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Estimating the Employment and GDP Multiplier of Emergency Cash Transfers in Brazil

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ABSTRACT: We estimate the subnational employment and GDP multiplier of Brazil's 2020 federal cash transfers to vulnerable households. Using two-stage least squares regressions we estimate a formal employment multiplier and then apply an analytical transformation to recover an implied GDP multiplier in the range of 0.5-1.5. The lower bound of this range lies below most estimates in the literature, which may result from the exceptional constraints imposed by the pandemic on supply chains and consumption. Nevertheless, even using the lower end of our range implies that federal cash transfers played an important role in supporting employment and GDP.

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WORKING PAPERS

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1 Introduction

In response to the COVID-19 pandemic, the Brazilian federal government provided substantial fiscal and financial support to the economy. Policies included tax relief for companies and households, temporary income support to vulnerable individuals, credit facilities for firms (mostly small and medium sized companies, which as a group employ the largest share of the population), a job-retention scheme with subsides for furlough workers, and debt relief and cash transfers to states and municipalities, to name a few. In all, fiscal measures in 2020 had a direct impact on the primary deficit of over 7 percent of GDP. In addition, public banks opened pandemic-related credit lines worth close to 5 percent of GDP. In tandem with the fiscal and quasi-fiscal support, Brazil's central bank cut the policy interest rate in quick succession to historical lows— equivalent to negative interest rates in real terms—and announced extensive liquidity and capital relief measures.

The Emergency Aid (henceforth EA) cash transfers program, which cost nearly BRL 300 billion (4.3 percent of GDP) in 2020, was the most emblematic pillar of the government's response package. Offering basic income to informal workers (employed or unemployed) and vulnerable households, the program was instrumental to stave off a dramatic rise in poverty and inequality which COVID-19 would have brought by its direct impact on labor markets, as shown by Flamini et al. (2021) and Cardoso (2020). For several months the EA more than offset labor income losses for households at the bottom four deciles of the income distribution, effectively increasing their real household income relative to pre-pandemic levels.

While the primary goal of the EA program was to provide social assistance in the exceptional context of the pandemic and forced social distancing, data on retail activity, mobility, and growth performance - as well as anecdotal evidence - suggests that the EA also provided an important cushion to the economy overall, avoiding a deeper recession in Brazil (with a contraction of around 4 percent of GDP, Brazil's recession was milder than roughly 75 percent of advanced economies and emerging markets). In this paper we aim to formalize the impact of EA on growth. We use monthly private formal employment data at the municipal level to estimate the employment effects of the EA, taking advantage of the large heterogeneity in the distribution of the EA eligibility across Brazil's several thousand municipalities. As in Chodorow-Reich (2019), we first estimate an employment multiplier (in our case a formal employment multiplier - the number of private formal sector jobs created by each BRL 100 thousand disbursed by the federal government on EA) and then propose an analytical transformation to translate the employment multiplier into an output multiplier. At the municipal level, no high-frequency data for the large informal sector (nearly 50 percent of the labor market) or public employment (5 percent) exists. This necessitates the choice to estimate a private formal sector employment multiplier rather than a total employment multiplier.[1] To obtain causal estimates, we instrument for EA spending with the pre-pandemic

[1] Informality rates vary from 16 to 97 percent across municipalities.

share of *Bolsa Familia* (longstanding conditional cash transfer program) recipients at the municipal level.

In the baseline estimations we find a formal employment multiplier around 0.5 (for the six-month window April-September 2020). This implies an annual cost per private formal job of over BRL 400,000 or USD 78,000. An important consideration, however, is the role of informality. In municipalities with low informality, estimating a private formal sector employment multiplier is similar to estimating a total employment multiplier. But in municipalities with high informality, the private formal sector employment multiplier is likely to be substantially below the total employment multiplier (in the limit, with informality at 100 percent, the private formal employment multiplier becomes meaningless and is equal to 0 as cost per job goes to ∞). Analyzing an expansion of the *Bolsa Familia* in 2009, Gerard et al. (2021) find that municipalities with a high informality rate have an underlying cost per formal job ten times larger than regions with low informality, meaning that the formal employment multiplier of informal municipalities is 1/10 of the ones with lower informality rate. To account for this heterogeneity in the formal sector employment multiplier, we also run regressions interacting the EA variable with the pre-pandemic structural informality rate. Taking a weighted average of the resulting multipliers to obtain a national estimate yields a private formal employment multiplier over 6 months of around 1.6 - that is, a cost per year-job of BRL 124,000 (or USD 24,000). This national multiplier is larger than the one obtained in the baseline regression - as well as a multiplier obtained through a simple conditional mean (around 0.9) - because municipalities with a higher share of formal employment in total formal employment (i.e., with higher weight) tend to have larger multipliers.

We derive analytical expressions which allow us to transform the estimated formal employment multiplier into a total employment multiplier and a GDP multiplier, similar to Chodorow-Reich (2019) but taking into account the share of formal and informal workers and their relative productivity. This yields a range of 1-3.5 for the annual total employment multiplier (annual cost per job of USD 6,000-24,000) and a broad range of 0.3-1.8 for the GDP multiplier, with a preferred range of 0.5-1.5 considering most adequate specifications. Essentially, lower estimates are obtained from specifications without the informality interaction term, while the upper estimates originate from specifications with such interaction term.

Conceptually, our estimates yield a cross-region transfer multiplier. Pennings (2021) shows that a transfer multiplier should be smaller than a purchase multiplier, depending on how large the marginal propensity to consume (MPC) is and on how much of the transfers are being spent locally (how open the economy - here municipality - is). The higher the MPC and the less open municipalities are, the higher will be the transfer multiplier.[2]. In addition, how permanent transfers

[2]Considering a corner example in which the households of a given municipality have a "home-bias" preference to fully spend their transfers in locally-produced goods/services, then the transfer multiplier would be 1, similar to a situation in which the government directly purchases goods/services from this municipality.

are also plays an important role, unless the share of hand-to-mouth households is very large. For the US, Pennings (2021) finds a cross-regional transfers multiplier of 1.5 for permanent transfers and 1/3 for one-off transfers.

There exists only limited empirical evidence on the cross-regional transfer multiplier in emerging markets. Given the wide range of theoretically plausible multipliers, we see as one of the main contributions of our paper that it provides a benchmark for the case of Brazil. It is also among the first studies of the impact of Covid-related response programs on economic activity in emerging markets. Last, we build on the literature by carefully considering the role of informality in obtaining multipliers in an emerging market. Closely related studies include Sadoulet et al. (2001), who find a multiplier range of 1.6-2.5 analyzing the PROCAMPO program in Mexico, and Egger et al. (2019), who estimate a local cash transfer multiplier of 2.6 using novel experimental evidence from Kenya. Using panel regressions Denes et al. (2018) estimate that the *Bolsa Familia* multiplier was as high as 4 in Brazil in the 2004-2010 period.[3]

Corbi et al. (2019) estimate formal employment purchase multipliers at the municipal level in Brazil. The authors exploit a discontinuity in the allocation of federal transfers to municipalities, based on population size thresholds, to study the impact of externally financed municipal government spending on formal employment over the period 1999-2014. They find a cost-per-annual-formal-job of USD 8,000-13,000 and a preferred GDP multiplier when accounting for the informal sector of 2.4.[4] This is at the very top of the range of direct spending (purchase) multipliers generally obtained in cross-sectional studies for the US. Chodorow-Reich (2019) cite a multiplier range of 1-2.5, with a preferred point estimate of 1.8, and Serrato and Wingender (2016) find a local multiplier between 1.7 and 2 using a Census shock to map expenditure changes that depend on the local population size.

In all, the empirical evidence for emerging markets has so far shown large local multipliers, with both purchase and transfer multipliers significantly above 1. The upper end of our estimated GDP multiplier range (0.5-1.5) corresponds to estimates previously found in the literature while the lower end lies substantially below most cross-sectional GDP multiplier estimates. Of course, the exceptional nature of the Covid-19 pandemic might plausibly explain lower estimates. It seems intuitive that forced social distancing and substantial restrictions on the supply of various services, with a (likely associated) sharp increase in aggregate household savings, would lead to lower multipliers ceteris paribus[5]. We nonetheless interpret our estimated local EA multiplier as providing

[3]Estimating national transfer multipliers in emerging markets, Bracco et al. (2021) find a general multiplier of 0.9 for Latin America, compared to 0.3 for developed economies. The difference is mainly explained by the larger share of hand-to-mouth households in EMs economies.Neri et al. (2013) find an implied GDP multiplier of *Bolsa Familia* of 1.8.

[4]Corbi et al. (2019) calibrate the productivity ratio of informal to formal workers to $\rho = 0.55$. Updating their estimation using recent work by Ulyssea (2018), we obtain $\rho = 0.81$ and, thus, an implied GDP multiplier of 3.5.

[5]Auerbach et al. (2020) provide evidence for the US that points in a similar direction. Looking at the average

a lower bound for what the corresponding national multiplier would be.[6] Chodorow-Reich (2019) for instance argues that local spending multipliers lay out a rough lower bound for the aggregated national (deficit financed) spending multiplier for a closed economy when monetary policy is passive. Similar factors are at play in this study. Brazil is a relatively closed economy, and surely more closed than its individual municipalities. In addition, monetary policy was accommodative in 2020. When real rates do not rise in response to higher government spending, the standard multiplier measured at the national level rises, but this effect is "netted" out in cross-sectional regressions, as all municipalities are equally affected by monetary policy.[7]

The remainder of this paper proceeds as follows. Section 2 provides more details on the EA program, motivating the subsequent discussion of data and research design in sections 3 and 4. Section 5 presents the results and section 6 presents brief concluding considerations. Additional tables and figures not presented in the main text can be found in the Appendix.

2 Background: The Brazilian Emergency Aid Cash Transfer Program

The EA was a means tested program of monthly disbursements, which covered roughly 60 percent of the total workforce in the initial months. It was initially also very generous, providing an estimated replacement rate of 40 percent of the average income in the informal sector and increasing the real household income of the bottom four deciles of the income distribution by 20 percent (at least in May and June 2020) according to Flamini et al. (2021). The original design (Law no. 13.983, April 2, 2020) offered support during 2020Q2. Given the continued outbreak of COVID-19, however, the authorities extended the program twice in 2020, first through end 2020Q3 and later for the whole year (at that stage with tighter eligibility and a 50 percent reduction in stipends).

Eligibility. The EA initially offered a monthly basic income of BRL600 (and twice as much for single parents) to all contributors to Brazil's public social security system (INSS), participants of the national single registry (*Cadastro Único*), citizens registered as individual micro-entrepreneurs (MEI), and informal workers not registered in other federal assistance programs. In addition, *Bolsa Família*[8] beneficiaries could temporarily migrate to the EA program. The eligibility age was 18 years or older. Participants must belong to a household with per capita monthly income of no

impact of Covid-related fiscal response measures in a large group of countries during 2020, Deb et al. (2021) also find that demand policies (including, though not restricted to, cash transfers) had less impact on economic activity during stringent lockdowns

[6] A national EA multiplier cannot be obtained given the very short time period under consideration.

[7] Chodorow-Reich (2019) considers the case when monetary policy response is restricted by a zero lower bound scenario instead. Similarly, real rates fall in that scenario following the increase in government spending.

[8] *Bolsa Família* was Brazil's most important social assistance program. Prior to the pandemic it covered around 14 million households, paying a monthly benefit of less than BRL 200, at a total annual cost of 0.4 percent of GDP.

more than BRL 522 (half the minimum wage) or total monthly income up to BRL 3,135 (thrice the minimum wage). Finally, participants could not have had annual taxable gross income greater than BRL 28.5 thousand in 2018.

Financial inclusion. A vast number of EA participants did not have a banking account at the time of the first transfer. Caixa Econômica Federal (CEF) thus offered digital banking accounts, debit cards, and cell phone apps to include them in the system. Participants with accounts in other institutions could decide which bank to use to withdraw the cash. Importantly, banks could not withhold EA transfers to citizens with outstanding debt or past due overdraft accounts. The social safety net got wider and digital.

Fiscal costs. The EA transferred approximately BRL 40 billion (1/2 percent of GDP) per month to recipients during 2020Q2 and 2020Q3. Owing to tighter controls over claimants' eligibility and reduction in monthly stipend, the cost of EA transfers fell to half the amount in 2020Q4.

3 Data

Brazil is a federal republic with three levels of government - federal, state and municipal. The unit of analysis in this paper are Brazil's municipalities. Our main (independent) variable of interest is the amount of Emergency Aid (EA) transfers disbursed by the federal government (Ministry of Citizenship) to the public bank CEF, which in turn was responsible for disbursing payments to individuals.

Ideally, we would like to use a measure of total municipal employment (or even a municipal GDP proxy) as the dependent variable. However, no suitable GDP proxy is available, and total employment data (covering both the formal and informal sector) is not available at the municipal level, even at annual frequency.[9] The dependent variable is thus private formal employment as measured by the government's administrative CAGED dataset. To account for extreme outliers linked to likely measurement problems, we exclude the top and bottom 0.5 percent of municipalities in terms of employment growth and EA per capita.[10] Below we briefly summarize the main data sources. Table 1 presents summary statistics while Figure 2 shows correlations between the main variables.

Emergency Aid: Data on EA payments at the municipal level are provided by the Brazilian Ministry of Citizenship. The first round of EA payments - six installments from April to September/2020 at the full original amount - represented 80 percent of total year-transfers (Figure1).

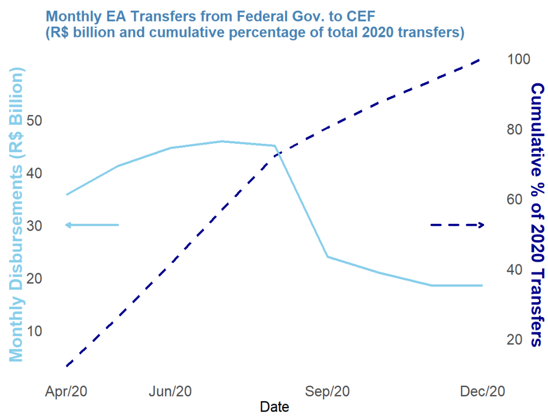
[9] The continuous household survey PNAD provides data at the national and state level for both the formal and informal sectors, but is not representative at the municipal level. Only the population census - conducted once every ten years - provides a full picture of employment at the municipal level.

[10] Regression results are not meaningfully different when outliers are retained, but parameter stability decreases somewhat.

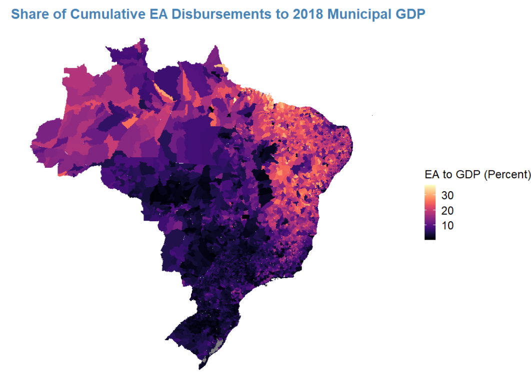
For each round, new beneficiaries were informed *ex ante* about the payment schedule of future installments.

Figure 1: EA Disbursements Over Time and Municipal Heterogeneity

(a) Monthly Disbursements



(b) Regional (municipal) Distribution



Formal Employment: CAGED is an administrative database that covers in principle the universe of private formal workers in Brazil. There was a significant change in its methodology at the end of 2019 and, thus, we chiefly focus on the series from 2020 onward to ensure consistency. We use CAGED's November 2021 vintage which offers the most up to date payroll series, after incorporating ex-post notifications of hiring/layoffs and correcting methodological issues.

Mobility: The google mobility index tracks more than 2,400 Brazilian Municipalities. We use the average of mobility indices for groceries and pharmacies, parks, retails and recreation, transit stations, and workplaces.

COVID-19 Deaths: New daily Covid-19 related deaths per million were computed using the administrative data from the Brazilian Ministry of Health.

2010 Census-based Indicators: Informality at the municipal level is defined as the ratio of informal employment to total employment (considering the occupied population over 10 years of age). The share of non-white population covers all individuals that did not declare themselves as white or Asian. Urbanization is calculated as the ratio of urban population to total population in each municipality. Agriculture as a share of total employment captures employment in agriculture as a share of total employment. Last, services as a share of total employment were computed taking into account the sectors outside of the perimeter of agriculture, manufacturing, and public administration.

Bolsa Familia Recipients: The share of the population receiving *Bolsa Familia* benefits in each municipality was calculated using administrative data from the Ministry of Citizenship, as of December 2019.

Job Protection Program: The Emergency Benefit for Preserving Employment and Income (BEm) was launched in April 2020, allowing for temporary reductions in working hours or contract suspension in the formal sector, by mutual agreement between employers and employees. The program backed workers by partially compensating for the associated salary losses, in an amount proportional to the unemployment insurance to which the employee would have been entitled to if she lost the job (i.e., pro-rated by the percentage reduction in working hours). Importantly, each employee could have more than one BEm agreement, either because she worked for more than one firm or for agreeing first to a cut in working hours and later to a contract suspension, or vice versa. The BEm data, from the Ministry of Economy, shows the number of monthly agreements aggregated at the municipal level.

Pandemic-related credit to SMEs: Besides the EA and BEm, pandemic-related lending facilities were the third largest pillar of the government's fiscal response. Among those, the Emergency Program for Access to Credit (PEAC), launched in June 2020, was the largest pandemic-related credit line to the real sector ($\approx$ 1.2 of the GDP). The program unlocked credit to SMEs, associations, private foundations, and cooperatives with underlying 2019 revenues between BRL360,000 and BRL300 million. The federal government provided guarantees to the credit lines, covering 80 percent of the face value of each operation. The PEAC data, from the Brazilian Development Bank (BNDES), shows monthly disbursements aggregated at the municipal level.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
Δ Formal Employment per Thousand	5,483	-0.4	13	-203.6	-0.3	348
Emergency cash transfers (EA) per capita	5,483	1,120	322	212	1,118	2,016
Share of *Bolsa Familia* Receivers	5,483	9	6	0	7	27
Share of non-white Population	5,472	52	24	1	57	99
Bolsa Familia (BF) Cover Ratio	5,472	1.08	0.23	0.22	1.09	2.90
Job Agreements per Formal Worker	5,333	0.31	0.28	0	0.23	9
PEAC Disbursements per capita	3,843	154	314	0.0	44	6,309
Δ Covid-19 Deaths per million	5,483	2	2	0	2	18
Urbanization Rate	5,479	64	22	4	65	100
Agriculture as Share of Employment	5,479	35	18	0	35	87
Services as Share of Employment	5,479	53	12	8	53	87
Informality Rate	5,478	64	17	16	67	97
GDP per capita (Thousand)	5,483	23	24	5	17	575
Population (Thousand)	5,483	38	225	1	12	12,325

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, EA cash transfers, and number of job protection agreements under the BEm program refer to the sum over April-September 2020. The share of the population receiving *Bolsa Familia* benefits in each municipality was calculated using administrative data from the Ministry of Citizenship, as of December 2019. The *Bolsa Familia* cover ratio is defined/estimated as the number of poor households receiving *Bolsa Familia* benefits as of end-2012 as a share of the estimated number of poor households according to the 2010 Census. Covid-19 deaths are measured as the average of daily new deaths over April -September 2020. GDP per capita is taken from the 2018 municipal accounts. At the average 2020 exchange rate to the USD, mean GDP per capita of BRL 23,000 corresponds to about USD 4,000. Population figures are collected from the Brazilian Institute for Geography and Economics (IBGE). We exclude the top and bottom 0.5 percent of municipalities in terms of the change in formal employment and emergency aid per capita.

4 Research Design

4.1 Baseline Econometric Specification and Identification

To estimate the cross-sectional *formal* employment multiplier we follow a standard approach, as set out for example in Chodorow-Reich (2019). Specifically, we regress the total change in private formal employment per capita between April and September 2020 on total EA disbursements per capita at the municipal level over the same period - which is the period with the bulk of EA disbursements.[11]

[11] In robustness exercises we change the window of analysis to the initial disbursement period (April-June) or the full 9-month period of EA disbursements (April-December).

By design, EA disbursements per capita are determined by the share of the local population which is eligible for the program. Given that eligibility at the individual (and, thus, municipal) level was determined based on data as of end-2019, it could be viewed as largely exogenous. However, selection into or out of the program can give rise to endogeneity concerns. In particular, households might either opt to not seek the EA even when eligible and non-eligible households could find a way around the proposed targeting, with the latter having occurred especially at the beginning of the program according to reports. We thus instrument for EA disbursements with the share of the population receiving conditional cash transfers under the *Bolsa Familia* program *pre-pandemic*. As explained above, being a *Bolsa Familia* recipient is one of the criteria for being eligible for EA disbursements. Figure 2 presents the correlations between the main variables used in the analysis. As a first takeaway, we note that there is a high correlation between EA disbursements per capita and the share of pre-pandemic *Bolsa Familia* recipients at the municipal level, already suggesting that the inclusion restriction for the instrument is likely to be satisfied.

There is a body of literature - e.g. Barrientos et al. (2016) and Ribas et al (2011)- pointing out the exogenous features of *Bolsa Familia* figures at the municipal level. According to Barrientos et al. (2016), even though the selection of *Bolsa Familia* receivers depends on their per capita household income, the placement at the municipal level depends mostly on the pre-programme poverty level of the municipality. As such, the pre-pandemic *Bolsa Familia* program assignment can be considered exogenous concerning the EA transfers and control variables.

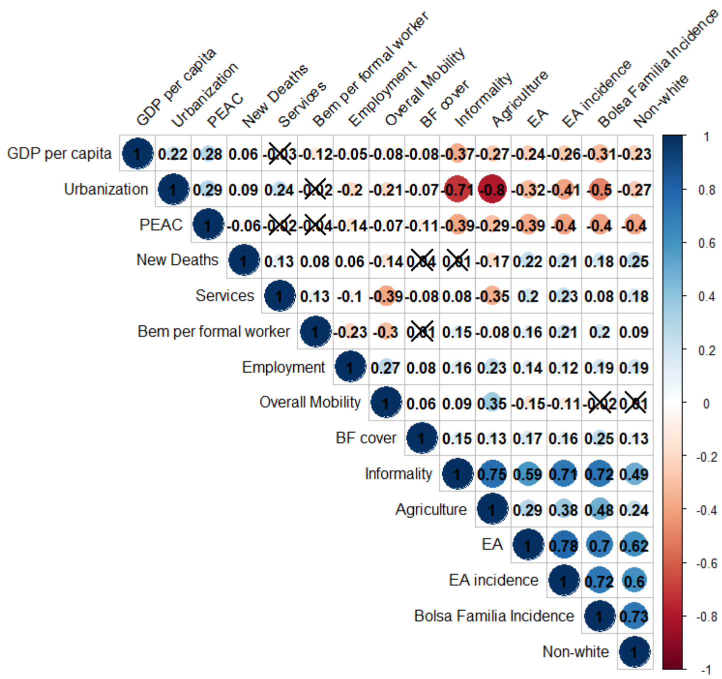
We estimate the following set of equations:

$$\sum_{t=0}^{h} fe_t^m = \alpha^s + \mu + \beta \sum_{t=0}^{h} \hat{ea}_t^m + \gamma' X^m + \varepsilon^m \tag{1}$$

$$\sum_{t=0}^{h} \hat{ea}_t^m = \alpha^S + \phi_0 + \phi_1 BF^m + \phi_2' X^m + \xi^m \tag{2}$$

where α^s and α^S are state fixed effects, fe_t^m denotes the monthly change in formal employment per capita at time t for municipality m, and $\hat{ea}_t^m$ indicates EA transfers per capita. BF^m stands for the share of individuals entitled to *Bolsa Familia* benefits pre-pandemic, X^m represents the set of control variables which in the baseline specification comprises the daily new COVID-19 deaths per million and formal employment trends (by taking into account the change in formal employment in Q1 2020 and in 2019). ε^m and ξ^m are robust standard errors. Last, we control for the municipal informality rate, given the direct link between formal job creation and the structural level of informality.

Figure 2: Correlation Matrix



Note: The matrix shows correlations for the variables summarized in Table 1. Correlations marked with "x" are not significant at 95 percent confidence levels.

5 Results

5.1 The (Formal) Employment Multiplier

Table 2 presents the results from the baseline specification (column (1)) as well as a number of robustness exercises and extensions. Specifically, column (2) adds the share of services in total employment as a control variable, column (3) controls for the urbanization rate, and column (4) includes google mobility as a control variable. The first stage F-statistic is highly significant across specifications (Table 8 in the Appendix shows the first stage results).

In the baseline specification we find a formal employment multiplier of 0.53 - in other words 100,000 of EA payments create 0.53 private formal jobs for a 6 month period. This implies an annual cost-per-formal-job of BRL 378,813 =(100,000/0.528)*2. At the average 2020 USD-BRL exchange rate, this corresponds to a cost per job of around USD 73,000. Comparing this with the simple OLS results presented in Table 7 of the Appendix, we see that the 2SLS multiplier estimate is around three times as large as the OLS one. This is consistent with the bias discussed in section 4.1, whereby worse pandemic outcomes and thus worse labor market outcomes would lead to higher EA per capita.

It is instructive to map the estimated coefficient for the formal employment multiplier to a total employment multiplier. This will allow to gain a fuller picture, facilitate comparisons with the literature, and obtain a GDP multiplier estimate, which we'll discuss in section 5.2.

The private (formal) employment multiplier β_{FE} is defined in the standard way as the change in private formal employment d_{FE} for a given change in government spending d_G. The total employment multiplier is defined equivalently and the expression can be rearranged as follows

$$d_E = \beta_E d_G \implies \beta_E = \frac{\frac{d_E}{E_t}}{\frac{d_G}{E_t}} \tag{3}$$

where E_t denotes the total number of jobs. Multiplying and dividing by $\frac{d_{FE}}{FE_t}$ and collecting terms gives

$$\beta_E = \Theta \beta_{FE} \frac{1}{\omega_{fe}} \tag{4}$$

where Θ is the elasticity of total employment to private formal employment and ω_{fe} is the formality rate. The ratio $\frac{1}{\omega_{fe}}$ aims to adjust the private formal employment multiplier by its relative size to total employment, considering the informal and public (formal) employment shares. We recover $\omega_{fe} = 0.45$ from the 2010 census data, which has the most comprehensive account of employment formality (using the number from the household survey PNAD[12], 0.46, would not make a big difference, however), yielding an adjustment factor of $\frac{1}{\omega_{fe}}$=2.22.

The elasticity of total employment to private formal employment, Θ, can be expressed as the sum of three underlying components:

$$\Theta = \omega_{fe} + \Psi \omega_{if} + \eta \omega_{pe} \tag{5}$$

.

$\omega_{if} = 0.5$ is the informality share and $\omega_{pe} = 0.05$ is the share of public employment. Additionally, we take into account the elasticity of informal employment to private formal employment, denoted by $\Psi = 2.35$[13] and obtained from PNAD (which includes monthly data on both formal and informal

[12]We do not rely on PNAD data for our regressions given that the PNAD survey is not representative at the municipal level).

[13]From 2019 to 2020 (after the labor reform of 2017/2018 was implemented) the mean of Ψ has been relatively stable around 2.4, with an underlying coefficient of variation close to 0.8

employment) for the same 6-month window used in the regressions (April-September 2020). We assume that the elasticity of public employment to changes in private formal employment, given by η, is zero considering that the public sector dynamics were most likely driven by the healthcare response and, thus, orthogonal to EA transfers. As a result, we find that Θ equals to 1.63.

Multiplying the estimated β_{FE} as set out in equation (4) yields a total employment multiplier of 1.6 for the 6-month window. In other words, around 1.6 jobs (0.5 formal and 1.1 informal) were generated for each BRL 100,000 of paid EA. Equivalently, the annual cost-per-job is around BRL 103,000, or USD 20,000.

Sectoral employment structure as a possible confounder While the baseline specification controls for state fixed effects and important structural municipal characteristics such as informality, one additional concern might be that a different local economic structure (for example in terms of sectoral composition) is correlated with the share of pre-pandemic *Bolsa Familia* recipients, while also impacting the sensitivity of formal employment to the pandemic shock. One plausible mechanism might be that structurally poorer municipalities have a larger services sector which in turn suffered more during the pandemic. At first sight the correlations shown in Figure 2 do not suggest that this is a particularly pronounced correlation, but in a robustness exercise we nevertheless include the share of services employment as a control[14]. In addition, we control for the urbanization rate; another potentially important structural municipal characteristic which could impact how the pandemic affected employment creation.

Looking across columns (2) and (3) of Table 2, the estimated formal employment multiplier drops marginally when adding service employment as a control variable and drops somewhat more to 0.44 when also adding the urbanization rate, but remains significant. Both additional control variables have the expected sign, with more services-intensive and urbanized municipalities experiencing weaker job growth.

Controlling for Google Mobility Google mobility data - for which we would like to control given the pandemic-induced variability in mobility and, hence, economic activity - is only available for 2,210 (slightly less than half of all) municipalities. However, these 2,210 municipalities account for 89 percent of national GDP, 93 percent of total formal employment, and 77 percent of total EA disbursements. Including mobility in the regressions thus has two effects - (i) a composition effect, whereby we exclude municipalities which are on average smaller, poorer, more informal, more rural and more dependent on agriculture, and (ii) the direct impact of adding the control variable for a constant sample.

The change in the estimated multiplier is large when including Google mobility data, roughly doubling in the restricted sample (column (4)). As mentioned above, municipalities in the sample for

[14] We also ran exercises controlling for employment in industry and in commodity-sensitive sectors, which yielded similar results to the ones shown in Table 2.

which mobility data is available are larger and richer than those without mobility data. The change in the coefficient is entirely due to this composition effect and not because of the importance of mobility as a control variable. To formally test this, we re-run the regressions with the reduced sample but without mobility as a control, concluding that this only marginally changes the coefficient. The coefficient on mobility has the expected sign, with higher mobility associated with larger formal employment creation.

Intuitively, whether mobility data, as captured by Google, is available or not for a specific municipality suggests important differences in its level of development or other characteristics, beyond the control variables we include. These differences could be perhaps along dimensions we cannot observe such as internet connectivity, smart phone usage and related factors which could determine how much remote work, for example, is feasible. We investigated the difference in coefficients between the full and restricted sample further (including by controlling for additional observable variables which differ between the two groups) but could not obtain a clear explanation - beyond the hypothesis that there might be a true difference in treatment effect based on some unobservable sample characteristic. We continue to refer to the results for the full sample as the baseline, but given that the restricted sample accounts for around 90 percent of national GDP and formal employment we do not discard the higher estimates it yields.

Interacting pre-pandemic informality with EA As mentioned above, there exists a direct relationship between the informality rate in a municipality and the number of formal jobs created per capita over any time period - a marginal formal job in a highly informal municipality likely requires a larger change in local economic activity. This is an important concern for our research design, which might be even more important during the pandemic since informal and formal jobs were affected at varying degrees by lockdowns and social distancing. To allow for a difference in treatment effect between more and less formal municipalities we include an interaction term between the pre-pandemic informality rate and the EA disbursement per capita (instrumented by the interaction between the pre-pandemic share of *Bolsa Familia* recipients and the pre-pandemic informality rate).

Table 3 repeats the order of Table 2 in terms of the control variables included in each column but adds the interaction term between EA and pre-pandemic informality to all specifications. The national formal employment multiplier is obtained by taking a weighted average of the sum of the main effect and interaction effect across all municipalities (using the municipalities' share in national formal employment as the weights).

The coefficient on the interaction term is highly significant and negative, indicating that more informal municipalities create less formal jobs for each BRL 100,000 of EA payment - an intuitive result. More interestingly, the average weighted formal employment multipliers we obtain are significantly higher than the ones in Table 2. The fact that more formal municipalities with a

Table 2: Baseline Regression Results

	Cumulative Change in Formal Employment per capita			
	Instrument: Share of Population Receiving Bolsa Familia (Pre-pandemic)			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	0.528***	0.443***	0.415***	0.666**
	(0.138)	(0.138)	(0.135)	(0.267)
Covid-19 Deaths	0.002	0.063	0.123	0.261
	(0.115)	(0.115)	(0.112)	(0.185)
Informality Rate	−0.0005	−0.0001	−0.006**	−0.010***
	(0.002)	(0.002)	(0.003)	(0.004)
Δ Formal Employment Q12020	−0.436**	−0.439**	−0.436**	−0.270
	(0.220)	(0.218)	(0.218)	(0.236)
Δ Formal Employment 2019	0.007***	0.004*	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.006)
Share of Services in Employment		−0.011***	−0.008***	0.002
		(0.002)	(0.002)	(0.003)
Urbanization Rate			−0.007***	−0.010***
			(0.001)	(0.002)
Overall Mobility				0.026***
				(0.003)
Constant	−0.007***	0.0003	0.006***	0.005
	(0.002)	(0.002)	(0.002)	(0.003)
States Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Implied Number of Year-Formal Jobs Created	633,557	531,614	498,444	799,007
Implied Cost per Year-Formal Job (BRL)	378,813	451,454	481,497	300,372
Implied Cost per Year-Formal Job (USD)	73,413	87,491	93,313	58,211
Implied Number of Year-Jobs (Formal and Informal) Created	2,287,845	1,919,720	1,799,939	2,885,306
Implied Cost per Year-Job (USD)	20,329	24,228	25,840	16,120
First Stage F statistic	417***	406***	400***	91***
Wu-Hausman	12.53***	8.53***	6**	2
Observations	5,478	5,478	5,478	2,210
Residual Std. Error	0.013 (df = 5446)	0.013 (df = 5445)	0.013 (df = 5444)	0.011 (df = 2175)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of population receiving *Bolsa Familia* is as of December/2019.

higher multiplier also account for a large share of total formal employment, leads to a national cross-sectional multiplier which is larger than the simple average relationship implied. Figure 3 makes this point visually by showing that municipalities with a higher multiplier also have a larger weight. Columns (1)-(4) show private formal employment multipliers of 1.5-1.7, implying an annual cost per formal job of BRL 132,000-117,000 (USD 23,000-26,000). The implied total employment multipliers are in the range of 5-6, with an annual cost per job as low as BRL 30,000 (around USD 6,000).

Instrumenting EA transfers using municipal ethnic patterns and BF cover ratio As an additional robustness exercise, we use the share of non-white population (NWP) measured by the 2010 Census and the estimated *Bolsa Familia* cover ratio of poor households to instrument EA transfers per capita[15]. Historically, the NWP has limited access to higher education in Brazil[16] and thus larger unemployment rates than white Brazilians. Figure 2 shows a high correlation between EA disbursements per capita and the share of non-white population at the municipal signalling the potential strength of the instrument. Aiming to capture some idiosyncratic components of municipal poverty features that are fully mapped by ethnics patterns, we use as an additional instrument the estimated *Bolsa Familia* cover ratio of poor households. The ratio takes into account the number of *Bolsa Familia* beneficiaries at end-2012 and the estimated number of poor Households according to 2010 Census[17].

Table 2.A is built such as Table 2 with the difference that EA transfers per capita are instrumented by the share of NWP instead of the share of *Bolsa Familia* receivers. The formal employment multiplier is, on average, twice as large as that detailed in Table 2. Moreover, the results shown by Table 2.A are in line with Table 3, pointing to a multiplier around 1.2. The tests reported in Table 2.A provide evidence of the strength of our instruments, indicating absence of endogeneity or over-identification issues.

Interacting pre-pandemic informality with EA using alternative instruments As highlighted before, it is useful to estimate the formal employment multiplier directly taking into account the formality level of different municipalities. Thus, like in Table 3, we add to Table 2.A's specifications an interaction term between the pre-pandemic informality rate and the EA disbursements per capita (instrumented by the interaction between the pre-pandemic share of NWP and the pre-pandemic informality rate, keeping the instruments already used in Table 2.A[18]).

[15] We also considered using either NWP or the BF cover ratio as single instrument to the EA transfers. However, considering the interaction with informality, the combined use of NWP and BF cover outperformed the isolated specifications as a feasible instrument.

[16] Mello (2021) provides a detailed discussion on this topic.

[17] Rougier et al (2018) argue that the municipal-level cover ratio of *Bolsa Familia* is a good indicator of the municipality's capacity to identify, enroll and register poor individuals. As a result, the authors claim that the ratio is a good exogenous predictor of the cross-municipality variation of *Bolsa Familia* to GDP ratio.

[18] We ran regressions instrumenting the interaction of informality with EA by the interaction of the BF cover

Similar to Table 3, Table 3.A shows the national formal employment multiplier taking a weighted average of the sum of the main effect and interaction effect across all municipalities. On average, the obtained formal employment multiplier is 20 percent larger than in Table 3.

Controlling for the government's Job Protection Program (BEm) and pandemic-related credit to SMEs (PEAC) As discussed in section 3, BEm was explicitly designed to limit formal sector job losses by allowing for a flexible reduction in working hours with partial income compensation. Trying to explicitly identify the impact of BEm on formal employment runs into an endogeneity problem that is significantly worse still than that of assessing the impact of the EA - municipalities in which the pandemic had a large impact would have seen higher selection into BEm participation. At the same time, the direct and mechanical impact of the BEm has to be an improvement in formal job dynamics relative to a counterfactual without BEm. PEAC credit lines face a similar endogeneity issue as the selection into the program was likely impacted by local economic conditions.

Given this difficulty, we do not aim to retrieve the impact of BEm and PEAC on employment (even though it is a very interesting question in its own right) and therefore did not include them as regressors in our baseline specifications. Nevertheless, given the direct link between BEm and formal employment and the impact of pandemic-related credit on formal employment, we investigate how our results change when BEm and PEAC are indeed controlled for. We opted for a specification in which BEm is normalized by total formal employment - in essence, the share of jobs protected by the program.

Table 4 adds the share of formal jobs covered by BEm as a control variable: column (1) adds the BEm variable to a specification otherwise identical to column (1) of Table 2, while columns (2), (3), and(4) do the same for column (1) of Tables 3, 2.A, and 3.A respectively.

The estimated formal employment multiplier drops significantly relative to the baseline without BEm and PEAC, by over 40 percent in the specification without the informality interaction (column (1)), by around 25 percent in the version with the informality interaction (column (2)) and when instrumenting EA transfers by ethnic patterns (column(3)), and about 10 percent in the specification instrumenting EA transfers by ethnic patterns and the BF cover ratio (column (4)). The specifications with BEm and PEAC as a control variables thus provide us with the lower end of our estimated multiplier range. Note that the (non-causal) coefficient of the BEm variable is highly significant and negative, suggesting that the negative selection effect dominates the positive mechanical association with formal employment retention.

ratio with the informality rate. The implied formal employment multiplier is about 25 percent larger but in all specifications we reject the null hypothesis of the Sargan Test that the model is not over-identified.

Figure 3: Formal Employment Multiplier and Formal Employment Weight by Municipalities

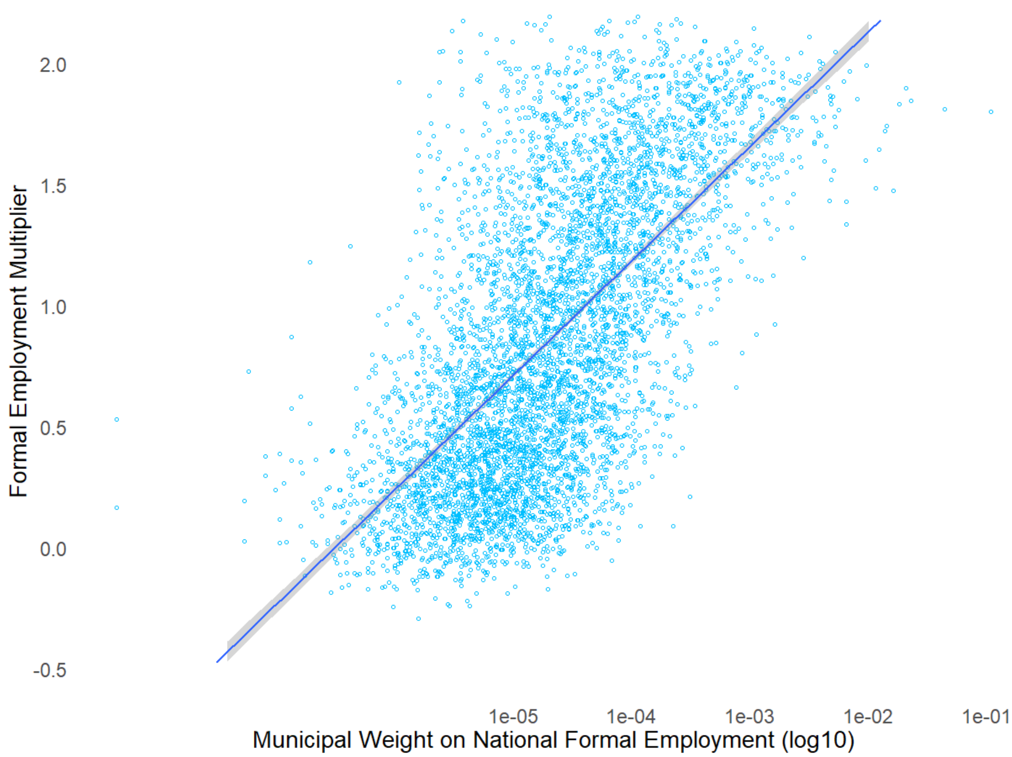


Table 3: Interaction with Informality Regression Results

	Cumulative Change in Formal Employment per capita			
	Instruments: Pre-pandemic Share of Population Receiving Bolsa Familia (BF) and BF*informality			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	3.118^{***}	3.096^{***}	3.003^{***}	3.380^{***}
	(0.434)	(0.433)	(0.425)	(0.648)
EA per capita (BRL 100K)*Informality	-3.491^{***}	-3.594^{***}	-3.502^{***}	-3.919^{***}
	(0.520)	(0.522)	(0.517)	(0.843)
Covid-19 Deaths	-0.152	-0.087	-0.026	-0.018
	(0.118)	(0.118)	(0.115)	(0.195)
Informality Rate	0.033^{***}	0.034^{***}	0.028^{***}	0.026^{***}
	(0.005)	(0.005)	(0.005)	(0.008)
Δ Formal Employment Q12020	-0.434^{**}	-0.432^{**}	-0.257	
	(0.221)	(0.218)	(0.218)	(0.240)
Δ Formal Employment 2019	0.005^{**}	0.001	0.0003	-0.003
	(0.002)	(0.002)	(0.002)	(0.006)
Share of Services in Employment		-0.012^{***}	-0.010^{***}	-0.003
		(0.002)	(0.002)	(0.003)
Urbanization Rate			-0.006^{***}	-0.009^{***}
			(0.001)	(0.002)
Overall Mobility				0.026^{***}
				(0.003)
Constant	-0.031^{***}	-0.024^{***}	-0.017^{***}	-0.016^{***}
	(0.004)	(0.004)	(0.004)	(0.005)
States Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Formal Employment Multiplier - Weighted Average Across Munis	1.624^{***}	1.558^{***}	1.504^{***}	1.703^{***}
	(0.497)	(0.499)	(0.487)	(0.643)
Implied Number of Year-Formal Jobs Created	1,949,041	1,870,596	1,805,242	2,044,448
Implied Cost per Year-Formal Job (BRL)	123,137	128,301	132,946	117,391
Implied Cost per Year-Formal (USD)	23,863	24,864	25,764	22,750
Implied Number of Year-Jobs (Formal and Informal) Created	7,038,204	6,754,930	6,518,928	7,382,730
Implied Cost per Year-Job (USD)	6,608	6,885	7,134	6,300
First Stage F statistic (EA)	1259^{***}	1272^{***}	1310^{***}	201^{***}
First Stage F statistic (EA*informality)	1531^{***}	1568^{***}	2122^{***}	196^{***}
Wu-Hausman	28^{***}	23^{***}	21^{***}	18^{***}
Observations	5,478	5,478	5,478	2,210
Residual Std. Error	0.013 (df = 5445)	0.013 (df = 5444)	0.013 (df = 5443)	0.011 (df = 2174)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of population receiving the *Bolsa Familia* benefit is as of December/2019. To compute the national formal employment multiplier, we calculate individually for all municipalities the implied effect for their specific level of informality and then calculate the average by weighting with formal employment.

Table 2.A: Regression Results Using Ethnic Patterns and BF cover as Instruments

	Cumulative Change in Formal Employment per capita			
	Instruments: Non-white Share of the Population and BF Cover			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	1.312***	1.263***	1.217***	1.158**
	(0.302)	(0.300)	(0.296)	(0.525)
Covid-19 Deaths	−0.054	0.003	0.066	0.170
	(0.110)	(0.110)	(0.109)	(0.214)
Informality Rate	−0.005*	−0.005*	−0.011***	−0.014**
	(0.003)	(0.003)	(0.003)	(0.006)
Δ Formal Employment Q12020	−0.548***	−0.551***	−0.547***	−0.274
	(0.171)	(0.169)	(0.169)	(0.241)
pre_e_2019	0.006***	0.002	0.001	0.002
Δ Formal Employment 2019	0.006***	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.006)
Share of Services in Employment		−0.011***	−0.008***	0.001
		(0.002)	(0.002)	(0.003)
Urbanization Rate			−0.007***	−0.010***
			(0.001)	(0.002)
Overall Mobility				0.028***
				(0.004)
Constant	−0.012***	−0.005**	0.001	0.004
	(0.002)	(0.002)	(0.002)	(0.004)
States Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Implied Number of Year-Formal Jobs Created	1,574,509	1,515,295	1,460,698	1,389,937
Implied Cost per Year-Formal Job (BRL)	152,428	158,385	164,305	172,669
Implied Cost per Year-Formal Job (USD)	29,540	30,694	31,842	33,463
Implied Number of Year-Jobs (Formal and Informal) Created	5,685,727	5,471,898	5,274,744	5,019,216
Implied Cost per Year-Job (USD)	8,180	8,500	8,817	9,266
First Stage F statistic	198***	198***	201***	68***
Wu-Hausman	18***	17***	15***	4**
Sargan	2.86*	1.32	3.3*	1
Observations	5,472	5,472	5,472	2,208
Residual Std. Error	0.013 (df = 5440)	0.013 (df = 5439)	0.012 (df = 5438)	0.011 (df = 2173)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of NWP comes from the 2010 Census. The estimated *Bolsa Familia* cover ratio of poor households takes into account the number of *Bolsa Familia* beneficiaries at end-2012 and the estimated number of poor households according to the 2010 Census.

Table 3.A: Interaction with Informality Regression Results (Alternative Instruments)

	Cumulative Change in Formal Employment per capita			
	Instruments: Non-white Share of Population(NWP), BF cover and NWP*Informality			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	4.073***	4.281***	4.056***	3.554***
	(0.679)	(0.680)	(0.672)	(0.926)
EA per capita (BRL 100K)*Informality	−4.350***	−4.769***	−4.480***	−4.071***
	(0.761)	(0.768)	(0.760)	(1.074)
Covid-19 Deaths	−0.188	−0.133	−0.070	−0.044
	(0.117)	(0.116)	(0.115)	(0.229)
Informality Rate	0.040***	0.045***	0.037***	0.027**
	(0.007)	(0.007)	(0.007)	(0.011)
Δ Formal Employment Q12020	−0.543***	−0.546***	−0.543***	−0.263
	(0.172)	(0.169)	(0.170)	(0.243)
Δ Formal Employment 2019	0.003	−0.001	−0.002	−0.003
	(0.002)	(0.002)	(0.002)	(0.006)
Share of Services in Employment		−0.013***	−0.010***	−0.004
		(0.002)	(0.002)	(0.004)
Urbanization Rate			−0.006***	−0.009***
			(0.001)	(0.002)
Overall Mobility				0.026***
				(0.004)
Constant	−0.040***	−0.034***	−0.027***	−0.017***
	(0.006)	(0.006)	(0.006)	(0.006)
States Fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Formal Employment Multiplier - Weighted Average Across Munis	2.212***	2.240***	2.139***	1.812***
Implied Number of Year-Formal Jobs Created	2,654,545	2,688,926	2,566,991	2,174,648
Implied Cost per Year-Formal Job (BRL)	90,410	89,254	93,494	110,362
Implied Cost per Year-Formal (USD)	17,521	17,297	18,119	21,388
Implied Number of Year-Jobs (Formal and Informal) Created	9,585,858	9,710,012	9,269,689	7,852,897
Implied Cost per Year-Job (USD)	4,852	4,790	5,017	5,922
First Stage F statistic (EA)	132***	132***	134***	47***
First Stage F statistic (EA*informality)	187***	185***	181***	52***
Wu-Hausman	19***	19***	17***	9***
Sargan	3.7*	1.8	3.6*	0.9
Observations	5,472	5,472	5,472	2,208
Residual Std. Error	0.013 (df = 5439)	0.013 (df = 5438)	0.012 (df = 5437)	0.011 (df = 2172)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of population receiving the *Bolsa Familia* benefit is as of December/2019. To compute the national formal employment multiplier, we calculate individually for all municipalities the implied effect for their specific level of informality and then calculate the average by weighting with formal employment.

Table 4: Controlling for The Job Support Program (BEm) and Pandemic-related Lending (PEAC) Regression Results

	Cumulative Change in Formal Employment per capita			
	Instruments:			
	Share of Population Receiving BF	BF and BF*informality	Non-white Share of Population(NWP) and BF cover	NWP, BF cover, and NWP*Informality
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	0.260	2.468***	1.265***	3.420***
	(0.198)	(0.484)	(0.403)	(0.851)
EA*Informality		−2.928***		−3.484***
		(0.597)		(0.912)
Number of BEm Agreements per formal worker	−0.010***	−0.009***	−0.009***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
PEAC per capita (BRL 100K)	0.132	0.203	0.193	0.249
	(0.176)	(0.176)	(0.172)	(0.175)
Covid-19 Deaths	0.122	−0.058	−0.022	−0.166
	(0.143)	(0.146)	(0.160)	(0.176)
Δ Formal Employment Q12020	−0.120	−0.113	−0.115	−0.112
	(0.183)	(0.184)	(0.187)	(0.187)
Δ Formal Employment 2019	0.007*	0.004	0.006	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	−0.003	−0.023***	−0.009***	−0.030***
	(0.002)	(0.004)	(0.003)	(0.007)
States Fixed effects	Yes	Yes	Yes	Yes
Formal Employment Multiplier - Weighted Average Across Munis	0.260	1.218***	1.264***	1.930***
	(0.141)	(0.410)	(0.292)	(0.675)
Implied Number of Year-Formal Jobs Created	311,474	1,461,114	1,516,800	2,315,573
Implied Cost per Year-Formal Job (BRL)	770,529	164,258	158,227	103,646
Implied Cost per Year-Formal Job (USD)	149,327	31,832	30,664	20,086
Implied Number of Year-Jobs (Formal and Informal) Created	1,124,767	5,276,245	5,477,333	8,361,791
Implied Cost per Year-Job (USD)	41,352	8,815	8,491	5,562
First Stage F statistic (EA)	1125***	619***	186***	77***
First Stage F statistic (EA*Informality)		789***		125***
Wu-Hausman	2	22***	11***	10***
Sargan			2	2
Observations	3,789	3,789	3,785	3,785
Residual Std. Error	0.012 (df = 3755)	0.012 (df = 3754)	0.012 (df = 3751)	0.012 (df = 3750)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of population receiving the *Bolsa Familia* benefit is as December/2019. Services as a share of total employment, urbanization rate, and the informality rate come from the 2010 census.

5.2 The Implied GDP Multiplier

Analytical Transformation

Our approach to obtain a GDP multiplier from the estimated (formal) employment multiplier closely follows Chodorow-Reich (2019), adjusting for the fact that we estimate a private formal employment multiplier rather than a total employment multiplier. The adjustment for the formal/informal dimension takes inspiration from the approach taken in Corbi et al. (2019).

Starting from the definition of formal employment multiplier, we derive (Y denotes the level of GDP and FE denotes the level of formal employment):

$$d_{FE} = \beta_{FE} d_G \implies \frac{d_{FE}}{FE_t} = \beta_{FE} \frac{Y_t}{FE_t} \frac{d_G}{Y_t} \tag{6}$$

The GDP multiplier β_Y, in turn, is equivalently defined as:

$$d_Y = \beta_Y d_G \tag{7}$$

which can be rearranged as

$$\beta_Y = \frac{\frac{d_Y}{Y_t}}{\frac{d_G}{Y_t}} \tag{8}$$

Now consider a production function $Y_t = A(N_t L_t)^{1-\alpha}$, where L denotes the stock of effective units of labor, and N indicates hours worked per worker. We define $L = FE + \rho IE + PE$ where IE equals informal employment, PE indicates public employment, and ρ is the relative productivity ratio of informal to formal workers. After totally differentiating the production function we obtain:

$$\frac{d_Y}{Y_t} = (\frac{d_N}{N_t} + \frac{d_L}{L_t})(1-\alpha) \tag{9}$$

Dividing (9) by $\frac{d_{FE}}{FE_t}$ and rearranging terms yields

$$\frac{d_Y}{Y_t} \frac{FE_t}{d_{FE}} = (\chi + \Theta^L)(1-\alpha) \tag{10}$$

where χ is the elasticity of hours per worker (N) to private formal employment (FE), and Θ^L is the elasticity of effective labor units (L) to FE, which is formally given by

$$\Theta^L = \omega^L_{fe} + \rho\Psi\omega^L_{if} + \eta\omega^L_{pe}. \tag{11}$$

Ψ and η are the elasticities of informal and public employment, respectively, to FE, while ω_{fe}^L, ω_{if}^L and ω_{pe}^L are the shares of private formal, informal, and public employment in effective labor.

Equation (11) is similar to equation (5), which defined the elasticity of total employment to formal employment Θ. However, since Θ^L maps the response of effective labor units, total employment is 'normalized' by the productivity ratio of informal to formal workers (ρ). Furthermore, we can rewrite the parameters ω_{fe}^L, ω_{if}^L and ω_{pe}^L as a function of their corresponding shares in total employment, as follows:

$$\omega_{fe}^L = \frac{E_t}{L_t}\omega_{fe} = \frac{1}{1-(1-\rho)\omega_{if}}\omega_{fe} \tag{12}$$

$$\omega_{if}^L = \frac{E_t}{L_t}\rho\omega_{if} = \frac{\rho}{1-(1-\rho)\omega_{if}}\omega_{if} \tag{13}$$

$$\omega_{pe}^L = \frac{E_t}{L_t}\omega_{pe} = \frac{1}{1-(1-\rho)\omega_{if}}\omega_{pe} \tag{14}$$

When ρ equals to 1, the underlying weight components of L_t are equivalent to their respective shares in total employment given that $E_t = L_t$, and, thus, $\Theta = \Theta^L$.

Plugging in equation (11) into (10) yields

$$\frac{d_Y}{Y_t}\frac{FE_t}{d_{FE}} = (\chi + \omega_{fe}^L + \rho\Psi\omega_{if}^L + \eta\omega_{pe}^L)(1-\alpha) \tag{15}$$

Multiplying and dividing (8) by $\frac{d_{FE}}{FE_t}$ and finally combining (15), (6), and (8), yields:

$$\beta_Y = (1-\alpha)(\chi + \omega_{fe}^L + \rho\Psi\omega_{if}^L + \eta\omega_{pe}^L)\frac{Y_t}{FE_t}\beta_{FE} \tag{16}$$

For a given private formal employment multiplier β_{FE}, and initial ratio of output per private formal worker $\frac{Y_t}{FE_t}$, the GDP multiplier β_Y increases with the labor share $(1-\alpha)$, with the elasticity of hours worked, informal employment or public employment to FE, and/or when private formal employment has a larger relative weight in effective labor L, either directly (higher share in total employment) or due to higher relative productivity (higher ρ).

It is worth noting the five differences with the transformation for the total employment multiplier obtained by Chodorow-Reich (2019). First, we have an explicit expression for the formality rate in the multiplicative factor. Second, we have an additional term in the multiplicative factor which captures the elasticity of informal employment to private formal employment adjusted for their relative productivity and the informality share. Third, we consider an extra term which measures the response of public employment to changes in private formal employment adjusted by the weight of public employment. Forth, we multiply by output per private formal worker rather than output per worker. Lastly, we use the elasticity of hours per worker to *formal* employment instead of *total* employment.

We demonstrate that the estimated GDP multiplier obtained from a total employment multiplier as a starting point is equivalent to the GDP multiplier derived from a private formal employment multiplier[19]. Furthermore, we show that when the informality rate is equal to zero we fall back to the exact equation defined in Chodorow-Reich (2019) given that ω_{if}^{L} goes to zero and $L_t = E_t$. Intuitively, the differences stem from the fact that we only observe a partial employment response, and the leap from the estimated private formal employment multiplier to a GDP multiplier is thus somewhat larger.

Calibration

As discussed in section 5.1, the continuous household survey PNAD allows us to observe the change in both informal and formal employment at the national level. We thus have a sense of how private formal, informal and public employment developed in both absolute and relative terms during the period of analysis - informal employment fell by more than formal employment, leading to a decrease in the informality rate, and public employment remained broadly stable[20].

We use the PNAD survey to calibrate Ψ, finding that for the 6 months period from April-September 2020, Ψ (seasonally adjusted) was equal to 2.35[21]. $\omega_{if}^{census} = 0.5$ is the weighted municipal informality rate from the 2010 Census. Based on the work of Ulyssea (2018), we estimate ρ to 0.81.[22] In line with Corbi et al. (2019), we calibrated the labor share, $(1-\alpha)$, to 2/3 and the elasticity of hours per worker to total employment, χ^E, to 0.12. As a result, the elasticity of hours per worker to the stock of effective units of labor can be written as $\chi^L = \frac{L_t}{E_t}\chi^E = 0.11$, implying that the elasticity of informal to formal employment is given by $\chi = \chi^L \Theta^L \approx 0.15$. As we mention before, we set $\eta \equiv 0$ considering the orthogonality of the reaction of public sector labor to EA transfers.

Results

Figure 4 shows the implied GDP multiplier retrieved from columns (1)-(4) of Tables 2, 3, 2.A, 3.A, and 4. The graph combines uncertainty both from the formal employment multiplier point estimate - which stems from the range obtained from different regression specifications - as well as the uncertainty from the confidence interval around each multiplier point estimate.

[19]See Lemma 1 in the Analytical Appendix for a detailed discussion.

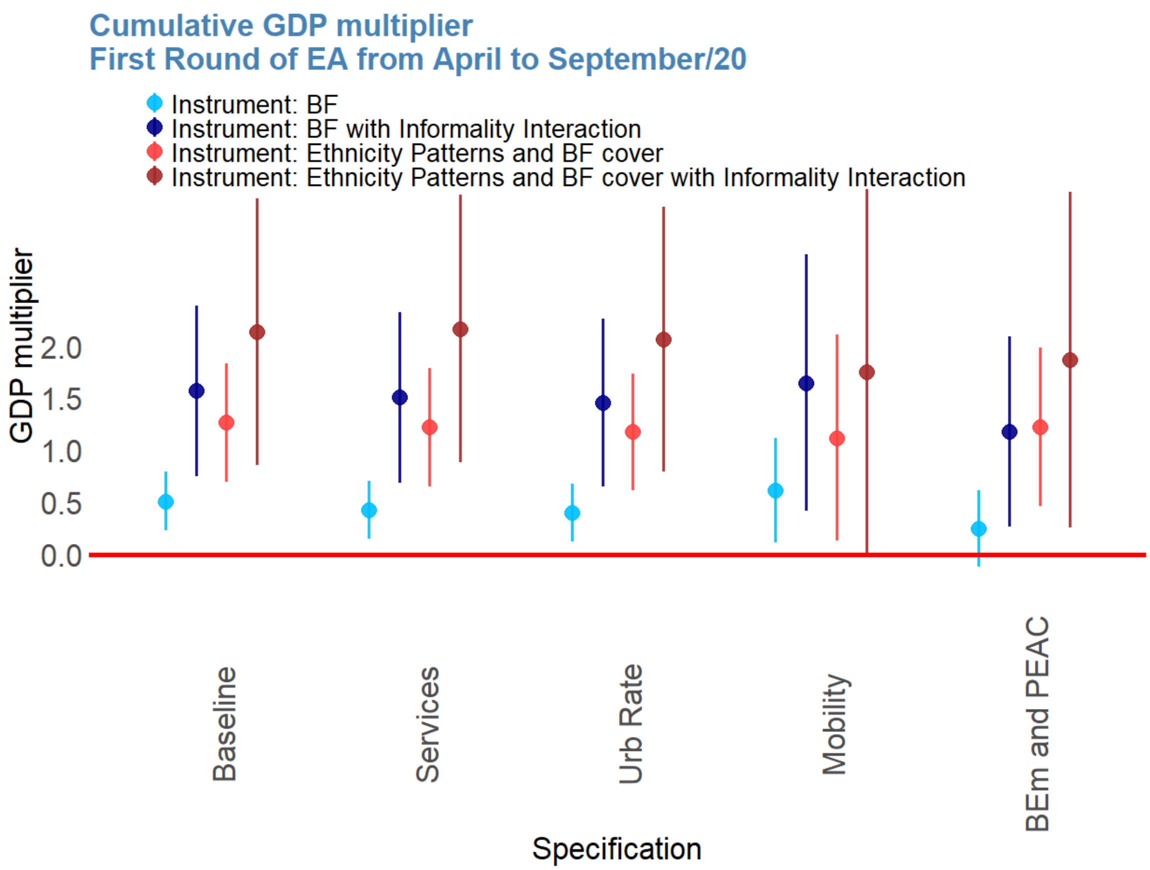
[20]Differently from the private sector, there are several legal protections granted to government employees implying that layoffs are not easily enacted. This imposes a downward rigidity to the level of public employees.

[21]The other parameters of the production function are calibrated using pre-pandemic data due to the lack of high frequency data to estimate unobservable variables.

[22]We proxy the productivity ratio of informal to formal workers (ρ) by the relative share of high skilled workers in the informal and formal sectors, using Ulyssea (2018)'s estimates for the Brazilian economy.

Incorporating the full range of uncertainty implied by the confidence intervals, we obtain a very wide range of multipliers,g from close to 0 to above 2. But focusing on the point estimates, a relatively consistent picture emerges. A GDP multiplier around 0.5 is obtained in specifications which use data from the full sample of municipalities and do not include the informality interaction. Instead, the estimated multiplier is around 1.5 when informality is accounted for by its interaction with the EA or when instrumenting EA transfers by ethnic patterns and the BF cover ratio.

Figure 4: Implied GDP Multiplier



Note: $\beta_Y = (1-\alpha)(\chi + \omega^L_{fe} + \rho\Psi\omega^L_{if})\frac{Y_t}{FE_t}\beta_{FE}$ is the baseline transformation from formal employment to GDP multiplier. $(1-\alpha) = 2/3$ is the labor share, $\chi = 0.15$ is the elasticity of hours per worker to formal employment, $\Psi = 2.35$ is the elasticity of informal to formal employment, ω^L_{fe}=0.5 and $\omega^L_{if} = 0.45$ are municipal private formal and informality rates derived from Census 2010, $\rho = 0.81$ is the productivity ratio of informal to formal workers, Y_t is the 2020 GDP, and FE_t is the stock of formal workers. The vertical lines represent a 95 percent confidence interval.

Importantly, the above results are derived from regressions which estimate the relationship between the EA and formal employment creation for the six month window between April-September 2020. As discussed in section 3, this seems the most natural window for the analysis given that it covers the bulk of EA disbursements. Nevertheless, we re-run the baseline specification with informality interaction (column (1) in Table 3) for both a three-month window (April-June 2020) and a nine-month window (April-December 2020, covering the full EA disbursement in 2020). Table 5 presents the implied formal employment and GDP multipliers for these different time windows. The implied GDP multiplier (for the whole year) is broadly stable across estimation windows, but the falling employment multiplier suggests that the impact on economic activity faded over time.[23] Taking this result at face value, a possible explanation would be that transfers were incident on liquidity constrained consumers (and so had a large immediate effect) at the pandemic onset. However, as the economy recovered there were fewer liquidity constrained households and so the transfers had a smaller multiplier even though they became better targeted. The relaxing of liquidity constraints throughout the pandemic is in line with the implied saving rates from our multipliers.

Table 5: Formal Employment and GDP Multiplier at Different Horizons

	Cumulative change in employment per capita		
	EA time Horizon:		
	3 months	6 months	9 months
	(1)	(2)	(3)
Formal Employment Multiplier	2.655***	1.624***	1.117**
	(0.596)	(0.434)	(0.468)
GDP Multiplier	1.568***	1.569***	1.485**
	(0.352)	(0.419)	(0.622)
Implied Number of Year-Jobs (Formal and Informal) Created	7,380,900	6,820,800	6,500,940
Implied Cost per Year-Job (USD)	6,301	6,819	7,154
Baseline Controls	*Yes*	*Yes*	*Yes*
Ψ PNAD	3.27	2.35	2.01
First Stage F statistic (EA)	967***	1,259***	1,046***
First Stage F statistic (EA*Informality)	1,154***	1,531***	1,202***
Wu-Hausman	56***	28***	9***
Observations	5,474	5,478	5,478
Residual Std. Error	0.010 (df = 5441)	0.013 (df = 5445)	0.014 (df = 5445)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-June 2020 (3 months), April-September 2020 (6 months), and April-December 2020 (9 months). The elasticity of informal to formal employment, Ψ, for each time horizon is computed using seasonally adjusted numbers from PNAD.

[23] The falling employment multiplier shown in the first row and the stable GDP multiplier are consistent in the sense that the GDP multiplier throughout the paper refers to an annual concept while the employment multiplier refers to the estimation window, e.g. 3-months in column (1)).

Further discussion

As discussed in the introduction, from a theoretical perspective a large set of cross-sectional transfer multipliers is plausible ex ante. Here we use our empirical estimate and compare it to a theoretical multiplier obtained from parameter estimates taken from the literature. From a new Keynesian model standpoint for a closed economy, Pennings (2021) shows that when monetary policy is passive, the local transfer multiplier collapses to the following equation: $\beta_Y = \frac{\omega_T \alpha}{1-\omega\alpha}$ where ω is the share of hand-to-mouth households, ω_T is the fraction of transfers targeted at those hand-to-mouth households, and α is the degree of home bias (a measure of how closed the economy is).

The targeting of transfers and the share of hand-to-mouth households, while by no means fully observable, can be gauged to some degree from the literature. Bracco et al. (2021) estimate a share of hand-to-mouth households around half for Brazil ($\omega \approx 1/2$). Flamini et al. (2021) show that in the initial months of EA disbursements, the bottom half of the income distribution (which we can loosely assume here are the hand-to-mouth households) received around 75 percent of total disbursements, yielding $\omega_T \approx 3/4$. As a first step, we thus take ω and and ω_T as given and ask what α would be consistent with our multiplier estimate. Taking our estimated range of 0.5-1.5 for the multiplier, we obtain a range of 0.5-1 for α, suggesting relatively closed local economies. Previous evidence for Brazil does indeed point towards rather closed municipal economies given (i) the large share of non-tradable services in the Brazilian economy, especially in poorer municipalities, and (ii) limited (formal) labor mobility. Dix-Carneiro and Kovak (2019) show evidence of imperfect interregional labor mobility after a negative labor demand shock (brought about by a trade policy reform). Dix-Carneiro and Kovak (2017) also find minimal effects of regional shocks on inter-regional worker mobility and Cavalcanti et al. (2019) find an important spatial segmentation of labor markets. Of course, the values for ω and ω_T might not be correctly measured and, moreover, parameters such as the share of hand-to-mouth households measured outside pandemic times might not accurately capture the dynamics during the pandemic.

One way to cross-check some of the intuition on how closed local economies are is to compare multipliers at the municipal level to those at a higher level of aggregation. Using state level data would lead to under-powered regressions. We thus exploit the fact IBGE provides an intermediate level of aggregation between municipalities and states, so called microregions. Given possible spillovers between neighboring municipalities, one would expect a higher multiplier for the microregion level regressions.

We compare the municipal level multiplier to the microregion level multiplier in two exercises. First, we focus on the restricted sample of municipalities for which we can observe (and, thus, control for) social mobility. Second, we consider the full sample of municipalities (not controlling for mobility). Since at the microregion level we have mobility data for all units of analysis, controlling for mobility does not give rise to the sample selection effect which arises at the municipal level.

Column (1) in Table 6 shows the GDP multiplier at the municipal level when controlling for mobility, while column (3) shows the municipal multiplier without controlling for mobility. Columns (2) and (4) show the corresponding microregion level multipliers. In line with intuition on the impact of openness, the estimated GDP multiplier increases somewhat at the microregion level. Furthermore, by comparing columns (2) and (4) one concludes that controlling for mobility per se has only a small impact on the estimated GDP multiplier. Therefore, to gauge the effect of using more aggregated regional data to estimate the GDP multiplier, the comparison between columns (3) and (4) - which avoids composition effects - seems most informative. The estimated multiplier increases from 1.45 in column (3) to 1.85 in column (4), a non-negligible difference which suggests that indeed some spillovers between neighboring municipalities occur.

Table 6: Additional Robustness tests: Changing the Unit of Analysis

	Controlling for Mobility		Not Controlling for Mobility	
	Municipalities	Microregion	Municipalities	Microregion
	(1)	(2)	(3)	(4)
GDP Multiplier	1.646***	1.733***	1.451***	1.852***
	(0.628)	(0.722)	(0.412)	(0.749)
Observations	2,208	547	5,478	547

*p<0.1; **p<0.05; ***p<0.01

Note: For columns (1) and (3), the unit of analysis is municipalities, the lowest administrative level in Brazil. For columns (2) and (4), the unit of analysis is micro regions. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Columns (1) and (2) use the specification detailed in column (4) of Table 3. Columns (3) and (4) use the specification detailed in column (3) of Table 3.

All in all, our estimated multiplier range is consistent with a plausible set of underlying parameters, especially when considering forced reductions in consumption due to lock-downs reducing the marginal propensity to consume.

6 Conclusion

We provide an estimate of the GDP impact of Brazil's emblematic Emergency Aid (EA) cash transfer program, implemented from the outset of the Covid-19 pandemic. To the best of our knowledge, ours is among the first studies to focus on the output effects of fiscal response policies during this period. Although there is considerable uncertainty around the exact multiplier, our preferred specifications imply that it falls in the range of 0.5-1.5. This is somewhat lower than estimates found in the related literature for the pre-Covid period - both for the US and EMs, notably Brazil -, possibly reflecting the effect of lockdowns and social distancing on supply chains and consumption opportunities (forced savings). We also find that the impact of the EA was strongest in the first three months, when liquidity constraints were perhaps more pervasive. Still, even when using our most conservative estimates, the results suggest that the EA played an important role in cushioning the downturn and facilitating a rapid recovery. The counter-factual without EA would have been one with at least one million formal sector jobs and two million total jobs less, while 2020 GDP would have fallen by at least 2 percentage points more.

Looking ahead to further work, while progress had been made on understanding the size and heterogeneity of different types of multipliers in emerging markets, more analysis is needed to allow policy makers to design policies in the most growth friendly and inclusive way.

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A Analytical Appendix

Lemma 1. Equivalence of the GDP multiplier derived from private formal employment and total employment multiplier

Let β_E^L denote the total employment multiplier adjusted for effective units of labor, χ^L represent the elasticity of hours per worker to the total stock of effective units of labor, and α, L_t and Y_t represent the same parameters described by equation (9). Then, we can recover the GDP multiplier shown by equation (16) as follows:

$$\beta_Y = (1-\alpha)(1+\chi^L)\frac{Y_t}{L_t}\beta_E^L \tag{17}$$

Proof. The proof of Lemma 1 comes directly from the definition of the elasticity of hours per worker to the total stock of effective units of labor, χ^L, and the transformation of private formal employment multiplier to a total employment multiplier adjusted for the stock of effective units of labor.

χ^L is formally given by

$$\chi^L = \frac{d_N}{N_t}\frac{L_t}{d_L} = \frac{d_N}{N_t}\frac{FE_t}{d_{FE}}\frac{d_{FE}}{FE_t}\frac{L_t}{d_L} = \frac{\chi}{\Theta^L} \tag{18}$$

Using the same steps that were implemented to estimate equation (4), we can translate the private formal employment multiplier into a total employment multiplier adjusted for effective units of labor, as follows:

$$\beta_E^L = \Theta^L \beta_{FE}(1/\omega_{fe}^L) \tag{19}$$

After substituting equation (18) and (19) in equation (17), we find that

$$\beta_Y = (1-\alpha)(1+\frac{\chi}{\Theta^L})\frac{Y_t}{L_t}\Theta^L\beta_{FE}\frac{1}{\omega_{fe}^L} = (1-\alpha)(\chi+\omega_{fe}^L+\rho\Psi\omega_{if}^L+\eta\omega_{pe}^L)\frac{Y_t}{FE_t}\beta_{FE} \tag{20}$$

$\square$

B Appendix

Table 7: Baseline Regression Results (OLS)

	Cumulative Change in Formal Employment per capita			
	OLS			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
EA per capita (BRL 100K)	0.130	0.132	0.161	0.312^{***}
	(0.112)	(0.112)	(0.112)	(0.096)
Covid-19 Deaths	0.036	0.086	0.136	0.331^{*}
	(0.122)	(0.123)	(0.123)	(0.178)
Informality Rate	0.001	0.001	-0.005^{**}	-0.008^{**}
	(0.002)	(0.002)	(0.002)	(0.003)
Δ Formal Employment Q12020	-0.430^{*}	-0.432^{**}	-0.430^{*}	-0.279
	(0.222)	(0.220)	(0.220)	(0.233)
Δ Formal Employment 2019	0.008^{***}	0.004^{*}	0.004	0.002
	(0.002)	(0.002)	(0.002)	(0.006)
Share of Services in Employment		-0.011^{***}	-0.008^{***}	0.002
		(0.002)	(0.002)	(0.003)
Urbanization Rate			-0.006	-0.009^{***}
			(0.008)	(0.002)
Overall Mobility				0.024^{***}
				(0.003)
Constant	-0.003^{*}	0.003^{*}	0.009^{***}	0.008^{**}
	(0.002)	(0.002)	(0.002)	(0.003)
States Fixed effects	Yes	Yes	Yes	Yes
Observations	5,478	5,478	5,478	2,210
R^2	0.091	0.098	0.102	0.160
Adjusted R^2	0.086	0.093	0.096	0.147
Residual Std. Error	0.013 (df = 5446)	0.013 (df = 5445)	0.013 (df = 5444)	0.011 (df = 2175)
F Statistic	17.626^{***} (df = 31; 5446)	18.508^{***} (df = 32; 5445)	18.660^{***} (df = 33; 5444)	12.164^{***} (df = 34; 2175)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of population receiving *Bolsa Familia* benefits is as of December/2019. Services as a share of total employment, urbanization rate, and the informality rate come from the 2010 census.

Table 8: Baseline Regressions First Stage Results

	Cumulative Change in EA Transfers per capita (BRL 100K)			
	Baseline	Adding Services Empl.	Adding Urbanization Rate	Adding Mobility
	(1)	(2)	(3)	(4)
Share of BF Receivers in Population	0.039^{***}	0.039^{***}	0.039^{***}	0.032^{***}
	(0.001)	(0.001)	(0.001)	(0.002)
Covid-19 Deaths	0.123^{***}	0.119^{***}	0.106^{***}	0.129^{***}
	(0.016)	(0.016)	(0.016)	(0.028)
Informality Rate	0.003^{***}	0.003^{***}	0.004^{***}	0.005^{***}
	(0.0002)	(0.0002)	(0.0002)	(0.001)
Δ Formal Employment Q12020	-0.003	-0.003	-0.004	-0.005
	(0.004)	(0.004)	(0.004)	(0.008)
Δ Formal Employment 2019	0.001^{***}	0.001^{***}	0.001^{***}	0.001
	(0.0002)	(0.0002)	(0.0002)	(0.001)
Share of Services in Employment		0.001^{***}	0.0003	0.001^{**}
		(0.0002)	(0.0002)	(0.0005)
Urbanization Rate			0.001	0.001^{***}
			(0.001)	(0.0004)
Overall Mobility				-0.004^{***}
				(0.0004)
Constant	0.007^{***}	0.006^{***}	0.005^{***}	0.003^{***}
States Fixed effects	Yes	Yes	Yes	Yes
Observations	5,478	5,478	5,478	2,210
R^2	0.704	0.705	0.709	0.587
Adjusted R^2	0.702	0.703	0.707	0.581
Residual Std. Error	0.002 (df = 5446)	0.002 (df = 5445)	0.002 (df = 5444)	0.002 (df = 2175)
F Statistic	417.249^{***} (df = 31; 5446)	406.133^{***} (df = 32; 5445)	400.971^{***} (df = 33; 5444)	91.105^{***} (df = 34; 2175)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of analysis is municipalities, the lowest administrative level in Brazil. Data on formal employment creation, and EA transfers refer to the sum over April-September 2020. Google mobility and Covid-19 deaths are measured as the average over April-September 2020. The share of Population Receiving the Bolsa Familia as December/2019. Services as a share of total employment, urbanization rate, and the informality rate come from the 2010 census.

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