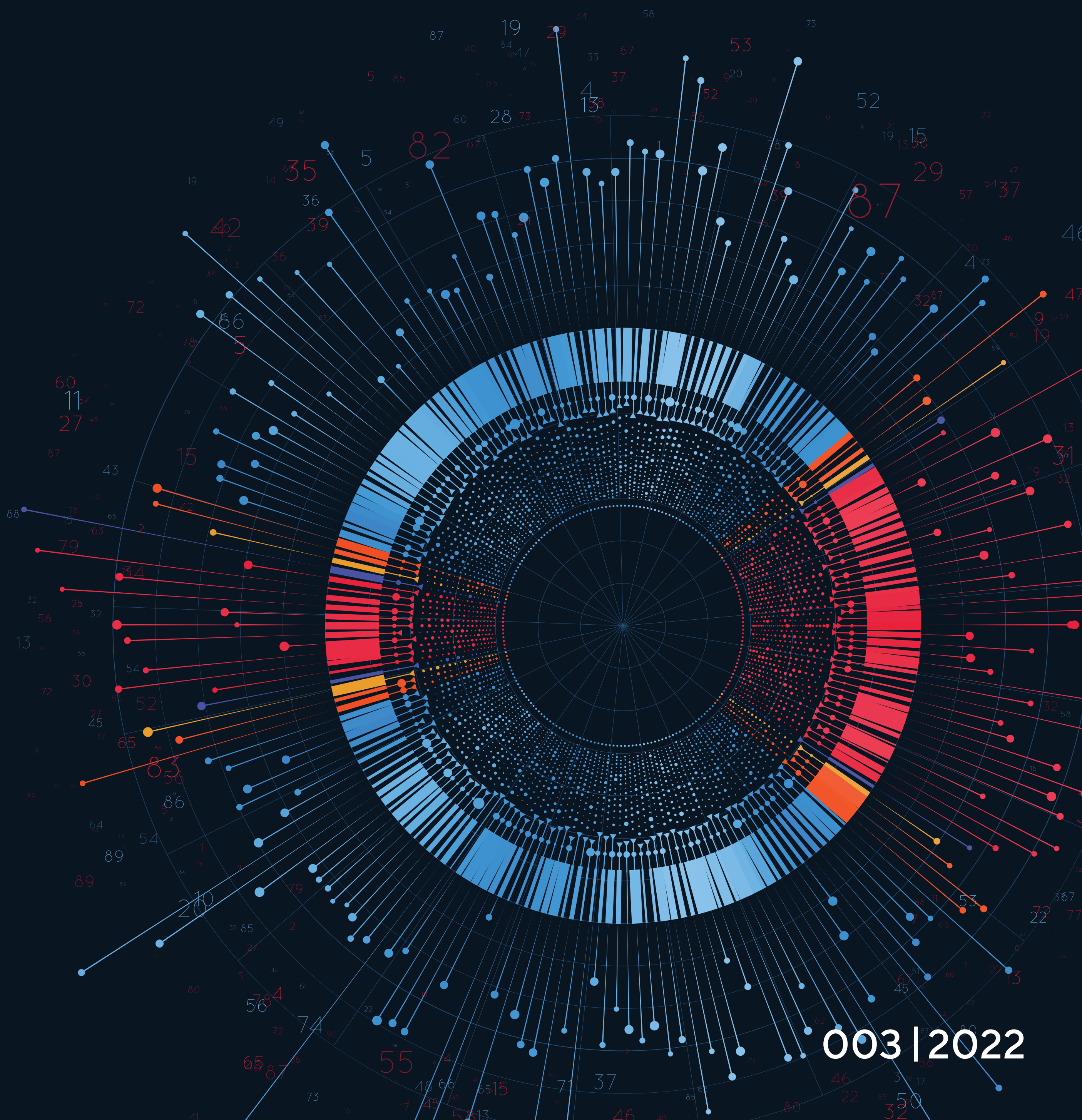
THE EFFECT OF POST-COVID RECOVERY POLICIES ON THE YOUNG POPULATION:

THE CASE OF COLOMBIA



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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

UNITED NATIONS DEVELOPMENT PROGRAMME, UNDP

Sara Ferrer Olivella
Resident Representative

Alejandro Pacheco
Deputy Resident Representative

Jaime Alejandro Urrego Mondragón
Development Economist

Javier Ignacio Pérez Burgos
National Head of Poverty and Inequality Reduction Area

Olga Victoria Dulce Salcedo
Sergio Armando Rueda Gómez
Juan Sebastián Vallejo Triana
María Camila de la Hoz Moncaleano
Technical Team, Poverty and Inequality Reduction Area

Lina María Montes Ramos
Design and Layout, Communications Unit

LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE, LSE

Adrian Fossaceca
Shipra Kumar
Lucas Lamby
Gabrielle Paoletti
Ana Laura Sobalbarro
Authors

Rafael Hortala-Vallve
Academic Advisor

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Elaborado por[1]:
Adrian Fossaceca
Shipra Kumar
Lucas Lamby
Gabrielle Paoletti
Ana Laura Sobalbarro

RESUMEN

La pandemia de COVID-19 trajo consecuencias devastadoras para las poblaciones vulnerables de países en desarrollo, particularmente en América Latina. Los gobiernos de la región pudieron crear y ampliar las transferencias de efectivo no condicionadas para aliviar rápidamente las presiones económicas de la crisis. Muchos gobiernos aún están tratando de comprender los verdaderos efectos de tales políticas. En el caso de Colombia, el Equipo de Desarrollo Humano del PNUD construyó un modelo de micro simulación inspirado en Díaz et al (2021) que se enfoca en comprender los efectos que tuvieron programas sociales implementados en las primeras fases de COVID-19 sobre la pobreza en el país. A medida que el mundo está saliendo de la pandemia de COVID-19, los países se están enfocando en desarrollar estrategias inclusivas y sostenibles para reactivar su fuerza laboral y su economía. Por lo tanto, este estudio tiene como objetivo mejorar el modelo del PNUD y Díaz et al., (2021) mediante la evaluación de los efectos de políticas tales como (1) una transferencia de efectivo incondicional y (2) un programa de empleo dirigido a la juventud colombiana. Los resultados sugieren que un programa de empleo en forma de subsidios de salario dirigido a jóvenes de bajos ingresos es mejor para reducir la pobreza general, pero las transferencias de efectivo son más eficientes para reducir la pobreza extrema a corto plazo. Sin embargo, a largo plazo, un programa de empleo tiene el mayor efecto en reducción de la pobreza para la pobreza monetaria y la pobreza extrema, mientras que las transferencias de efectivo no tienen efecto alguno. Este efecto también se replica para el caso de la pobreza juvenil y la pobreza extrema juvenil. El análisis de género realizado muestra que los modelos basados en focalizaciones perfectas son optimistas con respecto al impacto en las medidas de pobreza basadas en el género. La conclusión general es que los subsidios de salario son efectivos para impulsar la creación de empleo y, a su vez, reintegrar a los jóvenes a la fuerza laboral, aumentando su autosuficiencia y reduciendo su necesidad de transferencias adicionales.

Palabras Clave: Microsimulaciones; Transferencias de efectivo; Programas de empleo; Pobreza; Pobreza juvenil

Clasificación JEL: C15, J08, I38

1. Los autores son graduados de la maestría de administración pública del London School of Economics.

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Elaborated by[2]:
Adrian Fossaceca
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Lucas Lamby
Gabrielle Paoletti
Ana Laura Sobalbarro

ABSTRACT

The COVID-19 pandemic brought devastating consequences for low-income populations in the global south, particularly in Latin America. Governments in the region were able to create and expand unconditional cash transfers to quickly alleviate economic pressures from the crisis. Many governments today are still trying to understand the true effects of such policies in the short- and long-term. In the case of Colombia, the UNDP Human Development Team built a microsimulation model inspired by Diaz et al. (2021), focusing on the poverty effects of previous social programs undertaken during the early phases of COVID-19 in Colombia. As the world is now emerging out of the COVID-19 pandemic, countries are focusing on building inclusive and sustainable strategies to reactivate their workforce and economy. Therefore, this paper aims to enhance the UNDP and Díaz et al. (2021) model by assessing the policy effects of (a) an unconditional cash transfer and (b) an employment program targeting Colombian youth. The results suggest that an employment program in the form of in-work subsidies targeted at low-income youth is better for reducing overall poverty. Still, cash transfers are more efficient in reducing extreme poverty in the short-term. However, in the long-term, an employment program has the most significant poverty reduction effect for poverty and extreme poverty, while cash transfers have no effect at all. This effect is also replicated for the poverty within the youth population. The gender analysis shows that models based on a perfect targeting assumption will be overly optimistic regarding the impact of gender-based poverty measures. The overall conclusion is that employment programs are preferable. Their long-term benefits should be considered when deciding how to improve youth welfare. Temporary in-work subsidies effectively boost job creation and reintegrate the youth into the labour force, increasing their self-reliance and reducing their need for additional transfers.

Keywords: Microsimulations; Cash transfers; Employment programs; Poverty; Youth Poverty

JEL Classification: C15, J08, I38

2. The authors are graduates from the Master of Public Administration of the London School of Economics.

TABLE OF CONTENTS

FIGURES

TABLES

ACRONYMS

CCTs	Conditional Cash Transfers
COP	Colombian Pesos
DANE	Departamento Administrativo Nacional de Estadística
GAPS	Gender Action for Peace and Security
GDP	Gross Domestic Product
GEIH	Gran Encuesta Integrada de Hogares
ILO	International Labor Organización
IVA	Impuesto sobre el Valor Añadido
PAEF	Programa de Apoyo al Empleo Formal
UBI	Universal Basic Income
UCTs	Unconditional Cash Transfer
UN	United Nations
UNDP	United Nations Development Program
USD	United States Dollars
VAT	Value Added Tax
WB	World Bank

I. INTRODUCTION

During the year 2021, it is estimated that between 143 and 163 million individuals may have fallen into poverty globally due to the emergence of the COVID-19 pandemic (WB, 2021). In this regard, the global goal of reducing the level of people living under the international poverty line by 3% by the year 2030 (UN, 2022) appears to be a difficult objective to accomplish. The pandemic is forecasted to have enduring and long-term consequences on economies across the globe, but more distinctively on the livelihoods of low-income populations in developing countries (WB, 2021). As such, the pandemic has stimulated an interesting worldwide debate about the advantages of planning a robust and comprehensive poverty reduction strategy — to ensure sustainability and resilience in the post-pandemic period.

As a result of mechanisms such as lockdowns to stop the spread of the virus at the early stages of the pandemic, inequalities of income were aggravated, and levels of unemployment and poverty increased substantially (ILO, 2020). Additionally, developing countries are hit the hardest, especially since many of them were deprived of sophisticated insurance structures and shock prevention measures to couple with the COVID-19 pandemic (ibid.). Such a case could be observed in Colombia, which exhibited a negative GDP growth of 6.8% in 2020, and a concerning increase in the poverty rate, reaching 42.5% in the same year (DANE, 2020). Additionally, the country has been suffering from several political turmoil events and social protests between 2019 and 2020 (GAPS, 2021), demonstrating social dissatisfaction.

To address the reductions in social welfare during lockdowns, many Latin American countries expanded the use of cash transfers to provide quick relief during the height of the crisis. In Colombia, the national government has employed multiple social policies targeting the most vulnerable populations; such policies consisted of cash transfers (such as 'Ingreso Solidario' and 'Bogotá Solidaria') and VAT refunds ('Devolución del IVA') that ranged from a benefit of 75,000 to 423,000 COP and were paid out in monthly or bi-monthly instalments.

To better understand the impact of these policy interventions, the UNDP has designed a microsimulation-based model by building upon Díaz et al. (2021) to quantify the impact of cash transfer policies on poverty mitigation in Colombia. Diaz et al. (2021) evaluate a multitude of social assistance policies implemented during the emergency that could potentially mitigate the impact of poverty in Colombia. The policies are found to have reduced the poverty levels by 4 percentage points at the national level (ibid.). Nonetheless, the model cannot account for the deepening inequalities, which translated into different effects for different subsets of people in the poor population. For example, school closures caused by lockdowns had an impact on young people, and women's labour-force participation rates declined once they assumed most care roles in their households (GAPS, 2021). These are only a few consequences of the COVID-19 crisis that the current UNDP model cannot consider. In that regard, further research evaluation is needed to shed light on the effects of alternative social programs (including employment programs). Young people are one of the population subgroups severely impacted by the pandemic (WB, 2021). The current lack of an adequate model dedicated to analyzing the impact of the policies specifically targeted toward the youth forms the primary motivation of this study.

In this context, the study builds a microsimulation model that evaluates cash transfers and employment programs targeted at the youth population (individuals aged 18–28 years) in Colombia and that could be used to predict poverty mitigation effects after 2020 in the aftermath of COVID-19. As countries are exiting the pandemic with unprecedented vaccination efforts, the socio-economic recovery is prioritizing inclusion by ensuring that no one is left behind, regardless of their gender, ethnicity, or social characteristics. The model constructed in this study aims to derive essential policy recommendations that could shed some light on the type of interventions that should be implemented to promote an inclusive economic recovery that integrates youth into the economy and ensures a sustainable recovery.

The results from this analysis point out that, in the short-term (1 year after the policy implementation), cash transfer programs effectively reduce extreme poverty levels at the national level and also for the young people of Colombia (0.95pp and 1.82pp respectively). However, they are not as effective at reducing national and youth poverty (0.57pp and 1.11pp, respectively) compared to employment programs (0.86pp and 1.67pp, respectively). This is because the size of the cash transfer received by beneficiaries is not large enough to increase their income above the poverty line. In the long-term (five years after implementing both policies), the cash transfer program has no effect as benefited households revert to their initial income in our model. A subset of beneficiaries in the employment program keeps benefitting from the program by remaining employed and increasing their wages over time due to the returns of their increased experience. Therefore, the employment program has a positive long-term impact and reduces poverty and extreme poverty by 0.4pp and 0.35pp after five years. Those results are essential when considering how to reactivate the economy after a crisis and implement inclusive and sustainable policies.

In the first section of the study, an in-depth evaluation of the existing literature on microsimulation models will be presented. The second section delves into a thorough explanation of the data and the methodology developed to build the updated cash transfers program and the new employment programs targeting youth. In the third section, the paper analyzes results and assesses the impact in the short and long-term for both policy interventions. The last section presents policy recommendations, limitations, and conclusions.

II. LITERATURE REVIEW

The following sections are a review of the literature looking at different aspects of cash transfer microsimulation models. The last section also contains a review of the literature on employment programs that is relevant to the model studied.

Targeting

Targeting is essential for designing cash transfer programs for poverty alleviation. Even though a trade-off exists between efficiency and equity, policymakers will primarily aim at targeting the poorest or most vulnerable households to maximize the program's impact. However, there might be a discrepancy between who should have been targeted and who eventually received the cash transfer. Evaluating targeting in any policy is a central question as it directly affects the impact cash transfers can have. The closer the targeting of the evaluation model comes to reality, the larger the precision of the model.

The previous UNDP model identifies the eligible poor and vulnerable households to receive the Minimum Rent Program's cash transfer by replicating DANE's social classes and constructing the per capita spending unit's income distribution of the Colombian households from the GEIH survey. Every household with a per capita income of the spending unit below the poverty lines (poverty and vulnerability lines) is then identified as eligible to receive the cash transfers. This method can be qualified as mean testing targeting. As highlighted by the UNDP, this methodology assumes perfect targeting of the poor population. Therefore, the results of the program's evaluation rely on this assumption.

However, there are several reasons to believe that the "perfect targeting" assumption of the poor might not hold in reality. Numerous studies (Devereux et al., 2015; Coady et al., 2004) explain that all popular targeting methods – mean testing, community-based targeting, proxy mean test, self-targeting, categorical and spatial targeting – often lead to inclusions or exclusion errors. This finding implies that some non-eligible households receive the cash transfers or, on the contrary, eligible households do not. Depending on the size of these errors, they can significantly impact the effect of the cash transfers, having several implications for the field of microsimulation. In the context of Colombia, the high level of informality in the labour market is something to consider when using the GEIH survey's income distribution to base the targeting. Since "perfect targeting" does not exist, many studies acknowledge that the dataset recovered through survey data might not represent the income distribution compared to official statistics (Siebertova et al., 2016; National Research Council, 1991).

Finally, the capacity of the state to implement and deliver cash transfers might also be limited, preventing a perfect targeting of the poor. This heavily depends on the institutional context of the country and the program. While this issue is outside the program's impact. According to Devereux et al. (2015) and Coady et al. (2004), this issue is an essential factor in cash transfer's effectiveness.

Focusing on Youth

The study of the effects of cash transfers on youth during COVID-19 first requires qualifying whether cash transfers, in general, had any impact on the well-being of populations during COVID-19. Banerjee et al. (2020) discuss the effects of providing a universal basic income (UBI) during a pandemic like COVID-19 through a large-scale experiment conducted in rural Kenya. The study established that in the long-term, cash transfers had a modest impact on measures of well-being like hunger and depression during the pandemic. Moreover, there was evidence that long-term transfers also led to increased commercial risk-taking among the participants. This evidence may be because transfers reduced their vulnerability to hunger which helped rationalise income-generating risks.

The World Bank (Cuesta & Pico, 2020) published a report in 2020 to show how COVID-19 had impacted women in Colombia and how mitigation policies in the form of income payments and payroll subsidies significantly impacted poverty, using a microsimulation model. The mitigation policies reversed the effects of the poverty surge by 2.16 and 2.23 percentage points at the cost of COP 11,219 million (USD 2.99 billion). However, the report also noted that men and women fared similarly on poverty measures and the impact of mitigation policies was the same for men and women.

Altman et al. (2014) conducted a study using a microsimulation tax and benefit model to determine the impact on poverty measures and unemployment levels of youth (18-24-year-olds) in South Africa by providing them with potential conditional, unconditional social assistance to youth. Interventions of such nature were considered essential for achieving widespread poverty alleviation and enabling the economic participation of youth in South Africa.

Similar microsimulation studies evaluating the effect of cash transfers (PROGRESAR) on youth were done in Argentina (Giovambattista & Panigo., 2014) to show that income inequality among youth decreased substantially. Several other studies have also demonstrated that conditional cash transfers in rural Mexico, such as the “Oportunidades” program, formally called Progresa (Schwartz & Abreu, 2007) (Behrman et al., 2005), have had positive impacts on youth.

Considering Spending Patterns

The analysis of the effect of cash transfers focuses on their distributional impact and potential effects on poverty reduction. However, to conduct a holistic analysis of the effects of cash transfer, one should consider using the additional income. Therefore, understanding spending patterns is relevant when analyzing the impact of cash transfers, as changes in income can drive variations in consumption (Japelli and Pistaferri, 2010).

Two interesting findings exist from empirical research regarding the recipient of the income variation. First, the pooling hypothesis - stating that an extra dollar of income is spent in the same way by everyone - has been rejected by most literature (Phipps & Burton, 1998). Secondly, gender differences exist in the spending of additional income (ibid; Armand et al., 2016). Targeting women with cash transfers raises the proportion of households’ food expenditures compared to male recipients (ibid.).

The consumption response will vary depending on the characteristics of the income change, such as direction and duration. Regarding the direction of the consumption response, Shea (1995) found that consumption reacts more to predictable income decreases than increases. This finding is inconsistent with the economic assumptions of myopia. Hereby, agents are short-sighted, and therefore, consumption patterns directly react to present available income. This means consumption should symmetrically respond to known income increases and decreases. Moreover, the duration of an income change impacts its consumption response. Transitory shocks should have a small impact on consumption, according to the theory, and permanent shocks should lead to significant revisions in consumption (Japelli and Pistaferri, 2010). Therefore, these aspects need to be considered when analyzing the impact of an income change on spending patterns, as it cannot be simply generalized.

Whilst spending patterns and their change are not directly introduced in the microsimulation model, they help the qualitative understanding of the context and potential effect mechanisms.

Introducing Employment Programs

Previous sections have focused on improving the modelling of cash transfers or extending the analysis of downstream changes in spending. Even though cash transfers were a standard policy tool used by governments across the globe in the context of the pandemic, new policies are being considered for the medium- to long-term economic recovery. The focus of the discussion in many countries has shifted towards increasing employment opportunities to drive economic reactivation after the pandemic. Employment-related policy programs can take different shapes, and so do the appropriate microsimulation models that aim to investigate their possible effects. Their focus is on the long-term generation of welfare, and they aim to reduce hiring costs for employers. The policies aim to incentivize formal employment. One way of doing so is by helping firms directly in the form of a wage subsidy. This reduces the cost for firms to hire more and therefore boosts job creation. This subsidy can take different shapes, such as tax incentives or direct in-work wage subsidies.

Several microsimulation studies (Blömer & Peichl, 2020) have focused on modelling the impact of tax incentives on labour supply and employment. This area is the most significant in microsimulations in employment-oriented policies. In this context, microsimulations that analyze employment effects are often behavioural. They, therefore, differ from arithmetic models in that they estimate the behavioural response from individuals and households to changes in the benefit and tax system. On the other hand, arithmetic models assume that behaviour is exogenous to the tax and benefit system. For this reason, they only model "first-round effects" (Blömer & Peichl, 2020). The Díaz et al. (2020) study, which is the base of this paper, is an arithmetic microsimulation and does not consider behavioural responses.

The literature on employment-focused policies not centred around tax-based policies and simulations is less developed. One such example is the study by Figari (2009a) that focuses on in-work benefits and their effect on the labour market. Whilst this study is also based on a tax-microsimulation model, it effectively analyzes the subsidies for low-wage workers. It applies a policy introduced in the UK (the British Working Tax Credit) to Southern European countries (Greece, Italy, Portugal & Spain). The study then analyzes the effect on poverty rates and labour force participation. It also compares the differential impact of disbursing the subsidy on a household vs at the individual level. It finds that targeting the household achieves the redistributive purposes better, whilst individually based targeting provides better incentives for females to participate in the labour force.

Brown et al. (2007) analyze long-term effects of an in-work subsidy in Germany. The authors found that low wage subsidies and hiring credits show short-term positive effects on employment, but the policy faces diminishing returns (i.e., increments in the size of the subsidy and the hiring credits lead to lower welfare gains over time). Furthermore, the wage subsidy and the hiring credits reduced overall unemployment and helped reduce overall income inequality. The study found that the probability of workers joining the wage subsidy scheme is between 75 and 90 percent (Brown et al., 2007). The probability that workers will maintain the job after one year tends to be even higher than the initial "participation probability" (Brown et al., 2007). In a similar study, Armand et al. (2020) found that vulnerable unemployed individuals in North Macedonia were 71% more likely to work in a permanent job if they were offered subsidized jobs. Similarly, Lombardi et al. (2018) found that, on average most small firms in the sample doubled their workers' size after wage subsidies were implemented. Moreover, after one year, roughly less than 10% of workers left the firm. Among the potential reasons why individuals might not join the employment scheme are generous unemployment benefits, which could disincentivize people from seeking employment. In Canada, for example, it was found that generous unemployment benefits encourage people to remain unemployed, even if employment benefits are in place (HR Reporter, 2020). Furthermore, companies might also be demand constrained, meaning that they might not be willing to hire more workers even if employment subsidies are in place. In a comparable study using labour data from France during the 2008-2009 recession, authors found that hiring credits to low-wage workers also produced positive impacts on employment (Cahuc et al., 2014).

Within the socioeconomic context of Colombia, the in-work benefits related to wage subsidies are of primary interest as tax-based incentives do not reflect the labour market reality of Colombia well enough. For the case of in-work benefits, the approach of Figari (2009), Brown et al. (2007), Lombardi et al. (2018), and Cahuc et al. (2014) are informative. It would be possible to follow the process and design an in-work subsidy program that could potentially target young people (i.e., a wage subsidy to cover a percentage of the total remuneration). A similar program is running in Colombia (PAEF), which provides a subsidy of 40% of the minimum wage to employed men, 50% to employed women, and 25% to youth (18-28 years old) but only to a maximum of 50 workers for each company or firm that qualifies for the subsidy, regardless of size. This policy is expected to last until December 2022, and it has already cost the national government more than 7,000 million COP (~ USD 1.8 billion) since March 2021, benefitting more than 4 million workers in Colombia (41.9% being women) (Colombian National Government, 2020). Another program targeting unemployed people is also running in Colombia. As part of a government strategy focused on youth unemployment called 'Estrategia Sacúdete', wage subsidies have been offered to employers to hire new young workers formally. For those unemployed young individuals between the ages of 18 and 28, a subsidy equivalent to 25% of the minimum wage is given to employers. The subsidy equals 10% if the worker is unemployed and older than 28 years old and 15% if the worker is an unemployed woman and older than 28 years old. This program started to operate in August 2021 and is expected to last until August 2023 (Colombian National Government, 2021).

The models and frameworks most appropriate to the situation of Colombia are, therefore, those focusing on in-work subsidies. Building on the findings of this part of the literature review, the paper attempts to enhance the UNDP microsimulation model by simulating the benefits of an employment program targeted at young Colombians. This will be compared with the UNDP approach to simulate the impacts of a cash transfer program that has been adapted here to target young people. For comparability purposes, the same program budget is assumed. The analysis will consider different eligibility and targeting criteria. These different scenarios (henceforth "customized models") will target beneficiaries based on skills, education, gender, or geographic location. Lastly, the long-term benefits will be considered by including firm behaviour as stated in the literature and the returns to additional working experience. As an alternative to the perfect targeting assumption, this analysis includes a random targeting simulation where beneficiaries within the eligible groups are randomly assigned to the treatment.

III. METHODOLOGY TO ESTIMATE THE IMPACT OF SOCIAL PROGRAMS ON YOUTH POVERTY AND EMPLOYMENT

This paper is a follow-up to Diaz et al. (2020), which examined the effects of the COVID-19 pandemic on households and the distributional effect of a cash transfer program on decreasing poverty among low-income households. The novelty of this study is that it focuses on recovery efforts directed at a specific section of the population – youth – by examining the potential impact of youth-focused mitigation actions and their impact on overall poverty levels in Colombia to determine which is more effective[3].

The methodology employed is a micro-simulation approach to assess and analyze the possible impact of implementing cash transfers or employment programs to mitigate the negative effect of the COVID-19 pandemic in households with youth (individuals aged 18-28 years), as well as their distributive outcomes. Microsimulation refers to a variety of modelling approaches that function at the individual level, whether for organizations or people and are produced by imposing base deterministic or stochastic rules to estimate the outcome of their implementation (Figary et al., 2015). It enables the investigation of aggregated and distributive outcomes through interest groups since it offers estimates at the individual level.

The microsimulation is based on the microdata from the 'Gran Encuesta Integrada de Hogares' (GEIH) of 2019 and 2020 and the labour force and poverty modules derived from this survey. This is the integrated household data for Colombia, which covers data for key variables used in the model, like housing demographics, employment status, income, etc. The survey covers 24 departments or states, which includes both cities and rural areas of Colombia. This survey is called continuous because the consolidated national total is composed of 12 monthly samples, each representing an average of 8.3% of the total sample[4].

Similar to the Diaz paper, the variables from the GEIH database on which the impact of cash transfers and employment programs are assessed are per capita income of the spending unit, poverty, and inequality. Moreover, households from the GEIH database are also categorized as "extremely poor households" if they are unable to access a basic food basket, as "moderately poor households" if they are unable to access a basic food basket and non-food goods, and as "vulnerable households" for those facing a greater than 10% probability of falling into poverty (in this case having less than PPP$13 a day).

This study, similar to Diaz et al. (2020), employs static micro-stimulation, in which a set of arithmetic rules are applied to the GEIH sample to simulate the effects of (1) unconditional cash transfers to youth and (2) in-work subsidies on income and a variety of poverty indices. The microsimulation allows the analysis of employment programs and their potential effects compared with those from simple cash transfers. Microsimulation models have been commonly used for many similar analyzes like tax and benefits (Atkinson et al., 1983), transportation, or business location planning (Figary et al., 2015).

The microsimulation analyzes the effects on poverty of two mitigation programs that are focused on young people from low-income households: job creation through in-work subsidies and cash transfers. Both programs' micro-simulations are designed to demonstrate their impact by evaluating the reduction of poverty over two time periods. The periods are stipulated as follows:

3. Diaz et al. (2020) measure the impact of the policy bundle deployed by the Colombian government to mitigate the impact of the COVID-19 pandemic. This study differs from that approach as it focuses on the estimation of the impact of one specific policy targeting a specific subsection of the population – youth.
4. For more information regarding GEIH and its limitations please check the Methodological Data Large Integrated Household Survey – GEIH (link).

- **Immediate impact** – after 1 year
- **Long-term Impact** – after 5 years

In the next subsections, both programs modelled in the micro-simulation are described in depth. The features of the program, such as the targeted demographic, length, and conditions, are chosen in such a manner that their estimated impact is comparable.

1. Cash Transfers Program

As previously stated, the methodology used intends to assess the effects of unconditional cash transfers targeted to households with youth on poverty alleviation. This work falls into the continuation of Diaz et al. (2020) paper, looking specifically at cash transfer programs implemented in Colombia after the beginning of the pandemic[5].

Given that this study shares a similar background, the assessment of the impact of cash transfers targeted on youth uses similar microsimulation steps from Diaz et al. (2020). First, the poverty rates and inequalities indicators of the different categories of households defined above are calculated based on the per capita income of the spending unit, excluding government transfers but including imputed rent. The household's income distribution resulting from it represents the baseline scenario before the cash transfers program. Assuming perfect targeting and differing from the Diaz paper, only the poor households with youth between 18 and 28 years old will receive **240,000 COP per month for the poorest and 160,000 COP per month for the vulnerable** for 1 year until it reaches the cash transfers program budget limit of 648,000 million COP (172 million USD). In total, the cash transfers program reaches 175,000 extreme poor households, 175,000 poor households, and 150,000 vulnerable households[6]. The simulation results will give the updated per capita income of the targeted households. Poverty level and inequalities indicators are then recalculated, and the new income distribution of Colombian households after the transfers is established.

Measuring the impact of the cash transfer program

The impact of cash transfers will assume that the households that received cash transfers consume the entire transfer before the next year. This assumption is based on the argument that a permanent increase in income leads to smooth consumption, while a temporary increase leads to increasing consumption in the size of the surplus[7]. The result is compared with the baseline scenario, i.e. income without any transfers, for two time periods: 1 year or 5 years, at the end of the program (which lasted 1 year). The comparison illustrates how income per capita, and poverty evolved as a result of receiving cash transfers. To do so, the density function of their income distribution is plotted before and after the cash transfers program has been implemented. By comparing the income distributions at the end of different time periods, different impacts on poverty reduction can be measured.

- **Immediate Impact:** The immediate impact is measured at the end of the program, i.e. 12 months after it began.
- **Long-term Impact:** The long-term impact is measured 5 years after the program has lasted 1 year.

5. Checking Diaz et al. (2020), cash transfer model building instructions, is highly recommended for the reader. The details on the definition of the income receiving unit (household), income considered, and income assessment period, are provided in this paper.
6. This cash transfer program is partially based on the 'Ingreso Solidario' program, referenced in the literature review.
7. See Japelli and Pistaferri, (2010).

This analysis will also be useful in comparing how these results differ from the results obtained in the employment program. The following section will cover the employment program features and model.

2. Employment Program

To evaluate the possible impact of a low-income youth-targeted employment program on poverty reduction as compared to a direct transfer system, it is necessary to develop a program that can be represented in a microsimulation. The employment program is modelled as an in-work subsidy offered to businesses that agree to hire young people from low-income households[8]. To extend the understanding of the potential impact of an employment program, the model will include different scenarios. The key features and assumptions of the employment program are described in detail below.

2.1. Features of the employment program

The employment program has four distinct features:

Table 1: Features of the program

Features of the program
Type of program
Budget of the program
Length
Target population - Perfect targeting – Baseline scenario - Perfect targeting – Customized scenarios - Random targeting – Baseline and customized

Source: Author's illustration

2.1.1 Type of program

The employment program simulated in this study is an in-work subsidy equal to 40% of the monthly minimum wage in Colombia, equal to 360,000 COP per month. The firms receive a monthly subsidy if they hire young employees and pay for the residual of the wage.

2.1.2 Budget of the program

To ensure comparability, the total budget of the program in the model is the same as the total budget of the cash transfer program. The total amount of money for the employment program would then be 648,000 of million COP (172 million USD). Given the size of the subsidy defined above and the total amount of the program budget, the total targeted youth would therefore be 300,000. However, the number of people who receive the benefit may be lower due to supply and demand constraints. On the

8. The 'Programa de Apoyo al Empleo Formal' (PAEF) was used as a foundation for the features of the program. Refer to Literature review.

supply side, people might not be taking jobs[9]. On the demand side, there might be companies that are unable to hire employees even when their wages are subsidized[10].

2.1.3 Length[11]

The employment program will also last 1 year to make it as comparable as possible to the cash transfer program. Firms will receive the in-work subsidies for 12 months, and after this timeframe, workers' wages will no longer be subsidized.

2.1.4 Target Population

The targeted population are unemployed youth between 18 and 28. If among the eligible households there is more than one young unemployed individual, the model assumes that the one with the highest educational attainment is selected as a beneficiary as they are more likely to become employed based on their education. There will be different scenarios:

Perfect targeting: Baseline scenario

To make the employment program comparable to the cash transfer program, the selection of beneficiaries is based on the **perfect targeting** of households with unemployed youth from the lowest income levels. The employment program aims at reaching **105,000** extreme poor households, **105,000** poor households, and **90,000** vulnerable households. These numbers emerge by matching the budget size from the cash transfer program, calculating the maximum number of beneficiaries that can be reached given the subsidy of 360,000 COP, and applying the same distribution of 35%, 35%, and 30% across the extremely poor, poor, and vulnerable households.

This will be known as the **baseline scenario** of the targeted employment program. However, to consider the potential impact on poverty from targeting a sub-section of youth, the model includes three other scenarios with different targets.

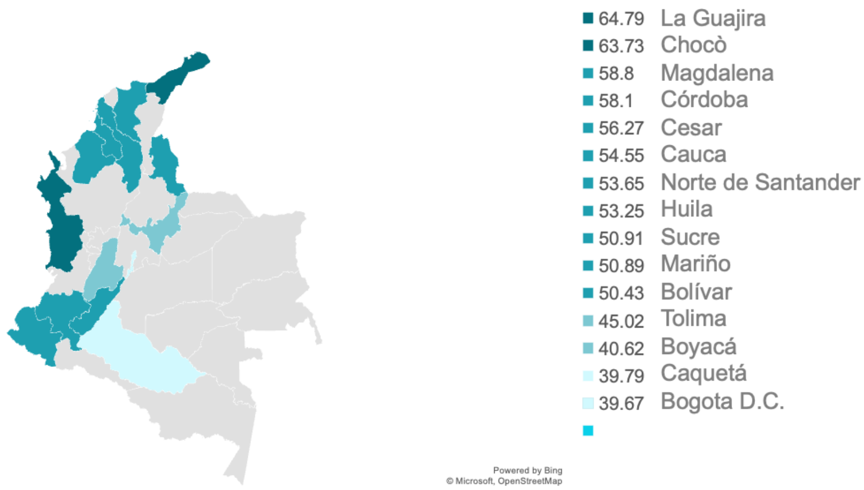
Perfect targeting: Customized scenarios

The **skill-based scenario** classifies the youth population according to their skills level – proxied by education level. The model classifies workers as low, medium, and high-skilled workers – approximated by their education level attainment (primary, secondary, and tertiary, respectively). In this scenario, only low- and medium-skilled unemployed young individuals are eligible.

The **spatial scenario** classifies the youth population according to the department where they live. In this scenario, only those unemployed youth living in the departments with the highest youth poverty rates are eligible. Focusing on certain locations may have a greater influence on poverty reduction.

9. See Section II Introduction, Introducing Employment Programs.
10. These restrictions to the usage of the budget are considered in Section 2.2 Assumptions of the Employment Program.
11. Robustness checks for program lasting 6 months and 2 years have been conducted. Similar results have been reached.

Table 2: Top 15 Colombian departments with the highest youth poverty rates



Source: Author's calculations, based on GEIH 2020

In the **gender scenario,** women receive a wage-subsidy equivalent to 500,000 COP per month, while men receive 360,000 COP (which is 40% of the minimum wage in 2020). The rationale behind this choice is to incentivize enterprises to hire more women as enterprises will have a smaller residual of the wage to pay. Through this scenario, the study will provide a positive analysis of how poverty would be reduced if women were the focused target of the employment program.

An empirical approach is used to simulate the fact that women will have a higher chance of being employed under this scenario. Based on the PAEF program,[12] 41.9% of the employed individuals through the program are women when firms are given a 500,000 COP subsidy (instead of 360,000 COP) to hire women. This percentage is used to target a corresponding number of women versus men in this scenario.

These three targeting scenarios are important from a policy standpoint because they will assist policymakers in understanding the many potential poverty reduction effects that the program could have based on the targets.

Random targeting

Lastly, there will be a **random targeting scenario.** In order to make the employment program the most realistic as possible, another targeting of beneficiaries is also used. Indeed, it is unlikely that firms can perfectly choose only to hire the poorest people, and it might be difficult for state agencies to ensure that only the poorest of the poor will be hired. Hence, in this scenario, beneficiaries are randomly selected within the extreme poor, poor, and vulnerable households' categories. Similar microsimulation steps are then applied. The random targeting is built for baseline and customized scenarios.

2.2 Assumptions of the employment program

The employment program has the following main assumptions that should be considered.

12. See "Decreto 639 de 2020" by the Colombian National Government.

2.2.1 Labour income

Workers exhibit several characteristics, such as their skill level, occupation, economic sector, and region of employment. These traits influence and affect their earnings. As a result, it is critical to account for these differences in the model in order to quantify the influence on poverty levels in a more realistic manner. The model's assumption relies on the fact that when a young person is employed thanks to the program, they will receive the average salary of young employed individuals with the same educational attainment living in the same department of Colombia. Table 4 shows the average wages by education level.[13]

Table 3: Average salaries by type of youth workers

Education level	Monthly Average Wage (COP)
Primary education	878,752
Secondary education	945,655
Tertiary education	1,277,744

Source: Author's calculations, based on GEIH 2020

2.2.2 Probability of accepting the job

The likelihood of people accepting and keeping the jobs offered is a factor in the effectiveness of the employment program. The program does not have perfect coverage since not all available jobs are filled or because people leave their jobs. The model incorporates this consideration to account for human behavior and prevents overestimating the impact of the program. Therefore, the reach of the program is assumed to be 75% of the overall target set by the program.[14] This indicates the program's budget is not being spend to its maximum potential in the microsimulation.

2.3 Measuring the impact of the employment program

The microsimulation compares the impact on income of in-work subsidies for youth against cash transfers targeted to households with youth. The impact of the employment program is also evaluated over two time periods - 1 year and 5 years, respectively to compare the two interventions. This provides both short and long-term perspectives.

2.3.1 Immediate impact – 12 months after the beginning of the program

The impact of the employment program after 1 year assumes that the firms hire 75% of the overall targeted number of people when the program lasts 12 months. This assumption is based on the argument that low-wage subsidies have positive short-term effects on the targeted population by increasing demand for employment and temporarily reducing their labour cost.[15]

13. See Appendix for the full table of the average wages by skill and departments.
14. Brown et al. (2007) as stated in the literature review section.
15. The theory suggests that low-wage subsidies should show positive short-term employment effects for the targeted worker population as they temporarily reduce their cost of labor, thus creating incentives for firms to employ more (Brown et al., 2007).

The microsimulation has **two steps** to determine the impact of in-work subsidies on the income of targeted households. First, the methodology explained above allows one to calculate the assumed beneficiary wage, given their educational level and department of residence. Second, for each scenario, the number of people that can benefit from the program is calculated, i.e., the number of newly employed youth, given the wage subsidy and the fixed total budget of the program. This allows to determine their aggregated income and, in turn, plot the new household income distribution of the overall population in Colombia. The comparison of the households' income distribution before and after the different scenarios of in-work subsidies program will allow to assess the impact of the program. Additionally, the comparison of the different poverty and inequality levels by scenario against those found with the cash transfers program will allow seeing whether an employment program is more or less effective than cash transfers in mitigating poverty and decreasing inequality in Colombia in the short-term.

2.3.2 Long-term impact – 5 years after the beginning of the program

The long-term impact is extremely helpful for policy implications since it helps to comprehend how a policy affects people's well-being and behavior. New assumptions need to be included in the model in order to measure the long-term impact. These assumptions are critical for modelling a realistic environment and inferring significant insights for policy application. It is critical to account for the many behavioral responses that households will have to both programs.[16] Moreover, these assumptions allow forecasting the potential impact on poverty and inequality that the employment program could have.

The model assumes that there is a probability of 85% of maintaining the job from year to year. This assumption is based on the finding that the probability of retaining a job is usually higher than the likelihood of being hired through a salary subsidy.[17] Therefore, each year, only 85% of the beneficiaries employed will keep the job next year. The others will not have the job anymore – illustrating being fired or quitting the job. The model also assumes that while working, workers gain experience that positively affects wages. This assumption is based on the fact that over time people do earn higher wages which is among others associated with experience.[18]

The model calculates a Mincer Regression to measure the average impact of one more year of labour experience on income for Colombian workers. The regression is as follows:

$$\ln(Wage_i) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\ exp_i + \boldsymbol{\beta_2}\ exp^2{}_i + \boldsymbol{\beta_3}\ edu_i + \boldsymbol{\beta_4}\ formality_i + \boldsymbol{\beta_5}\ gender_i + \boldsymbol{\delta_i} + \boldsymbol{\varepsilon_i}$$

In this model indicates fixed effects for departments, industry, and occupation. The regression, therefore, calculates the average return to one additional year of experience controlling for these factors. Therefore, each year that beneficiaries remain employed will have an increase in their salary. The salary for individual i in year t+1 is equal to:

$$Wage_{it+1} = Wage_{it} + Wage_{it}\ (\beta_1 * \exp_i + \beta_2 * exp_i^2)$$

---

16. Changes in firm behavior in response to government-implemented intervention are also possible. Due to a lack of data, this is not included in this model. However, the paper formulates a viable method to consider them for future revisions of the model in the appendix.
17. Armand et al., (2020), Lombardi et al., (2018) and Brown et al. (2007). See section Probability of accepting the job.
18. See Mora and Muro (2018) "Returns to Human Capital in Colombia" for returns to experience in Colombia.

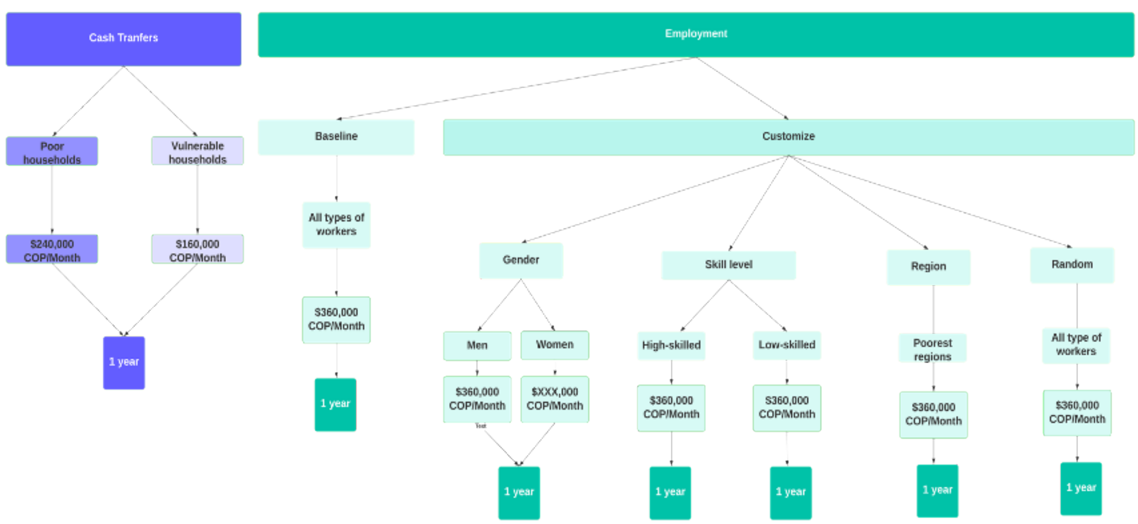
This increment will occur during the 5 years for the proportion of people who remain employed. Even when the program ends after 1 year, there will be people who retain their jobs. For these people, the model considers an increase in their salary to represent their potential promotions and/or increments due to increased labour experience.

The employment program's impact is separated from all other factors to simplify the model and measurements. As a result, the other variables, such as household composition, are assumed ceteris paribus (e.g., considered constant).

2.4 Scenario's flowchart and beneficiaries' income distribution

The model developed in prior sections of the methodology will enable the assessment of the immediate and long-term impacts of cash transfers and employment programs for different scenarios. To summarize, the flowchart in Figure 1 illustrates in detail the different scenarios included in the microsimulation.

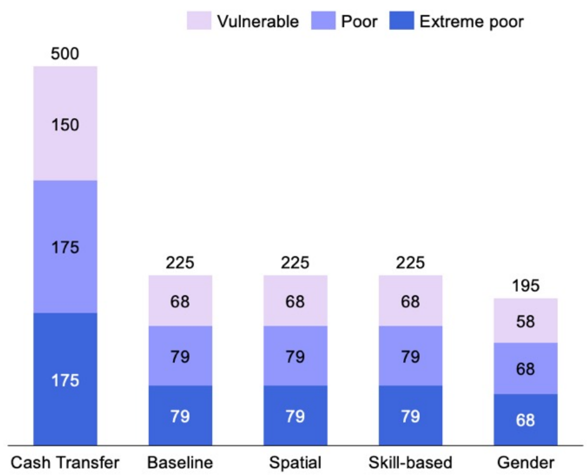
Figure 1: Microsimulation scenarios flow chart



Source: Author's illustration

Figure 2 shows the number of beneficiaries in each category. Both programs have the same exact budget, as stated in the target population section. However, the cash transfer provides a smaller benefit per person than the employment program, allowing the program to benefit more households. Furthermore, the cash transfer program does not consider the employment status of youth as a qualifying condition. While in the employment programs, only low-income households with unemployed youth are eligible. Finally, in the case of the gender-based employment program, the number of beneficiaries is smaller when compared to other employment programs. In this scenario, as explained in the customize section of employment programs, the size of the subsidy is larger for firms that hire young unemployed women, further reducing the number of program beneficiaries and resulting in the program having the lowest number of recipients when compared to any of the alternative programs.

Figure 2: Targeted populations under each policy for all poverty categories19



Source: Author's calculations, based on GEIH 2020

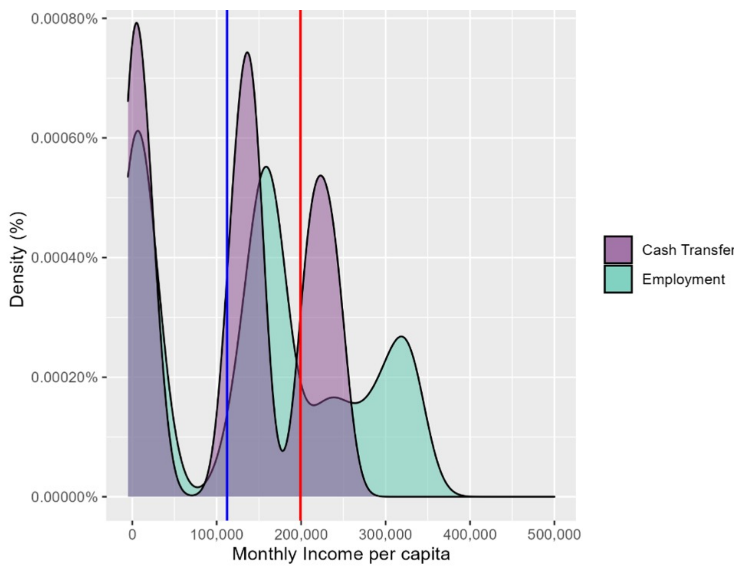
The program's beneficiaries will slightly differ, as well as their income distributions, between cash transfers, employment program and its customized scenarios, because of the differing selecting criteria. The next section illustrates the income distribution of the beneficiaries prior to the implementation of the programs based on the type of scenario and its conditions.

2.4.1 Baseline scenario (perfect targeting)

Figure 3 compares the income distribution before the employment and cash transfer programs of the selected beneficiaries. This income distribution considers total household income, including government transfers and imputed rent.[20] The targeted population is the low-income population.[21] The beneficiaries varied somewhat between programs. In comparison to cash transfer recipients, the distribution of beneficiaries in the employment program has a larger density of households in higher income levels within the targeted population. This can be explained because participation is conditioned in the employment program on being unemployed, while the cash transfers are distributed to all youth without regard to their work status. Of the young population in extremely poor and poor households in 2020, 44% and 38% are categorized as inactive. Moreover, from the unemployed population, individuals in poor and vulnerable households have, on average, a higher income (see Appendix II). It is important to consider the cash transfers program benefits 500,000 households with young people while the employment program benefits 225,000 households in all categories – extremely poor, poor, and vulnerable. Despite the benefit under the employment programs being larger than the cash transfer, the cash transfer program is targeting more than twice the targeting for the employment program.

19. As outlined in the methodology, the final beneficiaries of the employment program are 75% of the total aimed target of the government.
20. The beneficiaries of the program are chosen according to the total level of income as we need to target households considered poor in Colombia even after the government transfers.
21. See section "Target population" for reference.

Figure 3: Beneficiaries' income distribution in the general scenario[22]

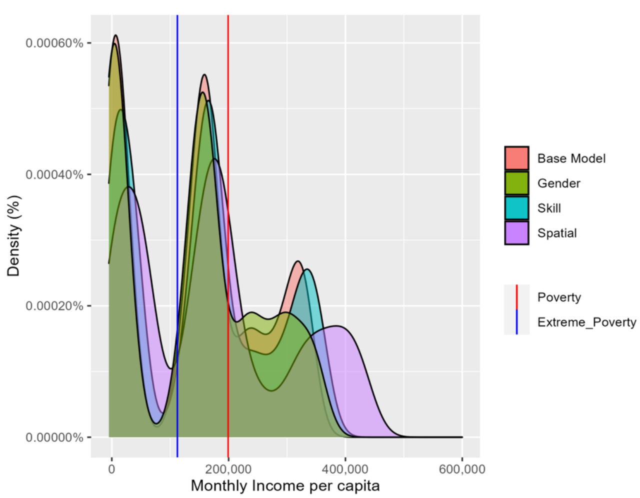


Source: Author's calculations, based on GEIH 2020

2.4.2 Customized scenarios (perfect targeting)

The employment program, by customized scenario, selects slightly different beneficiaries[23]. Figure 4 shows the beneficiaries' income distribution before the program is implemented. Compared to the baseline scenario, the skills and region scenarios select more people from higher income levels among the targeted low-income population. This suggests the baseline scenario is better at targeting lower-income households than the customized scenarios. The reason behind this is the perfect targeting assumptions (see Section 2.1.4).

Figure 4: Beneficiaries' income distribution in customized scenarios – perfect targeting



Source: Author's calculations, based on GEIH 2020

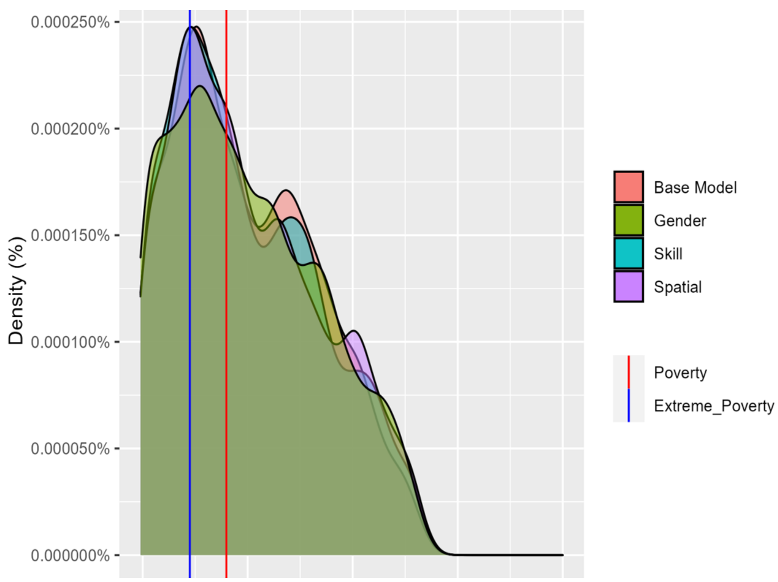
22. The poverty lines shown here are the minimum poverty lines. Colombia has different poverty lines depending on the cost of living in each department and its central and rural areas. They can, therefore, only be used as a visual aid in this context and do not accurately represent the poverty line for each household. This will be the case for all graphs displaying poverty lines.

23. The cash transfer simulation does not change as the eligibility criteria remains the same.

2.4.3 Random target (baseline and customized scenarios)

When randomizing the beneficiaries within each group – instead of using perfect targeting – it is ambiguous which scenario is able to select more beneficiaries in poor households. However, what is clear is that it chooses people that might be less poor than the perfect targeting scenarios. Furthermore, participants in the random scheme are more evenly dispersed in terms of income. Because it is not perfectly targeted, there is a greater chance that more persons from each category will be chosen. This is an important exercise since it more closely resembles reality. It is difficult for a government to enact a program that is properly targeted. However, in microsimulation, this is the standard procedure (see **Targeting**). As a result, this is an enhancement made by the model to mimic reality better.

Figure 5: Beneficiaries' income distribution in customized scenarios – random targeting



Source: Author's calculations, based on GEIH 2020

Overall, even if the income distributions vary slightly depending on the types of programs and the different scenarios, the beneficiaries all come from the same pool of low-income population, making them comparable.

2.5 Variable Importance (Random Forest Analysis)

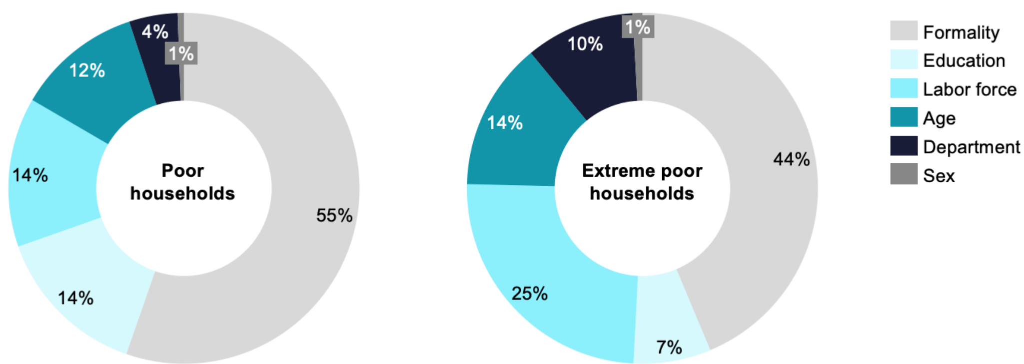
The variable importance feature of the random forest algorithm[24] was used for determining which variables are the most important factors for a person to be classified as poor or extremely poor in Colombia. The variables that are analyzed include the department, the maximum education level for a person, whether they are in the labour force or not, formality of the work, gender and age. This evaluation will also be helpful going forward to customize the model based on certain eligibility criteria. It informs the validity of differentiating the baseline model based on factors such as department, skill, and gender.

The variable importance feature of a random forest is used to evaluate which of the explanatory variables are important for the dependent variable, the dependent variable here being the classification of a

24. See Breiman, L. (1996) "Bagging Predictors".

person as poor and extremely poor. A random forest is a machine learning algorithm for regression or classification models that utilizes multiple decision trees to produce a more accurate result. A decision tree (see Appendix III) is an algorithm that determines a model that can predict the dependent variable based on learning simple decision rules from the training data. A decision tree starts from a node or root which can have any one of the variables and implements a binary search at each node by splitting the variable at a random value. This, however, may lead to errors in the simple decision tree model. A random forest takes multiple decision trees and averages over them to produce a more robust prediction. The variable importance feature characterizes the explanatory variables ordinally to give us the most important variable.

Figure 6: Variable importance



Source: Author's calculations, based on GEIH 2020

In the analysis, the variable that emerged as the most important in determining whether a person is poor or extremely poor is Formality. This means that the formality of the work that a person is engaged in is the most important variable when determining whether they are poor or not. The other variables that are slightly more important appeared to be Labor Force and Education for poor and Labor Force and Age for extremely poor. Gender did not feature as an important variable in both.

IV. RESULTS: CASH TRANSFERS AND EMPLOYMENT PROGRAMS

This section provides the microsimulation model's results, highlighting the nuances of each scenario. The results are based on the following indicators.

Table 4: Indicators measured [25]

Topic	Indicator	Description
Distribution	Income per capita distribution	The density function of the households' income distribution.
Poverty	Extreme poverty – total population and youth	National extreme poverty line is in current COP as calculated by DANE and included in the GEIH.
	Poverty – total population and youth	National extreme poverty line is in current COP as calculated by DANE and included in the GEIH.
Inequality	Gini coefficient	The Gini coefficient is a synthetic indicator of the level of inequality for a given variable and population. It varies between 0 (perfect equality) and 1 (extreme inequality).
Wage	Wage by quartile – immediate and long term	Wage shift within the first two quartiles of the income distribution.

Source: Author's illustration

Whilst the beneficiaries are targeted based on their total household income; the results are measured in comparison to the per capita income of the spending unit, excluding government transfers but including imputed rent. This is done to isolate the impact of the programs from any potential government transfer payments, comparably to Diaz et al. (2020).[26]

3. Immediate Impact (12 months after the beginning of the program)

The immediate impact results report the effect of the interventions one year after they were implemented. Therefore, the results are reported right after the end of the respective program. Households received cash transfers for a year, while those who were hired received their wage for the entire year. For comparison purposes, the results are shown in different sub-sections: A) cash transfers vs perfect targeted employment programs – including baseline, spatial and skill-based scenarios; B) perfect vs random targeting of employment programs applied to baseline, spatial and skill-based scenarios; and C) gender scenario.

3.1 Cash transfers vs employment program

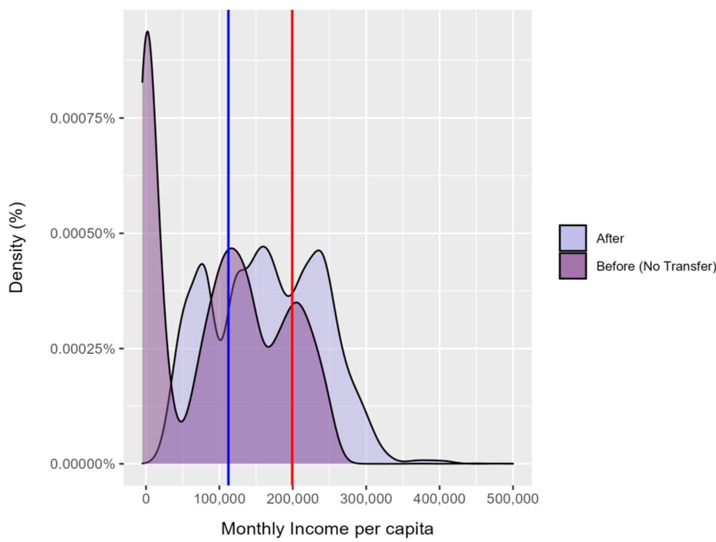
This sub-section will cover the results of both programs, specifically their income distributions, poverty, and inequality levels, with a deep dive into the youth population.

25. National Poverty lines are set by DANE. Because they are in PPP, the level of income required to be considered as poor differs across departments as it is respectively cheaper or more expensive to have the same purchasing power depending on the departments.
26. It is strongly advised to read Diaz et al (2020) for the reasoning behind this claim.

3.1.1 Income distribution

The comparison of the income distribution of recipients before and after the cash transfers program gives a first high-level impact analysis. After one year of the cash transfers program, the income distribution shifts right, meaning that recipients have a higher per capita income (Figure 7). After a one-year cash transfer, the per capita income distribution of the spending unit among recipients is smoother, with less concentration at the lowest income levels and showing an extended right tail above poverty levels. As expected, the number of households with 0 income equal to 0 prior to the cash transfer is now 0% at the end of the cash transfer program. However, even with cash transfers, there are still households below the poverty and extreme poverty thresholds[27].

Figure 7: Income shift after 1-year cash transfers program

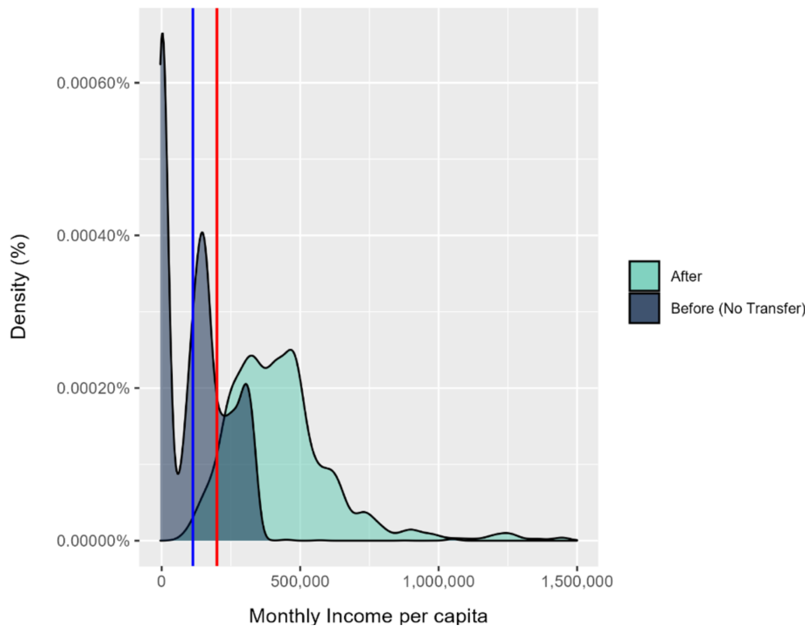


Source: Author's calculations, based on GEIH 2020

Similarly, after one year of the employment program, the income distribution shifts right (Figure 8). However, the shift is more significant because the increase in their incomes is greater than with the cash transfers, as the wage they receive is larger than the amount of the cash transfer. Among the beneficiaries of the program, more individuals are pushed above the poverty line, and nearly none remain below the extreme poverty line. As a result, even when there are fewer beneficiaries in the employment program, those targeted experience a significant improvement in their income, pushing them over the poverty line. Therefore, the distribution among beneficiaries after the program is more evenly distributed, with most of the **beneficiaries** having monthly per capita incomes between 200,000– 500,000 COP. Because there were households with slightly higher incomes selected into the program, and the wage they receive is aligned to the educational level of the young and unemployed individual, some households even reach an income of 1,5 million COP monthly. This implies that the impact at the household level for the beneficiaries is higher in the employment program. However, when measuring poverty at a national level, the results are more ambiguous.

27. As noted in Footnote 30, the poverty lines displayed here are the minimum poverty lines and should therefore only be taken as a visual aid as the poverty line varies by department and central/rural area.

Figure 8: Income shift after 1-year employment program



Source: Author's calculations, based on GEIH 2020

3.1.2 Poverty levels

Figure 9 and Figure 10 depict the different poverty levels and their reduction based on several short-term policy scenarios. The national poverty rate is 46.12% in the absence of any policy and transfers. It is lowered by 0.57pp with a cash transfer program, compared to 0.86pp under a baseline employment program. Poverty reduction was lower in the three customized programs. Those results suggest that the employment program has the greatest impact on graduating low-income households from poverty.

Figure 9: Poverty levels by scenario

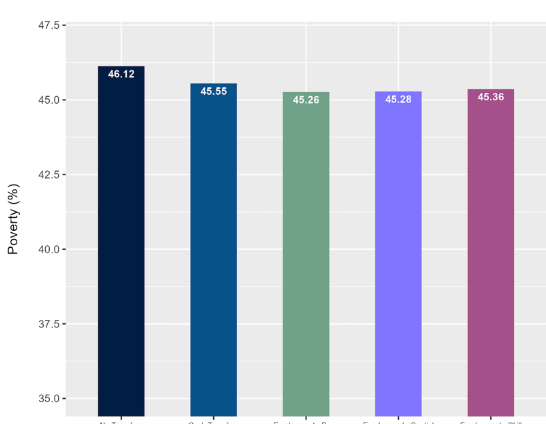
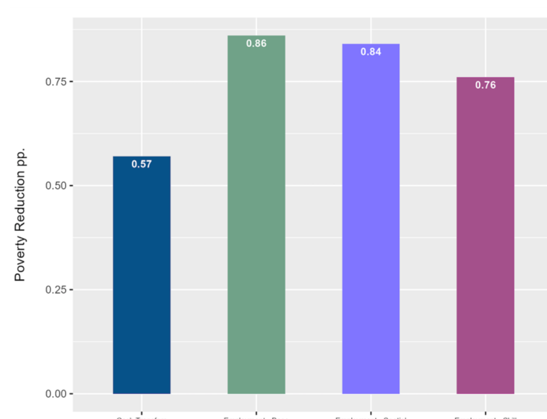


Figure 10: Poverty reduction by scenario



Source: Author's calculations, based on GEIH 2020

Figure 11 and Figure 12 illustrate extreme poverty levels and their reduction based on immediate impact scenarios. The national extreme poverty percentage is 19.82% in the absence of any intervention. Under a cash transfer program, it is reduced by 0.95pp whilst employment program scenarios show a smaller decrease in extreme poverty. In the baseline and spatial scenarios, it is reduced by 0.83pp the reduction in the skill scenario is 0.82pp.

Figure 11: Extreme poverty levels by scenario

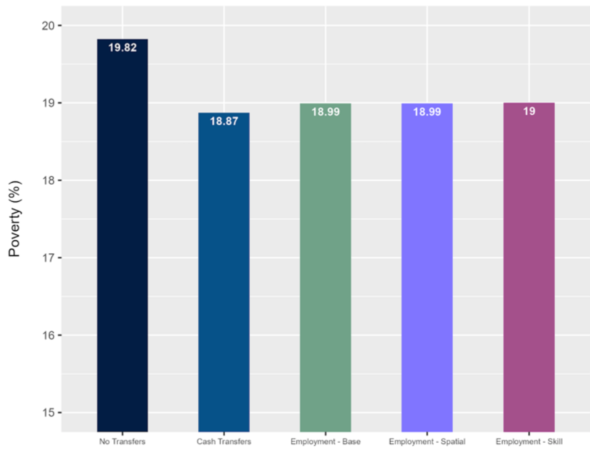
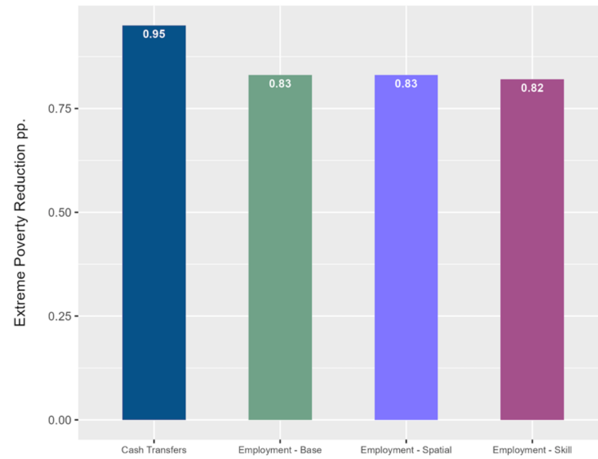


Figure 12: Extreme poverty reduction by scenario



Source: Author's calculations, based on GEIH 2020

The results shown above can be explained due to the limitations the employment program has in targeting all the youth (see Section 2.4). The cash transfer program is able to capture the highest number of low-income households when compared to the capturing bandwidth ability of all the employment programs designed. The cash transfers program has 175,000 beneficiaries among households with youth in extreme poverty (Figure 2). On the other hand, the employment program only benefits 78,750 extremely poor households (Figure 2). Cash transfers target the poorest of the poor. The limited income increase is sufficient to keep them over the extreme poverty line but not substantial enough to move them above the poverty line. As a result, cash transfers are more effective in alleviating extreme poverty than in alleviating poverty. Contrary to cash transfers, the employment program is more effective in reducing total national poverty. Among the employment scenarios, the most effective is the baseline. This can be explained by the fact that the baseline scenario is being able to choose poorer households as beneficiaries (see Section 2.4.2).

3.1.3 Youth poverty

Given the focus of this study on mitigation interventions aimed at youth, it is critical to examine poverty in this subgroup. Figure 13 and Figure 14 show youth poverty in Colombia under various policy scenarios in the short-term, as well as its relative decrease. The youth poverty rate is calculated as:

$$Youth\ Poverty\ Rate = \frac{Number\ of\ people\ in\ Poor\ Households\ with\ one\ young\ person}{Number\ of people\ in\ Households\ with\ one\ young\ person}$$

Without any policy, the youth poverty rate would be 49.05%. In comparison to this scenario, a cash transfer policy program reduces youth poverty by 1.11pp. The employment programs are more effective in decreasing youth poverty, with a baseline scenario decrease of 1.67pp, 1.63pp in the spatial program and 1.47pp in the skills program.

Figure 13: Youth poverty levels by scenario

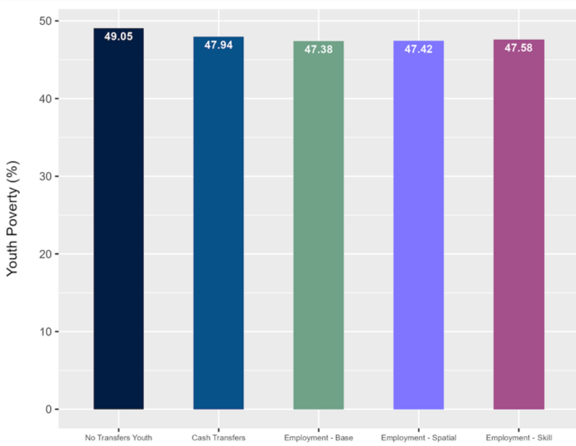
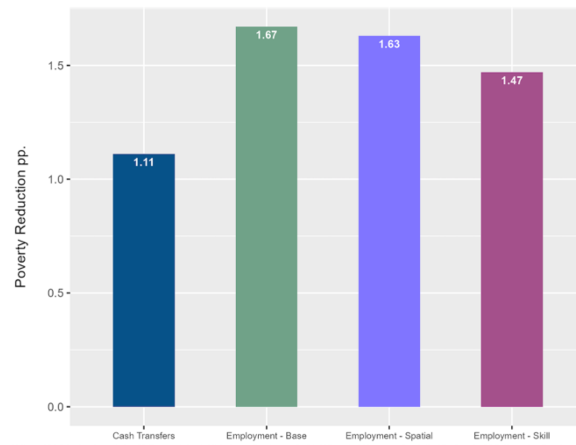


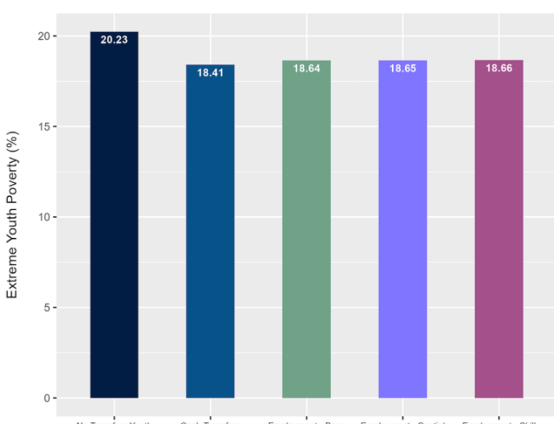
Figure14: Youth poverty reduction by scenario



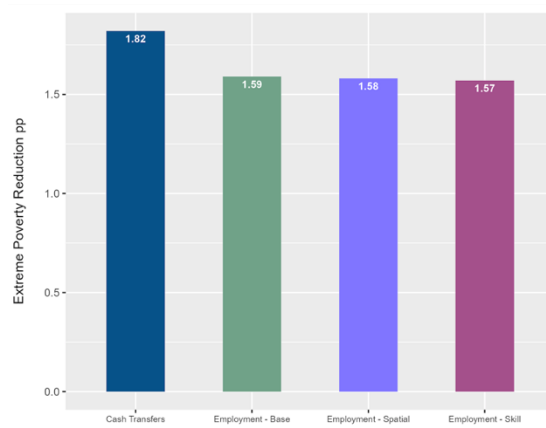
Source: Author's calculations, based on GEIH 2020

Figure 15 and Figure 16 outline extreme poverty among youth. In the absence of any policy, the youth extreme poverty rate is 20.23%. The youth extreme poverty rate falls by 1.82pp via a cash transfer policy intervention. Consistent with the overall poverty indicators, the reduction under employment programs is smaller than the reduction under cash transfers. It is 1.59pp in the baseline program and very similar in the spatial and skills (1.58pp and 1.57pp, respectively).

Figure 15: Youth extreme poverty level Figure



16: Youth extreme poverty reduction



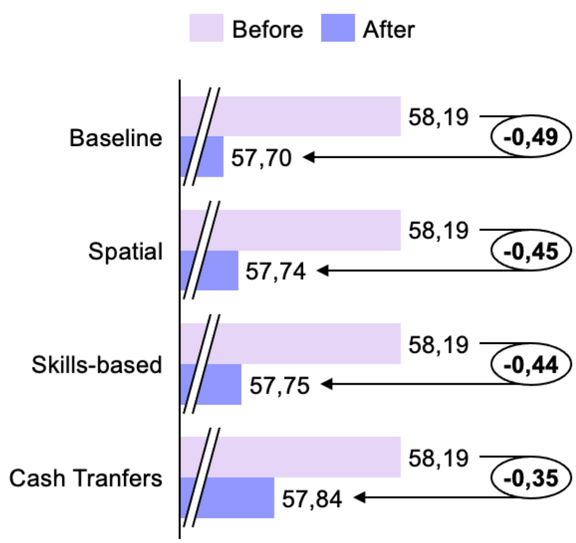
Source: Author's calculations, based on GEIH 2020

The impact of each program follows the same trend as the overall poverty analysis. The novelty of these graphs is the fact that youth poverty and extreme poverty are reduced significantly in most of the programs. This suggests the policy is accomplishing its objective of improving the poverty levels among youth. The baseline employment program is the one that shows the best results overall, as the reduction of both poverty and extreme poverty are significant given the large income increase that beneficiaries experience. The cash transfer is effective; however, its positive effects seem to be only limited to extreme poverty mitigation due to the smaller size of the benefit and its large targeting bandwidth. Moreover, the customized scenarios appear to be less effective. This has been evidenced earlier by variable importance for poor and extremely poor, where the most significant variable that appeared was the formality of work. It may also be the case that targeting a smaller group within a subgroup reduces the impact when measured at an aggregate level.

3.1.4 Inequality

Understanding the programs' potential impact on inequality is important to have a more holistic view of the policies. Figure 17 shows the Gini coefficients before and after each program. In terms of inequality, the Gini coefficient[28] without transfer payments and before any policy intervention is 58.19 at the national level. The employment baseline scenario has the greatest impact on reducing inequality, as it falls by 0.49 Gini points. The cash transfers reduced the coefficient by only 0.35 Gini points.

Figure 17: Gini coefficient national level



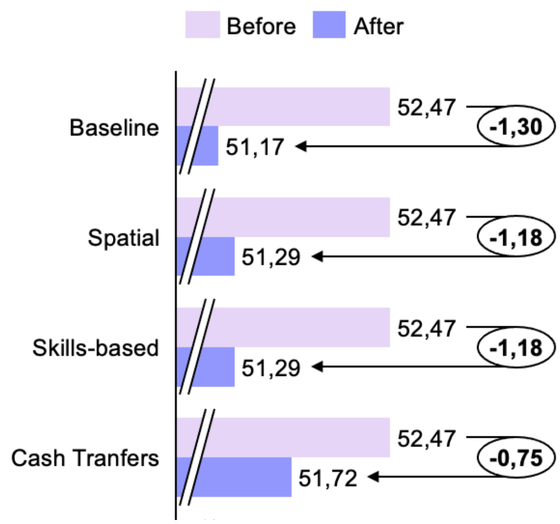
Source: Author's calculations, based on GEIH 2020

These findings show that there is the greatest decrease in inequality measures when the employment program does not specifically target a subset of the low-income youth population. Furthermore, because the benefit of the employment program is bigger than that of the cash transfer program, it narrows the gap between treated households and high-income households more. This larger increase in income seemingly takes precedence over the larger number of beneficiaries that the cash transfer program reaches.

The Gini coefficients for the youth population display a similar pattern. The largest impact is attributed to the baseline employment program. Nevertheless, all of the alternative employment programs perform better than the cash transfer program at reducing youth inequality levels.

28. All Gini coefficients are scaled up to 100 to facilitate analysis.

Figure 18: Gini coefficient in youth population



Source: Author's calculations, based on GEIH 2020

The magnitudes of reduction in inequality in youth are bigger than at the national level, similar to the poverty metrics. The fact that inequality decreased among youth by more than 1pp in all the employment programs allows to conclude targeting youth in Colombia could generate a positive impact on poverty (see previous sections) and inequality as poverty is more prevalent than at the overall national level. These findings are noteworthy for arguing why a youth-focused program would be beneficial.

3.2 Employment programs: Randomized vs Perfect targeting[29]

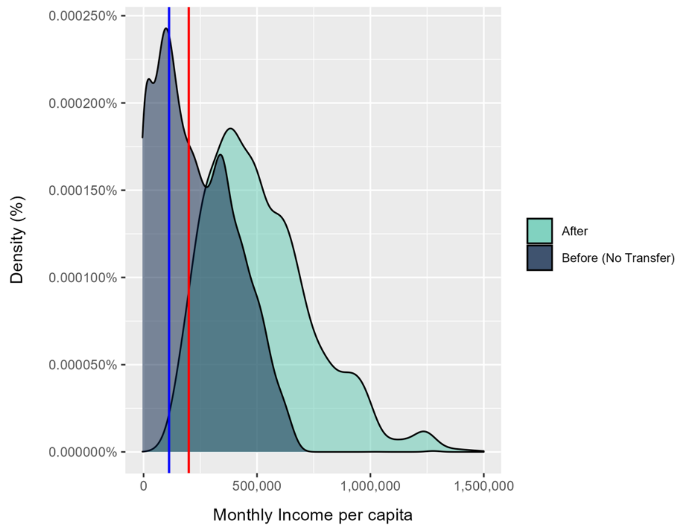
The results of the randomized employment program will not be compared to the performance of the cash transfers since the programs differ significantly, especially in terms of the recipients. It would be incorrect to compare the impact of two programs with such disparities in their concepts and beneficiaries. However, this algorithm picks recipients in a more realistic manner because it might be complicated for firms to have the capacity to actually hire the poorest of the poor. In terms of recruiting, it is hard to access income level data. Therefore, it is critical to incorporate the analysis. Each employment program with perfect targeting will be compared to random scenarios in this section.

3.2.1 Income distribution

After one year, the income distribution shifts right in the random scenario for the employment program (Figure 19). Similar to the ideal targeted situation, there are households that experience considerable changes in their income level as a result of the program. Where the random targeting differs from perfect targeting is because households with somewhat higher incomes were chosen in the random targeting scenario. Therefore, the final distribution is slightly more skewed to the right than in the baseline perfect targeting scenario.

29. This section will not go through the Gini Coefficients.

Figure 19: Income shift after 1-year employment program random scenario



Source: Author's calculations, based on GEIH 2020

3.2.2 Poverty

The reduction in national poverty and extreme poverty compared to the perfect targeting scenarios is lower (Figure 20 and Figure 21). This makes sense because, as stated above, by targeting in a random way, the model chooses, on average fewer households with the lowest income levels than the perfect targeting. An interesting fact is that when the program chooses randomly among the employment programs, the most effective in reducing poverty and extreme poverty is the spatial scenario. In contrast, in the perfect targeting, the baseline scenario was most effective. This suggests that when beneficiaries cannot be perfectly targeted, it is better to introduce certain conditions for the beneficiary pool. In this case, conditioning by the region of residence is most effective. This is relevant because the random model might approximate the implementation reality more closely. In this case, implementing the employment program in the poorest regions could improve its effectiveness.

Figure 20: Poverty reduction

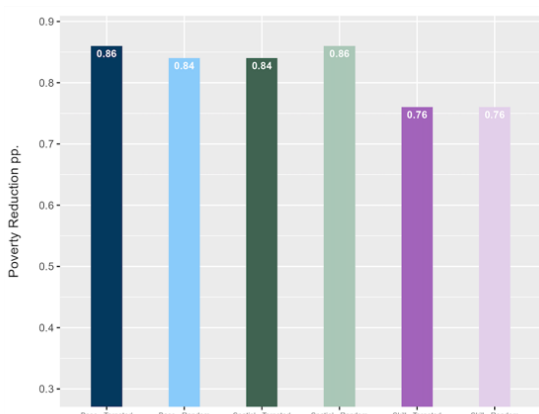
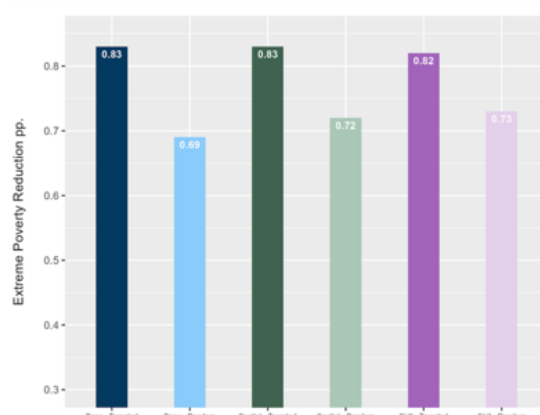


Figure 21: Extreme poverty reduction



Source: Author's calculations, based on GEIH 2020

3.2.3 Youth poverty

The results for extreme youth poverty follow the same patterns as overall poverty (Figure 23). It is worth noting that in the case of youth poverty, the effectiveness of the spatial scenario increases. Here, the random spatial scenario decreases poverty almost to the same extent as the targeted spatial scenario (Figure 22). The random skill program lowers poverty at the same rate as the targeted skill program. When just the impact on youth is considered, the perfect targeting baseline is most successful in decreasing poverty and extreme poverty, but for random targeting, the spatial program remains as effective as the targeted.

Figure 22: Youth poverty reduction

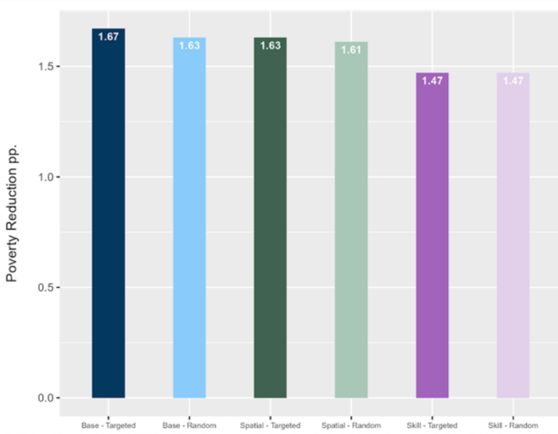
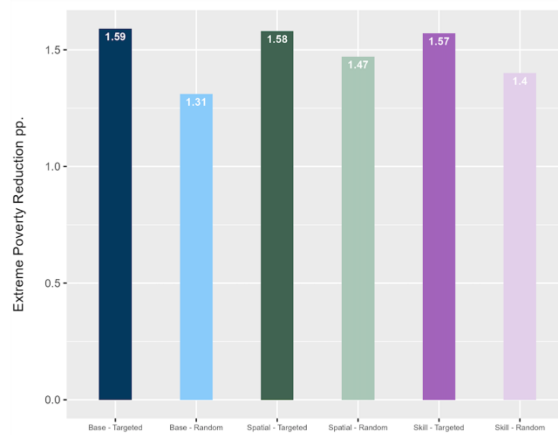


Figure 23: Youth extreme poverty reduction



Source: Author's calculations, based on GEIH 2020

3.3 Gender scenario

The gender scenario of the employment program is assessed independently and directly compared to the baseline scenario. The distinction is made as it is a unique scenario in terms of how it is built and its outcomes. In terms of construction, enterprises receive a larger subsidy if they employ young women (140,000 COP more). As a result, among the employment programs, the gender scenario is the only one with fewer and different beneficiaries. The overall number of households targeted diminishes from 225,000 to 195,000 (Figure 24 and Figure 25). Furthermore, within each sub-group (extremely poor, poor, and vulnerable), targeting is limited to roughly 42% of youth women, with the remainder being young males.

The purpose of this scenario is to simulate the PAEF program[30], which employs 42 percent of women by providing a 50% subsidy rather than a 40% subsidy. However, the gender scenario in this study differs from PAEF in that it is targeted toward young females. It is essential to compare this scenario to the baseline scenario in order to comprehend its effects on income distribution, poverty, and inequality. Figure 24 and Figure 25 show the total number of households targeted in the baseline and gender scenarios, classified according to whether households include young women or not and whether they are selected for the program or not. The instance when young women might not be directly picked – meaning a young man is chosen – is relevant because there might be a spill-over effect. The spill-over accounts for when young

30. See "Decreto 639 de 2020" by the Colombian Government.

women are not direct beneficiaries but are still part of a selected household. If it is the case, it is assumed that they are still affected since their households increase their overall income, and they are potentially out of poverty. Therefore, the respective shares shown among the households targeted are: 1) with no young females, 2) with young female spillover, and 3) young females who are directly targeted through the program.

This is interesting because, in the baseline scenario – in which beneficiaries are chosen using perfect targeting – the model selects 56% of young women (~125,000) to obtain a job, compared to the 42 % (~82,000) in the gender scenario. Also, in the gender scenario, there are more households who receive the benefit that do not have at least one young woman (36% vs 27%). On the other hand, the spill-over group is relatively similar (18% or ~40,000 in baseline and 22% or ~43,000 in gender).

Figure 24: Total households targeted: Baseline

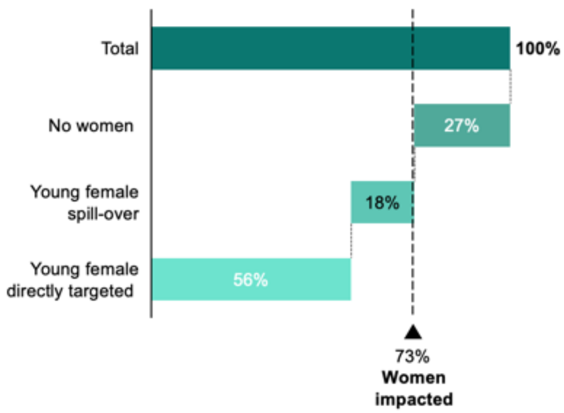
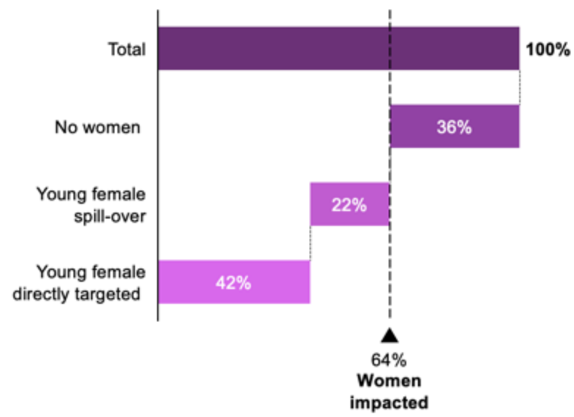


Figure 25: Total households targeted: Gender



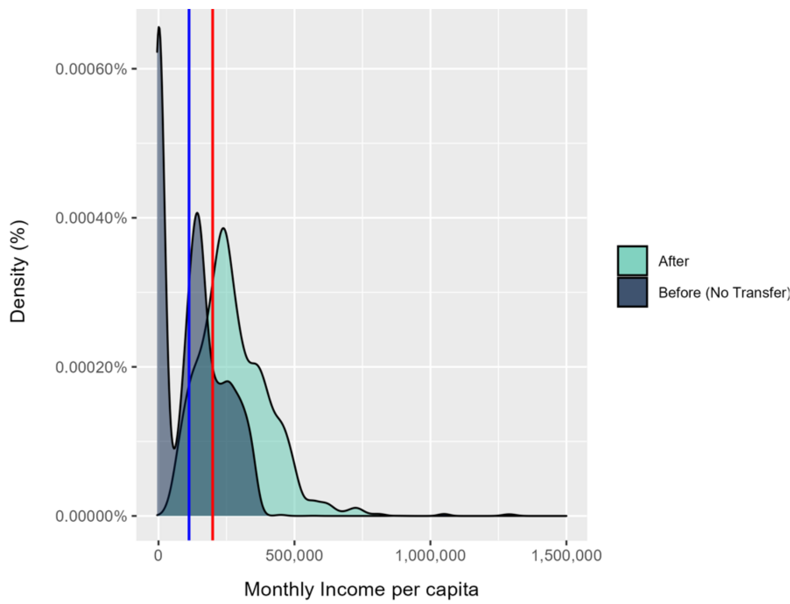
Source: Author's calculations, based on GEIH 2020

These findings provide important insights. Because of the model's mechanics in the baseline perfect targeting scenario, a large number of women are picked for the program (56%) because they comply with the selection criteria. However, in the gender scenario trying to replicate the PAEF program, just 42% of recipients are women. As a result, the baseline model may be excessively optimistic about the ability of these interventions to entice women to work.

3.3.1 Income distribution

In terms of proportions, the income distribution of the gender scenario before the employment program is implemented is comparable to previous employment scenarios, with the caveat that fewer households are selected (Figure 25). The post-program distribution resembles a normal distribution, with the median household living above the poverty line. Some households attain income levels close to 1.5 million COP, although they are much fewer than in the baseline employment scenario.

Figure 26: Income shift after 1-year employment program gender scenario



Source: Author's calculations, based on GEIH 2020

3.3.2 Poverty

Figure 27 exhibits the decreases in poverty and extreme poverty at the national level, as well as the reductions in poverty among female youth in both the baseline and gender scenarios. The poverty reduction among female youth is interesting to illustrate as this program is primarily aimed at them and provides insight into how effective interventions are. The female youth poverty rate is calculated as follows:

$$Female\ Youth\ PR = \frac{Number\ of\ people\ in\ Poor\ Households\ with\ one\ young\ female}{Number\ of people\ in\ Households\ with\ one\ young\ female}$$

In every situation, the poverty reduction in the gender scenario is significantly lower than the baseline. These results are expected since the gender program targets fewer people; hence the total impact of the program should be lower. Furthermore, the gender scenario decreases female youth poverty less than the baseline scenario.

Figure 27: Poverty levels and reductions (Baseline vs Gender)

Source: Author's calculations, based on GEIH 2020

As previously demonstrated, the baseline scenario results in a greater proportion of females being targeted (directly and indirectly through spillovers). As a result, it is understandable why the reduction in poverty is greater in the baseline condition. Again, in the gender scenario, the analysis is restricting the number of women targeted to 42% and paying extra for each of them, limiting the program's reach.

3.3.3 Inequality

In terms of inequality, the gender scenario is far less effective than the baseline scenario at lowering the Gini coefficient (and then all other employment scenarios). The explanation is based on the same rationale as the previous indicators. With fewer low-income households increasing their total income, inequality is reduced less at the national level and even among the youth. However, this scenario may provide more realistic inequality outcomes since it is similar to the current job program PAE.

Figure 28: Gini coefficient national level

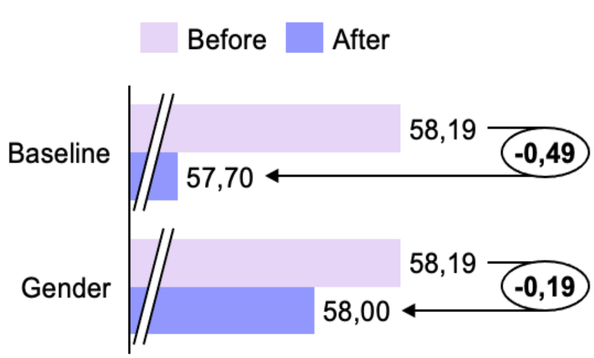
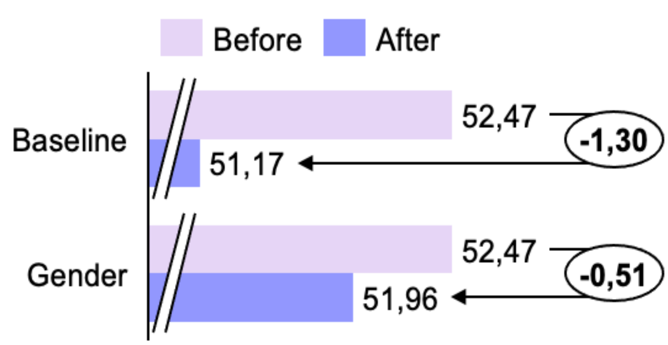


Figure 29: Gini coefficient youth



Source: Author's calculations, based on GEIH 2020

The gender scenario is interesting because it sheds light on the fact that the baseline scenario is benefiting a higher percentage of women than a current actual program (PAEF) not targeted to youth. This scenario shows that the reason why fewer women benefit from the employment program than men might not come from the demand side - firms hiring fewer women - but from the supply side – fewer women searching for jobs. Indeed, the analysis demonstrates that there are many young, unemployed, and highly educated women that could be eligible for an employment program but that the program fails to hire as many women as men even when the subsidy given to firms is higher for women. It must therefore be due to supply-side restrictions.

Overall, the immediate impact analysis of both programs suggests that, while the cash transfers program is more effective in decreasing extreme poverty, the employment program provides more significant advantages overall. This outcome is significant because what the employment program lacks in order to be entirely effective is a focus on the poorest of the poor. A long-term analysis of the impact of both programs will allow assessing whether the effect of both programs is persistent in time and, in turn, what program could be more suitable for a sustainable economic recovery in Colombia.

4. Long-term impact (5 years after)

The long-term impact results present the effect of the two interventions five years after they were implemented. The model performs a cut in time 5 years after the program's implementation, ceteris paribus, to understand the long-term impact of a cash transfer vs an employment program on household income, poverty, and inequality. This implies that it does not consider other government programs, spillover effects from the employment program, or the fact that employees who are fired or resign can find another job. The model separates everything such that just the impact of these two programs is measured.

The duration of the programs in this section is also one year. Households received cash transfers for one year, and the firms received the wage subsidies for one year. However, the youth who remain employed after the first year keep getting their wage. There is a proportion of people who each year lose or leave their job.[31] The long-term impact of the employment program also considers the fact that while working, workers gain experience that can positively affect wages.

Therefore, the results presented in this section will first look at the impact of experience on wage to then see how that influences extreme poverty and poverty in the long-term as well as inequality. An analysis of the shift in income within the first two quartiles of the households' income distribution is also presented to get a more granular understanding of the impact of both programs 5 years after they were implemented. The long-term results are essential as they provide very important insights for sustainable policymaking in the context of COVID-19 recovery. They suggest that, overall, an employment program is preferable to cash transfers.

4.1 Considering gains of experience

To model the potential increase in wages of the people who remain in the job, the return to experience is calculated through the Mincer regression – as illustrated in the Table 5. This table shows the effects of different variables on wages, namely, experience, experience squared, years of schooling, being female and being employed in the formal sector.

31. As explained in the methodology section of long-term impact

Table 5: Experimental Mincer regression results of experience on wage

	(1) Correlation	(2) Base Model	(3) Full Model
Experience	0.0272***	0.0190***	0.0171***
	(0.00230)	(0.00187)	(0.00168)
Experience Squ.	-0.000622***	-0.000163***	-0.000195***
	(0.0000458)	(0.0000385)	(0.0000339)
Years of Schooling		0.105***	0.0458***
		(0.00267)	(0.00283)
Female		-0.211***	-0.132***
		(0.0149)	(0.0159)
Formal Employment		0.616***	0.456***
		(0.0278)	(0.0288)
Occupation FE	No	No	Yes
Industry FE	No	No	Yes
State FE	No	No	Yes
Observations	26574	26574	26574

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

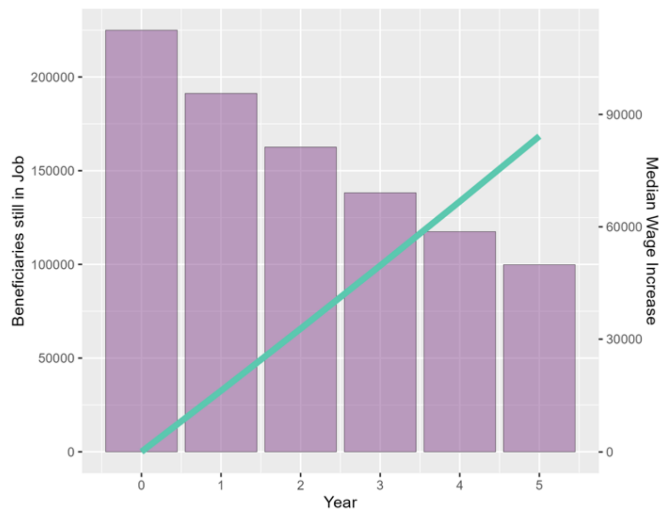
Source: Author's calculations, based on GEIH 2020

The first row shows positive and significant coefficients of an additional year of work experience at the 99% level of confidence for the three models. More precisely, the full model, which controls for occupation, industry and department fixed effects, shows that an additional year of experience leads to an increase in workers' wages by 1.7% every year. Moreover, the negative coefficients related to the experience squared account for the fact that experience has diminishing returns after a certain age. Unsurprisingly, more years of schooling and being formally employed have positive effects on wages, increasing them by 4.6%. However, being a woman has a negative impact on wages, decreasing them by 13%.

The experience coefficient of 1.7% is what is used in the long-term impact evaluation to predict the increase in wage for the workers that keep their job after being hired by a firm through the employment program. This is important to note as this wage increase is only taking place in the employment program and is part of what explains the difference in poverty reduction of both programs in the long-term.

Figure 30 illustrates the impact of the employment program over the years. There is a negative relationship between the number of beneficiaries and their wage. This is due to the fact that every year only 85% of the beneficiaries from the previous year keep their jobs as they might decide to quit the firm or be fired. The number of beneficiaries goes from 225,000 in the first year to 100,000 five years after the end of the program. However, the wage of the youth who keep their job increase over the years as they gain experience – as the Mincer regression results suggest (Table 5). An increase of 1,7% in wages every year translates into a total increase of almost 90,000 COP after 5 years. This result supports the idea that even an employment program targeted at youth that only lasts one year has large positive impacts on them in the long-term. It is likely that their households will be able to self-sustain and will not require more assistance from other state programs. Youth getting formal employment is therefore not only positive for their own welfare as after a while they might even be able to be autonomous outside their households, but it also has indirect positive consequences for the rest of the society.

Figure 30: Wage increase over the years for beneficiaries of the employment program



Source: Author's calculations, based on GEIH 2020

4.2 Poverty

Figure 31 and Figure 32 depict the evolution of poverty levels for cash transfer and employment programs in the long-term. As expected and consistent with the results described in the immediate impact section, the employment program diminishes poverty more than cash transfers in the short-term. However, whereas the impact of cash transfers is reduced to zero as poverty goes back to its initial level, the employment program keeps having an impact on poverty five years after the program was implemented. In the long-term, poverty is reduced by a little more than 0.4 pp from 46,1% to 45,7% in the case of the employment program, where 85% of the workers remain employed each year, whereas the cash transfers program has no effect. This is due to the fact that a share of the people hired through the employment program keep their job after the program has stopped, whereas, in the case of the cash transfer program, people stop receiving the money completely after one year. Therefore, in the long-term, an employment program targeted at youth is more effective in reducing poverty than a cash transfer program. Moreover, even in the case where a smaller share of workers would remain employed each year, for instance, if firms decide to fire more workers when they do not receive their subsidy anymore, the impact of the employment program on poverty reduction in the long-term would still be higher than the cash transfer. As shown in Figure 31, this is true even if 60% of the workers lose their job. However, above this percentage, poverty reverts back to its initial level before the introduction of the program. In any case, those results clearly show that an employment program has long-lasting positive effects, which is not the case with cash transfers.

In the case of extreme poverty, also as expected and consistent with the results above, the impact of cash transfers is bigger as more poor households are targeted in the short-term. However, in the long run, poverty also comes back to its original level, whereas the employment program effectively reduces extreme poverty by 0,35pp 5 years after the end of the program when 85% of the worker remain employed. Therefore, even if in the short-term cash transfers might provide more immediate relief for poor households in the time of crisis, an employment program is actually more effective for extreme poverty alleviation in the long-term. This is the case if at least half of the recruits remain employed each year. As for the poverty level, below this share, extreme poverty will revert back to the level before the employment program was implemented. Nonetheless, as Colombia is now focusing on a reactivation strategy that is inclusive and sustainable in the long run, an employment program seems more appropriate than a cash transfer.

Figure 31: Poverty levels after 5 years for both programs

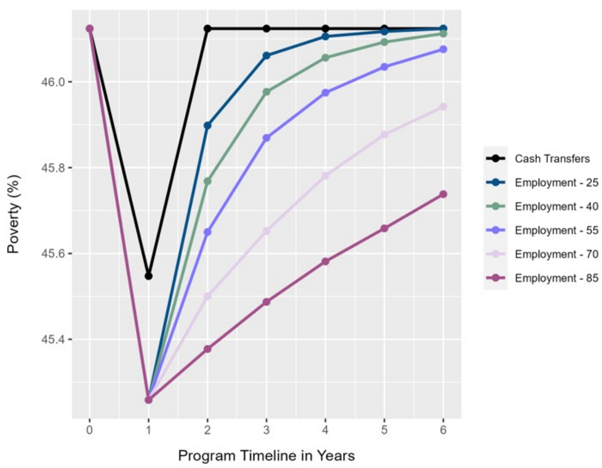
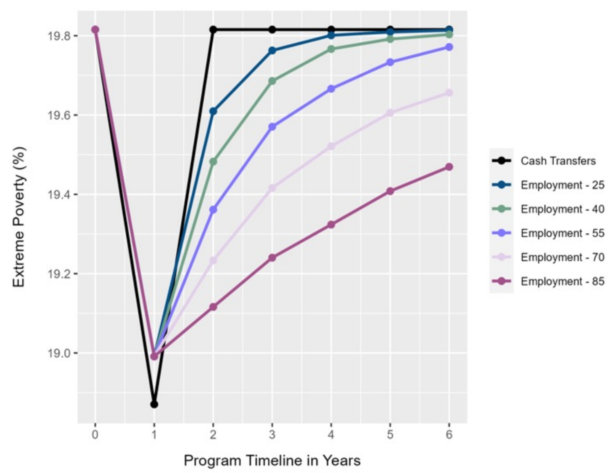


Figure 32: Extreme poverty levels after 5 years for both programs



Source: Author's calculations, based on GEIH 2020

4.3 Inequality

Figure 33 and Figure 34 show the inequality effect of both programs in the long-term. Following the poverty trend, the cash transfers program only reduces the Gini coefficient by 1 point from 52.5 to 51.4 at the end of the program and has no impact on inequality in the long-term. The employment program, on the other hand, keeps reducing inequality in the long run. Indeed, five years after the end of the program, the Gini coefficient is reduced by 0.6 Gini points compared to the initial inequality before the program. This signifies that not only will an employment program be effective in reducing poverty in the long-term, but also that inequality can be reduced through the same policy. This is noteworthy for policymaking as multiple objectives can be reached without reaching for further resources.

Figure 33: Gini coefficients for the cash transfers in the long-term

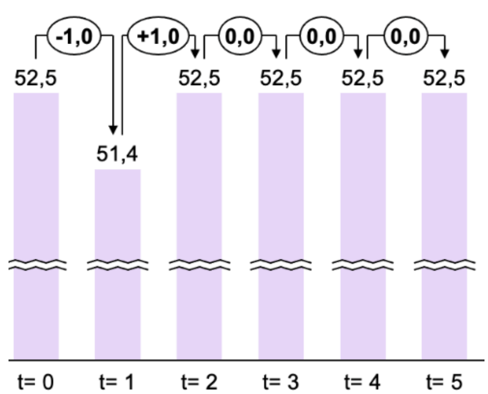
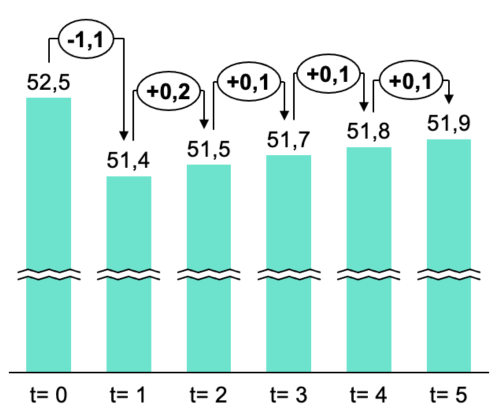


Figure 34: Gini coefficients for the employment program in the long-term



Source: Author's calculations, based on GEIH 2020

4.4 Wage quartiles

Figure 35 and Figure 36 depict the wage increase for beneficiaries in the first quartile and second quartile of the youth income distribution for the cash transfers and the employment program. For the households with youth present in the first 25% of the income distribution, their wage increases by almost 14,166 COP with cash transfers and by 16,666 COP with the employment program at the end of the first year. However, whereas the wage directly goes back to its initial level when the cash transfers stop, with the employment program, the wage is still 10,000 COP higher even 5 years after the end of the in-work subsidy. Those patterns are even clearer for the households with youth in the second quartile of the income distribution. Indeed, with the employment program, they experience a wage increase of more than 18333 COP one year after the beginning of the program, which goes to 8,156 COP after 5 years. However, in the case of cash transfers, even in the short-term, the increase in wage is almost insignificant (277 COP), and there is no effect of the program in the long-term. Those effects are explained by the fact that cash transfers target the poorest, but the amount of the transfers is not enough to make beneficiaries move to the second quartile of the income distribution. They manage to increase their income within the first quartile but do not jump over the threshold. On the contrary, as the employment program target slightly richer people (Figure 3) and as wages received through the employment program are larger, the employment program also has an effect on households in the 25th percent to 50th percent of the income distribution. Most importantly, those two figures show that the difference in impact between the two programs is more prevalent in the first quartile. Indeed, for the 25 poorest percent of the income distribution, when people benefit from the employment program, they earn 10,000 COP more than when receiving cash transfers after 5 years. Within the second quartile, this difference reduces to 8,156 COP. This further supports the fact that in the long-term, an employment program is actually more effective in improving the income of the poorest households with youth than cash transfers.

Figure 35: Wage increase of the first quartile of the youth income distribution

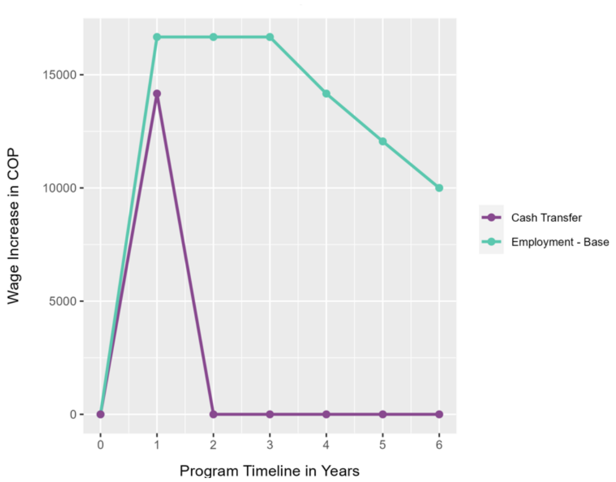
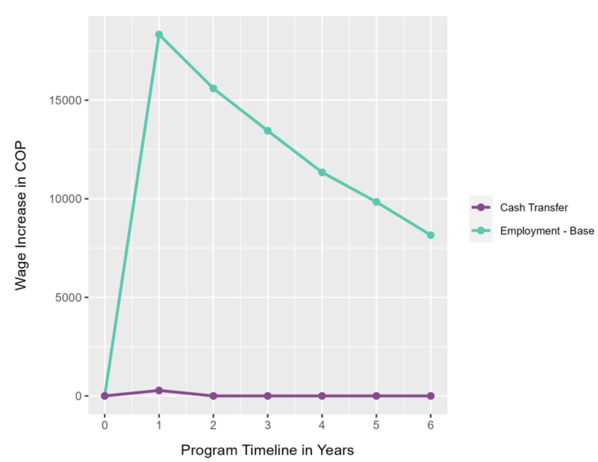


Figure 36: Wage increase of the second quartile of the youth income distribution



Source: Author's calculations, based on GEIH 2020

V. LIMITATIONS

Whilst the microsimulation model can improve the understanding of the impact that a cash transfer and an employment program targeted at young people in Colombia might have; it is important to acknowledge its limitations.

First of all, this model is deliberately aiming to isolate the potential effect that these two programs might have. It does, therefore, not consider how other factors might evolve over time and how they would interact with the possible effect mechanisms of the interventions modelled here. In general, unbundling first and second-order effects of cash transfers and employment programs is challenging. It is not feasible to isolate the channel in this model from gains in human capital or other types of support offered under similar programs that may have an influence in reality.

Similarly, the model does not consider the dynamic interaction between the existing government transfer system and the cash transfer or employment program. In practice, it is difficult to discern how much the policies may complement one other since there is space for complementarities between the interventions. Whilst the government will be able to reduce its transfers in instances where households sufficiently increase their income, these households will then, in turn, see a reduction in their income. This would reduce the net benefit of a household. In this microsimulation, the impact of both programs is measured against the "No Transfer" scenario under which the total household income is reduced by the government transfers that it receives. Whilst this comparison is therefore correct, the income benefit of comparing total household income before and after the intervention might be smaller due to the reduction in government transfers.

Another limitation is that the employment program simulation assumes that these individuals would, in a counterfactual scenario, not find employment. This, however, is something that cannot be observed and can, therefore, not be known. It might be the case that firms fill positions that they were aiming to fill regardless. However, since only previously unemployed youth are eligible for the program, it is unlikely that all of these individuals would have been hired regardless.

The model is also not able to fully account for possible demand or supply constraints. Even if the government subsidizes new employment, many firms might not have the capacity to hire additional workers, or a proportion of the unemployed youth might not take up the jobs offered. This model attempts to consider it by assuming that the final beneficiary number only reaches 75% of the initial target set out by the program. This assumption is based, amongst others, on the findings of Brown et al. (2007). As this assumption does not vary on any dimension, such as spatial or gender, the effects will not be very heterogeneous in that aspect.

Given that there is no explicit assumption made about the differential probability of males and females being beneficiaries of the program, the baseline model ends up being overly optimistic about the inclusion of females in the employment program. As Figure 23 shows, the pool of beneficiaries in the employment program includes 56% females. This is overly optimistic because the policy reality of PAEF shows that even when firms are offered a significantly larger subsidy for females, the share of females only reaches 41.9%. This clearly indicates that any modelling approach that does not include a differential probability for females and males will likely overestimate the impact on female poverty, hence why this study takes this into consideration in the gender scenario.

VI. POLICY RECOMMENDATIONS AND DISCUSSION

As the COVID-19 pandemic shocked economies across the globe and depressed especially the income of many low-income groups, many countries, including Colombia, have reverted to cash transfer programs to mitigate the immediate impacts. The analysis in this paper has shown that cash transfers are indeed more effective in reducing extreme poverty in the short-term as they are able to target more and poorer people. However, even in its immediate impact, an employment program, as modelled here, has a larger poverty reduction effect. The reason is that whilst it reaches fewer people, the income increase of the beneficiaries is larger so that more people are lifted out of poverty. This result regarding the immediate impact is interesting in itself, but as the policy focus shifts from mitigation to recovery and reactivation, the long-term effects of the policies are key. In the long-term, the employment program modelled here is clearly more effective than cash transfer programs. In cash transfer programs, beneficiaries revert back to their initial income level, holding everything else constant. In an employment program, on the other side, a certain proportion of the beneficiaries are able to keep their job and the according wage. This means that these beneficiaries will be less reliant on government transfers, a benefit that has not been directly considered in this simulation. Because beneficiaries remain employed beyond the termination of the program, an employment program has clear benefits in the long run (see Figures 29 and 30). Given the aim of reactivating the labour force and specifically young people, an employment program, therefore, seems to be preferable.

As Colombia is trying to reactivate its economy after the COVID-19 pandemic, this should also include the goal of tackling the high level of informality present in the country and, in turn, help reduce poverty. Indeed, as the random forest analysis suggests (see section 2.5), working in a formal job is the most important predictor of poverty or extreme poverty. This effect is based on the fact that in the long-term, working in a formal job provides benefits that informal or unemployed workers do not enjoy, like social care or higher wages. Therefore, creating more jobs in the formal sector would be an effective policy to reduce poverty in the long-term. In this sense, only an employment program could provide a tangible alternative as it does create formal jobs, unlike cash transfers. Moreover, even if not all beneficiaries keep their job every year, the gain in experience and the new social connections made certainly make it easier for them to be reemployed by another firm. Whilst the wage return to additional experience is included, the higher probability of being employed by a different firm has not been modelled here. This indirect impact could be the subject of future research. At the level of the households, having more members working in the formal sector will also mean higher earnings in the long-term and, in turn, a lower need for government transfers. Those positive externalities of formal employment can only be found in an employment program and support the claim that in-work subsidies seem more appropriate in the context of the recovery from COVID-19 in Colombia. To go even further, as Colombia is now thinking of different ways to be a more inclusive, resilient, and sustainable economy, hiring subsidies can be an effective means to boost job creation in specific sectors of the economy. Only firms in certain chosen sectors of the economy could receive the subsidy, which would, in turn, reallocate the labour force towards those more productive and socially optimal sectors (such as fewer polluting industries or digital services, for instance). However, favouring some sectors over others could lead to political capture of the employment program. In the case of the employment program modelled here, this is, however, not a concern as all firms can be beneficiaries of the subsidy regardless of their types of activities and size. Moreover, compared to cash transfers, the likeliness of political capture is lower. Indeed, in Colombia and most of the other countries in the region, assistance programs in the form of cash transfers tend to have the reputation of being highly politicized and used in the form of clientelism – i.e., using transfers in exchange for political support to the political party of the incumbent (Blofield, 2015). Considering the current political climate of Colombia with the recent Presidential election on May 29th this year and the political polarization that is affecting the country, cash transfers should therefore be used with even more caution than an employment program. This consideration is another argument in favour of putting in place in-work subsidies rather than maintaining cash transfers in Colombia.

However, other considerations regarding hiring subsidies need to be acknowledged to get a full picture of the potential impact such a program could have on the labour market. Indeed, Cahuc et al. (2014) find that hiring subsidies can have adverse effects on the labour market as firms adjust their behaviour. First, they can result in a crowding-out effect as in-work subsidies can put upward pressure on wages up to a point where firms eventually reduce their employment, which would be contrary to the intended effect of the program. Second, they can result in a substitution effect if nontargeted workers are hired less often. This would considerably reduce the impact of the program on the overall Colombian population. Third, a displacement effect can take place if hiring subsidies create unfair competition for non-benefiting firms, which might result in more layoffs on their part. Even if this is not a concern in this study, as there are no eligibility criteria for firms, this point is still worth considering, as creating selection criteria for firms could also be beneficial for other reasons (see paragraphs above). Finally, hiring subsidies can lead to a deadweight effect as some of the workers would have been hired anyway, even without the existence of the program. Doubt will always remain regarding the actual additional number of jobs created through the employment program, and that would not have been created otherwise. This last point is the biggest concern because it puts into question the necessity for such a job creation program in the first place. However, the better the state's capacity to monitor workers' employment history and, in turn, their eligibility criteria, the lower the concern there is for deadweight loss. In any case, the possible existence of those negative effects of wage subsidies explains why their temporary nature is a factor of primary importance. Indeed, firms do not instantly adjust their behaviours; for instance, changing wages requires time. These negative effects are less likely to happen if measures are temporary, as is the case in this study. Therefore, the length of the program needs to be considered to avoid behavioural reactions from firms that might have adverse effects.

This study has conducted an analysis of an employment program with perfect targeting where the poorest of the poor or vulnerable households are reached and a version with random targeting where households are targeted randomly within those categories (i.e., extremely poor, poor & vulnerable). The immediate impact on poverty is relatively similar to the perfect and random targeting models (see Figure 20-23). However, as the perfect targeting model targets the poorest of the poor households, its impact on extreme poverty is significantly larger than that of the random targeting model. Whether or not perfect targeting can be achieved depends on the capacity of implementing organizations to observe the overall income of possible beneficiaries. What emerges from this analysis is that in the case where random targeting might approximate reality better, an additional eligibility criterion, such as spatial targeting, will be able to improve the program's effectiveness in reducing poverty.

Given the focus of this study on Colombian youth, it is vital to consider certain specific situations that affect this subset of the population. First, firms might be hesitant to recruit young workers owing to a lack of job experience, untested quality, and high training expenses. As a result, it is critical to guarantee that incentives are large enough to balance employers' expenses for hiring young workers. It is important to note that youth labour-market trajectories differ significantly from those of the general population; particularly in Colombia, where young people face an unemployment rate twice as high as the national average (18.4% vs 11.3% respectively, as of June 2022[32]), have high rotation rates, and are concentrated primarily in the informal sector. Second, there may also be variation in responses across firms. Due to the considerable variation in training costs that companies encounter across sectors, evidence in Colombia implies that labour policies aimed at youth may cause a crowd-in effect in this group in low-skilled enterprises (Caicedo, Espinosa and Seibold, 2021). Firms have embraced flexible and informal employment arrangements that are temporary, seasonal, and dependent on unregulated labour contracts

32. DANE's Labor Market results June 2022 based on GEIH 2018. The Unemployment rates are for the period April – June 2022. Youth population is considered to be 15th to 28th years in this calculation

in the middle of the COVID-19 epidemic, and young people tend to be slotted for those positions as well (ibid). This occupational and sectoral segmentation into less profitable areas may play an important influence on the career and earning trajectories of youth, thereby increasing the wage gap for youth populations. Furthermore, this concentration in low-skill industries may reduce knowledge transfer and human capital buildup, so lowering overall wellbeing.

Women have been disproportionally affected by the COVID- 19 pandemic. Therefore, many interventions during the crisis have been trying to find ways to directly mitigate women's poverty as well as favour their reintegration into the labour force. The gender analysis conducted in this paper shows that the reason why fewer women benefit from the employment program than men might not come from the demand side - firms hiring fewer women - but from the supply side – fewer women searching for jobs. Indeed, the analysis demonstrates that there are many young, unemployed, and highly educated women that could be eligible for an employment program but that the program fails to hire as many women as men even when the subsidy given to firms is higher for women. Because of the persistence of gender norms, young women face additional challenges. Firms might establish preferences for male workers because of females' lack of working flexibility and gendered beliefs of low long-term commitment, among other barriers women may encounter in the workplace. Increased employment may not result in an improvement in welfare if women continue to carry the majority of unpaid labour and if working conditions and remuneration are inadequate. Building on this result, this suggests that more incentives should be given for women to join formal employment. For instance, as in Colombia, many women work informally in the care sector; improving the conditions of the care economy in Colombia could have an indirect positive impact on women's poverty that could potentially be even larger than an employment program directly targeted at them. Even if those considerations are beyond the scope of this paper, they are important to take into consideration when thinking about inclusive recovery strategies for Colombia.

VII. CONCLUSION

The study attempts to enhance the UNDP and Diaz et al. (2021) model in order to clearly understand the true impacts of COVID-19 mitigation social policies on youth, which are among the most affected groups in Colombia. The microsimulation model focuses on evaluating two distinctive policies: a cash transfer program and a dynamic employment program. It is possible to observe that the effectiveness of the two interventions varies significantly according to the poverty indicators measured and the time frame (short-term versus long-term).

In the short-term, cash transfers are more effective in reducing extreme poverty, while an employment program is similar or even more effective in reducing poverty. This is true for all the different employment scenarios. Moreover, in the case of random targeting, poverty reduction is largest when the beneficiary pool is restricted by their locations. This indicates that when perfect targeting is not viable, additional targeting criteria should be used. Regarding the gender analysis, the comparison between the perfect targeting baseline scenario and the gender scenario shows that most models will be overly optimistic in estimating gender-based poverty reduction.

In the long-term, an employment program always shows greater poverty reduction and inequality effects since a subset of beneficiaries can retain their jobs and increase their income over time due to the returns of additional experience. Given that this result persists even at lower bound estimates of job retention, employment programs are preferable to cash transfers in the long run. This is even more so the case as the policy focus in Colombia is shifting from immediate mitigation to sustainable economic reactivation.

However, it is important to acknowledge the inherent limitations of a microsimulation approach as the model does not consider how other factors might evolve over time and how these might interact with the mechanisms of the simulated policies.

Nonetheless, the findings of the study suggest that in the current policy environment, an employment program is beneficial when aiming to reactivate the Colombian youth. Future research could be conducted to better understand the extent of positive externalities resulting from an employment program, such as an increased probability of gaining subsequent employment with a different firm or deepening professional connections potentially benefiting the rest of the household.

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IX. APPENDIX

1. Education levels in Colombia by department

Departments	Primary education wages (COP)	Secondary education wages (COP)	Tertiary education wages (COP)
La Guajira	901266.3	900960.2	1421724.9
Chocó	828996.9	933372.6	1285925.3
Magdalena	799723.0	952346.9	1445402.7
Córdoba	877804.3	948991.1	1153954.0
Cesar	878239.8	955445.9	1181602.3
Cauca	906138.1	858094.9	1165666.9
Norte de Santander	821229.9	873752.4	1243733.4
Huila	931054.5	970553.2	1186605.7
Sucre	865780.0	912045.8	1374798.2
Nariño	1302544.3	888141.9	1149566.6
Bolívar	802778.7	867133.3	1207467.9
Tolima	908334.5	1086125.9	1389590.2
Boyacá	698018.9	1003399.8	1232784.4
Caquetá	640600.6	1091977.7	1284304.7
Bogotá D.C.	878723.3	949284.6	1120538.0
Santander	1068217.0	961764.0	1325307.9
Quindío	431700.8	962727.5	1194251.1
Meta	923939.8	922576.1	1145102.4
Atlántico	862908.2	883983.6	1127744.0
Risaralda	642204.5	881397.9	1143211.5
Valle del Cauca	962843.0	957516.0	1260970.3
Antioquia	852716.1	903878.8	2228391.6
Caldas	956143.9	886031.4	1114880.1
Cundinamarca	647201.2	978331.0	1257296.9

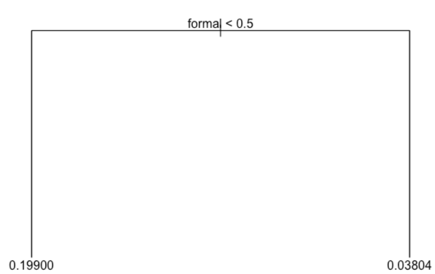
Source: Author's calculations, based on GEIH 2020

2. Income by quintiles of beneficiary pool by program

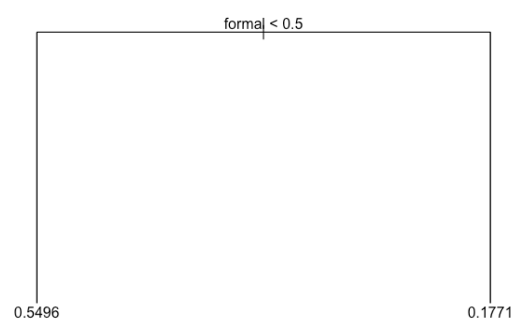
Quintile	Extreme poor		Poor		Vulnerable	
	Cash transfer pool	Employment pool	Cash transfer pool	Employment pool	Cash transfer pool	Employment pool
First	-	-	112,487	112,505	199,333	199,927
Second	40,000	30,000	180,000	192,333	34,862	368,943
Third	80,000	75,000	233,333	249,071	446,583	455,000
Fourth	108,889	108,169	299,529	311,667	535,000	536,799
Fifth	184,333	183,333	455,000	454,555	674,237	666,288

3. Decision tree

Extreme poor



Poor



Source: Author's calculations, based on GEIH 2020

4. Long-term further considerations

FIRM BEHAVIORAL RESPONSES

ARGUMENT. IN-WORK SUBSIDIES HAVE DIMINISHING RETURNS AS THE SUBSIDY INCENTIVIZES FIRMS TO RECOVER THEIR LABOR FORCE IN THE SHORT-TERM BUT HIRING DIMINISHES OVER TIME[1].

ASSUMPTION: THE IMPACT OF WORK-IN SUBSIDIES IS DIMINISHING AS COMPANIES HIRING DIMINISHES.

1. Empirical evidence (Armand et al., 2020, Brown et al 2007) suggests that low-wage subsidies have diminishing returns.

After the first year, firms will reduce the usage of the subsidy offered by the government. To model this, the model considers a reduction in the new jobs offered by the firms in the second year. To approximate reality as much as possible, the reduction will be given by the rate of decline needed to achieve the normal level of new jobs created in Colombia in a given year by the end of the program. The study will consider the new jobs created in 2019 (prior to COVID-19). Therefore, the CAGR will be calculated between the new jobs from the program and the new jobs in 2019. The calculation is as follows:

$$\left|\left(\frac{New\ jobs\ 2019}{New\ jobs\ program}\right)^{\left(\frac{1}{years}\right)} - 1\right| * 100$$

$$= \left|\left(\frac{XXX}{260{,}000}\right)^{\left(\frac{1}{2}\right)} - 1\right| * 100$$

$$= XX\%$$

Given xx% is the rate of decline, the jobs offered in the second year by the firms will be equal to:

$$= [260{,}000 - (260{,}000 * XX\%)]$$

$$= YYYY$$

Therefore, even if the subsidy is available, because of our assumption, the subsidy will not be fully used.

IMPACT IN THE LONG-TERM OF BEING EMPLOYED ON SAVINGS

One potential impact of an employment program is that savings increase because the household has more income. However, the study will not include this part in the model because the sample is limited to low-income households. According to empirical literature, low-income households may have a negative saving rate (owing in part to high debt levels), and if they do, the return on such small sums of money is negligible[2]. However, the paper will still present the methodology it would have followed if a change in savings were to be considered.

ARGUMENT. A PERMANENT INCREASE IN INCOME LEADS TO SMOOTH CONSUMPTION, WHILE A TEMPORARY INCREASE LEADS TO INCREASING CONSUMPTION IN THE SIZE OF THE SURPLUS.

2. See Schwefel and Leidl, (1987) “Remarks on the Social Meaning of Savings of the Poor”.

ASSUMPTION: CONSUMPTION BEHAVIOR WILL DEFER BETWEEN THE TWO POLICIES.

The households with employed youth through the employment program will smooth their consumption. While the households that receive the cash transfer will consume the lump sum amount completely.

ARGUMENT. AS INCOME INCREASES, THE SPENDING PATTERNS VARY AS THE PROPORTION OF SAVINGS VS CONSUMPTION INCREASES[3].

ASSUMPTION: FOR EACH THRESHOLD, THERE WILL BE AN AVERAGE PATTERN OF SPENDING IN TERMS OF SAVINGS AND CONSUMPTION.

This can be modeled by obtaining the saving rate of households in different income brackets. To get the saving rate, it is known income is consumed or saved. Therefore, by following the economic property:

$$\mathrm{Y} = \mathrm{C} + \mathrm{S}$$

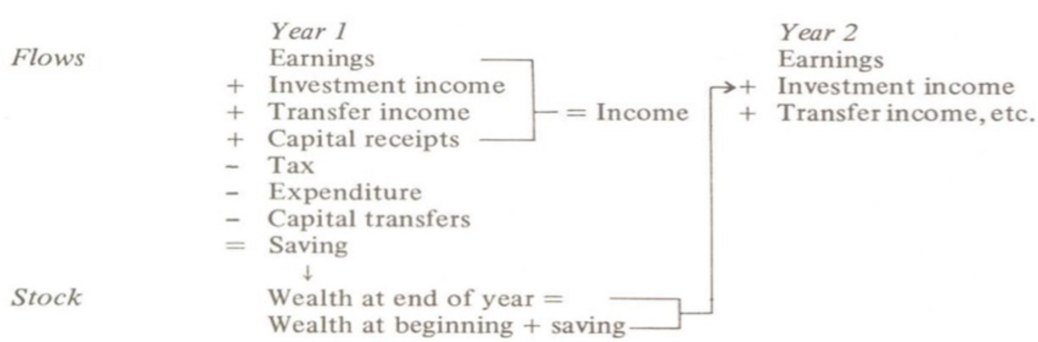
$$1 = \mathrm{MPC} + \mathrm{MPS}$$

Given from the data it is possible to get the MPC as:

$$\mathrm{MPC} = \frac{\mathrm{dC}}{\mathrm{dY}}$$

It is also possible to get the MPS as the residual. With this the savings rate can be observed by the income threshold. To this level of savings by household, the analysis would apply the rate of return on deposits in Colombia. Therefore, it will make it possible to calculate the new income for the following years.

Figure 37: Income composition



Source: LSE PP4X6 Welfare Analysis Measurement slides based on A.B. Atkinson

3. Refer to Japelli and Pistaferri (2010)," The Consumption Response to Income Changes".

pnudcol
@PnudColombia
@pnudcolombia
pnudcol
PNUDenColombia
comunicaciones.co@undp.org

Calle 84A #10-50, Piso 3
+57 (1) 4889000
Bogotá, Colombia