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Social transfers and growth

The missing evidence from luminosity data

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Abstract: The effects of social transfers on growth are still unclear. The limitations of aggregated data at sub-national levels have confined the analysis to the use of simulation models and household surveys. As an alternative, this paper contributes to the empirical literature by assessing the effects of Colombia's *Familias en Accion*, a human development cash transfer programme, on municipality level growth rates during its initial stage of implementation between 2000 and 2004. The natural experiment that resulted from the scaling-up of the intervention facilitated the set-up of a difference-in-differences analysis. The lack of sub-national GDP accounts is tackled by using luminosity data generated by satellites orbiting the earth, which have demonstrated to be a suitable proxy for economic growth and per capita growth. The results show that the programme can generate large positive effects on municipality level economic growth rates. Robustness checks confirm the reliability of these findings.

Keywords: social transfers, economic growth, local economy effects, Familias en Accion, difference-in-differences treatment effects
JEL classification: I38, O10, R10

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1 Introduction

The causal relation between social transfers and economic growth still remains controversial. While in OECD countries the evidence tends to demonstrate negative effects of social spending on growth, in developing countries some authors find important positive effects (Damerau 2011). In the particular case of human development cash transfer programmes (popular anti-poverty interventions in Latin America), abundant existing evidence demonstrates relevant direct effects on the recipient's human capital (Rawlings and Rubio 2005). Experiments or quasi-experiments from which such evidence has emerged have failed to provide reliable support to the relation between the transfers and the economic activity beyond beneficiary households. To date, most of the existing empirical literature linking anti-poverty programmes to economic growth effects has been based on simulations and indirect impact assessments focused on non-beneficiaries. The causal inference in this context has been limited by the nature of the interventions and the absence of consistent aggregated data that allows the comparison of treated and untreated communities under a counterfactual setting.

An extensive amount of literature in OECD countries has come into view demonstrating the ambiguous effects of social transfers on growth. The recent integration of welfare benefit providers with employment services has been supported by time-series evidence showing that government spending on social transfers could deter growth, while labour activation policies could boost it (Arjona et al. 2003). Contrary, the evidence from developing countries shows different figures. General equilibrium simulations have exhibited positive effects of social transfers on growth. These effects are dependent on how programmes are funded and on how prices respond to a liquidity injection into the economy (Coady and Harris 2004; Levy and Sherman 2014).[1] Similarly, relying on microeconomic models and evidence from household-based impact evaluations, authors have been able to detect symptoms of extended economic activity originated by social transfers. For instance, Barrientos and Sabatés-Wheeler (2009) and Angelucci and De Giorgi (2009) have examined the effects of Mexico's *Oportunidades* cash transfer programme on the ineligible population, finding important increases in consumption by non-claimant households cohabiting with recipients in the same village. In spite of the efforts to link social transfers and growth, a commonality in the research of this issue in developing countries has been the lack of reliable aggregated data, combined with the strong assumptions made by simulations.

This paper intends to generate counterfactual evidence on the relation between social transfers and growth and per capita growth with a proxy for aggregated regional data. The initial implementation of the *Familias en Accion* cash transfer programme in Colombia offers a unique opportunity to produce unconfounded estimates. The scaling up of the programme at the municipality level between 2000 and 2004 creates a special natural experiment to set up a difference-in-differences (DID) treatment effects estimation comparing eligible treated and untreated villages. The availability

[1] A recent introduction of a cash transfer programme in Indonesia motivated the simulation of its effects on GDP growth (Yusuf 2013). Using a general equilibrium model he demonstrates that the introduction of the programme hindered economic growth if it was funded with value added taxes. However, this effect could be reduced if the programme was funded by dismantling fuel subsidies.

of a panel dataset facilitates the definition of the identification strategy by testing the parallel-paths assumption on DID following Mora and Reggio (2012). As a proxy for economic growth, the estimation relies on the economic activity captured by the luminosity data recorded by satellites before and after the implementation period of *Familias en Accion*. These data have demonstrated to be a consistent predictor of the gross domestic product (GDP) at national and sub-national levels (Henderson et al. 2012). The measurement of economic activity from satellite data has confirmed a significant correlation between artificially-generated night lights and conventional measures of income or GDP, in spite of the fact that national accounts and satellite-generated data may be contaminated with measurement errors. On one hand, official statistics agencies may rely on inaccurate surveys and formal transactions that over- or underestimate the calculations of the GDP. On the other, atmospheric conditions, such as humidity, snow and temperature may affect how satellites capture night lights. A main concern could arise if these measurement errors are not independent, in the sense that they may generate confounded significant correlations. In a cautious comparison between national accounts and luminosity data, Pinkovskiy and Sala-i-Martin (2014) have found that both measurement errors are uncorrelated. Thus, the capture of luminosity data from the space as proxy for GDP and the implementation of *Familias en Accion* provide an exceptional opportunity to assess the impact of social transfers on GDP. The results show that the programme increased the growth rates of the municipalities where it was initially introduced.

This paper makes a relevant contribution to the evidence-based discussion on the relation between social transfers and growth. As the quantification of this relation has been difficult (Barrientos and Scott 2008), the proposed methodology will be able to estimate the effects of *Familias en Accion* on municipal growth rates identifying their counterfactual levels in absence of the programme. Unlike previous findings based on simulations or household survey data, the identification strategy here will provide a certain estimation of the average treatment effects with a panel data of 732 Colombian municipalities eligible to the programme between 1998 and 2004. Thus, the assumptions of the previous simulated evidence are relaxed, whereas consistent estimations are provided.

This study is divided into five sections. The second section reviews the current discussion on the relation of social transfers and growth. The third section details how the introduction of *Familias en Accion* at the municipality level bring a suitable setting for a DID treatment effects estimation. The fourth section describes the data and shows the results of the empirical exercise and, finally, the fifth section presents the conclusions of the overall approach.

2 Linking social transfers and growth

The term *social transfers* has been treated as synonym of *social assistance* or *anti-poverty programmes*.[2] Barrientos (2013) defines it as transfers of income delivered to households or individuals aimed at alleviating poverty. They are encompassed within social protection along with non-contributory insurance schemes and active or passive labour markets policies.

[2] Also referred as *Social Safety Net*.

The relation between social transfers and growth in developing countries has been uncertain due to the lack of reliable evidence. Some authors are still sceptical to acknowledge the contribution of social assistance to economic growth. Levy (2007, 2006) intuitively asserts that the scope of the delivery of income to households in poverty (such as Mexico's *Oportunidades*) can be diluted by the fact that transfers represent, at the most, one-fifth of their total income. On one hand, social transfers can generate positive effects on growth via a better human capital provision of children in participating households. On the other, these effects are detectable only in the long run, when current children become adults and participate actively in the labour markets.[3] Levy's assumptions depend on the fact that general equilibrium effects are ignored; apparently once households receive the income transfer the response of local markets to the increase in the demand of goods and services is considerably weak in the short run. Nonetheless, there are arguments that support the idea that a relevant injection of liquidity into the communities where social transfers traditionally operate can benefit beneficiaries and non-beneficiaries (Taylor 2012). When social transfers are introduced the demand of goods and services expands, particularly food (Hoddinott and Skoufias 2004), savings and investment are boosted at the household level and capital and labour are also demanded (Gertler et al. 2012). Therefore, the arguments on the relevant positive effects of transfers on growth cannot be dismissed.[4]

Some authors have used computable general equilibrium models (CGEM) or local economy-wide impact evaluation methods (known as LEWIE) to determine the direction of the effects of transfers on growth. For instance, Coady and Harris (2004) simulate the general equilibrium effects of *Oportunidades*, finding that the programme can generate distortionary negative effects when the programme is financed with taxes. The effects could be positive if the programme is financed substituting other subsidies. In contrast to the funding argument, it has been found that the emergence of a significant number of social transfer programmes in developing countries has been facilitated by revenues from natural resources which buffer the pressure on taxes (Barrientos 2009). Similar evidence on these effects is obtained by simulations provided by Thome et al. (2013) on Kenya's cash transfer for Orphan and Vulnerable Children (CT-OVC). Employing a LEWIE approach, they find that local production increases by 1.14 shillings for each shilling transferred to beneficiary households. Despite the outstanding value of CGEM and LEWIE approaches, the simulations on which they are based are supported on strong assumptions about the behaviour or agents and markets.

Recent analytical contributions have emerged to explain the channels through which social transfers affect growth (Alderman and Yemtsov 2014). Barrientos (2012) offers a suitable micro-founded framework on this relation. He identifies six main mediating processes that focus on direct household effects. The first one is the alleviation of credit constraints in the context of imperfect financial markets. A constant flow of income delivered by social transfer supports the liability of the

[3] Levy (2007) also argues that these programmes can be detrimental to economic growth as they generate incentives to create low quality informal jobs.

[4] However, some other authors use general equilibrium models to demonstrate that social transfers can generate undesired effects on prices and salaries. These effects depend on the type of transfers delivered: cash and in-kind transfers can generate different incentives on local markets (Gelan 2006; Levy and Sherman 2014).

household in the access to credit, while the transfer may work as collateral.[5] The second is shaped by improvements in household consumption and asset security, through which households influence the demand and production of local goods and services. Similarly, the transfers allow the households to engage in investment projects around higher risk and profits activities that they would otherwise not undertake.[6] The third one, is in regards to improvements in household resource allocation, achieved by the modified bargaining power of agents within the households. In particular, the fact that some transfers are given to female caregivers has demonstrated higher positive effects on children's health and nutrition status (Duflo 2003). Forth, social transfers provide asset protection and accumulation, which entails the prioritisation of human capital accumulation through the introduction of compulsion components attached to some social transfers (e.g. human development conditional cash transfers). Fifth, the labour market effects of social transfers, despite ambiguous, may mediate in the relation between social transfers and growth. Most of the recent empirical finding suggest that anti-poverty programmes do not discourage labour supply and, rather, can lead to increases in labour supply for some household members (Barrientos and Villa 2013a).

Finally, and more relevant to this paper, local economy effects are the sixth element of the mediating process. Social transfers inject liquidity into the communities where they operate. The incidence of some programmes in a single village could reach 80 per cent of the population while national coverage can be as high as 25 per cent (Soares et al. 2010). Angelucci and De Giorgi (2009) examined the effects of *Oportunidades* on ineligible households living in the same villages where the programme was put into operation. They found significant increases in their consumption and assets ownership due to the local economy effects of the transfers. If this occurs at the locality level, there are indications that social transfers can also generate positive effects on aggregate figures.

The characterisation the of local economy effects in the short- and medium-run, Figure 1 shows an analytical flow of an economy with the relevant elements affected by a social transfer programme.

The delivery of the transfers have immediate effects on household consumption and either savings or credit. The local demand is boosted, which can generate increases in prices and import of goods or a higher local production and trade. The local push on local production results in a higher demand of factors, involving the demand for productive assets by beneficiaries and non-beneficiaries. On the other hand, demand for labour also increases at the local level, resulting in higher household consumption. If the delivery of transfers is constant over time, this cycle can create important increases in local production which can be detected by counterfactual evaluations.

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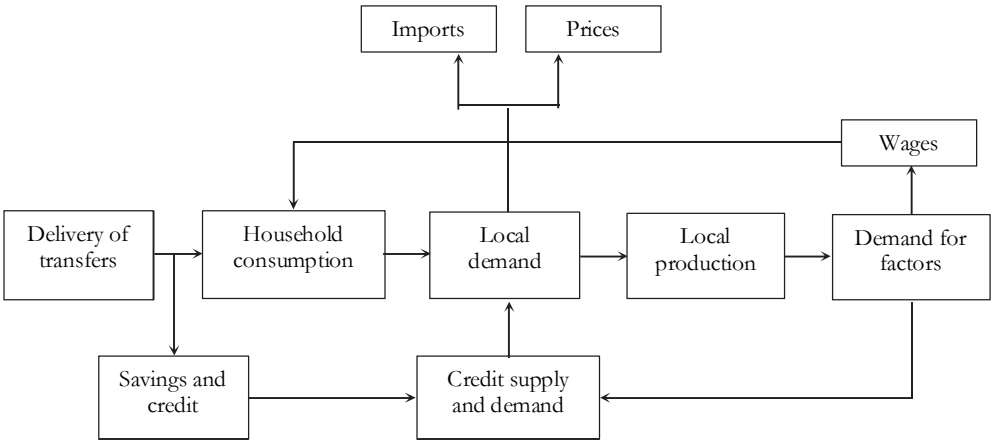
[55] For instance, participating households in the Ecuadorian CCT, *Bono de Desarrollo Humano*, are able to borrow money from state-owned banks. The loans are available for up to 24 times the value of the monthly cash transfer (Samaniego and Tejerina 2010).

[6] Gertler et al. (2012) found that it takes 18 months to detect profitable investments undertaken by beneficiary households in Mexico's *Oportunidades* programme.

Figure 1: Analytical flow of local economy effects



Source: Author's compilation.

To sum up, the causal relation between social transfers and growth is one of the hardest to measure. Theoretical approaches provide insights on the channels through which anti-poverty programmes impact growth. Most of the empirical evidence has been obtained by general equilibrium models on the basis of simulations and strong assumptions. Other approaches have used household survey data to detect the effects on cohabitant members at the locality level. None of the studies have quantified the effects of the transfers on growth at aggregated level using reliable data.

3 Introduction of *Familias en Accion* as a DID setting

The economic crisis of the second part of the late 1990s reached most of the Latin American countries. In 1999 the Colombian GDP shrank 4.9 per cent after a decade of positive growth. The symptoms of the economic crisis were manifested by high unemployment rates, malnutrition of young children and school dropouts, especially hitting households in the lowest income quintile (DNP 2001). The Colombian government responded through the introduction the human development conditional cash transfer programme, known as *Familias en Accion*, whose similar features had evidenced relevant positive outcomes in Mexico.[7]

The programme was established in 2000 with a pilot phase beginning in December and ending in April 2001. At the geographic level, in the period 2000-04 the intervention aimed at covering municipalities with a population below 100,000 inhabitants by 1999, and with availability of a private or public bank branch.[8] The geographical eligibility criteria remained unchanged until 2005.

[7] *Familias en Accion* was initially funded by loans from the World Bank and the Inter-American Development Bank. These multilaterals organisations also facilitated the adoption of these social transfers in Colombia (Barrientos and Villa 2013b).

[8] 264 out of 1100 municipalities were not equipped with at least one bank branch in Colombia by 1999.

Under these parameters, 732 municipalities were identified and considered for the operations of the programme. Its expansion started in 2001 with the aim of registering 340,000 households in extreme poverty. By 2003 this goal was achieved, while in 2004 the programme started its consolidation and no additional households were registered (Accion Social 2010).[9]

The initial introduction of *Familias en Accion* offers an opportunity for the identification of treatment effects with a DID setting. Table 1 shows that the gradual registration of municipalities defined a cumulative number of comparison and treated municipalities. From the total 732 eligible municipalities, two were registered in 2000, 360 in 2001, 244 in 2002 and six in 2003. As a result, by 2003 and 2004 the number of comparison municipalities was reduced to 120, while the number of treated reached 612. The gradual introduction of the programme was made on a non-random basis. Which municipalities were registered earlier or later between 2000 and 2003 was decided by the administration of the programme according to unobserved institutional factors. Any comparison with the resulting composition of comparison and treated municipalities would be contaminated by administrative bias that, for the sake of simplicity, is considered constant over time. In fact, despite 732 municipalities share similar geographic selection, the single difference in the selected outcomes between the 612 treated and the final 120 comparison municipalities would be confounded unless an identification strategy is taken into consideration.

As for household registration in the selected municipalities, the initial individual selection of participants was straightforward. Since 1993 the Colombian government had introduced a socioeconomic classification system known as *Sisben*. The *Sisben* would consist of a proxy mean test assigning a score between 0 and 100 to every individual household (with 0 being the poorest and 100 the wealthiest). The programme obtained the *Sisben* information and selected those households with the lowest scores by 1999. The programme would transfer an average of 25 US$ per month to registered households with children under the age of 18. Transfers are conditional on regular school attendance and health check-ups of participating children. Despite the initial goal of the programme was the registration of 340,000 families, by 2004 the number of registered households reached 406,458 with a total amount of 238 million US$ at current prices in 612 municipalities (see Table 1).[10]

[9] In 2005 and 2006 the programme was expanded to the rest of municipalities, including households in extreme poverty and displaced population.

[10] According to the impact evaluation report of the programme in the period 2001-04 by IFS-Econometría-SEI (2006), school attendance increased by 5.1 and 7.2 percentage points in urban and rural areas for children between 12-17 years of age, respectively. The programme reduced the number of repeated school years by 0.12 for children between 14-17 years. As for labour markets, child labour was almost eradicated by a reduction of 5.5 percentage points in rural areas while the number of weekly worked hours by adults remained unaffected. There were no significant impacts on household incomes while consumption was increased by 5 percentage points in rural areas. Similarly, food consumption increased 15 per cent in rural areas (especially cereals and proteins). Thus, the programme reduced food poverty exclusively in rural areas by 12.6 per cent while multidimensional living condition indexes were unmodified.

Table 1: Expansion of Familias en Accion and DID setting in the period 2000-04

Year	Municipalities				Families (in registered municipalities)		
	Eligible	Registered	Comparison	Treated	Eligible	Registered	Transfers delivered, in US$*
2000	732	2	730	2	1,184	993	-
2001	732	360	370	362	320,145	236,901	3,340,729
2002	732	244	126	606	247,257	164,098	45,228,673
2003	732	6	120	612	6,672	4,466	94,262,460
2004	732	0	120	612	0	0	95,408,507
Total	732	612	120	612	575,258	406,458	238,240,368

Source: Familias en Accion (2004).

The DID setting is suitable when before and after intervention data is available for treated and comparison groups. It accounts for unobserved time-invariant selection bias (Abadie 2005). In this particular case, the DID treatment effects are obtained by estimating ordinary least squares and fixed effects models with several pre- and post-treatment years over the period 1998-2004, with the intervention starting in 2000 and no exposure to the programme prior to 1999 (Imbens and Wooldridge 2009).[11] Several choices are available for identifying the DID effects of the programme on growth over its initial stage between 2001 and 2004. As no transfers were delivered in 2000, this year is ignored as focus of analysis. The first approach here considers a pre- and post-treatment period of analysis as specified by Card and Krueger (1994). This considers the pooled dataset of municipalities comparing those before and after the introduction of *Familias en Accion* regardless of the year they were registered. In this sense, a linear regression is specified as follows:

$$y_i = \beta_0 + \beta_1 \cdot P_i + \beta_2 \cdot D_i + \beta_3 \cdot P_i \cdot D_i + \beta_4 X_i + e_i \quad (1)$$

Where, for each municipality, i, y_i represents the outcome variable (growth and per capita growth). β_0 is the average outcome of the comparison group, $D_i = 0$, in the pre-treatment period, $P_i = 0$. The sum of coefficients $\beta_0 + \beta_1$ is the average outcome of the comparison group in the post-treatment period, $P_i = 1$; The estimated β_2 is the single difference in the outcome between treated, $D_i = 1$, and comparison groups in the pre-treatment period. The sum $\beta_0 + \beta_2$ denotes the average outcome of the treated group in the pre-treatment period, while the sum $\beta_0 + \beta_1 + \beta_2 + \beta_3$ is the average of the treated group in the post-treatment period, $D_i = 1$. β_4 is the coefficient for an additional covariate, X_i, included in the regression. Finally, the average effect of the programme on the outcome variable is given by the coefficient β_3.

In the second approach, despite the traditional DID setting is based on the analysis of the effects with a single baseline and follow up dataset, the panel structure of the data facilitated by the gradual introduction of the cash transfers provides an opportunity to specify a complementary linear fixed

[11] Despite the programme was rolled out in 2000, no transfers were delivered in that year and only two municipalities were registered in December. However, 2000 is considered as the starting point of the intervention.

effect analysis.[12] Bearing his in mind, the following stochastic equation determines the estimation of the DID treatment effects:

$$y_{it} = \nu_i + e_{it} + \sum_{t=2001}^{2004} \beta_{1t} \cdot D_{it} \cdot Y_t + \sum_{t=1998}^{2004} \beta_{2t} \cdot Y_t + \beta_3 \cdot X_{it} \quad (2)$$

Where in year t, y_{it} denotes the outcome variable (growth and per capita growth), ν_i is the time invariant municipality effect (which disappears with the within regression) and e_{it} defined as the idiosyncratic effect. The estimands β_{1t} are the effects of the programme in each year, t. These effects are generated by the interaction between D_{it} (which obtains values of 1 if the municipality, i, is treated by the programme and 0 otherwise in year t), and a binary variable, Y_t, indicating each year in the post-treatment period. The estimands β_{2t} denote the level of the outcome variable for the comparison group resulting from including the time trend, Y_t, into the equation. Finally, β_3 represents the coefficient of an additional time-varying control covariate.

Several assumptions and tests are considered within this setting. First, the DID is assumed to account for parallel-paths of the outcome variable prior to the intervention for treated and comparison groups. Despite the parallel-paths assumption can be visually checked, further tests are provided in the next section. Second, the standard errors obtained by the fixed effects model could be serially correlated, increasing the significance of the estimands (Bertrand et al. 2004). Therefore, a test of serial correlation is conducted as evidence of the efficiency of the effect estimations.

4 Data and results

Several sources of data were considered for the estimations of the DID effects. The final working panel dataset is composed of 5,124 observations corresponding to 732 municipalities over 8 years. Part of the information was provided from the administrative and public records of *Familias en Accion* during its initial stage of implementation (2000-04). Some additional covariates, related to revenues of the municipalities and regions from the national government, are also obtained from open data sources. Finally, the outcome variables, the growth and per capita growth rates, are measured from the luminosity data that is detailed below.

One of the main limitations to the assessment of the effects of social transfers on growth is the lack of reliable data at the sub-national levels in which these interventions are introduced. In Colombia, national accounts and household surveys do not disaggregate at the municipality level. An alternative is the use of luminosity data captured by satellites that observe and store information of night artificially-generated lights on any spot of the earth between the latitudes of 65 degrees north and south. The National Oceanic and Atmospheric Administration (NOAA) stores the luminosity data, although the information is primarily generated by the United States Air Force Defence Meteorological Satellite Program since 1992.[13] Potential contamination from lunar cycles, fires and

[12] This panel data model approach allows for the consideration of a higher number of observations and better power and significance of the estimates.

[13] Available at http://ngdc.noaa.gov/eog/download.html

northern lights is removed in order to prevent confounded results. The images are generated globally between 20:00-22:00 hrs with a recording capacity of 3,000 km and 14 orbits per day (Elvidge et al. 2009). In the stable version, the intensity of the lights is provided in the form of an index between 1 and 63, indicating 1 absence of luminosity and 63 the brightest spots. The sum of the lights is obtained for Colombian municipalities with a raster calculator tool, filtering and cleaning the data with Q-GIS open software on geographic information system.

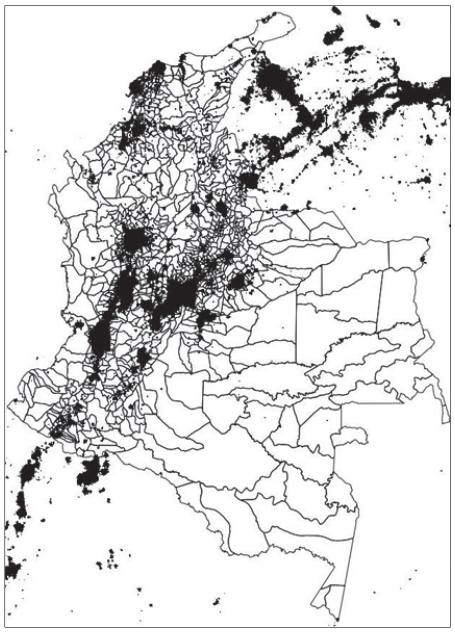
Areas with high luminosity will reflect a higher economic activity with a consistent correlation between the measure of luminosity and national accounts (Chen and Nordhaus 2011). The use of this information for the assessment of economic growth at sub-national levels has been recently scrutinised. Despite the recordings from satellites around the earth can contain measurement error, they have proved to be a reliable approach of economic activity (Henderson et al. 2012, 2011). As regards the comparison with national account and survey data, Pinkovskiy and Sala-i-Martin (2014) demonstrate that the measurement error emerging from luminosity data are uncorrelated with those from official accounts. In particular, the generating process of the luminosity data is evidently independent from the one generating official aggregated data and household surveys. The fact that measurement errors are uncorrelated implies that revised correlations between GDP and luminosity data are not confounded. It is reliable to use luminosity as proxy for economic activity.

Turning now the attention to Colombian municipalities over the period of adoption of *Familias en Accion*, the luminosity data reveals changes between 1998 and 2004. Figures 2 and 3 present the images in inverted scales showing the spots of high concentrations of human settlements and economic activities. The centre of the country has historically concentrated industrial production and higher income generation, although the northern areas have experience a notable growth. As households in extreme poverty in some municipalities were made participants in *Familias en Accion* since 2001, the main insight of this analysis is to establish the extent to which the programme influenced the changes in the economic activity resulting in a higher emission of lights.[14]

An initial exercise was done to grasp the relevance of the transfer on municipal economic activity. The lights index in the country was summed to obtain the participation of each municipality in total economic activity. The resulting proportion was multiplied by the value of Colombian GDP according to the national accounts with the aim of obtaining a proxy of municipal GDP in 2004. The total proxy for GDP calculated for treated municipalities added up US$245 million at nominal prices, that is, only 3 per cent of Colombian total GDP. Since the transfers were almost 95 million US current dollars, the proportion of the transfers in reference to a proxy of local economic activity could reach 38.6 per cent. This proportion makes it difficult to ignore that the expected impact of the programme on growth is relevant to the treated municipalities.

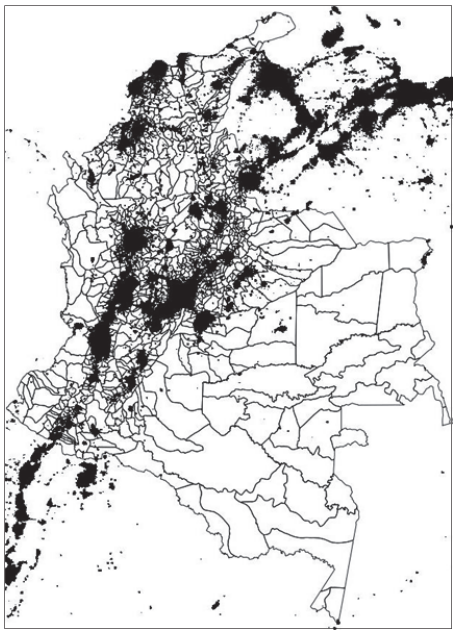
[14] According to DNP (2005) the energy coverage in the municipalities of analysis had reached 87 per cent by 2003.

Figure 2: Luminosity captured by satellite in 1998 (inverted scale)



Source: NOAA (2014).

Figure 3: Luminosity captured by satellite in 2004 (inverted scale)

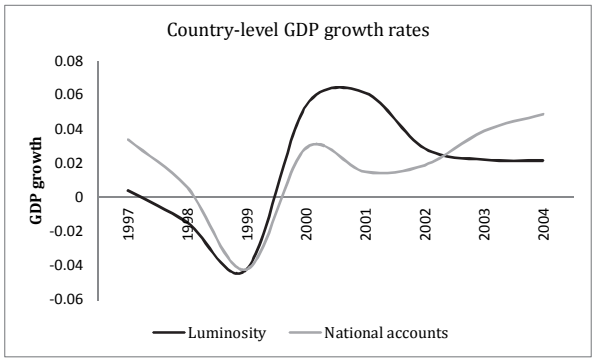


Source: NOAA (2014).

To look into the evolution of the luminosity growth as a proxy for GDP growth, the next two figures show their evolution over the period of analysis (per capita growth will also be considered later on). Figure 4 compares the GDP growth measured by the Colombian official statistics office (DANE) and the one generated by the luminosity data provided by NOAA. What is interesting in this figure is that both measures of growth behave similarly. For instance, the luminosity data predicted accurately the economic crisis in the late 1990s, despite after 2001 both measure tend to diverge.

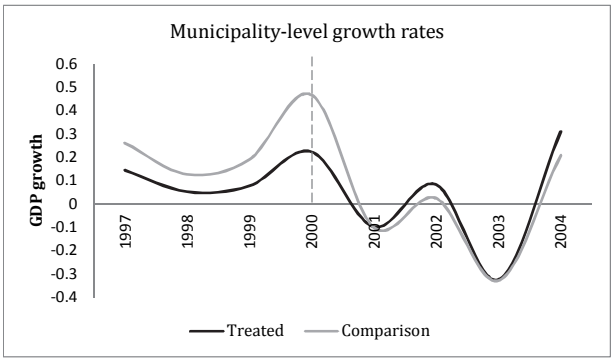
Figure 5 shows the municipality level growth rates measured by the luminosity data for treated and comparison groups defined for the operation of the programme in 2003-04. Unlike the aggregated data, these municipalities do not follow the same trend nor experienced a similar cycle. Instead of following the same country level trend, their growth rate plummeted in 2003 and sharply recovered in 2004. Lack of documentation makes it difficult to detect what drove the proxy of economic activity to plummet in 2003. Nonetheless, the most striking observation that emerges from this figure is that before the programme was introduced, treated and comparison groups experienced similar trends. After the year 2000 the growth rates of both groups started to behave differently, with a higher growth rate for the treated group in 2004 (precisely when the programme was consolidated and no new municipalities were covered). In a nutshell, the fact that both groups experience a similar trend prior to the treatment is an important visual asset in the identification strategy of the DID setting.

Figure 4: Country level growth rates



Source: DANE (2014); NOAA (2014).

Figure 5: Municipality level growth rates



Source: NOAA (2014).

Despite visually treated and comparison groups showed similar growth trends prior to the intervention, the parallel-paths assumption was tested following Mora and Reggio (2012). This assumption indicates that in absence of the programme the growth rates of treated and comparison groups would follow the same trend. In other words, it implies that the differences in the growth level before and after the intervention are time-invariant. Mora and Reggio (2012) propose a method that focuses on the behaviour of the double difference of the outcome variable to test a parallel-growths assumption as alternative to the parallel-paths assumption. It is based on the analysis of q baseline periods before the treatment and s periods after it. If the parallel-growths assumption is met, then the comparison group is an accurate counterfactual for the treated group, similar to the parallel-paths assumption. Table 2 shows the results of the test based on Mora and Reggio (2014). For each baseline period the hypothesis of parallel-growth is not rejected, while the overall test of hypothesis of common pre-dynamics is also not rejected. Thus, the DID identification strategy denotes that, on average, comparison municipalities are a suitable counterfactual for the treated group.

Table 2: Parallel-paths assumption test

Post-treatment (*s*)		*s*=1	*s*=2	*s*=3	H0: *q=q-1*	H0: *s=s-1*
Pre-treatment (*q*)	*q*=1	-0.1305	-2.2184	0.10721		6.758114
		(0.145)	(2.303)	(0.085)		[0.1492]
	q=2	-0.0926	-2.1426	0.22087	-0.03789	5.375049
		(0.197)	(2.314)	(0.319)	[0.6461]	[0.2509]
	q=3	-0.0155	-1.9114	0.68322	-0.07706	5.76619
		(0.294)	(2.380)	(1.092)	[0.5895]	[0.2173]

Notes: H0: Common pre-dynamics = 0.3069; p-value = 0.8578.

(1) Parallel-paths assumption test based on Mora and Reggio (2012) with output table from Mora and Reggio (2014); (2) Sample period: 1998-2004; (3) Treatment period: 2000-04; (4) Robust standard errors in parenthesis; (5) p-values in brackets.

Source: NOAA (2014).

Despite the parallel-paths assumption was tested, additional time-varying covariates were taken into consideration. Table A1 in the Appendix shows the statistics for the outcomes and selected covariates for treated and comparison groups in the pre-treatment status in 1999 at different post-treatment years. T-statistics are provided to test difference in means. The outcomes of growth and per capita growth did not report relevant unbalances between groups at the baseline. The two first covariates are relevant to control for the dynamics of luminosity data. The proportion of households having electricity and the electricity prices were thus considered with no important differences between treated and comparison groups.[15] On the other hand, the population of the municipalities was also taken into consideration with no significant differences. Tax transfers from the national government and royalties revenues were also considered. They can externally affect growth and per capita growth of the municipalities and alter programme participation through higher local public spending and investment. Despite these two variables could be related to local economic growth, transfers from the national government to the municipalities, as well as their royalties revenues, are determined exogenously by a mandate of the Colombian constitution, while royalties depend on the mineral and oil endowments of each territory. They can account for up to 90 per cent of local fiscal revenues (Chaparro et al. 2004). Transfers from the national government to regional level public administration were also included into the analysis. The latter showed significant unbalances for all post-treatment years, especially for treated and comparison groups as defined by the programme coverage in 2001. These variables are included in the regression analysis as additional controls.

The final consideration is focused on the estimation of the standard errors. Bertrand et al. (2004) demonstrates that auto-correlated residuals can lead to an underestimation of the standard errors and wrong significant coefficients. The Wooldridge (2001) autocorrelation test for panel data was conducted following Drukker (2003). Two outcome variables were considered. First, the GDP growth measured with the luminosity data shows that autocorrelation cannot be accepted ($F(1, 732)=1.445$; Prob > 0.229). Second, the per capita GDP also demonstrated absence of autocorrelation ($F(1, 732)=1.432$; Prob > 0.231). Hence, the standard errors obtained from the fixed effects estimation are reliable under current settings.

Turning now to the results, Table 4 presents the outputs of the estimation of Equation 1. Two different outcomes were considered: growth and per capita growth from luminosity data. The table arranges the estimated coefficients such that the average levels of the comparison and treated group are displayed. Columns 1 and 4 estimate the effects of the programme on growth and per capita growth with the complete sample. As consistency and robustness checks, columns 2 and 5 rule out the pre-treatment year of 1998, while columns 3 and 6 include the selected covariates in the estimation. In this first approach, considering the pooled dataset and the single pre- and post-treatment status, the estimation of the DID yielded negative but not significant results.

[15] Information on coverage and prices was obtained from the *Unidad de Planeacion Minero Energetica* (UPME) (Unit for Mining and Energy Planning, in English).

Table 3: DID estimation with linear regression, single pre and post-treatment

Estimands/variables	(1) Growth rate	(2) Growth rate	(3) Growth rate	(4) Per capita growth	(5) Per capita growth	(6) Per capita growth
Pre-programme						
Comparison	0.071	0.060	0.127	0.064	0.051	0.155
Treated	0.064	0.076	0.102	0.066	0.079	0.138
Difference	-0.007	0.016	-0.025	0.002	0.027	-0.016
	(0.060)	(0.090)	(0.060)	(0.060)	(0.090)	(0.060)
Post-programme						
Comparison	0.004	0.144	0.184	0.140	0.140	0.213
Treated	0.017	0.124	0.144	0.121	0.121	0.174
Difference	0.012	-0.020	-0.040	-0.020	-0.020	-0.039
	(0.014)	(0.040)	(0.038)	(0.037)	(0.040)	(0.038)
DID	-0.030	-0.036	-0.016	-0.022	-0.047	-0.023
	(0.026)	(0.098)	(0.070)	(0.070)	(0.098)	(0.070)
Covariates						
Electricity coverage			0.000			0.000
			(0.003)			(0.002)
Electricity price (Kw/h)			0.001***			0.001***
			(0.000)			(0.000)
Population			0.000***			0.000***
			(0.000)			(0.000)
National transfers			0.016			0.016
			(0.013)			(0.013)
Royalties			-0.058			-0.011
			(0.052)			(0.010)
Regional transfers			-0.009			0.021
			(0.010)			(0.003)
Regional royalties			0.021***			0.000
			(0.003)			(0.001)
Observations	5,071	4,353	5,071	5,071	4,353	5,071
R-squared	0.001	0.014	0.014	0.001	0.002	0.050
Municipalities	732	732	732	732	732	732

Notes: (1) Means, standard errors and differences are estimated by linear regression; (2) 1 per cent of each side of the growth distribution was trimmed for this analysis; (3) Electricity price and transfers are at 2004 prices; (4) Inference: *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: NOAA (2014); Familias en Accion; DNP (2013); UPME (2014).

Table 4 presents the estimates of Equation 2, in which the year of gradual introduction of *Familias en Accion* is explicit in the analysis. Columns 1 and 4 show the fixed-effects estimation with no consideration of additional covariates. The coefficients of interest are those that result from the treatment status and year. Strong evidence of the positive effects of the programme on growth was found, especially for the year 2004, when the programme was consolidated after its initial introduction stage between 2001 and 2003 (recall that nearly 400,000 families and 238 million US$ had been transferred). This effect translated into a 0.11 higher growth rate for treated municipalities in 2004.

Table 4: Fixed effects linear regression results

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Growth	Growth	Growth	Per capita growth	Per capita growth	Per capita growth
D2004*Y2004	0.149***	0.150***	0.151***	0.148***	0.149***	0.150***
	(0.049)	(0.053)	(0.049)	(0.048)	(0.051)	(0.048)
D2003*Y2003	-0.054	-0.049	-0.052	-0.054	-0.049	-0.053
	(0.032)	(0.030)	(0.031)	(0.033)	(0.031)	(0.032)
D2002*Y2002	0.018	0.024	0.019	0.021	0.027	0.021
	(0.038)	(0.035)	(0.037)	(0.038)	(0.035)	(0.037)
D2001*Y2001	-0.081	-0.081	-0.080	-0.087	-0.087	-0.087
	(0.063)	(0.094)	(0.029)	(0.029)	(0.032)	(0.030)
Y1998	-0.049		-0.048	-0.051		-0.050
	(0.056)		(0.061)	(0.057)		(0.061)
Y1999	-0.058	-0.010	-0.057	-0.058	-0.008	-0.057
	(0.068)	(0.032)	(0.074)	(0.069)	(0.032)	(0.074)
Y2000	0.105	0.153***	0.107	0.101	0.151***	0.104
	(0.064)	(0.037)	(0.068)	(0.065)	(0.037)	(0.069)
Y2001	-0.140***	-0.092***	-0.138**	-0.140***	-0.090***	-0.138**
	(0.044)	(0.029)	(0.052)	(0.045)	(0.030)	(0.052)
Y2002	-0.006	0.037	-0.006	-0.012	0.032	-0.012
	(0.058)	(0.041)	(0.060)	(0.059)	(0.041)	(0.061)
Y2003	-0.372***	-0.329***	-0.372***	-0.376***	-0.331***	-0.375***
	(0.057)	(0.047)	(0.059)	(0.059)	(0.047)	(0.060)
Y2004	0.203***	0.250***	0.201***	0.198***	0.248***	0.197***
	(0.060)	(0.052)	(0.061)	(0.059)	(0.051)	(0.060)
Electricity coverage			-0.008			0.017
			(0.116)			(0.118)
Electricity price (Kw/h)			0.000			0.000
			(0.000)			(0.000)
Population			0.000			0.000
			(0.000)			(0.000)

National transfers			-0.017			-0.016*
			(0.010)			(0.009)
Royalties			0.005			0.006
			(0.006)			(0.005)
Regional transfers			0.000			0.000
			(0.003)			(0.003)
Regional royalties			-0.000			-0.000
			(0.000)			(0.000)
Constant	0.100**	0.052***	0.067	0.101**	0.051***	0.081
	(0.042)	(0.017)	(0.067)	(0.043)	(0.016)	(0.075)
Observations	5,037	4,320	5,037	5,037	4,320	5,037
R-squared	0.254	0.303	0.254	0.251	0.300	0.251
Number of municipalities	732	732	732	732	732	732

Notes: (1) Fixed effects model with robust standard errors at regional level (in parentheses); (2) 1 per cent of each side of the growth distribution was trimmed for this analysis; (3) Electricity price and transfers are at 2004 prices; (4) Inference: *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: NOAA (2014); Familias en Accion (2004); DNP (2013); UPME (2014).

Several checks were conducted in order to confirm the robustness of these results, in particular for year 2004. Columns 2 and 5 show the estimations with a different baseline, instead of considering 1998, it considered 1999. In both cases, growth rate and growth rate per capita, the results are still robust to this change despite a slight difference in the coefficients.[16] The inclusion of additional covariates also confirms the robustness of the initial results. Indeed, coverage and prices of electricity were not statistically significant and their coefficients were close to zero. Columns 3 and 6 reveal that, accounting for exogenous factors that may affect local growth and programme coverage (such as population and revenues from the central government), the results from column 1 and 3 still hold. Under these specifications the effects of the programme on growth in 2004 are roughly 0.11.

In sum, the luminosity data provides a reliable proxy for GDP growth and per capita growth of Colombian municipalities initially selected by *Familias en Accion*. This offered an opportunity to identify a treated and comparison group to assess the effect of *Familias en Accion* on growth rates under a DID setting. The identification strategy included the confirmation of the parallel-paths assumption and the absence of autocorrelation. The results revealed that the programme caused a positive effect of 0.11 in the growth rate and growth rate per capita on treated municipalities in

[16] Externally, it was proved that the confidence intervals of these coefficients overlap ([95% CI: 0.045 - 0.183] and [95% CI: 0.040 - 0.183]).

2004, when it was completely consolidated during its first stage. These results are robust to a change in the baseline and the inclusion of additional exogenous covariates.

5 Conclusions

This paper examined the existing evidence on the effects of social transfers on economic growth. The lack of reliable data and the focus of impact evaluations on household surveys have limited the scope of the study of this relation. To date, most of the empirical evidence has emerged from simulations with CGEMs and the comparison of treated and control households. This paper set out to fill the gap of the effects of transfers on growth by using alternative measure of economic activity at the municipality level in Colombia.

Still some authors are reluctant to acknowledge the influence of social assistance on growth. As for conditional cash transfer programmes in Latin America, more of the expectations are centred around the effects of these interventions on growth in the long run, when children join the labour markets equipped with higher levels of human capital. Nonetheless, based on the framework provided by Barrientos (2012), it is feasible to believe in short term effects at the local level. Previous findings have shown that an injection of liquidity into the economy, in the hand of households in extreme poverty, can benefit non-beneficiaries by means of increasing income and consumption. Local economy effects cannot be neglected as a potential source of growth.

This paper has shown that social transfers in the form of cash transfers generate positive effects on growth and per capita growth. The initial introduction of *Familias en Accion* in Colombia between 2000 and 2004 offered a suitable natural experiment to set up a DID approach, identifying treated and comparison groups of municipalities. Replicating former geographic selection criteria, 732 municipalities were considered for the empirical exercise. As national accounts do not disaggregate the GDP at the municipality level, this paper has relied on luminosity data captured by satellites orbiting the earth. The use of luminosity data has demonstrated to offer a suitable proxy for GDP at the national or sub-national levels. After testing the DID setting against potential sources of confoundedness, the results showed that the programme generated an impact of 0.11 on municipal growth and per capita growth rates in 2004. Robustness checks confirmed the strength of this finding.

The results from this paper have made a relevant contribution to the current literature. This is the first counterfactual approach to determine the sign and magnitude of the effects of social transfers on growth and per capita growth. The theoretical approaches based on the local economy effects are certainly confirmed on the basis of the employment of rich data and the fulfilment of the DID assumptions. This is also the first approach to the use of luminosity data for the assessment of social transfer interventions, especially at the sub-national level. Unlike previous simulations and the detection of indirect treatment effects, the findings here provide direct assessments without making strong assumptions.

Finally, it must be acknowledged that spill-over effects may arise among treated and municipalities. Further research could include the clarification of whether the spill-over effects over- or underestimate the detected impact. In addition, despite the effects of social transfers on growth

have been estimated, more research is needed to determine whether the growth generated by these interventions is inclusive in the short run. Although previous impact evaluations have detected significant effects on human capital formation of children in Latin America, it is still necessary to assess to which extent adult beneficiaries are obtaining economic benefits from the additional growth generated by social transfers.

Appendix

Table A 1: Means and differences between treated and comparison groups at the baseline

Variable	Comparison	Treated	Difference	t-test	Pr(|T|>|t|)
2003-04					
Growth	0.060	0.076	0.016	0.26	0.7938
Per capita growth	0.051	0.079	0.027	0.44	0.6568
Electricity coverage	0.801	0.816	1.442	0.94	0.3452
Electricity price (Kw/h)	149.5	148.5	-0.999	0.47	0.6362
Population (x 1,000)	26.59	28.18	1.596	0.52	0.601
National transfers	0.218	0.266	0.049	1.2	0.029
Royalties	0.137	0.329	0.192	1.05	0.295
Regional transfers	0.998	6.476	5.478	7.32	0.000***
Regional royalties	5.931	11.982	6.052	2.42	0.016**
N (2003-04)	377	362		739	
2002					
Growth	0.053	0.078	0.025	0.41	0.6842
Per capita growth	0.044	0.08	0.036	0.59	0.5529
Electricity coverage	0.800	0.816	1.646	1.10	0.2725
Electricity price (Kw/h)	149.8	148.4	-1.360	0.66	0.5118
Population (x 1,000)	26.10	26.90	0.804	0.28	0.779
National transfers	0.216	0.227	0.011	0.54	0.588
Royalties	0.133	0.312	0.179	1.12	0.263
Regional transfers	1.072	0.663	-0.409	1.89	0.059*
Regional Royalties	5.764	10.822	5.058	2.15	0.032**
N (2002)	133	606		739	
2001					
Growth	0.042	0.106	0.064	1.40	0.1623
Per capita growth	0.036	0.113	0.077	1.69	0.0910*
Electricity coverage	0.800	0.827	2.70	2.36	0.0187**
Electricity price (Kw/h)	149.2	148.2	-0.981	0.62	0.5382
Population (x 1,000)	22.71	23.18	0.470	0.34	0.737
National transfers	0.236	0.215	-0.021	1.66	0.0975*

Royalties	0.192	0.371	0.179	1.76	0.078*
Regional transfers	1.033	0.584	-0.450	3.76	0.000***
Regional royalties	8.166	18.014	9.848	6.19	0.000***
N (2001)	377	362		739	

Notes: (1) Baseline in 1999. Treated and comparison defined in each reference year; (2) Differences and significance test are generated by Stata's t-test based on Villa (2011); (3) Electricity price and transfers are at 2004 prices; (4) Inference: *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: Familias en Accion (2004); DNP (2014); UPME (2014).

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