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Too little but not too late.

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

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Abstract

The economic crisis triggered by COVID-19 is causing a world-wide massive economic downturn, and what is likely to be the deepest GDP contraction for Latin America since the beginning of the XXth century. We microsimulate the short-run effect of the crisis on the poverty rate for the Uruguayan case based on household survey data, publicly available information on both cash-transfers and the increase in unemployed formal wage-earners applying for unemployment benefits, as well as macro-economic estimates of the likely GDP contraction. By combining these data sources, we are able to estimate the effect of the crisis on formal, informal and self-employed workers, while providing full micro-macro consistency to our results. We find that during the first full month of the lock-down, the poverty rate reaches 11.7%, an increase of over 36%. Moreover, new cash transfers implemented by the government have a positive but very limited effect in mitigating this poverty spike. We estimate that most of this increase in poverty could be neutralized with cash-transfers worth less than 0.5% of Uruguay's annual GDP.

Key words: COVID-19, nowcasting, poverty, microsimulations, developing countries, Uruguay.

JEL classification: D04, D31, I32

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Resumen

La crisis económica desencadenada por la COVID-19 está causando una recesión de grandes proporciones a escala mundial, y lo que probablemente sea la contracción más profunda del PIB para América Latina desde comienzos del siglo XX. En este artículo, microsimulamos el efecto de corto plazo de la crisis en la tasa de pobreza para el caso uruguayo en base a datos de encuestas de hogares, información disponible sobre transferencias monetarias y el incremento en las solicitudes de seguro de desempleo, así como estimaciones macro-económicas de la probable contracción del PIB. Al combinar estas fuentes de información, podemos estimar el efecto de la crisis en trabajadores formales, informales y cuentapropistas, al tiempo que aseguramamos la consistencia micro y macro-económoca de nuestros resultados. Encontramos que durante el primer mes completo reducción de actividades, la tasa de pobreza alcanzó el 11.7%, un aumento de más de 36%. Las nuevas transferencias monetarias implementadas por el gobierno tienen un efecto positivo pero muy limitado para mitigar este pico de pobreza. Estimamos que la mayor parte de este incremento podría neutralizarse con transferencias monetarias por un valor inferior al 0,5% del PIB anual de Uruguay.

Palabras clave: COVID-19, *nowcasting*, pobreza, microsimulaciones, países en desarrollo, Uruguay.

Clasificación JEL: D04, D31, I32

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. Negative external shocks through retraction of trade, tourism and capital together with social distancing measures affect economic activities through a variety of channels, and the duration of the downturn will probably exceed the time span of the sanitary crisis (Boissay and Rungcharoenkitkul, 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 in the XXth century (ECLAC, 2020b).

One of the most visible effects of the COVID-19 crisis is the rapid increase in poverty, which many early studies are estimating through different approaches. Sumner et al. (2020) estimate that the number of people living in poverty could increase by 420–580 million worldwide. For Latin America, ECLAC[1] estimates an increase in poverty rates of up to 4.4 percentage points, which means over 28 million additional people under the poverty line (ECLAC, 2020c). Moreover, Ruiz Estrada (2020) visually shows how quarantines can generate, among other negative effects, an expansion of poverty from a multidimensional perspective. 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%. For the case of Asia, Nizamani and Waheed (2020) identify vulnerable jobs depending on the probability of working from home and conclude that only 18.5 percent of the working population can do so in Pakistan, while Suryahadi et al. (2020) estimate an increase in poverty rates from 9.2% to 9.7% by the end of 2020 for Indonesia. Finally, Bonavida Foschiatti and Gasparini (2020) use micro-simulations together with estimations of the probability of being able to work from home and calculate a 4 percentage point increase in poverty rates for Argentina, even after accounting for cash-transfers.

In this article we quantify the effect on poverty of the contraction in employment and income stemming from the effects of COVID-19 in general an of a lock-down in particular, for the case of Uruguay in April 2020. The main questions we seek to answer are: how many people have fallen below the poverty line since the pandemic began? To what extent have the measures implemented by the government neutralized these negative effects? How many additional resources are needed to maintain the poverty rate at pre-crisis levels? To answer them, we perform microsimulations based on a Household Survey and three major inputs: (i) official data on around 140,000 laid off formal workers that applied for unemployment benefits (over 5% of adult population and more than 10% of all formal workers); (ii) an estimated loss in employment and income levels for informal and self-employed workers, consistent with the expected contraction of the economy; (iii) the main countervailing cash-transfers measures deployed by the government. We simulated a wide range of alternative scenarios, varying the

[1] The United Nations' Economic Commission for Latin America and the Caribbean.

contraction in economic activity and the patterns of distribution of the negative shock among workers and sectors of activity, yielding very similar results.

The key contribution of the paper is to combine the approach based on the feasibility of working from home or in close proximity with others, with estimates of the shock for the informal and self-employed sectors anchored in macro-economic estimates of the effects of the pandemic, leading to a micro-simulated set of scenarios that bridge a gap in the literature. In particular, we propose a specific methodology to solve the issue of how to assess the effect of the shock on informal and self-employed workers, with is of utmost importance in developing countries where social security coverage tends to be low.

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 the longest period of uninterrupted growth in its history since 2004, 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).[2] This rapid economic growth, coupled with a wide range of redistributive policies (Bucheli et al., 2013; Amarante et al., 2014), resulted in a steep decrease in poverty from 32.5% in 2006 to 8.8% in 2019 (INE, 2020). 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 and vulnerable to negative economic shocks.[3] Although the consensus in the literature is that poverty is a multidimensional social phenomenon (Sen, 1993; Ravallion, 2011), income-based poverty can experience significant changes in the short run, which may have longer term consequences in the presence of poverty traps, which has proven to be the case in past crises both in Uruguay and elsewhere (Arim et al., 2013; Banerjee et al., 2019). Thus, from a multidimensional perspective, different studies estimate that around 40% of the Uruguayan population is still vulnerable to adverse economic shocks in 2020 (Colafranceschi et al., 2018; Failache et al., 2016). According to all available estimates (IMF, 2020; ECLAC, 2020b; World Bank, 2020), the COVID-19 economic crisis will be harder and deeper than any shock that could have been anticipated only a few months ago. In this context, this paper finds three main results.

First, poverty increases very rapidly. In our *central scenario*, based on a 3.5% drop in GDP,[4] the poverty rate (after accounting for the new cash-transfer programs) increases by 3.2 percentage points and lies between 11.4% and 12.5% depending on the scenario. This represents

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

[3]Survey-based household per-capita income inequality Gini index experimented an impressive reduction of 0.07 points from 2008 to 2013. Nevertheless, tax-records based estimations indicate that there is still very high income concentration, with a top 1% share of over 15% (higher income than the entire bottom 50% combined) (Burdin et al., 2020)

[4]This estimate lies between the -3% contraction estimated in IMF (2020) and the -4% one estimated in ECLAC (2020b). Later on in the document, we test the sensitivity of the results to the chosen GDP shock.

between 99,000 and 138,000 additional individuals below the poverty line, an increase of around 36.7% with respect to pre-pandemic levels. In a sensitivity analysis we find that each additional 0.1% contraction in GDP increases our estimate of the poverty rate by about 0.21 percentage points.

Second, the new cash-transfers implemented by the government as a result of the crisis slightly moderate the increase in poverty, but are insufficient to neutralize it. We focus on the three main new measures announced and deployed since the pandemic arrived to the country: (i) a 50% increase in cash transfers corresponding to the *Tarjeta Uruguay Social* program (TUS in spanish), which targets highly vulnerable households; (ii) a 50% increase in cash transfers corresponding to a wider-scope child-transfers program (*Asignaciones Familiares-Plan de Equidad*, AFAM-PE by its acronym in spanish), limited to household not recipients of TUS[5]; (iii) the distribution of a food basket worth 1,200 Uruguayan Pesos (about 27 USD) to informal workers not covered by other programs.[6] These measures entail an additional transfer, on average, of 1,622 Uruguayan Pesos (about 37 USD) per recipient household (around 400 Uruguayan Pesos per person, about 9 USD). This represents approximately 4% of the income of the beneficiary households. As a result, we estimate that these three policies mitigate the increase in poverty by around 20%.[7]

Third, the increase in poverty is largely avoidable. Although the medium and long-term effects of the pandemic on poverty, inequality, well-being and development are still uncertain and will require a wide range of policies, the increase in short-term poverty in Uruguay can be neutralized through (modest) additional cash transfers. In particular, the amounts of resources that we estimate are needed to keep all affected households above the poverty line are well within existing budget restrictions. Concretely, we estimate that maintaining poverty at 2019 levels would require additional transfers of about 22.6 million USD per month. The yearly cost of this policy represents about 0.44% of Uruguay's 2019 GDP. Although this estimation 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 scope of public policies.[8]

The paper makes a number of contributions to the literature. First, it adds empirical evidence to the growing literature on potential impacts of the pandemic on poverty, of great importance in the case of developing countries. Moreover, even though the static-mechanic

[5]Both 50% increases were announced as a doubling of the transfer (100% increase), for one time only, but in two monthly installments, which means in practice a 50% increase in April.

[6]Initially the government announced the delivery of a physical basket of goods, but later on transformed the initiative into cash transfers worth 1,200 Uruguayan Pesos.

[7]In the absence of the policies, an additional 26,000 people would have fallen below the poverty line, reaching a poverty rate of 12.4%.

[8]Note that in April and May several agencies confirmed the investment grade qualification for Uruguay. The Ministry of Economics and Finance reported in May that there were about 1.800 million United States Dollars (USD) of contingent credit lines with multilateral credit institutions yet to be used (Ministerio de Economía y Finanzas , 2020); and the government has been working to expand access to credit.

microsimulations approach presents a number of drawbacks, it allows for a relatively precise estimation of the short-run effects of the crisis on important economic dimensions such as poverty (Bourguignon and Spadaro, 2006). By estimating poverty on April, we aim to capture the *real time* incidence of the crisis on poverty, i.e. a very short run effect, in which behavioral changes or general equilibrium effects are unlikely to happen. Moreover and as a key contribution, we anchor micro-economic income effects on estimations of the macro-economic shock, hence providing full consistency with other key dimensions of the crisis. This approach is of utmost importance for other developing countries that also face difficulties in estimating the effect of the pandemic on informal or self-employed workers, which constitute a large fraction of the workforce.[9] Moreover, we not only contribute to both the understanding of how the macroeconomic and COVID-19 crisis translates into household incomes, but also contribute with a *real time* evaluation of the short-run actual policy responses by the government, and quantify the resources needed to neutralize the negative shock, evaluating specific alternative proposals that would improve the situation at low cost. Finally, and as the future is uncertain, in the event of a scenario of entry and exit of social and physical distancing measures akin to an 'on/off' strategy, this paper contributes with estimates of poverty in an 'off' situation.

The paper is structured as follows. Section 2 presents a basic context of Uruguay and a chronology of the pandemic, and Section 3 introduces the data and variable construction and explains the methodology in general. Section 4 describes in greater detail the simulation techniques and assumptions. Section 5 presents results and Section 6 concludes.

2 Context and chronology of the pandemic in Uruguay

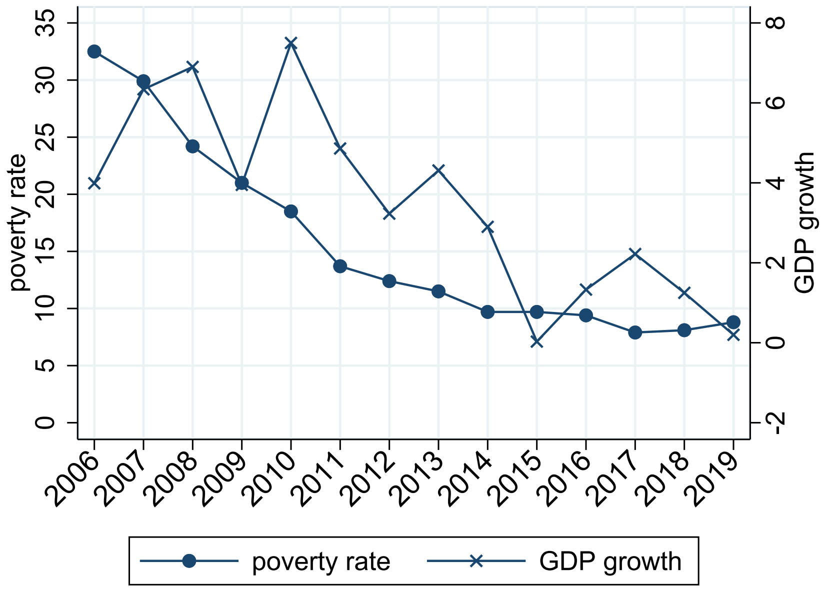
Figure 1 presents poverty estimates, depicting a substantial decrease in the last fifteen years. This results from high economic growth (especially in the first half) and a wide range of cash transfers and other redistributive policies implemented by a center-left government (Amarante et al., 2014).[10] 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 years old, regardless of parent's job status; (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

[9] In particular, our proposed method to impute an effect on informal and self-employed workers, anchored in macro-economic estimates, is one of the differentiating features of our paper with respect to Bonavida Foschiatti and Gasparini (2020).

[10] The center-left party (*Frente Amplio* in spanish) took office in 2005 for the first time in the country's history, won the two following elections, and lost to a center-right coalition in 2019. The new government took office on March 1^{st} 2020, as depicted in 2.

poverty by 1.66 percentage points (OPP, 2018). Poverty rates have been stable around 8% for since 2015, but the decreasing growth rates depicted in Figure 1, coupled with increasing unemployment rates which reached the 10% threshold 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.

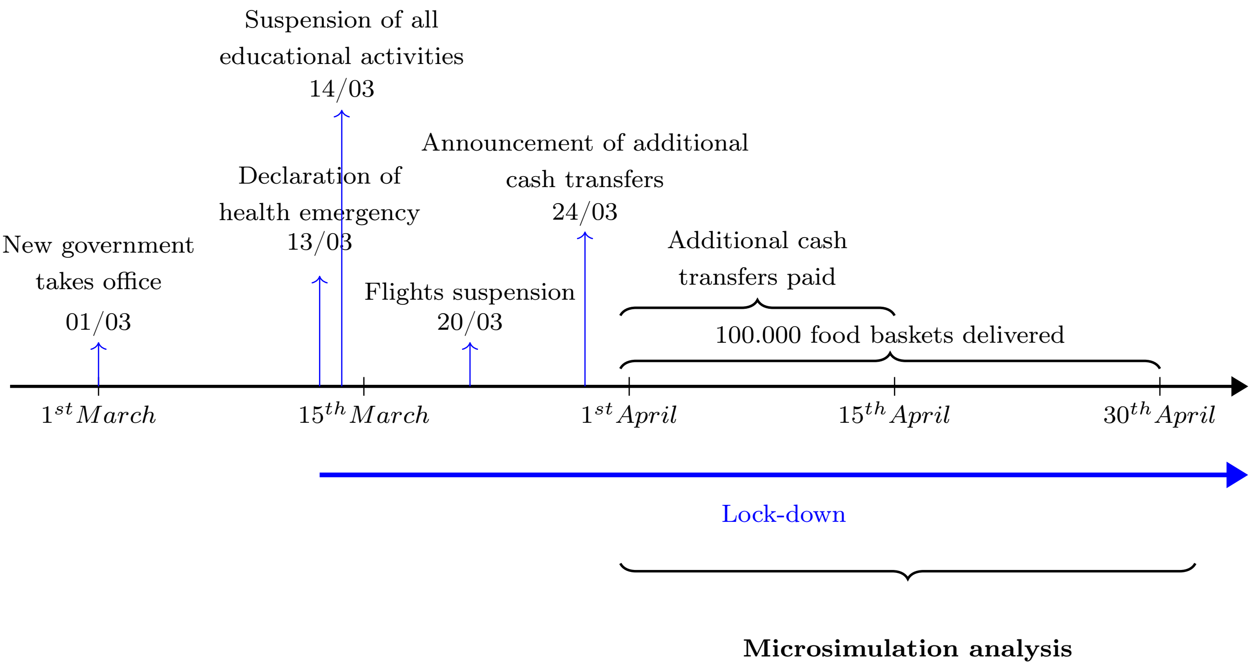
Figure 1: Poverty rate (individuals) and GDP growth, 2006-2019



Note. Official poverty series by the National Statistics Institute (INE, 2020) and GDP from World Bank and Uruguayan Central Bank (for 2019).

Uruguay held elections in 2019 and a new (center-right) government took office on the 1st of March. Hence the monitoring of 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 being devoted to the transition. The chronology of the main events is depicted in Figure 2.

Figure 2: Chronology of main events, during 2020



Note. Own elaboration based on press reports.

The pandemic officially arrived to Uruguay on March 13^{th} with the detection of 4 cases (from Europe). 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.

In the context of the lock-down, the government announced on March 24^{th} a transitory expansion of cash transfer programs and the launch of a new program, which are described in subsection 3.1.4, and were executed in April. A number of additional measures to such as soft credits for small businesses, creations of transitory shelters for homeless individuals were announced in several press conferences during the second half of March. However, overall public spending as a response to the crisis has has been relatively modest in international and especially regional comparison.[11]

[11] See Inter-American Development Bank blog: https://blogs.iadb.org/gestion-fiscal/es/politica-y-gestion-fiscal-durante-la-pandemia-y-la-post-pandemia-en-america-latina-y-el-caribe/.

3 Data and methodology

3.1 Data and variable construction

3.1.1 Household survey

The main data source for our study is the Uruguayan Household Survey (*Encuesta Continua de Hogares*, ECH in spanish), carried out by the National Statistics Institute (INE in spanish) on a weekly basis throughout the year, that is nationally representative of all Uruguayan households. After-tax income information is gathered for each household member aged 14 years or older. This includes all sources of income (e.g. labour income), of all types (cash and in-kind), and for all earners (self-employed, business owners, pensioners, etc.). The survey also collects information on tasks and activity for each occupation of every employed individual, and whether she works in the formal or informal sector.[12] All information is separately recorded for the main occupation and others if it is the case.[13] 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 computed by INE. We exclude business owners from the analysis, as we consider that these are the least likely to be 'fired' due to the pandemic. Also, due to the functioning of the social security system, they are not entitled to unemployed benefits. Business owners are defined by INE as individuals who run or exploit their own business and employ one or more paid workers. These individuals are firm owners, who may or may not actually work in their firms and are entitled to benefits, dividends, etc; and represent 3.7% of all employed individuals. There is an important distinction between business owners and self-employed workers. The latter are defined by INE as individuals who do not depend on a business owner to exploit or run their own economic activity, and do not employ paid workers (though they may be assisted by unwaged family members). INE distinguishes between the self-employed with some type of capital or investment needed to carry with their activities (e.g. a locksmith, a family-run small shop) and those without (e.g. a shoe shiner). These two categories represent 21.2% and 2.5% of all employed individuals. Additionally, we exclude public sector workers, as they are not at risk of being fired due to the pandemic, since the institutional setting of Uruguay makes it extremely hard to actually fire a public worker even if desired, involving a process that takes months and may even have to go through Congress. Thus, we focus on private sector workers, workers in cooperative firms, and the self-employed,

[12]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.

[13]90.7% of all employed individuals has only one job.

and consider labour earnings from the main occupation.[14]

3.1.2 O*NET dataset

*O*NET* refers to the US Department of Labour'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 a wide variety of occupations (on a 1 to 5 scale).[15]. We also draw from Mongey and Weinberg (2020), who use the same O*NET 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 fine levels (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 (*workhome* and *prox*) and compute the mean for each SOC code, and then aggregate them at the ISCO-08 level taking a simple average.[16] We end up with two variables on a 1 to 5 scale measuring an Uruguayan worker's ability to perform her 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.

3.1.3 Complementary data sources

To estimate the full effect of the crisis we need information on the number and characteristics of the affected workers. Our first source is publicly available information on the number of formal workers that applied for unemployment benefits between March 1 and April 19 (143,944 individuals).

Note that there are three different unemployment benefits schemes in operation in Uruguay at this point: (i) 'pure layoff', in which the worker is fired, receives decreasing benefits for a six months and the link with the firm is broken; (ii) 'suspension', in which the worker is 'suspended', receives unemployment benefits for one month but then (potentially) can return to work for the firm (or can be properly laid off); (iii) 'reduction', in which the worker reduces

[14] 92.2% of non-public and non-business owners has only one occupation.

[15] To do so, the authors check whether an occupation requires, for instance, 'work outdoors' or 'operating vehicles, mechanized devices, or equipment', which implies that this occupation cannot be performed from home. They cross-check their classification with others used in the literature, showing general consistency and robustness

[16] We kindly thank Rafael Guntín for sharing his code, which we used to generate these variables Uruguay. Note that Guntin (2020) harmonizes SOC to ISCO-08 codes using the work of Hardy et al. (2018), based on Acemoglu and Autor (2011). Also, Guntin (2020) is not the first paper to classify occupations according to the capacity of working from home or with no proximity to others. The author reviews the literature and mentions that Kaplan et al. (2020), Leibovici et al. (2020), Dingel and Neiman (2020), and Mongey and Weinberg (2020) do so for the United States. Gottlieb et al. (2020) and Dingel and Neiman (2020) do so for variety of countries. For Uruguay, Caporale et al. (2020) constitute and important precedent.

the amount of hours worked in a month (e.g. from 40 to 20 a week), and receives government compensation for the fall in worked hours (maintaining the link with the firm). We will refer to these three types as 'full layoff', 'suspension' and 'reduction'.[17]

We reconstruct the number of formal workers that applied for unemployment benefits across unemployment schemes and sectors of activity. We *reconstruct* this number as the official number of applications for unemployment benefits and its distribution across sectors has not been officially published by the Social Security Agency (*Banco de Previsión Social*, BPS in spanish).[18] Part of this information was shared with the press by the workers' representatives in BPS's board, in several opportunities. We then take the total number of formal workers that were laid off, suspended of reduced, and applied for unemployment benefits. We combine information published on March 1st by the newspaper *El Observador*[19], on April 7 by the newspaper *La Diaria*[20], and published on April 22 on a radio (*Radio Universal*) website.[21] These sources allow us to estimate the total number of formal workers that applied for unemployment benefits (by scheme) from March 1st up to April 19th (143,944). We distribute them across eleven activity sectors (ISIC 2 digits) based on information reported on March 1st in *El Observador*, which includes the distribution of applications by unemployment scheme and ISIC. Our reconstruction exercise yields the number of formal workers applying to benefits by unemployment scheme and industry, and is reported in Table A.1 in the Appendix.

We make two assumptions in working with this data. First, as we simulate the situation in April, we assume that all the workers that became unemployed in March, remain unemployed in April. Second, we work with *applications* to unemployment benefits, up to the date in which we started to work on this paper (19th of April). We are aware that a fraction of those applications may be rejected, and hence the true number of formal workers collecting unemployment benefits may be lower (which implies that our poverty estimates are a lower bound, as we impute a nonexistent unemployment benefit). Still, the government made very clear that given the nature of the crisis it would make an effort to streamline the application process and be broad an lenient, so we anticipate low rejection rates. Moreover, in May 8 the newspaper *La República*[22] reported a total of 176.159 applications for unemployment benefits for the whole of March and April. Then, our estimated number of affected formal workers

[17]Note that the government announced later on extensions of the duration of 'suspension' and 'reduction' schemes.

[18]Information that has been requested by several organizations under freedom of information regulations.

[19]See https://www.elobservador.com.uy/nota/maldonado-lidera-en-solicitudes-de-subsidio-por-desempleo-mira-el-resto-del-pais–202033017320

[20]See https://trabajo.ladiaria.com.uy/articulo/2020/4/casi-40000-solicitudes-de-seguro-de-paro-la-primera-semana-de-abril/

[21]See https://970universal.com/2020/04/22/banco-de-prevision-social-recibio-57-900-solicitudes-por-subsidio-por-desempleo/.

[22]See https://www.republica.com.uy/176-159-trabajadores-fueron-enviados-al-seguro-de-desempleo-id764699/

that effectively receive unemployment benefits (143,944) is consistent with an acceptance rate of 81.7% of applications received in March and April. In fact, a BPS authority reported in an interview on May 18 in *La Diaria*[23] an acceptance rate of 99.5% for the three schemes for the whole month of March. This implies that our estimates are, again, a lower bound.[24] The estimation of the number of informal and self-employed workers affected by the pandemic and the loss of income associated, is detailed in section 4.2.

3.1.4 COVID-related transfers policies

Upon the first case of COVID-19 detected in Uruguay the government started announcing different sanitary and economic measures. In this paper we focus on three measures. The first two measures (announced on March 24) reinforce existing cash transfer programs: a 50% increase in the cash transfer corresponding to the TUS Program, and a 50% increase in the cash transfer corresponding to the AFAM-PE, both described in Section 2. Note that these increases do not overlap: households already receiving TUS are not entitled to the additional AFAM-PE funds.[25] The third measure, announced on April 1, consisted in the distribution of 100,000 baskets of first-necessity goods (rice, cooking oil, etc; valued in 1,200 Uruguayan Pesos, about 28 USD), targeted to informal workers not covered by other government programs (mainly TUS and AFAM-PE).[26] Though the initial announcement referred to a baskets of goods, the government later on implemented a system based on a smartphone app, allowing chosen beneficiaries to spend up to 1,200 Uruguayan pesos in selected supermarkets and other stores. We were not able to simulate a small fourth policy, a transfer of 6,800 Uruguayan Pesos (about 154 USD) to beneficiaries of the existing program 'MIDES *monotributistas*' (loosely translated from spanish as 'flat-rate contributers') that covers about 10,000 individuals, as we were unable to identify beneficiaries in the ECH.[27] We contemplate the potential impact of this small policy later on when analyzing our results.

[23]See https://trabajo.ladiaria.com.uy/articulo/2020/5/director-del-bps-preocupado-por-el-futuro-de-los-trabajadores-despues-de-los-cuatro-meses-de-seguro-de-paro-por-suspension/

[24]Informal conversation with BPS staff indicates that the pre-pandemic acceptance rate hovered around 80%.

[25]Specifically, the government announced a doubling of the transfers, for one time only, to be paid in two monthly installments. This in practice is equivalent to a 50% raise in a given month).

[26]Individuals receiving other sources of transfers, as unemployment benefits, disability pensions and other types of pensions are also not eligible.

[27]This is a small program that aims to increase formality among poor and vulnerable workers and self-employed individuals. The expenditures needed to enter formality are too steep in some cases, and the *monotributista* program allows individuals to access the benefits of social security with initially lower (flat-rate) contributions that progressively increase month after month until the individual fully complies with the required contributions.

3.2 Methodology

3.2.1 Measuring poverty

In this paper, poverty is measured with the monetary approach, with the same methodology used by the National Statistics Institute (INE), which is based on absolute poverty lines as in most Latin American countries. Thus, a household is considered poor, if the current income[28] of the household is lower than the poverty line for that household (which takes into account a basic food basket, a non-food basket and the number of household members). Poor people are hence those who belong to a poor household (INE, 2020).

Therefore, the poverty line depends on the geographic location of the household (as the price level differs e.g. between the capital city and the rest of the country) and its number of members. As an example, the poverty line for a three-member household in the capital city (Montevideo), updated to March 2020, is of 38,933 Uruguayan Pesos (about 883 USD). Household income includes all income received: formal and informal labour, all government transfers in money and in kind, and all other income (e.g. non-labour) in cash or kind. Following this methodology and the estimates published by INE, 8.8% of people lived in households below the poverty line in 2019. Since 2014, poverty has remained relatively stable and below 10%, after a sharp drop from 32.5% in 2006.

3.2.2 Prediction of the present or *nowcasting*

This simulation exercise is framed in the techniques of 'prediction of the present' or *nowcasting*. Within these methodologies, the aim 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 after a certain amount of time has passed after the phenomenon, but when some explanatory variables are measured more regularly, such that it is possible to estimate the likely evolution of key variable. 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). In the case Uruguay, the poverty estimates from INE and the microdata of the Household Survey (necessary to independently compute poverty) are both published the following year. For example, poverty rates for 2019 were published on March 31, 2020 (INE, 2020), and 2019 microdata was made available on April 1.

In the context of the current crisis, it is clearly not convenient to wait until 2021 to have precise estimates of the evolution of contemporary poverty. The forecasted contraction of the economy will for sure affect mainly or to a greater extent various low-income and vulnerable

[28]Current income 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, and is counted as household income.

individuals (ECLAC, 2020a), currently being targeted by the government's new measures. In order to assess the adequacy of these measures, it is necessary to have estimates that, although imperfect, are able to quantify in real time the evolution of poverty as well as the (likely) impact of the government's measures.[29]

We define the income of each earner before the COVID-19 shock (2019 values updated to March 2020) as Y_{before}. We consider three possible changes: (i) a formal income shock (S_{formal}), which includes both the loss of income associated with unemployment and the transfer from unemployment benefits; (ii) a shock to informal and self-employed workers' income ($S_{informal}$); (iii) increases in transfers ($S_{transfers}$) due to the new policies. Then, Y_{after} captures the impact of the crisis and the mitigation measures, as defined in Equation 1:

$$Y_{after} = Y_{before} - S_{formal} - S_{informal} + S_{transfers} \tag{1}$$

Then, we use our simulated income for each individual (Y_{after}) to recalculate household income (for all households) and re-compute the poverty rate. We acknowledge that this approach is mechanical, static, and of partial equilibrium. This means that it does not take into account individuals' potential behavioral responses (e.g. changes in their economic decisions due to shocks or policies), that it does not incorporate impacts derived from the temporary accumulation of the effects of the shock, and that it does not take into account the effect of shocks or policies through changes in other markets or sectors of activity (general equilibrium effects). But, by estimating poverty on April, we are capturing a very short-run effect in which behavioral changes or general equilibrium effects are unlikely to happen or to 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 Simulated scenarios

We simulate 21 scenarios, based on three different assumptions on the shock on formal workers and seven on the shock on informal and self-employed 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 also describe and include results for different combinations of other scenarios, to check results' robustness.

[29]For poverty estimates for Uruguay based only on changes in formal employment and the effect of unemployment benefits, see Bai et al. (2020).

4.1 Simulating shocks over formal workers

We start from the information on the number of formal workers that applied for unemployment benefits on three different schemes, between March 1 and April 19 (143,944 individuals), as reported in Table A.1 in the Appendix.[30] Based on this, our exercise consists of simulating on ECH the loss of income from unemployment and the gain of unemployment benefits for this number of individuals, among all eligible workers. That is, we need to 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.[31] In a nutshell, 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); labourers on daily contracts must have worked 150 days but contributed for at least 180 days (again, not necessarily consecutively or on the same job), while piece-rate workers need both a minimum of 180 days in a formal job and a minimum level of earnings. More complex rules applies for workers in the fishing and rural sectors, or domestic workers (housemaids). Moreover on March 18 the government relaxed some criteria (mainly, those who already had received unemployment benefits in the last 12 months are not eligible, and this restriction was lifted). In practice, the ECH does not allow to accurately asses the eligibility of each worker (e.g. it does not record formal days of work in previous job spells, nor distinguishes between monthly paid workers and day labourers, among others). We focus on the main requirement for all schemes (minimum of 180 days in a formal job) and define eligible workers as those that have been working in their current job for 6 months or longer. Hence our pool of eligible workers underestimates the true pool of formal workers that could receive unemployment benefits.

The methodological challenge is how to choose which eligible workers to shock. To do so, we start from international and local evidence that shows that the probability of being affected (losing their job or part of their income) rises with the difficulty of performing their jobs from home and/or without direct contact with other people, which implies that the most affected are usually of lower income.[32] We then use an econometric model to estimate the probability of being affected by the pandemic based on the two variables measuring the ability of workers to carry out their tasks from home or without proximity to others.[33] Appendix A.3 presents

[30] By formal workers we refer to dependent workers, that is, employed by a firm. Self-employed workers may be formal in the sense of make the appropriate contributions to the social security system but different rules apply to them (e.g. they are not eligible for unemployment benefits). Whenever we refer to formal workers we are thus focusing on workers in a relation of dependency (employees).

[31] See the official website of BPS, https://www.bps.gub.uy/4802/subsidio-por-desempleo.html.

[32] For the case of Uruguay, this is precisely the conclusion in Guntin (2020) and Caporale et al. (2020). For other countries, similar conclusions feature in the work of 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).

[33] Guntin (2020) and Caporale et al. (2020) recently used this information to estimate how many and what

details of the econometric model and regression results. Under various assumptions, the model estimates the probability of being affected (e.g. of an eligible formal worker being laid off, reduced or suspended). The model displays a pseudo-R^2 statistic close to 20%. Based on this, in our *central scenario* for formal workers, 80% of the shock is assigned randomly, and 20% of the shock is assigned based on the probability of being affected predicted by the model.[34]

Alternatively, we use two other criteria to allocate the negative shock across eligible formal workers. First, we assign the entire shock randomly (*random scenario*). Clearly this is unrealistic and potentially optimistic if unemployment is higher among low-income workers with greater difficulties in working from home or without contact with others, as the literature suggests. However, we include it as a benchmark 'optimistic case' for comparison with other scenarios. Second, we assign 50% of the shock randomly and the remaining 50% in ascending order based on a crude measure of the probability of being affected, unrelated to the econometric model (what we call the *50%-50% scenario*).[35]

In each scenario, formal workers that receive unemployment benefits for 'suspensions' or 'full layoffs' lose all labour earnings from their main occupation, and receive a transfer corresponding to 66% or 50% of their lost income respectively, as per the official regulations.[36] As the official regulations are hard to implement with ECH data, we made the following assumptions. First, the unemployment benefit should be calculated as an average of total labour earnings for the last six months (not available in the ECH). We then assigned benefits based on the reported value for the surveyed month. Second, we applied benefits caps.[37] Finally, note that unemployment benefits amount to 66% the first month but falls later on; as we simulate the effect on one month only, we used 66%. Also, in all cases we augmented the benefits by 20% if the applicant is part of a'constituted household' (loose translation of 'hogar constituido' in spanish. These include individuals married or cohabiting with a partner, and/or households with children below 21 years old, or disabled members).[38] For 'reduced' formal workers, we

types of workers would be most affected in a quarantine scenario in Uruguay.

[34]For example, if the data indicates that 10 eligible formal workers were laid off and applied for unemployment benefits in an industry that employs 100 workers in total, using ECH data we lay off 8 eligible workers randomly, and lay off another 2 eligible ones based on the probability predicted by the model.

[35]We take the minimum of the two variables measuring the feasibility of working from home and without proximity to others. We then choose the remaining 50% eligible workers in ascending order based on this minimum. For example, if a worker performs tasks evaluated as 3 (out of 5) on the scale of proximity but 1 on the scale of easiness of remote work, we assign her a 1. Then, we select 50% of the eligible workers starting from the lowest values until completing the remaining number of affected workers.

[36]On April 14th government augmented the unemployment benefit for the case of 'suspensions' to 75%, but it did not announce the starting date of the raise. We kept the initial 50% benefit but in Table A.2 in the Appendix we report all results with the 75% subsidy for the 'suspension' scheme, which shows little variation in the results.

[37]There is a minimum benefit of 5,574.33 Uruguayan Pesos (about 127 USD) for 'full layoffs' and 'suspensions'. There are also upper bounds ofv61,329.58 Uruguayan Pesos (1,418 USD) for 'full layoffs' for the first month, and of 44,606.60 Uruguayan pesos (1,031 USD) for 'suspensions'.

[38]Note that 'full layoff' unemployment benefits covers 66% of lost income for the first month and falls to

assume that they keep half of their earnings from their main occupation, lose the other half, and receive a subsidy of 25% of their lost income.[39]

Note that the simulation of the shock on formal workers is a lower bound estimate of the true difficulties faced by them. Undoubtedly some formal workers experienced income or job losses, but did not apply for unemployment benefits.[40]

4.2 Simulating shocks over informal and self-employed workers

Unlike the case of formal workers, there is no public information available on the number of informal workers who have lost their job or part of their income due to the contraction in activity levels, nor on self-employed workers who probably have experienced income losses.[41] Note that, by definition, informal workers cannot apply for unemployment benefits, while the self-employed (even when making the appropriate contributions to the social security system, that is, are formalized) are technically (micro) firm owners and are also left out of unemployment benefits. Then, in the case of informal and self-employed workers we deploy three different ways of estimating the size of the shock, and four ways of distributing the shock among workers, totaling seven different scenarios. Again, we present our *central scenario* in detail, but include the others in the results.

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

Our method starts with estimating the mass of informal and self-employed workers' labour income that should be lost due to the crisis, based on the share of GDP's contraction affecting them. To do so, we translate an annual estimated shock to GDP, measured from a macroeconomic perspective, to a monthly shock on informal and self-employed workers' labour incomes, captured in survey micro-data. This approach is presented in Equation 2.

$$L_{informal} + L_{selfemployed} = Shock_{2020} \times Sh_{April} \times Sh_{labour} \times Sh_{survey/GDP} - L_{formal} \tag{2}$$

The left hand side of the equation represents the mass of labour income that should be lost due to the crisis: $L_{informal}$ and $L_{selfemployed}$ represents the sum of informal and self-employed workers' labour income that should be lost, respectively. On the right hand side of the equation,

40% in the sixth month, so that in subsequent months the negative effects of the crisis for these workers will grow. Fortunately, 'full layoffs' represent only 7.1% of total applications to unemployment benefits.

[39] E.g., they work 20hs instead of 40hs a week, and receive a subsidy equal to 10hs a week.

[40] An opinion survey conducted by the pollster firm *Equipos* (Equipos Consultores, 2020), found that more up 66% of self-employed and business owners reduced their working hours and/or lost income.

[41] Still, recall that Equipos Consultores (2020) found that 66% of self-employed and business owners experienced a loss in income.

$Shock_{2020}$ represents GDP's estimated contraction (in Uruguayan pesos), Sh_{April} is the share of the contraction occurring in April, and Sh_{labour} is the share of GDP corresponding to labour income. Hence, $Shock_{2020} \times Sh_{April} \times Sh_{labour}$ represents the contraction in all labour income that should be experienced by the economy in April, consistent with a given GDP contraction. $Sh_{survey/GDP}$ adjusts this mass by the fraction of that macroeconomic income mass actually captured by the household survey micro-data, and L_{formal} represents the sum of lost income already experienced by formal workers as estimated in Section 4.2. Hence the right hand side of the equation represents the mass of labour income that informal and self-employed individuals should lose in the ECH after accounting for the shock in the formal sector and measurement problems of ECH. Equation 2 is important since it not only allows us to estimate the overall effect on informal and self-employed workers, but also because is represents the bridge between macro- and micro-economic estimates of the impact of the crisis, and ensures micro-macro consistency of our exercise.

$Shock_{2020}$) is based on 2019's GDP combined with the estimated percentage contraction in 2020, taken from international agencies as ECLAC, the World Bank or the IMF, but it is essentially the main exogenous input. Our assumption for Sh_{april} is that 35% of the negative economic shock estimated for all of 2020 occurs during April, to the extent that the physical distance measures were applied throughout the month (this percentage is based on estimates in CINVE (2020)). Estimations of Sh_{labour}, that includes both wages and other labour income (also accounting for the share of mixed income that is closest to labour income) is estimated at 60%, based on (De Rosa et al., 2018), since Uruguay's National Accounts do not report this information.[42] Finally, $Sh_{survey-GDP}$ is directly computed from the data and equals 57%.

Estimating the right hand side of the equation we obtain $L_{informal} + L_{self}$, and we distribute this mass of losses as follows. First, if selected, each informal or self-employed worker loses a share of her labour earnings equal to the predicted probability of being affected (from the econometric model).[43] Second, we randomly choose informal and self-employed workers until the accumulated lost labour earnings reach 80% of the total lost labour earnings estimated in Equation 2 ($L_{informal} + L_{self}$). Third, we choose among remaining informal and self-employed workers based on the probability of being affected (in an analogous way to the method used for the *central scenario* for formal workers) until completing the remaining 20% of the total labour earnings to be lost. This methodology constitutes our *central scenario* for informal and self-employed workers.

Still, we consider four other methods to allocate the mass of lost labour earnings across

[42]This implies the assumption that the crisis does not affect the functional distribution of the economy, which is unlikely to be the case given historical experience (De Rosa et al., 2018) and the short-run nature of our exercise. Again, we are taking an optimistic stand on this assumption to make sure we are not overestimating poverty increases.

[43]If the probability is 90%, she will lose 90% of her income, if selected in the simulation.

informal and self-employed individuals:

In *scenario A.1*, the share of labour earnings lost by each informal and self-employed worker (if chosen) is assigned randomly, using a uniform distribution (0% to 100%).[44] Then, we select among informal and self-employed workers randomly until the accumulated total lost labour earnings matches our estimation from Equation 2.

In *scenario A.2*, the share of labour 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 select among informal and self-employed workers randomly until the accumulated total lost labour earnings matches our estimation from Equation 2.

In *scenario A.3*, the share of labour 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 labour earnings to be lost according to our estimates from Equation 2. 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 labour earnings.[45]

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 (as in scenario A.3) until accumulating the remaining 50% of total lost earnings estimated in Equation 2.

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

The ability of scenarios A.1 to A.4 and our *central scenario* to estimate the true situation of informal and self-employed workers hinges on the participation of labour earnings on GDP and on the estimated negative shock to GDP growth. To avoid relying only on scenarios that depend on these macroeconomic assumptions, we compute two other scenarios with different methodologies.

In *scenario B*, we rely exclusively on the estimated probability of being affected by the pandemic stemming from the econometric model. The model is run using data for eligible

[44] Each worker is assigned a potential income loss: 1% would lose 1% of their labour income, another 1% would lose 2% of their income, and so on and so forth. Only 1% of the workers loses 50% of their income (akin to a 'reduction' scheme), and only 1% of the workers loses 100% of their income (akin to 'full layoff' or 'suspension').

[45] This comes from the minimum of the two variables measuring the feasibility of working from home and without proximity to others. See footnote 35.

formal workers, and we use regression 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.[46] Then, for each selected informal and self-employed worker we subtract a share of their labour earnings equal to the estimated probability of being affected.[47] 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 labour 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.

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

Finally, *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.[48]. 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 eleven 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. That is, if 25% of workers in a given industry are informal or self-employed, and 3 formal workers have been laid off, suspended or reduced, one informal or self-employed worker must be laid off, suspended or reduced as well, respectively. 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).[49] 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. Those assigned as 'suspended' or 'fully laid off' lose 100% of their income (lose their job), and those assigned as 'reduced' lose 50% of their income. They do not receive unemployment benefits.

This is an unlikely scenario as it assumes that the shock to informal and self-employed

[46]Suppose three informal workers, with estimated probabilities of being affected by the pandemic of 10%, 50% and 90%, respectively. In each case we 'toss a coin' with probabilities 10%, 50% and 90% of a 'being affected' outcome.

[47]In the previous example, workers would lose 10%, 50% and 90% of their labour earnings.

[48]An affected sector is one for which we know formal workers have been laid off, suspended or reduced and have applied to unemployment benefits, as seen in Table A.1 in the Appendix

[49]Informal and self-employed workers do not have access to the same unemployment benefit schemes than formal workers do. Still, we estimate the number of informal and self-employed workers affected by type of scheme in order to have a guideline on the size of the shock.

workers concentrates only in eleven industries, and also assumes random assignment of the shock across workers within industries (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.

4.3 Simulating new cash transfers by the government

We focus on three main new policies implemented by the government. First, a 50% increase in the cash transfer corresponding to TUS and AFAM-PE programs, to all the individuals/households that declare receiving this transfers in the ECH.[50] Second, we simulate the cash transfer of 1,200 Uruguayan pesos to 100,000 informal and self-employed workers not covered by any other program (mainly TUS and AFAM-PE).[51] Note that there are 321,149 eligible individuals for these additional transfers, limited in principle to 100,000 beneficiaries. We simulate an optimistic scenario, and choose beneficiaries based on their income under a perfect focalization assumption. In other words, we assigned 100,000 transfers starting from the poorest individual, upwards. This implies that our scenarios that incorporate the effect of government policies are 'upper bounds', as they assume that the government has the capacity to target these 100,000 transfers to those most in need.

5 Results

In this section we first present our estimates of poverty rates for April 2020, with and without the effect of the three main government policies. Second, we estimate the cost and effect on poverty of two different, alternative policies.

5.1 Poverty rates by scenario: with and without government policies

Table 1 below shows the predicted poverty rate for the 21 scenarios considered. An additional scenario, with no shock to informal and self-employed workers is also included, to facilitate comparisons. Table 2 computes the number of additional individuals under the poverty line in

[50]If the household receives both transfers, we increase the value of TUS only, as the new policy explicitly avoids duplication.

[51]Individuals receiving other transfers, as unemployment benefits, disability pensions and other types of pensions are also not eligible.

each case.[52] The baseline poverty rate is 8.5%.[53]

Our *central scenario* (in dark green) implies an increase of approximately 3.2 points in the poverty rate, from 8.5% to 11.7%. This represents about 110,037 additional people below the poverty line.[54] Note that the four alternative ways of simulating the shock on informal and self-employed workers based on the participation of labour earnings on GDP and the GDP shock (scenarios A.1, A.2, A.3, A.4, in light green in column 4) display very similar results, with poverty rates from 11.4% to 12.5% (99,531 to 138,373 individuals). This indicates that our results do not strongly depend on the assumptions chosen and, therefore, provide greater reliability to the conclusions. Likewise, given our preferred way of simulating the shock on informal and self-employed workers (*Central* row), changes in the way of estimating the shock on formal workers (in light green in columns 1, 2, 4 and 5) also do not generate significant changes in the results either (poverty rates are stable around 11.5%).

Table 1: Poverty rates 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	9.4%	8.7%	9.6%	8.8%	9.4%	8.7%
A.1	11.8%	11.1%	12.1%	11.4%	11.8%	11.1%
A.2	12.0%	11.3%	12.4%	11.6%	12.0%	11.3%
Central	12.1%	11.3%	12.4%	11.7%	12.1%	11.4%
A.3	12.4%	11.7%	12.8%	12.0%	12.4%	11.7%
A.4	12.9%	12.1%	13.2%	12.5%	12.9%	12.1%
B	15.1%	14.5%	15.3%	14.6%	15.2%	14.5%
C	11.2%	10.5%	11.4%	10.6%	11.2%	10.5%

Note. Own elaboration based on ECH microdata from INE. Results results from 200 simulations; 95% confidence intervals are reported in table A.3 in the Appendix.

More generally, results are similar within a row across columns (varying the estimating procedure for the shock on formal workers). Nevertheless, for each method used to estimate the shock on formal workers (within columns), we do observe differences between the block of

[52]Each scenario depends to a certain extent on a random component. Thus, we repeat each estimation 200 times to establish 95% confidence intervals, presented in Appendix A.2. In all cases the confidence intervals are small; for example, the 95% confidence interval for our *central scenario* implies a +/- 0,02 percentage point variation.

[53]This figure is slightly lower than the official poverty line computed by INE for 2019 (of 8.8%). This responds to a recalculation of the actual cash transfers received by households from the AFAM-PE program, which are not properly computed in the ECH.

[54]Figure A.2 shows that such a steep increase in poverty rates has not been seen since the 2002 crisis.

estimates based on the share of labour earnings on GDP and the size of GDP shock (scenarios A.1 to A.4 and our *central scenario*), and the other two methodologies (scenarios B and C). In particular, scenario B presents 'upper bound' estimates, with the largest number of affected informal and self-employed workers. These results arise directly and exclusively from applying the econometric model that estimates the probability of being affected by the pandemic. The poverty rate in this scenario, even after accounting for new government policies, is very close to 14.5% (consistent with GDP contraction beyond the -3.5% of our *central scenario*). In contrast, scenario C presents'lower bound' estimates, with the fewest number of affected informal and self-employed workers. In this case only informal and self-employed workers in eleven industries are affected (an unreasonable assumption). Note that even in the most optimistic (and unreal) scenario and after accounting for new government policies, poverty rates still reach around 10.5%, representing at least 68,713 new individuals below the poverty line.

Our results show that the effectiveness of the new government policies vary by scenario. In our *central scenario*, the new policies reduce poverty by approximately 19.3%: in the absence of the policies, an additional 26,243 people would have fallen below the poverty line. Recall that unemployment benefits and pre-existing transfers (e.g. the regular cash transfers corresponding to TUS and AFAM-PE) are already considered in the simulation in households' income in the 'without policies' case. In other words, we are quantifying the additional effect of the three main new government policies. We find that these policies represent an average transfer of about 1,622 Uruguayan Pesos (38 USD) per receiving household (about 400 Uruguayan Pesos per person, 9 USD). This amounts to only 4% of the targeted households' income, hence the moderate impact on poverty rates should be unsurprising.

Table 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	30,102	4,645	36,654	9,964	30,330	4,894
A.1	114,912	89,002	126,623	99,531	115,649	89,645
A.2	123,209	98,180	136,001	109,728	123,831	98,856
Central	123,999	98,895	136,280	110,037	124,366	99,461
A.3	135,509	109,940	149,772	123,108	135,852	110,252
A.4	152,190	126,837	164,934	138,373	152,290	127,010
B	232,607	209,449	239,325	214,598	233,039	209,878
C	93,756	68,713	100,192	73,826	94,059	69,035

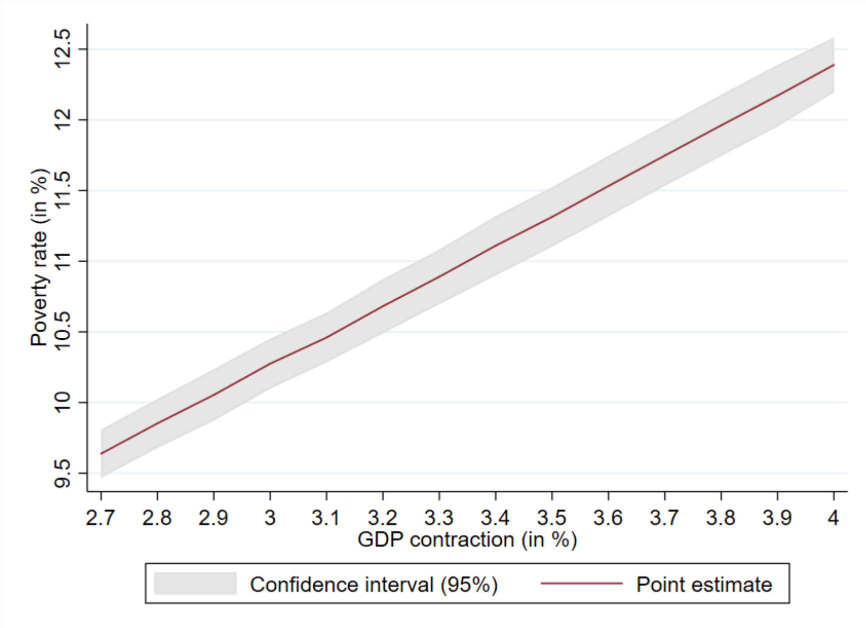
Note. Own elaboration based on ECH microdata from INE. Results come from 200 simulations; 95% confidence intervals are reported in table A.4 in the Appendix.

The only case in which the new policies neutralize more than 70% of the poverty increase is under the assumption of no shock for informal or self-employed workers (first row). Of course, this scenario is unrealistic: informal and self-employed workers *are* affected and, in fact, this is the main reason advocated by the government to enact the three new policies in the first place. Still, although the poverty rate hardly increases in this first row when policies are applied, this hides an important change in the *composition* of individuals below the poverty line. While a group of formal workers falls into poverty, the new policies (which aim mainly at informal and self-employed workers uncovered by other programs) lifts a almost equally sized group of individuals above the poverty line. This small change in net poverty rates involves many formal workers falling below the poverty line and many informal ones raising above it. Besides, although the cancellation effect is blurred when the shock over informal and self-employed workers is incorporated in other scenarios, the change in the composition of poverty persists.

Recall that our *central scenario* estimates the new poverty rate based on an assumed (-3.5%) shock to GDP. As a robustness check, we repeat the exercise for this scenario considering contractions from -2.7% (World Bank, 2020) to -4% (ECLAC, 2020b). 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 0.21 percentage points.[55]

[55] Poverty rises to 9.6%, 10.3% and 12.4% for GDP shocks of -2.7%, -3% and -4%, respectively.

Figure 3: Poverty rates in the *central scenario*, by GDP shock



Note. Own elaboration based on ECH microdata from INE. Point estimates correspond to 200 simulations for the *central scenario*. The gray area represents the 95% confidence interval.

5.2 Cash transfers required to avoid poverty increases

The previous subsection showed that the new policies are insufficient to prevent the increase in poverty, especially for informal and self-employed workers.[56] In this subsection we estimate the resources needed to fully avoid the negative effects of the pandemic. Concretely, we calculate the additional amount of resources that *each affected individual in our simulation* must receive to keep her household exactly above the poverty line.[57]

It is important to clarify that here we estimate the total amount of resources needed to prevent the increase in poverty rates due to the pandemic shock (e.g. preventing *only* the affected individuals to fall below the poverty line), and implies an assumption of perfect targeting of funds. Our estimates are not a quantification of the true actual costs of such policy, for two reasons. First, the cost of the policy exceeds that of the transfers itself due to administrative cost (and the impossibility of perfect targeting of the policy). Second, our estimations take the households that fell below the poverty line exactly to that income level,

[56]Recall that in Table A.2 in the Appendix we use a 75% unemployment subsidy for the 'suspension' scheme and find very similar results: poverty in the *central scenario* falls only by 0.7 percentage points.

[57]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 5.6 million USD are needed to revert the *central scenario* to pre-pandemic levels.

and not beyond. This policy would not be advisable in a widespread crisis as the current one, as low-income households (just on the poverty line) would still be highly vulnerable. In other words, it is important to avoid being too narrow when targeting anti-poverty policies in such an extended crisis scenario. Even after these caveats, our estimations in Table 3 below illustrate *orders of magnitude* of the transfers needed to stop poverty increases, which we still think are informative, as discussed later on.

Table 3: 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	889	924	890	20.5	21.3	20.6
A.2	934	976	938	21.6	22.5	21.7
Central	939	979	939	21.7	22.6	21.7
A.3	979	1,025	980	22.6	23.7	22.6
A.4	1,071	1,109	1,071	24.7	25.6	24.7
B	1,460	1,473	1,461	33.7	34.0	33.7
C	812	824	813	18.7	19.0	18.8

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

Results show the total amount of transfers needed to avoid poverty increases in each scenario after accounting for the new policies. In our *central scenario* avoiding poverty increases costs about 22.6 million USD (per month), and total costs range between 21.3 to 25.6 million USD a month in scenarios A.1 to A.4. This is equivalent to about 0.44% of Uruguays' 2019 annual GDP. The lower bound is 19 million USD (scenario C) and the upper bound is 34 million USD (scenario B), though recall these are extremely optimistic and pessimistic cases respectively. Although we understand the limitations of this exercise, these estimates are useful as they show that it is possible to greatly reduce the effects of the pandemic on poverty. In fact, our estimates indicate non-prohibitive amounts of resources, that are achievable by public policy, even in the case of a budget-constrained developing country as Uruguay.[58]

[58]Recall that Uruguay counts with an investment grade qualification and about 1.800 million USD of contingent credit lines with multilateral credit institutions yet to be used (Ministerio de Economía y Finanzas , 2020).

Under the assumption of perfect targeting, approximately 22.6 additional million USD a month are needed to neutralize the increase the poverty rate. This exercise, with a strictly illustrative objective, is however 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, which imply an additional expenditure of about 400 million Uruguayan pesos per month (barely below 10 million USD).[59] We simulate this policy in Table 4 and find a reduction in the increase in poverty rates for our *central scenario* of 1.3 percentage points (falling from 11.7% to 10.4%), cutting poverty increases almost by half. This implies about 43,543 less individuals under the poverty line. More importantly, Table 4 shows the potential impact of an *immediate* expansion of *existing* transfers on poverty. Implementing this policy has minimal administrative and logistical costs (as the government already has information on beneficiaries), which illustrates the central importance of these estimates, particularly in the current context.

Table 4: Poverty rates in April 2020, by scenario. Policies based on De Rosa et al. (2020).

	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%	7.4%	9.6%	7.5%	9.4%	7.4%
A.1	11.8%	9.8%	12.1%	10.1%	11.8%	9.8%
A.2	12.0%	10.1%	12.4%	10.4%	12.0%	10.1%
Central	12.1%	10.1%	12.4%	10.4%	12.1%	10.1%
A.3	12.4%	10.4%	12.8%	10.8%	12.4%	10.4%
A.4	12.9%	10.9%	13.2%	11.2%	12.8%	10.9%
B	15.1%	13.3%	15.3%	13.4%	15.2%	13.3%
C	11.2%	9.2%	11.4%	9.4%	11.2%	9.2%

Note. Own elaboration based on ECH microdata from INE. Results come from 200 simulations; 95% confidence intervals are reported in table A.6.

Finally, recall that all scenarios omit the transfer of 6,800 Uruguayan Pesos (about 154 USD) to MIDES *monotributistas* (about 10,000 beneficiaries according to the government). Though it was impossible to identify potential beneficiaries in the ECH, this omission should not have a large effect on our estimations. First, the total monthly transfer rises to 68 million Uruguayan pesos, which represents approximately 6.8% of our monthly estimate of one billion pesos in the *central scenario*; it should have little impact on the poverty rate. Second, even under the strong assumption that each *monotributista* integrates a household of three people,

[59]This proposal *does* allow overlapping of transfers: households that receive both TUS and AFAM-PE see a 100% increase in both. It also allows households receiving other transfers (as pensions) to be beneficiaries.

and that the transfer in *all* cases lifts the whole household above the poverty line, this optimistic and upper-bound scenario implies about 30 thousand fewer people below the poverty line, which yields a poverty rate still above 10.8% (around 80 thousand additional poor individuals). Furthermore, recall that we simulated the new policy of 100,000 cash transfers under upper-bound assumption of perfect targeting of the policy, so that in any case, part of the effect of omitting the *monotributista* policy should be absorbed by this optimistic assumption.

6 Concluding remarks

In this paper we perform micro-simulations to estimate the likely evolution of poverty rates in real time for the case of Uruguay, in the face of the COVID-19 crisis. We implement a methodology such that our main results are fully consistent on a micro-macro level with estimates of the potential contraction of the GDP. Moreover, we propose a specific methodology to solve the issue of how to assess the effect of the shock on informal and self-employed workers, with is of utmost importance in developing countries where social security coverage tends to be low. We consider these two key contributions of the paper.

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 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 summarize our results, we find (i) a rapid increase of over 36% in poverty rates; (ii) positive but modest ameliorating effects of new government policies deployed; (iii) the possibility of greater reductions in poverty rates at low cost (around 0.5% of the GDP on annual basis).

Although the simulations were performed for the Uruguayan case, they provide useful information to assess the impact of the crisis on other countries. That is, another contribution of the paper is to add empirical evidence of the growing literature on potential impacts of the pandemic on poverty, of great importance in the case of developing countries. Precisely, many other developing countries in general and Latin American countries in particular share similar structural problems such as high unemployment rates, low long-run growth and per-capita GDP, high inequality and a large informal sector. Thus, this exercise may provide important insights for similar contexts. Besides, we also contribute with a methodology proposal that allows a *real time* evaluation of the short-run policy responses by the government, and other alternative policies proposed as well.

The recent relaxation of the physical and social distancing measures taking shape in Uruguay and elsewhere is likely to have a positive effect on economic activity and thus on poverty. However, 2020 will be a year of recession and reduced economic activity, with a negative impact on poverty levels as well. In other words, although this paper estimates the poverty rate in different scenarios for April, these estimates are relevant and useful to understand and anticipate what might happen in the coming months. In particular, we think that the first effect of the slow reactivation of activity levels will be the reduction in layoffs and a reduction in the deepening of the crisis, rather than a quick return to the pre-crisis situation.[60] Note also that a large part of the new policies have a very limited duration (such as the increase in TUS and AFAM-PE transfers), so a slight recovery in employment and (informal and formal) workers' income accompanied by a retraction of the palliative measures, can also have pernicious results on poverty. Additionally, the eventuality of an 'on / off' strategy, of entry and exit of the physical and social distancing measures depending on the evolution of the spread of COVID-19 across the country, will quickly lead to scenarios such as those estimated in this paper. That is, we think that our simulations approximate the situation of an 'off' moment and are useful for potential future situations.

Finally, a central message of this paper is that the new public policies deployed have positive but 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.

[60]For instance, the newspaper *El Observador* reported on May 19 that from May 1 to May 12, there had been 57.386 new applications from formal workers for unemployment benefits in the three schemes. See https://www.elobservador.com.uy/nota/seguro-de-paro-parcial-se-dispara-en-mayo-y-supera-a-las-causales-tradicionales-20205181770

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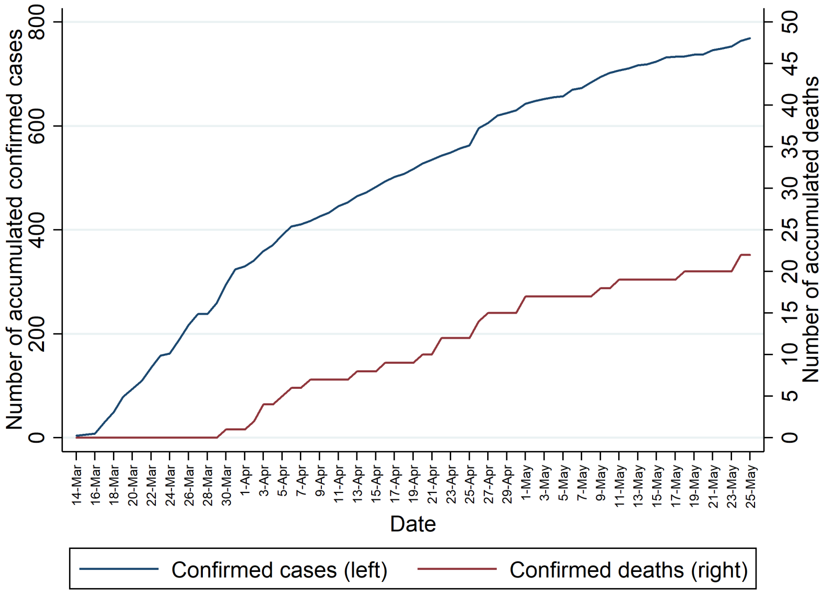
A Appendix

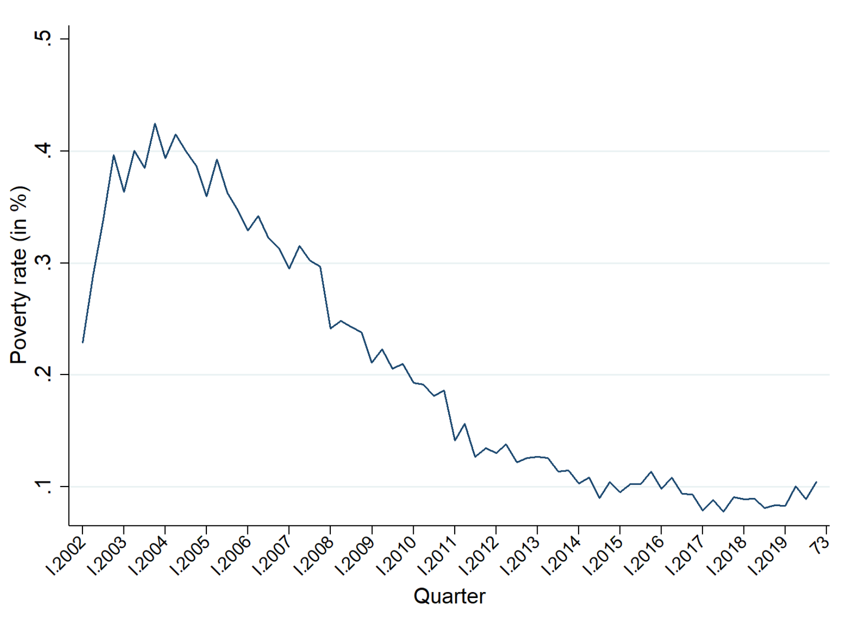
A.1 Additional Figures and Tables

Figure A.1: COVID 19



Note. Official series by the National Emergency System of Uruguay (SINAE, in spanish).

Figure A.2: Poverty rates by quarter. 2002-2019.



Note. Source: Own elaboration based on ECH microdata from INE.

Table A.1: Number of laid off formal workers that applied for unemployment benefits, by scheme and activity sector

Sector		Number of workers, by scheme			
Industry (ISIC 2 digits)	Name	Suspension	Reduction	Layoff	Total
45, 46 y 47	Wholesale and retail trade; repair of motor vehicles and motorcycles	40,143	953	2,194	43,290
10 al 33	Manufacturing	16,554	6,307	1,439	24,300
55 y 56	Accommodation and food service activities	19,852	851	1,382	22,085
49 al 53	Transportation and storage	12,369	509	895	13,773
77 al 82	Administrative and support service activities	7,690	392	753	8,834
41 to 43	Construction	4,159	477	2,000	6,636
97 y 98	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	3,604	1,473	585	5,663
94, 95 y 96	Other service activities	4,989	213	348	5,550
85	Education	4,599	760	183	5,541
90 al 93	Arts, entertainment and recreation	3,730	712	237	4,679
86, 87 y 88	Human health and social work activities	3,041	337	209	3,587
Total		120,730	12,985	10,225	143,940

Note. Own elaboration based on BPS data reported in the press.

Table A.2: Poverty rates in April 2020 by scenario. Unemployment benefits for 'suspension' scheme set to 75%.

	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	8.9%	8.2%	8.9%	8.2%	8.9%	8.2%
A.1	11.3%	10.6%	11.5%	10.7%	11.3%	10.5%
A.2	11.5%	10.8%	11.7%	11.0%	11.5%	10.8%
Central	11.5%	10.8%	11.7%	11.0%	11.5%	10.8%
A.3	11.9%	11.1%	12.1%	11.4%	11.9%	11.1%
A.4	12.3%	11.6%	12.5%	11.8%	12.3%	11.6%
B	14.6%	13.9%	14.6%	13.9%	14.6%	13.9%
C	10.7%	10.0%	10.7%	10.0%	10.7%	10.0%

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations; 95% confidence intervals are reported in table A.7.

A.2 Confidence intervals

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

	Shock to formal workers					
	Random		*Central*		50%-50%	
Shock to informal / self-employed workers	With Policies	With Policies	With Policies	With Policies	With Policies	With Policies
No shock	0.08%	0.08%	0.06%	0.06%	0.09%	0.09%
A.1	0.20%	0.21%	0.19%	0.19%	0.20%	0.21%
A.2	0.20%	0.21%	0.19%	0.19%	0.20%	0.20%
Central	0.22%	0.20%	0.17%	0.17%	0.21%	0.22%
A.3	0.20%	0.22%	0.18%	0.18%	0.21%	0.21%
A.4	0.20%	0.20%	0.14%	0.14%	0.21%	0.21%
B	0.15%	0.15%	0.13%	0.14%	0.15%	0.15%
C	0.15%	0.15%	0.13%	0.14%	0.15%	0.15%

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations.

Table A.4: 95% confidence interval for Table 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	2,961	2,897	2,185	2,228	3,299	3,275
A.1	6,936	7,518	6,625	6,734	7,186	7,250
A.2	6,860	7,298	6,794	6,523	6,902	6,914
Central	7,589	7,170	6,082	6,103	7,415	7,601
A.3	7,109	7,568	6,166	6,249	7,555	7,461
A.4	7,023	7,167	4,897	4,925	7,530	7,563
B	5,364	5,212	4,524	4,834	5,274	5,445
C	5,357	5,258	4,669	4,754	5,345	5,312

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations.

Table A.5: 95% confidence interval for Table 3

	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	25.9	23.9	23.6	0.6	0.6	0.5
A.2	32.2	26.1	28.7	0.7	0.6	0.7
Central	29.9	27.6	27.4	0.7	0.6	0.6
A.3	29.0	18.2	26.8	0.7	0.4	0.6
A.4	30.2	17.2	28.5	0.7	0.4	0.7
B	20	18	19	0.5	0.4	0.4
C	21	20	20	0.5	0.5	0.5

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations.

Table A.6: 95% confidence interval for Table 4.

	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	0.08%	0.07%	0.06%	0.05%	0.08%	0.08%
A.1	0.18%	0.19%	0.17%	0.17%	0.20%	0.20%
A.2	0.21%	0.20%	0.18%	0.19%	0.19%	0.19%
Central	0.21%	0.20%	0.18%	0.18%	0.20%	0.21%
A.3	0.21%	0.20%	0.16%	0.17%	0.22%	0.20%
A.4	0.19%	0.19%	0.11%	0.13%	0.19%	0.20%
B	0.16%	0.15%	0.15%	0.14%	0.16%	0.15%
C	0.14%	0.14%	0.14%	0.14%	0.14%	0.15%

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations.

Table A.7: 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	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
A.1	0.08%	0.08%	0.08%	0.09%	0.08%	0.09%
A.2	0.11%	0.11%	0.08%	0.10%	0.09%	0.09%
Central	0.10%	0.10%	0.09%	0.09%	0.10%	0.10%
A.3	0.09%	0.10%	0.08%	0.08%	0.10%	0.10%
A.4	0.09%	0.09%	0.05%	0.05%	0.09%	0.09%
C	0.07%	0.07%	0.07%	0.07%	0.07%	0.07%
C	0.07%	0.07%	0.06%	0.07%	0.06%	0.07%

Note. Own elaboration based on ECH microdata from INE. Results come from 100 simulations.

A.3 Econometric model

The econometric model implemented below estimates the correlation between the probability for an eligible formal worker to be laid off, suspended or reduced and apply for unemployment benefits (in any of the three schemes considered), and the capacity 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. This model is estimated based on the information on applications for unemployment benefits by industry reported in Table 1, and the variables *workhome* and *prox* constructed based on the O*NET data set merged with ECH information following (Guntin, 2020).

Now, Table A.1 above shows the number of eligible workers that applied for unemployment benefits for eleven activity sectors (ISIC 2 digits). We then calculate the total number of formal workers (with the exceptions described above) eligible for unemployment benefits in each sector and compute the proportion of eligible formal workers by industry that applied for unemployment benefits (for all three schemes). That is, we construct a measure of the fraction of total eligible workers effectively applying for unemployment benefits ($Shares$). We then add a twelfth sector, comprising all eligible formal workers in all remaining sectors (e.g. there were no laid off fishermen appliying to unemployment benefits in the period), to whom we assign a $Shares = 0$. Then, the estimating sample consists of all the eligible formal workers in the economy. With this sample, we estimate the logit model presented in Equation 3:

$$Share_s = workhome_{is} + workhome_{is}^2 + prox_{is} + prox_{is}^2 + e_{is} \tag{3}$$

Here $Share_s$ represents the proportion of eligible formal workers in sector s that applied for unemployment benefits, *workhome* and *prox* were previously defined and measure the capacity of a worker of conducting her activities from home and without proximity to others, and are included as linear and quadratic terms. 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 in each case. e_{is} represents the error term, and the model is estimated using robust standard errors. A.8 below presents regression results (Column 1).

The results indicate that both variables have the expected effect on applications for unemployment benefits in each sector: 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 for benefits. Quadratic terms indicate that the positive effect is decreasing. Note that the pseudo-R^2 statistic is close to 0.2. Estimates from a probit model for a robustness check produced similar results, as we show in Column 2 of Table A.8.[61]

Strictly speaking, the dependent variable is not the probability of being affected, but we make the conceptual jump as an assumption. Also, we understand that the dependent variable is constant for all workers in the same industry. But, although the same model could be estimated using the average of the variables of interest computed at the industry level, this involves losing information, since the same average can arise from different distributions of the

[61] 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 that produces predictions bounded between 0 and 1.

variables within each industry. For this reason we ran the regression using individual data. As previously reported, we can then use the logit regression results to predict the probability of being laid off, suspended, or reduced, for the whole sample (including informal and self-employed workers).

Table A.8: Predicting the probability that eligible formal workers apply for unemployment benefits: probit and logit estimations

	Eligible formal worker share applying for unemployment benefits	
Variables	Logit	Probit
workhome	10.68***	5.962***
	(0.0530)	(0.0302)
$workhome^2$	-2.018***	-1.129***
	(0.00980)	(0.00559)
prox	7.066***	4.259***
	(0.0602)	(0.0315)
$prox^2$	-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	0.1881	0.1896

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 applied for unemployment benefits, by activity sector (ISIC 2 digits).