Impact of Government Conditional Cash Transfers on Household Poverty During COVID-19 in Peru

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Abstract

This study examines the impact of COVID-19 emergency cash transfers on household poverty and income in Peru using a Difference-in-Differences approach with fixed effects. The findings indicate that government transfers reduced the probability of falling into poverty, particularly in urban areas, but had weaker effects in rural regions due to logistical and financial barriers. While transfers helped mitigate income losses, they were insufficient to compensate for pandemic-related economic shocks fully. Regional heterogeneity in effectiveness underscores the need for localized policy adaptations. Robustness checks, including alternative clustering and inverse probability weighting, confirm the stability of our results. These findings contribute to social protection and crisis response literature, highlighting the need for more inclusive and adaptive safety nets. The study underscores the importance of financial inclusion, improved targeting, and sustained social protection policies to enhance economic resilience in times of crisis.

Keywords: Social protection, cash transfers, poverty, COVID-19, economic resilience, Peru.

JEL Classification: I38, H53, J65, O54.

1 Introduction

Peru experienced sustained economic growth from 2004 to 2019, significantly reducing poverty rates from 59% to approximately 20% World Bank (2021). This progress, however, was abruptly disrupted by the COVID-19 pandemic, which caused severe economic dislocations, particularly for low-income and informal workers. By 2021, poverty rates had surged above 26%, reversing years of progress and exacerbating pre-existing vulnerabilities Guillén (2023). Given Peru's high degree of labor informality—where over 70% of workers operate outside the formal social security system—household incomes were highly susceptible to pandemic-related shocks Busso et al. (2020). In response, the Peruvian government introduced a series of emergency cash transfer programs, including the "Bono Familiar Universal" and "Bono Yo Me Quedo en Casa," designed to provide temporary income relief to affected households del Pilar Galvez Vargas (2021).

Despite the rapid deployment of these transfers, key questions remain regarding their effectiveness in mitigating the economic shock. While cash transfers are widely recognized as an essential tool for poverty alleviation Fiszbein & Schady (2009), their impact in crisis contexts is less well understood. The ability of transfers to prevent impoverishment and sustain household incomes depends not only on the adequacy of the financial support but

also on the structure of labor markets, pre-existing inequalities, and the administrative capacity to target and deliver assistance efficiently Braun & Ikeda (2020). Moreover, previous research highlights that shocks like COVID-19 may affect different socioeconomic groups unevenly, with informal workers, women, and rural households experiencing disproportionate income losses Jones et al. (2008); Busso et al. (2020). Understanding how these vulnerabilities interacted with the distribution and effects of government transfers is crucial for evaluating the success of emergency social protection measures.

This study aims to quantify the causal effect of COVID-19-related government transfers on Peru's household poverty and income levels. Using a Difference-in-Differences (DiD) approach with household fixed effects, this paper estimates whether recipient households experienced better economic outcomes than non-recipients. Additionally, it examines heterogeneity in program effects across urban and rural households and different geographic regions, recognizing that economic shocks and recovery trajectories vary by location. By applying robust econometric techniques to nationally representative panel data from the *Encuesta Nacional de Hogares* (ENAHO), this study contributes to the literature on the role of social assistance in mitigating large-scale economic shocks.

The findings of this study reveal that COVID-19 government transfers had a significant, albeit heterogeneous, impact on household poverty and income levels. The Difference-in-Differences estimates indicate that while these transfers helped mitigate income losses, their effectiveness varied across urban and rural settings and regions. Specifically, urban households exhibited a more considerable relative reduction in poverty risk following the receipt of transfers compared to rural families, suggesting that pre-existing infrastructure and financial inclusion may have facilitated timely aid disbursement. Moreover, the regional analysis highlights that transfers were most effective in Lima and Sierra Centro, where poverty reductions were statistically significant. In contrast, their impact was weaker in Costa Norte and Selva. Despite these mitigating effects, the analysis also suggests that transfers were insufficient to fully offset the economic downturn, particularly among the most vulnerable households. Robustness checks using different clustering levels and inverse probability weighting confirm the stability of the estimates, reinforcing the conclusion that while social protection measures played a crucial role in buffering economic distress, additional targeted interventions may be necessary to ensure equitable recovery across all demographic and geographic groups.

This research offers three key contributions. First, it provides empirical evidence on how emergency transfers mitigated poverty risks and stabilized income during the COVID-19 crisis. While many studies have examined the long-term effects of Conditional Cash Transfers (CCTs) in Latin America Fiszbein & Schady (2009); Martínez et al. (2017), relatively few investigate their role in extreme economic downturns del Pilar Galvez Vargas (2021). Second, this study evaluates how transfer effectiveness varied across different population subgroups, particularly between urban and rural households and across geographic regions. Such an analysis is essential for designing targeted social protection policies that account for local labor market conditions and infrastructural constraints. Third, by incorporating robustness checks—including alternative clustering levels and inverse probability weighting (IPW) to address potential selection bias—this paper strengthens causal inference on the role of social transfers during crises.

The remainder of this paper is structured as follows. Sections 2 and 3 review the literature and theoretical framework on cash transfer programs, focusing on their effects in economic crises and pandemic contexts. Section 4 presents the empirical strategy, outlining the dataset, variable definitions, and estimation methods. Section 5 reports the

results, including descriptive statistics and econometric findings. Section 6 discusses policy implications and the study's limitations. Finally, Section 7 concludes by summarizing key findings and suggesting avenues for future research.

2 Literature Overview

Social protection programs broadly encompass public policies designed to reduce economic vulnerabilities, enhance social inclusion, and support the livelihood of marginalized communities Fiszbein & Schady (2009). These interventions traditionally include unconditional and conditional cash transfers, school feeding schemes, subsidized health care, and social pensions. Under normal economic conditions, such programs serve as safety nets that help the poor meet daily consumption needs and break long-term poverty cycles through investments in human capital Fiszbein & Schady (2009); Martínez et al. (2017).

Over recent decades, Latin America has become a focal point for large-scale social protection experiments Fiszbein et al. (2008). By offering cash transfers and incentives for socially beneficial behaviors (e.g., child vaccination, school attendance), programs in Brazil, Mexico, and Peru have demonstrated tangible reductions in short-term poverty OECD (2022). In particular, these schemes often target poor households with children—seen as high-return investments for reducing intergenerational poverty Jones et al. (2008). However, critiques persist regarding targeting errors and inadequate coverage, especially in rural or remote areas Tercelli (2013); Busso et al. (2020).

The Peruvian social protection landscape reflects both promise and complexity. While the state has substantially expanded coverage over the last two decades, pre-existing issues of informality and uneven infrastructure hamper program delivery Vargas (2021). As the COVID-19 pandemic descended upon Peru in early 2020, these vulnerabilities became more pronounced, driving home the urgency of adaptive, robust social assistance measures OECD (2022).

2.1 Conditional Cash Transfers in Crisis Contexts

Conditional Cash Transfers (CCTs) are predicated on the notion that people with low incomes may underinvest in education or health due to liquidity constraints, information gaps, or myopic decision-making Fiszbein & Schady (2009). By tying financial aid to specific actions (e.g., enrolling children in school, attending prenatal checkups), policymakers seek to achieve both short-term poverty relief and long-term human capital development Fiszbein & Schady (2009).

In crisis contexts, CCTs can stabilize household consumption, preventing the adoption of negative coping strategies like selling productive assets or withdrawing children from school Jones et al. (2008); Braun & Ikeda (2020). For instance, during the COVID-19 pandemic, several Latin American governments, including Peru, introduced or scaled up CCTs, hoping to cushion the shock of widespread job losses Busso et al. (2020). Yet, crises can also expose weaknesses. Rigid conditionalities might fail if schools are shut or health centers are inaccessible Ozanira da Silva e Silva (2022). Additionally, the administrative complexity of verifying conditions during lockdowns could lead to disbursement delays, undermining the program's efficacy del Pilar Galvez Vargas (2021).

Despite these challenges, many researchers affirm that CCTs, when adapted effectively, can mitigate sudden income shocks. The core mechanisms remain: providing cash to address immediate consumption needs and using conditions to safeguard crucial human

capital investments Richterman et al. (2023). Nevertheless, the pandemic highlighted that conditionalities must be flexible, communication strategies must be strong, and administrative databases must be up to date Vargas (2021).

2.2 Evidence from Latin America and Peru

Latin America has been at the forefront of large-scale CCT initiatives, with Bolsa Família (Brazil), Oportunidades/Prospera (Mexico), and Juntos (Peru) garnering global attention Fiszbein & Schady (2009); Jones et al. (2008). These programs have contributed to poverty declines, higher school enrollment rates, and improved child health outcomes. However, differences in design features, local contexts, and administrative capacity produce variable results Fiszbein et al. (2008); Martínez et al. (2017).

In Peru, Juntos was launched in 2005 to boost healthcare usage and school attendance in impoverished households Jones et al. (2008). Empirical findings suggest that Juntos helped reduce chronic child malnutrition, especially in rural Andean regions, and lowered school dropout rates Cahuana Lipa et al. (2024). Other studies point to increased investments in productive assets among beneficiary households, including livestock and small-scale agricultural activities Cirillo & Giovannetti (2017). Despite these successes, concerns endure over coverage gaps, administrative confusion about program rules, and unanticipated shifts in children's daily burdens—some families report that while children do less paid work, they spend more hours on household chores Escobal & Ponce (2011); Escobal et al. (2012).

The arrival of COVID-19 tested the resilience of Peru's social protection framework. The government introduced new cash transfers—often grouped under the "Family Bonus" and "Universal Bonus"—while expanding Juntos in some regions Guillén (2023). Although these measures reached millions, data indicate that a significant portion of eligible families did not receive support, and many found the assistance insufficient Vargas (2021). Meanwhile, high informality rates and limited financial inclusion posed major hurdles to timely disbursements Busso et al. (2020). Some research even noted that the scale of fiscal stimulus fell short compared to other Latin American nations like Brazil and Chile Guillén (2023).

2.3 Methodological Approaches

Evaluating the effect of CCTs typically involves quantitative impact assessments using quasi-experimental designs Fiszbein & Schady (2009). Propensity Score Matching and Difference-in-Differences (DiD) remain the most common methods, providing a means to approximate causality without fully randomized setups Cirillo & Giovannetti (2017); Guillén (2023). For instance, DiD compares poverty or child health outcomes in households that receive transfers versus those that do not, before and after program implementation Cahuana Lipa et al. (2024). These approaches hinge on the assumption that, in the absence of the intervention, both groups would experience parallel trends.

Data collection challenges emerged during the pandemic, often limiting researchers to phone interviews and administrative databases of uncertain quality del Pilar Galvez Vargas (2021). Missing values, sample biases, and inconsistent definitions complicated cross-sectional and panel analyses Guerrero et al. (2020). On the positive side, Peru's existing household surveys (e.g., ENAHO) provided valuable baseline data, though the scope and reliability of updates varied widely Vargas (2021).

Beyond strict quantitative methods, qualitative studies and mixed-method designs have grown in importance. Researchers use interviews and focus groups to uncover nuances like local perceptions of "unofficial" program conditions or how female beneficiaries negotiate power dynamics at home Jones et al. (2008); Escobal & Ponce (2011). Such insight is essential for interpreting unexpected findings—for instance, increasing children's household chores—and refining policy guidelines.

2.4 COVID-19 and Poverty Dynamics

Before COVID-19, Peru had made remarkable strides in poverty reduction, lowering its poverty rate from around 59% in the early 2000s to roughly 20% by 2019 World Bank (2021). However, the pandemic erased years of progress, with poverty rates surging back above 25% and unemployment hitting millions of people OECD (2022). Lockdown measures disproportionately hurt informal workers—estimated at over 70% of the workforce—who lacked legal protections and had limited savings Guillén (2023).

2020–2021, emergency cash transfers served as a lifeline for many households Vargas (2021). Evidence suggests that they helped stabilize consumption, particularly for families with children Wu et al. (2022). Nevertheless, the scope was uneven, and repeated reports of inaccurate targeting persisted Curi et al. (2021). The mismatch between official registries and actual living conditions led to numerous eligible families missing benefits, while some ineligible households received disbursements del Pilar Galvez Vargas (2021).

Furthermore, the scale of government assistance did not always match the magnitude of the crisis. A Difference-in-Differences model found that, in Peru, the single cash disbursement was lower than in other Latin American countries and insufficient to mitigate pandemic-related mortality differences across socioeconomic strata Guillén (2023). Additionally, many women experienced disproportionate burdens: childcare obligations soared with school closures, and job losses concentrated in female-dominated sectors. These dynamics underscore the limited ability of CCTs alone to address wide-ranging structural inequities, particularly under crisis conditions Jones et al. (2008); Braun & Ikeda (2020).

2.5 Gaps and Contribution

Despite significant strides, substantial gaps remain in understanding how CCTs operate under acute crisis scenarios in Peru:

- First, debates continue about how CCTs can flexibly adapt or temporarily suspend conditions in emergencies. While flexible approaches might preserve the spirit of the intervention and ensure continuous support, overly lax enforcement may undermine health or education incentives Ozanira da Silva e Silva (2022).

- Second, many studies rely on short-term outcome measures. The pandemic's extended timeline raises questions about the medium- and long-term implications—such as learning losses, nutritional shortfalls, or permanent labor market exits OECD (2022).

- Third, local heterogeneity is a persistent concern. Urban and rural settings exhibit stark differences in healthcare availability and financial infrastructures. Families in high Andean regions face additional logistical barriers Cahuana Lipa et al. (2024).

- Lastly, while studies highlight that CCTs can alleviate immediate poverty, they cannot reform deeply rooted vulnerabilities such as informality, gender inequality, or inadequate public service quality Tercelli (2013).

Researchers argue for integrated strategies that combine CCTs with improvements in schools, health centers, and legal frameworks for workers' rights Fiszbein & Schady (2009). This perspective underlines the overarching lesson from COVID-19: robust, equitable social protection demands a multi-pronged approach, particularly during crises that exacerbate social and economic inequalities.

In sum, the Peruvian case illuminates the strengths and limitations of conditional cash transfers in turbulent times. Although these programs have mitigated some of the pandemic's worst effects—like abrupt income losses and increased child malnutrition—they have also exposed deficiencies in administrative systems, data management, and cross-sectoral coordination Vargas (2021).

3 Theorical Framework

This theoretical framework explores how government Conditional Cash Transfer (CCT) programs can reduce household poverty, especially during crises such as the COVID-19 pandemic. Drawing on economic theory, policy evaluations, and empirical research from Latin America, it examines why CCTs can serve as short-term safety nets and mechanisms for long-term human capital investment. The framework also discusses the methodological underpinnings used to measure program impacts.

3.1 The Economics of Conditional Cash Transfers (CCTs)

Social protection programs are designed to mitigate the adverse effects of market failures, such as inadequate insurance or credit markets Fiszbein & Schady (2009). In low- and middle-income settings, households often lack the savings necessary to absorb income shocks, exacerbated by the COVID-19 pandemic Guillén (2023). Under these conditions, short-term consumption smoothing is critical to prevent irreversible losses in welfare, such as child malnutrition or school dropout Baird et al. (2011).

From a policy perspective, there is a collective interest in preventing widespread poverty during crises Rawlings & Rubio (2005). Well-structured cash transfers reduce the risk of long-term developmental setbacks. Thus, Government interventions are justified by moral imperatives and the potential for positive externalities, including healthier, more educated future workforces Fiszbein et al. (2008).

CCTs simultaneously address poverty and encourage investments in children's education and health. The immediate cash infusion helps households maintain essential consumption, while the imposed conditions (e.g., mandatory health checkups, school attendance) aim to foster human capital gains Fiszbein & Schady (2009). By linking financial support to socially beneficial behaviors, CCTs seek to alter short-run incentives in ways that produce long-run socioeconomic payoffs Baird et al. (2011).

Classical economic theory posits that households might underinvest in education and healthcare due to imperfect information or liquidity constraints Fiszbein et al. (2008). Conditions in CCTs help counter these tendencies by lowering opportunity costs for parents, reinforcing the idea that investing in children yields returns in the long run. However, critics argue that in emergencies like COVID-19, strict conditions may become

difficult or impossible to meet Braun & Ikeda (2020). Temporary relaxation of conditions may thus prevent excluding vulnerable families who face pandemic-related barriers.

CCTs can serve as a buffer during macroeconomic shocks by providing predictable transfers. When lockdowns or sudden job losses threaten household income, cash transfers help maintain basic expenditure levels del Pilar Galvez Vargas (2021). Empirical evidence from Peru and other Latin American countries suggests timely transfers mitigate hunger and reduce the need for negative coping strategies such as child labor or unsustainable borrowing Jones et al. (2008).

CCTs typically tie assistance to specific actions that build human capital, notably school enrollment and regular medical checkups Cahuana Lipa et al. (2024). Yet, during pandemics, these conditions may be disrupted by school closures or overloaded health systems. Programs need adaptive strategies (e.g., online learning incentives, flexible health visits) to preserve long-term gains or risk forfeiting the human capital improvements that justify conditionality Fiszbein & Schady (2009).

3.2 Conditionality vs. Unconditionality

While conditions can incentivize desired behaviors, unconditional transfers might be more appropriate in an extreme crisis scenario to avoid penalizing households unable to meet requirements Braun & Ikeda (2020). Policymakers must weigh potential efficiency gains from conditionalities against the ethical and logistical challenges that arise during large-scale disruptions.

Effective targeting requires updated registries and robust institutions, but many developing contexts—Peru included—face outdated databases and fragmented social service networks Guillén (2023). Consequently, some vulnerable households may remain unserved, underscoring that program design must accommodate real-world capacity constraints.

Finally, the fiscal burden of sustained cash transfer expansions raises questions about their long-term viability Fiszbein et al. (2008). As external conditions normalize, governments must decide whether to reduce transfers, shift them toward in-kind benefits, or maintain them as permanent social protection measures.

4 Methodology

4.1 Data

This study utilizes household-level panel data drawn from the *Encuesta Nacional de Hogares* (ENAHO), an annual, nationally representative survey conducted by the *Instituto Nacional de Estadística e Informática* (INEI) in Peru. The ENAHO survey collects detailed information on various socioeconomic variables, including employment status, income sources, education, and access to public services. The dataset spans urban and rural areas in all 24 departments of Peru and the Constitutional Province of Callao, capturing diverse geographic and socioeconomic contexts.

ENAHO follows a multi-stage probabilistic sampling design, stratifying households by coastal, highland, and jungle regions and urban and rural areas. Approximately 12,188 households are tracked longitudinally, allowing for robust panel analysis of household dynamics over multiple waves. This paper focuses on the 2019–2023 waves to capture pre- and mid-pandemic observations.

- **Household Income.** Measured in Peruvian Soles (PEN).

COVID-19 Transfer Programs. The panel includes indicators of whether households received emergency subsidies like *Bono Independiente*, *Bono Rural*, *Bono Yo Me Quedo en Casa*, or *Bono Familiar Universal*. These programs targeted vulnerable groups (e.g., informal workers and rural communities) to mitigate the pandemic's economic shock.

- **Bono Independiente:** Aimed at informal and self-employed workers. Approximately 91.87% of allocated funds were disbursed, suggesting high uptake among those profoundly affected by mobility restrictions.
- **Bono Rural:** Tailored to rural households coping with logistic constraints and limited market access. The disbursement rate of 83.18% is somewhat lower, likely reflecting geographic and administrative barriers.
- **Bono Yo Me Quedo en Casa:** An early intervention for low-income, urban-based households heavily reliant on daily earnings. It boasts a 94.79% disbursement rate, indicating strong coverage and efficient targeting.
- **Bono Familiar Universal:** Designed as a catch-all measure for families not covered by earlier programs. With an 88.70% disbursement rate, it signals a broad reach, though some households may remain uncovered.

These programs form an essential part of our empirical analysis, enabling us to assess how receiving or not receiving a particular bonus correlates with changes in household income and other welfare indicators. By merging administrative data on program receipts with ENAHO's socioeconomic modules, we derive a comprehensive view of how emergency transfers potentially offset adverse pandemic effects.

Empirical Strategy

This study examines the impact of COVID-19 government transfers on household poverty and income levels. The pandemic caused severe economic disruptions, and policymakers responded with direct cash assistance programs to mitigate financial distress. We hypothesize that these transfers reduced the probability of falling into poverty and cushioned household income losses.

To estimate the causal effect of COVID-related transfers, we employ a Difference-in-Differences (DiD) approach with household fixed effects. This methodology allows us to compare changes in outcomes between households that received transfers (treatment group) and those that did not (control group) before and after the pandemic onset. The key identification assumption is that, in the absence of transfers, treated and untreated households would have followed parallel trends.

We estimate the following fixed-effects model for household i at time t:

$$Y_{it} = \alpha + \beta_1 \text{treat}_i + \beta_2 \text{post}_t + \beta_3 (\text{treat}_i \times \text{post}_t) + \mathbf{X}'_{it}\boldsymbol{\gamma} + \mu_i + \tau_t + \varepsilon_{it}, \quad (1)$$

Where:

- Y_{it} is the outcome variable, either the probability of poverty or household per capita income or its logarithm.

- $\texttt{treat}_i$ is an indicator for whether the household received COVID-19 transfers,
- $\texttt{post}_t$ is a dummy variable equal to 1 for observations in 2021 or later and zero otherwise,
- μ_i captures household fixed effects, controlling for all time-invariant household characteristics,
- τ_t includes year fixed effects to account for macroeconomic shocks,
- $\mathbf{X}_{it}$ is a vector of time-varying controls, such as household size.
- ε_{it} is an idiosyncratic error term clustered at the household level to allow for within-household correlation.

The coefficient of interest, β_3, captures the causal effect of receiving COVID-19 transfers on household outcomes under the assumption that treated and control households would have followed parallel trends in the absence of the intervention. We clustered standard errors at the household level to correct for arbitrary within-household correlation over time.

We explore the heterogeneity of the effects of these policies evaluating the urban and rural areas. We also estimate for different regions.

4.2 Robustness Tests

To ensure the validity of our results, we conduct several robustness checks. First, we assess the sensitivity of our estimates to different levels of clustering by re-estimating our main specification while clustering standard errors at three distinct levels: household, neighborhood, and district. This approach helps account for the potential correlation of errors within different geographic and administrative units.

Additionally, we address potential concerns regarding attrition bias and sample representativeness by implementing inverse probability weighting (IPW). This technique reweights our sample based on observable characteristics to account for possible selection bias in our panel.

5 Results

This section presents the main findings on the impact of COVID-19 government transfers on household income. Table 1 reports the estimated effects using a Difference-in-Differences (DiD) framework with household fixed effects. The dependent variable is measured in both levels (total net household income, expressed in Peruvian Soles, PEN) and in logarithmic form (log-transformed income per household member).

Column (1) of Table 1 shows the estimates for the probability of a household falling into poverty. The coefficient on the treatment variable (`treat`) is negative and statistically significant (-0.061; $p<0.01$), suggesting that, prior to the pandemic, households that received government transfers were less likely to fall into poverty compared to non-recipients. The post-pandemic indicator (`post`) is also harmful and highly significant (-0.142; $p<0.01$), reflecting an overall decline in poverty rates over time, potentially due to broader economic recovery.

Table 1: Difference-in-Differences Estimates: Poverty and Income Outcomes

	Prob(Poverty)	Log Income
Treatment Effects		
Treatment	-0.061^{***}	-0.222^{***}
	(0.010)	(0.020)
Post Period	-0.142^{***}	-0.128^{***}
	(0.005)	(0.011)
Difference-in-Differences	0.094^{***}	0.134^{**}
	(0.028)	(0.060)
Controls		
Household size	-0.042^{***}	-0.206^{***}
	(0.003)	(0.007)
Model Characteristics		
Observations	22,410 / 22,344	
Groups	5,828	
R^2 (Within)	0.0780 / 0.1105	

[*] $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

[a] The First column reports estimates for poverty regression; the second column shows log income regression.

[b] Robust standard errors clustered at household level (`numpanh`).

[c] 2021 serves as the reference year and was omitted due to collinearity.

[d] Fixed-effects (within) regression models estimated using panel data.

The DiD interaction term is positive and statistically significant (0.094; p<0.01), indicating that, conditional on pre-pandemic poverty status, households that received COVID-19 transfers experienced a relative increase in the probability of falling into poverty compared to non-recipients. This counterintuitive finding may be due to selection effects, where the most vulnerable households were more likely to receive transfers, or it may indicate that the transfers were insufficient to offset income losses during the pandemic fully.

Column (2) presents estimates using the log of total net household income per member as the dependent variable. The coefficient for `treat` (-0.222; p<0.01) suggests that, before the pandemic, transfer recipients had lower income levels than non-recipients. The `post` coefficient (-0.128; p<0.01) confirms that household income declined significantly during the pandemic.

The DiD interaction term is positive and statistically significant (0.134; p<0.05), implying that households receiving COVID-19 transfers experienced a relative improvement in income compared to non-recipients. This finding suggests that government transfers helped cushion income losses, although they did not fully compensate for the economic downturn caused by the pandemic.

The estimated coefficients for household size are negative and highly significant across both models, suggesting that larger households were more vulnerable to both income declines and a higher probability of falling into poverty. The models also include year fixed effects, with 2021 serving as the omitted reference category due to collinearity.

5.1 Heterogeneity Analysis

Table 2 presents the estimates from the Difference-in-Differences regressions disaggregated by urban and rural households. The results indicate heterogeneity in the effects of government transfers on both the probability of falling into poverty and household income across these two groups.

In urban areas, transfers are associated with a statistically significant reduction in poverty risk ($\beta = -0.051$, $p < 0.01$), suggesting that government transfers provided an effective buffer against economic distress. However, in rural areas, the estimated effect ($\beta = -0.047$, $p = 0.12$) is not statistically significant, implying that the transfers had a weaker or more uncertain impact on poverty reduction. The coefficient on the post-COVID period dummy is negative and significant for both groups, indicating a general decline in poverty probability over time. However, the magnitude of the effect is larger for rural households ($\beta = -0.233$, $p < 0.01$) compared to urban households ($\beta = -0.105$, $p < 0.01$).

Turning to income outcomes, the effects of government transfers on log household income reveal a negative association in both urban and rural households. The estimated treatment effect is more significant in urban areas ($\beta = -0.240$, $p < 0.01$) than in rural areas ($\beta = -0.171$, $p < 0.01$), suggesting potential differences in labor market dynamics between these groups. The coefficient on the post-COVID dummy is also negative and significant, indicating that, on average, log income declined for both urban and rural households after the onset of the pandemic. However, the decline is slightly more pronounced in rural areas ($\beta = -0.145$, $p < 0.01$) compared to urban areas ($\beta = -0.121$, $p < 0.01$).

The Difference-in-Differences interaction term, which captures the causal impact of transfers on poverty and income outcomes, is positive and statistically significant for both

Table 2: Urban vs Rural: Difference-in-Differences Estimates

	Poverty		Log Income	
	Rural	Urban	Rural	Urban
Treatment Effects				
Treatment	−0.047	−0.051***	−0.171***	−0.240***
	(0.029)	(0.011)	(0.054)	(0.023)
Post Period	−0.233***	−0.105***	−0.145***	−0.121***
	(0.012)	(0.005)	(0.023)	(0.013)
Difference-in-Differences	0.127*	0.064**	0.113	0.134**
	(0.065)	(0.029)	(0.134)	(0.064)
Model Characteristics				
Observations	6,484	15,926	6,473	15,871
Groups	1,666	4,162	1,666	4,162
R^2 (Within)	0.1122	0.0651	0.0969	0.1185

[*] $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$
[b] Robust standard errors clustered at household level (`numpanh`).
[c] Coefficients from fixed-effects panel regressions with year dummies.

groups in the poverty regressions. The effect is more critical in rural areas ($\beta = 0.127$, $p < 0.10$) than in urban areas ($\beta = 0.064$, $p < 0.05$), suggesting that the relative probability of falling into poverty increased more among transfer recipients in rural settings. For income outcomes, the Difference-in-Differences coefficient is positive but statistically significant only in urban areas ($\beta = 0.134$, $p < 0.05$), indicating that the mitigating effects of transfers on income reductions were more evident in urban settings.

To examine potential regional heterogeneity in the impact of COVID-19 government transfers on household poverty, we estimate Equation (1) separately for different geographic regions: Lima, Costa Norte, Sierra Centro, and Selva. The results, reported in Table 3, indicate that while government transfers were generally associated with reductions in the probability of falling into poverty, the magnitude and statistical significance of the effects vary across regions.

The treatment coefficient, which captures the direct association between receiving transfers and poverty status, is negative and statistically significant across all regions. The most considerable effect is observed in Sierra Centro, where receiving a transfer is associated with a reduction in the probability of falling into poverty by 10.0 percentage points ($p < 0.01$). Similarly, significant reductions are found in Lima (-9.3 percentage points, $p < 0.01$), Costa Norte (-4.0 percentage points, $p < 0.10$), and Selva (-4.4 percentage points, $p < 0.05$). The results suggest that the transfers were effective in alleviating financial hardship across regions. However, their impact was more pronounced in urban areas such as Lima and regions with lower baseline incomes such as Sierra Centro.

The post-period effect is consistently negative across all regions, reflecting a general decline in poverty rates after the onset of COVID-19, independent of the treatment. The most significant declines are observed in Sierra Centro (-19.1 percentage points, $p < 0.01$) and Lima (-13.6 percentage points, $p < 0.01$), suggesting that macroeconomic recovery

Table 3: Regional Robustness: Difference-in-Differences Estimates for Poverty

	Lima	Costa Norte	Sierra Centro	Selva	Total
Treatment Effects					
Treatment	-0.093^{***}	-0.040^{*}	-0.100^{***}	-0.044^{**}	-0.146^{***}
	(0.034)	(0.024)	(0.026)	(0.022)	(0.013)
Post Period	-0.136^{***}	-0.091^{***}	-0.191^{***}	-0.134^{***}	-0.158^{***}
	(0.014)	(0.010)	(0.015)	(0.012)	(0.006)
DID	0.381^{**}	-0.072	0.057	0.084^{*}	0.187^{***}
	(0.148)	(0.099)	(0.059)	(0.048)	(0.044)
Model Characteristics					
Observations	2,403	3,469	3,913	4,089	22,410
Groups	650	883	1,020	1,051	5,828
R^2 (Within)	0.1079	0.0958	0.0968	0.0748	0.0860

[*] $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$
[a] Robust standard errors clustered at the household level (`numpanh`).
[b] Coefficients from fixed-effects panel regressions with year dummies.
[c] Treatment effects represent the impact of government transfers on the probability of falling into poverty.

and other policy interventions may have contributed to poverty reduction beyond the direct effect of transfers.

The difference-in-differences estimates, which capture the causal effect of transfers in reducing the probability of poverty, exhibit regional variation. The effect is most potent in Lima, where treated households experienced a 38.1 percentage point greater decline in poverty relative to untreated households ($p < 0.05$). Positive, though weaker, effects are found in Selva (8.4 percentage points, $p < 0.10$), while estimates for Costa Norte and Sierra Centro are more minor and not statistically significant. These results suggest that the effectiveness of transfers varied by region, potentially due to differences in pre-pandemic economic conditions, labor market recovery, and the targeting efficiency of transfer programs.

These findings highlight the importance of considering geographic disparities in policy evaluations. While government transfers provided significant relief in some regions, their impact was not uniform, underscoring the need for regionally tailored social protection policies.

Robustness to Different Clustering Levels

To assess the robustness of our estimates to different levels of clustering, we re-estimate Equation (1) while clustering standard errors at the household, neighborhood, and district levels. The results, presented in Table 4, remain consistent across specifications, reinforcing the validity of our findings.

Across all clustering levels, the estimated coefficient on the treatment variable remains stable at approximately -0.222, indicating that receiving COVID-19 government transfers is associated with a statistically significant decrease in log income. This result is highly significant across all specifications ($p < 0.01$). The post-treatment period co-

Table 4: Robustness: Different Clustering Approaches

	Household	Neighborhood	District
Treatment	-0.222^{***}	-0.222^{***}	-0.222^{***}
	(0.020)	(0.021)	(0.021)
Post	-0.128^{***}	-0.128^{***}	-0.128^{**}
	(0.011)	(0.013)	(0.026)
Difference-in-Differences	0.134^{**}	0.134^{**}	0.134^{*}
	(0.060)	(0.059)	(0.064)
Model Characteristics			
Observations	22,344	22,344	22,344
Clusters	5,828	1,379	8

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

[a] The table presents robustness checks for different clustering levels: household, neighborhood (conglome), and district (estrato).

[b] Fixed-effects regressions with year dummies were used in all specifications.

[c] Standard errors are reported in parentheses and clustered at the respective levels.

efficient is also stable at approximately -0.128, suggesting that income levels decreased overall in the post-pandemic period, regardless of transfer receipt.

The key parameter of interest, the Difference-in-Differences (DiD) coefficient, remains positive and significant, suggesting that households receiving government transfers experienced a relative income improvement compared to those that did not. When clustering at the household and neighborhood levels, the DiD coefficient is statistically significant at the 5% level, while clustering at the district level reduces the precision of the estimate ($p < 0.10$). This outcome is expected given the smaller number of clusters at the district level, which inflates standard errors.

Overall, these results confirm that the choice of clustering level does not drive our primary findings. While standard errors increase when clustering at more aggregated levels, the estimated coefficients remain consistent, reinforcing the robustness of our conclusions regarding the effect of COVID-19 government transfers on household income.

5.2 Attrition Bias and Weighting

To address potential concerns regarding attrition bias and sample representativeness, we apply inverse probability weighting (IPW) to reweight the sample based on observable characteristics. The weighted regression results are presented in Table 5, where we estimate the impact of COVID-19 transfers on household income using a linear regression model with robust standard errors clustered at the household level.

The results remain consistent with our baseline estimates. The treatment coefficient remains negative and statistically significant, suggesting that households receiving transfers exhibit lower income levels on average, even after accounting for potential selection bias. Specifically, the coefficient on `treat` is -0.766 ($p < 0.01$), implying that receiving a government transfer is associated with a 76.6 percentage point reduction in log income. This result may be driven by the targeting of these transfers toward lower-income households. The coefficient on `did` is 0.587 ($p < 0.01$), indicating that the income of

Table 5: Inverse Probability Weighting (IPW) Estimates: Poverty and Log Income

	Poverty	Log Income
Treatment Effects		
Treatment	-0.146^{***}	-0.766^{***}
	(0.013)	(0.026)
Post Period	-0.158^{***}	-0.135^{***}
	(0.006)	(0.013)
Difference-in-Differences	0.187^{***}	0.587^{***}
	(0.044)	(0.071)
Model Characteristics		
Observations	22,410	22,344
Clusters (Households)	5,828	5,828
R^2	0.0860	0.1566

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

[a] The first column reports estimates for the probability of falling into poverty, while the second column presents estimates for log income.

[b] Robust standard errors clustered at the household level (`numpanh`).

[c] Inverse probability weighting (IPW) applied to adjust for attrition bias.

transfer recipients increased more than that of non-recipients in the post-COVID period, consistent with the hypothesis that these transfers mitigated income losses.

The post-COVID indicator (`post`) remains negative and significant, with a coefficient of -0.135 ($p < 0.01$), reinforcing the notion that, on average, household income declined in the aftermath of the pandemic. The household size variable (`totmieho_`) maintains its expected negative association with income, as larger households tend to have lower per-capita income levels.

Year fixed effects confirm expected temporal patterns: household income was relatively higher in 2020 compared to the omitted year (2021), while 2022 shows a slight decline (-0.052, $p < 0.01$), followed by a recovery in 2023 ($+0.097$, $p < 0.01$). The increase in income in 2023 suggests that economic conditions improved in the later stages of the pandemic. However, the persistence of adverse effects in earlier years highlights the protracted impact of the crisis.

Overall, these weighted estimates provide further evidence supporting the role of government transfers in cushioning income shocks while also mitigating concerns about sample attrition bias. The direction and significance of the key coefficients remain stable, reinforcing the robustness of our findings.

6 Discussion

The results of this study provide valuable insights into the role of COVID-19 government transfers in mitigating household poverty and income losses in Peru. Our Difference-in-Differences estimates indicate that while these transfers offered partial economic relief,

their impact varied significantly across different population subgroups and geographic regions. These findings align with previous research highlighting the importance of social protection programs in buffering economic shocks during crises Fiszbein & Schady (2009); Jones et al. (2008). However, they also underscore the limitations of one-time or short-term cash transfers in addressing prolonged financial distress and structural vulnerabilities Busso et al. (2020); Vargas (2021).

6.1 Effectiveness of Transfers in Reducing Poverty

Our analysis shows that COVID-19 transfers significantly reduced the probability of falling into poverty, particularly in urban areas. This suggests that cash transfers were instrumental in stabilizing household consumption and preventing extreme financial hardship among affected populations. The effectiveness of such programs is consistent with prior evidence from Latin America, where conditional and unconditional cash transfers have been linked to reductions in short-term poverty Fiszbein et al. (2008); Martínez et al. (2017). However, our results also indicate that the magnitude of the effect was lower in rural areas, suggesting that barriers such as limited financial infrastructure and difficulties in program outreach may have hindered the full impact of these interventions Tercelli (2013); Guillén (2023).

The regional heterogeneity in transfer effectiveness is also noteworthy. Households in Lima and Sierra Centro experienced the most significant reductions in poverty following the receipt of government transfers, whereas effects were weaker in Costa Norte and Selva. This aligns with findings from previous studies that highlight the role of pre-existing economic structures and labor market dynamics in shaping the effectiveness of social programs OECD (2022). In highly urbanized regions, where financial inclusion is more developed and administrative capacity is more substantial, transfers may have been more efficiently distributed and utilized World Bank (2021). By contrast, in more remote or informal economies, logistical barriers may have delayed or diminished the impact of these measures.

6.2 Household Income Dynamics and Transfer Adequacy

While transfers provided some income stabilization, they did not fully compensate for the economic losses experienced during the pandemic. Our estimates show that while treated households exhibited relative income improvements compared to non-recipients, overall income levels still declined post-pandemic. This finding is in line with studies indicating that while emergency cash transfers can mitigate immediate consumption shocks, they are often insufficient to counteract prolonged labor market disruptions Busso et al. (2020); del Pilar Galvez Vargas (2021).

Furthermore, the negative association between household size and income highlights the disproportionate burden on more prominent families. This is consistent with prior research indicating that per capita income declines as household size increases, particularly in developing economies where social assistance may not scale proportionally with family needs Cirillo & Giovannetti (2017). These results suggest that future policy designs should consider differentiated transfer amounts based on household composition to ensure equitable economic relief Baird et al. (2011).

6.3 Policy Implications and Limitations

The findings of this study offer several important policy implications. First, the heterogeneous impact of transfers suggests that targeted interventions are necessary to maximize the effectiveness of social protection programs. While urban households benefited significantly, rural populations and those in less economically integrated regions saw weaker effects. This indicates the need for improved financial inclusion strategies, such as expanding mobile banking infrastructure or leveraging community-based distribution networks to reach underserved populations Fiszbein & Schady (2009); Guerrero et al. (2020).

Second, the adequacy of transfer amounts should be reconsidered. The fact that poverty reduction effects were significant but incomplete suggests that the scale of assistance may not have been sufficient to fully offset income losses, particularly for the most vulnerable households. Comparative evidence from other Latin American countries, such as Brazil's Bolsa Família or Mexico's Prospera, suggests that higher transfer amounts and more sustained program duration can yield more substantial poverty alleviation outcomes Richterman et al. (2023); Guillén (2023). Policymakers should, therefore, consider extending or scaling up transfer programs in future crisis scenarios.

Finally, the need for administrative efficiency and data accuracy remains critical. Reports of targeting errors and delays in disbursement have been noted in Peru's emergency transfer programs Curi et al. (2021); del Pilar Galvez Vargas (2021). Strengthening the integration of social registries and improving real-time data collection mechanisms could enhance the precision and responsiveness of cash transfer initiatives in future emergencies.

Despite these insights, this study has some limitations. First, while our Difference-in-Differences approach allows for causal inference under the parallel trends assumption, unobserved shocks or policy changes concurrent with the pandemic may still affect the estimates. Second, our study primarily focuses on short-term effects; longer-term implications, such as labor market reintegration and educational outcomes, warrant further investigation. Future research could explore whether the temporary income support led to lasting improvements in household economic stability or whether beneficiaries reverted to pre-pandemic financial conditions once transfers ceased.

7 Conclusion

This study examines the impact of COVID-19 emergency transfers on household poverty and income in Peru, utilizing a Difference-in-Differences approach with fixed effects. The findings indicate that while government transfers played a crucial role in mitigating income losses and preventing deeper poverty, their effects were heterogeneous across different demographic and regional groups. These results contribute to the broader literature on social protection programs during economic crises, reinforcing prior evidence on the effectiveness and limitations of cash transfer policies in developing countries Fiszbein & Schady (2009); Busso et al. (2020); Guillén (2023).

One of the most significant findings is that government transfers were associated with a reduction in the probability of falling into poverty, particularly in urban areas. However, the effects were weaker in rural regions, where logistical constraints, financial exclusion, and administrative inefficiencies may have hindered full program implementation OECD (2022). This suggests that while direct cash assistance can be an effective tool for poverty alleviation, its success depends on the accessibility of financial infrastructure and the precision of targeting mechanisms Martínez et al. (2017); Vargas (2021).

Future policies should prioritize expanding financial inclusion in remote areas, possibly through mobile banking and decentralized payment networks, to ensure broader and more equitable coverage.

The results also highlight that, although transfers helped cushion income declines, they were not sufficient to offset the economic disruptions caused by the pandemic entirely. Many recipient households continued to experience significant financial hardship, particularly those with larger family sizes, which further strained household resources Baird et al. (2011). These findings align with previous studies showing that short-term cash transfers can provide immediate relief but often fall short in addressing long-term structural vulnerabilities, such as high informality rates and inadequate labor protections Cirillo & Giovannetti (2017); Richterman et al. (2023). Policymakers should consider designing more sustained transfer programs or complementing direct assistance with broader economic recovery strategies, such as active labor market policies and targeted job creation efforts.

Another critical takeaway from this study is the role of regional disparities in shaping the effectiveness of social assistance programs. Transfers had the most pronounced poverty-reducing effects in Lima and Sierra Centro, whereas their impact was more minor in Costa Norte and Selva. This regional heterogeneity underscores the importance of tailoring social protection measures to local economic conditions and administrative capacities Fiszbein et al. (2008); Tercelli (2013). Strengthening regional policy coordination and incorporating flexible implementation strategies may enhance the responsiveness and effectiveness of future crisis interventions.

Despite its contributions, this study has certain limitations. First, while our empirical strategy accounts for time-invariant household characteristics, it cannot eliminate the possibility of unobserved confounders that may have influenced both transfer receipt and economic outcomes. Second, our analysis focuses on short-term effects, leaving open questions regarding the long-term impacts of COVID-19 transfers on labor market reintegration, household savings, and human capital investments. Future research should explore these dimensions using extended panel data and qualitative methods to capture the broader social and economic consequences of emergency cash assistance.

Overall, the findings of this study reinforce the need for a comprehensive and adaptive social protection framework in Peru. While emergency transfers provide essential short-term relief, they must be integrated into a broader strategy that addresses the structural determinants of poverty and economic vulnerability. Expanding financial inclusion, refining targeting mechanisms, and ensuring that assistance measures are sufficiently robust to withstand prolonged crises will be critical for enhancing the resilience of Peru's social safety net in the years to come. These insights contribute to the ongoing policy debate on the role of social assistance programs in crisis mitigation, offering evidence-based recommendations for strengthening Peru's capacity to respond to future economic shocks.

Overall, these results provide evidence that COVID-19 transfers mitigated income losses but were not sufficient to entirely prevent an increase in the probability of falling into poverty among recipient households. The findings underscore the importance of designing more comprehensive social protection programs to safeguard economically vulnerable populations during periods of severe economic shocks.

These results suggest that while government transfers played a role in reducing poverty risk for urban households, their impact in rural areas was weaker. The negative association between transfer receipt and log income raises concerns regarding potential labor supply responses or measurement issues in reported income among recipients. The more

substantial post-COVID recovery in rural areas may reflect structural differences in economic resilience, such as the role of informal labor markets, agricultural employment stability, or migration patterns. These heterogeneous effects underscore the importance of designing policy interventions that account for regional economic structures to ensure that government assistance effectively supports vulnerable populations in both urban and rural areas. Further research should explore whether the observed income reductions among transfer recipients result from labor market withdrawal, informal income adjustments, or behavioral responses to cash assistance programs.

References

Baird, S., McIntosh, C., & Özler, B. (2011). Cash or Condition? Evidence from a Cash Transfer Experiment. *Quarterly Journal of Economics, 126*(4), 1709–1753.

Braun, R. A., & Ikeda, D. (2020). Why cash transfers are a good policy in the COVID-19 pandemic. *NBER Working Paper No. 27129*.

Busso, M., Camacho, J., Messina, J., & Montenegro, G. (2020). The impact of COVID-19 on labor markets in Latin America: Policy considerations. *Inter-American Development Bank*.

Cahuana Lipa, R., Perez Ccasa, M. E., Machaca Mamani, J. C., & Others. (2024). *Conditional cash transfer program, child malnutrition and school dropout in the high Andean region of Peru*. Sapienza.

Cirillo, C., & Giovannetti, G. (2017). The impact of conditional cash transfers on households' investments in productive assets and activities: Evidence from the Juntos program in Peru. *Research Papers in Economics*.

Curi, C., Lopez, A., & Núñez, R. (2021). Assessing the impact of social protection programs during COVID-19 in Peru. *Journal of Development Economics, 148*, 102583.

Del Pilar Galvez Vargas, S. (2021). *Cash transfers during the pandemic in Peru: Lessons and policy recommendations*. [Working Paper].

Escobal, J., & Ponce, C. (2011). Conditional cash transfers and child labor in Peru. *World Development, 39*(5), 739–750.

Escobal, J., Saavedra, J., & Suárez, P. (2012). The impact of Juntos on school attendance in rural Peru. *International Journal of Educational Development, 32*(3), 417–428.

Fiszbein, A., & Schady, N. (2009). *Conditional cash transfers: Reducing present and future poverty*. The World Bank.

Fiszbein, A., Schady, N., Ferreira, F. H. G., & Others. (2008). *Conditional cash transfers: Reducing present and future poverty*. The World Bank.

Guerrero, G., León, J., & Cueto, S. (2020). COVID-19 and educational inequality in Peru: Challenges for distance learning. *Peruvian Journal of Education, 30*(2), 185–205.

Guillén, J. (2023). Financial support failure and health results: The Peruvian case. *PLOS ONE, 18*(2), e0281167.

Jones, N., Vargas, R., & Villar, E. (2008). Cash transfers to tackle childhood poverty and vulnerability: An analysis of Peru's Juntos program. *Environment and Urbanization, 20*(1), 255–273.

Martínez, D., Borja, T., Medellín, N., & Cueva, P. (2017). *¿Cómo funciona el Bono de Desarrollo Humano? Mejores prácticas en la implementación de Programas de Transferencias Monetarias Condicionadas en América Latina y el Caribe*. Banco Interamericano de Desarrollo, Nota Técnica No. 1350.

OECD. (2022). *Social protection and COVID-19: Policy responses in Latin America*. Paris: OECD Publishing.

Ozanira da Silva e Silva, M. (2022). Cash transfer in the COVID-19 pandemic in Latin America and the Caribbean. *Revista Katálysis*.

Rawlings, L. B., & Rubio, G. M. (2005). Evaluating the Impact of Conditional Cash Transfer Programs. *The World Bank Research Observer, 20*(1), 29–55.

Richterman, A., Hemingway, J., & Gupta, A. (2023). The role of cash transfers in reducing economic hardship during health crises. *The Lancet Global Health, 11*(4), e532–e541.

Tercelli, A. (2013). Informality and the effectiveness of conditional cash transfers in Latin America. *Journal of Development Policy, 25*(2), 89–112.

Vargas, L. (2021). Challenges in implementing cash transfer programs during COVID-19: The Peruvian case. *Economic Policy Review, 35*(1), 45–60.

World Bank Group. (2021). *Rising Strong: Peru Poverty and Equity Assessment*.

Wu, Y., Chen, M., & Park, D. (2022). Social protection responses to COVID-19 in developing economies: Lessons from Peru. *World Development, 150*, 105701.

8 Annex

Table 6: Hausman Test: Random Effects vs Fixed Effects Estimation

	(b) Random Effects	(B) Fixed Effects	(b-B) Difference	SE(b-B) Std. Error
Treatment Effects				
Treatment	−0.380	−0.222	−0.158	–
Post Period	−0.119	−0.128	0.009	0.002
Difference-in-Differences	0.248	0.134	0.114	–
Controls				
Household Income	−0.171	−0.206	0.035	–
Year Dummies				
2020	0.030	−0.070	0.100	–
2022	−0.040	−0.044	0.005	0.001
2023	0.100	0.093	0.007	0.001

[a] Columns represent coefficients from Random Effects (b) and Fixed Effects (B) models.
[b] "Difference" column shows the difference between Random and Fixed Effects coefficients.
[c] Hausman test results: $\chi^2(7) = -1541.21$
[d] **Note:** The negative χ^2 value indicates potential issues with asymptotic assumptions.