Impact of Government-to-Person Payments(G2P) on Income distribution in Africa

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Abstract

This study examines the impact of the digitization of G2P on income distribution using a panel dataset 46 African countries over the period 1990 to 2020 and Difference-in-Difference method. Our results suggest a significant improvement in income distribution following the introduction of digital G2P payment systems. Robustness checks, support the validity of our results and indicate that they are not affected by spurious trends or confounding factors, nor by other concurrent reforms. Our study uncovers heterogeneity in the impact of G2P on income distribution, influenced by macroeconomic conditions and structural factors. These results underscore for policymakers that the adoption of G2P has the potential to significantly reduce income inequality. However, the inadequacies of information systems for identification, verification, and payment of government benefits, prevalent in Africa, highlight the need to strengthen foundational identification systems and social registries. To achieve sustainable inclusive growth, prioritizing the digitization of social protection service delivery is critical to effectively address current and future poverty challenges.

Keywords: Mobile money; Difference in Difference; Income distribution; Developing countries

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1 Introduction

The COVID 19 pandemic and the impact of war in some parts of the world threaten to set back years of progress—by increasing poverty, inequality and social exclusion—and compromise the achievement of the Sustainable Development Goals (SDGs). Given current trends,World-Bank (2022) estimated that 574 million people—nearly 7 percent of the world's population—will still be living on less than 2.15 US dollar a day in 2030, with most in Africa. In some developing countries, these recent crises have acted as a catalyst and "the great accelerator", challenging the capacity and efficiency of governments to deliver services in response to shocks and highlighting the need for accelerating technological progress (Lindert et al., 2020; Hai et al., 2021; Lee and Trimi, 2021; Amankwah-Amoah et al., 2021; Popkova et al., 2022). Globally, the capacity of governments to effectively reach workers and households with basic assistance varies considerably across countries, depending on the availability of key delivery components Davidovic et al. (2020) such as, a universal identification system, socioeconomic data on households, and a delivery system. During pandemic, social distancing measures and the large penetration of mobile phones have encouraged government-to-person(G2P) transfers through mobile platforms. Then, recent global trend is towards digital transformation including e-government and widespread adoption of government-to- person payment systems. E-government is the digital transformation of government bodies, where most of administrative transactions are conducted electronically, to improve government performance, boost coordination, and faster service delivery for the citizens Rombach and Steffens (2009). This process is expected to fundamentally reshape service delivery, administration and the governance. In Africa, under the initiative of Africa-Union (2020) countries jointly embraced the Digital Transformation Strategy. Most of them are currently in the process of modernizing their foundational identification (fID) systems and integrating advanced digital identity verification features. These endeavors are intricately connected to broader national, regional, and continental strategies focused on accelerating the transition to digital governance, economies, and societies.

Increasing income inequality and poverty continue to be the most challenging economic trend facing African countries. A major component of government intervention is the distribution of goods and services through social programs such as cash transfers, subsidies, child care, training, or labor services. To date, service delivery has been fragmented and challenging for recipients to navigate Lindert et al. (2020). The persistence of poverty and inequality is compounded by the challenges of inclusion and coordination, two recurrent and perennial challenges for social protection systems. Digitizing G2P payments has the potential to dramatically reduce costs, increase efficiency and transparency, and help recipients build familiarity with digital payments Klapper and Singer (2017a).

Government-to-person (G2P) mobile payment adoption refers to the process of governments implementing and promoting the use of mobile payment solutions to deliver social transfer programs or welfare payments directly to individuals or households in need. It can play a critical role in facilitating effective and equitable recovery, resilience, and response efforts to deliver services and social assistance to people in need. Today, G2P payment systems represent an opportunity to provide access to financial services to unbanked beneficiaries by channeling a steady flow of money into financial accounts (Kemal, 2019; Pazarbasioglu et al., 2020).

Instead of traditional methods like cash, digital G2P mobile payment adoption leverages mobile technology to facilitate secure and efficient financial transactions between government and beneficiaries. Branchless banking is one way to make such payments and services more accessible, while reducing the cost and increasing the efficiency of the payment process itself. In most cases, government payment schemes are organized welfare schemes, government salaries and small savings schemes, direct transfers, subsidies such as fertilizer subsidies, income generating assets, services including payment for school infrastructure, teachers' salaries and school supplies, education and health information and awareness. Therefore, digitizing the social protection payment process is a prerequisite not only for government efficiency, but also for better coverage, targeting and overall efficiency of social assistance mechanisms.

While there is a large literature on mobile money, to date there is little on G2P adoption that examines multiple outcomes. Indeed, evidence shows that mobile money adoption reduces consumption volatility Apeti (2023a).This effect is driven by financial inclusion and migrant remittances. In exploring the long-term effects of mobile money Suri and Jack (2016) shed light on its positive effect on Kenyan households by bringing 2 percent of Kenyans out of poverty. Their findings undescore the transformative potential of mobile money, elucidating shifts in financial behavior–increasing financial resilience and savings–and an efficient labor allocation resulting in a shift from agriculture to business. Focusing on rural households in Uganda, Munyegera and Matsumoto (2016) show that mobile money adoption increases welfare–measured by real per capita consumption–of households through its ability to facilitate remittances. Globally, numerous studies have echoed these affirmative outcomes. (Wieser et al., 2019; Batista and Vicente, 2020) have documented how mobile money increases household consumption expenditures, food security and per capita consumption. Moreover mobile money have a positive effect on self-entrepreneurship, on the ability of households to get well paid jobs, receive remittances, save, invest, deal with unexpected shocks, and on firms' performance (Suri and Jack, 2016; Islam et al., 2018; Hamdan, 2019; Aggarwal et al., 2020; Batista and Vicente, 2020; Donovan, 2012; Wieser et al., 2019; Ahmed and Cowan, 2021; Koomson et al., 2021; Yao et al., 2023).

Finally, some studies identify mobile money as a mechanism for business formalization, redistribution (Asongu, 2015; Mawejje and Lakuma, 2019). Aker et al. (2016) investigate the impact of a mobile money cash transfer programme on poverty reduction in Niger. And Hjelm et al. (2017) explore the impact of cash transfers on poverty and perceived stress. Other studies focus on improving financial conditions, in particular, how a household's saving behaviour affects its economic activity.

To date, no study has examined the digitizing of G2P as determinant of social welfare efficiency. This is surprising because digital G2P payments have potential benefits - such as increased security and reduced crime, increased financial inclusion, enhanced women's economic empowerment, more transparency and reduced leakage, improved speed and timely delivery, lower costs for governments and recipients - to social welfare in African countries. As we navigate the post-pandemic landscape, understanding the nuances of G2P payment ecosystems becomes imperative for shaping resilient and inclusive societies. This research aims to delve into the intricacies of successful G2P models, examining the key components that contribute to their effectiveness. By identifying best practices and potential pitfalls, we seek to provide actionable insights that can guide policymakers, financial institutions, and technology providers in enhancing their payment infrastructures.

The focus of our study is clearly on measuring the impact of G2P on income inequality. Understanding the sensitivity of the adoption of new system of delivery to social welfare is crucial for countries because it can have a significant impact on their development. Moreover, today issue of poverty can be more frequent and severe in future due to multiple shocks and vulnerability related to climate change. By addressing this relation, countries could better manage their resource and develop more resilient economies. In doing so, our study aims to provide new insights into the varied challenges encountered by African economies, where the need for equitable growth and poverty reduction is paramount. In order to provide both rational and constructive policy responses to this study, the following mains concerns was identified: How does government to person payment affect social welfare? Can government to person payment adoption serve as a resilient shield, and how does it help mitigate the adverse effects of negative shocks, such as health, energy and geopolitical conflicts, on income inequality and poverty? We attempt to shed light on the mechanisms by which recent technologies such as G2P exacerbates or mitigates income inequalities through a rigorous assessment of his impact.

In order to provide a robust identification of the causal effect of G2P, we have adopted the difference-in-difference (DiD) impact analysis methodology developed by Callaway and Sant'Anna (2021a). Our analysis is based on a comprehensive sample of African countries, covering a period from 1990 to 2020, allowing us to explore in depth the impact of G2P payments on income distribution. The results of our study indicate a significant improvement in income distribution following the introduction of G2P digital payment systems in the countries that have adopted them. By focusing on the impact of G2P payments on income inequality, our study seeks to shed light on the challenges faced by Africa, highlighting the crucial importance of equitable growth and poverty reduction. Our findings indicate that cash transfers to low-income populations through these programmes can not only reduce immediate poverty, but also facilitate access to essential services, while stimulating human capital formation and boosting demand in various economic sectors. These robust results are validated by several robustness tests, including the use of alternative estimation methods such as the DiD on staggered adoption Wooldridge (2021), the DiD proposed by Borusyak et al. (2022), the entropy balancing method of Hainmueller (2012), the instrumental variable strategy, the placebo test, as well as an analysis of the anticipation effect on the effective application of G2P and the reduction of the control window due to structural changes. Furthermore, we emphasise the diversity of the impact of G2P on income distribution, underscoring the influence of macroeconomic conditions and structural factors. These observations are of significant importance for policy makers, demonstrating the potential of G2P payments to significantly reduce income inequality. However, it is crucial to acknowledge the persistent gaps in information systems for the identification and payment of government benefits, which are of particular concern in African countries. This highlights the pressing need to reinforce basic infrastructure to guarantee the efficacy of G2P initiatives. In a post-pandemic world, a comprehensive grasp of G2P payment ecosystems becomes vital to fostering resilient and inclusive societies. Our research is dedicated to delving into these nuances by identifying the pivotal factors influencing the effectiveness of G2P models.

The remainder of the paper is organised as follows. The following section presents the background and channel of transmission. This is followed by a description of data and methodology in section 3. Section 4 presents the stylized facts, while section 5 describes the Empirical results. Finally, Section 6 concludes the study and provides the key policy suggestions deduced from the results.

2 Channel of transmission: G2P and Income Distribution

Why is the distribution of income more equal in some countries than in others? What determines the distribution of income in a given country at a specific time? Can government intervention change the distribution of income? These questions have been raised with increasing frequency in the debate on development economics. In modern societies where most adult citizens, rich or poor, have the right to vote for those who will represent them in government, there is less tolerance or acceptance of high inequality. As a result, policymakers are under pressure to introduce policies that are designed to make the distribution of income or more equal. G2P can support inclusive growth. Government-to-Person Payments can significantly influence income distribution, social welfare and inclusive growth through many mechanisms. Inclusive growth refers to economic development that benefits all segments of the population, ensuring that the benefits of economic growth are distributed equitably, and no one is left behind. Capitalizing on the existing literature, Government-to-Person payments (G2P) emerge as pivotal instruments in shaping income distribution dynamics, particularly within contexts characterized by institutional fragilities. Through the Payment of employees and social transfers, including conditional and unconditional transfers, G2P payment can directly target and assist those living in poverty. This targeted approach directly addresses income disparities by providing a financial and social safety net for the economically marginalized, thereby bolstering their overall welfare and contributing to a more equitable income distribution landscape Grosh et al. (2022). By providing cash transfers to low-income population, these programs can alleviate immediate poverty and improve them to access education, vocational training, healthcare, and other essential services Klapper and Singer (2017b); Davidovic et al. (2020). When G2P payments are used to support education and skill development, they can contribute to building human capital These programs enable individuals to strengthen human capital and acquire skills that can lead to better job opportunities and higher incomes. This, in turn, improves the productivity Ubah et al. (2023) and employability of the workforce, leading to higher income levels and reduced income inequality. Moreover, they are more likely to spend a larger portion of their income on goods and services. Then, increased consumption by the lower-income population can drive demand in various sectors, leading to business growth and job creation. G2P interventions can influence individuals' behavior, including labor force participation, work choices, and entrepreneurship. For example, cash transfer programs might provide individuals with a safety net, encouraging them to take more risks, invest in productive activities. Such behavioral changes can potentially lead to increased income and reduced income inequality. Also, government payment programs can be used as a tool to promote financial inclusion by encouraging beneficiaries to open bank accounts and access formal financial services. This inclusion can lead to increased savings, access to credit, and participation in the formal economy. Globally, G2P programs can reduce social disparities and mitigate potential social tensions caused by income inequality. When more people have access to basic resources and opportunities, it can foster inclusive and sustainable economic development.

However, If the targeting mechanisms of the payment programs are not adequately designed to reach those who are most in need, the benefits may end up being received by households with higher incomes (Authors). This can widen the income gap by providing additional resources to those who are already better off, while neglecting the most economically disadvantaged. In some cases, government-to-personal payment programs

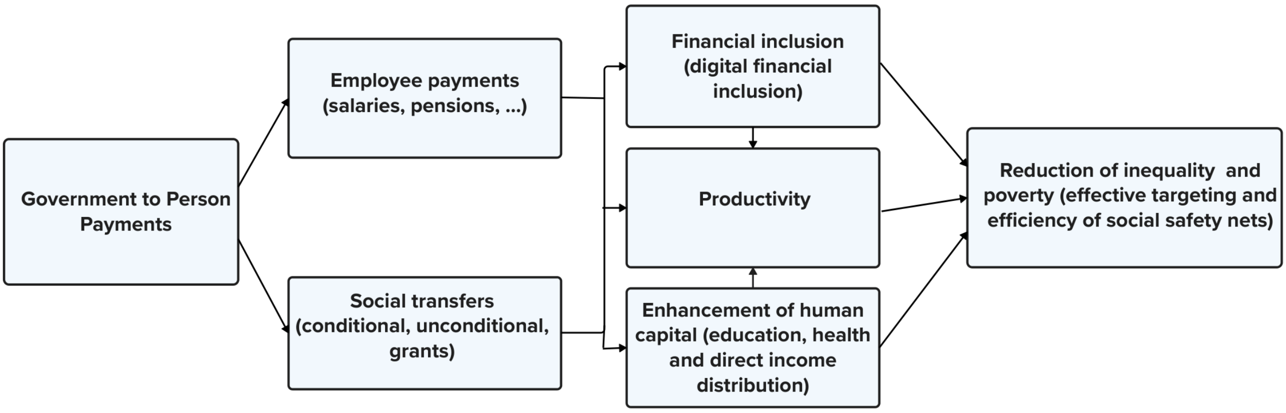


Figure 1: Modelling the transmission mechanisms.

Source: Author's construction

can distort labor markets, leading to unintended consequences (Authors). For example, if the payment amounts are set at a level that exceeds the income individuals could earn from working, it can discourage labor force participation, particularly among lower-income individuals. This can result in a reduction of available jobs and overall productivity, potentially exacerbating income inequality. Disparities in access to government payment programs can exclude certain segments of the population from receiving benefits due to administrative barriers, lack of Internet literacy, limited access to technology tools, and information. This can disproportionately affect vulnerable groups, perpetuating income inequality. Government-to-personal payment programs need to be accompanied by complementary policies that address the structural drivers of income inequality. Without comprehensive measures that tackle issues such as unequal access to quality education, healthcare, and productive assets, the impact of payment programs alone may be limited in reducing income inequality. In addition, Careful design and effective targeting, and thoughtful consideration of potential unintended consequences are crucial to ensuring that these programs adoption can effectively contribute to reducing income inequality.

3 Methodology

3.1 Data

The data used in this paper come from various sources such as World Bank development and governance indicators. These datasets provide an interesting and wide range of detailed data about the Subsaharian African countries.

First, to assess the effect of treatment adoption, we compute the indicator of income equality distribution for each country. The computation is relatively simple. We change the gini index of each country by expressing it in base 100, before to make a soustraction following Afonso et al. (2008). So, the outcome variables will be like:

$$outcome_{it} = 100 - Gini_{it} \quad (1)$$

It's important to note that we use both gini measures available on the World Bank database. These indexes are gini index for market income (before taxes and social transfers) and for disposable income (after taxes and social transfers).

The treatment variable is a dummy which takes 1 if G2P transfer mechanism is implemented in a country and 0 otherwise. It comes from the GSMA database.

Table 1: Repartition of treatment

Treated	134
Untreated	826

The control variables are a set of covariates used in the literature about income inequality and mobile money which can also affect the likelihood to adopt or not G2P.

Sulemana et al. (2019) for example found evidence of a positive association between urbanization and income inequality in the sub-Saharan African region, while Ha et al. (2019) found a negative effect for Vietnam. Dorn et al. (2022) showed that trade openness have different effects according to the countries, but a positive relationship between income inequality and trade openness in China and transition countries. Khoso et al. (2021) for example found a negative relationship between trade openness and income inequality. Signor et al. (2019) showed that the structure of the economy can affect income inequality such as another macroeconomic variables and corruption for which the way of the relationship is unclear (Keneck-Massil et al. (2021)). All the variables have a year lag to tackle or reduce the endogeneity.

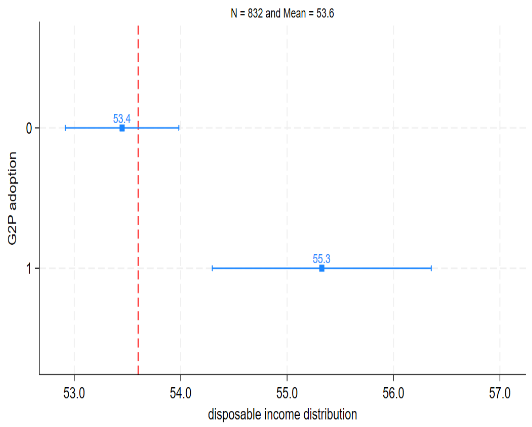
The following table (2) summarizes the main variables used in the estimation process.

Table 2: Summary statistics

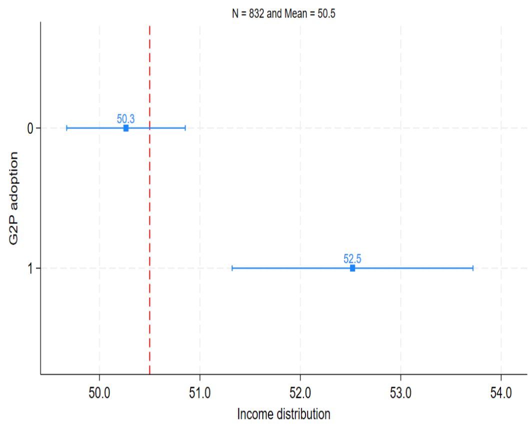
Variable	Mean	Std. Dev.	Min.	Max.	N
llog(GDP per capita)	6.604	1	4.603	9.237	927
lTrade Openess	61.055	25.654	1.219	156.862	838
lnatural ressources	11.987	10.311	0	59.684	927
lurbanization_pop	37.999	15.405	11.076	89.741	960
lpopultion growth	2.657	1.135	-13.058	10.2	960
lMobile subsciption	30.442	39.659	0	166.943	949
lAcces to public services	0.303	0.074	0.188	0.579	960
lCorruption	2.185	0.97	0	5	960

3.2 Stylized facts

The graphs 2a and 2b highlights a comparison between the average income distribution (disposable and market) for the treated (1) and untreated units (0). The adopters seem to have a more equitable income distribution than the non-adopters. This result seems to suggest that G2P adopters have a better income equality than the others. However, this correlation means nothing in terms of causes and consequences because a correlation does not necessarily imply causality.



(a) Income distribution for disposable income



(b) Income distribution for market income

Figure 2: Average income distribution by status

3.3 Identification strategy

The identification method used is a Difference in Difference (DiD) strategy, using a comprehensive panel dataset. We focus on the income distribution for both measures, market income (before taxes) or disposable income (after taxes). The decision to adopt G2P in each country is not random. Therefore, the main challenge is to correct for selection into the reform, i.e., to account for differences between adopter and non-adopter jurisdictions that could have influenced the outcome. The DiD identification strategy makes it possible to correct for the initial difference in public expenditures and thus estimate the differential changes in these outcomes across countries before and after each wave of adoption.

However, using several years of data makes our approach closer to two-way fixed effects (TWFE) linear regression. Recent methodological papers characterize the potential issues surrounding TWFE with multiple periods and multiple treatments (Callaway and Sant'Anna (2021b), Borusyak et al. (2022) Goodman-Bacon (2021) and De Chaisemartin and d'Haultfoeuille (2020)). One issue addressed in this literature is the cross-unit heterogeneity of treatment. Other issues include the time-heterogeneity of treatment and the use of units that eventually become treated as control groups. When extending to 1991–2020, we try to capture longer-term effects and check if there is an increasing advantage of early adoption. we also acknowledge a group of countries that have adopted G2P after the first wave, which might slightly perturbate the control group as some units become treated. To address this, we suggest additional estimations where we explicitly account for the two types of treatment. In technical terms, we estimate the following equation in which $y_i t$ is the outcome variable, i.e., income inequality for country i in year t = 1, ..., T

$$Y_{it} = \alpha + \beta^W {D_{it}}^W + \rho X_{it} + \theta_i + \gamma_t + \epsilon_{it} \tag{2}$$

With the treatment dummy variable equal to 1 if the country i belongs to the group of countries that have adopted G2P in year k and are observed after that year.

To slightly enhance the DiD setup, we use the Callaway and Sant'Anna (2021b) DiD approach. The Callaway and Sant'Anna (2021b) DiD estimator allows us to use inverse probability weighting as in Abadie (2005). As with Abadie (2005), we must estimate the propensity score. However, because we have multiple treatment dates for multiple groups, there is a unique propensity score for every group. However, we do not have the luxury of a large reservoir of untreated units necessarily in many applications with multiple periods and differential timing. To create implicit pairings of units in the treatment and comparison groups, Callaway and Sant'Anna (2021b) allows two options. We are using a pool of units as our comparison group who never are treated during the duration of the panel. Or we may use a pool of units that have simply not yet been treated by the time of treatment. Another key concept in Callaway and Sant'Anna (2021b) is the group-time ATT. The group-time ATT is a unique ATT for a cohort of units treated at the same point in time.

The *csdid* package used for this estimation allows us to estimate with Callaway and Sant'Anna (2021b) methods an estimator like Abadie (2005), but by considering the staggered adoption and heterogeneous effects. This type of approach usually brings flexibility to traditional DiD setups. Most importantly, it is used here to try to reduce unobserved time-varying differences between early- and late-G2P-adopting countries that could confound our results. For this, we are going to mobilize a set of variables X_{it} that are assumed to be correlated to some extent with time-varying confounders and that allow for comparing subgroups of treated and control countries that are more alike.

For example, if countries with the greatest GDP per capita are the ones that implemented G2P first and, at the same time, are the ones that have a lower income inequality (internal validity issue) or stand to benefit most from G2P adoption because their important GDP per capita can mean greatest interest for civil society. So, it can increase the interest of central governments to tackle income inequality and/or implemented a more important social security scheme (external validity issue), and then we might overstate the benefits of the G2P adoption.

Assuming that the unobservable advantages (e.g. economic and cultural dynamics, political leverage, or interest) are correlated with observable characteristics (e.g. population size, autonomy, GDP per capita), we could reduce the bias by comparing treated and control countries that are most similar along a relevant set of observed characteristics of that sort. Rather than using matching on many different characteristics, which brings a ‘curse of dimensionality issue, we rely on a propensity score (PS) that concentrates all the useful information from these characteristics. The propensity score, denoted p hereafter, is obtained as the prediction of a first-stage estimation of a G2P dummy on the set of relevant variables including key demographic dimensions such as GDP per capita, the share of natural resources rent in the GDP, the size of population, urbanization rate, the corruption level, the mobile phone subscription, and trade openness. To consider treated and untreated countries that are more like each other according to these different criteria simultaneously, we reweight observations using the inverse propensity score, as suggested by Abadie (2005) for the DiD approach. In this way, the modified estimation gives more weight to the late (early) G2P adopters that are most similar to the early (late) G2P adopters. We will also explore the heterogeneous impact of the reform by explicitly zooming in on groups with similar characteristics (e.g. treated and controlled countries with high wealth). All estimations are clustered at the countries level to account for autocorrelation.

3.4 Parallel trend assumption

The following graph (3) has been inspired by the work of Rambachan and Roth (2023) on a more credible approach to the parallel trend assumption. They propose some tools for robust inference in difference-in-differences and event-study designs where the parallel trends assumption may be violated. Instead of requiring that parallel trends hold exactly, they impose restrictions on how different the post-treatment violations of parallel trends can be from the pre-treatment differences in trends ("pre-trends"). They recommend that researchers use their methods to construct robust confidence intervals, under restrictions on the possible violations of parallel trends that are motivated by domain knowledge in their empirical setting. According to them, there are some key concerns about the pre-trend assumption. Despite the statistical or visual results, it's important to consider some macroeconomic shocks that can disturb the pre-trend evolution. Figure **??** shows robust confidence sets for the treatment effect, using different values of Mbar [1]. The figure shows that if we impose Mbar<1, meaning that we restrict the post-treatment violations of parallel trends to be no larger than the maximal pre-treatment violation of parallel trends, then we obtain a robust confidence set for the causal effect on the expenditures share. This is wider than the original (without covariates) confidence interval, which is only valid if parallel trends hold exactly, but rule out a null effect on expenditures share.

The intuition for why the confidence sets are larger through time is that we have bound the violation of parallel trends across consecutive periods by Mbar times the max in the pre-treatment period. Thus, the identified set will be larger for later periods, since the treatment and control groups have more time to diverge. If we are willing to bound the magnitude of economic shocks by the max in the pre-treatment period, we will thus typically obtain wider confidence sets for parameters involving later periods. As suggested by Rambachan and Roth (2023) the figure 3 available in the appendix summarizes the different bands of confidence interval according to the Mbar values.

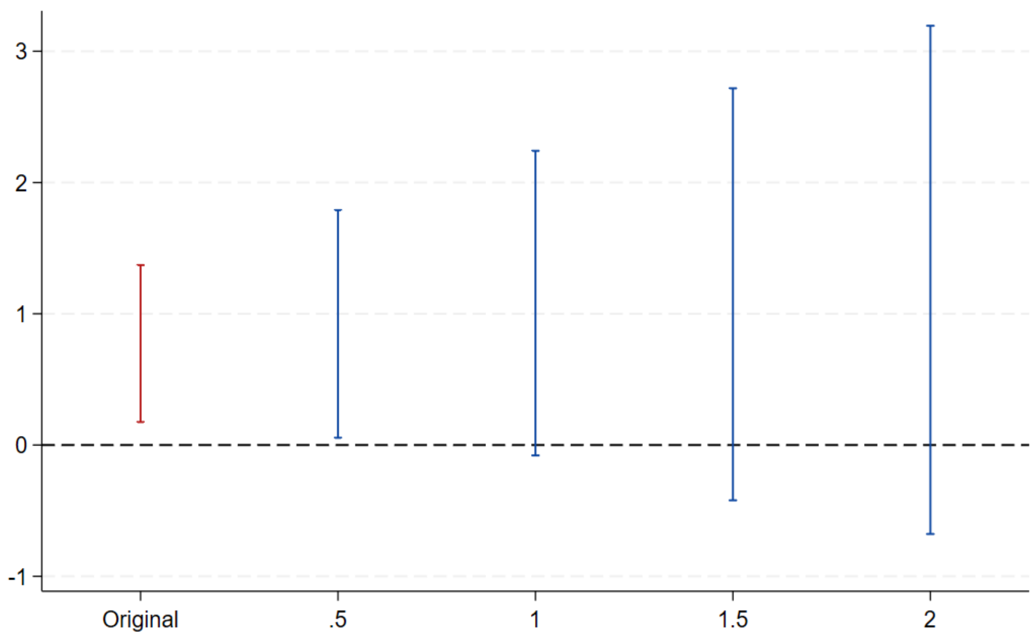


Figure 3: Parallele trend Rambachan and Roth (2023)

[1]Mbar is a degree of smoothness, or how much we allow a violation of pre-trend assumption

4 Results

4.1 Treatment effects

Table 3: Diff in Diff results with covariates

ATT	Income distribution market	Income distribution disposable
G2P	1.527***	0.961***
	(2.94)	(2.58)
Observations	568	568
Time FE	Yes	Yes
Country FE	Yes	Yes
Covariates	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results show a positive and statistically significant effect of G2P adoption on income distribution as we measure it. Indeed, G2P payments has the potential to dramatically reduce costs, increase efficiency and transparency, and help recipients build familiarity with digital payments (Klapper and Singer (2017a)). Through the direct link between the funder and the population, G2P reduces the intermediaries and the different stakeholders within the social protection scheme. By this way, the risk of corruption and administrative cost are reduced by the G2P adoption. The decrease of administrative costs and corruption's risk improve the effectiveness and efficiency of social protection schemes. However, we can observe that the effect' size is less important if we introduce the countries fixed effects. This change can be explained by the fact that G2P is a change in a cash-transfer process and its effectiveness will depend on the physical infrastructure, the quality of mobile broadband and the willingness of the country to effectively reduce inequality or provide some effective social safety nets to the most vulnerable. In addition, mobile money system is a complex ecosystem with lots of tension and dependent on local circumstances (Nesse et al. (2018))

To ensure that the G2P effect is not a one shot effect, we tried to assess it through the time after the adoption. The results are present in the next table.

4.2 Does G2P effects persist through the time

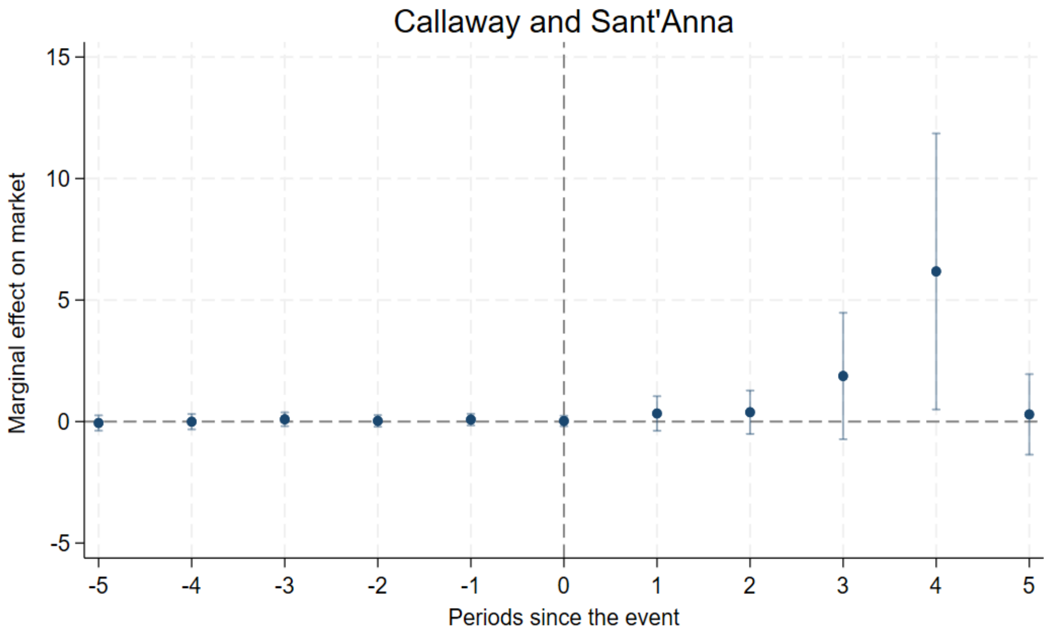


Figure 4: Event study results for market income

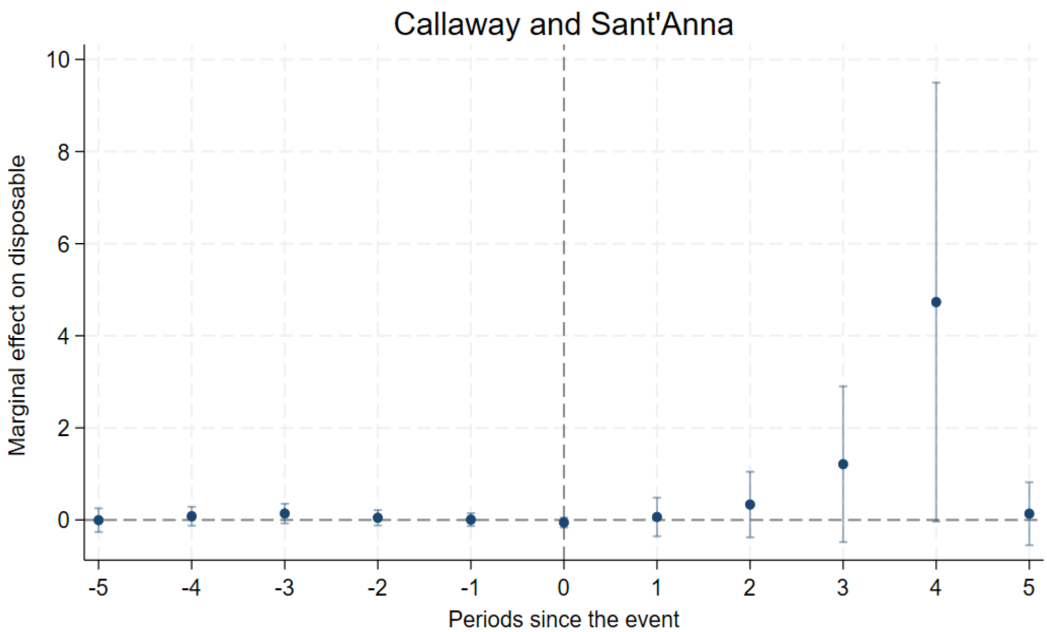


Figure 5: Event study results for disposable income

As we can see in the figure 6 and 7, the effects of G2P adoption are still positive through the time and their size tends to increase through the time. We can suppose that G2P adoption leads to a more effective social protection system and improve the income redistribution within the country. However, this positive effect seems to take a little tme to be fully effective as suggested by the previous figures.

5 Robustness Check

5.1 Alternative DiD estimator

As a robustness check, we use Wooldridge (2021) DiD framework which has been built to be suitable for staggered adoption.Wooldridge (2021) establishes the equivalence between the two-way fixed effects (TWFE) estimator and an estimator obtained from a pooled ordinary least square regression that includes unit-specific time averages and time-period specific cross-sectional averages, which he calls the two-way Mundlak (TWM) regression. The approach allows considerable heterogeneity in treatment effects across treatment intensity, calendar time, and covariates. The equivalence implies that standard strategies for heterogeneous trends are available to relax the common trends assumption. The author concludes that there is nothing inherently wrong with using TWFE in situations such as staggered interventions – a point that is also clear from Sun and Abraham (2021). Because we know that TWFE is consistent for unbalanced panels (as the cross-sectional sample size grows with T fixed), even when selection is correlated with additive, unobserved heterogeneity, it has advantages over other estimators that include time-constant cohort indicators and time effects. The point for him is not to conclude that other recent approaches – such De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021b), Borusyak et al. (2022), among others – are not valuable and cannot improve over flexible TWFE methods. However, he is recommending not abandoning simple regression approaches because they can identify the treatment effects of interest very generally and can be made very flexible. According to Wooldridge (2021), another nice feature of a flexible TWFE approach is that it is easily extended to allow for heterogeneous trends, which can help when one suspects the common trends assumption is violated. Callaway (2023) concludes that the regression approaches in Wooldridge (2021) may be particularly appealing in applications where the researcher is primarily interested in estimating and conducting inference on the group-time average treatment effects themselves. To consider the cohorts' effects, we rely on this approach as a robustness check. The results for the global average effect and the event study are available below.

Table 4: Wooldridge Diff in Diff results

	market	disposable
ATT	0.995**	0.638**
Observations	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

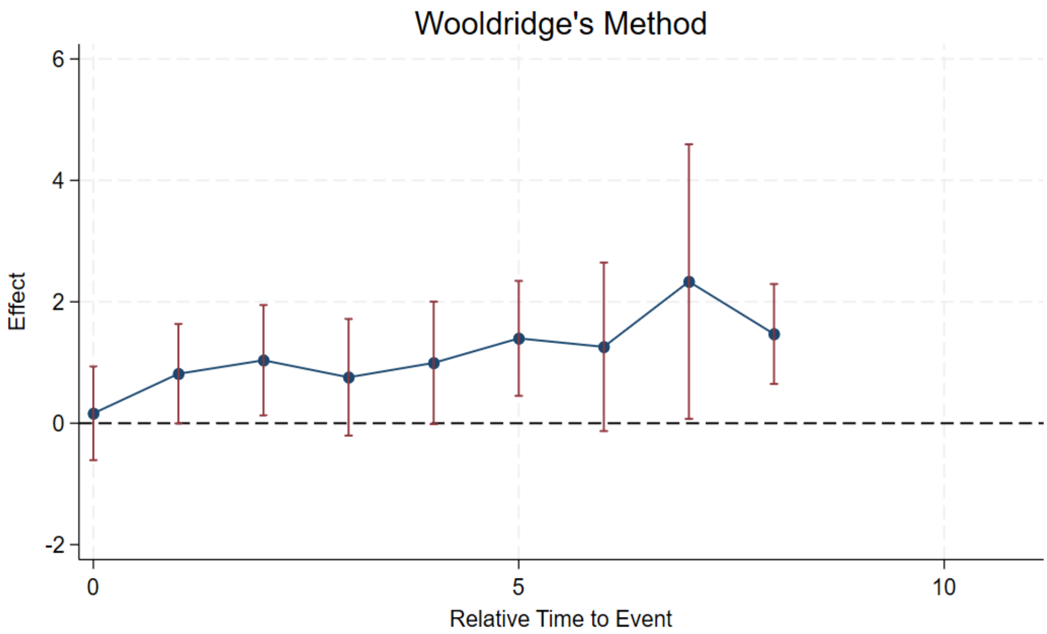


Figure 6: Wooldridge Event study results for market income

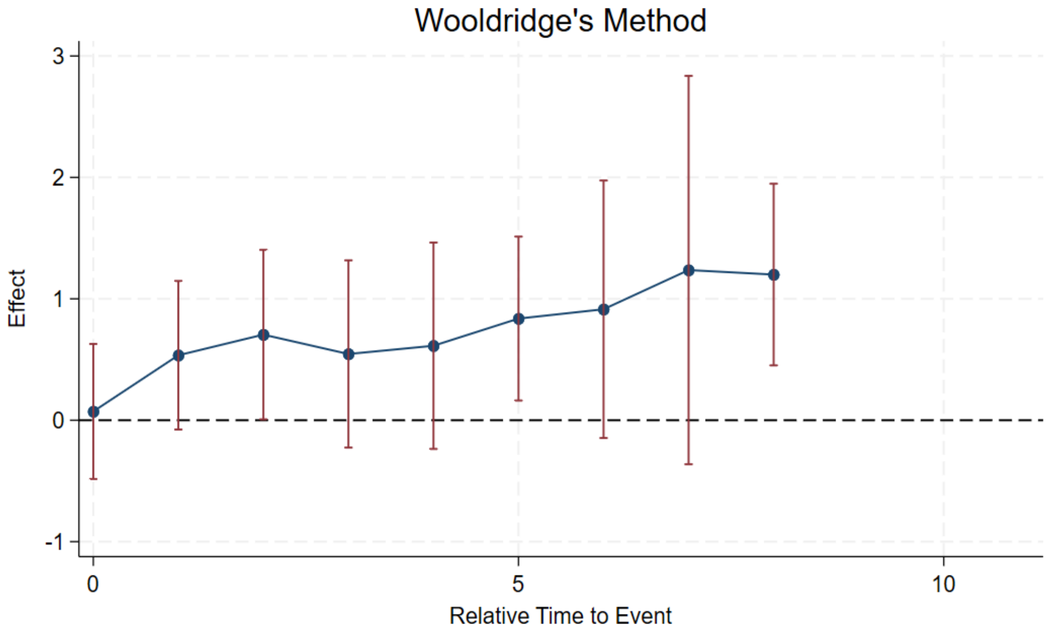


Figure 7: Wooldridge Event study results for disposable income

This results suggest a positive effect of G2P adoption on income distribution through the time. Social assistance through government-to-person (G2P) programs, play a vital role in enhancing societal resilience against income shocks and reducing income inequality over time. By providing direct assistance to individuals and families during periods of financial instability or crisis, these programs help mitigate the adverse effects of sudden income loss or unexpected expenses by smoothing consumption and income (Apeti (2023a)). This support enables individuals to maintain a basic standard of living, meet essential needs, and avoid falling into poverty. Moreover, by bolstering household economic security, G2P initiatives contribute to overall societal stability and resilience. Over time, consistent access to social safety nets can lead to greater economic empowerment and mobility, as individuals are better equipped to weather economic downturns and invest in their long-term well-being. Additionally, by targeting vulnerable populations, G2P programs can help address systemic inequalities and promote more equitable distribution of resources within society. Thus, through sustained implementation and expansion, G2P initiatives have the potential to foster greater economic stability and reduce income disparities across communities.

Alternative method of Borusyak

There is a huge literature about the DiD estimators, but to check the robustness of our analysis, in addition to Wooldridge (2021) we will consider the estimators proposed by Borusyak et al. (2022) estimator.

The estimator in Callaway and Sant'Anna (2021b) uses the last period before units get treated (t_s-1), as the baseline outcome, while the estimator in Borusyak et al. (2022) uses the average outcome from period 1 to t_s-1. This is why the latter estimator is often more precise. However, it is also more biased, when parallel trends do not exactly hold and the discrepancy between groups' trends gets larger over longer horizons, as would, for instance, happen when there are group-specific linear trends. In such instances, Roth (2022) notes that leveraging earlier pre-treatment periods increases the bias of a DID estimator since one makes comparisons from earlier periods. If, on the other hand, parallel trends fail due to anticipation effects arising a few periods before t_s, the estimator in Borusyak et al. (2022) is less biased than Callaway and Sant'Anna (2021b)'s one. Another difference between these approaches is that Borusyak et al. (2022) imposes parallel trends for every group and between every pair of consecutive periods. Callaway and Sant'Anna (2021b), on the other hand, imposes a weaker parallel trends assumption: from period t onwards, cohort W must be on the same trend as the never-treated groups, but before that cohort W may have been on a different trend. The assumption in Callaway and Sant'Anna (2021b)is the minimal assumption, but it is conditional on the design: which groups are required to be on parallel trend at which dates depends on groups' realized treatments. Overall, this discussion suggests that whether the estimators in Borusyak et al. (2022) should be preferred to Callaway and Sant'Anna (2021b) may depend on one's degree of confidence in the parallel trends assumption, on the type of violations of this assumption that seems more likely to arise in the application at hand, and on one's willingness to undertake a sensitivity analysis such as the one proposed by Rambachan and Roth (2023). The event study graph of the Borusyak et al. (2022) estimator is available in the graph 8 and 9 below.

This graph as the previous ones suggests a positive relationship between G2P adoption and a better income distribution within the economy.

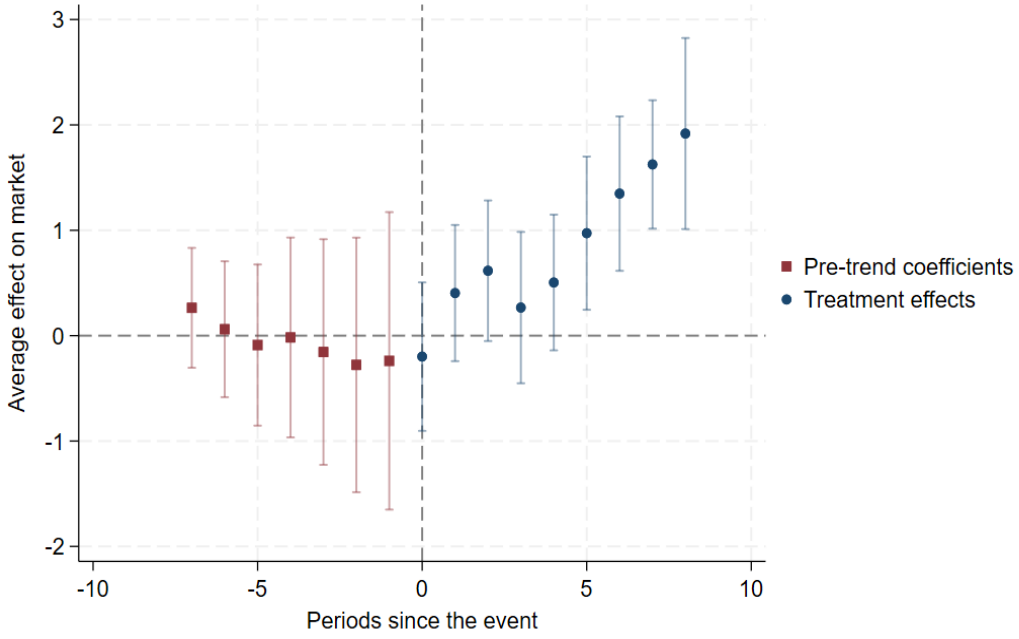


Figure 8: Borusyak Event study results for market income

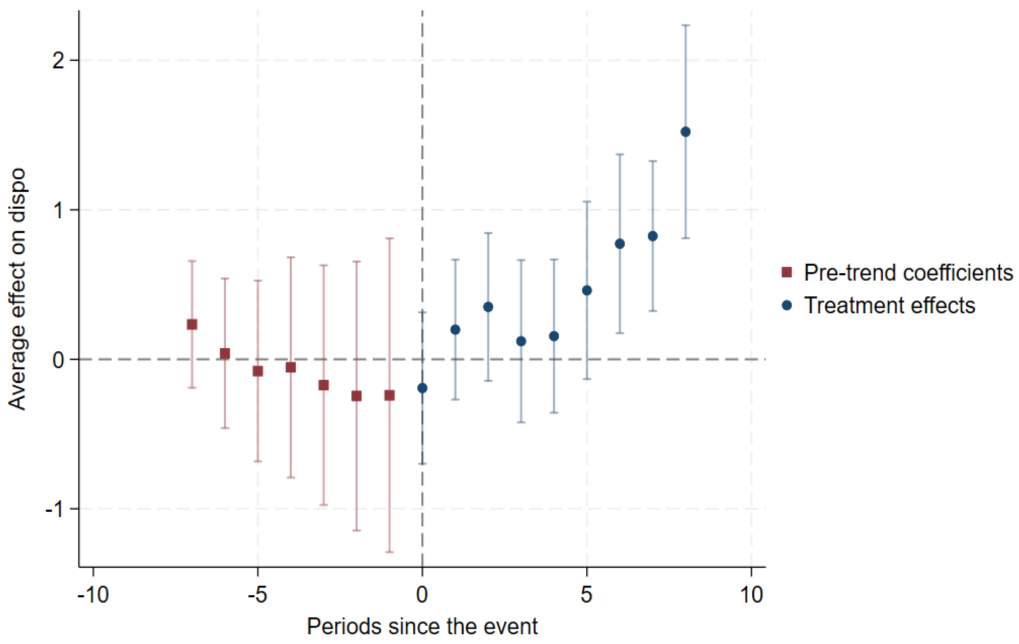


Figure 9: Borusyak Event study results for disposable income

5.2 Entropy Balancing

Methodological concept

For further robustness check, we also use the entropy balancing method of Hainmueller (2012) like Apeti and N'doua (2023) and Combes et al. (2024).

Because many macroeconomic shocks have been able to change the expectations of the population, state rulers, or local administrations. The announcement of the g2p adoption could also raise the expectations of the population in terms of public service quality.At the same time, the state rulers could have the incentive to improve the quality of their public spending to get the people's favor, even if they have not adopted G2P. The competition effect can affect the pre-trends and bias the results. For this reason, we use several DiD estimators which are less restrictive on the pre trends assumptions, but also the entropy balancing of Hainmueller (2012) which doesn't require the pre-trend assumption.

In general, the idea of matching estimators is to mimic randomization regarding the assignment of the treatment. The unobserved counterfactual outcome is imputed by matching the treated units with untreated units that are as similar as possible regarding all pre-treatment characteristics that are associated with selection into treatment and influence the outcome of interest. Entropy balancing is a pre-processing procedure that allows researchers to create balanced samples for the subsequent estimation of treatment effects. The pre-processing consists of a reweighting scheme that assigns a scalar weight to each sample unit such that the reweighted groups satisfy a set of balance constraints that are imposed on the sample moments of the covariate distributions. The balance constraints ensure that the reweighted groups match exactly at the specified moments. The weights that result from entropy balancing can be passed to any standard model that the researcher may want to use to model the outcomes in the reweighted data—the subsequent effect analysis proceeds just like with survey sampling weights or weights that are estimated from a logistic propensity score covariate model. The pre-processing step can reduce the model dependence for the subsequent analysis since entropy balancing orthogonalized the treatment indicator concerning the covariate moments that are included in the reweighting. Entropy balancing is implemented in two steps. First, weights are computed that are assigned to units not subject to treatment. These weights are chosen to satisfy pre-specified balanced constraints involving sample moments of pre-treatment characteristics by remaining, at the same time, as close as possible to uniform base weights. In our analysis, the balance constraints require equal covariate means across the treatment and the control group, which ensures that the control group contains, on average, units not subject to treatment that are as similar as possible to units that received treatment. Second, the weights obtained in the first step are used in a regression analysis with the treatment indicator as an explanatory variable. This yields an estimate for the Average Treatment on Treated (ATT), that is, the conditional difference in means for the outcome variable between the treatment and control group. The advantage of entropy balancing over the other treatment effects methods is the fact that entropy balancing is not a parametric method. Indeed, this method does not need a specific empirical model for either the outcome variable or selection into treatment needs to be specified. Hence, potential types of misspecifications like those, for instance, regarding the functional form of the empirical model, which likely leads to biased estimates, are ruled out. Moreover, with conventional matching methods, each untreated unit either receives a weight equal to 0, in the event it does not represent a best match for a treated unit, or equal to 1, in the event it does represent a best match for one treated unit. And when the number of untreated units is limited and the number of pre-treatment characteristics is large, this procedure does not guarantee a sufficient balance of pre-treatment characteristics across the treatment and control groups. This is a serious problem, as a low covariate balance may lead to biased treatment effect estimates where the vector of weights assigned to non-treated units is allowed to contain non-negative values. Finally, by combining a reweighting scheme with a regression analysis, entropy balancing allows us to properly address the panel structure of our data. We can control for both state-fixed as well as time-fixed effects in the second step of the matching approach, that is, the regression analysis. The inclusion of state-fixed effects is particularly helpful in accounting for potential unobserved heterogeneity across countries. The estimation of the ATT based on the matching will be:

$$\pi ATT(x) = E[Y(1)|T = 1, X = x] - E[Y(0)|T = 0, X = x] \tag{3}$$

Where Y represents the dependant variable, x is a vector of relevant pre-treatment characteristics, E[Y(1)| T = 1, X = x] is the expected outcome for the units that received treatment, and E[Y(0)| T = 0, X = x] is the expected outcome for the treated units best matches. As pointed out by Neuenkirch and Neumeier (2016), entropy balancing has several advantages over traditional matching methods. First, unlike the propensity score matching methods or the difference-in-differences estimator, entropy balancing is a non-parametric approach, thus requiring no specification of the functional form of the empirical model or the treatment assignment procedure, which may avoid specification errors or collinearity problems. Second, entropy balancing ensures a sufficient balance of pre-treatment characteristics between treatment and control groups, even in the presence of a small sample or a limited number of untreated units. This makes it possible to construct a suitable control group, representing a near-perfect counterfactual of the treated group. Finally, in the second step, the estimator exploits the longitudinal nature of the data by including individual and time effects to control for unobserved heterogeneity across units and biases due to changes over time, independent of treatment. Tübbicke (2022) and Zhao and Percival (2017) also show that entropy balancing is doubly robust concerning linear outcome regression and logistic propensity score regression. It reaches the asymptotic semiparametric variance bound when both regressions are correctly specified. They suggest that entropy balancing is a very appealing alternative to the conventional weighting estimators that estimate the propensity score by maximum likelihood. Our empirical equation to estimate the effects of the treatment on the outcome variable will be:

$$Y_{i_t} = \beta_1 D_{it} + \alpha_1 X_{it} + \mu_i + \psi_t + \epsilon_{it} \tag{4}$$

Where Y is the income equality distribution in country i at period t, and D is the treatment variable. The treatment takes the value 1 if the state has introduced g2p and 0 otherwise. X_{it} is a set of time-varying characteristics of countries. μ_i and ψ_t account respectively for countries and time-fixed effects, capturing specific characteristics that may be correlated with the treatment. Finally, $\epsilon_i t$ is the usual idiosyncratic error term assumed to be uncorrelated with the treatment.

Correlation issue

Table 5 shows a simple comparison of pre-weighting sample means of all matching covariates between treated (Column [2]) and control (Column [1]) states, which represent the potential synthetic group. Column [5] shows significant differences between the two groups for all pre-treatment variables, as some p-values are below the threshold of 5%. Such differences could bias the true treatment effect due to a potential selection problem. Therefore, in Panel B (Column [1]), we compute a synthetic control group by re-weighting the control units, using the pre-treatment covariates from the benchmark specification. This approach allows us to make the means of the pre-treatment covariates of the synthetic group as comparable as possible to those of the treated units. As can be seen in Column [5] of Panel B, the weighting eliminated any significant pre-treatment difference between the means of the treated and synthetic covariates. Thus, we can consider the synthetic group as a perfect counterfactual of the treated group.

Table 5: Balance Statistics

Variable	treated	untreated	Difference	t statistics	p-value
Unweighted Balance Statistics:					
	(1)	(2)	(3)	(4)	(5)
l. log(GDP per capita)	7.048	6.651	0.397	-6.4013	0.0000
l. Mobile_sub	71.30	26.13	45.17	-18.5143	0.0000
l. Urbanization	38.20	37.74	0.46	-0.3946	0.3468
l. Trade openess	59.02	64.4	-5.38	2.9127	0.0019
l. Natural resources rent	10.33	11.49	-1.16	1.7782	0.0382
l. population growth	2.723	2.646	0.77	-1.5613	0.0598
l. corruption index	1.827	2.292	-0.465	6.6431	0.0000
l. access to public services	0.2984	0.311	-0.126	2.1533	0.0162
Weighted Balance Statistics:					
	(1)	(2)	(3)	(4)	(5)
l. log(GDP per capita)	7.048	7.048	0.0000	-0.002	0.999
l. Mobile_sub	71.30	71.27	0.03	0.012	0.990
l. Urbanization	38.20	38.21	-0.01	-0.010	0.992
l. Trade openess	59.02	59.03	-0.01	-0.009	0.995
l. Natural resources rent	10.33	10.33	0.0000	0.001	0.991
l. population growth	2.723	2.723	0.0000	-0.000	1.0000
l. corruption index	1.827	1.827	0.0000	-0.001	0.998
l. access to public services	0.2984	0.2985	-0.0001	-0.000	0.998

Results

Tables 6 and 7 summarize the results of entropy balancing for the market generated income equality distribution index. The results of entropy balancing for this outcome seem to suggest a positive effect of g2p adoption on the equality of income distribution within the countries that have adopted it.

Table 6: Results for Entropy balancing

	(1)	(2)	(3)	(4)
	income_market	income_market	income_market	income_market
G2P	2.331***	1.969***	1.714***	1.871***
	(4.30)	(3.69)	(3.60)	(4.22)
N	568	568	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Results for Entropy balancing

	(1)	(2)	(3)	(4)
	income_disposable	income_disposable	income_disposable	income_disposable
G2P	1.777***	1.474***	1.252***	1.409***
	(3.74)	(3.14)	(2.99)	(3.69)
N	568	568	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Instrumental variables

We use an instrumental variable for treatment adoption to tackle the potential endogeneity issues which can be raised between g2pp adoption and income inequality. Indeed, the g2p adoption can affect income distribution, and an important level of income inequality could lead to a g2p adoption to reduce it.

An instrumental variable is a third variable introduced into regression analysis that is correlated with the predictor variable, but uncorrelated with the response variable. By using this variable, it becomes possible to estimate the true causal effect that some predictor variable has on a response variable. Indeed, we use an instrumental for two reasons. One of the common instruments used by the scholars is the lagged value of treatment variable. In our case we decided to use the adoption or not of g2p by the other countries weighted by an inverted distance matrix. The results of this method will be available in the table 8 in the appendix section.

5.4 Placebo Test

We now examine whether there are confounding factors that could affect the results, which have remained stable so far (especially for education expenditures share). The empirical literature shows that the adoption of an economic policy is generally associated with parallel reforms, making the adoption of g2p a non-random factor. One could therefore imagine that unobservable variables correlated with policy adoption and potentially with the outcome variable could affect the baseline results. While we are aware that the empirical — method used in this study aims to address these types of concerns, we still — strengthen the results by conducting a placebo test on g2p adoption. To do this, we follow Apeti (2023b) and Apeti and Edoh (2023) in setting placebo or arbitrary dates for g2p, computed by randomly assigning g2p episodes to countries in our sample after removing the actual adoption years. The main idea behind this test is that if the results are biased by unobservable variables, the placebo — test might also show significant effects. Random treatments within the sample do not affect both outcomes (Table 9, in Appendix). Therefore, we can rule out the possibility of confounding — factors influencing our results.

5.5 Anticipation effects

Always to check the robustness of our results and be sure that the effects observed are due to the treatment adoption, we change the date of the adoption to test for potential anticipation effects. An example of anticipation effects could be the fact that the reform could be discussed in newspapers years prior to their adoption and that there are economic or political reasons for rulers to change spending allocation prior to reforms. So, the anticipation effect can have an impact on the size of the outcome and the treatment effects estimation (Mertens and Ravn (2012) and Metiu (2021))

However, we change the adoption wave date by considering that the treatment has been adopted two years before the effective date of adoption to test the presence or not of anticipation effects. The results got by using Callaway and Sant'Anna (2021b) are presented in the appendix section at the table 10.

The results show a non-significant effect for our alternative adoption waves. We can conclude to an absence of anticipation effects of g2p adoption on the outcomes.

5.6 Narrowing the control window

Finally, the effect captured in this work may suffer from some problems. Indeed, g2p adoption can lead to a change in States' environments. In this sense, the effect captured may not be due to g2p but to changes in institutional, political, social, or economic conditions after its adoption. Also, any other characteristic that may determine g2p adoption may be a source of endogeneity. To circumvent these problems, we employ a similar approach as Neuenkirch and Neumeier (2015), Apeti (2023b) and Apeti and Edoh (2023) by removing all observations before and after the initial year of adoption. Thus, we expect that this narrow time window characterizing our new mobile money variable should provide a more robust estimate of its effect on public expenditures since the (generally slow changing) institutional, political, social, and economic environment is more likely to be stable over a narrow time window. In total, we explore the robustness of our findings with a modification to the sample period. In addition to the first adoption period, we consider (i) a window of five years before it.

Using entropy balancing with this narrow time window, table 11 provides results that reinforce our previous findings. Thus, we can conclude that it seems unlikely that the estimated effects of g2p are due to a coincidental change in the institutional, political, social, and economic environment in the g2p adopters States' or to any other characteristics that may predict its adoption.

6 Conclusion and policy implications

This study examines the relationship between government-to-person (G2P) payments and income inequality in African countries, using a panel dataset from 1990 to 2020 and a difference-in-difference (DiD) strategy. We find a significant positive impact of G2P adoption on income distribution, highlighting its role in poverty reduction and inclusive growth. Our analysis shows that G2P payments contribute to inclusive growth and poverty reduction by targeting cash transfers and social safety nets to those in need, while promoting education, skills development and financial inclusion. The digitization of social protection service delivery has shown significant potential to improve targeting, reduce leakages, and lower the cost of delivering assistance. However, our analysis has also shed light on the challenges hindering the effective implementation of G2P programs, particularly the lack of a trusted and inclusive identification system. As highlighted by the World Bank, an estimated 196 million people in the ECOWAS region - including both children and adults - do not have an official form of identification. Of those aged 15 and above, approximately 20 percent do not have a National Identity Document (NID), making it difficult for them to access basic services such as mobile money accounts. This lack of identification is a significant barrier to the successful delivery of G2P payments. For example, during the pandemic, many governments combined unique ID numbers with existing databases to determine eligibility. This enabled the creation of digital service windows and mass enrollment of beneficiaries. To address these challenges, policymakers must prioritize the establishment of inclusive identification systems to ensure the effectiveness of G2P initiatives and promote equitable development. In addition, many countries do not pay banks any fees for disbursing government payments. For banks, the primary motivation for paying G2P beneficiaries, other than the government mandate itself, is not the potential revenue or access to a new customer base, but rather the possibility of future business with the government. To make the business case work better for banks, the is to activate no-frills accounts and develop new products. Banks seem particularly interested in credit, although they are unsure how best to offer it to this customer segment. Successful implementation of G2P programs requires careful design, effective targeting, and consideration of potential unintended consequences, including addressing structural drivers of income inequality. In this process, international organizations can provide technical and financial support for programs and policies that aim to closing social exclusion to promote inclusive development. However, programs such as the West Africa Unique Identification for Region Integration and Inclusion (WURI), which is currently being implemented, need to be extended to other areas of African countries to strengthen the basic identification system with a view to strengthening the social protection system. Investing in G2P payment infrastructures and complementary social protection programs is critical as we strive for equitable post-pandemic recovery. Leveraging digital technologies and adopting tackling income inequality by promoting inclusive growth can build resilient economies and promote sustainable development.

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7 Appendix

7.1 Instrumental variables

7.2 Placebo test

	(1)	(2)
	market	disposable
placebo	-0.0286	4.00e-08
	(-1.62)	(0.41)
N	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Results for placebo test

7.3 Anticipation effects

Table 10: Anticipation effects results

	market	disposable
ATT	0.482	0.351
	(1.47)	(1.18)
Observations	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.4 Narrowing control window

	(1)	(2)
	income_distribution_market	income_distribution_disposable
g2p	1.802**	1.397**
	(2.29)	(2.12)
N	383	383

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Narrowing control window

	(1) income distribution market	(2) income distribution disposable
G2P	4.502**	2.269*
	(2.43)	(1.89)
lloggdppc	-1.430**	-0.735*
	(-2.39)	(-1.94)
lTrade_Openess	-0.00800	-0.00287
	(-1.39)	(-0.78)
lNatural_Rent	0.0191	0.00768
	(1.04)	(0.67)
lUrban_pop	0.116***	0.0661***
	(3.41)	(3.06)
lPop_Grow	0.276**	0.248***
	(2.23)	(2.86)
lMobile_sub	-0.0171***	-0.00846***
	(-3.31)	(-2.62)
lv2peapsecon_osp_sd	5.970	-0.155
	(0.60)	(-0.02)
lCorruption	-0.0318	-0.0448
	(-0.34)	(-0.76)
N	568	568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Instrumental variables results