Too little but not too late.

Nowcasting poverty and cash transfers' incidence during COVID-19's crisis.*

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Abstract

The economic crisis triggered by COVID-19 has caused a world-wide economic downturn, and the deepest GDP contraction in Latin America since the beginning of the XXth century. One of the most dramatic outcomes of the crisis is the increase in poverty, but its extent will remain unknown until household income data is collected and analyzed. We propose a simple approach to provide early estimates, micro-simulating the short-run effect of the crisis on the poverty rate. It combines household level micro-data, estimates on the feasibility of working from home, information on key public policies (e.g., cash-transfers, unemployment insurance), and forecasts of GDP contraction. This approach, which can be easily adapted and applied to different countries, allows to *nowcast* the current poverty level and the poverty-reducing effect of public policies, while providing full micro-macro consistency between heterogeneous impacts on households and the shock to aggregate GDP. Moreover, it enables to estimate the effect on informal and self-employed workers, of utmost importance in developing countries. We illustrate the methodology with an application for Uruguay, finding that during the first full trimester of the crisis, the poverty rate grew by more than 38%, reaching 11.8% up from 8.5%. Moreover, cash transfers implemented by the government in the period had a positive but very limited effect in mitigating this poverty spike, which could be neutralized with additional transfers worth under 0.5% of Uruguay's annual GDP.

Key words: COVID-19; nowcasting; poverty; microsimulations; Latin America; Uruguay.

JEL classification: D04, D31, I32

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1 Introduction

The spread of COVID-19 and the measures that have proven to be more effective to prevent it, entail deep and far-reaching economic consequences (IMF, 2020; World Bank, 2020). Negative external shocks through retraction of trade, tourism and investment together with social distancing measures, affect economic activities through a variety of channels, hence the length of the downturn will probably exceed the time span of the sanitary crisis (Boissay et al., 2020; Baker et al., 2020; McKibbin and Fernando, 2020). In this context, Latin America faces yet another crisis, which is likely to be the deepest economic contraction since the beginning of the XXth century (ECLAC, 2020a).

One of the most visible effects of the COVID-19 crisis is the rapid increase in poverty, which many early studies estimated through different approaches. Sumner et al. (2020) estimate that the number of people living in poverty could increase by 420–580 million worldwide. The United Nations' Economic Commission for Latin America and the Caribbean (ECLAC) estimates an increase in poverty rates for this region of up to 4.4 percentage points, which means over 28 million additional people under the poverty line (ECLAC, 2020b). Diop and Asongu (2020) use GDP contraction estimates to shift the poverty line and simulate poverty rate changes in Africa, finding increases of up to 35.9%. For the case of Pakistan, Nizamani and Waheed (2020) identify vulnerable jobs depending on the feasibility of working from home and conclude that only 18.5% of the working population can do so, while Suryahadi et al. (2020) estimate an increase in the poverty rate from 9.2% to 9.7% by the end of 2020 for Indonesia. Bonavida Foschiatti and Gasparini (2020)2020), on the other hand, use micro-simulations and estimations of the feasibility of working from home to calculate a 4 percentage point increase in the poverty rate for Argentina (after accounting for cash-transfers). Martin et al. (2020) use a theoretical model and predict a temporal increase in poverty for the San Francisco Bay Area from 17.1% to 25.9%. Conversely, Buheji et al. (2020) review from a multidisciplinary perspective the socio-economic impact of the crisis on the poor around the world, while Ruiz Estrada (2020) visually shows how quarantines can generate, among other negative effects, an expansion of poverty from a multidimensional perspective, beyond monetary measures.

This rapidly expanding literature has the merit of providing close to real-time assessment of the impact of the crisis on poverty, but presents a number of caveats. In particular, it fails to simultaneously consider aggregate GDP shocks and household heterogeneity, in particular the fact that the crisis has uneven effects on individuals depending on their ability to work from home. In this paper, we use a simple approach to estimate the poverty rate, microsimulating (i) the income reduction for formal sector workers, based on data on lay-offs and unemployment benefits, combined with estimations on workers' feasibility of working from home or in close proximity with others; (ii) the effect of covid-triggered additional cash-transfers; (iii) the re-

duction on informal and self-employed workers' income and employment based on estimations of the aggregate GDP shock. The last point assures micro-macro consistency and tackles the issue of how to assess the effect of the shock on informal and self-employed workers, which is of utmost importance in developing countries where social security coverage tends to be low. Though we perform this exercise for Uruguay, the general procedure proposed could be easily adapted for other countries and settings with different data availability. We illustrate the methodology for the case of Uruguay in the second trimester of 2020, i.e. the period that withstood the full impact of the crisis. We focus on three key questions: how many people fell below the poverty line in this period? Did the measures implemented by the government neutralize the negative shock? How many additional resources are needed to maintain the poverty rate at pre-crisis levels based on the same public policies already implemented? To answer them, we considered: (i) official data on around 140,000 formal workers that applied for unemployment benefits (over 5% of the adult population and more than 10% of all formal workers); (ii) the main cash-transfers measures deployed by the government, mostly targeted to poor households; (iii) an estimated loss in employment and income levels for informal and self-employed workers consistent with a 4.2% GDP contraction. We simulated a number of alternative scenarios (varying the contraction in economic activity and the patterns of distribution of the negative shock among workers and sectors of activity), and performed a variety of robustness checks, yielding very similar results. In summary, we find that first, the poverty rate (after accounting for the new cash-transfer programs) increases by 3.3 percentage points and lies between 11.6% and 12.4% depending on the scenario. This represents over 115,000 additional individuals below the poverty line, an increase of around 38.7% compared to pre-pandemic levels. Second, the new cash-transfers implemented by the government as a result of the crisis slightly lessen the increase in poverty by about 18%, but are, then, insufficient to neutralize it. Third, the increase in poverty is largely avoidable: we estimate that maintaining poverty at 2019's level would require additional transfers of about 23.7 million USD per month, which represent a yearly cost of about 0.46% of Uruguay's 2019 GDP. Although this estimate hinges on various assumptions, it does suggest orders of magnitude that indicate that a better response to the challenges imposed by the crisis is within the reach of Uruguay's capacity.

The paper is structured as follows. Section 2 provides a basic context of Uruguay and a chronology of the pandemic, while section 3 outlines the general methodological approach. Sections 4 and 5 describe the data used and discuss specific details of the estimation for the case of Uruguay. Finally, results are presented in section 6 and section 7 concludes.

2 Context and chronology of the pandemic in Uruguay

Uruguay is a small South American country located between Brazil and Argentina, with roughly 3.5 million inhabitants. After decades of repeated economic crises, it experienced in 2004– 2019 the longest period of uninterrupted growth in its history, with rates of over 5% until 2015 and significantly lower but still positive since then, reaching a per-capita income of around USD 22.000 in PPP (around half of the OECD average).[1] This rapid economic growth, coupled with a wide range of redistributive policies (Bucheli et al., 2013), resulted in a sharp decrease in poverty rates from 32.5% in 2006 to 8.8% in 2019 (INE, 2020b). Despite the major progress in poverty reduction, and the significant decrease in income inequality in recent years, the combination of relatively low per-capita GDP and high income concentration implies a large number of individuals with very modest earnings, vulnerable to negative economic shocks.[2]

Figure 1: Poverty rate (individuals) and GDP growth, 2006-2019
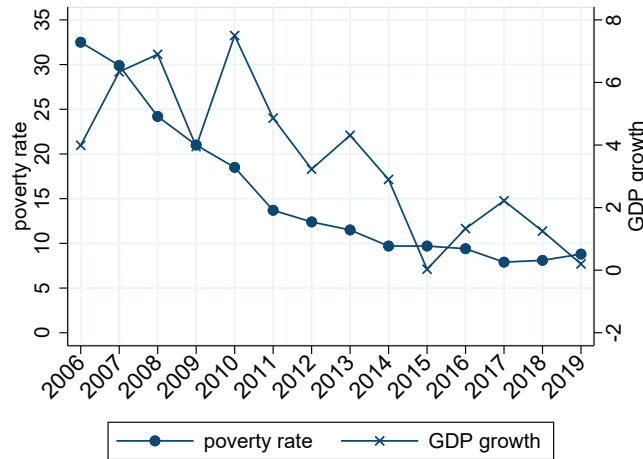
Note. Official poverty series by the National Statistics Institute (INE, 2020b) and GDP from World Bank and Uruguayan Central Bank (for 2019).

Figure 1 presents monetary poverty estimations, showing a substantial decrease in the last fifteen years. This results from high economic growth (especially in the first half) and a wide range of cash transfers and other redistributive policies (Amarante et al., 2014). The cash-transfers system has four main components: (i) a large child allowance program, AFAM-PE, which provides transfers to around 40% of those under 18, regardless of parent's job status;

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[1]See https://data.worldbank.org

[2]The Gini index (based on household survey data) fell 0.07 points in 2008-2013. Nevertheless, estimations based on tax records data show very high income concentration, with a top 1% share of over 15% (Burdin et al., 2020). Moreover, different studies estimate from a multidimensional perspective that around 40% of the Uruguayan population was still vulnerable to adverse economic shocks (Colafranceschi et al., 2018; Failache et al., 2016).

(ii) a smaller child allowance program to formal workers exclusively (reaching 14% of all children); (iii) an additional cash transfer scheme targeting the poorest 10% of households (TUS); (iv) tax deductions for direct income taxation for households with children. The four programs combined have a cost of around 0.5% of GDP and reduce poverty by 1.66 percentage points (OPP, 2018). Poverty rates remained stable around 8-9% since 2015, however stagnating growth shown in Figure 1, coupled with increasing unemployment rates (reaching 10% in February 2020), and a fiscal deficit nearing 5% of GDP were already accumulating pressure on macroeconomic equilibriums and on poverty prior to COVID-19's arrival.

After elections in 2019, Uruguay transitioned from a center-left to a center-right government on March 1st, 2020, hence monitoring the situation in China and Europe in the weeks prior to the arrival of COVID-19 was split between two administrations, and the first weeks of March were still devoted to the transition. Figure 2 The pandemic officially arrived in Uruguay on March 13th, and in spite of the ongoing transition the detection of the first four cases triggered a response by the government, followed by subsequent sanitary and economic measures. These measures have proven to be successful in containing the spread of COVID-19; the evolution of the accumulated total number of confirmed cases and total number of accumulated deaths is presented in Figure A.1 in the Appendix.

Figure 2: Chronology of main COVID-19 related events (2020)
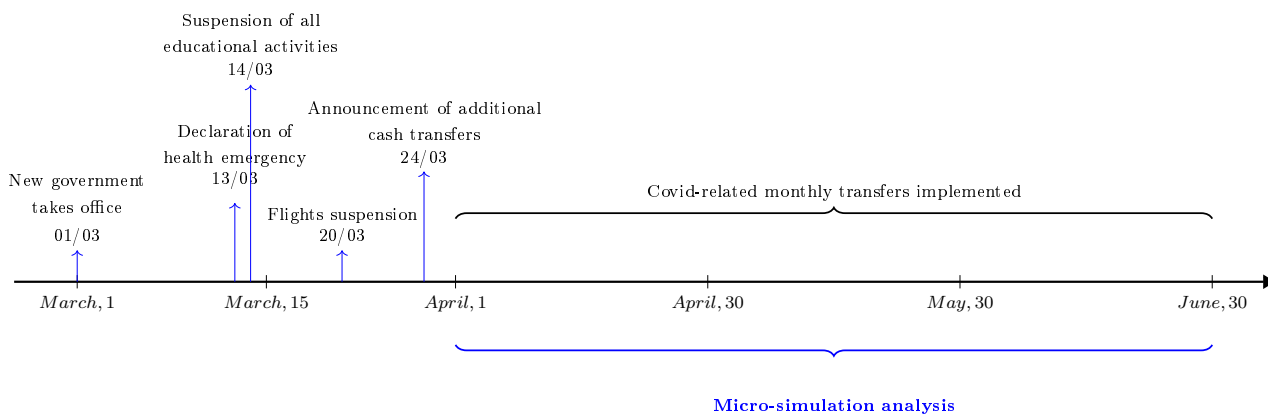
Note. Own elaboration based on press reports.

In the context of the lock-down, the government announced on March 24th a transitory expansion of cash transfer programs and the launch of a new program, which are described in subsection 5.2, and were executed since April. A number of additional measures, such as soft credits for small businesses or creation of transitory shelters for homeless individuals were announced in several press conferences during the second half of March. However, the small-scale policies and overall public spending as a response to the crisis has been the lowest in South America, and the third lowest in Latin America and the Caribbean (ECLAC, 2020c).

3 Methodological approach

This section summarizes the methodological approach proposed for the estimation of current poverty levels. Both the application in the Uruguayan case and alternatives for its use in different settings are outlined in broad terms, while in-depth discussion of the data and specifics on the estimation procedure in the Uruguayan setting are presented in sections 4 and 5 respectively.

3.1 The concept of poverty and poverty *nowcasting*

Although the consensus in the literature is that poverty is a multidimensional social phenomenon (Sen, 1993; Ravallion, 2011), income-based poverty can significantly change in the short run, with important long term consequences in the presence of poverty traps, as was the case in past crises both in Uruguay and elsewhere (Arim et al., 2013; Banerjee et al., 2019). In this paper poverty is measured with the monetary approach, based on absolute poverty lines (as in most Latin American countries), although any poverty line (absolute or relative) may be used. A household is therefore considered poor if its current income is lower than the corresponding poverty line (which takes into account a basic food basket, a non-food basket and the number of household members); poor individuals are those who belong to a poor household. For the Uruguayan example, we use the same methodology as the National Statistics Institute (INE) (INE, 2020b). Current income in this case includes imputed rent. This is an approximation of the market value of the rent that the household should have to pay if the dwelling was not owned by a member. It also includes all income received: from formal and informal labor, all government transfers (cash or in kind), and all other income (e.g. non-labor) in cash or in kind. Moreover, the official Uruguayan poverty line depends on the geographic location of the household and its number of members. Thus, the poverty line for a three-member household in the capital city (Montevideo) in March 2020 rose to about 883 USD.

This simulation exercise is framed in the techniques of 'prediction of the present' or *nowcasting*. The aim of these methodologies is to estimate the value of key economic variables in the present, near future or even very recent past (see for example Bańbura et al. (2013), or Clements and Hendry (2011)). These techniques are applied when official estimates are available with a substantial lag but other explanatory variables are measured more regularly, thus the likely evolution of key variables can be estimated.[3] In the case of Uruguay, the poverty estimates from INE and the household level microdata necessary to independently compute poverty are both published with a one year lag.[4] Amidst the current crisis, it is clearly not

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[3]These techniques have been used, for example, to estimate the real-time evolution of GDP (as the official estimates for each quarter are generally published a few months later) or poverty rates (Aguilar et al., 2019).

[4]For example, poverty rates for 2019 were published on March 31, 2020 (INE, 2020b), and 2019 microdata was made available in April 2020.

convenient to wait until 2021 to have precise estimates of ongoing poverty rates.

3.2 Poverty estimation

We define the income of each earner before the COVID-19 crisis as Y_b. We consider three shocks: (i) a formal income shock (S_f), including the loss of income due to unemployment and the gain from unemployment benefits; (ii) an informal and self-employed workers' income shock (only loss of income) (S_i); and (iii) increases in cash-transfers (S_t). Thus, Y_a captures the impact of the crisis *and* the mitigation measures, as defined in Equation 1:

$$Y_a = Y_b - S_f - S_i + S_t \tag{1}$$

To estimate equation 1, we proceed as follows:

1. Use the latest household survey, update values using consumer price index data, and compute Y_b.

2. Calculate the number of formal workers affected by the crisis, the extent of the income loss and the corresponding unemployment benefits (S_f), using social security data and workers' ability of working from home.

3. Simulate the effect of cash-transfers policies S_t, by households' characteristics.

4. Estimate the aggregate loss of labor-income earnings stemming from the estimated GDP contraction, subtract the income loss already estimated for formal workers (S_f) and obtain the aggregate loss of income for informal and self-employed workers (S_i).

5. Allocate the aggregate loss of income for informal and self-employed workers in the household survey based on individual characteristics and workers' ability of working from home.

6. Compute Y_a and the new poverty rate.

The starting point for step 1 is straightforward: individual incomes and the poverty line of the latest household survey are updated to 2020 values using consumer price index data. The key input is thus a household survey, available not only in Uruguay but in most countries. In step 2, we use official social security data to quantify the number of laid-off workers by industry (more on this in Section 4.3). We select workers in the household survey to be affected following a mixed strategy combining random sampling and an econometric model that predicts the probability of being laid off (based on the ability of working from home). This is further discussed in Section 5, but the key issue at this stage is to simulate the shock on formal workers based on whatever information is available as accurately as possible. In the worst case scenario, the shock may be distributed randomly within formal workers, to match either the total number of laid-off workers or the total amount of social security insurance paid, depending on data availability. In general, there is also publicly available information on cash-transfers, the amounts and the criteria for its distribution, which enables a precise micro-simulation of

its effects, necessary for step 3. In the Uruguayan case, the main policies implemented were an increase in transfers of two already existing programs and the creation of a new one, for individuals not covered by the other two, so an accurate simulation was possible.

While information on the impact on formal workers and cash transfers is usually available, since they are part of Governments' public policies and accounting systems, the negative shock on self-employed and informal workers is much harder to assess. We proceed by first estimating the aggregate income loss for this population in step 4, and then distribute it among self-employed and informal workers in step 5. In step 4, we translate an annual estimated shock to GDP, measured from a macroeconomic perspective, to a monthly shock on informal and self-employed workers' labor incomes, captured in survey micro-data. Thus, we estimate the mass of informal and self-employed workers' labor income that should be lost due to the crisis, based on the share of GDP's contraction affecting them. This approach is presented in Equation 2.

$$L_{in} + L_{se} = Shock_{2020} \times Sh_{mo} \times Sh_{la} \times Sh_{su/GDP} - L_{fo} \tag{2}$$

On the left hand side, L_{in} and L_{se} represent the sum of informal and self-employed workers' labor income that should be lost, respectively. On the right hand side, $Shock_{2020}$ represents GDP's estimated contraction (in aggregate monetary terms), Sh_{mo} is the share of the contraction on the time-frame considered in monthly terms[5], and Sh_{la} is the share of GDP corresponding to labor income. Therefore, $Shock_{2020} \times Sh_{mo} \times Sh_{la}$ represents the contraction in all labor income experienced by the economy, consistent with a given GDP shock. The first two terms come from aggregate GDP shocks estimated by any external source (e.g. Central Bank, macroeconomic forecast models, etc) and may be subject to sensitivity analysis (as in this study), while the latter is usually estimated in National Accounts. $Sh_{su/GDP}$ adjusts the resulting aggregate income by the fraction of that macroeconomic income mass actually captured by the household survey micro-data, equivalent to the ratio of the two totals, while L_{fo} represents the sum of lost income already experienced by formal workers, estimated in step 2.

The right hand side thus estimates the mass of labor income that informal and self-employed individuals lose (in the survey), after accounting for the shock in the formal sector and the discrepancies between labor income in macro national accounts and micro-level data. Equation 2 is important since it not only allows us to estimate the overall effect on informal and self-employed workers, but also because it is the bridge between macro and micro-microeconomic estimates of the impact of the crisis, and ensures micro-macro consistency of our exercise.

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[5]As most household surveys account for monthly incomes, one needs to consider the equivalent of the shock in the considered time-frame in terms of monthly shock. For example, if (as in this case), we are estimating the shock in one trimester, we need to consider the average income shock in each month of the trimester in order to compute the effect on monthly incomes in the survey or, alternatively, multiply all incomes by three.

Finally, in step 5 we distribute the aggregate income loss of self-employed and informal workers based on their characteristics and ability of working from home, similarly to what is done for formal workers (more on this in Section 5.3.1). Then, we use the simulated individual income estimated in step 6 (Y_a) to recalculate household income and re-compute the poverty rate.

This approach is mechanical, static, and of partial equilibrium; it does not take into account individuals' potential behavioral responses (e.g. changes in their economic decisions due to shocks or policies); it does not incorporate impacts derived from the temporary accumulation of the effects of the shock; and it does not take into account the effect of shocks or policies through changes in other markets or sectors of activity (general equilibrium effects). However, by estimating poverty on the second trimester, we are capturing a very short-run effect in which behavioral changes or general equilibrium effects are unlikely to happen or be large. Moreover, our approach has the advantage of being simple to implement and to obtain results for short-term analysis, such as the one presented here (Bourguignon and Spadaro, 2006).

4 Data

4.1 Household survey

The main data source for the empirical exercise is the Uruguayan Household Survey (*Encuesta Continua de Hogares*, ECH in Spanish), carried out by the National Statistics Institute on a monthly basis throughout the year, that is nationally representative of all Uruguayan households (INE, 2020a). After-tax income information is gathered for each household member aged 14 years or older. This includes all sources of income (e.g. labor income), of all types (cash and in-kind), and for all earners (self-employed, business owners, pensioners, etc.). The ECH also collects information on tasks and activities for each occupation of every employed individual, and whether they work in the formal or informal sector[6] All information is separately recorded for the main occupation and others if it is the case. Transfers (mainly from the government) are separately registered for each individual and include: cash transfers, in-kind transfers, pensions, unemployment benefits and other non-contributory benefits.

We use the most recent microdata available (2019), and update all monetary values to March 2020 using the Consumer Price Index, constructing Y_b from step 1 in Section 3.2. We exclude public sector workers: they are not at risk of being dismissed due to the pandemic, since the institutional setting of Uruguay makes it extremely hard to actually fire a public worker, involving a process that takes months and may require Congress approval. We also exclude business owners from the analysis for several reasons, though they only represent 3.7% of all

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[6]Tasks coded by the International Standard Classification of Occupations 08 (ISCO-08), four digits; firm/activity coded by the International Standard Industrial Classification (ISIC Rev. 4), four digits.

employed individuals[7], but we do include self-employed workers (which differ from business owners).[8] Thus, we focus on private sector workers, workers in cooperative firms, and the self-employed, and consider labor earnings from the main occupation.[9]

4.2   O*NET dataset

*O*NET* refers to the US Department of Labor's Occupational Information Network surveys, which ask workers about their 'work context' and 'generalized work activities'. Dingel and Neiman (2020) use two waves of the survey to construct a variable (*workhome*) measuring the feasibility of working from home for many occupations (on a 1 to 5 scale).[10]. Mongey and Weinberg (2020) use the same surveys to construct a variable (*prox*) measuring, for each occupation, the implied proximity to other individuals in the workplace (on a 1 to 5 scale). These two variables are constructed using the Standard Occupational Classification (SOC) at 5 and 6 digits, while the ECH uses ISCO-8 codes at 4 digits. We follow Guntin (2020) and take the normalized value of each variable, compute the mean for each SOC code, and then the average at the ISCO-08 level.[11] We obtain two variables on a 1 to 5 scale measuring Uruguayan workers' ability to perform their work from home or without proximity to others. These variables are the basis for the econometric model used later on to predict the probability of being affected by the pandemic.

4.3   Social Security data

In the period of analysis there are three different unemployment benefits schemes: (i) 'full layoff', in which the worker is fired, receives decreasing benefits and the link with the firm is broken; (ii) 'suspension', in which the worker is 'suspended', receives unemployment benefits for one month (later extended) and later returns to the firm or is laid off; (iii) 'reduction', in which

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[7]Business owners are defined by INE as individuals who run or exploit their own business and employ one or more paid workers. They are firm owners, who may or may not actually work in their firms and are entitled to benefits, dividends, etc. They are not entitled to unemployment benefits through the social security system. We consider business owners as the least likely (after public sector workers) to loose their jobs due to the pandemic.

[8]Self-employed workers are defined by INE as those who do not depend on a business owner to run their own economic activity, and do not employ paid workers (they may be assisted by unwaged family members).

[9]92.2% of non-public and non-business owners only have one occupation.

[10]The authors study if an occupation requires, for instance, 'work outdoors' or 'operating vehicles, mechanized devices, or equipment', which implies it cannot be performed from home. They cross-check their classification with others in the literature, showing general consistency and robustness.

[11]We thank Rafael Guntín for sharing his code. Guntin (2020) harmonizes SOC to ISCO-08 codes using Hardy et al. (2018), based on Acemoglu and Autor (2011). Other papers that classify occupations according to the capacity of working from home or with no proximity to others include Kaplan et al. (2020), Leibovici et al. (2020), Dingel and Neiman (2020), and Mongey and Weinberg (2020) for the United States, and Gottlieb et al. (2020) and Dingel and Neiman (2020) for other countries. Caporale et al. (2020) are an important precedent for Uruguay.

the worker significantly reduces monthly worked hours, and receives government compensation for the reduction (maintaining the link with the firm). Our main data sources are official reports on the number of applications for these unemployment schemes that were received and granted by Uruguay's social security agency (Banco de Previsión Social, BPS), by industry (ISIC 2 digits) for April, May and June. We use this data to estimate the average monthly stock of formal workers in each unemployment scheme by industry, reported in Table A.1 in the Appendix.

5 Simulated scenarios

Following the procedure discussed in section 3, we simulate 21 scenarios based on three different assumptions on the shock on formal workers and seven on the shock on informal and selfemployed workers. Newly implemented cash-transfers are simulated under a single assumption. We present in detail only our central scenario, which we believe is the most likely, though we include other results as robustness checks.

5.1 Simulating shocks over formal workers

In order to proceed with step 2 in section 3.2, we start with the average number of formal workers receiving unemployment benefits in a given month of the trimester.[12] Then, we simulate on the ECH the loss of income from unemployment and the gain of unemployment benefits for this number of individuals, among all eligible workers. To do so, we choose a subset of eligible workers within industries that matches the actual number of laid off, suspended and reduced workers. Note that eligibility rules for unemployment benefits are complex, vary by scheme, and changed in the period.[13] In practice, the ECH does not allow to accurately assess the eligibility of each worker (e.g. it does not record formal days of work in previous employment spells, nor distinguishes between monthly paid workers and day laborers, among others). We focus on the main requirement for all schemes and define eligible workers as those working in their current job for 6 months or longer. Thus our set of eligible workers underestimates the number of formal workers that could receive unemployment benefits.

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[12]By formal workers we refer to dependent workers (employed by a firm). Self-employed workers may make the appropriate contributions to the social security system. However, in Uruguay different rules apply to them and they are not eligible for unemployment benefits.

[13]The main requirement for monthly paid workers is having had a formal job for at least 180 days (not necessarily consecutively or on the same job); laborers on daily contracts must have worked 150 days but contributed for at least 180 days (again, not necessarily consecutively or on the same job); piece-rate workers need both a minimum of 180 days in a formal job and a minimum level of earnings. More complex rules apply for workers in the fishing and rural sectors, or domestic workers (housemaids). Moreover, in March the government relaxed some criteria.

The methodological challenge is how to choose *which* eligible workers to shock. To do so, we start from international and local evidence showing that the probability of job or income loss rises with the difficulty of working from home and/or without direct contact with other people, which implies that the most affected are usually of lower income.[14] We then use an econometric model to estimate the probability of being affected (laid off, reduced or suspended) by the pandemic, based on the two variables measuring workers' ability to work from home or without proximity to others. Appendix A.3 presents the model and regression results. The model displays a pseudo-R^2 statistic close to 20%, thus in our *central scenario* 80% of the shock is assigned randomly, and 20% is assigned based on the probability of being affected predicted by the model.

We also allocate the negative shock across eligible formal workers in two other ways. First, we assign the entire shock randomly (*random scenario*). This is unrealistic and optimistic (as the literature suggests that unemployment is higher among low-income workers with greater difficulties in working from home or without contact with others), but we include it as a benchmark 'optimistic case' for reference. Second, we assign 50% of the shock randomly, and 50% based on a crude measure of the probability of being affected, unrelated to the econometric model (*50%-50% scenario*).[15]

In all scenarios, workers in 'suspensions' or 'full layoffs' lose all labor earnings from their main occupation, and receive a transfer corresponding to 66% or 50% of their lost income respectively, as per the official regulations.[16] Official unemployment eligibility criteria is difficult to reproduce in the data; as the ECH lacks information on earnings for the last six months (among other issues), we calculate unemployment benefits based on the earnings reported in the surveyed month and apply legal caps on benefits.[17] Benefits increase an additional 20% if the worker is part of a 'constituted household' ('hogar constituido' in Spanish; which refer to individuals married or cohabiting with a partner, and/or households with children up to 21 years old, or disabled members). For 'reduced' formal workers, we assume that they keep half of their earnings from their main occupation, lose the other half, and receive a subsidy of 50% of their lost earnings.

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[14]Acemoglu and Autor (2011), Kaplan et al. (2020), Leibovici et al. (2020), Dingel and Neiman (2020), Mongey and Weinberg (2020), and Gottlieb et al. (2020) reach similar conclusions for other countries, as Guntin (2020) and Caporale et al. (2020) do for Uruguay.

[15]We take the minimum of the two variables measuring the feasibility of working from home and without proximity to others. We choose the 50% of eligible workers in ascending order based on this minimum.

[16]In April the government announced increased (75%) benefits for 'suspensions', with no starting date. We use the 50% benefit (actual policy); results with higher benefits barely change and are available upon request.

[17]The minimum benefit for 'full layoffs' and 'suspensions' is of about 127 USD, and the upper bound is of about 1,418 USD and 1,031 USD respectively.

5.2 Simulating new cash transfers by the government

After the detection of the first COVID-19 case in Uruguay, the government started announcing different sanitary and economic measures. To compute cash-transfers in step 3 in Section 3.2, we focus on the main three shown in Figure 1. The first two reinforce existing cash transfer programs: a 50% increase in the transfer through the TUS Program, and a 50% increase in the transfer through the AFAM-PE program, both described in Section 2. Note that households already receiving TUS are not entitled to the additional AFAM-PE funds. Simulating these policies is straightforward as beneficiaries are adequately identified in the ECH.

The third measure consisted of the distribution of an average of 160,000 baskets per month of first-necessity goods valued in about 28 USD, targeted to informal workers not covered by other government programs. Though initially the government delivered actual baskets of goods, it later deployed a smartphone app allowing beneficiaries to directly spend the transfer in selected stores. We assigned the 160,000 transfers assuming imperfect focalization: approximating the imperfect capacity of the government to target the poorest individuals but maintaining an important coverage of the desired population.[18] Our method implies a failure rate of 1/3 (one out of three individuals that should receive a basket fail to get one).[19] We were unable to simulate a fourth policy ('monotributistas MIDES', a transfer of about 154 USD to circa 10,000 individuals aimed at increasing formality among poor, vulnerable and self-employed individuals), as the ECH does not identify beneficiaries. We contemplate the potential impact of this small policy later on when analyzing results.

5.3 Simulating shocks over informal and self-employed workers

There is no information available on the number of informal or self-employed workers who lost their job or part of their income due to the contraction in activity levels. This is a pervasive problem in many developing countries and our estimation strategy is one of the main contributions of this paper. Note that informal workers cannot apply for unemployment benefits by definition, although under Uruguayan law the self-employed (even when contributing to the social security system) are technically (micro) firm owners and are also left out of unemployment benefits. Thus, to apply steps 4 and 5 in Section 3.2, we use three different ways of estimating the number of affected informal and self-employed workers, and four ways of assigning individual income losses, totaling seven different scenarios. We present our *central scenario* in detail, but include the others in the results.

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[18]We ordered individuals from the poorest onward. Then, we skipped the first and assigned a transfer to the following two, skipped the fourth and covered the fifth and sixth, and so on and so forth.

[19]We also simulated a perfect focalization policy with very similar results, which are available upon request.

5.3.1 Estimating the size of the shock based on the labor income's share in GDP and the negative shock to GDP

Following equation 2 in Section 3.2, $Shock_{2020}$ and Sh_{mo} are based on 2019's GDP and the contraction forecast for 2020 by the *Centro de Investigaciones Económicas* (CINVE, 2020). This projection implies a contraction of -4.175% for the whole 2020, of which 72% falls on the second trimester of the year, which is equivalent to a 24% fall in each month. Note that the negative shock is conservative, as ECLAC's latest forecast is a 5% downturn for Uruguay (ECLAC, 2020d). Still, we chose the estimation by CINVE (2020) as it is the only one that provides a disaggregation by trimester.[20] Given the importance of these assumptions, they are subject to sensitivity checks in Section 6. It is worth stressing that the approach allows to easily incorporate new data inputs as they become available. In particular, when official GDP contraction estimations by the Central Bank for the second trimester become available, they can be used to re-compute the poverty spike with more accurate data.

Sh_{la} is not reported in National Accounts and is estimated at 60%, based on (De Rosa et al., 2018). This share includes both wages and other labor income, accounting for the share of mixed income that is closest to labor income. We assume that the crisis does not affect the functional distribution of the economy, which is unlikely given historical experience, hence it underestimates the aggregate effect. Finally, $Sh_{su/GDP}$ is directly computed from the data and equals 65.4%.

After estimating all the components of the right hand side of Equation 2 we obtain $L_{in} + L_{se}$, and we distribute this mass of lost income as follows. First, we define an income loss for each informal or self-employed worker as a share of her labor earnings equal to the predicted probability of being affected (from the econometric model). Second, we randomly choose informal and self-employed workers until the accumulated lost labor earnings reach 80% of ($L_{in} + L_{se}$). Third, we choose among remaining informal and self-employed workers based on the probability of being affected (same method used for the *central scenario* for formal workers) until completing the remaining 20% of ($L_{in} + L_{se}$). This methodology constitutes our *central scenario* for informal and self-employed workers.

We consider four other methods to allocate the mass of lost labor earnings across informal and self-employed workers (scenarios *A.1* to *A.4*). We vary the income lost by each informal and self-employed worker (using a uniform distribution or the econometric model predictions) and the way the workers are chosen (e.g. randomly, part random and part based on the ability of working from home or based on the econometric model predictions). These scenarios show sensitivity of results to different ways of choosing affected workers and assigning individual

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[20]*Centro de Investigaciones Económicas* (CINVE) is a prestigious private economic research center, that regularly produces GDP and other key economic variables forecasts, widely used locally. We thank CINVE for sharing their estimations.

income shocks. We further consider two other scenarios, that do not guarantee micro-macro consistency. In *scenario B* we base both the probability of being affected and the share of labor income lost for informal and self-employed workers on the econometric model, but without the cap given by the macroeconomic estimates of lost earnings. In *Scenario C* we assume the ratio of formal to informal and self-employed workers is constant within affected industries and holds for lay-offs, reductions and suspensions, and use the data on affected formal workers to estimate the corresponding number of non-formal affected workers. All these additional scenarios are explained in detail in Appendix A.4.

6 Poverty increase in Uruguay

In this section we first present our estimates of the increase in the poverty rate for the second trimester of 2020, with and without the effect of the three main government policies. Second, we calculate the cost of neutralizing the poverty spike based on the existing public policies.

6.1 Poverty rates by scenario: with and without government policies

Table 1 shows the predicted poverty rate for the 21 scenarios. A scenario with no shock to informal and self-employed workers is also included, to facilitate comparisons.[21]. Given a random component in each scenario, we repeat each estimation 200 times to compute standard errors; in all cases 95% confidence intervals (reported in Appendix A.2) are small. The baseline poverty rate is 8.5%.[22]

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[21]Table A.2 in the Appendix presents results in absolute terms.
[22]This is lower than the official poverty line for 2019 (8.8%), due to corrected cash transfers from the AFAM-PE program.

Table 1: Poverty rates, second trimester 2020 by scenario, with and without new government policies.

| | Shock to formal workers | | | | | |
| | Random | | Central | | 50%-50% | |
Shock to informal / self-employed workers	Without Policies	With Policies	Without Policies	With Policies	Without Policies	With Policies
No shock	9.4%	8.6%	9.1%	8.3%	9.4%	8.7%
A.1	10.7%	9.9%	12.3%	11.6%	10.7%	9.9%
A.2	10.8%	10.0%	12.5%	11.8%	10.8%	10.0%
Central	10.8%	10.0%	12.5%	11.8%	10.8%	10.1%
A.3	11.2%	10.4%	12.8%	12.1%	11.2%	10.4%
A.4	11.3%	10.5%	13.1%	12.4%	11.3%	10.5%
B	14.5%	13.8%	14.1%	13.5%	14.5%	13.8%
C	11.2%	10.5%	10.9%	10.2%	11.2%	10.5%

Note. Own elaboration based on ECH microdata from INE. Results from 200 simulations; 95% confidence intervals are reported in table A.4 in the Appendix.

Our *central scenario* entails an increase of approximately 3.3 points in the poverty rate, from 8.5% to 11.8%. This represents about 115,969 additional poor individuals.[23] Note that scenarios *A.1* to A.4 display very similar results. This indicates that results based on a micro-macro consistent method do not strongly depend on the specific assumptions chosen regarding size and way of distributing the shock to formal and non-formal workers. We do observe differences when applying other methodologies (scenarios B and C). Scenario B presents 'upper bound' estimates, with the largest number of affected informal and self-employed workers and a poverty rate above 13%. Scenario C presents 'lower bound' estimates, with the fewest number of affected informal and self-employed workers (as only non-formal workers in eleven industries are affected).

Our results show that in general the new government policies have very modest results. In our *central scenario*, the new policies reduce poverty by approximately 17.6%: in the absence of policies, an additional 24,758 people would have fallen below the poverty line. As mentioned above, unemployment benefits and pre-existing transfers (e.g. regular TUS and AFAM-PE cash transfers) are already considered in the 'without policies' simulations; we are quantifying the *additional* effect of the three main new government policies. The moderate impact on poverty rates come as no surprise as these policies represent an average transfer of about 38 USD per receiving household (around 4% of the targeted households' income). The only case in which the new policies are effective is under the unrealistic assumption of no shock for informal or self-employed workers (first row).

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[23]Such a sharp increase in poverty rates has not been seen since the 2002 crisis.

Figure 3: Poverty rates in the *central scenario*, by GDP shock
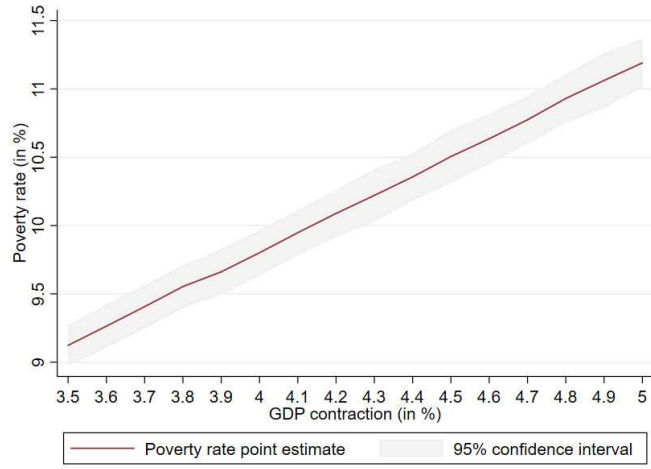
As mentioned above, our *central scenario* estimates the new poverty rate based on a -4.175% contraction of annual GDP. As a robustness check, we repeat the exercise for this scenario considering contractions from -3.5% to -5% (ECLAC, 2020d). Results in Figure 3 show that the poverty rate increases with the assumed economic shock: each additional -0.1% GDP shock increases the estimated poverty rate by approximately 0.14 percentage points. Moreover, our *central scenario* estimates the new poverty rate based on a concentration of 72% of the annual shock on the second trimester (24% per month). We also repeat the exercise for this scenario considering monthly concentrations from 19% to 34%; results are presented in Figure A.2 in the Appendix.[24]

6.2 Cash transfers required to avoid poverty increases

In this subsection we first calculate the additional amount of resources that *each affected individual in our simulation* must receive to keep their household exactly above the poverty line.[25] Concretely, we estimate the total amount of resources needed to prevent *only* the individuals

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[24]Note that equation 2 involves a multiplication of both assumptions ($Shock_{2020} \times Sh_{mo}$), sensitivity analysis of the first term are equivalent to sensitivity analysis of the second term: a 0.1 percentage point change in the GDP contraction used is equivalent to a 0.24 percentage point change in the share of the annual shock affecting a specific month. Both exercises are equivalent to a grid search centered on our main assumptions, that is, sensitivity analysis to changes in both $Shock_{2020}$ and Sh_{mo} at the same time.

[25]We set *the same* individuals that were affected by (our simulated) shock above the poverty line. This differs from computing reducing poverty rates to pre-crisis levels through transfers to *any* individual (affected or not). Results for this alternative case are available upon request; we find that about 6.3 million USD are needed to revert the *central scenario* to pre-pandemic levels.

affected by COVID-19 to fall below the poverty line, which implies perfect targeting of funds. Note that our estimates are not a quantification of the true actual costs of such policy, due to administrative costs and to the empirical impossibility of perfect targeting. Furthermore, these estimations move households that fell below the poverty line exactly to that income level. This policy would not be advisable in a widespread crisis such as the current one, as low-income households (exactly on the poverty line) would still be highly vulnerable and probably affected by poverty along non-monetary dimensions. Beyond these caveats, our estimates in Table 2 illustrate orders of magnitude of the transfers needed to prevent poverty increases, which are still informative and useful.[26]

Results show that in our *central scenario*, avoiding poverty increases would cost about 23.7 million USD (per month), which is equivalent to about 0.46% of Uruguays' 2019 annual GDP. The lower and upper bounds (16.5 and 30.8 million USD) correspond to extremely optimistic and pessimistic scenarios but still show that it is possible to greatly reduce the effects of the pandemic on poverty. Our estimates indicate that a substantial reduction in the negative effects of COVID-19 on poverty is achievable by public policy with non-prohibitive amounts of resources (in the case of a budget-constrained developing country as Uruguay).[27]

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[26]This exercise is related to policies that could actually be easily implemented. For instance, De Rosa et al. (2020) propose a full doubling of the TUS and AFAM-PE transfers (allowing overlapping of transfers), with an additional cost of about 10 million USD per month. We simulated this policy and found a reduction in the increase in poverty rates for our *central scenario* of 1.2 percentage points, cutting poverty increases almost by half (results available upon request). More importantly, this exercise shows the potential impact of an *immediate* expansion of *existing* transfers on poverty, with minimal administrative and logistical costs.

[27]Finally, as mentioned above, all scenarios omit the MIDES *monotributistas* program. This should have a small effect on our estimations: the total monthly transfer rises to about 1.6 million USD per month (6.8% of our monthly estimate for the *central scenario*); it should have little impact on the poverty rate. Moreover, even assuming that each beneficiary integrates a household of three people, and that the transfer in *all* cases lifts them above the poverty line, this leads to 30 thousand fewer poor individuals, which yields a poverty rate still above 11.2% (around 95 thousand additional poor individuals).

Table 2: Transfers needed to take the affected individuals just above the poverty line.

	Shock to formal workers					
	Uruguayan Pesos (millions)			US Dollars (millions)		
	Random	*Central*	50%-50%	Random	*Central*	50%-50%
Shock to informal / self-employed workers	With Policies	With Policies	With Policies	With Policies	With Policies	With Policies
A.1	715	983	715	16.5	22.7	16.5
A.2	729	1,025	730	16.8	23.7	16.9
Central	730	1,028	730	16.8	23.7	16.9
A.3	789	1,059	789	18.2	24.5	18.2
A.4	785	1,115	786	18.1	25.8	18.2
B	1,331	1,297	1,332	30.7	29.9	30.8
C	812	781	813	18.8	18.0	18.8

Note. Own elaboration based on ECH microdata from INE. Results come from 200 simulations; 95% confidence intervals are reported in table A.6. Our estimates report the transfers needed to push back the same individuals affected by the crisis exactly above the poverty line. Uruguayan Pesos to USD exchange rate set to 43,3

7 Concluding remarks

In this paper we propose a micro-simulation approach to estimate the likely evolution of poverty rates in real time in the face of the COVID-19 crisis. Our procedure provides estimates that are fully consistent on a micro-macro level with estimates of the potential contraction of the GDP, while addressing the issue of how to assess the effect of the shock on informal and self-employed worker s.

We illustrate the details of our methodology with an application to the case of Uruguay. Due to the imperfect nature of the data, our estimations should not be taken as precise measurements. Nevertheless, we consider a broad set of assumptions and perform sensitivity analysis, and conclude that the general direction and magnitude of the changes in the number of people below the poverty line is accurate. To sum up, results show (i) a rapid increase of over 38% in poverty rates; (ii) positive but modest ameliorating effects of new government policies; (iii) the possibility of greater reductions in poverty rates at low cost (around 0.5% of GDP).

Finally, a central message of this paper is that the new public policies deployed have positive yet insufficient effects, and that increasing their effectiveness is within reach, economically, logistically and administratively. This message is valid also for other developing countries and is of particular importance if the future leads us to further restrictions of activity, with new rounds of negative effects on workers. For this reason, we argue that vigorous and sustained public policies are of capital importance and within reach, right now.

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A Appendix

A.1 Additional Figures and Tables

Figure A.1: Evolution of COVID 19 cases and deaths in Uruguay
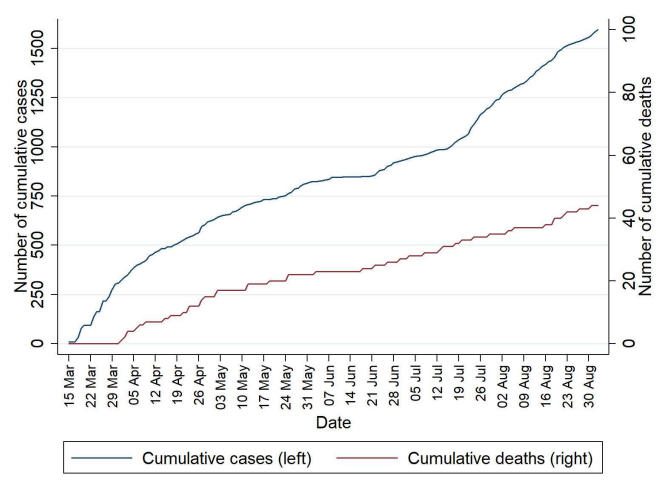
Note. Official series by the National Emergency System of Uruguay (SINAE, in Spanish).

Figure A.2: Poverty rates in the *central scenario*, by monthly concentration of the shock
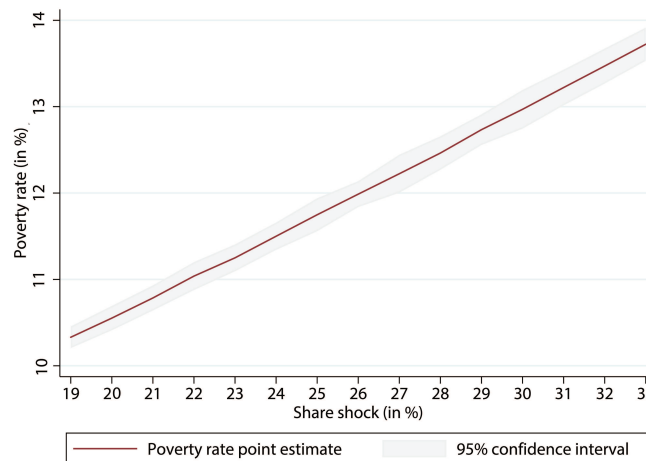
Note. Own elaboration based on ECH microdata. Point estimates correspond to 100 simulations for the *central scenario*. The gray area represents the 95% confidence interval.

Table A.1: Number of laid off formal workers that receive for unemployment benefits, by scheme and industry, monthly average in second trimester 2020

Industry (ISIC 2 digits)	Sector Name	Suspension	Reduction	Layoff	Total
45, 46 and 47	Wholesale and retail trade; repair of motor vehicles and motorcycles	39,043	927	2,134	42,105
10 to 33	Manufacturing	16,101	6,135	1,399	23,635
55 and 56	Accommodation and food service activities	19,308	828	1,344	21,480
49 to 53	Transportation and storage	12,030	495	870	13,396
77 to 82	Administrative and support service activities	7,479	381	732	8,593
41	Construction	4,045	464	1,945	6,455
97 and 98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	3,506	1,433	569	5,508
94, 95 and 96	Other service activities	4,852	207	339	5,398
85	Education	4,473	739	178	5,390
90 to 93	Arts, entertainment and recreation	3,628	692	231	4,552
86, 87 y 88	Human health and social work activities	2,957	328	203	3,489
Total		117,422	12,632	9,946	140,000

Note. Own elaboration based on BPS data. The table reports the monthly average number of workers that applied for and were granted unemployment benefits, by unemployment scheme and industry.

Table A.2: Number of additional individuals below the poverty line in April 2020 by scenario, with and without new government policies.

	Shock to formal workers					
	Random		*Central*		50%-50%	
Shock to informal / self-employed workers	Without Policies	With Policies	Without Policies	With Policies	Without Policies	With Policies
No shock	29,407	3,404	18,843	-6,393	29,739	3,705
A.1	75,759	48,959	132,667	106,362	76,190	49,334
A.2	79,292	53,091	140,617	115,764	79,591	53,298
Central	79567	53,314	140,727	115,969	80,012	53,695
A.3	93,612	66,101	150,528	124,131	93,630	66,041
A.4	95,661	68,195	162,289	137,763	95,745	68,384
B	209,828	185,377	196,827	173,228	210,160	185,746
C	94,533	68,692	82,957	57,867	94,819	68,931

Note. Own elaboration based on ECH microdata from INE. Results from 200 simulations; 95% confidence intervals are reported in table A.5 in the Appendix.

A.2 Confidence intervals

Table A.3: 95% confidence interval for Table 1

Shock to informal / self-employed workers	Shock to formal workers					
	Random		*Central*		50%-50%	
	Without Policies	With Policies	Without Policies	With Policies	Without Policies	With Policies
No shock	0.05%	0.05%	0.04%	0.03%	0.04%	0.04%
A.1	0.09%	0.09%	0.10%	0.10%	0.09%	0.09%
A.2	0.09%	0.09%	0.09%	0.10%	0.09%	0.09%
Central	0.09%	0.09%	0.10%	0.10%	0.08%	0.08%
A.3	0.10%	0.10%	0.09%	0.09%	0.12%	0.10%
A.4	0.07%	0.07%	0.09%	0.10%	0.07%	0.07%
B	0.08%	0.08%	0.08%	0.08%	0.08%	0.08%
C	0.08%	0.08%	0.07%	0.07%	0.08%	0.08%

Note. Own elaboration based on ECH microdata from INE. Results from 200 simulations.

Table A.4: 95% confidence interval for Table 2

Shock to informal / self-employed workers	Shock to formal workers					
	Uruguayan Pesos (millions)			US Dollars (millions)		
	Random	*Central*	50%-50%	Random	*Central*	50%-50%
	With Policies	With Policies	With Policies	With Policies	With Policies	With Policies
A.1	4.9	12.6	5.3	0.11	0.29	0.12
A.2	4.7	14.4	3.8	0.11	0.33	0.09
Central	4.1	15.0	4.6	0.09	0.35	0.11
A.3	4.7	13.6	4.6	0.11	0.31	0.11
A.4	3.3	16.9	3.5	0.08	0.39	0.08
B	16.9	16.2	17.1	0.39	0.37	0.39
C	4.2	4.4	4.3	0.10	0.10	0.10

Note. Own elaboration based on ECH microdata from INE. Results from 200 simulations.

Table A.5: 95% confidence interval for Table A.2

| | Shock to formal workers | | | | | |
| | Random | | *Central* | | 50%-50% | |
Shock to informal / self-employed workers	Without Policies	With Policies	Without Policies	With Policies	Without Policies	With Policies
No shock	1664	1608	1267	1211	1551	1421
A.1	3097	3046	3355	3413	3157	3124
A.2	3076	3168	3274	3353	3119	3012
Central	3050	3011	3363	3521	2752	2836
A.3	3682	3687	3017	3100	4059	3638
A.4	2484	2471	3301	3406	2517	2519
B	2955	2966	2705	2735	2840	2908
C	2809	2686	2631	2625	2943	2811

Note. Own elaboration based on ECH microdata. Results come from 200 simulations.

A.3 Econometric model

The econometric model estimates the correlation between the probability for an eligible formal worker to be affected (laid off, suspended or reduced) and apply and obtain unemployment benefits, and the ability of that worker to carry out her work from home and without close contact with others. We focus on eligible formal workers (excluding informal and self-employed workers, business owners and public sector employees). We use the number of affected workers (Table A.1) and the variables *workhome* and *prox* constructed following (Guntin, 2020).

We calculate the number of formal workers (with the exceptions mentioned) eligible for unemployment benefits by industry and compute the proportion of eligible formal workers by industry that applied and obtained unemployment benefits (by scheme). In other terms, we construct a measure of the fraction of total eligible workers effectively obtaining unemployment benefits (*Shares*). We add a twelfth sector comprising all eligible formal workers (with exceptions) in the remaining sectors and assign them $Shares = 0$. With this sample, we estimate the following logit model:

$$Share_s = workhome_{is} + workhome_{is}^2 + prox_{is} + prox_{is}^2 + e_{is} \qquad (3)$$

Here $Share_s$ represents the proportion of eligible formal workers in sector s that applied for unemployment benefits, *workhome* and *prox* measure a worker's ability of working from home and without proximity to others.[28] e_{is} represents the error term, and the model is estimated using robust standard errors. Strictly speaking, the dependent variable is not the probability of being affected, but we make the conceptual jump as an assumption. Though the dependent variable is constant for all workers in the same industry, estimating he model using the average of the variables of interest computed at the industry level involves losing information, since the same average can arise from different distributions of the variables within each industry. For this reason we ran the regression using individual data. A.6 below presents regression results

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[28]These variables were redefined so that 1 represents the greatest ease of working from home and the least need to work in close proximity with other people, and 5 is the opposite.

(Column 1).

Results indicate that both variables have the expected effect: less ability to work from home and greater need to work in contact with others are associated with a higher proportion of eligible formal workers applying and obtaining benefits. Quadratic terms indicate that the positive effect is decreasing. Note that the pseudo-R^2 is close to 0.2. Estimates from a probit model (Column 2) for a robustness check produced similar results.[29]

Table A.6: Predicting the probability that eligible formal workers receive unemployment benefits: probit and logit estimations

| | Eligible formal worker share receiving unemployment benefits | |
Variables	Logit	Probit
workhome	13.652***	7.757***
	(0.053)	(0.030)
workhome^2	-2.533***	-1.441***
	(0.010)	(0.006)
prox	6.401***	3.856***
	(0.057)	(0.031)
prox^2	-0.794***	-0.489***
	(0.00888)	(0.00458)
Constant	-26.60***	-15.32***
	(0.124)	(0.0675)
Observations	872,074	872,074
(pseudo) R^2	0.190	0.188

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 The dependent variable is the share of eligible formal workers that received unemployment benefits, by activity sector (ISIC 2 digits).

A.4 Alternative simulated scenarios

Alternative estimation based on the labor income's share in GDP and the negative shock to GDP

We considered four different scenarios, beyond the central one. In *scenario A.1*, the share of labor earnings lost by each informal and self-employed worker (if chosen) is assigned randomly, using a uniform distribution (0% to 100%). Then, we choose informal and self-employed workers randomly until the accumulated total lost labor earnings matches our estimation. In *scenario A.2*, the share of labor earnings lost by each informal and self-employed worker (if chosen) is equal to the predicted probability of being affected (from the econometric model). Then, we choose informal and self-employed workers randomly until the accumulated total lost labor earnings matches our estimation.

In *scenario A.3*, the share of labor earnings potentially lost by each informal and self-employed worker comes from the uniform distribution. Then, we randomly select informal and self-employed workers until we accumulate 50% of the overall labor earnings lost according to

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[29]We ruled out a linear probability model since, although it may yield adequate estimates for the average, we are particularly interested in predicting the probability of being affected, hence the need for a method with predictions bounded between 0 and 1.

our estimates. We choose among remaining informal and self-employed workers in ascending order based on a cruder measure of the probability of being affected by the pandemic, until accumulating the remaining 50% of our estimated total lost labor earnings.[30] In *scenario A.4*, the amount lost by each informal and self-employed worker comes from the estimated probability of being affected (from the econometric model). Then, we randomly select informal and self-employed workers until we accumulate 50% of the overall earning losses estimated. We then choose among remaining informal and self-employed workers in ascending order based on a cruder measure of the probability of being affected until accumulating the remaining 50% of total lost earnings estimated.

Estimating the size of the shock based on the probability of being affected by the pandemic

In *scenario B*, we use only the estimated probability of being affected by the pandemic, from the econometric model. The model is run using data for eligible formal workers, and we use results to predict the probability of being affected for all informal and self-employed workers. We then use these probabilities to draw a sub-sample of affected informal and self-employed workers. Then, for each selected informal and self-employed worker we subtract a share of their labor earnings equal to the estimated probability of being affected. This is the most pessimistic scenario, as it predicts the largest number of affected individuals. But, it has the advantage of neutralizing potential problems of using the participation of labor earnings on GDP and on relying on specific assumptions of GDP contractions as starting points. Still, as it is based on a simple econometric model (with a pseudo-R^2 of almost 20%), we present these results mostly as robustness checks.

Estimating the size of the shock based on the relationship between formal and informal/self employed workers in each sector

Scenario C is the least sophisticated, and is based on the share of formal and informal and self-employed workers observed in each of the eleven affected sectors. In a way, it is a crude approximation to a 'production function' approach. First, based on the ECH, we calculate the share of informal and self-employed workers in each of the affected industries. Second, we assume that the relationship between formal and informal and self-employed workers within each industry is constant, and holds even for layoffs, suspensions and reductions. In abstract terms, we use the structural distribution of workers between formal and informal and self-employed within each industry to estimate the number of informal and self-employed workers that should be laid off, suspended or reduced (and apply to unemployment benefits, if they could). Then, after computing the number of informal and self-employed workers that should be affected within each industry, we assign this number randomly within industry in the ECH. 'Suspended' and 'fully laid off' workers lose 100% of their income, and 'reduced' ones lose 50% of their income. There are no unemployment benefits. This is an unlikely scenario as it assumes that the shock to informal and self-employed workers concentrates only in eleven industries, and also assumes random assignment of the shock across workers within industries (even when we know low-income workers are more likely to be affected). Then, it is the most optimistic, as it generates the fewest number of affected informal and self-employed workers. Still, we present these results mostly as robustness checks.

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[30]This comes from the minimum of the two variables measuring the feasibility of working from home and without proximity to others. See footnote 18.