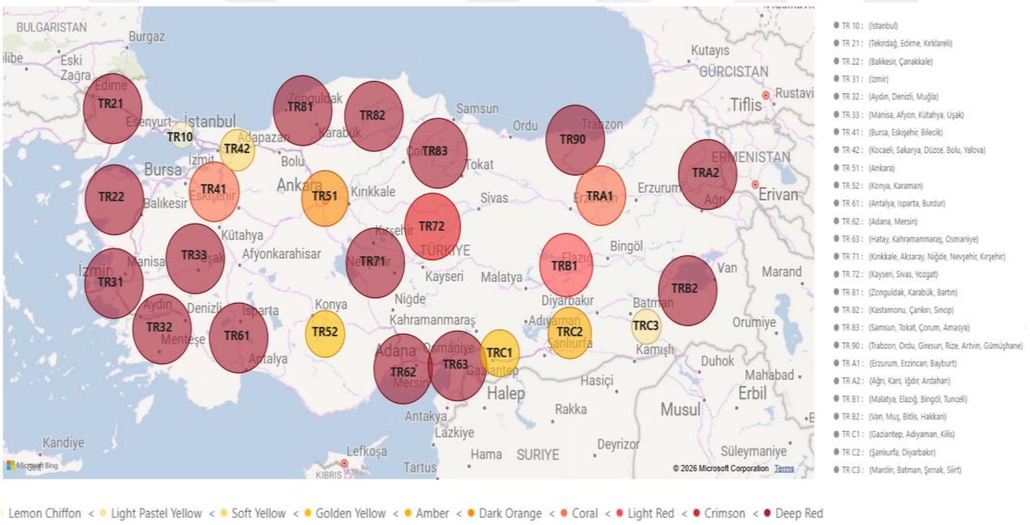

Figure 2.7 : Personal Financing Credits in GDP by Region.

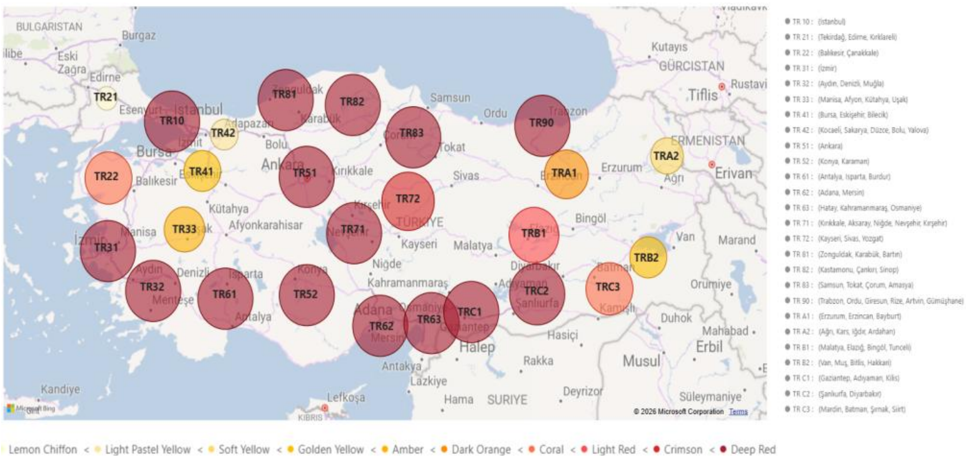

Figure 2.8 : Consumer Credit Cards in GDP by Region.

3. LITERATURE REVIEW

Income inequality has been an issue that governments have historically struggled to address because its impact is not limited to the economy but also extends to social life. As with any problem, solving income inequality requires first identifying the factors that give rise to it. Therefore, numerous empirical and theoretical studies in the academic literature address the causes and impacts of income inequality. While some examine factors such as economic growth, international trade, and technological advancements as contributing factors to income inequality, studies examining the impact of inflation on income inequality warrant particular attention because inflation, the independent variable, is one of the most frequently confronted macroeconomic challenges faced by governments. However, because earlier studies generally focus on the impact of growth, studies on the impact of inflation on income inequality have been relatively recent. This is also partly due to the fact that academic studies on income inequality began in the 1970s (Girişken, 2025). Furthermore, the varied conclusions across theoretical and empirical studies demonstrate that the relationship between these two indicators is multifaceted and complex.

3.1 Theoretical Literature

In economic theory, multiple hypotheses exist regarding the impact of inflation and financial development on income inequality. The differing conclusions reached by these hypotheses reflect the multidimensional and complex nature of these relationships. This divergence stems from differences in countries' economic dynamics and institutional structures, as well as from the distinct mechanisms emphasized by each theoretical framework. Furthermore, the impact of inflation on income inequality may vary depending on the anti-inflationary policies implemented by governments. Therefore, the existence of differing theoretical conclusions is not surprising.

The distribution of income within an economy not only influences individuals’ access to financial markets but also shapes their responses to monetary policy. In economies where a large share of households are hand-to-mouth, the transmission of monetary policy may be weaker. For instance, Akarsu, Aktuğ, and Küçükbayrak (2025) show that hand-to-mouth households constitute a significant share of the population in Türkiye and exhibit limited responsiveness to monetary policy changes.

Individuals respond differently to inflation depending on their income groups and sources of income. While low-income earners generally rely on wages and government transfers, high-income earners can also generate income from capital. Income inequality increases when profit margins remain unaffected while wages are not adjusted to inflation, leading to a decline in real wages (Fischer and Modigliani, 1978). Furthermore, high-income earners have easier access to financial markets and can protect their income against inflation, while low-income earners face barriers to entry. For example, banks require different kinds of collateral such as proof of income, property, sureties, or letters of guarantee from borrowers. This difference in protection against inflation is another factor that exacerbates income inequality (Siami-Namini and Hudson, 2015). Furthermore, the failure of government transfer spending to adjust for inflation negatively impacts low-income earners and exacerbates income inequality.

On the other hand, some argue that inflation erodes government debt and that governments use the real reduction in debt to increase transfer spending, thereby reducing income inequality (Jovanovic, 2014). However, the main basis for those who argue that inflation reduces income inequality is the debtor-creditor hypothesis. This hypothesis states that debt decreases in real terms during inflationary periods and assumes that savings, investments, and loans in the economy are generally not indexed to inflation (Meh and Terajima, 2009). In many economies, debtors generally come from lower-income groups, while lenders come from higher-income groups, and the real erosion of debt leads to a redistribution of income between the two (Park, 2015). A study conducted by the Central Bank of the Republic of Türkiye on inflation expectations and credit behavior in Türkiye found that when firms anticipate high inflation expectations in the medium term, they increase their credit use, anticipating lower future repayments, thereby providing empirical support for the debtor-creditor hypothesis (Akgündüz, Çolak, Özbekler & Yılmaz, 2025).

Another approach, based on the unemployment-inflation relationship, argues that unemployment leads to income inequality. This approach relies on the Phillips Curve, which illustrates the negative relationship between inflation and unemployment in economic theory. It argues that policies that reduce inflation lead to increased unemployment and worsening income inequality in the short run. In the long run, however, a new equilibrium is reached, and income inequality begins to decline. Thus, a non-linear relationship between inflation and income inequality emerges (Siami-Namini and Hudson, 2015).

Begg et al. (2014) argue that societies often confuse nominal and real variables, and that while the purchasing power of money may decline, incomes actually increase, allowing access to the same goods and services. Many individuals fail to recognize that their incomes are also increasing and suffer from inflation illusion. Likewise, some people confuse relative price increases with increases in the general price level, leading to incorrect conclusions about the relationship between inflation and income inequality (Baumol and Blinder, 2010). These two hypotheses suggest that there is no, or only a minimal, relationship between inflation and income inequality.

There is also theoretical literature suggesting that income inequality may cause inflation. In an environment of income inequality, wealthy political groups that benefit from inflation may support expansionary policies that generate higher inflation. Furthermore, people support politicians who promise to improve their incomes, and these politicians, in turn, can drive inflation higher through populist policies to gain electoral support.

There are also different hypotheses regarding the relationship between financial development and income inequality. Greenwood and Jovanovic (1990) adapted the Kuznets Curve, originally proposed by Simon Kuznets in 1955 to illustrate the relationship between economic growth and income inequality, to the field of finance and introduced the Financial Kuznets Curve. This hypothesis proposes an inverted-U-shaped relationship between financial development and income inequality and suggests that although low-income groups may face barriers to entry into financial markets, these barriers will disappear with the development of financial markets, initially increasing income inequality but decreasing it over time.

Galor and Zeira (1993) categorized workers into skilled and unskilled, noting that unskilled workers face difficulties accessing credit due to barriers to entry into financial markets. Over time, as a result of financial market development, these barriers will diminish, and unskilled workers will be able to use credit to invest in areas of personal development and become skilled workers. This will enable them to move into higher-income segments and reduce income inequality.

Conversely, some studies argue that financial development increases income inequality. They suggest that financial resources are largely available to upper-income groups, such as large corporations and investors, and that increased financial development also largely benefits this segment, thereby increasing income inequality (Rajan & Zingales, 2003).

3.2 Empirical Literature

Consistent with the theoretical literature, empirical studies also produce divergent findings. An examination of the existing literature reveals that the results can be divided into five groups: those that find a positive relationship between inflation and income inequality, those that find a negative relationship, those that argue for a non-linear (U-shaped or inverted U-shaped) relationship, those that find no significant relationship, and those that identify a bidirectional effect between income inequality and inflation.

Thalassinos, Uğurlu, and Muratoğlu (2012) used data from 2000 to 2009 for 13 countries that joined the European Union before 2000 (excluding Luxembourg and Ireland) to examine the relationship between income inequality and inflation in these countries. They used inflation rate, trade openness, employment rate, and GDP growth rate as independent variables, with the GINI coefficient as the dependent variable. Using a fixed-effects panel data model, they concluded that there is a positive relationship between inflation and income inequality. Maurer and Yesin (2004) used the Three-Stage Least Squares (3SLS) method and data from 1980-2000 for 48 countries with different characteristics and concluded that rising inflation rates lead to increased income inequality. Khattak et al. (2014) focused on Pakistan and conducted the Johansen Cointegration Test and the Augmented Dickey–Fuller Unit Root Test using Gini coefficient, GDP, and inflation data for the period 1980–2002. The study concluded that there is a long-term positive relationship between inflation and income inequality. The authors recommend that the Pakistani government control inflation to reduce income inequality.

On the other hand, some studies, on the contrary, find a negative relationship. Emek (2020) conducted a study using fixed- and random-effects models with data from 17 developed and 18 developing countries for the period 1991-2015 and concluded that inflation redistributes income in favor of low-income individuals in both developed and developing countries. These findings suggest that inflation is negatively related to income inequality. Likewise, Gülmez and Altıntaş (2015) examined the effects of inflation and trade openness on income distribution using data from Türkiye for the period 1981-2011. They applied the Vector Error Correction Model (VECM) and the Johansen Cointegration Test. Impulse-response analysis and variance decomposition analysis indicate that inflation reduces income inequality.

The third group of studies supports the nonlinearity of the relationship between inflation and income inequality. For example, Nantob (2015) conducted panel data analysis using Pooled OLS, Fixed Effects, Random Effects, and GMM models, using data from 46 developing countries for the period 2000-2012. The study concluded that there is an "inverted U"-shaped relationship between inflation and income inequality. While income inequality initially increases as inflation begins to rise, it declines after a certain level. Another study investigating the impact of monetary policy and inflation on income inequality used data from the United States for the period 1967-1999 and 15 OECD countries for the period 1973-1996. The common characteristic of the countries used in the study is that they have low inflation rates. The study found a long-term "U-shaped" relationship between inflation and income inequality (Galli & Hoeven, 2001).

A separate strand of the literature indicates that there is no relationship between the two economic indicators. For example, Yue (2011) examined the relationship between inflation, income distribution, and economic growth in Korea between 1980 and 2002 using OLS and Error-Correction Models and concluded that there is no relationship between income inequality and inflation. Similarly, Dilber and Hatipoğlu (2022) applied the Dumitrescu-Hurlin Panel Causality Test to data from eight developing OECD countries between 2007 and 2019, found no relationship between income inequality and inflation, nor between inflation and income inequality.

A different line of research on inflation and income inequality finds bidirectional causality between the two indicators. Younsi and Bechtini (2018) investigated the relationship between economic growth, financial development, and income inequality in the BRICS countries for the period 1995-2015 using the Pedroni Panel Cointegration Test and the Kao Residual Panel Cointegration Test. Inflation is one of the independent variables in their model. The study concluded that there is a bidirectional causal relationship between inflation and income inequality. Consistent with these findings, Kara (2025) examined the relationship between inflation, income inequality, and economic growth in Türkiye using the Hatemi-J Asymmetric Causality Test for the period 1987-2023, and found a bidirectional causal relationship between inflation and income inequality.

The role of various factors in shaping the relationship between household income distribution and inflation has also been analyzed in the literature. Yoshino (1993) examined the relationship between household income distribution and macroeconomic indicators in Japan between 1963 and 1999, dividing inflation into expected and unexpected components. The study concluded that both expected and unexpected inflation increased income inequality. Li and Zou (2002), on the other hand, applied OLS regression analysis to data from 1949 to 1994 for 77 developed and developing countries to investigate the impact of inflation on income distribution and economic growth, separately examining its effects across income groups. They concluded that inflation had a negative impact on lower-income groups and a positive impact on upper-income groups. Similarly, Berisha, Dubey, and Gharehgozli (2023) examined whether the effect of inflation on income inequality in US states between 1990 and 2017 varied across different levels of income inequality using a Panel Quantile Regression Model with Fixed Effects and found that the negative effect of inflation on income inequality intensified as income inequality levels increased. In another study, Walsh and Yu (2012) examined the effects of food-related and non-food-related inflation on income inequality using data from Indian states for 1990-2004, Chinese states for 1994-2006, and various countries for the same period. Using OLS, FE, RE, and GMM methods and models, the study found that non-food inflation exacerbated income inequality, whereas the effect of food inflation varied across country groups.

In the literature, institutional and political factors have also been emphasized. Beetsma and Van Der Ploeg (1996) analyzed 66 countries using data from 1960 to 1980, dividing them into democratic and non-democratic. They concluded that there was a positive relationship between income inequality and inflation in democratic countries, but none in non-democratic countries. It is important to note that, unlike the previously mentioned studies, which examine the impact of inflation on income inequality, this study concluded that the direction of causality runs from income inequality to inflation.

Chen, Huang, and Ku (2015) used an endogenous switching regression model and data from 12 developed and 45 developing countries for the period 1980 to 2010 to examine whether inflation targeting would affect the relationship between inflation, income inequality, and openness to trade. They concluded that high inflation leads to higher income inequality in both inflation-targeting and non-inflation-targeting countries and that this effect is greater in inflation-targeting countries. Central bank independence is another factor whose role in the relationship between inflation and income inequality has been emphasized. A study by Fawaz and Rahnamamoghadam (2024) provides a representative example. Using data from more than one hundred developed and developing countries between 1970 and 2020, the study examined the effects of certain variables, referred to as potential growth determinants in the economic growth literature, on income inequality. The authors categorized countries by democratic status, income group, and central bank independence. Using a fixed-effects model in a dynamic panel framework, they concluded that there was a negative relationship between inflation and income inequality in countries with central bank independence, while this relationship was positive in countries without central bank independence.

The literature also includes studies that examine the relationship between debt and income inequality from different perspectives. Wood (2020) examined whether debt causes income inequality, noting the significant impact of individual debt on the financialization of the British economy. Using British data from 1966 to 2016 and applying an Error Correction Model, the study found that household debt increases the proportion in the upper income distribution and further widens the gap between the middle and high income classes. Similarly, Berisha, Meszaros, and Olson (2018) examined the relationship between the stock market, interest rates, household debt, and income inequality in the United States covering the period 1919 to 2019 and using the structural VAR model with Generalized Variance Decomposition and Generalized Impulse Response methods. The results of the applied models and methods indicated that household debt increases income inequality. Unlike previous studies, Jestl (2023) investigated the impact of income inequality on household debt using data from 13 European countries from 2010. While the study identified a positive relationship in some European countries, the overall correlation between income inequality and indebtedness was weak. Toplu (2025) similarly studied the impact of income inequality on household debt. Using instrumental variables (IV) methodology with data from 21 developed countries between 1970 and 2021, the author found a significant, positively correlated relationship between the aforementioned variables.

The literature can also be divided into studies focusing on the relationship between financial development and income inequality. As with the relationship between inflation and income inequality, the literature on financial development and income inequality also presents different classifications based on varying empirical findings. Destek, Okumuş, and Manga (2017) examined the relationship between income distribution and financial development in Türkiye using the ARDL bounds test and the VECM Granger Causality Method with data from 1977 to 2013. They used the share of domestic private-sector loans in GDP as an indicator of financial development. Inflation was another independent variable in the study. The study found an inverted-U-shaped relationship between financial development and income inequality and concluded that higher inflation increases income inequality. The study's causality test found bidirectional causality between inflation and income distribution. Consistent with these findings, Nikoloski (2013) found an inverted-U-shaped relationship between financial development and income inequality using multivariate dynamic panel data analysis on a sample of 77 developed and developing countries covering the period 1962–2006. The study measured financial development by the share of credit provided by financial intermediaries to the private sector as a percentage of GDP. Although both the number of developed and developing countries used (78) and the year range (1960-2006) were similar, Kappel (2010) used standard OLS and 2SLS methods and found a negative relationship between financial development and income inequality. Furthermore, unlike previous studies, the study included more than one indicator as a financial development indicator. One of these indicators is the ratio of private credit to GDP. Similarly, Younsi and Bechtini (2018) found a negative relationship between financial development and income inequality using data from the BRICS countries for the period 1995–2015. They employed the Pedroni and Kao panel cointegration tests, the fixed-effects estimation method, the Granger causality test, pooled OLS (POLS), and GMM estimation techniques. As in Kappel's study, the study used multiple financial development indicators. Among these indicators, the ratio of domestic credit to the private sector and the banking sector's ratio of domestic credit to GDP are related to financial debt. In contrast, some studies have found a positive relationship. One such study, Jautch and Watzka (2016), focusing on the relationship between financial development and income inequality using 138 developed and developing countries between 1960 and 2008, uses the ratio of private credit to GDP as an indicator, as does Kappel (2010). Another study, which similarly found a positive relationship, used data from 45 developing countries for the period 1987-2011 using dynamic system GMM models. Unlike previous studies, this study considered the banking sector's contribution to financial development not only through loans but also through five ratios, including deposits and liabilities (Seven and Coşkun, 2016).

This thesis differs from existing studies in terms of its methodology and the period covered by its dataset. Furthermore, unlike most studies in the literature, it examines both the direct effects of two variables and the indirect effect of a third variable. It is also valuable in highlighting potential regional differences by addressing regions within Türkiye. The results of the econometric study may provide guidance for households in their credit decisions and offer insights for policymakers by accounting for the possible effects of their actions on income distribution when employing the credit channel in a high-inflation environment.

4. DATA AND METHODOLOGY

4.1 Explanation of the Data

This study uses NUTS2-level data covering 26 regions of Türkiye and the period 2014-2023. The provinces covered by each NUTS-2 region are given in Table 3.1. I organized the provincially published data used in the study according to NUTS-2 regions and incorporated them into the dataset. To ensure that the study covers different dimensions of income inequality, the dependent variables are the Gini coefficient, the P80/P20 ratio, and the shares of the lowest 20%, the highest 20%, and the median 20% income groups. The data source for the dependent variables is TurkStat's Income Distribution Statistics database. Due to differences in scale between the P80/P20 ratio and the other dependent variables, I took the logarithm of the P80/P20 ratio and included it in the model.

In this study, the independent variables consist of the share of different credit groups and total deposits in GDP, and interaction terms formed by multiplying these shares by inflation rates. I used the Gross Domestic Product by Provinces dataset published by TurkStat for GDP, and the Banking Sector Data by Provinces (Fintürk) published by the BRSA (Banking Regulation and Supervision Agency) for loan and total deposit amounts by different groups. When classifying loans, I divided total loans into two categories: consumer loans (individual loans) and institutional loans. I also further divided consumer loans into four categories: housing loans, vehicle loans, personal financing, and individual credit cards. Although institutional loans include both SME and commercial/corporate loans, I did not include their subcategories in this study due to the lack of regional data. I included Consumer Price Index (CPI) data, also obtained from TurkStat and used as the inflation indicator, in the dataset by assigning the same value to each region, since, unlike other variables, it is not shared at the provincial level. In addition, I used population, economic growth, unemployment, the share of the foreign trade balance in GDP, and average years of schooling as control variables in the constructed models. I obtained the indicators other than unemployment from TurkStat's Address-Based Population Registration System Results, Gross Domestic

Product by Provinces, Foreign Trade Statistics, and National Education Statistics databases, respectively. Because the average years of schooling, one of the control variables, is published at the provincial level, I included it in the model by taking a weighted average based on each province's population, while organizing the data by NUTS-2 regions. Due to the suspension of the Provincial Labor Force Statistics publication by TurkStat between 2013 and 2022, I used the number of registered unemployed individuals reported in İŞKUR's Statistical Yearbooks and Labor Market Research Reports as the unemployment indicator.[1] Because the control variables population and unemployment are measured at different scales compared to the other variables in the model, I included their logarithms in the model to mitigate the impact of scale differences. Summary statistics of the variables used in the model are presented in Table 3.2.

Table 4.1 : NUTS-2 Regions of Türkiye.

TR10	İstanbul
TR21	Tekirdağ, Edirne, Kırklareli
TR22	Balıkesir, Çanakkale
TR31	İzmir
TR32	Aydın, Denizli, Muğla
TR33	Manisa, Afyon, Kütahya, Uşak
TR41	Bursa, Eskişehir, Bilecik
TR42	Kocaeli, Sakarya, Düzce, Bolu, Yalova
TR51	Ankara
TR52	Konya, Karaman
TR61	Antalya, Isparta, Burdur
TR62	Adana, Mersin
TR63	Hatay, Kahramanmaraş, Osmaniye
TR71	Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir
TR72	Kayseri, Sivas, Yozgat

[1] While both are indicators of unemployment, İŞKUR's definition of the registered unemployed and TurkStat's definition of the unemployed differ. According to TurkStat, an individual must have applied within the last 4 weeks and be able to start work within 2 weeks to be considered unemployed. On the other hand, according to İŞKUR, an individual must have applied within the last 12 months and for whom İŞKUR has not yet found employment. Although the period mentioned in İŞKUR's definition is longer, TurkStat also considers applications submitted not only to İŞKUR but also to other job search channels.

Table 4.1 : NUTS-2 Regions of Türkiye. (Continued)

TR81	Zonguldak, Karabük, Bartın
TR82	Kastamonu, Çankırı, Sinop
TR83	Samsun, Tokat, Çorum, Amasya
TR90	Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane
TRA1	Erzurum, Erzincan, Bayburt
TRA2	Ağrı, Kars, Iğdır, Ardahan
TRB1	Malatya, Elazığ, Bingöl, Tunceli
TRB2	Van, Muş, Bitlis, Hakkari
TRC1	Gaziantep, Adıyaman, Kilis
TRC2	Şanlıurfa, Diyarbakır
TRC3	Mardin, Batman, Şırnak, Siirt

Table 4.2 : Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
P80/P20 Ratio	259	6.581	.903	4.33	9.428
Gini Coefficient	259	.358	.033	.281	.451
Bottom 20% Share	259	.074	.008	.058	.094
Middle 20% Share	259	.157	.009	.132	.177
Top 20% Share	259	.436	.028	.37	.524
Inflation	260	24.929	21.343	8.17	64.77
Total Credits in GDP	260	49.5	16.753	24.088	109.565
Vehicle Credits in GDP	260	.233	.084	.086	.455
Mortgage Credits in GDP	260	4.391	1.655	.884	8.301
Personal Financing Credits in GDP	260	6.81	1.834	2.935	12.427
Credit Cards in GDP	260	3.17	.844	1.886	7.22
Institutional Credits in GDP	260	34.896	15.884	13.391	94.721
Total Deposit in GDP	260	25.484	9.31	8.568	56.653
GDP Growth	260	33.528	31.61	-8.75	134.736
Foreign Trade Balance in GDP	260	.087	1.723	-8.718	5.416
Year of Schooling	260	24.842	9.193	8.395	47.029
Log of Population	260	6.41	.261	5.879	7.202
Log of Unemployment	260	4.972	.249	4.307	5.773

Due to the February 6 earthquake, which occurred in Türkiye in 2023 and was called the "Disaster of the Century", the Income and Living Conditions Survey could not be conducted in the TR63 (Hatay, Kahramanmaraş, Osmaniye) region, causing one observation missing from the dependent variables used in the model.

4.2 Methodology

This section will introduce the methods and models used in the study. Since the aim of the study is to investigate whether regional bank-based borrowing affects the impact of inflation on income inequality in Türkiye, I first examined whether the impact of inflation on income inequality varies across regions. For this purpose, I created dummy variables initially for each NUTS-2 region. Then, I multiplied these dummy variables by inflation rates to form interaction terms. Using the heterogeneous-effect pooled OLS method, I conducted an analysis. The model used in the analysis is as follows:

$$Y_{it} = \sum_{k=1}^{K} \beta_k \left(INF_t \times NUTS2Dummy_{k,i}\right) + X'_{it}\delta + \gamma_t + \varepsilon_{it} \qquad (4.2.1)$$

In the model above, $\mathbf{X_{it}}$ is the vector of control variables consisting of economic growth, log of population, log of unemployment, the share of the foreign trade balance in GDP, and average years of schooling; and $\boldsymbol{\delta}$ is the vector of coefficients belonging to these variables. In addition, γ_t represents the year fixed effects while ε_{it} represents the error term. To avoid perfect multicollinearity, I did not include inflation, a variable that does not change by region and is measured countrywide, in the model individually because of the presence of the variable γ_t. To examine the effect of inflation on regional income inequality in greater depth, I replaced the generic dependent variable Y_{it}, with alternative measures of income inequality, namely $GINI_{it}$, $\mathrm{P80/P20}_{it}$, $FsQuantile_{it}$, $TQuantile_{it}$, and $FiQuantile_{it}$ and estimated separate models for each indicator. $FsQuantile_{it}$, $TQuantile_{it}$, and $FiQuantile_{it}$ indicate the share of the lowest 20% income group, the share of the median 20% income group, and the share of the upper income group, respectively. To avoid the dummy-variable trap, I used the TR10 (İstanbul) region as the reference category and did not include it in the model. For that reason, the symbol K used in the summation function, representing the number of regions, is 25. Furthermore, although year fixed effects were included in the model to control for cyclical macroeconomic changes, I examined them in the analysis but did not report them in the results tables because their interpretation did not serve the study's purpose. Furthermore, I used robust standard errors to obtain more reliable standard error estimates. In addition, I applied the Wald test, with the null hypothesis that all regional interaction terms are equal to zero, to determine whether there is a statistically significant difference between regions. When the results showed that the impact of inflation on income inequality varied by region, I proceeded to investigate the role of bank-based borrowing in this relationship.

In the second part, which specifically focuses on regional borrowing, to comparatively examine periods of high and low inflation, I created two dummy variables: pre-shock and post-shock, using the year variable, similar to the approach used in Card (1992). I defined 2020, the year in which inflation increased rapidly, as the reference year for the shock. Given that the inflation data in the main database do not vary by province and that each region has distinct characteristics, in the models in the second part, I first used fixed-effects panel-data models that incorporate interaction terms. To capture the impact of the inflation shock, I created interaction terms by multiplying loan and deposit shares in GDP with the post-shock dummy variable. Moreover, to assess the impact of bank credit uptake on income inequality not only after the inflation shock but also during normal periods, I also added the share of loan types and total deposits in regional GDP as independent variables to the model. Second, given that the variables in the specified models might be endogenous and persistent, I added one-period lags of the dependent and control variables to the panel fixed-effects models, and then constructed dynamic models using the system GMM method. By comparing the results obtained from both methods, I sought to determine which approach was more appropriate given the characteristics of the variables.

Although the GMM method includes lagged values in the models, in the second part of this study, I used 4 main models and 7 sub-models, each with various credit combinations. The reason for using sub-models is to identify the independent effects of each credit type and total deposits. In the first main model, as independent variables, I used the shares of consumer credit (housing, vehicle, personal financing loans, and personal credit cards), corporate credit, and total deposits in GDP, and interaction terms formed by multiplying these shares by inflation. I constructed main model 2 by excluding the total deposits variable from main model 1 to examine the effect of loans alone. Main model 3 only includes the consumer loan variables, excluding institutional loans. Main model 4 is more aggregated than the other main models, containing only variables related to total loans and total deposits. The main models established using the panel fixed-effects method are as follows:

$$Y_{it} = \beta_0 + \sum_{j \in \mathcal{C}_m} \beta_j S_{it}^{(j)} + \sum_{j \in \mathcal{C}_m} \theta_j \left(Post_t \times S_{it}^{(j)} \right) + X_{it}' \delta + \gamma_t + \alpha_i + \varepsilon_{it} \tag{4.2.2}$$

$$\begin{aligned} \mathcal{C}_1 = \{&ShareofDeposit, ShareofComcor, ShareofVehicle, \\ &ShareofMortgage, ShareofCCC, ShareofPersonal\} \end{aligned} \tag{4.2.3}$$

$$\begin{aligned} \mathcal{C}_2 = \{&ShareofComcor, ShareofVehicle, ShareofMortgage, \\ &ShareofCCC, ShareofPersonal\} \end{aligned} \tag{4.2.4}$$

$$\mathcal{C}_3 = \{ShareofVehicle, ShareofMortgage, ShareofCCC, ShareofPersonal\} \tag{4.2.5}$$

$$\mathcal{C}_4 = \{ShareofDeposit, ShareofTotal\} \tag{4.2.6}$$

$$\begin{aligned} \mathcal{C}_m = \{j\}, \quad j \in \{&ShareofTotal, ShareofMortgage, ShareofVehicle, \\ &ShareofPersonal, ShareofCCC, ShareofComcor, ShareofDeposit\} \end{aligned} \tag{4.2.7}$$

Models 5–11 are designed to examine the individual effects of total loans, mortgage loans, vehicle loans, personal financing loans, individual credit cards, institutional loans, and total deposits on selected income inequality measures.

In all 11 models mentioned above, I generated regional dummy variables, and, as in the previous study conducted with the pooled OLS method, I used the Gini coefficient, the P80/P20 ratio, and income percentiles instead of Y_{it} to examine whether the models yield consistent results across different income inequality indicators.

Furthermore, although I assumed that regions have time-invariant unobservable characteristics, I conducted tests to determine whether the fixed-effects or random-effects model was more appropriate and to identify the suitable standard error specification. The Baltagi-Li (1995) fixed-effects autocorrelation test and the Wooldridge random-effects autocorrelation test indicated that autocorrelation existed regardless of whether the fixed-effects or random-effects model was used, therefore, I employed clustered robust standard errors. Furthermore, because the Hausman test used to decide between fixed and random effects is based on homoscedastic variance-covariance matrices and cannot be used with robust standard errors, I used the Sargan-Hansen test, which indicated that a fixed-effects model was appropriate. Therefore, I estimated all the main and sub-models above using clustered robust standard errors and the fixed-effects model approach. The main and sub-models estimated using the system GMM method are presented below in the same order:

$$Y_{it} = \rho Y_{it-1} + \sum_{j\in\mathcal{C}_m} \beta_j S_{it}^{(j)} + \sum_{j\in\mathcal{C}_m} \theta_j \left(Post_t \times S_{it}^{(j)}\right) + X'_{it}\delta + X'_{it-1}\phi + \gamma_t + \alpha_i + \varepsilon_{it} \tag{4.2.8}$$

The dynamic models I constructed above using the GMM method include the one-period lagged values of both the dependent and control variables. The lagged coefficient, ρ, for the dependent variable indicates the degree of persistence in income inequality over time. In addition, to understand whether the models are working correctly, I checked whether the number of instruments in the models is reasonable compared to the number of cross-sectional units and also used two tests: the Arellano-Bond AR(2) test, which measures whether there is second-order autocorrelation, and the Hansen Test, which measures whether the instruments are valid. I report the test results below the Stata output tables.

5. RESULTS

5.1 Results on the Effect of Inflation on Regional Income Inequality

Tables 5.1 and 5.2 present the results of the models that I construct using the heterogeneous-effects pooled OLS method to test for regional differences. In Table 5.1, I use the Gini coefficient and the logarithm of the P80/P20 ratio as dependent variables, while in Table 5.2, I use different income quantiles. To avoid the dummy-variable trap, I exclude the interaction term between inflation and TR10 (İstanbul); therefore, when interpreting the table, comparisons should be made with the TR10 region. The values next to the independent variables represent the estimated coefficients, and I indicate their statistical significance with asterisks. The values in parentheses below the coefficients represent the corresponding standard errors.

Table 5.1 : Heterogeneous-Effects Pooled OLS Results – Regional Differences in the Impact of Inflation (Dependent Variables: Gini and P80/P20 Ratio).

	(1) Gini	(2) P80/P20
InflationxTR21	0.0000	0.0006
	(0.0003)	(0.0007)
InflationxTR22	0.0001	0.0010
	(0.0004)	(0.0007)
InflationxTR31	0.0001	0.0006
	(0.0003)	(0.0005)
InflationxTR32	-0.0008**	-0.0006
	(0.0003)	(0.0005)
InflationxTR33	-0.0009***	-0.0002
	(0.0003)	(0.0005)
InflationxTR41	-0.0011***	-0.0013**
	(0.0004)	(0.0006)
InflationxTR42	-0.0016***	-0.0023***
	(0.0003)	(0.0006)
InflationxTR51	0.0003	-0.0001
	(0.0003)	(0.0006)
InflationxTR52	0.0003	0.0014***
	(0.0003)	(0.0005)
InflationxTR61	-0.0001	0.0005
	(0.0003)	(0.0007)

Table 5.1 : Heterogeneous-Effects Pooled OLS Results – Regional Differences in the Impact of Inflation (Dependent Variables: Gini and P80/P20 Ratio). (Continued)

	(1) Gini	(2) P80/P20
InflationxTR62	0.0002	0.0006
	(0.0003)	(0.0006)
InflationxTR63	-0.0003	0.0001
	(0.0003)	(0.0006)
InflationxTR71	0.0003	0.0012**
	(0.0003)	(0.0006)
InflationxTR72	0.0000	0.0006
	(0.0003)	(0.0005)
InflationxTR81	-0.0011***	-0.0017**
	(0.0004)	(0.0007)
InflationxTR82	-0.0001	0.0006
	(0.0004)	(0.0007)
InflationxTR83	-0.0004	0.0002
	(0.0003)	(0.0005)
InflationxTR90	-0.0007*	-0.0005
	(0.0004)	(0.0006)
InflationxTRA1	0.0004	-0.0004
	(0.0003)	(0.0007)
InflationxTRA2	0.0006*	0.0012*
	(0.0003)	(0.0006)
InflationxTRB1	-0.0009**	-0.0023**
	(0.0004)	(0.0009)
InflationxTRB2	-0.0006*	-0.0019***
	(0.0004)	(0.0007)
InflationxTRC1	-0.0006*	-0.0015**
	(0.0004)	(0.0007)
InflationxTRC2	-0.0011***	-0.0018***
	(0.0003)	(0.0006)
InflationxTRC3	-0.0001	-0.0007
	(0.0004)	(0.0007)
GdpGrowth	-0.0454**	-0.1000*
	(0.0216)	(0.0529)
LogPopulation	0.0955***	0.1120*
	(0.0298)	(0.0587)
LogUnemployment	-0.0086	-0.0407
	(0.0288)	(0.0540)
TradeBalanceShare	-0.2170*	-0.3660
	(0.1190)	(0.2540)
StudyPeriod	-0.0159***	-0.0145**
	(0.0033)	(0.0071)
Observations	259	259

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.2 : Heterogeneous-Effects Pooled OLS Results – Regional Differences in the Impact of Inflation (Dependent Variables: Income Quantiles).

	(3) Fsquantile	(4) Tquantile	(5) Fiquantile
InflationxTR21	-0.0000	-0.0000	0.0000
	(0.0001)	(0.0001)	(0.0003)
InflationxTR22	-0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0003)
InflationxTR31	-0.0001^{*}	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0002)
InflationxTR32	0.0002^{***}	0.0001	-0.0006^{**}
	(0.0001)	(0.0001)	(0.0003)
InflationxTR33	0.0001^{*}	0.0002^{**}	-0.0007^{***}
	(0.0001)	(0.0001)	(0.0002)
InflationxTR41	0.000^{***}	0.0002^{***}	-0.0009^{***}
	(0.0001)	(0.0001)	(0.0003)
InflationxTR42	0.0003^{***}	0.0003^{***}	-0.0013^{***}
	(0.0001)	(0.0001)	(0.0003)
InflationxTR51	-0.0000	-0.0002^{**}	0.0004
	(0.0001)	(0.0001)	(0.0003)
InflationxTR52	-0.0001	-0.0001^{**}	0.0003
	(0.0001)	(0.0001)	(0.0002)
InflationxTR61	-0.0001	0.0000	-0.0002
	(0.0001)	(0.0001)	(0.0003)
InflationxTR62	-0.0001^{*}	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0002)
InflationxTR63	-0.0000	0.0001	-0.0003
	(0.0001)	(0.0001)	(0.0003)
InflationxTR71	-0.0001	-0.0001	0.0003
	(0.0001)	(0.0001)	(0.0003)
InflationxTR72	-0.0001	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0003)
InflationxTR81	0.0002^{**}	0.0001	-0.0008^{***}
	(0.0001)	(0.0001)	(0.0003)
InflationxTR82	-0.0001	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0003)
InflationxTR83	-0.0000	0.0001^{*}	-0.0004^{*}
	(0.0001)	(0.0001)	(0.0002)
InflationxTR90	0.0001	0.0002^{*}	-0.0006^{**}
	(0.0001)	(0.0001)	(0.0003)

Table 5.2 : Heterogeneous-Effects Pooled OLS Results – Regional Differences in the Impact of Inflation (Dependent Variables: Income Quantiles). (Continued)

	(3) Fsquantile	(4) Tquantile	(5) Fiquantile
InflationxTRA1	-0.0000	-0.0002**	0.0004
	(0.0001)	(0.0001)	(0.0003)
InflationxTRA2	-0.0003***	-0.0002*	0.0005*
	(0.0001)	(0.0001)	(0.0003)
InflationxTRB1	0.0002**	0.0001	-0.0008**
	(0.0001)	(0.0001)	(0.0003)
InflationxTRB2	0.0001	0.0002*	-0.0006*
	(0.0001)	(0.0001)	(0.0003)
InflationxTRC1	0.0003***	-0.0001	-0.0003
	(0.0001)	(0.0001)	(0.0003)
InflationxTRC2	0.0002***	0.0002***	-0.0009***
	(0.0001)	(0.0001)	(0.0003)
InflationxTRC3	0.0000	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0003)
GdpGrowth	0.0118*	0.0090*	-0.0386**
	(0.0060)	(0.0050)	(0.0176)
LogPopulation	-0.0149*	-0.0248***	0.0922***
	(0.0079)	(0.0068)	(0.0242)
LogUnemployment	0.0041	-0.0028	-0.0091
	(0.0077)	(0.0066)	(0.0233)
TradeBalanceShare	0.0367	0.0749**	-0.2120**
	(0.0280)	(0.0296)	(0.0974)
StudyPeriod	0.0014*	0.0054***	-0.0160***
	(0.0009)	(0.0009)	(0.0027)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The coefficients of the statistically significant interaction terms between inflation and the regional dummy variables exhibit both positive and negative signs, indicating heterogeneity in the effect of inflation on income inequality across regions. For example, in model 1, the coefficient of the interaction between inflation and TRB2 (Van, Muş, Bitlis, Hakkari) region is -0.000639 at the 10% significance level, while the coefficient of the interaction between inflation and TRA2 is 0.000643 at the same significance level. This indicates that, despite both being located in the Eastern

Anatolia Region, inflation decreases the Gini coefficient in the TRB2 region, unlike increasing it in the TRA2 region compared to the reference region TR10 (Istanbul). This variability, in fact, substantiates our initial assumption that inflation affects income inequality differently across regions.

When calculating the conditional marginal effects based on the tables, the coefficients of the independent variables should not be interpreted individually; rather, they should be added to the coefficient of the independent variable inflation, which represents the effect of the reference region TR10. For example, since the coefficient of the interaction between inflation and TR41 (Bursa, Eskişehir, Bilecik) in model 1 is −0.00107, I add it to the coefficient of inflation in the same model (0.162), yielding 0.16093. This implies that a one-percentage-point increase in inflation in this region increases the Gini coefficient by 0.16093.

Regional differences can be observed in Tables 5.1 and 5.2 and are illustrated more clearly in Figures 5.1-5.5. In the figures, the vertical lines passing through the regional points represent confidence intervals. Points whose vertical lines do not intersect the horizontal zero line indicate that the coefficient in that region is statistically significant. Furthermore, areas below the horizontal zero line indicate negative coefficients, while areas above it indicate positive coefficients. Furthermore, statistical significance becomes stronger as the points move further away from the horizontal zero line.

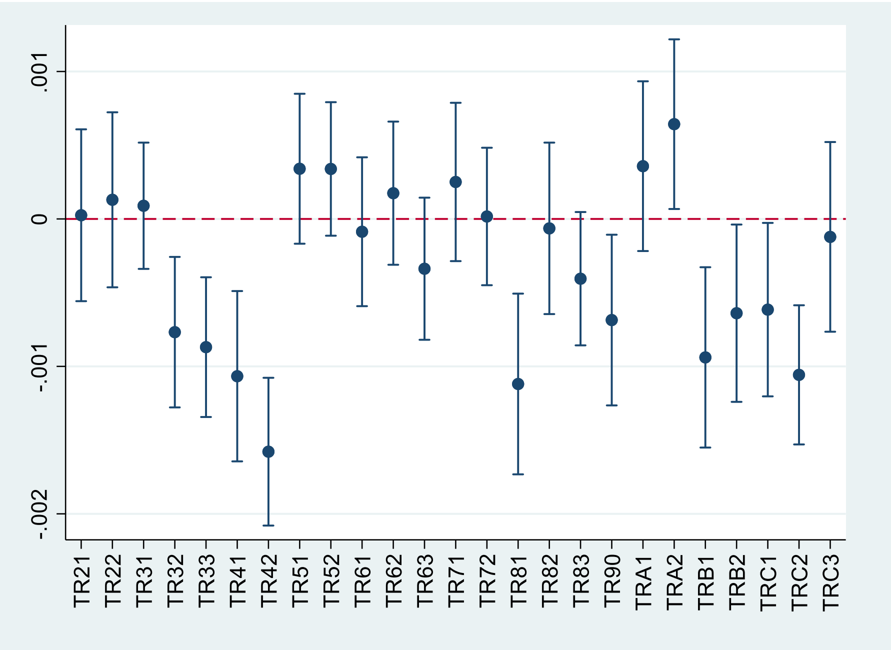

Figure 5.1 : Regional Differences in the Impact of Inflation (Dependent Variable = Gini Coefficient).

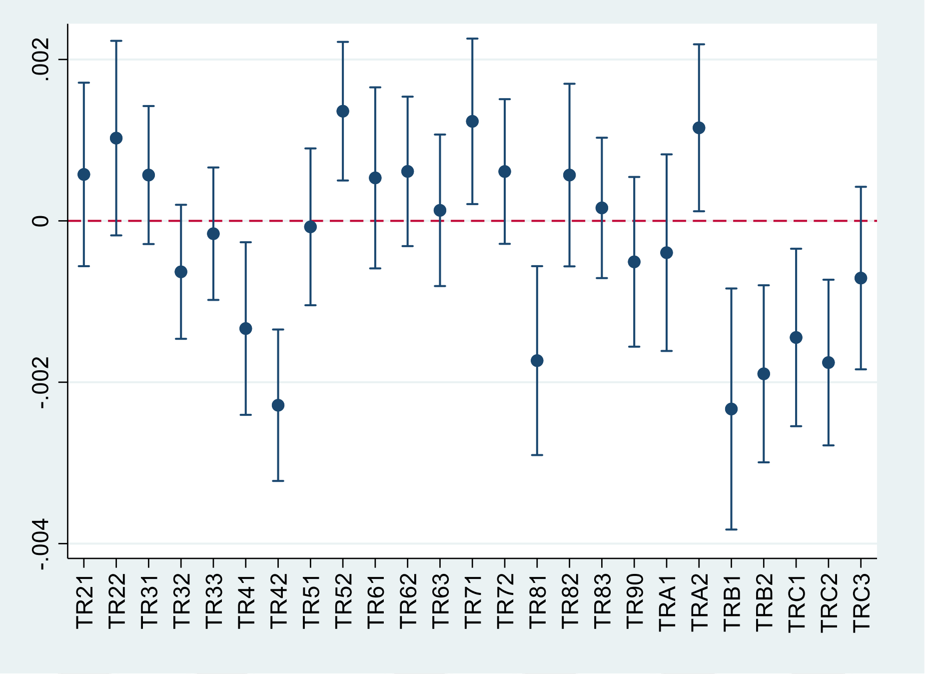

Figure 5.2 : Regional Differences in the Impact of Inflation (Dependent Variable = P80/P20 Ratio).

Figure 5.3 : Regional Differences in the Impact of Inflation (Dependent Variable = Fsquantile).

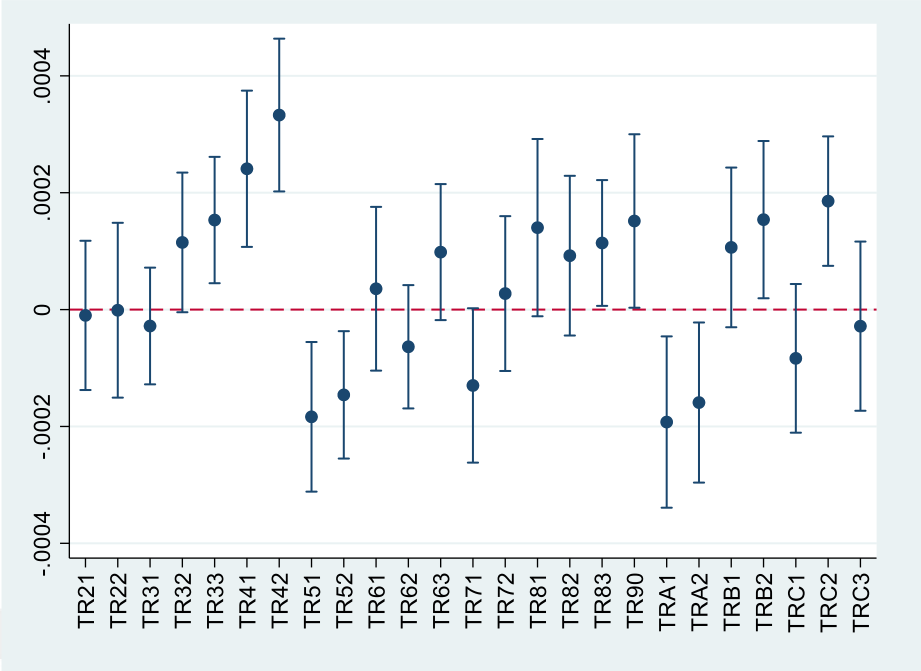

Figure 5.4 : Regional Differences in the Impact of Inflation (Dependent Variable = Tquantile).

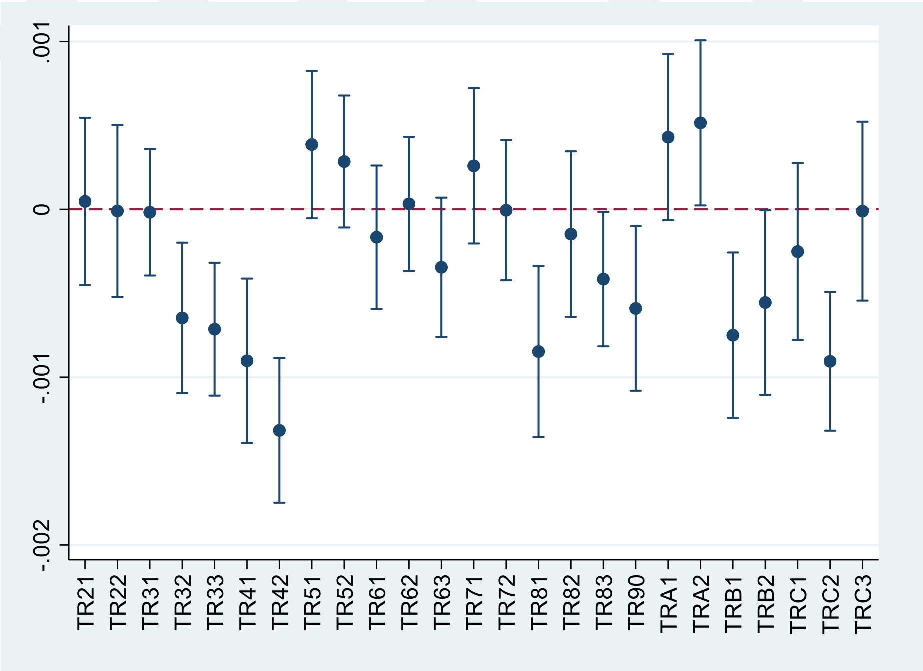

Figure 5.5 : Regional Differences in the Impact of Inflation (Dependent Variable = Fiquantile).

Additionally, I used the Wald test to determine whether regional differences were statistically significant overall. The results of the Wald test, which tests the null hypothesis that all interaction terms are equal to zero, are presented in Table 5.3. The Wald tests for all models yielded very large F values and p-values of 0.0000, thus rejecting the null hypothesis in all models. The rejection of the null hypothesis indicates that there are statistically significant differences in the impact of inflation on income inequality across regions.

Table 5.3 : Wald Test of Joint Significance of Regional Interaction Terms (Pooled OLS).

Model No	Dependent Variable	Null Hypothesis	F Statistic	P-Value	Decision
1	Gini	InflationxTR21 = InflationxTR22 = ….. = InflationxTRC3 = 0	11.63	0.0000	Reject H_0
2	P80/P20	InflationxTR21 = InflationxTR22 = ….. = InflationxTRC3 = 0	16.75	0.0000	Reject H_0
3	Fsquantile	InflationxTR21 = InflationxTR22 = ….. = InflationxTRC3 = 0	13.08	0.0000	Reject H_0
4	Tquantile	InflationxTR21 = InflationxTR22 = ….. = InflationxTRC3 = 0	10.57	0.0000	Reject H_0
5	Fiquantile	InflationxTR21 = InflationxTR22 = ….. = InflationxTRC3 = 0	13.08	0.0000	Reject H_0

5.2 Results on the Impact of the Inflation Shock on Income Inequality

Tables 5.4-5.8 present the results of the main models that measure the impact of bank loans on income inequality after 2020, when inflation began to rise significantly. These results use a panel fixed-effects approach with interaction terms. Tables 5.9-5.13 show the output tables for the same main models using the system GMM method. I have included the results of the sub-models (Models 5-11) that measure the individual effects of the variables used in the main models in the appendix. Tables A.1-A.9 in the appendix show results using the panel fixed- effects approach, while tables A.10-A.14 show results using the system GMM method. In this section, I focus on the results of model 1, as it is the most comprehensive specification, including all loan types, both consumer loans and institutional loans, as well as total deposits. Because the dependent variables measure different dimensions of income inequality using different methods, differences in the results may arise. Furthermore, it is normal for sub-models using individual independent variables for various loan types to yield different results than models incorporating them interactively with other loan types.

When we look at the results of the model one with Gini coefficient as dependent variable, while the marginal impact of institutional loans and housing loans after the shock is significant at the 5% level, the share of individual credit cards in regional GDP is significant at the 1% level. The interaction terms are insignificant for other loan types and total deposits. Furthermore, the coefficients for housing loans and individual credit cards are negative, while the coefficient for institutional loans is positive. This indicates that, during the normal period, a one-percentage-point increase in the share of credit cards in GDP reduces the Gini coefficient by 0.0271, whereas during the post-inflation shock period, the marginal effect of the mortgage loan share changes by −0.0124 in the post-shock period relative to the normal period. Conversely, the marginal effect of a one-percentage-point increase in the institutional loan share is 0.0006 higher compared to the normal period. Table A.1 contains models showing the individual effects of the variables included in the relevant model. Consistent with the main model results, the same variables in Table A.1 are individually statistically significant. Additionally, the variable measuring the marginal effect of total credit after the shock is also positive and significant. This is consistent with the results of model 4, one of the main models. Similarly, in both the main and sub-models using the Gini coefficient, when the dependent variable is the P80/P20 ratio, the same independent variables are statistically significant in the same direction and at the same level of significance. These results are shown in Table 5.5 and Table A.2.

Table 5.4 : Fixed Effects Results – Main Model – Dependent Variable: Gini.

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ShareofMortgage	0.0105	0.0116^{*}	0.0102	
	(0.0077)	(0.0067)	(0.0065)	
Post2020xShareofMortgage	-0.0124^{**}	-0.0126^{***}	-0.0085^{**}	
	(0.0047)	(0.0045)	(0.0041)	
ShareofVehicle	0.0810	0.0848	0.0838	
	(0.0726)	(0.0733)	(0.0789)	
Post2020xShareofVehicle	-0.0545	-0.0613	-0.0503	
	(0.0826)	(0.0787)	(0.0773)	
ShareofPersonal	-0.0028	-0.0020	0.0008	
	(0.0034)	(0.0038)	(0.0039)	
Post2020xShareofPersonal	0.0032	0.0030	-0.0008	
	(0.0038)	(0.0039)	(0.0032)	
ShareofCCC	-0.0271^{***}	-0.0273^{***}	-0.0311^{***}	
	(0.0082)	(0.0083)	(0.0074)	
Post2020xShareofCCC	0.0118	0.0130^{*}	0.0166^{**}	
	(0.0075)	(0.0072)	(0.0074)	
ShareofInstitutional	-0.0005	-0.0004		
	(0.0007)	(0.0007)		
Post2020xShareofInstitutional	0.0006^{**}	0.0005^{**}		
	(0.0002)	(0.0002)		
ShareofDeposit	0.0007			0.0013
	(0.0016)			(0.0014)
Post2020xShareofDeposit	-0.0002			-0.0004
	(0.0006)			(0.0005)
ShareofTotal				-0.0008
				(0.0006)
Post2020xShareofTotal				0.0004^{*}
				(0.0002)
GDPGrowth	-0.0343	-0.0334	-0.0335	-0.0327
	(0.0245)	(0.0238)	(0.0264)	(0.0231)
LogPopulation	-0.0786	-0.0699	-0.0816	-0.1550
	(0.2540)	(0.2440)	(0.2500)	(0.2250)
LogUnemployment	0.0043	0.0052	0.0077	0.0038
	(0.0343)	(0.0343)	(0.0395)	(0.0346)
TradeBalanceShare	-0.3550	-0.3830^{*}	-0.4070^{*}	-0.2230
	(0.2300)	(0.2050)	(0.2160)	(0.2790)
StudyPeriod	-0.0340	-0.0365	-0.0422^{*}	-0.0313
	(0.0283)	(0.0250)	(0.0231)	(0.0258)
Observations	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.5 : Fixed Effects Results – Main Model – Dependent Variable: P80/P20.

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
ShareofMortgage	0.0120	0.0156	0.0131	
	(0.0137)	(0.0112)	(0.0110)	
Post2020xShareofMortgage	-0.0189**	-0.0183**	-0.0087	
	(0.0077)	(0.0077)	(0.0064)	
ShareofVehicle	0.2110	0.2300	0.2300	
	(0.1590)	(0.1590)	(0.1660)	
Post2020xShareofVehicle	-0.2150	-0.2380	-0.2130	
	(0.1830)	(0.1730)	(0.1690)	
ShareofPersonal	-0.0066	-0.0041	0.0018	
	(0.0068)	(0.0069)	(0.0075)	
Post2020xShareofPersonal	0.0059	0.0056	-0.0030	
	(0.0060)	(0.0057)	(0.0056)	
ShareofCCC	-0.0527***	-0.0544***	-0.0622***	
	(0.0163)	(0.0163)	(0.0159)	
Post2020xShareofCCC	0.0125	0.0176	0.0265	
	(0.0185)	(0.0167)	(0.0164)	
ShareofInstitutional	-0.0009	-0.0006		
	(0.0011)	(0.0011)		
Post2020xShareofInstitutional	0.0012**	0.0012***		
	(0.0005)	(0.0003)		
ShareofDeposit	0.0023			0.0028
	(0.0032)			(0.0027)
Post2020xShareofDeposit	-0.0003			-0.0008
	(0.0011)			(0.0011)
ShareofTotal				-0.0018*
				(0.0011)
Post2020xShareofTotal				0.0009*
				(0.0005)
GDPGrowth	-0.0739	-0.0717	-0.0734	-0.0612
	(0.0545)	(0.0531)	(0.0574)	(0.0529)
LogPopulation	-0.4260	-0.3980	-0.3990	-0.4600
	(0.6540)	(0.6260)	(0.6330)	(0.5830)
LogUnemployment	0.0648	0.0626	0.0713	0.0740
	(0.0725)	(0.0698)	(0.0803)	(0.0753)
TradeBalanceShare	-0.7490	-0.8420*	-0.8920*	-0.4790
	(0.4810)	(0.4120)	(0.4370)	(0.5670)
StudyPeriod	-0.0596	-0.0709	-0.0852*	-0.0836
	(0.0537)	(0.0473)	(0.0445)	(0.0516)
Observations	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tables 5.6, 5.7, and 5.8 present the main model results examining how the inflation shock affects different income groups. The results for the sub-models, using the share of different income groups as the dependent variable, are in Tables A.3 through A.9. Table 5.6 contains the results for the share of the bottom 20% income group, Table 5.7 contains the results for the share of the middle 20% income group, and Table 5.8 contains the results for the share of the top 20% income group. The first column of Tables A.3 through A.9 contains the results for the lower-income group, the second column for the middle-income group, and the third column for the upper-income group. In the lowest-income group, a one-percentage-point increase in the share of housing loans during the normal period reduces the income share of the bottom 20% by 0.0037, while a one-percentage-point increase in the share of personal credit cards increases it by 0.0064. In contrast, in the post-shock period, the post-shock interaction term indicates a positive change in the marginal effect of housing loans relative to the normal period. The variable showing the share of personal credit cards after the shock is not statistically significant. Although the institutional loan ratio after the shock is significant, as in the models including the Gini coefficient and the P80/P20 ratio, its coefficient is negative, indicating a decrease in the share of the lowest-income group. The effects of housing loans in the normal period and of institutional loans in the post-shock period are not significant for the lowest-income group in the sub-models. In Table 5.7, for the middle-income group, the variable on the effect of personal credit cards in the normal period is positive, while the variable on the effect of institutional loans after the shock is negative. This indicates that, during the normal period, a one-percentage-point increase in the share of credit cards in GDP increases the share of the middle-income group by 0.0059, whereas during the post-inflation shock period, the marginal effect of a one-percentage-point increase in the share of institutional loans in GDP on the same income group changes by -0.0002 lower than during the normal period. Although the same variables show higher statistical significance (1%) in the output tables for the upper income group, the coefficients are in the exact opposite direction to those in the middle income group. Similarly, the post-shock interaction term for the mortgage-loan share has opposite signs across income groups: it is positive for the lower-income group and negative for the upper-income group. Results from sub-models with different income groups as dependent variables also support those from the main models. In short, when examining models containing different dependent variables that address different aspects of income inequality, I found that the share of individual credit cards, which is statistically significant across the quantile specifications in the normal period, increases the share of the lower- and middle-income groups and decreases the share of the upper-income group, thus reducing income inequality. Furthermore, the post-shock interaction terms indicate that the relationship between housing loans and income shares shifts in a direction that is consistent with a reduction in inequality, whereas the post-shock interaction terms for institutional loans shift in a direction consistent with higher inequality, as reflected by lower shares for the lower- and middle-income groups and a higher share for the upper-income group.

Table 5.6 : Fixed Effects Results – Main Model – Dependent Variable: Bottom 20% Share.

	(1)	(2)	(3)	(4)
	Model 1a	Model 2a	Model 3a	Model 4a
ShareofMortgage	-0.0037*	-0.0036**	-0.0035**	
	(0.0020)	(0.0017)	(0.0016)	
Post2020xShareofMortgage	0.00314**	0.0033**	0.0026**	
	(0.00122)	(0.0013)	(0.0011)	
ShareofVehicle	-0.0330	-0.0314	-0.0317	
	(0.0214)	(0.0221)	(0.0224)	
Post2020xShareofVehicle	0.0207	0.0199	0.0179	
	(0.0179)	(0.0175)	(0.0174)	
ShareofPersonal	0.0012	0.0012	0.0008	
	(0.0007)	(0.0008)	(0.0007)	
Post2020xShareofPersonal	-0.0013	-0.0013	-0.0006	
	(0.0010)	(0.0009)	(0.0007)	
ShareofCCC	0.0064***	0.0062***	0.0067***	
	(0.0017)	(0.0016)	(0.0016)	
Post2020xShareofCCC	-0.0026	-0.0023	-0.0031**	
	(0.0018)	(0.0014)	(0.0015)	
ShareofInstitutional	-0.0000	0.0000		
	(0.0001)	(0.0001)		
Post2020xShareofInstitutional	-0.0001*	-0.0001*		
	(0.0001)	(0.0000)		
ShareofDeposit	0.0001			-0.0002
	(0.0004)			(0.0003)
Post2020xShareofDeposit	0.0000			0.0001
	(0.0001)			(0.0001)
ShareofTotal				0.0000
				(0.0001)
Post2020xShareofTotal				-0.0000
				(0.0000)
GDPGrowth	0.0040	0.0039	0.0043	0.0047
	(0.0070)	(0.0072)	(0.0074)	(0.0062)
LogPopulation	0.0377	0.0385	0.0353	0.0902
	(0.0641)	(0.0624)	(0.0591)	(0.0565)
LogUnemployment	-0.0033	-0.0041	-0.0052	-0.0035
	(0.0109)	(0.0111)	(0.0116)	(0.0104)
TradeBalanceShare	0.0689	0.0659	0.0690	0.0389
	(0.0531)	(0.0466)	(0.0451)	(0.0543)
StudyPeriod	0.0102	0.0094	0.0107*	0.0091
	(0.0069)	(0.0059)	(0.0058)	(0.0062)
Observations	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.7: Fixed Effects Results – Main Model –

Dependent Variable: Middle 20% Share.

	(1) Model 1b	(2) Model 2b	(3) Model 3b	(4) Model 4b
ShareofMortgage	-0.0014	-0.0020	-0.0017	
	(0.0017)	(0.0016)	(0.0015)	
Post2020xShareofMortgage	0.0016	0.0019*	0.0011	
	(0.0012)	(0.0010)	(0.0011)	
ShareofVehicle	-0.0070	-0.0081	-0.0077	
	(0.0180)	(0.0178)	(0.0194)	
Post2020xShareofVehicle	-0.0001	0.0040	0.0017	
	(0.0271)	(0.0253)	(0.0247)	
ShareofPersonal	0.0000	-0.0006	-0.0012	
	(0.0012)	(0.0012)	(0.0012)	
Post2020xShareofPersonal	-0.0001	0.0000	0.0009	
	(0.0009)	(0.0010)	(0.0008)	
ShareofCCC	0.0059**	0.0059**	0.0068***	
	(0.0024)	(0.0024)	(0.0021)	
Post2020xShareofCCC	-0.0024	-0.0030	-0.0037*	
	(0.0018)	(0.0019)	(0.0019)	
ShareofInstitutional	0.0002	0.0001		
	(0.0002)	(0.0002)		
Post2020xShareofInstitutional	-0.0002**	-0.0001*		
	(0.0001)	(0.0001)		
ShareofDeposit	-0.0004			-0.0005
	(0.0004)			(0.0003)
Post2020xShareofDeposit	0.0002			0.0002
	(0.0002)			(0.0001)
ShareofTotal				0.0003
				(0.0002)
Post2020xShareofTotal				-0.0002**
				(0.0001)
GDPGrowth	0.0097	0.0090	0.0089	0.0090
	(0.0070)	(0.0067)	(0.0071)	(0.0062)
LogPopulation	0.0144	0.0090	0.0136	0.0018
	(0.0679)	(0.0657)	(0.0682)	(0.0596)
LogUnemployment	0.0012	-0.0003	-0.0006	0.0009
	(0.0090)	(0.0082)	(0.0095)	(0.0089)
TradeBalanceShare	0.1060*	0.1230**	0.1290**	0.0750
	(0.0556)	(0.0485)	(0.0534)	(0.0688)
StudyPeriod	0.0058	0.0068	0.0079	0.0053
	(0.0079)	(0.0072)	(0.0065)	(0.0062)
Observations	259	259	259	259

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8 : Fixed Effects Results – Main Model –

Dependent Variable: Top 20% Share.

	(1) Model 1c	(2) Model 2c	(3) Model 3c	(4) Model 4c
ShareofMortgage	0.0073	0.0089	0.0076	
	(0.0063)	(0.0055)	(0.0055)	
Post2020xShareofMortgage	-0.0096**	-0.0100**	-0.0061*	
	(0.0041)	(0.0037)	(0.0035)	
ShareofVehicle	0.0549	0.0601	0.0591	
	(0.0596)	(0.0593)	(0.0655)	
Post2020xShareofVehicle	-0.0364	-0.0469	-0.0367	
	(0.0752)	(0.0713)	(0.0698)	
ShareofPersonal	-0.0016	-0.0002	0.0023	
	(0.0033)	(0.0034)	(0.0037)	
Post2020xShareofPersonal	0.0019	0.0015	-0.0020	
	(0.0030)	(0.0032)	(0.0026)	
ShareofCCC	-0.0225***	-0.0228***	-0.0263***	
	(0.0074)	(0.0075)	(0.0066)	
Post2020xShareofCCC	0.0090	0.0107	0.0141**	
	(0.0066)	(0.0067)	(0.0068)	
ShareofInstitutional	-0.0005	-0.0003		
	(0.0006)	(0.0006)		
Post2020xShareofInstitutional	0.0006***	0.0005***		
	(0.0002)	(0.0002)		
ShareofDeposit	0.0011			0.0015
	(0.0013)			(0.0012)
Post2020xShareofDeposit	-0.0003			-0.0006
	(0.0005)			(0.0004)
ShareofTotal				-0.0009
				(0.0005)
Post2020xShareofTotal				0.0005**
				(0.0002)
GDPGrowth	-0.0349	-0.0334	-0.0334	-0.0328
	(0.0211)	(0.0202)	(0.0225)	(0.0200)
LogPopulation	-0.0950	-0.0813	-0.0923	-0.1100
	(0.2170)	(0.2070)	(0.2170)	(0.1950)
LogUnemployment	-0.0068	-0.0048	-0.0026	-0.0066
	(0.0282)	(0.0272)	(0.0322)	(0.0287)
TradeBalanceShare	-0.3310	-0.3750**	-0.3970**	-0.2160
	(0.1940)	(0.1720)	(0.1870)	(0.2420)
StudyPeriod	-0.0258	-0.0294	-0.0347*	-0.0245
	(0.0239)	(0.0214)	(0.0196)	(0.0214)
Observations	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

When the same models are estimated using the GMM method by adding lags of the control variables at time t-1, some results are similar to those obtained with the fixed effects model, while others are unique. The results for the main models are presented in Tables 5.9-5.13; the results for the sub-models are presented in Tables A.10-A.14. Looking at the first model, where the dependent variable is Gini, contrary to the results from the fixed effects model, the share of individual credit cards, which was significant and negative in the normal period, is positive here. Although institutional loans appear positive and significant in the post-shock period, the post-shock interaction term indicates that the marginal effect of a one-percentage-point increase in the share of institutional loans in GDP on the Gini coefficient changes by 0.0006 relative to the normal period; housing loans are not statistically significant here. Instead, the marginal effect of a one-percentage-point increase in the share of personal financing loans in GDP on the Gini coefficient is 0.0078 higher than in the normal period, while a one-percentage-point increase in the share of individual credit cards has a marginal effect on the Gini coefficient that is 0.0204 lower than in the normal period. It is noteworthy that the share of individual credit cards is in the opposite direction after the shock compared to the normal period.

When we change the dependent variable in the first model to the P80/P20 ratio, contrary to the model including the Gini coefficient, we find that a one-percentage-point increase in the share of personal financing loans in the normal period reduces the logarithm of the P80/P20 ratio by 0.0154, while the share of individual credit cards is not significant. In the post-shock period, personal financing loans, consumer credit cards, and institutional loans are statistically significant, in line with the previous model results, and the coefficient directions are the same. Interestingly, although personal financing loans are statistically significant in both periods, they have a negative coefficient in the normal period and a positive coefficient in the post-shock period. In contrast, the deposit variable is negative and significant in the post-shock period.

Table 5.9 : System GMM Results – Main Model – Dependent Variable: Gini.

	Model 1	Model 2	Model 3	Model 4
Gini (t-1)	1.2070***	1.2026***	1.1707***	1.0669***
	(0.3201)	(0.2671)	(0.2520)	(0.2444)
ShareofMortgage	-0.0058	-0.0046	-0.0058	
	(0.0051)	(0.0049)	(0.0051)	
Post2020xShareofMortgage	0.0066	0.0037	0.0074	
	(0.0053)	(0.0043)	(0.0047)	
ShareofVehicle	0.0536	0.0483	0.0528	
	(0.0634)	(0.0623)	(0.0614)	
Post2020xShareofVehicle	0.0157	0.0213	0.0153	
	(0.0793)	(0.0812)	(0.0764)	
ShareofPersonal	-0.0038	-0.0040	-0.0022	
	(0.0029)	(0.0024)	(0.0020)	
Post2020xShareofPersonal	0.0078***	0.0074***	0.0040*	
	(0.0023)	(0.0022)	(0.0021)	
ShareofCCC	0.0173*	0.0162**	0.0131*	
	(0.0088)	(0.0068)	(0.0068)	
Post2020xShareofCCC	-0.0204**	-0.0218**	-0.0171*	
	(0.0096)	(0.0088)	(0.0088)	
ShareofInstitutional	-0.0003	-0.0003		
	(0.0003)	(0.0003)		
Post2020xShareofInstitutional	0.0006***	0.0005***		
	(0.0002)	(0.0002)		
ShareofDeposit	0.0000			-0.0000
	(0.0008)			(0.0005)
Post2020xShareofDeposit	-0.0007			-0.0003
	(0.0005)			(0.0005)
ShareofTotal				-0.0000
				(0.0003)
Post2020xShareofTotal				0.0003
				(0.0003)

Table 5.9 : System GMM Results – Main Model –

Dependent Variable: Gini. (Continued)

	Model 1	Model 2	Model 3	Model 4
AfterShock	-0.0349*	-0.0287*	-0.0132	0.0018
	(0.0176)	(0.0166)	(0.0167)	(0.0089)
GDPGrowth	0.0050	0.0026	0.0014	0.0040
	(0.0132)	(0.0126)	(0.0130)	(0.0082)
GDPGrowth (t-1)	0.0110	0.0146	0.0112	0.0051
	(0.0215)	(0.0209)	(0.0193)	(0.0108)
LogPopulation	0.2859	0.3441	0.3663	0.5087
	(0.4267)	(0.4347)	(0.4322)	(0.4123)
LogPopulation (t-1)	-0.3017	-0.3730	-0.3871	-0.5169
	(0.4306)	(0.4381)	(0.4370)	(0.4221)
LogUnemployment	-0.0066	-0.0041	-0.0048	-0.0101
	(0.0235)	(0.0240)	(0.0229)	(0.0217)
LogUnemployment (t-1)	-0.0086	0.0038	-0.0005	0.0076
	(0.0184)	(0.0204)	(0.0208)	(0.0187)
TradeBalanceShare	-0.3253*	-0.3199*	-0.3033*	-0.2199
	(0.1851)	(0.1812)	(0.1703)	(0.1649)
TradeBalanceShare (t-1)	0.1830	0.1777	0.1627	0.0943
	(0.1365)	(0.1324)	(0.1267)	(0.1064)
StudyPeriod	0.0118	0.0012	0.0065	0.0038
	(0.0284)	(0.0265)	(0.0260)	(0.0249)
StudyPeriod (t-1)	-0.0032	0.0054	-0.0012	-0.0025
	(0.0286)	(0.0262)	(0.0253)	(0.0241)
Constant	0.0348	0.0610	0.0460	0.0265
	(0.0859)	(0.0598)	(0.0520)	(0.0329)
Observations	233	233	233	233
Instruments	26	24	22	18
AR(2) (p-value)	0.201	0.194	0.182	0.155
Hansen test (p-value)	0.726	0.576	0.486	0.249

Standard errors in parentheses.

All control variables are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.10 : System GMM Results – Main Model – Dependent Variable: P80/P20.

	Model 1	Model 2	Model 3	Model 4
P80/P20 (t-1)	1.3413*	1.2569**	1.2672**	1.1667**
	(0.7700)	(0.4950)	(0.5092)	(0.4790)
ShareofMortgage	-0.0094	-0.0045	-0.0075	
	(0.0246)	(0.0152)	(0.0136)	
Post2020xShareofMortgage	0.0304	0.0194	0.0268**	
	(0.0240)	(0.0123)	(0.0116)	
ShareofVehicle	0.1720	0.1445	0.1501	
	(0.1969)	(0.1444)	(0.1384)	
Post2020xShareofVehicle	0.1176	0.1728	0.1656	
	(0.2685)	(0.2464)	(0.2414)	
ShareofPersonal	-0.0154*	-0.0170***	-0.0142***	
	(0.0079)	(0.0056)	(0.0051)	
Post2020xShareofPersonal	0.0185***	0.0178***	0.0123*	
	(0.0061)	(0.0059)	(0.0061)	
ShareofCCC	0.0461	0.0405***	0.0372**	
	(0.0340)	(0.0143)	(0.0163)	
Post2020xShareofCCC	-0.0637**	-0.0670***	-0.0607***	
	(0.0282)	(0.0191)	(0.0207)	
ShareofInstitutional	-0.0004	-0.0004		
	(0.0009)	(0.0005)		
Post2020xShareofInstitutional	0.0012*	0.0008*		
	(0.0007)	(0.0005)		
ShareofDeposit	-0.0005			-0.0005
	(0.0029)			(0.0021)
Post2020xShareofDeposit	-0.0018*			-0.0009
	(0.0010)			(0.0013)
ShareofTotal				0.0002
				(0.0006)
Post2020xShareofTotal				0.0007
				(0.0006)

Table 5.10 : System GMM Results – Main Model –
Dependent Variable: P80/P20. (Continued)

	Model 1	Model 2	Model 3	Model 4
AfterShock	-0.0924	-0.0722	-0.0499	0.0126
	(0.0681)	(0.0570)	(0.0614)	(0.0267)
GDPGrowth	0.0341	0.0211	0.0186	0.0338*
	(0.0346)	(0.0288)	(0.0286)	(0.0196)
GDPGrowth (t-1)	0.0586	0.0697	0.0598	0.0039
	(0.0697)	(0.0515)	(0.0511)	(0.0302)
LogPopulation	1.0521	1.0999	1.1621	1.8007
	(1.0279)	(1.0712)	(1.0624)	(1.0648)
LogPopulation (t-1)	-1.1390	-1.2135	-1.2660	-1.8296
	(1.0924)	(1.1266)	(1.1181)	(1.1312)
LogUnemployment	-0.0101	-0.0026	-0.0060	-0.0638
	(0.0752)	(0.0695)	(0.0679)	(0.0457)
LogUnemployment (t-1)	0.0270	0.0529	0.0481	0.0745
	(0.0663)	(0.0945)	(0.0978)	(0.0688)
TradeBalanceShare	-0.6133	-0.6086	-0.6030	-0.3662
	(0.8366)	(0.5054)	(0.4993)	(0.4657)
TradeBalanceShare (t-1)	0.1536	0.1557	0.1564	0.0334
	(0.6875)	(0.4452)	(0.4436)	(0.2643)
StudyPeriod	-0.0888	-0.1144	-0.1083	-0.1027*
	(0.0954)	(0.0788)	(0.0800)	(0.0545)
StudyPeriod (t-1)	0.0940	0.1099	0.1037	0.0938
	(0.1106)	(0.0797)	(0.0812)	(0.0582)
Constant	0.1631	0.3124*	0.2739	0.0683
	(0.3902)	(0.1595)	(0.1653)	(0.2087)
Observations	233	233	233	233
Instruments	26	24	22	18
AR(2) (p-value)	0.212	0.172	0.168	0.029
Hansen test (p-value)	0.415	0.272	0.230	0.010

Standard errors in parentheses.

All control variables are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Regarding the models constructed using the GMM method and employing the shares of various income groups as the dependent variable, the results of the first model show no statistically significant variables affecting the lower income group. This suggests that the credit-based effects identified using the P80/P20 ratio and the Gini coefficient stem from income transfers between the middle and upper income groups. Indeed, the model examining the share of the middle-income group concludes that the marginal impact of a one-percentage point increase in the shares of personal financing and institutional loans on the middle-income group is 0.0019 and 0.0002 lower respectively in the post-inflation shock period than in the normal period.

Table 5.11 : System GMM Results – Main Model –
Dependent Variable: Bottom 20% Share.

	Model 1	Model 2	Model 3	Model 4
Fsquantile (t-1)	0.8407	0.8916***	0.8774***	0.7362***
	(4.3723)	(0.2599)	(0.2526)	(0.2478)
ShareofMortgage	0.0002	0.0003	0.0006	
	(0.0187)	(0.0009)	(0.0008)	
Post2020xShareofMortgage	-0.0009	-0.0008	-0.0017**	
	(0.0239)	(0.0010)	(0.0008)	
ShareofVehicle	-0.0058	-0.0060	-0.0068	
	(0.1550)	(0.0131)	(0.0132)	
Post2020xShareofVehicle	-0.0102	-0.0098	-0.0097	
	(0.2776)	(0.0179)	(0.0175)	
ShareofPersonal	0.0014	0.0010**	0.0007*	
	(0.0098)	(0.0004)	(0.0004)	
Post2020xShareofPersonal	-0.0016	-0.0015**	-0.0007	
	(0.0066)	(0.0005)	(0.0005)	
ShareofCCC	-0.0021	-0.0028*	-0.0023	
	(0.0214)	(0.0014)	(0.0016)	
Post2020xShareofCCC	0.0049	0.0058***	0.0050**	
	(0.0216)	(0.0019)	(0.0022)	
ShareofInstitutional	0.0001	0.0001		
	(0.0004)	(0.0000)		
Post2020xShareofInstitutional	-0.0002	-0.0001**		
	(0.0009)	(0.0000)		
ShareofDeposit	-0.0002			-0.0001
	(0.0027)			(0.0001)
Post2020xShareofDeposit	0.0002			0.0001
	(0.0017)			(0.0001)

Table 5.11 : System GMM Results – Main Model –
Dependent Variable: Bottom 20% Share. (Continued)

	Model 1	Model 2	Model 3	Model 4
ShareofTotal				0.0000
				(0.0000)
Post2020xShareofTotal				-0.0001**
				(0.0000)
AfterShock	0.0035	0.0030	-0.0004	-0.0009
	(0.0518)	(0.0048)	(0.0046)	(0.0026)
GDPGrowth	-0.0014	-0.0010	-0.0006	-0.0012
	(0.0643)	(0.0030)	(0.0031)	(0.0018)
GDPGrowth (t-1)	-0.0076	-0.0079**	-0.0069*	-0.0001
	(0.0785)	(0.0038)	(0.0037)	(0.0017)
LogPopulation	0.0088	0.0545	0.0527	0.0279
	(0.0605)	(0.0820)	(0.0815)	(0.0750)
LogPopulation (t-1)	0.0000	-0.0447	-0.0446	-0.0275
	(.)	(0.0817)	(0.0813)	(0.0771)
LogUnemployment	-0.0011	-0.0029	-0.0028	0.0029
	(0.0758)	(0.0047)	(0.0045)	(0.0040)
LogUnemployment (t-1)	-0.0055	-0.0055	-0.0044	-0.0055
	(0.0476)	(0.0058)	(0.0059)	(0.0047)
TradeBalanceShare	0.0636	0.0581	0.0540	0.0276
	(0.3787)	(0.0383)	(0.0374)	(0.0325)
TradeBalanceShare (t-1)	-0.0224	-0.0109	-0.0078	0.0054
	(0.4214)	(0.0443)	(0.0449)	(0.0321)
StudyPeriod	0.0051	0.0080	0.0066	0.0044
	(0.1350)	(0.0063)	(0.0066)	(0.0063)
StudyPeriod (t-1)	-0.0043	-0.0078	-0.0063	-0.0035
	(0.1107)	(0.0062)	(0.0064)	(0.0062)
Constant	-0.0189	-0.0154	-0.0093	0.0231
	(0.3779)	(0.0293)	(0.0282)	(0.0329)
Observations	233	233	233	233
Instruments	26	24	22	18
AR(2) (p-value)	0.937	0.524	0.528	0.317
Hansen test (p-value)	0.428	0.863	0.799	0.433

Standard errors in parentheses.

All control variables are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.12 : System GMM Results – Main Model –
Dependent Variable: Middle 20% Share.

	Model 1	Model 2	Model 3	Model 4
Tquantile (t-1)	1.2839**	1.2753**	1.2477**	1.1859**
	(0.5347)	(0.5030)	(0.4525)	(0.4388)
ShareofMortgage	0.0012	0.0009	0.0013	
	(0.0013)	(0.0013)	(0.0015)	
Post2020xShareofMortgage	-0.0007	0.0000	-0.0009	
	(0.0018)	(0.0016)	(0.0016)	
ShareofVehicle	-0.0188	-0.0177	-0.0189	
	(0.0120)	(0.0126)	(0.0130)	
Post2020xShareofVehicle	-0.0061	-0.0079	-0.0071	
	(0.0199)	(0.0208)	(0.0199)	
ShareofPersonal	0.0005	0.0006	0.0002	
	(0.0007)	(0.0007)	(0.0006)	
Post2020xShareofPersonal	-0.0019**	-0.0017*	-0.0008	
	(0.0009)	(0.0009)	(0.0007)	
ShareofCCC	-0.0024	-0.0022	-0.0015	
	(0.0023)	(0.0022)	(0.0018)	
Post2020xShareofCCC	0.0022	0.0026	0.0016	
	(0.0026)	(0.0027)	(0.0025)	
ShareofInstitutional	0.0001	0.0001		
	(0.0001)	(0.0001)		
Post2020xShareofInstitutional	-0.0002**	-0.0001*		
	(0.0001)	(0.0001)		
ShareofDeposit	-0.0000			-0.0000
	(0.0002)			(0.0001)
Post2020xShareofDeposit	0.0002			0.0001
	(0.0002)			(0.0002)
ShareofTotal				0.0000
				(0.0001)
Post2020xShareofTotal				-0.0001
				(0.0001)

Table 5.12 : System GMM Results – Main Model –

Dependent Variable: Middle 20% Share. (Continued)

	Model 1	Model 2	Model 3	Model 4
AfterShock	0.0114	0.0095	0.0054	-0.0008
	(0.0072)	(0.0069)	(0.0057)	(0.0027)
GDPGrowth	0.0002	0.0011	0.0015	-0.0006
	(0.0044)	(0.0043)	(0.0043)	(0.0027)
GDPGrowth (t-1)	0.0010	0.0003	0.0011	-0.0011
	(0.0056)	(0.0055)	(0.0049)	(0.0046)
LogPopulation	-0.2126***	-0.2245***	-0.2278***	-0.2410***
	(0.0737)	(0.0791)	(0.0780)	(0.0838)
LogPopulation (t-1)	0.2116**	0.2269**	0.2283**	0.2402**
	(0.0785)	(0.0836)	(0.0825)	(0.0892)
LogUnemployment	0.0063	0.0061	0.0061	0.0084
	(0.0091)	(0.0092)	(0.0089)	(0.0085)
LogUnemployment (t-1)	0.0059	0.0023	0.0035	-0.0007
	(0.0073)	(0.0070)	(0.0071)	(0.0071)
TradeBalanceShare	0.0887	0.0907	0.0875	0.0756
	(0.0607)	(0.0572)	(0.0543)	(0.0481)
TradeBalanceShare (t-1)	-0.0702	-0.0699	-0.0661	-0.0552
	(0.0571)	(0.0576)	(0.0523)	(0.0422)
StudyPeriod	-0.0090	-0.0065	-0.0077	-0.0046
	(0.0104)	(0.0106)	(0.0104)	(0.0099)
StudyPeriod (t-1)	0.0063	0.0043	0.0058	0.0037
	(0.0103)	(0.0105)	(0.0100)	(0.0099)
Constant	-0.0760	-0.0816	-0.0713	-0.0532
	(0.1272)	(0.1270)	(0.1201)	(0.1131)
Observations	233	233	233	233
Instruments	26	24	22	18
AR(2) (p-value)	0.277	0.269	0.236	0.230
Hansen test (p-value)	0.683	0.924	0.953	0.616

Standard errors in parentheses.

All control variables are reported.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conversely, the impact of the same loan groups on the upper-income groups is positive. In addition, the effect of individual credit cards, which was positive and significant in the normal period, was not significant in the post-shock period. On the other hand, when examining the sub-model results, we obtain significant results in the same direction as the main model results for some variables, but in the opposite direction for others. Even significant results are obtained in the sub-models, while the main model shows no significance, or vice versa. This finding indicates that, in models created using the System GMM method, the effects of some variables appear independently, while those of others emerge only when they interact with other variables. Thus, caution is needed even when offering incentives for a single type of credit.

Table 5.13 : System GMM Results – Main Model – Dependent Variable: Top 20% Share.

	Model 1	Model 2	Model 3	Model 4
Fiquantile (t-1)	1.1856***	1.1666***	1.1080***	0.9746***
	(0.3422)	(0.3052)	(0.2702)	(0.2681)
ShareofMortgage	-0.0055	-0.0044	-0.0053	
	(0.0049)	(0.0048)	(0.0052)	
Post2020xShareofMortgage	0.0040	0.0016	0.0049	
	(0.0055)	(0.0046)	(0.0051)	
ShareofVehicle	0.0494	0.0442	0.0477	
	(0.0602)	(0.0589)	(0.0575)	
Post2020xShareofVehicle	-0.0007	0.0056	-0.0004	
	(0.0708)	(0.0730)	(0.0675)	
ShareofPersonal	-0.0036	-0.0039	-0.0022	
	(0.0026)	(0.0023)	(0.0019)	
Post2020xShareofPersonal	0.0072**	0.0069**	0.0034	
	(0.0026)	(0.0027)	(0.0023)	
ShareofCCC	0.0164*	0.0151*	0.0112	
	(0.0089)	(0.0074)	(0.0069)	
Post2020xShareofCCC	-0.0163	-0.0170*	-0.0114	
	(0.0101)	(0.0096)	(0.0087)	
ShareofInstitutional	-0.0003	-0.0003		
	(0.0003)	(0.0003)		
Post2020xShareofInstitutional	0.0006***	0.0005***		
	(0.0002)	(0.0002)		
ShareofDeposit	-0.0000			0.0000
	(0.0007)			(0.0004)

Table 5.13 : System GMM Results – Main Model –

Dependent Variable: Top 20% Share. (Continued)

	Model 1	Model 2	Model 3	Model 4
Post2020xShareofDeposit	-0.0004			-0.0002
	(0.0006)			(0.0005)
ShareofTotal				-0.0000
				(0.0002)
Post2020xShareofTotal				0.0003
				(0.0003)
AfterShock	-0.0324	-0.0265	-0.0097	0.0009
	(0.0192)	(0.0177)	(0.0171)	(0.0090)
GDPGrowth	-0.0001	-0.0026	-0.0038	0.0032
	(0.0131)	(0.0126)	(0.0129)	(0.0078)
GDPGrowth (t-1)	0.0023	0.0049	0.0009	0.0083
	(0.0222)	(0.0214)	(0.0190)	(0.0109)
LogPopulation	0.1977	0.2295	0.2538	0.3548
	(0.3167)	(0.3208)	(0.3251)	(0.3158)
LogPopulation (t-1)	-0.1995	-0.2393	-0.2545	-0.3448
	(0.3238)	(0.3265)	(0.3323)	(0.3267)
LogUnemployment	-0.0146	-0.0125	-0.0128	-0.0091
	(0.0242)	(0.0241)	(0.0229)	(0.0209)
LogUnemployment (t-1)	-0.0118	-0.0036	-0.0077	-0.0055
	(0.0177)	(0.0187)	(0.0187)	(0.0168)
TradeBalanceShare	-0.2755	-0.2644	-0.2486	-0.1942
	(0.2059)	(0.1982)	(0.1881)	(0.1777)
TradeBalanceShare (t-1)	0.1766	0.1658	0.1476	0.0971
	(0.1495)	(0.1424)	(0.1343)	(0.1171)
StudyPeriod	0.0147	0.0067	0.0128	0.0104
	(0.0380)	(0.0362)	(0.0347)	(0.0300)
StudyPeriod (t-1)	-0.0053	0.0006	-0.0072	-0.0102
	(0.0387)	(0.0366)	(0.0343)	(0.0298)
Constant	-0.0081	0.0169	0.0105	0.0104
	(0.1181)	(0.0838)	(0.0711)	(0.0484)
Observations	233	233	233	233
Instruments	26	24	22	18
AR(2) (p-value)	0.189	0.186	0.165	0.170
Hansen test (p-value)	0.393	0.321	0.248	0.151

Standard errors in parentheses.

All control variables are reported.

[*] $p < 0.1$, [**] $p < 0.05$, [***] $p < 0.01$

In panel fixed-effects models, while a one-percentage-point increase in the share of individual credit cards in GDP reduces income inequality in the normal period, housing loans have a similar effect in the post-shock period. On the other hand, institutional credit use worsens income inequality in the post-shock period. The results obtained from dynamic models created using the System GMM method show that, in the normal period, the effect of individual credit cards is positive in models that use the Gini coefficient and the share of the highest income group as dependent variables; this is contrary to the results obtained from panel fixed-effects models. This suggests that the results of the fixed-effects model may be influenced by simultaneity bias. The fact that the effect of institutional credit use after the shock is similar across the models estimated by both methods indicates that the post-inflation effect of this credit channel is robust across estimation methods. When a dynamic model is constructed using the System GMM method, taking into account the persistence and endogenous nature of the variables, the statistically significant results of personal financing loans and individual credit card effects after the shock, unlike the static fixed effects model, indicate that the effect of these variables is dynamic rather than short-term.

Overall, a key finding from the System GMM models is that personal financing and corporate loans increase the share of the upper classes and decrease the share of the middle classes in the post-shock period, thereby exacerbating income inequality. This result can be explained by the argument advanced by Siami-Namini and Hudson (2015) that lower-income groups face greater barriers to accessing financial markets than higher-income groups. Corporate loans are given to SMEs, large companies, and institutions. The owners of these companies belong to the upper-income group. Therefore, it is not surprising that this increases the share of the upper-income group. Personal financing loans, on the other hand, are a short-term type of loan compared to other consumer loans, so banks are cautious in granting loans to lower-income groups who do not have the opportunity to increase their income in the short term, considering that they may have difficulties in repayment. Upper-income groups, however, can easily access this type of loan. Similarly, I observe that personal credit card use increases the share of the upper-income group in normal times, thereby increasing the Gini coefficient and, consequently, income inequality. Conversely, in the post-shock period, the coefficients for individual credit cards are consistent with lower values of the Gini coefficient and the P80/P20 ratio relative to the normal period, thereby positively impacting income distribution. This can be explained by the fact that lower-income groups increase their credit card spending to maintain their pre-shock consumption levels. This is consistent with the debtor-creditor hypothesis advocated by Meh and Terajima (2009). Debtors are generally from lower-income groups, while lenders are from higher-income groups. In inflationary periods, the decrease in the real value of debts leads to a more favorable income distribution for debtors. Although total deposits converted into loans by banks do not differ statistically significantly across income groups and regions, this may be because deposits are not the only source of savings, and during periods of high inflation, individuals and legal entities invest their savings in other areas with higher return potential (such as investment funds, precious metals, and cryptocurrencies).

5.3 Policy Implications

One of the main findings of the study is that the impact of inflation on income inequality varies regionally. Therefore, policymakers need to consider that anti-inflationary policies may yield different results across regions and should design measures that account for regional heterogeneity. For example, Figures 2.3 and 2.4 show the regional ratios of consumer loans and individual credit cards and institutional loans to GDP, respectively. An examination of these figures shows that some regions rely more heavily on consumer loans, while others rely more heavily on institutional loans. On the other hand, in some regions both ratios are higher compared to others, while in others they are lower. Thus, when designing incentives for institutional loans, policymakers should consider that different outcomes may arise in regions with a high proportion of institutional loans compared to those with a high proportion of consumer loans.

Another finding of the study is that personal credit card use, which normally increases the share of the upper-income group and worsens income inequality, has contributed to a more equitable income distribution in the post-shock period compared to the normal period. Therefore, in an inflationary environment, policymakers may consider facilitating access to credit cards for lower-income groups to help them maintain their pre-shock purchasing power. On the other hand, personal financing loans, a type of short-term borrowing like personal credit cards, benefit the upper-income group and reduce the share of the middle-income group, unlike personal credit card use. This result can be attributed to barriers that limit lower-income groups' access to this type of credit, based on the assumption that they will experience short-term repayment problems. On the other hand, upper-income groups, which are more resilient to inflation, can access credit more easily, increase their income share, and thereby exacerbate income inequality. Therefore, personal financing loans could be structured in a way that supports lower-income groups, similar to personal credit cards. Similarly, since the results show that corporate loans increase the share of the upper-income group and worsen income inequality, policymakers may consider regulating the supply of corporate loans during inflationary periods, monitoring their allocation, and directing incentives toward selected sectors.

6. CONCLUSION

This thesis focuses on the role of bank-sourced borrowing in the impact of inflation on income inequality and attempts to understand whether borrowing by individuals and legal entities during inflationary periods improves or worsens income distribution. Using NUTS-2 level macroeconomic, financial, social welfare, and income distribution indicators for Türkiye covering the period 2014–2023, the study is structured into two stages, each using a different method. The dependent and control variables are the same in both stages. To understand income inequality in all its dimensions, the models utilize different income inequality indicators such as the Gini coefficient, the P80/P20 ratio, and the shares of total income received by the lowest, the middle, and the highest income groups as dependent variables, while the control variables are GDP growth, the logarithm of population and unemployment, the ratio of the foreign trade deficit to GDP, and years of schooling. In the first stage, I used a model constructed with the heterogeneous-effects pooled OLS method to test whether the effect of inflation on income inequality varied by region. The model includes interaction terms formed by multiplying inflation rates by region-specific dummy variables, treated as independent variables. To avoid the dummy-variable trap, I selected the TR10 Istanbul region as the reference region and excluded its dummy variable from the model. In addition, I also included yearly fixed effects in the model. The model results show that the effect of inflation on income inequality varies regionally, with positive effects in some regions and negative effects in others. The Wald test also supports these findings.

In the second stage, I examined the impact of regional bank-sourced borrowing on income inequality during inflationary periods using the shares of different loan types and total deposits in GDP. First, I selected 2020, the year in which inflation began to rise in the dataset, as the starting point for the inflation shock, and created dummy variables for the pre-shock and post-shock periods using the year variable. I obtained interaction terms by multiplying these dummy variables by the shares of different loan types and total deposits, and used these interaction terms as independent variables in the specified models. In addition, to observe their effects during normal periods, I also added the shares of loan types and total deposits within regional GDP to the models on an individual basis. First, I estimated the models I constructed using panel fixed-effects. Since both the Baltagi-Li (1995) and Wooldridge autocorrelation tests showed the existence of autocorrelation, I used clustered robust standard errors in the models. The Sargan-Hansen test, a version of the Hausman test that also works with clustered robust errors, provided support for the fixed-effects specification. Then, considering the possibility of the variables in the models being endogenous and persistent, I created dynamic models using the System GMM method by including one-period lags of both the dependent and control variables.

Both estimation methods show that, in the normal period, only one credit group has a statistically significant effect: individual credit cards. On the other hand, while individual credit cards appear to reduce income inequality by decreasing the share of the upper income group and increasing the share of other income groups when estimating with the fixed effects method, the dynamic results obtained using the System GMM method show the opposite pattern, increasing the share of the upper income group and further worsening income distribution. Looking at the post-shock period, housing loan usage, which appears to favor the lower-income group and disadvantage the upper-income group, does not show a significant effect in the System GMM model results. Corporate loans, however, have a significant effect on the models generated by both methods, demonstrating robustness across estimation methods. Across all specifications, corporate loans reduce the share of the lower-income group and increase the share of the upper-income group in the post-shock period. Personal financing loans also yield the same results as corporate loans in the dynamic models generated using the System GMM method. These findings support the hypothesis that, during the inflationary period, the upper-income group has easier access to financial markets, thereby redistributing income in its favor. Conversely, another type of credit that shows significance in the post-shock period in dynamic models is personal credit cards. More accessible to lower- and middle-income groups than personal financing loans, this type of borrowing positively impacts income equality. The findings support both the borrower-creditor hypothesis, which argues that inflation reduces income inequality, and the hypothesis that differences in access to financial markets among different income groups increase income inequality. The results obtained using the System GMM method provide a more comprehensive dynamic perspective than those from the panel fixed-effects method because dynamic models also account for the endogeneity of the variables and their persistence relative to the previous period. In matters with long-term effects, such as income inequality, the System GMM method provides more reliable insights for revealing marginal effects.

Studies that examine credit types individually and in groups within the context of the relationship between inflation and income inequality are very limited. This study differs from existing research because it uses current data from Türkiye, separates credit types to examine the impact of each credit type and its interacting conditions, takes regional differences into account, and employs pooled OLS, panel fixed-effects, and dynamic System GMM methods together to obtain methodologically robust results compared to similar studies. In this respect, this study may provide guidance for policymakers in designing credit policies aimed at combating inflation, while accounting for regional differences and maintaining fairness in income distribution.

This study analyzes only bank borrowing, as it uses a NUTS-2 level dataset that accounts for regional differences. On the other hand, it is also important to recognize that borrowing can occur both within the financial system through consumer finance companies and savings finance companies, and outside the financial system through individual borrowing among economic actors. Future research that employs different datasets and methodologies and considers other forms of borrowing, could offer a broader perspective on the role of borrowing in the relationship between inflation and income inequality.

REFERENCES

Akarsu, O., Aktug, E., & Kucukbayrak, M. (2024). *Hand-to-mouth Households in the Eurosystem and the Transmission of Monetary Policy*. SSRN. https://doi.org/10.2139/ssrn.5014446

Akgündüz, Y. E., Çolak, M. S., Özbekler, M. D., & Hasan, M. (2025). *Research Notes in Economics*. *2025*.

Baumol, W. J., & Blinder, A. S. (2011). *Economics: Principles and policy* (11th ed., 2010 update). South-Western/Cengage Learning.

Beetsma, R. M. W. J., & Van Der Ploeg, F. (1996). Does inequality cause inflation?: The political economy of inflation, taxation and government debt. *Public Choice*, *87*(1), 143–162. https://doi.org/10.1007/BF00151733

Begg, D., Vernasca, G., Fischer, S., & Dornbusch, R. (2014). *EBOOK: Economics*. McGraw Hill.

Berisha, E., Dubey, R. S., & Gharehgozli, O. (2022). *Inflation and income inequality: Does the level of income inequality matter?* https://doi.org/10.48550/arXiv.2202.05743

Berisha, E., Meszaros, J., & Olson, E. (2018). Income inequality, equities, household debt, and interest rates: Evidence from a century of data. *Journal of International Money and Finance*, *80*, 1–14. https://doi.org/10.1016/j.jimonfin.2017.09.012

Card, D. (1992). Using Regional Variation in Wages to Measure the Effects of the Federal Minimum Wage. NBER Working Papers, NBER Working Papers, Article 4058. https://ideas.repec.org//p/nbr/nberwo/4058.html

Chen, Y.-H., Huang, H.-C., & Ku, K.-P. (2015). The effects of inflation and openness on inequality across alternative monetary regimes. *Applied Economics Letters*, *22*(4), 291–298. https://doi.org/10.1080/13504851.2014.939369

Dilber, C., & Hatipoğlu, M. (2022). ENFLASYON VE GELİR DAĞILIMI ARASINDAKİ NEDENSELLİK İLİŞKİSİ: GELİŞMEKTE OLAN OECD ÜLKELERİ ÜZERİNE BİR ARAŞTIRMA. *Finans Ekonomi ve Sosyal Araştırmalar Dergisi*, *7*(3), 342–347. https://doi.org/10.29106/fesa.1092827

Fatma Serap Girişken. (2025). *Enflasyonun Gelir Dağılımına Etkisi Türkiye İncelemesi* (Tez No: 926792) [Yüksek Lisans Tezi, Gaziantep Üniversitesi / Sosyal Bilimler Enstitüsü / İktisat Ana Bilim Dalı]. https://tez.yok.gov.tr/UlusalTezMerkezi/

Fawaz, F., & Rahnamamoghadam, M. (2024). A Refinement of the Relationship Between Central Bank Independence, Inflation, and Income Inequality in Developing Countries. Journal of Central Banking Theory and Practice, 13(1), 117–131. https://doi.org/10.2478/jcbtp-2024-0006

Fischer, S., & Modigliani, F. (1978). Towards an Understanding of the Real Effects and Costs of Inflation. *Weltwirtschaftliches Archiv*, *114*(4), 810–833.

Galli, R., & Hoeven, R. (2001). Is inflation bad for income inequality: The importance of the initial rate of inflation. *ILO Employment Paper*.

Galor, O., & Zeira, J. (1993). Income Distribution and Macroeconomics. *The Review of Economic Studies*, *60*(1), 35. https://doi.org/10.2307/2297811

Greenwood, J., & Jovanovic, B. (1990). Financial Development, Growth, and the Distribution of Income. *Journal of Political Economy*, *98*(5), 1076–1107.

Gülmez, A., & Altıntaş, N. (2015). TÜRKİYE'DE TİCARİ AÇIKLIK VE ENFLASYONUN GELİR DAĞILIMINA ETKİSİ: EKONOMETRİK BİR ANALİZ. *Kafkas Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *6*(9). https://doi.org/10.18025/kauiibf.27930

Jauch, S., & Watzka, S. (2016). Financial development and income inequality: A panel data approach. *Empirical Economics*, 291–314. https://doi.org/10.1007/s00181-015-1008-x

Jestl, S. (2023). The impact of income inequality on household indebtedness in euro area countries. *European Journal of Economics and Economic Policies: Intervention*, *20*(2),

Jovanovic, B. (2014). *Inflation and the Rich After the Global Financial Crisis*.

Kappel, V. (2010). The Effects of Financial Development on Income Inequality and Poverty. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1585148

Kara, F. (2025). *Gelir Eşitsizliği, Enflasyon ve Büyüme Arasındaki Asimetrik İlişkiler: Türkiye Örneği*.

Khattak, D., Muhammad, A., & Iqbal, K. (2014). Determining the Relationship between Income Inequality, Economic Growth & Inflation. *International Journal of Social Economics, Vol. 1*, 104–114.

Li, H., & Zou, H. (2002). *Inflation, Growth, and Income Distribution: A Cross-Country Study*.

Maurer, M. R., & Yesin, P. A. (2004). *Income Inequality and Inflation*.

Meh, C., & Terajima, Y. (2009). Unexpected Inflation and Redistribution of Wealth in Canada. *Bank of Canada Review*, *2009*(Spring), 45–52.

Nantob, N. (2015). Income Inequality and Inflation in Developing Countries: An Empirical Investigation. *Economics Bulletin*, *35*(4), 2888–2902.

Nikoloski, Z. (2013). Financial Sector Development and Inequality: Is There a Financial Kuznets Curve? *Journal of International Development*, *25*(7), 897–911. https://doi.org/10.1002/jid.2843

Okumuş, İ., Manga, M., & Destek, M. A. (2017). Türkiye de Finansal Gelişim ve Gelir Dağılımı İlişkisi: Finansal Kuznets Eğrisi. *Doğuş Üniversitesi Dergisi*, *2*(18), 153–165. https://doi.org/10.31671/dogus.2018.37

Ömer Fazıl Emek. (2020). *Enflasyonun Gelir Eşitsizliği Üzerindeki Etkisinin Panel Veri Analizi ile İncelenmesi* (Tez No: 620258) [Doktora Tezi, İstanbul Üniversitesi / Sosyal Bilimler Enstitüsü / İktisat Ana Bilim Dalı]. https://tez.yok.gov.tr/UlusalTezMerkezi/

Park, C.-Y., & Mercado, R. J. (2015). Financial Inclusion, Poverty, and Income Inequality in Developing Asia. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2558936

Rajan, R. G., & Zingales, L. (2003). The great reversals: The politics of financial development in the twentieth century. *Journal of Financial Economics*, *69*(1), 5–50. https://doi.org/10.1016/S0304-405X(03)00125-9

Seven, U., & Coskun, Y. (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. *Emerging Markets Review*, *26*, 34–63. https://doi.org/10.1016/j.ememar.2016.02.002

Siami-Namini, S., & Hudson, D. (2019). Inflation and income inequality in developed and developing countries. *Journal of Economic Studies*, *46*(3), 611–632. https://doi.org/10.1108/JES-02-2018-0045

Thalassinos, E., Ugurlu, E., & Muratoglu, Y. (2012). Income Inequality and

Inflation in the EU. *European Research Studies Journal*, *XV*(1), 127–140.
Toplu, M. (2025). *Gelir Eşitsizliğinin Hanehalkı Borcu Üzerindeki Etkisi: Panel Veri Analizi (1970-2021)* (Tez No: 924129) [Yüksek Lisans Tezi, Galatasaray Üniversitesi / Sosyal Bilimler Enstitüsü / İktisat Ana Bilim Dalı]. https://tez.yok.gov.tr/UlusalTezMerkezi/
Walsh, M. J. P., & Yu, J. (2012). *Inflation and Income Inequality: Is Food Inflation Different?* International Monetary Fund.
Wood, J. (2019). Can household debt influence income inequality? Evidence from Britain: 1966–2016. *The British Journal of Politics and International Relations*, *22*, 136914811988883. https://doi.org/10.1177/1369148119888830
Yoshino, O. (1993). Size Distribution of Workers' Houseiiold Income and Macroeconomic Activities in Japan: 1963–88. *Review of Income and Wealth*, *39*(4), 387–402. https://doi.org/10.1111/j.1475-4991.1993.tb00469.x
Younsi, M., & Bechtini, M. (2018). Economic Growth, Financial Development and Income Inequality in BRICS Countries: Evidence from Panel Granger Causality Tests. *MPRA Paper*, Article 85182. https://ideas.repec.org//p/pra/mprapa/85182.html
Yue, H.-Y. (2011). *INCOME INEQUALITY, ECONOMIC GROWTH AND INFLATION: A STUDY ON KOREA*.
Zoramawa, L., Ismail, M. T., & Ayyash, M. (2025). *Dynamic panel threshold effects of inflation and income inequality nexus in advanced economies*

APPENDICES

APPENDIX A : Sub-Model Output Tables

APPENDIX A

Table A.1 : Fixed Effects Results – Sub-Model – Dependent Variable: Gini.

	(1) Model 5	(2) Model 6	(3) Model 7	(4) Model 8	(5) Model 9	(6) Model 10	(7) Model 11
ShareofMortgage		0.0032 (0.0063)					
Post2020xShareofMortgage		-0.0052 (0.0042)					
ShareofVehicle			0.0453 (0.0693)				
Post2020xShareofVehicle			-0.0730 (0.0678)				
ShareofPersonal				0.0001 (0.0037)			
Post2020xShareofPersonal				-0.0012 (0.0028)			
ShareofCCC					-0.0196^{**} (0.0083)		
Post2020xShareofCCC					0.0053 (0.0072)		
ShareofInstitutional						-0.0005 (0.0006)	
Post2020xShareofInstitutional						0.0003^{*} (0.0002)	

Table A.1 : Fixed Effects Results – Sub-Model – Dependent Variable: Gini. (Continued)

	(1) Model 5	(2) Model 6	(3) Model 7	(4) Model 8	(5) Model 9	(6) Model 10	(7) Model 11
ShareofDeposit							0.0003 (0.0010)
Post2020xShareofDeposit							0.0001 (0.0004)
ShareofTotal	-0.0005 (0.0005)						
Post2020xShareofTotal	0.0003* (0.0001)						
GDPGrowth	-0.0353 (0.0217)	-0.0258 (0.0236)	-0.0279 (0.0191)	-0.0309 (0.0245)	-0.0437* (0.0213)	-0.0335 (0.0207)	-0.0261 (0.0220)
LogPopulation	-0.1510 (0.2150)	-0.0831 (0.2170)	-0.0638 (0.2110)	-0.1320 (0.2220)	-0.2100 (0.2360)	-0.1630 (0.2140)	-0.0942 (0.2230)
LogUnemployment	0.0063 (0.0345)	0.0086 (0.0344)	0.0051 (0.0373)	0.0051 (0.0364)	0.0103 (0.0398)	0.0045 (0.0348)	0.0082 (0.0348)
TradeBalanceShare	-0.2830 (0.2540)	-0.2760 (0.2970)	-0.2710 (0.3020)	-0.2790 (0.2780)	-0.3830* (0.2100)	-0.2820 (0.2520)	-0.2560 (0.3060)
StudyPeriod	-0.0276 (0.0237)	-0.0475* (0.0267)	-0.0364 (0.0215)	-0.0349 (0.0259)	-0.0150 (0.0201)	-0.0303 (0.0237)	-0.0333 (0.0253)
Observations	259	259	259	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2 : Fixed Effects Results – Sub-Model – Dependent Variable: P80/P20.

	(1) Model 5	(2) Model 6	(3) Model 7	(4) Model 8	(5) Model 9	(6) Model 10	(7) Model 11
ShareofMortgage		0.0031 (0.0116)					
Post2020xShareofMortgage		-0.0086 (0.0061)					
ShareofVehicle			0.1260 (0.1350)				
Post2020xShareofVehicle			-0.2160 (0.1380)				
ShareofPersonal				-0.0003 (0.0081)			
Post2020xShareofPersonal				-0.0046 (0.0047)			
ShareofCCC					-0.0430^{**} (0.0162)		
Post2020xShareofCCC					0.0059 (0.0143)		
ShareofInstitutional						-0.0011 (0.0010)	
Post2020xShareofInstitutional						0.0008^{**} (0.0004)	
ShareofDeposit							0.0004 (0.0022)

Table A.2 : Fixed Effects Results – Sub-Model – Dependent Variable: P80/P20. (Continued)

	(1) Model 5	(2) Model 6	(3) Model 7	(4) Model 8	(5) Model 9	(6) Model 10	(7) Model 11
Post2020xShareofDeposit							0.0004
							(0.0009)
ShareofTotal	-0.0012						
	(0.0009)						
Post2020xShareofTotal	0.0007*						
	(0.0004)						
GDPGrowth	-0.0668	-0.0502	-0.0496	-0.0621	-0.0860*	-0.0622	-0.0465
	(0.0494)	(0.0529)	(0.0448)	(0.0565)	(0.0490)	(0.0473)	(0.0514)
LogPopulation	-0.4620	-0.3330	-0.2350	-0.4600	-0.6220	-0.4940	-0.3200
	(0.5390)	(0.4990)	(0.5460)	(0.5600)	(0.5790)	(0.5360)	(0.5620)
LogUnemployment	0.0770	0.0825	0.0745	0.0713	0.0851	0.0718	0.0846
	(0.0702)	(0.0731)	(0.0768)	(0.0762)	(0.0801)	(0.0707)	(0.0758)
TradeBalanceShare	-0.6020	-0.5930	-0.5740	-0.6030	-0.8490*	-0.6000	-0.5540
	(0.5080)	(0.5990)	(0.6280)	(0.5570)	(0.4390)	(0.5010)	(0.6240)
StudyPeriod	-0.0774	-0.1120**	-0.0993**	-0.0935*	-0.0494	-0.0835*	-0.0880*
	(0.0484)	(0.0521)	(0.0433)	(0.0514)	(0.0380)	(0.0484)	(0.0502)
Observations	259	259	259	259	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3 : Fixed Effects Results – Sub-Model: Total Credits – Dependent Variable: Income Quantiles.

	(1) Model 5a	(2) Model 5b	(3) Model 5c
ShareofTotal	0.0000	0.0002	-0.0005
	(0.0001)	(0.0001)	(0.0004)
Post2020xShareofTotal	0.0000	-0.0001**	0.0003**
	(0.0000)	(0.0001)	(0.0002)
GDPGrowth	0.0049	0.0099	-0.0355*
	(0.0061)	(0.0059)	(0.0190)
LogPopulation	0.0868	-0.0043	-0.0992
	(0.0557)	(0.0575)	(0.1870)
LogUnemployment	-0.0045	-0.0011	-0.0023
	(0.0107)	(0.0082)	(0.0276)
TradeBalanceShare	0.0458	0.0963	-0.2820
	(0.0454)	(0.0637)	(0.2210)
StudyPeriod	0.0082	0.0033	-0.0194
	(0.0056)	(0.0057)	(0.0198)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4 : Fixed Effects Results – Sub-Model: Mortgage Credits – Dependent Variable: Income Quantiles.

	(1) Model 6a	(2) Model 6b	(3) Model 6c
ShareofMortgage	-0.0022	0.0001	0.0016
	(0.0013)	(0.0017)	(0.0056)
Post2020xShareofMortgage	0.0018*	0.0005	-0.0039
	(0.0009)	(0.0010)	(0.0036)
GDPGrowth	0.0020	0.0081	-0.0280
	(0.0069)	(0.0062)	(0.0202)
LogPopulation	0.0694	-0.0212	-0.0361
	(0.0535)	(0.0528)	(0.184)
LogUnemployment	-0.0046	-0.0020	0.0007
	(0.0098)	(0.0086)	(0.0282)
TradeBalanceShare	0.0419	0.0951	-0.2780
	(0.0511)	(0.0772)	(0.2660)
StudyPeriod	0.0144**	0.0065	-0.0357
	(0.0062)	(0.0062)	(0.0222)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5 : Fixed Effects Results – Sub-Model: Vehicle Credits – Dependent Variable: Income Quantiles.

	(1) Model 7a	(2) Model 7b	(3) Model 7c
ShareofVehicle	-0.0301	0.0044	0.0204
	(0.0184)	(0.0190)	(0.0602)
Post2020xShareofVehicle	0.0323**	0.0022	-0.0499
	(0.0134)	(0.0205)	(0.0614)
GDPGrowth	0.0041	0.0080	-0.0288
	(0.0055)	(0.0054)	(0.0169)
LogPopulation	0.0646	-0.0203	-0.0234
	(0.0529)	(0.0545)	(0.182)
LogUnemployment	-0.0022	-0.0024	-0.0010
	(0.0116)	(0.0088)	(0.0302)
TradeBalanceShare	0.0472	0.0921	-0.2690
	(0.0509)	(0.0765)	(0.2680)
StudyPeriod	0.0092*	0.0058	-0.0282
	(0.0050)	(0.0051)	(0.0180)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6 : Fixed Effects Results – Sub-Model: Personal Financing Credits – Dependent Variable: Income Quantiles.

	(1) Model 8a	(2) Model 8b	(3) Model 8c
ShareofPersonal	0.0009	-0.0010	0.0017
	(0.0007)	(0.0012)	(0.0034)
Post2020xShareofPersonal	-0.0003	0.0008	-0.0021
	(0.0006)	(0.0007)	(0.0024)
GDPGrowth	0.0064	0.0070	-0.0291
	(0.0070)	(0.0061)	(0.0204)
LogPopulation	0.0741	0.0067	-0.1110
	(0.0582)	(0.0606)	(0.1870)
LogUnemployment	-0.0051	0.0001	-0.0050
	(0.0108)	(0.0086)	(0.0293)
TradeBalanceShare	0.0417	0.1010	-0.2880
	(0.0467)	(0.0713)	(0.2450)
StudyPeriod	0.0056	0.0088	-0.0322
	(0.0060)	(0.0069)	(0.0221)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7 : Fixed Effects Results – Sub-Model: Consumer Credit Cards – Dependent Variable: Income Quantiles.

	(1) Model 9a	(2) Model 9b	(3) Model 9c
ShareofCCC	0.0030*	0.0051**	-0.0176**
	(0.0016)	(0.0023)	(0.0073)
Post2020xShareofCCC	-0.0000	-0.0016	0.0047
	(0.0015)	(0.0018)	(0.0064)
GDPGrowth	0.0074	0.0115*	-0.0423**
	(0.0058)	(0.0058)	(0.0186)
LogPopulation	0.1110*	0.0028	-0.1390
	(0.0554)	(0.0632)	(0.2060)
LogUnemployment	-0.0044	-0.0027	0.0024
	(0.0109)	(0.0097)	(0.0329)
TradeBalanceShare	0.0659*	0.1210**	-0.3720*
	(0.0383)	(0.0581)	(0.1910)
StudyPeriod	0.0047	0.0009	-0.0098
	(0.0054)	(0.0044)	(0.0159)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8 : Fixed Effects Results – Sub-Model: Institutional Credits – Dependent Variable: Income Quantiles.

	(1) Model 10a	(2) Model 10b	(3) Model 10c
ShareofInstitutional	0.0000	0.0002	-0.0005
	(0.0001)	(0.0002)	(0.0005)
Post2020xShareofInstitutional	0.0000	-0.0001**	0.0004**
	(0.0000)	(0.0000)	(0.0001)
GDPGrowth	0.0049	0.0094	-0.0339*
	(0.0059)	(0.0057)	(0.0181)
LogPopulation	0.0874	-0.0000	-0.1130
	(0.0562)	(0.0568)	(0.1850)
LogUnemployment	-0.0044	-0.0005	-0.0042
	(0.0108)	(0.0082)	(0.0277)
TradeBalanceShare	0.0457	0.0964	-0.2820
	(0.0448)	(0.0629)	(0.2180)
StudyPeriod	0.0081	0.0042	-0.0222
	(0.0056)	(0.0056)	(0.0198)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9 : Fixed Effects Results – Sub-Model: Total Deposits– Dependent Variable: Income Quantiles.

	(1) Model 11a	(2) Model 11b	(3) Model 11c
ShareofDeposit	-0.0001	-0.0001	0.0004
	(0.0002)	(0.0002)	(0.0009)
Post2020xShareofDeposit	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0004)
GDPGrowth	0.0044	0.0068	-0.0259
	(0.0061)	(0.0056)	(0.0188)
LogPopulation	0.0891	-0.0256	-0.0334
	(0.0555)	(0.0591)	(0.1950)
LogUnemployment	-0.0034	-0.0018	0.0003
	(0.0106)	(0.0085)	(0.0283)
TradeBalanceShare	0.0403	0.0864	-0.2520
	(0.0540)	(0.0818)	(0.2770)
StudyPeriod	0.0092	0.0060	-0.0265
	(0.0062)	(0.0062)	(0.0212)
Observations	259	259	259

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.10 : System GMM Results – Sub-Model – Dependent Variable: Gini.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Gini (t-1)	1.068***	1.074***	1.082***	1.067***	1.097***	1.069***	1.067***
	(0.225)	(0.223)	(0.213)	(0.211)	(0.219)	(0.223)	(0.240)
ShareofMortgage		-0.000					
		(0.002)					
Post2020xShareofMortgage		0.004					
		(0.003)					
ShareofVehicle			0.037				
			(0.033)				
Post2020xShareofVehicle			0.029				
			(0.053)				
ShareofPersonal				-0.001			
				(0.001)			
Post2020xShareofPersonal				0.003*			
				(0.002)			
ShareofCCC					0.005*		
					(0.002)		
Post2020xShareofCCC					-0.006		
					(0.005)		
ShareofInstitutional						-0.000	
						(0.000)	
Post2020xShareofInstitutional						0.000	
						(0.000)	
ShareofDeposit							-0.000
							(0.000)
Post2020xShareofDeposit							0.000
							(0.000)
ShareofTotal	-0.000						
	(0.000)						
Post2020xShareofTotal	0.000						
	(0.000)						

Table A.10 : System GMM Results – Sub-Model – Dependent Variable: Gini. (Continued)

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
AfterShock	-0.002	-0.011	0.005	-0.017	0.028**	0.003	0.009
	(0.010)	(0.017)	(0.009)	(0.014)	(0.013)	(0.008)	(0.008)
GDPGrowth	0.005	0.011	-0.005	0.007	0.002	0.004	0.001
	(0.007)	(0.011)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)
GDPGrowth (t-1)	0.006	0.012	-0.002	0.008	0.009	0.005	0.003
	(0.010)	(0.012)	(0.011)	(0.010)	(0.014)	(0.010)	(0.010)
LogPopulation	0.533	0.510	0.468	0.474	0.477	0.534	0.515
	(0.424)	(0.418)	(0.389)	(0.438)	(0.418)	(0.424)	(0.420)
LogPopulation (t-1)	-0.545	-0.520	-0.480	-0.482	-0.495	-0.547	-0.525
	(0.435)	(0.428)	(0.400)	(0.446)	(0.424)	(0.435)	(0.431)
LogUnemployment	-0.009	-0.008	-0.001	-0.013	-0.006	-0.009	-0.010
	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
LogUnemployment (t-1)	0.011	0.008	-0.001	0.012	0.014	0.012	0.011
	(0.020)	(0.017)	(0.022)	(0.018)	(0.020)	(0.020)	(0.019)
TradeBalanceShare	-0.215	-0.233	-0.211	-0.250	-0.221	-0.214	-0.228
	(0.164)	(0.164)	(0.159)	(0.163)	(0.176)	(0.165)	(0.161)
TradeBalanceShare (t-1)	0.095	0.112	0.094	0.133	0.115	0.094	0.103
	(0.099)	(0.101)	(0.101)	(0.109)	(0.109)	(0.100)	(0.106)
StudyPeriod	-0.001	0.002	0.015	0.003	0.003	-0.000	0.003
	(0.025)	(0.027)	(0.023)	(0.025)	(0.024)	(0.025)	(0.024)
StudyPeriod (t-1)	0.001	-0.001	-0.013	-0.002	-0.002	0.001	-0.001
	(0.024)	(0.026)	(0.022)	(0.024)	(0.022)	(0.024)	(0.024)
Constant	0.036	0.021	0.027	0.026	0.015	0.035	0.012
	(0.030)	(0.025)	(0.027)	(0.033)	(0.024)	(0.033)	(0.031)
Observations	233	233	233	233	233	233	233
Instruments	16	16	16	16	16	16	16
AR(2) (p-value)	0.152	0.152	0.174	0.156	0.154	0.151	0.150
Hansen test (p-value)	0.212	0.226	0.374	0.227	0.286	0.214	0.222

Standard errors in parentheses.
Control variables are included but not reported.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.11 : System GMM Results – Sub-Model – Dependent Variable: P80/P20.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
P80/P20 (t-1)	1.135**	1.064**	1.255***	1.039*	1.235***	1.129**	1.155**
	(0.494)	(0.513)	(0.385)	(0.528)	(0.357)	(0.487)	(0.530)
ShareofMortgage		0.005					
		(0.007)					
Post2020xShareofMortgage		0.021**					
		(0.008)					
ShareofVehicle			0.131***				
			(0.046)				
Post2020xShareofVehicle			0.185				
			(0.133)				
ShareofPersonal				-0.006			
				(0.007)			
Post2020xShareofPersonal				0.011*			
				(0.006)			
ShareofCCC					0.016**		
					(0.006)		
Post2020xShareofCCC					-0.031**		
					(0.012)		
ShareofInstitutional						0.000	
						(0.001)	
Post2020xShareofInstitutional						0.000	
						(0.000)	
ShareofDeposit							-0.001
							(0.002)
Post2020xShareofDeposit							-0.000
							(0.001)
ShareofTotal	0.000						
	(0.000)						
Post2020xShareofTotal	0.000						

Table A.11 : System GMM Results – Sub-Model – Dependent Variable: P80/P20. (Continued)

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
AfterShock	-0.001	-0.078*	-0.008	-0.064	0.108***	0.010	0.030
	(0.021)	(0.042)	(0.023)	(0.052)	(0.037)	(0.016)	(0.029)
GDPGrowth	0.037	0.085***	-0.010	0.040	0.027	0.033	0.025
	(0.022)	(0.025)	(0.026)	(0.023)	(0.019)	(0.022)	(0.020)
GDPGrowth (t-1)	0.009	0.064	-0.031	0.016	0.036	0.007	-0.004
	(0.025)	(0.048)	(0.022)	(0.043)	(0.031)	(0.024)	(0.035)
LogPopulation	1.759	1.552	1.873*	1.424	1.762	1.743	1.793
	(1.237)	(1.192)	(0.998)	(1.218)	(1.042)	(1.223)	(1.153)
LogPopulation (t-1)	-1.797	-1.582	-1.924*	-1.442	-1.833	-1.780	-1.814
	(1.309)	(1.247)	(1.052)	(1.292)	(1.077)	(1.297)	(1.218)
LogUnemployment	-0.058	-0.027	-0.018	-0.069	-0.050	-0.059	-0.066
	(0.046)	(0.062)	(0.050)	(0.051)	(0.041)	(0.046)	(0.046)
LogUnemployment (t-1)	0.081	0.048	0.039	0.077	0.107	0.082	0.081
	(0.079)	(0.083)	(0.083)	(0.091)	(0.064)	(0.079)	(0.072)
TradeBalanceShare	-0.403	-0.446	-0.366	-0.549	-0.421	-0.393	-0.381
	(0.434)	(0.385)	(0.406)	(0.409)	(0.511)	(0.452)	(0.463)
TradeBalanceShare (t-1)	0.089	0.120	0.060	0.198	0.133	0.079	0.059
	(0.289)	(0.259)	(0.308)	(0.319)	(0.340)	(0.298)	(0.289)
StudyPeriod	-0.111*	-0.103	-0.071	-0.111*	-0.118**	-0.110*	-0.105*
	(0.059)	(0.068)	(0.056)	(0.063)	(0.051)	(0.059)	(0.061)
StudyPeriod (t-1)	0.098*	0.088	0.064	0.101	0.106**	0.098*	0.097
	(0.057)	(0.066)	(0.053)	(0.063)	(0.049)	(0.056)	(0.067)
Constant	0.112	0.103	0.046	0.162	0.021	0.110	0.008
	(0.199)	(0.203)	(0.151)	(0.146)	(0.150)	(0.188)	(0.258)
Observations	233	233	233	233	233	233	233
Instruments	16	16	16	16	16	16	16
AR(2) (p-value)	0.032	0.083	0.055	0.052	0.029	0.030	0.034
Hansen test (p-value)	0.007	0.020	0.075	0.008	0.029	0.007	0.008

Standard errors in parentheses.
Control variables are included but not reported.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.12 : System GMM Results – Sub-Model – Dependent Variable: Bottom 20% Share.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Fsquantile (t-1)	0.768*** (0.226)	0.765*** (0.235)	0.763*** (0.217)	0.746*** (0.229)	0.792*** (0.240)	0.766*** (0.225)	0.732*** (0.250)
ShareofMortgage		-0.000 (0.000)					
Post2020xShareofMortgage		-0.001** (0.001)					
ShareofVehicle			-0.005 (0.009)				
Post2020xShareofVehicle			-0.010 (0.012)				
ShareofPersonal				0.000 (0.000)			
Post2020xShareofPersonal				-0.001* (0.000)			
ShareofCCC					-0.001 (0.001)		
Post2020xShareofCCC					0.003** (0.001)		
ShareofInstitutional						0.000 (0.000)	
Post2020xShareofInstitutional						-0.000* (0.000)	
ShareofDeposit							-0.000 (0.000)
Post2020xShareofDeposit							0.000 (0.000)
ShareofTotal	0.000 (0.000)						
Post2020xShareofTotal	-0.000* (0.000)						

Table A.12 : System GMM Results – Sub-Model – Dependent Variable: Bottom 20% Share. (Continued)

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
AfterShock	0.001	0.005	0.000	0.003	-0.010**	0.000	-0.003
	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
GDPGrowth	-0.001	-0.004	0.001	-0.001	-0.000	-0.001	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDPGrowth (t-1)	-0.000	-0.003	0.002	-0.000	-0.005*	-0.000	0.000
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
LogPopulation	0.022	0.030	0.027	0.041	0.036	0.023	0.032
	(0.077)	(0.072)	(0.071)	(0.081)	(0.077)	(0.078)	(0.077)
LogPopulation (t-1)	-0.020	-0.028	-0.025	-0.039	-0.032	-0.020	-0.031
	(0.079)	(0.073)	(0.072)	(0.083)	(0.078)	(0.080)	(0.079)
LogUnemployment	0.003	0.001	0.001	0.004	0.001	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
LogUnemployment (t-1)	-0.007	-0.005	-0.004	-0.008	-0.008	-0.007	-0.007
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
TradeBalanceShare	0.030	0.030	0.027	0.035	0.037	0.029	0.029
	(0.032)	(0.031)	(0.031)	(0.034)	(0.034)	(0.032)	(0.033)
TradeBalanceShare (t-1)	0.007	0.006	0.009	0.004	0.000	0.007	0.004
	(0.036)	(0.036)	(0.039)	(0.036)	(0.039)	(0.036)	(0.032)
StudyPeriod	0.006	0.005	0.003	0.005	0.006	0.005	0.004
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
StudyPeriod (t-1)	-0.005	-0.005	-0.002	-0.004	-0.005	-0.005	-0.003
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.017	0.018	0.017	0.016	0.016	0.017	0.025
	(0.031)	(0.031)	(0.028)	(0.032)	(0.031)	(0.031)	(0.032)
Observations	233	233	233	233	233	233	233
Instruments	16	16	16	16	16	16	16
AR(2) (p-value)	0.288	0.403	0.405	0.364	0.342	0.287	0.326
Hansen test (p-value)	0.330	0.383	0.481	0.300	0.508	0.331	0.362

Standard errors in parentheses.
Control variables are included but not reported.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.13 : System GMM Results – Sub-Model – Dependent Variable: Middle 20% Share.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Tquantile (t-1)	1.178**	1.177***	1.199***	1.203***	1.178***	1.188**	1.187***
	(0.426)	(0.376)	(0.384)	(0.407)	(0.399)	(0.437)	(0.422)
ShareofMortgage		-0.000					
		(0.001)					
Post2020xShareofMortgage		-0.001					
		(0.001)					
ShareofVehicle			-0.012				
			(0.009)				
Post2020xShareofVehicle			-0.015				
			(0.016)				
ShareofPersonal				0.000			
				(0.000)			
Post2020xShareofPersonal				-0.001			
				(0.001)			
ShareofCCC					-0.000		
					(0.001)		
Post2020xShareofCCC					-0.000		
					(0.001)		
ShareofInstitutional						0.000	
						(0.000)	
Post2020xShareofInstitutional						-0.000	
						(0.000)	
ShareofDeposit							0.000
							(0.000)
Post2020xShareofDeposit							-0.000
							(0.000)
ShareofTotal	0.000						
	(0.000)						
Post2020xShareofTotal	-0.000						

Table A.13 : System GMM Results – Sub-Model – Dependent Variable: Middle 20% Share. (Continued)

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
AfterShock	0.000	0.000	-0.001	0.003	-0.002	-0.001	-0.003
	(0.003)	(0.006)	(0.003)	(0.006)	(0.004)	(0.002)	(0.002)
GDPGrowth	-0.001	-0.002	0.003	-0.002	-0.000	-0.001	0.000
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
GDPGrowth (t-1)	-0.001	-0.002	0.002	-0.002	0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
LogPopulation	-0.248^{***}	-0.243^{***}	-0.231^{***}	-0.243^{***}	-0.243^{***}	-0.250^{***}	-0.245^{***}
	(0.088)	(0.084)	(0.072)	(0.084)	(0.082)	(0.088)	(0.082)
LogPopulation (t-1)	0.249^{**}	0.243^{**}	0.232^{***}	0.242^{**}	0.243^{***}	0.250^{**}	0.245^{**}
	(0.093)	(0.089)	(0.078)	(0.089)	(0.086)	(0.093)	(0.088)
LogUnemployment	0.008	0.008	0.004	0.009	0.008	0.008	0.009
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
LogUnemployment (t-1)	-0.002	-0.001	0.003	-0.001	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
TradeBalanceShare	0.075	0.078	0.072	0.081	0.076	0.075	0.078
	(0.048)	(0.049)	(0.049)	(0.053)	(0.048)	(0.049)	(0.047)
TradeBalanceShare (t-1)	-0.056	-0.058	-0.053	-0.067	-0.059	-0.056	-0.057
	(0.042)	(0.041)	(0.043)	(0.043)	(0.039)	(0.043)	(0.039)
StudyPeriod	-0.003	-0.004	-0.009	-0.005	-0.005	-0.003	-0.005
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
StudyPeriod (t-1)	0.002	0.003	0.008	0.004	0.004	0.002	0.004
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Constant	-0.054	-0.051	-0.061	-0.052	-0.050	-0.055	-0.051
	(0.110)	(0.106)	(0.108)	(0.112)	(0.111)	(0.111)	(0.115)
Observations	233	233	233	233	233	233	233
Instruments	16	16	16	16	16	16	16
AR(2) (p-value)	0.221	0.196	0.242	0.197	0.207	0.224	0.208
Hansen test (p-value)	0.525	0.547	0.972	0.550	0.517	0.532	0.526

Standard errors in parentheses.
Control variables are included but not reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.14 : System GMM Results – Sub-Model – Dependent Variable: Top 20% Share.

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Fiquantile (t-1)	0.979*** (0.263)	0.985*** (0.243)	1.039*** (0.228)	0.993*** (0.243)	1.015*** (0.259)	0.982*** (0.266)	0.972*** (0.259)
ShareofMortgage		-0.000 (0.002)					
Post2020xShareofMortgage		0.002 (0.003)					
ShareofVehicle			0.035 (0.031)				
Post2020xShareofVehicle			0.015 (0.049)				
ShareofPersonal				-0.001 (0.001)			
Post2020xShareofPersonal				0.002 (0.002)			
ShareofCCC					0.004 (0.003)		
Post2020xShareofCCC					-0.003 (0.005)		
ShareofInstitutional						-0.000 (0.000)	
Post2020xShareofInstitutional						0.000 (0.000)	
ShareofDeposit							-0.000 (0.000)
Post2020xShareofDeposit							0.000 (0.000)
ShareofTotal	-0.000 (0.000)						
Post2020xShareofTotal	0.000 (0.000)						

Table A.14 : System GMM Results – Sub-Model – Dependent Variable: Top 20% Share. (Continued)

	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
AfterShock	-0.001	0.002	0.008	-0.008	0.017	0.003	0.007
	(0.010)	(0.016)	(0.007)	(0.015)	(0.014)	(0.008)	(0.007)
GDPGrowth	0.003	0.003	-0.006	0.003	0.001	0.002	0.001
	(0.007)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
GDPGrowth (t-1)	0.009	0.009	0.001	0.007	0.004	0.008	0.006
	(0.010)	(0.011)	(0.011)	(0.009)	(0.013)	(0.010)	(0.010)
LogPopulation	0.371	0.362	0.320	0.336	0.347	0.374	0.364
	(0.322)	(0.322)	(0.301)	(0.326)	(0.316)	(0.321)	(0.317)
LogPopulation (t-1)	-0.363	-0.351	-0.315	-0.327	-0.344	-0.367	-0.354
	(0.333)	(0.332)	(0.311)	(0.335)	(0.322)	(0.332)	(0.328)
LogUnemployment	-0.008	-0.011	-0.003	-0.013	-0.007	-0.008	-0.009
	(0.021)	(0.021)	(0.020)	(0.022)	(0.022)	(0.021)	(0.021)
LogUnemployment (t-1)	-0.004	-0.004	-0.012	-0.001	-0.002	-0.003	-0.003
	(0.018)	(0.016)	(0.019)	(0.017)	(0.018)	(0.018)	(0.017)
TradeBalanceShare	-0.184	-0.200	-0.183	-0.212	-0.182	-0.183	-0.201
	(0.177)	(0.181)	(0.174)	(0.179)	(0.190)	(0.178)	(0.173)
TradeBalanceShare (t-1)	0.091	0.106	0.097	0.117	0.105	0.089	0.104
	(0.112)	(0.115)	(0.113)	(0.119)	(0.116)	(0.113)	(0.115)
StudyPeriod	0.008	0.012	0.021	0.010	0.011	0.008	0.010
	(0.030)	(0.032)	(0.031)	(0.032)	(0.030)	(0.030)	(0.030)
StudyPeriod (t-1)	-0.008	-0.011	-0.019	-0.009	-0.009	-0.008	-0.009
	(0.030)	(0.031)	(0.030)	(0.031)	(0.029)	(0.029)	(0.029)
Constant	0.014	-0.004	0.000	0.012	-0.010	0.014	-0.003
	(0.045)	(0.031)	(0.031)	(0.041)	(0.035)	(0.050)	(0.041)
Observations	233	233	233	233	233	233	233
Instruments	16	16	16	16	16	16	16
AR(2) (p-value)	0.171	0.154	0.168	0.159	0.167	0.172	0.159
Hansen test (p-value)	0.141	0.140	0.239	0.144	0.179	0.143	0.137

Standard errors in parentheses.
Control variables are included but not reported.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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