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What makes the poor stay poor? Poverty dynamics in Peru

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Abstract

This paper investigates the dynamics of monetary poverty in Peru between 2015 and 2022, with a particular focus on the impact of the COVID-19 pandemic. Using panel data from the National Household Survey (ENAHO), we examine three key questions: the extent of poverty persistence, household characteristics associated with an increase in the probability of being poor, and changes in poverty dynamics following the pandemic. Our analysis employs transition matrices and probit regression techniques, offering a comprehensive exploration of these dynamics.

Our main findings highlight the enduring nature of poverty in Peru, with over half of impoverished households remaining in poverty the subsequent year. The pandemic-induced economic shocks led to a transient surge in poverty persistence to 60% between 2019 and 2020. Additionally, five-year intervals show increased poverty persistence in the 2018-2022 period, suggesting heightened economic vulnerability after the pandemic.

We find that demographic, social, and economic factors correlate with poverty persistence. Households led by females or older individuals exhibit lower persistence, while the presence of children, lack of access to health insurance, and informality are linked to higher poverty persistence. Probit regression analysis confirm the protective effect of education, and how the influence of natural hazard events, the demographic dependence in the household, and precarious jobs increases the probability of being poor.

Keywords: Poverty, Peru, Persistence, Dynamics, Probit

JEL Classification: I32; O54

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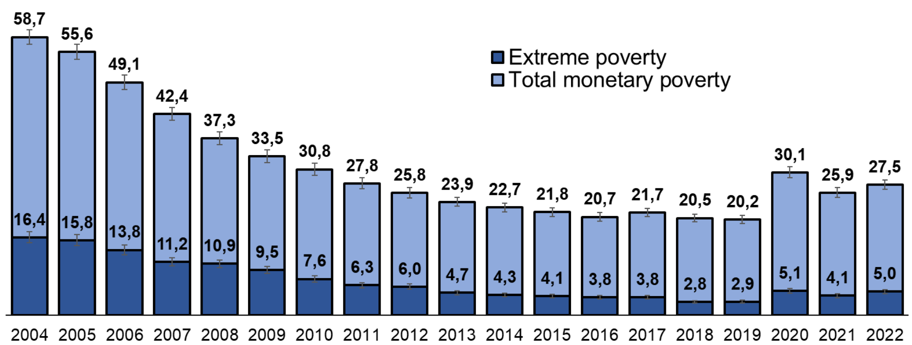
1 Introduction

In Peru, a household is considered poor if its per capita expenditure falls below the poverty line. This poverty line is updated annually and represents the monetary value of a basic consumption basket, comprising both food and non-food essentials. Following the 2020 pandemic, poverty in Peru has persisted above 2019 levels, marking a departure from the pre-pandemic trend of poverty reduction. A similar trend is observed in the extreme poverty rate, which is calculated using an extreme poverty line equal to the food component of the basic consumption basket.

Figure 1

Peru: Total and extreme monetary poverty* (%), 2004 – 2022



* As measured by household per capita expenditure and the national poverty line.

Source: Based on data from the National Household Survey, ENAHO.

In this context, this paper examines monetary poverty dynamics in Peru from 2015 to 2022, focusing on three key questions:

- How persistent is monetary poverty in Peru?
- Which household characteristics are linked to a higher probability of experiencing poverty?
- How have poverty dynamics changed after the COVID-19 pandemic?

To address these inquiries, we use a panel database sourced from the "Encuesta Nacional de Hogares" (ENAHO) or National Household Survey, an annual household survey conducted by the Peruvian National Institute of Statistics and Information (INEI).[4] ENAHO tracks the evolution of income, expenditure, and monetary poverty, offering a comprehensive array of socioeconomic and demographic indicators. Additionally, this survey follows a subset of households up to a five-year interval. We pull the 2015-2019 and 2018-2022 panel datasets to examine changes before and after the onset of the COVID-19 pandemic.

To conduct our analysis, we employ two distinct quantitative research methods. First, we use transition matrices to examine the movement of households between poverty and non-poverty statuses. This approach follows Gambetta (2007) and Herrera & Cozzubo (2016), who used similar methods to characterize household mobility.[5] Specifically, we calculate the percentage of initially poor households that remain in poverty in the following year to get a measure short-term poverty persistence. For a longer-term perspective, we repeat this analysis over five-year periods. Additionally, we categorize households based on geographic,

[4] ENAHO is a stratified and clustered survey. It allows for inference at the national and regional level, as well as by geographical domains defined in the survey's design.

[5] For a deeper discussion of how to measure social mobility, we suggest referring to Fields (2001).

demographic, economic, and social characteristics, and compute separate transition matrices for each group. This approach allows us to explore variations in the persistence of poverty among different subpopulations.

Our second method extends the descriptive analysis with a probit regression. Our objective is to examine the variables displaying the strongest associations with the likelihood of experiencing poverty in the short term. On this regard, the works of Gambetta (2007), Chumpitaz & Jara (2009) and Herrera & Cozzubo (2016) find that demographic variables, such as the dependency ratio and the age of the household members, significantly affect the probability of continued poverty and economic vulnerability in Peru. Additionally, various economic and social factors, including the employment status and skills, monetary transfers, and the occurrence of adverse economic shocks, are considered pertinent predictors variables. These findings align with similar research conducted in other developing economies.[6]

Our main findings reveal that poverty persistence remains high in Peru, with more than half of impoverished households staying in poverty the following year. However, the COVID-19 pandemic had a transitory effect on these dynamics. Between 2019 and 2020, poverty persistence surged to 60%, primarily due to the adverse economic shocks induced by the crisis, encompassing job losses and income reductions. When examining five-year intervals, we observe an escalation in poverty persistence and a decrease in non-poverty persistence during the 2018-2022 period compared to the preceding 2015-2019 period, potentially indicating heightened economic vulnerability following the pandemic. Furthermore, in assessing how frequently households fell into poverty over three-year intervals, we observed a significant rise in the likelihood of experiencing poverty more than once among lower quintiles.

Moreover, we identify various demographic, social, and economic characteristics linked to changes in the persistence of poverty. For instance, households headed by females or older individuals exhibit lower poverty persistence, as well as the ones with access to health insurance and financial inclusion. Conversely, the presence of children in the household is associated with heightened persistence, similar to when the head of the household is self-employed or engages in the informal sector.

The probit regression analysis offers valuable insights into the relationship of select variables with the probability of transitioning into poverty. Notably, higher levels of education for the household head are linked to a reduced likelihood of experiencing poverty, highlighting education's protective role against economic vulnerability. Additionally, demographic factors, such as the presence of children in the household, show a positive correlation with poverty persistence, indicating that larger families may grapple with sustaining stable consumption patterns. We also note that adverse natural shocks and transitions into formal employment are significant predictors.[7] Interestingly, public transfers assumed a pivotal role in reducing the likelihood of experiencing poverty, but only following the onset of the pandemic.

Our research provides a valuable contribution to existing literature by employing well-established methods to measure poverty persistence in the aftermath of the 2020 global pandemic. The crisis induced a shift in poverty dynamics within Peru and other developing economies, with the poverty rate remaining high despite recent economic recovery efforts. Thus, our study expands the discourse surrounding the movement in and out of poverty by using the most recent dataset that includes the pandemic period. We thoroughly analyze how the relationships between selected variables and poverty status change before and after the Covid crisis and provide interpretation for the results. Additionally, by examining demographic and

[6] Some examples are Alem (2015), Quisumbing (2011), Bauch & Dat (2011), May et al (2011), and Bigsten & Shimeles (2008).

[7] To our knowledge, this is the first paper that highlights the importance of transitions in the labor market (employment/unemployment, formal/informal sector) as predictors of poverty dynamics.

socioeconomic factors, we aim to inspire further prescriptive analyses on how policies could contribute to mitigating poverty persistence.

The rest of the paper is structured as follows. Section 2 presents the aggregate transition matrices for households in Peru. Section 3 presents a condensed version of these matrices, grouping households according to demographic and socioeconomic characteristics. Section 4 presents the probit model and discusses its results. Finally, Section 5 gives the concluding remarks.

2 Transition matrices: A first approximation to poverty persistence

In the transition matrices, each row represents the status of a household in the initial period (t=0), and each column represents the final status of that household at the ending period (t=1). These matrices are defined as conditional probability matrices, such that the sum across columns adds up to 1. This is exemplified by Figure 2. In this matrix, poverty persistence is proxied by the parameter λ_{pp}, which represents the percentage of poor households that remain in poverty between periods. Meanwhile, λ_{nn} is the persistence of non-poverty, being equal to the percentage of non-poor households that stay out of poverty.

Figure 2

Transition matrix of households between poverty and non-poverty statuses

		Household condition in t=1		
Household condition in t=0		**Poor**	**Non-poor**	**Total**
	Poor	λ_{pp}	λ_{pn}	**1**
	Non-poor	λ_{np}	λ_{nn}	**1**

Source: Based on an example by Gambetta (2007).

To calculate these transition matrices, we use panel database from the National Household Survey, ENAHO, employing two distinct datasets that track different sets of households up to a five-year period: the 2015-2019 and the 2018-2022 datasets. For the case of two consecutive years, the panel data includes over a quarter of the total households surveyed annually in the ENAHO.[8] When extending the timeframe to a five-year continuous period, information is available for less than 6 percent of the initial households.

Table 1

ENAHO: Number of households in the panel and annual datasets

	Number of households in the panel dataset	Number of households in the annual dataset (Initial year)	Ratio of households covered by the panel dataset (%)
2-year panels			
2015-2016	9 479	32 188	29,4
2016-2017	9 399	35 785	26,3
2017-2018	9 466	34 584	27,4
2018-2019	9 823	37 462	26,2
2019-2020	9 986	34 565	28,9
2020-2021	9 280	34 490	26,9
2021-2022	9 364	34 245	27,3
5-year panels			
2015-2019	1 866	32 188	5,8
2018-2022	1 945	37 462	5,2

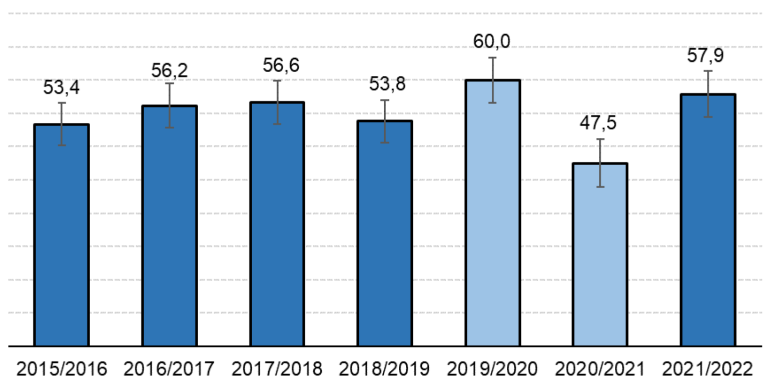
Source: Based on data from the National Household Survey, ENAHO. We use two panel datasets: 2015-2019 and 2018-2022

[8] Every year, INEI selects a random subset of data to create a panel dataset. The size of this subset is predetermined to be approximately one-quarter of the annual observations. Initially, these subsets are designed to ensure that comparisons between different years can be made. This means that, in addition to selecting households for surveying the following year, INEI also randomly chooses households from the total sample to be surveyed for a third, fourth, and fifth time (this, evidently, from the subgroup of households who have already been surveyed).

After computing the year-on-year transition matrix, we get the λ_{pp} (persistence of poverty) parameter, which is reported below. We find that, on average, more than half of poor households remain in poverty the following year. In other words, for a poor household, the chances of escaping poverty in the next year are slightly less than a 50-50 outcome, akin to a coin toss.

The pandemic apparently had a transitory effect on these dynamics. Between 2019 and 2020, poverty persistence rose to 60 percent, induced by the negative economic shock of the COVID-19 crisis. This increase in poverty persistence can be attributed to factors such as job losses, reduced income, and economic disruptions caused by the pandemic. Indeed, real per capita expenditure contracted by 16% according to ENAHO, and real GDP per capita decreased by 11%. The subsequent drop in poverty persistence between 2020 and 2021 (12,5 percentage points) is consistent with the economic recovery (real GDP per capita rose by 13% that year) and partial reversion in the poverty rate in 2021.

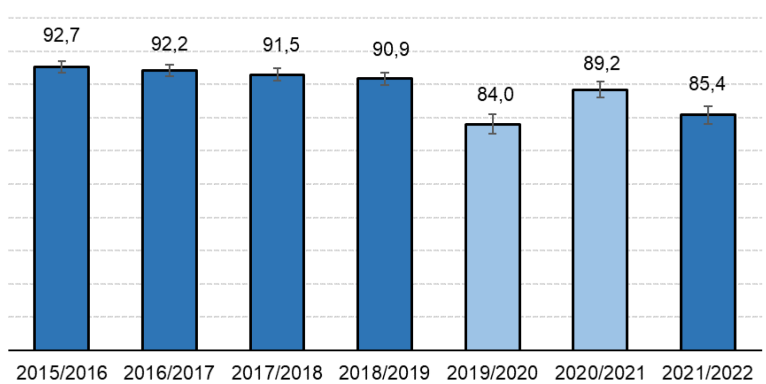
Figure 3
Poor households that remain in poverty the following year (%)



Note: 95% confidence intervals are shown in the graph above.
Source: Based on data from the National Household Survey, ENAHO.

The other important parameter in the transition matrix is λ_{nn}, i.e., non-poverty persistence. Before the pandemic, 9 out of 10 non-poor households remained out of poverty the following year. Therefore, non-poor households had, on average, only a 10% probability of falling into poverty in the subsequent year.

Figure 4
Non-poor households that remain out of poverty the following year (%)



Note: 95% confidence intervals are shown in the graph above.
Source: Based on data from the National Household Survey, ENAHO.

This may explain how, despite medium poverty persistence, the poverty rate kept a decreasing path before the pandemic started. However, between 2021 and 2022, non-poverty persistence decreased by 5 percentage points compared to the pre-pandemic period. We interpret this as an increase in economic vulnerability, a phenomenon that might not be evident when only considering poverty persistence.

When examining five-year intervals between 2015 and 2019, and 2018 and 2022, we observe an increase in poverty persistence and a decrease in non-poverty persistence in the latest period. Specifically, a poor household in 2015 had a 40% probability of being in poverty five years later, while a poor household in 2018 faced a 60% probability for the same outcome. This result may again be indicative of an increase in economic vulnerability after the pandemic.

Table 2
5-year transition matrices for poverty and non-poverty statuses (%)

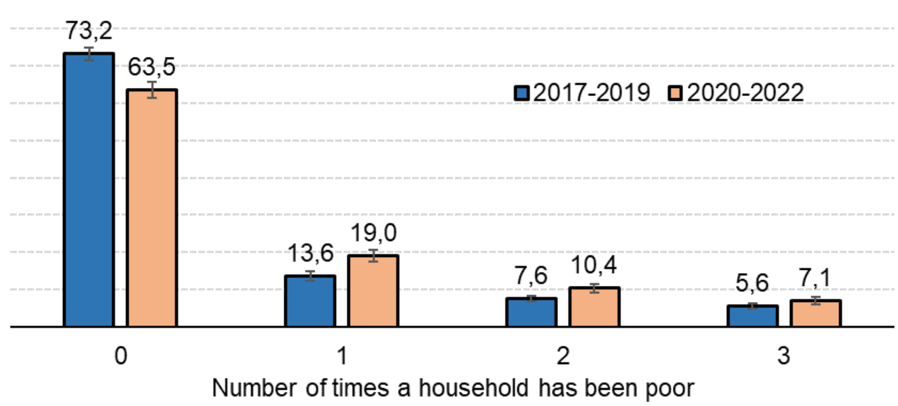
Household in 2015 \ Household in 2019	Poor	Non-Poor	Total
Poor	**42,7**	57,3	100
Non-Poor	9,5	**90,5**	100

Household in 2018 \ Household in 2022	Poor	Non-Poor	Total
Poor	**60,1**	39,9	100
Non-Poor	15,2	**84,8**	100

Source: Based on data from the National Household Survey, ENAHO.

The previous exercise focuses exclusively on the initial and ending point. For instance, in the right panel of Table 2, the measure of poverty persistence only considers households that were poor in 2018 and 2022, ignoring what happened in between those years. To overcome this gap in the diagnosis, in Figure 5 we compute how many times a household has been categorized as poor throughout a set of years. Since we are interested in describing how the dynamics changed after the pandemic, we compare the 2017-2019 and 2020-2022 periods (i.e., we count how many times households have been identified as poor in these 3-year periods).

Figure 5
Distribution of households according to the number of years in poverty (%)



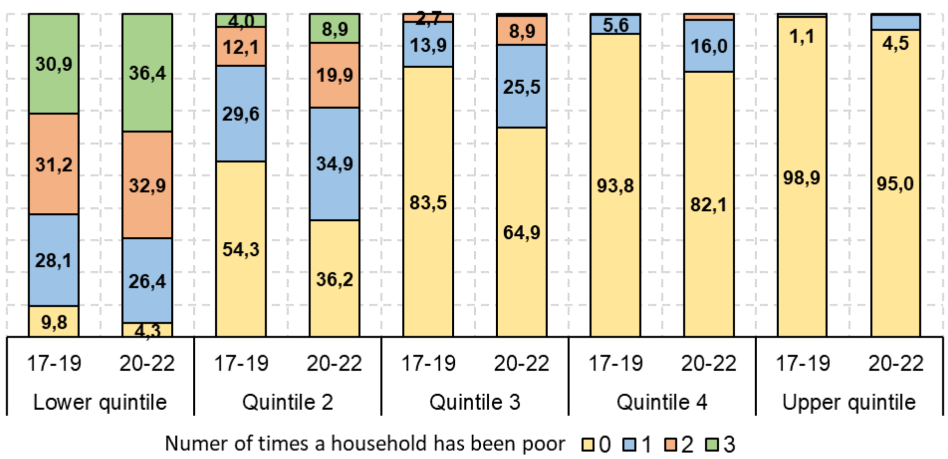
Note: 95% confidence intervals are shown in the graph above.
Source: Based on data from the National Household Survey, ENAHO.

Between 2017 and 2019, 73,2% of households remained out of poverty throughout all those years, 13,6% were poor once, 7,6% were poor twice, and 5,6% endured poverty every year. After the pandemic, the distribution shifts significantly. There is a substantial decrease in the percentage of households that never experienced poverty, dropping by approximately 10 percentage points. Conversely, the percentages of households experiencing poverty twice and thrice increased between 2020 and 2022.

We can determine whether this increase in economic vulnerability is concentrated among poorer households by computing the above measure across quintiles. Since poverty is measured using per capita expenditure, quintiles are calculated based on this variable. The findings indicate that economic vulnerability increased across the expenditure distribution. For all subgroups, the probability of not being poor decreased. Moreover, the lower quintiles experienced a significant increase in the probability of experiencing poverty more than once in the 3-year period.

Figure 6

Distribution of households according to the number of years in poverty, by quintiles (%)



Note: Quintiles of real expenditure per capita.

Source: Based on data from the National Household Survey, ENAHO.

Finally, to gain a deeper understanding of poverty dynamics in Peru, we examine year-on-year transition matrices for three distinct categories: extreme poverty, non-extreme poverty, and non-poverty. According to Appendix 1, the persistence of extreme poverty has consistently been lower than the persistence of non-extreme poverty, even after the pandemic. On average, a household in extreme poverty has a 33% chance of remaining in this situation the following year. However, it is more challenging for a household in extreme poverty to transition out of poverty altogether, with less than a quarter achieving this transition, compared to nearly half of households in non-extreme poverty.

3 Stylized facts of poverty persistence

In this section, we categorize households based on several factors, including geography, demographics, economics, and social characteristics. We then compute transition matrices for each group, with the goal of exploring heterogeneities in poverty persistence. To enhance the readability of our results, we choose to report only the persistence of poverty and the persistence of non-poverty for each group. However, it is worth reminding that, as depicted in Figure 1 above, these parameters are sufficient for reconstructing the complete transition matrices.

Location of the household

We first classify households into groups according to their geographical location. ENAHO identifies urban and rural areas according to the number of private residences that are contiguous to each other. Furthermore, the survey allows for the classification of households into natural regions (coast, highlands, and jungle), which are a prominent unit of analysis for academic and policy analysis in Peru.[9]

Households in urban areas exhibit a lower persistence of poverty and a higher persistence of non-poverty in most years of analysis. This result is intuitive, given that urban households typically enjoy higher incomes, more robust social protection, and broader access to basic services. For instance, in 2022, per capita household income was 80% higher in urban areas compared to rural regions. Furthermore, while 88% and 98% of impoverished urban individuals had access to potable water and electric lighting, only 71% and 81% of their rural counterparts had such connections, respectively. Educational attainment levels, job formalization, and financial inclusion also tended to be higher among the urban poor.

Table 3

Persistence of poverty and non-poverty by location of household (%)

	Persistence of poverty							Persistence of non-poverty						
	2015/ 16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22	2015 /16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22
Geographic area														
Rural	62,8	67,9	63,4	61,4	59,7	55,5	64,6	83,3	83,4	82,0	80,7	75,4	79,4	76,8
Urban	44,0	44,7	50,3	47,1	60,2	44,2	54,5	94,7	94,0	93,5	93,1	85,8	91,4	87,3
Natural region														
Coast	44,0	45,4	48,5	45,8	64,8	41,7	53,4	95,1	94,2	93,3	93,1	84,8	91,0	87,0
Highlands	58,9	61,2	63,3	58,2	59,0	56,1	61,2	88,6	89,1	88,5	86,9	81,3	86,0	82,7
Jungle	53,8	61,5	52,7	58,0	51,9	43,9	64,4	90,3	89,2	90,1	90,2	87,2	89,4	85,0

Source: Based on data from the National Household Survey, ENAHO.

However, between 2019 and 2020, urban households experienced a sharp increase in poverty persistence (from 47% to 60%), whereas there was no statistically significant change for their rural counterparts. This outcome underscores the heterogeneity in the economic impact of the pandemic. The economic downturn was partly triggered by government-imposed restrictions on face-to-face activities, which had a larger effect on the services, commerce, and construction sectors (the agricultural and mining sectors could operate without many limitations). These former sectors hold greater relevance in urban areas. Consequently, per capita household income contracted by 22% in urban areas between 2019 and 2020, in stark contrast to the 9% decline observed in rural areas. Similarly, poverty incidence surged by 11 percentage points in urban areas, while rural areas experienced a more modest increase of 5 percentage points between those years.

When examining the classification by natural regions, households in the coastal region exhibit lower levels of poverty persistence and a higher rate of non-poverty persistence. This pattern is consistent with the higher urbanization rate in this area than in other parts of the country. Additionally, there is a sharp increase in

[9] On average, the coast if more urbanized than the rest of the country and encompasses the richest households (the capital, Lima, which has the highest income per capita, is located there). Meanwhile, the highlands (called like that because of the Andes) have more rural areas, and it is where the poorest households (usually from districts in the higher altitudes) reside. The jungle (called like that because of the Amazon rainforest) is the part of the country that was most recently settled in Peruvian history, and therefore faces stronger infrastructure deprivations despite its recent economic development.

poverty persistence within this region between 2019 and 2020 (from 46 to 65%), analogous to the dynamics of urban households.

Demographic characteristics

When analyzing demographic characteristics, we find that families with female and older heads of households show less persistence of poverty than their counterparts. As adult men tend to earn higher wages and have higher occupation rates, this result merits further investigation. However, it is worth noticing that households with female heads experienced the highest increase in persistence in the 2019-2020 period. Among age groups, households with adults between 30 and 64 years old had the sharpest rise.

Meanwhile, the presence of children in the household appears to be positively correlated with poverty persistence and negatively associated with the persistence of non-poverty. This finding is consistent with the results reported by Gambetta (2007) and Chumpitaz & Jara (2009). One possible explanation is that a higher proportion of children in the household increases its dependency ratio, making it harder to sustain consumption patterns. Moreover, families whose head of household has a physical disability tend to show a higher persistence of poverty. This may be explained by the head's capacity to generate income.

Table 4

Persistence of poverty and non-poverty by demographic characteristics (%)

	Persistence of poverty							Persistence of non-poverty						
	2015 /16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22	2015 /16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22
Sex of household head														
Female	48,2	49,3	54,4	51,0	62,5	46,3	55,0	94,9	93,5	93,8	93,0	87,0	91,2	85,8
Male	56,2	58,2	57,2	56,7	59,3	48,2	58,9	91,5	91,5	90,4	89,8	82,7	88,1	85,1
Age of household head														
18 to 29	61,5	73,1	53,0	66,7	70,6	44,7	62,1	93,1	87,4	91,9	86,7	84,6	90,1	85,5
30 to 64	52,9	55,9	58,3	54,9	61,9	48,1	58,1	92,8	92,4	91,3	90,8	82,6	88,5	85,5
65 +	52,9	52,9	52,9	49,2	51,9	45,6	55,9	92,3	92,3	91,8	91,7	87,4	91,1	85,3
Number of children in the household														
No children	51,0	48,1	50,8	49,4	52,2	42,6	52,1	93,5	93,6	93,2	93,0	89,1	91,1	88,2
Children (<15 years old)	56,8	62,5	60,1	59,1	65,8	67,7	61,3	90,7	89,8	88,7	87,4	75,3	80,7	80,2
Physical disability of household head														
No disability	54,3	56,6	56,2	55,1	60,9	47,4	57,1	92,6	92,1	91,7	90,9	84,2	89,3	85,7
Disability	54,1	54,6	62,1	57,0	52,6	52,4	67,8	89,6	91,4	88,3	90,3	84,4	87,3	80,9

Source: Based on data from the National Household Survey, ENAHO.

Social characteristics

Throughout the period of analysis, families whose heads of household had secondary education experienced less persistence of poverty compared to cases where they only achieved primary education or had no formal instruction. Although the category of tertiary education appears to show less persistence in most years, those statistics should be interpreted with caution due to the small number of observations and the high standard error.[10] Indeed, few impoverished households (around 5%) have household heads with undergraduate or graduate education.

Table 5

Persistence of poverty and non-poverty by social characteristics (%)

	Persistence of poverty							Persistence of non-poverty						
	2015 /16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22	2015 /16	2016 /17	2017 /18	2018 /19	2019 /20	2020 /21	2021 /22
Education of household head														
Primary	57,8	60,1	59,0	57,8	58,7	51,8	60,0	88,9	88,8	87,0	86,1	80,6	85,7	80,3
Secondary	43,7	47,0	51,1	49,2	64,1	44,4	52,8	94,4	93,6	93,7	93,7	83,2	89,2	86,5
Tertiary[1/]	30,6	46,8	44,1	39,3	64,8	24,2	59,8	97,6	97,2	98,1	96,9	93,3	96,3	95,4
Health insurance of household head														
No insurance	55,1	57,3	57,7	56,4	61,1	50,3	59,8	92,6	91,7	90,9	90,8	84,3	88,6	85,3
Insurance	51,7	53,3	52,4	50,1	55,5	38,0	47,0	92,0	93,2	93,3	91,1	83,6	91,3	85,8
Financial inclusion of household head[2/]														
No inclusion	55,3	57,1	56,7	56,1	59,7	49,8	59,6	90,5	89,3	88,6	87,0	79,4	85,4	81,0
Inclusion	45,3	51,9	56,4	45,4	61,0	41,8	54,0	95,9	95,9	94,7	95,3	89,2	92,9	89,2
Affiliation to Pension 65														
Not affiliated	52,6	56,0	56,3	53,4	61,2	46,8	58,1	93,4	92,7	92,1	91,6	84,1	89,8	86,2
Affiliated	58,1	56,8	59,1	56,5	52,1	55,0	55,8	77,1	81,3	80,1	78,6	81,8	80,8	72,5
Affiliation to Juntos														
Not affiliated	47,4	50,6	52,9	48,5	56,3	43,4	56,0	93,6	93,3	92,4	92,2	85,3	90,6	86,6
Affiliated	66,7	69,0	66,1	67,5	69,9	61,8	65,2	77,8	75,4	76,2	69,9	60,6	72,0	66,8

1/ This statistic should be interpreted with caution due to the small number of observations.
2/ It measures access to bank accounts and/or credit cards through a financial institution.
Source: Based on data from the National Household Survey, ENAHO.

Conversely, households with access to health insurance and financial products experience lower levels of poverty persistence compared to their counterparts. This phenomenon underscores the households' ability to maintain stable consumption patterns in the face of adversity. Health insurance plays a pivotal role in mitigating the financial burden of illness, while financial inclusion typically correlates with improved access to loans, providing additional financial resilience.

We also examine the role of anti-poverty cash-transfer programs. Pension 65 provides S/ 250 (about 65 US dollars) every two months to senior citizens aged 65 or older who do not receive pensions from other institutions. To qualify, their household must be classified as poor according to the national Household Targeting System (known as 'Sistema de Focalización de Hogares' or SISFOH in Spanish).

On the other hand, Juntos offers S/ 200 (about 52 US dollars) every two months to households with a pregnant woman or a child under 19 years old who has not completed secondary education. Similar to Pension 65, eligibility for Juntos requires the household to be classified as poor according to SISFOH.

[10] On this regard, out of the more than 1000 observed poor households in the sample each year, less than 40 have heads of households with tertiary education.

However, unlike Pension 65, Juntos is a conditional transfer program, where the household must fulfill specific education and health-related responsibilities.[11]

Families receiving financial assistance from Juntos consistently exhibit higher poverty persistence and lower non-poverty persistence compared to the rest throughout the analysis period. This trend may reflect the greater economic and social vulnerability of Juntos households, making them less capable than the average household to increase their income and expenditures. However, it is worth noting that between 2019 and 2020, the increase in the persistence of poverty among Juntos recipients was significantly lower. This could be attributed to the program's financial aid, but it may also be linked to the fact that most Juntos households reside in rural areas. Most of these conclusions also apply to families with recipients of Pension 65. However, there is no statistically higher level of poverty persistence among Pension 65 households compared to not affiliated households in many periods. This could be related to differences in the program designs (Pension 65 is targeted towards individuals) or may reflect targeting issues.

Economic characteristics

Table 6 categorizes households based on the job characteristics of their head, including the type of occupation, informality, and the economic sector. Self-employed and informal workers appear to be the most vulnerable group, experiencing a higher level of poverty persistence. These workers often lack social protection, contend with lower wages, and face more extensive credit constraints. On the other hand, a greater persistence of poverty is observed among workers in the manufacturing and extractive sectors.

Table 6

Persistence of poverty and non-poverty by economic characteristics (%)

	Persistence of poverty							Persistence of non-poverty						
	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22
Occupation														
Employer	52,2	42,9	33,9	53,0	49,7	52,9	44,6	95,3	96,1	94,3	96,1	86,7	96,7	90,1
Employee	49,3	47,0	58,4	46,6	61,6	42,2	52,1	94,4	94,2	93,0	93,1	85,8	91,4	88,3
Self-employed	58,6	63,9	58,7	58,4	60,1	52,9	60,7	88,5	88,9	88,4	86,3	81,4	84,9	81,9
Formality														
Informal	55,8	57,8	56,7	56,7	60,8	49,3	58,6	90,5	90,1	89,8	88,3	81,9	87,4	83,3
Formal	30,6	35,0	54,8	35,0	45,7	27,5	46,0	97,7	97,5	95,8	97,4	90,4	94,9	92,8
Economic sector														
Extractive	62,5	64,0	63,3	59,9	59,1	53,4	60,9	84,0	83,9	83,5	82,3	77,2	82,1	78,2
Manufacture	35,1	29,3	47,8	62,7	60,7	51,1	66,2	92,3	93,9	92,0	90,7	83,7	91,8	86,3
Services	44,3	51,9	49,9	51,6	57,3	47,0	54,0	96,3	95,3	93,9	93,8	86,0	92,5	89,3
Construction	53,2	51,2	59,8	37,2	70,3	54,4	50,8	92,6	90,5	88,2	90,7	81,3	88,2	87,4
Commerce	44,0	54,5	36,7	39,7	68,8	32,6	49,1	93,7	95,6	95,8	92,1	86,5	90,5	86,2

Source: Based on data from the National Household Survey, ENAHO.

[11] Pregnant women must do regular prenatal checkups, and infants between 0 and 3 years old must also undergo frequent health controls. Additionally, all children under 19 years old are expected to attend school.

4 Characterizing the transition into poverty in the short-term

4.1 Model and conceptual framework

Another way to analyze the dynamics of poverty in Peru is to characterize the likelihood of being poor. In our probabilistic model, the dependent variable Y_{it} takes the value of 1 if the household is in poverty in year t and 0 otherwise. The probit specification models the average conditional probability that Y_{it} equals 1 using the standard normal cumulative distribution function Φ, as shown below:

$$\Pr(Y_{it} = 1|X_t, X_{t-1}, z_{t-1}) = \mathbb{E}[\mathrm{Y}_{i,t}/X_{i,t}, X_{i,t-1}, Y_{i,t-1}] = \Phi(X'_{i,t}\beta + X'_{i,t-1}\theta + \boldsymbol{\alpha Y_{i,t-1}})$$

In this specification, the explanatory variable $Y_{i,t-1}$ takes the value of 1 if the household was in poverty in the previous year. Therefore, the α coefficient determines the extent to which a household is more likely to remain in poverty in a specific period, given that it was already in poverty the previous year. This is called state dependence, i.e. poverty today affects the likelihood of poverty tomorrow. We expect a positive and significant α, as it is related with the short-term persistence of monetary poverty.

Simultaneously, the vectors $X_{i,t}$ and $X_{i,t-1}$ encompass various control variables from both the current and preceding period. These variables include demographic characteristics such as the age and gender of the household head, along with the count of children and total household members. They also encompass social and economic factors, including years of education, physical disabilities, social transfers, and the employment status of the household head.

The estimation considers regressors at the annual level for the entire sample, thereby controlling for trends and other related impacts. Additionally, it considers variables at the geographical level (urban/rural) and natural region level to capture the unique characteristics of each unit.

In another specification, three variables are incorporated to gauge whether households have encountered adverse economic (such as job loss or family business bankruptcy), health-related (like illness or a serious accident involving a household member), or natural shocks.

In the third and final specification, we introduce "dynamic" variables related to the household's labor situation. Specifically, we explore the effects of: (i) an increase in the number of household members engaged in employment; (ii) an increase in the number of members with formal employment; (iii) the continuity of formal employment for the household head; (iv) the transition from informal to formal employment for the head; and (v) the acquisition of employment by the household head after experiencing unemployment in the two consecutive years. This specification also incorporates a demographic variable that measures whether the household gained an additional member aged between 0 and 5 years between one year and the next.

We selected this set of variables for our analysis, considering that the dependent variable is monetary poverty. Poverty is conceptualized as the lack of resources to meet basic needs, proxied in the Peruvian case by a minimum per capita expenditure level for households. In essence, we are assuming that a per capita expenditure above a certain threshold (i.e., the poverty line) indicates the household's economic capacity to command basic needs, which include a diverse set of goods and services.

As a result, movements in and out of poverty must be linked to individual and common factors associated with the likelihood of reducing or increasing expenditure. Since expenditure is partly explained by income, variables predicting household members' earnings are relevant for our analysis. This is where demographic and socioeconomic characteristics of the head of the household, often the primary earner, gain significance. Characteristics such as age, education, employment, and financial inclusion tend to predict the capacity of generating income. Following this framework, economic dependency of the household, public transfers, and adverse economic shocks faced by families must also be considered.

In the economics literature, some research has explored the relationship between poverty dynamics and the variables introduced in our model for the Peruvian context. For instance, Gambetta (2007) identifies a higher probability of transitioning into poverty among families with a larger number of members, with less education and who experienced a decrease in public transfers. Chumpitaz & Jara (2009) reveal relationships between higher poverty persistence and lower education, credit constraints, adverse health and natural shocks, as well as with a larger number of underage or senior household members. Meanwhile, Herrera & Cozzubo (2016) find that higher economic vulnerability, defined as the risk of falling into poverty, is related to geographical location (altitude), an increase in the economic dependency ratio, fewer years of education for the head of the household, and the presence of adverse natural shocks (other adverse shocks were not significant). All these papers also use the ENAHO data for the estimation of binomial regression models. However, none of these cover the post pandemic period.

Similar research has been done for other developing countries. For instance, Bigsten & Shimeless (2008) analyze poverty persistence in Ethiopia and find a significant difference for urban and rural households, as well as a relationship with demographic characteristics and the occupational status of the head of household. Quisumbing (2011) does a similar analysis for rural households in Bangladesh. The author finds that the probability of being chronically poor is negatively associated with years of schooling of the household head, and the proportion of children below 15 and adults 55 and older. Household size and the schooling of the household head also seem to be important for poverty dynamics in Vietnam (Baulch & Dat, 2011).

4.2 Estimation results

The estimations use data of biennial panels, spanning two-year periods, for each specification proposal and are conducted using the 2015-2019 and 2018-2022 panel datasets.[12] In the estimation, observations from 2015 are excluded as there is no information on how these households behaved in the previous year. Subsequently, we divide the sample, retaining only the post-pandemic period (2020-2022) and comparing it with the preceding years (2016-2019). Since ENAHO is a clustered and stratified survey, we account for these characteristics throughout the estimation procedures.

Table 7 reports the average marginal effects of the probit regressions. Most of the results align with the prior descriptive findings. Firstly, we notice that, on average, the probability of falling into poverty increases by more than 25 percentage points if the household was already poor the previous year ($Y_{it-1} = 1$). According to the third specification for the entire period (2016-2022), the average probability of falling into poverty in the subsequent period rises from 13% to 39% between a non-poor and a poor household. These probabilities are computed by substituting $Y_{it-1} = 0$ and $Y_{it-1} = 1$, and solving for the total probability of being poor using the average value of the remaining predictors.

[12] The ENAHO panel datasets cover households for a maximum of 5 years. However, we can keep only the observations from the biennial panels, and then append them to create an expanded dataset that surpasses the initial 5-year period. Specifically, we can partition the 2018-2022 panel dataset into four samples representing households interviewed in consecutive years: 2018-2019, 2019-2020, 2020-2021, and 2021-2022, while preserving their respective sample probability weights. The same approach can be applied to the 2015-2016, 2016-2017, 2017-2018, and 2018-2019 periods from the 2015-2019 panel dataset, and the resulting datasets can be appended to create a unified dataset composed of all the biennial panels within the relevant time horizon.

Table 7

Selected average marginal effects: Households being poor in period t

	Specification 1			Specification 2			Specification 3		
	2016-19	2020-22	2016-22	2016-19	2020-22	2016-22	2016-19	2020-22	2016-22
Poverty persistence									
Poor$_{(t-1)}$	0,280***	0,260***	0,275***	0,277***	0,259***	0,273***	0,264***	0,248***	0,260***
Geography									
Urban household$_{(t)}$	-0,054***	-0,059***	-0,059***	-0,048***	-0,057***	-0,055***	-0,037***	-0,047***	-0,044***
Demographic characteristics									
Age (years)$_{(t-1)}$	0,000	-0,001***	-0,000**	0,000	-0,001***	-0,000**	0,000	-0,001**	0,000
Male$_{(t-1)}$	0,027***	0,012*	0,019***	0,026***	0,012*	0,018***	0,027***	0,015**	0,020***
Physical disability$_{(t-1)}$	0,024***	0,041***	0,031***	0,022**	0,041***	0,029***	0,020**	0,035***	0,026***
# Members of the household$_{(t-1)}$	0,012***	0,026***	0,018***	0,013***	0,026***	0,018***	0,014***	0,026***	0,019***
# Kids between 0 and 5 years old $_{(t-1)}$	0,051***	0,063***	0,056***	0,052***	0,063***	0,057***	0,051***	0,065***	0,057***
# Kids between 6 and 15 years old $_{(t-1)}$	0,019***	0,035***	0,026***	0,019***	0,035***	0,025***	0,018***	0,037***	0,026***
Social and economic characteristics									
Years of education$_{(t-1)}$	-0,011***	-0,011***	-0,011***	-0,011***	-0,011***	-0,011***	-0,009***	-0,009***	-0,009***
Employed$_{(t-1)}$	0,006	-0,015	-0,005	0,004	-0,015	-0,006	0,014	-0,018	-0,001
Financial inclusion [a/]	-0,041***	-0,057***	-0,047***	-0,041***	-0,057***	-0,047***	-0,025***	-0,038***	-0,029***
Var. in public transfers$_{(t)}$ [a/]	0,002	-0,037***	-0,031***	0,002	-0,038***	-0,031***	0,003	-0,038***	-0,031***
Negative shocks									
Economic shock$_{(t)}$				-0,015	0,018	0,010	-0,018	0,023*	0,012
Health shock$_{(t)}$				0,007	-0,013	0,000	0,005	-0,012	-0,001
Natural shock$_{(t)}$ [c/]				0,036***	0,024*	0,035***	0,031***	0,021*	0,031***
Employment changes									
Increase in employed household members$_{(t)}$							-0,004	-0,021**	-0,012**
Head of household finds a job (previously unemployed)$_{(t)}$							-0,003	-0,032**	-0,018*
Increase in employed household members in the formal sector$_{(t)}$							-0,053***	-0,051***	-0,053***
Head of household finds job in the formal sector (previously informal)$_{(t)}$							-0,044***	-0,068***	-0,055***
Head of household remains in the formal sector (previously formal)$_{(t)}$							-0,076***	-0,100***	-0,088***
Demographic changes									
Increase in kids between 0 and 5$_{(t)}$							0,097***	0,087***	0,085***
Fixed effects [d/]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Number of observations	36 740	27 986	64 726	36 740	27 986	64 726	36 740	27 986	64 726

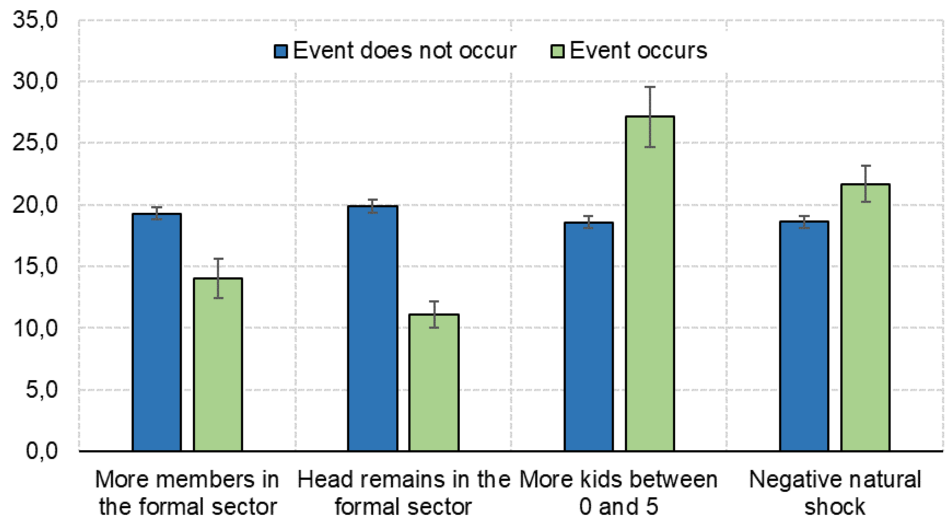
a/ The variable is rescaled so that the coefficients show the marginal effects of an increase in S/ 100 (26 US dollars) in public transfers. Transfers include Juntos and Pension 65 payments, as well as the unique unconditional cash transfers made during the pandemic (Bono "Yo Me Quedo en Casa", Bono Rural, Bono Independiente and Bono Universal in 2020, Bono 600 and Bono Yanapay in 2021, and Bono Alimentario in 2022).
b/ Financial inclusion is defined as having a savings account, a checking account or a credit card in a financial institution.
c/ Includes plagues, draughts, floods, among others.
d/ Includes dummies per year and per natural region (coast, highlands, and jungle).
* p-value<0,10; ** p-value<0,05; ***p-value<0,01

Demographic, social, and economic characteristics of the household are also linked to changes in the likelihood of experiencing poverty. For instance, each additional year of education for the head of the household is associated with a 1 percentage point decrease in the probability of experiencing poverty. If the head of the household had only completed one year of education, the average probability of experiencing poverty is 26%. In contrast, if the head of the household has achieved 16 years of education (postgraduate), the average probability decreases to 12%. Additionally, being male, younger, and having a physical disability increases the probability of experiencing poverty in the following period.

Similarly, the size and composition of the household are significant factors. More members and more children in the household are associated with an increased probability of experiencing poverty. In this context, single-person households have, on average, a 14% chance of experiencing poverty, while this rate rises to 21% for households with five members.

The negative shocks and the dynamic variables included are also significant in explaining the likelihood of experiencing poverty. The occurrence of natural hazard events, an increase in the number of employed household members in formal sectors, the continued employment of the head of the household in the formal sector, and an increase in the number of children between 0 and 5 years old all have a significant impact on the probability of falling into poverty across the sample. The corresponding average probabilities are depicted in Figure 7 below. These results emphasize the importance of formal jobs for poverty reduction. It also hints at the fact that a greater dependency ratio and economic hardship due to climate factors prevents households from sustaining their wellbeing. Evidently, all these variables are also related to household income, being this a direct channel through which they could influence poverty dynamics.

Figure 7
Predicted average probability of being poor according to selected events (%)



Finally, we examine the changes in poverty dynamics between the pre-pandemic and pandemic periods. For most demographic, social, and economic characteristics, there are no significant alterations in the coefficient values. However, there is an exception concerning the impact of variations in public transfers, which encompass Juntos and Pension 65 payments, as well as the unique unconditional cash transfers provided during the pandemic (the Bono "Yo Me Quedo en Casa", Bono Rural, Bono Independiente, and Bono Universal in 2020, Bono 600 and Bono Yanapay in 2021, and Bono Alimentario in 2022).

Before the pandemic, an increase of S/ 100 (approximately 26 US dollars) in public transfers did not significantly affect the likelihood of experiencing poverty. In contrast, during the pandemic, each additional S/ 100 reduced the probability of falling into poverty by approximately 4 percentage points. This finding is noteworthy due to the substantial size of the exceptional unconditional transfers disbursed between 2020 and 2022. Over these three years, a total of approximately S/ 22 billion (equivalent to 5,8 billion US dollars) were distributed to Peruvian households through these programs, representing around 2% of the current GDP. As this assistance was reduced in 2022 and completely discontinued by 2023, it may exacerbate poverty dynamics.

We also observe that certain employment variables became significant during the pandemic. In the 2017-2019 sample, an increase in the number of employed household members and the head of the household finding a job (after previously being unemployed) did not have significant effects on the probability of experiencing poverty. Meanwhile, in the 2020-2022 sample, the average probability of falling into poverty is reduced by 2 percentage points if there are more employed members in the household. In the same period, if the head of the household finds employment after a period of unemployment, the reduction in probability is 3 percentage points. All these results may be indicative of how securing any type of job became a more relevant proxy of household wellbeing after the 2020 economic crisis severely affected the labor market.

One concern regarding the previous results is the presence of endogeneity that may bias the estimators. It is plausible to have some unobserved variables that are correlated both with the poverty status and with some of the covariates included in the estimation (for example, the beliefs or attitudes of the household members). We address this issue by estimating a linear regression with individual fixed effects at the household level. We use the algorithm of Guimaraes & Portugal (2010), which facilitates the estimation of models with high-dimensional fixed effects. The incorporation of household fixed effects should account for any bias induced by omitted variables. However, two considerations arise. The first one is that the fixed effects should account for all the state dependence in poverty dynamics, given that the correlation between poverty in the previous and current year reflects the characteristics of poor households. Thus, we omit the Y_{it-1} variable in the linear regression. The second consideration is that the algorithm drops "singletons", i.e., households with only one observation in the data set. In our study, these would be the households that participated in only one of the biannual panel surveys. To make the probit and the linear regression more comparable, we thereby estimate the probit model with a subsample of households with more than one observation in the 2018-2022 panel data set. Appendix 2 shows the results of the estimations, concluding that most of the point estimators preserve the same sign.[13]

4.3 Additional exercise: Marginal effect of having previously experienced poverty

In this subsection we present an additional exercise to further explore our results. We estimate how the short-term persistence of monetary poverty (the estimate of α parameter) changes due to the inclusion of control variables in the regression. This way, we show how an important fraction of the state dependence of poverty may be explained by socioeconomic characteristics of the households.

Figure 8 shows how the marginal effect of being poor the previous year (Y_{it-1}) diminishes as more controls are added to the probit regression.[14] When the regression includes only the variable Y_{it-1}, the marginal effect stands at 44 percentage points, with an average probability of 55% for a household to remain in poverty after experiencing poverty the previous year (consistent with the observed persistence of poverty, as depicted in Figure 3). The subsequent addition of control variables proceeds with the following sets:

- Variable Set 1: Geographical controls (urban/rural household and natural region)
- Variable Set 2: Year control
- Variable Set 3: Demographic characteristics of household head (age, sex, and physical disability)
- Variable Set 4: Socioeconomic characteristics of household head (employment, financial inclusion, and education)
- Variable Set 5: Characteristics of the household (household size, number of children under the age of 5, number of children under the age of 15, and variation in public transfers)

[13] Some results, including the ones for the household size, economic dependency, and natural shock, are not statistically significant in the linear regression. However, this may have been induced by the presence of heteroskedasticity, which is an attribute of the linear probability model.

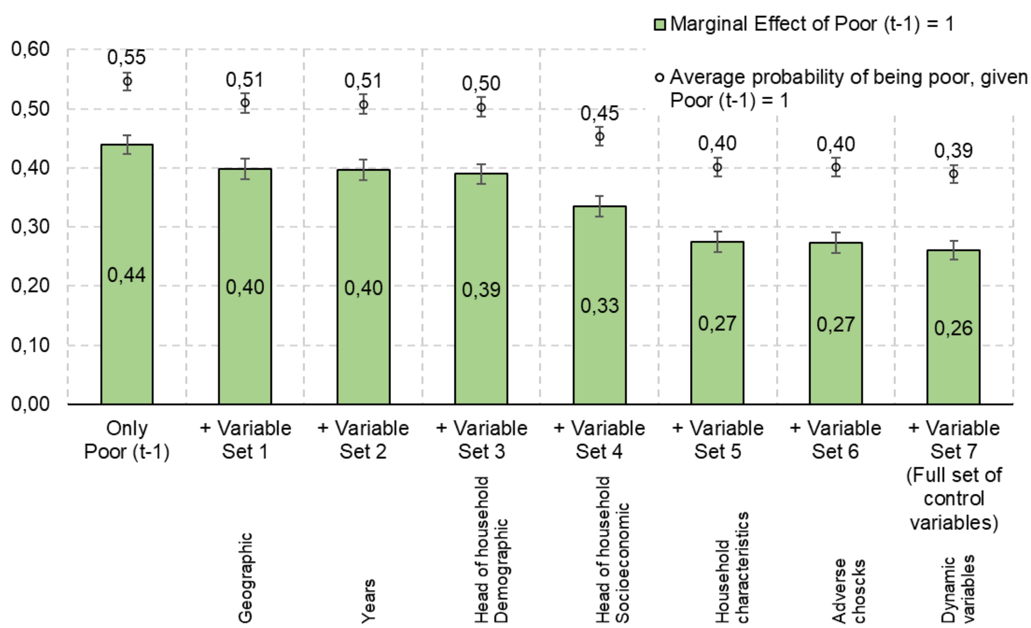
[14] We use the full sample (2016-2022) for this exercise.

- Variable Set 6: Adverse shocks (economic, health and natural event related)
- Variable Set 7: "Dynamic" variables (all changes in employment status of the household head and the members of the household and change in the number of children under 5 years).

Upon incorporating geographic controls, the marginal effect drops to 0,40. Subsequently, with the inclusion of all the characteristics of the household head, it further decreases to 0,33. Finally, the addition of household-level characteristics yields a marginal effect of 0,27. Incorporating adverse shocks and changes in employment and child status does not bring about significant variations. These results mean that the initial state dependence of poverty is reflecting some other characteristics of the household and its context. As Ahmed et al (2007) discuss, there are major causes of persistent poverty in developing countries, including slow growth, conflict, prevalence of adverse shocks, poor health, limited access to education and economic exclusion. The final value of the marginal effect shown in Table 7 must therefore be understood as the reflection of some structural and transitory factors that create state dependence in poverty status.

Figure 8

Marginal effect of being poor the previous period and average probability of being poor given that the household experienced poverty the previous period



Note: 95% confidence intervals are shown in the graph above.

5 Final remarks

Our analysis of monetary poverty dynamics in Peru from 2015 to 2022 sheds light on the persistence of poverty and its evolution, particularly in response to the COVID-19 pandemic. Several key findings have emerged, offering insights for policymakers and future research:

Firstly, poverty persistence in Peru remains a significant challenge, with over 50% of poor households continuing to experience poverty year-on-year. This underscores the need for the discussion of measures to break this cycle. Secondly, the pandemic acted as a disruptor, temporarily increasing poverty persistence due to job losses and income reductions. While the overall poverty rate decreased post-pandemic, the risk of economic vulnerability for certain groups heightened, emphasizing the importance of building resilience in the face of external shocks.

Demographic and socioeconomic characteristics play a key role in poverty persistence. Policies should prioritize support for vulnerable groups, including families with children and those working in the informal sector. Efforts to promote education may contribute to poverty reduction.

Public transfers proved effective in reducing the likelihood of poverty during the COVID crisis. Although it would be inefficient to persist with unconditional transfers to the broader population, policymakers could consider sustained and well-targeted social safety nets to protect vulnerable populations.

One limitation of this paper is that it has mostly focused on the characteristics of the head of household. This warrants further investigation on how the attributes of non-head household members may also be related to changes in the likelihood of experiencing poverty, and how this may affect policy prescriptions. For instance, Alem (2015) shows that, for urban households in Ethiopia, international remittances and the labor market status of non-head household members also play a role.

Finally, our study underscores the importance of comprehensive poverty alleviation strategies that consider both short-term and long-term dynamics. Fostering economic resilience, improving access to education, and strengthening social safety nets are critical steps towards reducing poverty persistence and enhancing well-being. Further research should explore the nuanced impacts of these policy measures to refine and optimize poverty reduction efforts.

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7 Appendix

Appendix 1: 2-year transition matrices for extreme poverty, non-extreme poverty, and non-poverty statuses, 2015-2022

2015/2016	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**35,7**	43,2	21,1	100,0
Non-extreme poor	6,1	**41,9**	52,0	100,0
Non-poor	0,5	6,9	**92,7**	100,0

2016/2017	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**39,1**	44,8	16,1	100,0
Non-extreme poor	7,7	**43,4**	48,8	100,0
Non-poor	0,5	7,4	**92,2**	100,0

2017/2018	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**28,9**	49,6	21,5	100,0
Non-extreme poor	6,3	**46,1**	47,5	100,0
Non-poor	0,5	8,0	**91,5**	100,0

2018/2019	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**31,0**	51,4	17,6	100,0
Non-extreme poor	6,5	**43,4**	50,1	100,0
Non-poor	0,5	8,6	**90,9**	100,0

2019/2020	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**35,8**	37,3	26,8	100,0
Non-extreme poor	11,9	**46,1**	42,0	100,0
Non-poor	1,3	14,7	**84,0**	100,0

2020/2021	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**21,6**	44,2	34,2	100,0
Non-extreme poor	5,9	**38,3**	55,7	100,0
Non-poor	1,1	9,7	**89,2**	100,0

2021/2022	Extreme poor	Non-extreme poor	Non-poor	Total
Extreme poor	**38,7**	40,0	21,3	100,0
Non-extreme poor	11,6	**43,2**	45,2	100,0
Non-poor	1,8	12,8	**85,4**	100,0

Appendix 2: Estimation results for the probit and linear probability model with household-level fixed effects. Panel data 2018-2022.

Selected average marginal effects: Households being poor in period t

	Pobit model	Linear probability model with household-level fixed effects
Poverty persistence		
Poor$_{(t-1)}$	0,249***	
Geography		
Urban household$_{(t)}$	-0,048***	-
Demographic characteristics		
Age (years)$_{(t-1)}$	-0,001***	0,000
Physical disability$_{(t-1)}$	0,030**	0,017
# Members of the household$_{(t-1)}$	0,024***	-0,006
# Kids between 0 and 5 years old $_{(t-1)}$	0,059***	0,023
# Kids between 6 and 15 years old $_{(t-1)}$	0,035***	0,015
Social and economic characteristics		
Years of education$_{(t-1)}$	-0,009***	0,004**
Employed$_{(t-1)}$	-0,003	-0,047**
Financial inclusion [a/]	-0,035***	-0,002
Var. in public transfers$_{(t)}$ [a/]	-0,039***	-0,039***
Negative shocks		
Economic shock$_{(t)}$	0,024*	0,015
Health shock$_{(t)}$	-0,003	0,020
Natural shock$_{(t)}$ [c/]	0,021*	0,022
Employment changes		
Increase in employed household members$_{(t)}$	-0,020***	-0,039*
Head of household finds a job (previously unemployed)$_{(t)}$	-0,013	-0,042**
Increase in employed household members in the formal sector$_{(t)}$	-0,048***	-0,010
Head of household finds job in the formal sector (previously informal)$_{(t)}$	-0,066***	-0,061**
Head of household remains in the formal sector (previously formal)$_{(t)}$	-0,104***	-0,076***
Demographic changes		
Increase in kids between 0 and 5$_{(t)}$	0,088***	0,013
Fixed effects [d/]	✓	✓
Household-level fixed effects		✓
Number of observations	30 646	30 288

Notes:

- The probit estimation only considers households with more than one observation in the dataset (i.e., households that participated in more than one of the biannual panel datasets).
- The urban/rural and the natural region variables are dropped in the linear probability model given the household-level fixed effects.
- Since the data corresponds to the 2018-2022 panel dataset, the year 2018 is dropped due to the lack of the information for the households' characteristics in the previous year.

a/ The variable is rescaled so that the coefficients show the marginal effects of an increase in S/ 100 (26 US dollars) in public transfers. Transfers include Juntos and Pension 65 payments, as well as the unique unconditional cash transfers made during the pandemic (Bono "Yo Me Quedo en Casa", Bono Rural, Bono Independiente and Bono Universal in 2020, Bono 600 and Bono Yanapay in 2021, and Bono Alimentario in 2022).

b/ Financial inclusion is defined as having a savings account, a checking account or a credit card in a financial institution.

c/ Includes plagues, draughts, floods, among others.

d/ Includes dummies per year and per natural region (coast, highlands, and jungle).

* p-value<0,10; ** p-value<0,05; ***p-value<0,01