Multiplier effect of social security during the COVID-19 pandemic: insights from Brazil's Emergency Aid program*

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Abstract: Fiscal multipliers have gathered attention for the last twenty years. Social spending multipliers are specially prominent today because of the COVID-19 pandemics and its economic burden on societies. So far, research seems to be mostly based on structural vector autoregression, which may be due to data scarcity regarding subnational levels. We try to address this gap with a dynamic panel. Using quarterly data obtained from the Continuous National Household Sample Survey, we estimate a simple social protection multiplier based on 146 geographical strata (which aggregate municipalities according to proximity and socio-economic integration). Results suggest the Emergency Aid (*Auxílio Emergencial*) had a multiplier effect of approximately 3. These results generally align with existing research and underscore the countercyclical effects of social protection during recessions.

Keywords: Fiscal policy; Fiscal multipliers; Social protection.

JEL codes: C1, E6, H56.

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1. Introduction

Studies on the multiplier effect of fiscal policy have gained prominence in recent years. From the 2000s onwards, there was a surge of research whose aim was to test and evaluate macroeconomic postulates, particularly those of Keynesian hue. This type of approach has probably become more popular for several reasons. Firstly, the financial crisis that erupted in 2008 and the quantitative easing agenda raised questions about the effectiveness of monetary policy for income stabilization and economic recovery. In parallel, social protection programs gained importance due to rising unemployment, leading to doubts about the sustainability of public debt (Rodriguez-Vivez and Kezbere, 2019). In this context, fiscal policy and its multiplier effect gained more attention, both from policymakers and the academic community.

However, there is a relative scarcity of studies that analyze the multiplier effect of social spending. Most econometric analyses focus on multipliers associated with shocks in public spending and tax shocks. Furthermore, these studies typically work with aggregate data, which necessarily implies inaccuracies, as different types of public spending exert different multiplier effects (Pereira and Wemans, 2013).

The COVID-19 pandemic has not only made it urgent to study fiscal policy, but also to do so with particular attention to social spending. This is justified by its significant spike in public finance from 2020 onwards and by the criticisms that such expenditures have attracted among some academics and policymakers (Sanches and Carvalho, 2022).

In this paper, we begin with a description of social expenditure in Brazil during the COVID-19 pandemic and present some preliminary econometric exercises concerning social expenditure and its effect on income. Section 2 overviews the Brazilian social protection system and its main policy during the pandemic, the *Auxílio Emergencial* (hereafter Emergency Aid). Section 3 describes the methodology. Section 4 provides the results, its analyses, and offers some comparison with recent work. Finally, we mention some possibilities for further investigation.

2. Social protection in Brazil before and during the pandemic

Brazil's current social protection system was instituted with the promulgation of Federal Constitution in 1988. The Constitution laid the groundwork for democratic governance and established a framework for social rights and protections. This was imperative since the military dictatorship that preceded it aggravated social problems (Souza, 2018).

Comprising a mix of public policies, welfare programs, and social security initiatives, the system aims to provide a safety net for vulnerable groups. It includes programs like *Bolsa Família* (Family Allowance), a conditional cash transfer initiative targeting impoverished families, and *Benefício de Prestação Continuada* (Continuous Cash Benefit), which guarantees a minimum wage to the elderly and to people with disabilities.

This social protection system has been very important in the last decade: in Brazil, the 2010s have had an uncanny resemblance with the 1980s, when the foreign debt crisis entailed a "lost decade", i.e., years of negative or zero growth. The 2015-2017 recession shed roughly 7% of the country's GDP.

Therefore, the COVID-19 pandemic hit an already frail economy and triggered the need for immediate responses to mitigate socio-economic distress. Among these responses, the Emergency Aid was a mainstay: it provided cash to informal workers and low-income households impacted by the pandemic's economic repercussions. Its capilarity was facilitated by the existing social assistance system and its framework: citizens previously eligible for Family

Allowance program were automatically evaluated and eventually more than 60 million (roughly a third of the population) were included among the beneficiaries of the Emergency Aid[1]. This temporary aid aimed to alleviate financial strains by providing monthly stipends, assisting those facing job loss or reduced income due to lockdowns and economic slowdowns. For 2020, its cost ammounted to approximately 4% of the GDP (Figure 1).

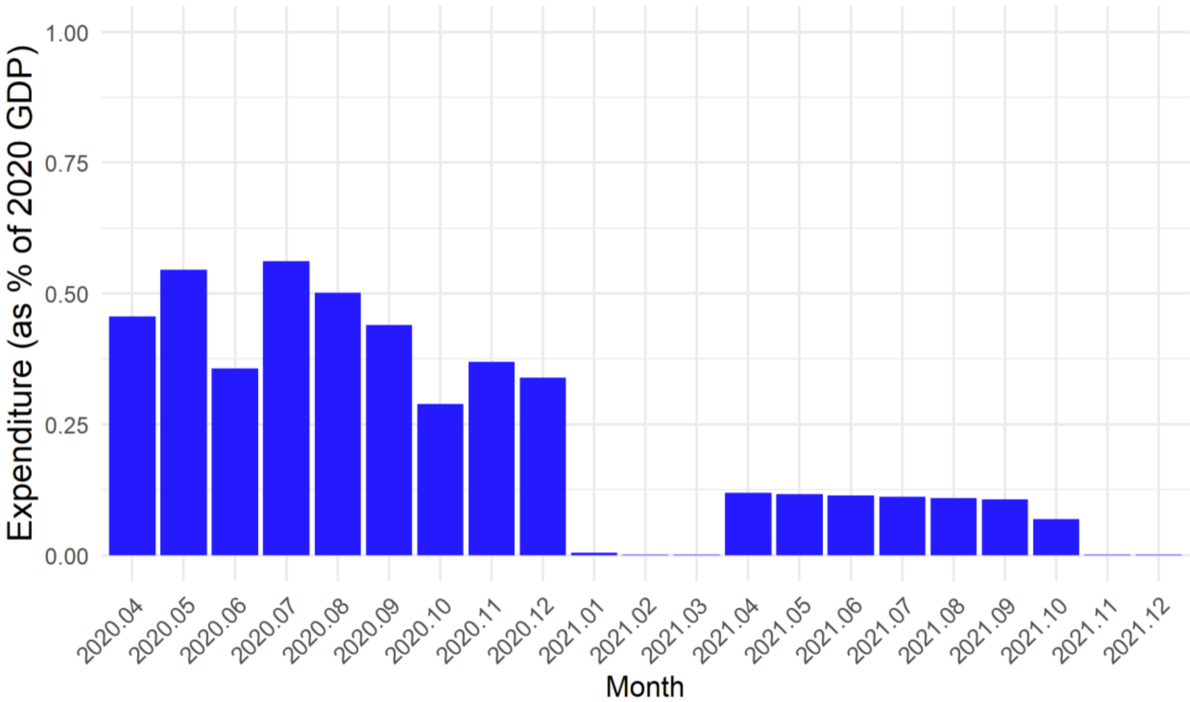

Figure 1: Expenditure with Emergency Aid in Brazil.

Source: Institute for Applied Economic Research (IPEA), 2023.

As can be seen in Figure 2, mean *per capita* income actually increased in 2020, probably as a reflection of the Emergency Aid. This increase was less pronounced in the North and Northeast regions (Figure 3), which historically have had their economy more closely dependent on the service and commerce sectors

[1] This know-how (and know-who) was an important feature of the Brazilian response to the pandemic. The American *Stimulus Check*, for instance, failed to reach the poorest citizens (cf. Licio, 2023).

and hence suffered the most with the pandemic (Brazilian Institute of Geography and Statistics – IBGE, 2021).

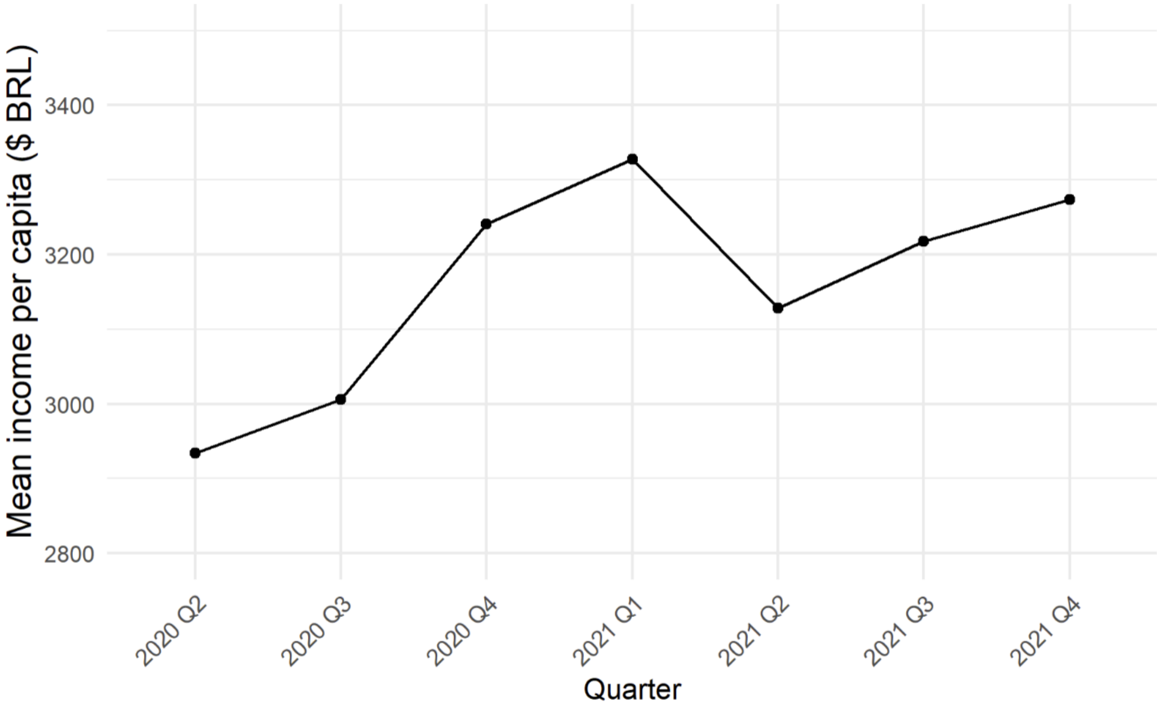

Figure 2: Mean deflated *per capita* income by quarter.

Source: Continuous National Household Sample Survey – Brazilian Institute of Geography and Statistics (IBGE – 2023).

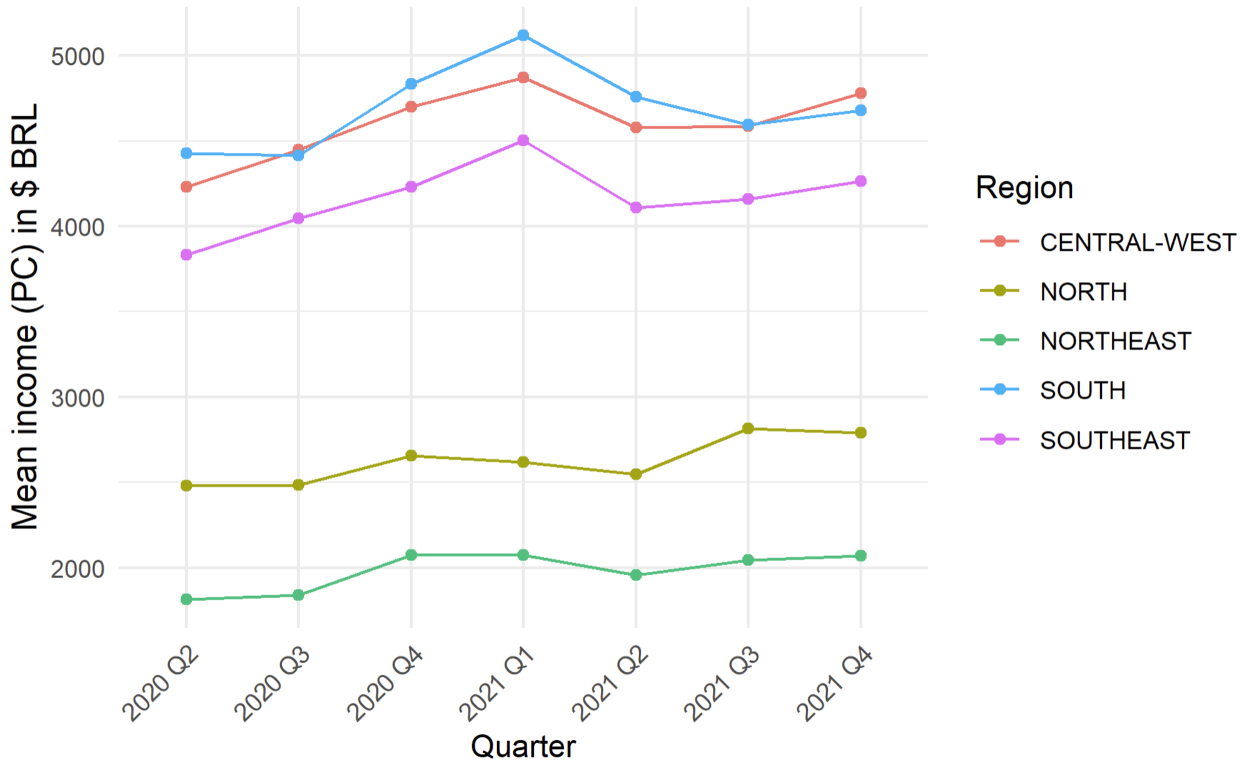

Figure 3: Mean deflated *per capita* income by quarter and region.

Source: Continuous National Household Sample Survey – Brazilian Institute of Geography and Statistics (IBGE – 2023).

Recent studies describe the economic impact of fiscal multipliers during the pandemic. Auerbach *et al* (2022) examine regional baseline differences in economic circumstances, lockdown measures, and U.S. government expenditure, and conclude that the impact of government spending effect was only notable in cities that were not subjected to stay-at-home directives. Since it is reasonable to think that lockdowns have the potential to reduce economic activity, in the next section we describe our tentative approach to deal with this. Kinda *et al* (2022) base their approach on the local projections methodology and conclude that cumulative fiscal multipliers are approximately twice as large in health crises periods when compared to typical periods, especially within advanced economies.

Few studies analyse the economic impact of the Brazilian Emergency Aid. Cunha *et al* (2022) use cross-sectional data and point that the “preferred range” of the short-run GDP multiplier effect of the benefit is 0.5 - 1.5. Rosa *et al* (2021) use an input-ouput model to address regional and state-level indirect impact of the Emergency Aid, since the configuration of production networks could lead to income spillovers across regions. The authors conclude that even though the Emergency Aid program achieved its social protection objetive, states with more complex productive structures were the most benefited in the long-run.

However, to the best of our knowledge, there are no studies that address both spatial and temporal dimensions of the Emergency Aid by means of longitudinal data. Thus, we hope our approach addresses some preliminary steps for future work concerning social protection and its effects on the Brazilian economy.

3. Methodology

3.1 Data extraction

We begin with a brief description of the data collection and preparation and then proceed to describe the econometric specifications employed.

The box below provides a simple overview of the data employed and its sources.

Independent variables: social benefits	Dependent variable: *per capita* income
Emergency Aid (monthly data by municipality – 4/2020 to 12/2021)	Continuous National Household Sample Survey (quarterly data by geographical stratum – 2020 Q2 to 2021 Q4)
Family Allowance (monthly data by municipality – 4/2020 to 12/2021)	
Brazil Aid (monthly data by municipality – 11/2021 a 12/2021)	
Continuous Cash Benefit (monthly data by municipality – 4/2020 to 12/2021)	

Box 1: Data sources and their respective frequencies.

The independent variable is the *per capita* expenditure with the Emergency Aid. Control variables are the *per capita* expenditures with Family Allowance[2] and Continuous Cash Benefit. Furthermore, a control variable derived from Google's COVID-19 Community Mobility Reports (Google LLC, 2023) reflects time spent at home, since restrictions on mobility can significantly impact economic activity. The dependent variable is *per capita* income, calculated from the Continuous National Household Sample Survey. It should be highlighted that this survey only assesses labor-related income.

To obtain the dependent variable in the desired format and frequency, we used R language and 'PNADcIBGE' package (Braga and Assunção, 2021). More specifically, we downloaded survey micro-data for different quarters and years, ensuring the data was adjusted for inflation. Since the Continuous National Household Sample Survey is not statistically representative at the municipal level, we chose to work with geographical stratum level. The geographical strata are an

[2] Familly Allowance program was temporarily renamed *Auxílio Brasil* (Brazil Aid) in 2021, which appears in the left portion of the diagram but whose data was merged with FA data.

intermediate level of aggregation, standing in-between municipalities and states. In our empirical procedure, we added geographical stratum information to the dataset by mapping codes to predefined geographical areas (IBGE, 2022a). We then calculated the total *per capita* income for each geographical stratum by summing up the deflated income values and dividing them by the estimated population of that stratum as provided by the 2022 Census (IBGE, 2022b).

The independent variables concerning social benefits were obtained from the Transparency Portal (Portal da Transparência do Governo Federal, 2023). For the Emergency Aid, Family Allowance and Continuous Cash Benefit, the process was similar: the micro-data provide the list of beneficiaries of these programs by municipality. We summed its value by geographical stratum and divided it by the stratum population (obtained from the 2022 Census).

3.2 Dynamic panel specifications

Our basic model consists of

$$y_{it} = \delta y_{i,t-k} + \beta x'_{i,t-k} + u_{it}$$

and

$$u_{it} = \mu_i + v_{it}$$

where $\delta < 1$, $i = 1, \dots, 146$ is the number of geographical strata, $t = 1, \dots, 7$ is the time dimension, x is the vector of regressors, μ_i is the geographical stratum individual effect which, together with v_{it}, correspond to the error term.

Autocorrelation and endogeneity mean that ordinary least squares (OLS) is biased and inconsistent, while the *"within"* transformation for fixed effects is biased and inconsistent if t is small (Nickell, 1981; Baltagi, 2008). Because income is expected to be persistent, difference GMM would likely lead to biased and inefficient estimates, since in this case lagged levels are weak instruments for first differenced variables. Therefore, system GMM (Blundell and Bond, 1998) was chosen for estimation, since it is particularly well-suited for addressing endogeneity issues and biases arising from omitted variables or unobserved heterogeneity.

We used the *plm* package (Croissant and Millo, 2008) to perform the estimations. Models were estimated in first differences and incorporated time-fixed effects. Estimations were conducted in both their original levels and in logarithmic form. To account for finite-sample biases, all specifications incorporated Windmeijer's (2005) robust covariance matrix correction. All instrumental variables available were used, and instrument count was restricted to 2 (cf. Roodman, 2009). Variations of lags and estimation methods are provided with the results.

4. Results and discussion

Results are presented in Tables 1 and 2. Models were selected based on diagnostic tests (also provided) and are highlighted in boldface. For the regressions conducted in levels, the coefficient represents directly the multiplier. For the regressions conducted in logarithmic form, coefficients indicate the elasticity of income with respect to government expenditure. The estimates for transfers other than the Emergency Aid are either insignificant or contradictory, and their standard errors reflect this. This is the reason why these variables were excluded from the final model, even though results are robust when they included. To a certain extent this outcome is expected, since part of the beneficiaries of these social benefits were not allowed to accumulate them with the Emergency Aid. This probably led to temporary (but important) modifications of the beneficiaries database.

Table 1: Regression results – models in levels

	Income					
	Model (1)	Model (2)	**Model (3)**	Model (4)	Model (5)	Model (6)
Income (Lag 1/1)	0.981***			0.911***		
	(0.008)			(0.011)		
Income (Lag 1/2)		0.759***			0.733***	
		(0.027)			(0.022)	
Income (Lag 2/2)		0.239***			0.229***	
		(0.026)			(0.020)	
Income (Lag 1/3)			**0.479*****			0.676***
			(0.104)			(0.133)
Income (Lag 2/3)			**0.403****			0.177
			(0.127)			(0.130)
Income (Lag 3/3)			**0.127**			0.246**
			(0.080)			(0.089)
Emergency Aid	0.024	1.070**	**3.651*****	0.090	0.811*	3.777***
	(0.163)	(0.343)	**(0.782)**	(0.154)	(0.332)	(1.115)
Family Allowance				-3.227***	-1.412**	2.372
				(0.444)	(0.653)	(2.300)
Continuous Cash Benefit				-0.217	-0.145	-0.849
				(0.330)	(0.461)	(1.381)
Time spent at home	-40.938***	-53.217***	**-59.761**	-15.619*	-38.813**	-23.968
	(12.205)	(13.504)	**(32.695)**	(7.390)	(11.996)	(34.825)
Diagnostic tests (p-value)						
Sargan test	0.003	0.012	0.430	0.163	0.298	0.999
Autocorrelation test (1)	0.000	0.000	0.022	0.000	0.000	0.000
Autocorrelation test (2)	0.437	0.022	0.088	0.456	0.000	0.597
Wald test (coefficients)	0.000	0.000	0.000	0.000	0.000	0.000
Wald test (time dummies)	0.000	0.000	0.000	0.000	0.000	0.000

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 2: Regression results – models in logarithmic form

	Income					
	Model (1)	Model (2)	**Model (3)**	Model (4)	Model (5)	Model (6)
Income (Lag 1/1)	0.986***			0.860***		
	(0.006)			(0.035)		
Income (Lag 1/2)		0.736***			0.695***	
		(0.037)			(0.038)	
Income (Lag 2/2)		0.240***			0.220***	
		(0.036)			(0.036)	
Income (Lag 1/3)			**0.741*** **			0.532***
			(0.066)			(0.087)
Income (Lag 2/3)			**0.096**			0.032
			(0.075)			(0.098)
Income (Lag 3/3)			**0.140* **			0.238**
			(0.076)			(0.104)
Emergency Aid	0.069***	0.070***	**0.074*** **	0.096***	0.075***	0.074***
	(0.017)	(0.016)	**(0.017)**	(0.018)	(0.017)	(0.018)
Family Allowance				-0.089***	-0.045*	-0.138**
				(0.026)	(0.027)	(0.064)
Continuous Cash Benefit				-0.011	0.003	0.048
				(0.021)	(0.022)	(0.045)
Time spent at home	-0.011***	-0.018***	**-0.022*** **	-0.001	-0.013**	-0.011
	(0.004)	(0.005)	**(0.005)**	(0.004)	(0.005)	(0.008)
Diagnostic tests (p-value)						
Sargan test	0.018	0.118	0.651	0.200	0.298	0.250
Autocorrelation test (1)	0.000	0.000	0.000	0.000	0.000	0.000
Autocorrelation test (2)	0.366	0.006	0.053	0.042	0.146	0.415
Wald test (coefficients)	0.000	0.000	0.000	0.000	0.000	0.000
Wald test (time dummies)	0.000	0.000	0.000	0.000	0.000	0.000

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

The regression conducted in levels suggests a multiplier effect of approximately 3.6 (CI 95%: 2.09 – 5.21). Since the regression conducted in logarithmic form provides the elasticity of income with respect to expenditure, we derive a generic multiplier based on Restrepo (2020), Spilimbergo *et al* (2009) and Pires (2014). The elasticity between variables Y and X is defined as

$$\varepsilon_{Y,X} = \frac{\frac{\Delta Y}{Y}}{\frac{\Delta X}{X}} = \left(\frac{\Delta Y}{Y}\right)\left(\frac{X}{\Delta X}\right) = \left(\frac{\Delta Y}{\Delta X}\right)\left(\frac{X}{Y}\right)$$

Since $\left(\frac{\Delta Y}{\Delta X}\right)$ is the multiplier, we can obtain it through the division of $\varepsilon_{Y,X}$ by $\left(\frac{X}{Y}\right)$. For the seven quarters of our sample, the average ratio of *per capita* expenditure with Emergency Aid over GDP is 0.0255. Hence, the coefficient obtained (0.074) implies a multiplier of 2.9 (CI 95%: 1.56 – 4.23).

These estimates are in agreement with those obtained by Sanches and Carvalho (2023) and Resende (2019), which find a cumulative[3] multiplier (for two years) of 2.9 and 4.3, respectively. Although high, these results are not uncommon: Reeves *et al* (2013), for example, analyse a panel of 25 European Union countries and estimate a multiplier of 3 for social benefits. Such numbers contrast with Konstantinou and Partheniou (2021), for example, which find multipliers of up to 0.9.

Our results might be somewhat higher than what is commonly found in the literature for some reasons. Firstly, since our dependent variable reflects labor-related income, it is reasonable to assume that estimations that assess general income could lead to smaller multipliers, given that labor-related income may imply a higher marginal propensity to consume. The second reason is related to

[3] This cumulative multiplier is not the same as the one posited by Ramey and Zubairy (2018).

the economic setting: the pandemic implied high unemployment and resource underutilization, which tipically entail higher multipliers when compared to periods of expansion (Auerbach and Gorodnichenko, 2011). Finally, our results should be interpreted cautiously, since they are not based on a formal impulse-response function and do not reflect a dynamic setting. These pitfalls are explored by Ramey and Zubairy (2018).

In summary, our results suggest that the Emergency Aid had an important multiplier effect during the COVID-19 pandemic.

5. Future directions

Exploring Ramey and Zubairy's (2018) cumulative multiplier and investigating multipliers derived from Jordà's (2005) local projections method seems promising. In the context of dynamic panel models (rather than time series models), assessing the applicability of these multipliers is relevant and might provide a more comprehensive view of fiscal multipliers. The impact the Emergency Aid had across different regions also warrant future investigation, since economic complexity has been shown (Rosa *et al*, 2021) to be related to the diverse effects of this aid. Finally, it is also promising to verify whether the impact of the Emergency Aid varied based on race, gender, age, education and other demographic factors.

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