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Cash transfers and health outcomes: Evidence from Italian municipalities

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ABSTRACT

Background: Cash transfer programs are widely used to support household income and improve socioeconomic well-being. We examine the health impact of a nationwide transfer introduced in Italy in 2015, targeted at middle-income groups and providing up to €960 annually per beneficiary.
Objective: To assess the effect of the program on municipal all-cause mortality.
Methods: Leveraging panel data for all municipalities from 2010 to 2019, we exploit variation in treatment intensity induced by eligibility rules. Intensity is measured via per capita disbursements and share of beneficiaries. We estimate fixed-effects regressions with socio-demographic and economic covariates, regional time trends, and controls for spatial dependence.
Results: Increased transfer intensity is significantly associated with lower mortality: an additional €1 per capita corresponds to 0.004 fewer deaths per 1000 residents, while a one-percentage-point increase in the beneficiary share corresponds to a 0.03 decrease in the same outcome. Heterogeneity analyses suggest stronger effects in municipalities with higher education levels and better healthcare access, indicating that these factors enhance the translation of income support into health gains.
Conclusions: Although not designed with health objectives, broad-based income support programs can yield measurable improvements in population health, particularly when complemented by education and healthcare investments.

Research in context

What is already known about the topic?

Cash transfer programs are widely used to reduce poverty and improve socioeconomic well-being. Evidence on their health effects is substantial but mainly concerns conditional transfers in low- and middle-income countries, with limited insights into unconditional or broad-based transfers in high-income settings.

What does this study add to the literature?

We study a nationwide tax credit program introduced in Italy in 2015. It targeted middle-income workers, reached more than 11 million people, and provided up to €960 annually per beneficiary. Using variation in program intensity across municipalities, we find that higher transfers are associated with significant reductions in all-cause mortality. Effects are stronger in municipalities with higher education levels and better healthcare access, suggesting that education and healthcare accessibility were key for translating income gains into health improvements.

What are the policy implications?

While not designed with health objectives, the program supported modest improvements in population health. Its simple delivery, minimal conditionality, and broad coverage likely facilitated its effectiveness. Stronger impacts where education and healthcare access were higher highlight the value of coordinated policies that combine income support with investments in human capital and health system capacity.

1. Background

Cash transfer programs have become important tools for reducing poverty and improving socioeconomic well-being by increasing consumption or enabling asset building. Drawing on extensive literature

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regarding the social determinants of health [1–3], several studies have investigated how cash transfer programs, and more in general social assistance programs, influence multiple aspects of individual well-being and health [3,4]. Building on the conceptual model presented in [3], cash transfers can be viewed as a complement to the broader socioeconomic determinants of health, acting through multiple mediating pathways. Some mediators influence health directly – for instance, by improving material or environmental conditions such as housing quality and food security. Others enhance access to healthcare by reducing financial barriers to utilization, facilitate adherence to treatment, and enabling more timely recourse to medical services. In this sense, financial security mitigates delays in seeking care, especially for chronic conditions, thereby preventing complications that may otherwise result in higher mortality.

Although the literature generally supports the positive impact of cash transfers on health outcomes, results vary depending on the type of transfer (conditional vs. unconditional), the national context (low- and middle-income vs. high-income), and the outcomes considered. Most systematic reviews focus on low- and middle-income countries, which limits the relevance of their findings for high-income settings, where the conditions faced by people living in poverty differ substantially [5–7]. Other studies focus narrowly on particular outcomes, such as infant or mental health [8–10,38]. A recent scoping review, however, highlights the beneficial health effects also for middle-income individuals in high-income countries [11]. Programs like the Earned Income Tax Credit (EITC) and Child Tax Credit in the U.S., and the Canada Child Benefit, have shown positive impacts across various health domains – including access to routine care [e.g., 12], mental health [e.g., 13], food security [e.g., 14], and childcare [e.g., 15].

Our paper contributes to this literature by providing evidence on the health effects of a broad-based tax credit program targeting middle-income groups. Indeed, the positive relationship between income and health persists across the income distribution and is not limited to the lowest income brackets [16]. While lower-income individuals are at higher risk of poor health and may benefit more on an individual basis from cash transfer programs, middle-income groups are larger in number and programs reaching them can generate a substantial aggregate impact [17]. We exploit the introduction of a tax credit program implemented in Italy in April 2014, the so-called "80-euro" or "Renzi" bonus, named after the prime minister at the time. The policy provided a monthly tax credit of €80 to all payroll employees with a gross annual income between €8145 and €26,000. Allocation was entirely automatic: eligible workers received the bonus directly in their paychecks through reduced withholding of pension contributions. The policy followed a long period of recession in Italy, which had eroded households' purchasing power, and was explicitly designed to stimulate consumption by restoring disposable income for middle-income employees.

We employ a panel dataset of Italian municipalities spanning 2010–2019. To study the relationship between the program and health outcomes, we leverage administrative data on beneficiaries and total amounts disbursed at the municipal level from 2015 onward. Although the program was implemented nationwide, there is substantial cross-municipality variation in intensity, driven by differences in local eligibility. Identification relies on such variation, conditional on a rich set of time-varying covariates and municipality and year fixed effects.

We document a robust negative association between program intensity and local mortality rates. An additional euro in per capita transfers is associated with a 0.004 reduction in deaths per 1000 residents, while a one-percentage-point increase in the share of beneficiaries corresponds to an approximate 0.03 decrease. These results remain stable across alternative specifications that flexibly account for regional trends, spatially correlated unobservables, and spillovers. Furthermore, we assess whether demand and supply-side factors, such as educational attainment and healthcare access, influence policy effectiveness.

2. Methods

2.1. Data

We use a panel dataset of 7914 Italian municipalities over 2010–2019. Descriptive statistics are presented in Table 1. Data processing and empirical analyses were performed in Stata 17.

To measure treatment – that is, the distribution of the monetary transfer – we rely on administrative data from the Department of Finance of the Italian Ministry of Economics and Finance (MEF). This dataset provides municipal-level information on both the number of individuals who received the €80 monthly bonus and the total amount distributed per municipality, starting from 2015 (when the program was made permanent). From 2015 to 2019, approximately 11.7 million people received the transfer each year, for a total annual cost of about €9.5 billion (a detailed program description is provided in Appendix A).

Eligibility depends on two criteria – being a payroll employee and having an annual income between €8145 and €26,000. To account for these conditions, we collect data on (i) the number of payroll employees in each municipality, and (ii) the number of individuals within the €10,000–€26,000 income bracket (it was not possible to isolate the €8145–€10,000 range, as it is aggregated into the broader €0–€10,000 income class). These data are from MEF.

Our outcome variable is the all-cause mortality rate at the municipal level. Mortality data are sourced from the Italian National Institute of Statistics (ISTAT) and are measured as deaths per 1000 inhabitants.

Using all-cause mortality to assess the impact of a relatively small income increase –up to €960 per year per beneficiary– may appear conservative, both because it is a late-stage outcome and because aggregation may dilute individual-level effects. Nonetheless, this choice is motivated by several considerations. First, mortality rates are a well-established and policy-relevant indicator in the literature on income and health and are known to be particularly sensitive to changes in income (e.g., [18–20]). Secondly, when cash transfers alter the socio-economic status of beneficiaries, they can affect a range of risk factors and health conditions [21]. In such cases, overall mortality becomes a more appropriate indicator of health effects than disease-specific outcomes. Third, to our knowledge, mortality is the only health outcome available with consistent coverage and granularity at the municipal level. Finally, since the program targets a substantial share of the population, aggregate measures are well suited to capturing its potential impacts, including indirect effects on household members.

The dataset also includes a set of socio-demographic and economic variables from multiple sources: total resident population, the share aged 65+, the share of females, the share with at least upper secondary education (ISTAT), and per capita disposable income (MEF). Since annual municipal data on educational attainment are not available for the full period, we construct a proxy using ISTAT data available for 2011 and 2018–2022. Values for the intermediate years are linearly interpolated to obtain a continuous series up to 2019. Given that educational attainment changes gradually and typically follows smooth, monotonic trends, linear interpolation represents a reasonable approximation [22].

Finally, to capture healthcare accessibility and local supply, we collect information on the per capita regional public healthcare expenditure (Health for All), which proxies the availability and quality of health services at the regional level. We also construct a spatially weighted measure of hospital bed availability, using data from the Italian Ministry of Health. For each municipality-year, we calculate the number of beds per 1000 inhabitants in public and accredited private hospitals within a 50 km radius, weighing inversely by distance. Beds from nearby areas are given greater weight than those farther away, reflecting the assumption that proximity improves access. The weighted sum of beds is normalized by the similarly weighted population within the same area, yielding a measure of hospital beds per 1000 residents.

Table 1
Summary statistics.

	Count	Mean	SD	P25	P50	P75
Mortality (per 1000 inhabitants)	78,825	12.30	5.66	8.78	11.17	14.45
Bonus1 (€ per capita)	39,313	160.63	32.55	137.64	161.03	183.97
Bonus2 (% beneficiaries over population)	39,313	19.78	3.88	17.08	19.79	22.43
Pop (Municipal population)	78,831	7608.76	41,795.52	1052.00	2517.00	6354.00
Over65 (Share of population over 65)	78,825	23.57	5.71	19.77	22.97	26.65
Gender (Share of women)	78,825	50.65	1.60	49.93	50.78	51.55
Education (% with secondary education or more)	78,705	37.49	6.90	32.93	37.56	42.14
Income (Income per capita)	78,289	11,947.70	3142.27	9255.56	12,245.76	14,193.75
Pub_Sp (Regional healthcare spending, € per capita)	79,203	1851.65	112.58	1774.00	1833.00	1925.00
Beds (Hospital beds per 1000 inhabitants)	79,220	9.90	5.81	6.68	9.10	11.97
Income_range (% earning yearly income 10–26 K)	78,262	32.64	6.42	27.79	33.86	37.30
Payroll (% payroll employees)	78,289	34.05	6.67	29.55	33.95	38.35

Notes: the table presents descriptive statistics for the full sample of Italian municipalities during the period 2010–2019. Bonus1 and Bonus2 variables are summarized over years after 2015 (included).

2.2. Identification strategy

To estimate the impact of the cash transfer program on mortality rates, we construct two alternative measures of treatment intensity at the municipal level: the first (*Bonus1*) being the per capita amount (total amount divided by the resident population in the municipality, as described in Equation B.1), and the second (*Bonus2*) being the percentage of beneficiaries relative to the resident population, as described in Equation B.2.

In both cases, the treatment variable is continuous and takes on positive values for all municipalities after the policy introduction, with varying degrees of exposure across municipalities (Fig. 1). Identification relies on a generalized difference-in-differences strategy, exploiting cross-sectional variation in treatment intensity across units rather than a binary treated/untreated distinction [23–26]. The pre-treatment period is 2010–2014, the post-treatment period 2015–2019. Our baseline specification is in Eq. (1):

$$y_{i,t} = \beta_1 Bonus_{i,t-k} + \beta_2 SocioEco_{i,t} + \beta_3 HealthSupply_{i,t} + \tau_t + \nu_i + \epsilon_{i,t} \quad (1)$$

The dependent variable $y_{i,t}$ represents the mortality rate in municipality i and year t ($t = 2010,\ldots,2019$). The explanatory variable $Bonus_{i,t\text{-}k}$ is the treatment, lagged either by one or two years ($k = 1,2$), to mitigate simultaneity bias and capture delayed effects [27–29].

Controls include socio-economic and demographic factores

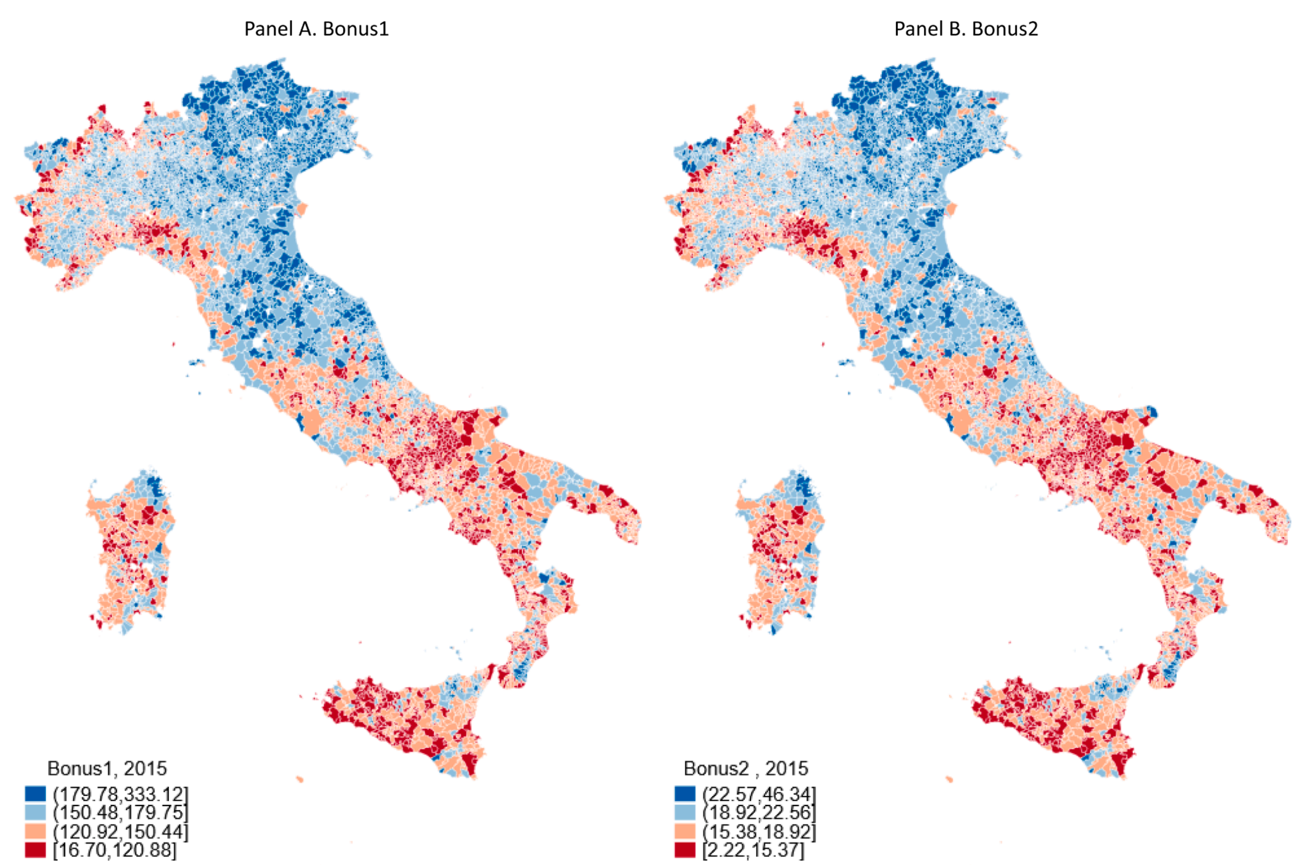

Fig. 1. Treatment distribution across municipalities.
Notes: The two maps illustrate the geographical distribution of treatment across Italian municipalities in 2015. The left panel displays the per capita amount in euros of the total bonus allocated to each municipality, whereas the right panel displays the proportion of individuals who received the bonus out of the total municipal population.

($SocioEco_{i,t}$): share of population over 65 (expected to be positively associated with mortality [30,31]), share of women (expected to have a negative or null association with overall mortality, as women typically exhibit lower mortality rates [32,33]), share with at least upper secondary education (expected to have a negative correlation with mortality, reflecting the well-documented role of education on health outcomes [45]), per-capita income (expected to reduce mortality by enabling better living conditions and access to care [21]) and municipal population. Health supply controls ($HealthSupply_{i,t}$) include lagged regional per capita public healthcare expenditure and a spatially weighted measure of hospital beds per 1000 residents. Both are expected to reduce mortality, as these reflect better access and quality of care [35–37]. Finally, year-fixed effects τ_t control for time-specific factors that may affect the dependent variable across all municipalities, and municipality fixed effects ν_i capture time-invariant unobserved local characteristics.

2.3. Identification issues

A potential concern in our empirical framework is that municipalities with different treatment intensity may also differ in characteristics that affect mortality, potentially confounding the relationship between treatment and outcome. Fig. 1 shows clear geographical clustering: municipalities in the top quartiles are concentrated in the North, while those in the bottom quartiles are mainly in the Centre-South. This pattern reflects the number of payroll employees with annual income between €8145 and €26,000, the program's target group.

Such patterns must be accounted for, as municipalities receiving more intensive treatment may differ significantly from less treated ones in characteristics that also influence mortality trends. If not properly addressed, these differences could introduce bias into the estimates and compromise the comparability between municipalities, potentially distorting the relationship between treatment and outcome.

We address this concern in two ways. First, in our main specification, we explicitly control for the two eligibility criteria that determine access to the bonus: (1) being a payroll employee and (2) having an annual income between €8145 and €26,000. We proxy these with the share of payroll employees in the municipal population and the share of residents earning between €10,000 and €26,000. Both variables are included in order to capture two distinct sources of variation, which jointly shape variation in treatment intensity across municipalities. This approach is aimed to mitigate the potential bias arising from pre-existing differences in local labor market composition and income distribution – factors that affect treatment assignment and may also be independently associated with mortality trends.

Secondly, we check whether municipalities with different treatment intensities exhibited different mortality trends prior to the treatment onset. We begin with a visual inspection. Municipalities are grouped according to treatment intensity (deciles of the cumulative per capita bonus disbursed in each municipality over the 2015–2019 period). For clarity, Fig. 2 only displays the first and last decile of this distribution (all deciles are shown in Figure C.1). The visual evidence suggests that mortality trends for the highest- and lowest-intensity deciles appear roughly parallel paths to the policy's introduction. This supports the validity of the chosen identification strategy, as it implies that there are no systematic pre-treatment differences in mortality trends associated with treatment levels. The trends begin to diverge following the treatment onset, with the line for the most treated decile displaying a flatter pattern relative to the least treated.

After this preliminary visual assessment, we formally test the plausibility of the parallel trends assumption using an event-study specification (Equation B.3) that allows the treatment effect to vary over time [24,25,39]. In this framework, $Bonus_{i,2015}$ measures the treatment assigned to municipality i in 2015 (either per capita transfer or share of recipients) and is interacted with year dummies $1(Year_t)$ spanning 2010–2019. The interaction with 2014 is omitted as the reference year. X_{it} includes the full set of controls (socio-demographics, health supply, and eligibility criteria). Finally, τ_t and ν_i denote year and municipality fixed effects. The results of this empirical exercise are shown in Figure C.2. The estimated pre-treatment coefficients are generally small in magnitude and not statistically different from zero, which we interpret as suggestive evidence in support of the parallel trends assumption.

3. Results

3.1. Main results

We start by outlining the baseline results, presented in Table 2 and Figure C.3. The estimates suggest a modest but consistent association between cash transfers and reduced mortality: a one-euro increase in per capita transfers is associated with approximately 0.004 fewer deaths per 1000 residents. Likewise, a one percentage point increase in the share of program beneficiaries within a municipality corresponds to a reduction of about 0.03 deaths per 1000 inhabitants. These results are robust to the

Fig. 2. Trends in mortality rates before and after intervention.
Notes: The figure plots the trend in average mortality rates in municipalities grouped by treatment intensity, before and after the introduction of the 80-euro bonus. The two lines in the figure represent the first and the tenth decile respectively of the cumulative per capita bonus distribution in 2019, with 1 being the least treated (first decile) and 10 being the most treated (tenth decile).

Table 2
Main results.

	Bonus1 (€ per capita)				Bonus2 (% beneficiaries)			
	1st lag		2nd lag		1st lag		2nd lag	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bonus1	−0.004***	−0.003**	−0.004***	−0.004***				
	(0.001)	(0.001)	(0.001)	(0.001)				
Bonus2					−0.038***	−0.023**	−0.038***	−0.035***
					(0.010)	(0.012)	(0.010)	(0.012)
Over65		0.776***		0.778***		0.775***		0.777***
		(0.042)		(0.042)		(0.042)		(0.042)
Gender		0.027		0.032		0.027		0.031
		(0.056)		(0.055)		(0.056)		(0.055)
Education		−0.185***		−0.190***		−0.185***		−0.190***
		(0.031)		(0.030)		(0.031)		(0.030)
Income		−0.0003***		−0.0003***		−0.0003***		−0.0003***
		(0.000)		(0.000)		(0.000)		(0.000)
Pop		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Pub_Sp		−0.001**		−0.001*		−0.001**		−0.001**
		(0.001)		(0.001)		(0.001)		(0.001)
Beds		−0.036*		−0.034*		−0.036*		−0.034*
		(0.019)		(0.019)		(0.019)		(0.019)
Income_range		−0.077***		−0.083***		−0.077***		−0.082***
		(0.022)		(0.021)		(0.022)		(0.021)
Payroll		0.046**		0.047**		0.045**		0.046**
		(0.022)		(0.022)		(0.022)		(0.022)
Observations	78,744	70,326	78,794	70,326	78,744	70,326	78,794	70,326
R-squared	0.014	0.437	0.012	0.438	0.015	0.438	0.013	0.438
Number of id	7914	7870	7914	7870	7914	7870	7914	7870
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	–	Yes	–	Yes	–	Yes	–	Yes

Notes: The table reports the estimated β coefficients in Eq. (1). In all columns, the dependent variable is the mortality per thousand inhabitants. The variable Bonus1 represents the per capita bonus disbursed in each municipality, while the variable Bonus2 represents the share of the beneficiary population over the total. Municipality and year fixed effects are always included. Control variables include socio-demographic characteristics (population share aged 65+, share of women, education level, per capita income, population), health care supply (regional per capita health expenditure, spatially weighted hospital beds within 50 km), and bonus-eligibility criteria (payroll share, income range share). Standard errors in parentheses are clustered at the municipal level. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0$.

inclusion of alternative temporal lag structures and remain stable after controlling for socio-demographic characteristics, local healthcare supply, and economic factors that may influence the distribution of the treatment.

3.2. Robustness checks

We now perform additional checks that account for potential sources of bias not addressed in the baseline specification. First, we augment the baseline specification (Eq. (1)) by including region-by-year fixed effects. This adjustment allows us to control for potential unobserved heterogeneity in regional health policies and other time-varying regional factors. Results are shown in Table C.1. Under this more demanding specification, only the two-year lagged treatment effect retains statistical significance, lending support to the hypothesis of a delayed impact of the policy on mortality outcomes. Notably, once region-by-year fixed effects are included, the coefficients on health supply variables lose significance. This is expected, as these variables vary primarily at the regional level and their identifying variation is largely absorbed by the fixed effects. Overall, while this approach mitigates concerns about omitted variable bias, it also reduces residual variation and may inflate standard errors, especially for region-level covariates.

Second, we explicitly address the spatial structure of the data to account for potential spatial dependence in the residuals. Indeed, local unobserved confounders that are spatially correlated across neighbouring units may introduce bias in baseline estimates if not properly addressed. Moreover, we test for potential spillover effects of the treatment across municipal borders – e.g., through inter-municipal mobility or local economic interactions. To this end, we estimate a spatial error model (SEM), which captures spatial autocorrelation in the error term (equations B.4), and a spatial Durbin error model (SDEM), which extends the SEM by including a spatial lag of the treatment variable, thereby allowing for spillover effects from neighboring municipalities (equation B.5). In both cases, W is defined as a row-standardized first-order contiguity (queen) matrix, and λ denotes the spatial autoregressive parameter, capturing the average strength of spatial dependence in the residuals. X_{it} includes the full set of controls. The coefficient β_1 represents the direct (local) effect of treatment. In the SDEM specifications, γ_1 captures the indirect (spillover) effect of treatment in neighbouring units. The total effect is given by the sum $(\beta_1 + \gamma_1)$ [40]. Results are presented in Table C.2. First, we note that the estimated λ parameter is consistently statistically significant, indicating the presence of spatial correlation in the residuals and supporting our choice to include spatial models as a robustness check. Nonetheless, our key results remain broadly consistent with the more parsimonious baseline estimates. More specifically, the estimated impact of the bonus is consistently negative and statistically significant across all specifications of the SEM. In the SDEM specifications, the treatment effect appears predominantly local and becomes statistically significant at the two-year lag, suggesting a delayed response to the intervention. Evidence of spillover effects is limited: only the one-year lag of the per-capita bonus shows a weakly significant indirect effect, which is not robust across other specifications. Finally, while the local and spillover components are not always individually significant in the SDEM models, the total impact is consistently significant across specifications. Overall, the results confirm the association between treatment intensity and mortality outcomes, which operates primarily at the local level.

3.3. Heterogeneity analysis

After establishing a negative association between bonus intensity and mortality rates, we now turn to explore whether this relationship varies across local contexts. Specifically, we test for heterogeneity along municipal characteristics that are theoretically relevant for moderating the health effect of additional income.

We focus on two broad categories of moderators: demand-side factors (educational attainment) and supply-side conditions (local healthcare provision). These dimensions reflect plausible enabling mechanisms through which income support may translate into better health outcomes.

Education, particularly that of mothers (see e.g., [41]), is often identified as a strong predictor of health outcomes. It contributes to human capital by fostering a range of cognitive and non-cognitive skills that influence health-related behaviours and responses to illness. Individuals with higher levels of education are more likely to engage in health-promoting behaviours, such as maintaining a balanced diet and regular physical activity, and to manage their health more effectively through preventive care, adherence to treatment, and proactive interactions with healthcare providers [34]. Taken together, these insights point to education as a potential moderator of the policy's health effects, as it enhances individuals' capacity to translate additional income into improved health outcomes.

On the other hand, the effects of cash transfers on health outcomes may be constrained by the availability of healthcare resources [42]. Indeed, many authors point out that addressing supply-side obstacles, such as geographical inaccessibility of services or poor-quality care, is a prerequisite for supporting the increased demand resulting from the additional income provided [43,44]. Consequently, healthcare supply can act as a critical moderator of the policy's impact, by facilitating or constraining the translation of increased income into tangible health gains.

We augment Eq. (1) by introducing interaction terms between the treatment variable and, alternatively, each of the local factors – education and healthcare supply – considered as potential moderators of the bonus effect. To facilitate interpretation, both moderators are centered around their annual mean. This allows the coefficient on the treatment variable to be interpreted as the estimated effect of the bonus at average levels of the moderator (i.e., average education or health supply) rather than at zero – a value not observed in the data and lacking empirical relevance. Notably, centered and uncentered models are algebraically equivalent and yield identical marginal effects [45,46].

A first result is that the negative association between cash transfers and mortality is significantly stronger in municipalities characterized by higher levels of education and better access to health services, as indicated by the interaction term coefficients (Table C.3). As shown in Figure C.4, marginal effects of the bonus increase in absolute magnitude along the distribution of the moderator variables. Table C.4 further shows statistically significant differences between the bonus marginal effects across relevant values (25th and 75th percentiles) of both education and health service accessibility. Taken together, these findings suggest that the impact of the cash transfer program is heterogeneous, as it varies with local education levels and with access to health infrastructure. This pattern is consistent with existing literature, which identifies education as a key enabling factor in translating income gains into health improvements, while accessibility to health services represents a conducive structural condition. While not a formal analysis of transmission channels, this exercise offers insights on the conditions under which the policy appears more or less effective.

4. Discussion

In this paper, we evaluate the effects of a large-scale cash transfer program introduced in Italy in 2015. We use a panel dataset of Italian municipalities covering the period 2010–2019. Program intensity is measured using both per capita disbursements and the share of beneficiaries at the municipal level. Identification primarily relies on cross-sectional variation in treatment intensity across municipalities in the post-treatment period, conditional on a rich set of covariates as well as municipality and year fixed effects. Additional robustness checks account for region-specific time trends and spatial dependence in both the outcome and the error term.

The analysis reveals a negative and statistically significant association between program intensity and all-cause mortality at the local level. A one-euro increase in per capita transfers is associated with approximately 0.004 fewer deaths per 1000 residents, while a one-percentage-point increase in the share of beneficiaries corresponds to a reduction of about 0.03 deaths per 1000.

These findings align with the broader literature linking income support measures to improved health outcomes [5,6,28]. Nonetheless, our study has several limitations that should be acknowledged. First, while we document a robust association between cash transfers and lower mortality, the observed effect may reflect several mechanisms, such as changes in consumption, reduced financial stress, improved access to healthcare services [7]. In the absence of individual-level data on consumption behavior, healthcare utilization, or lifestyle changes, we are unable to directly test these mediation channels. To partially address this limitation, we adopt a complementary approach by analyzing heterogeneity across relevant municipal characteristics, which may act as enabling conditions for policy effectiveness.

Second, and relatedly, while all-cause mortality is a valuable, widely used outcome sensitive to income changes, it is a late-stage health indicator that captures only a limited subset of potential health responses to the policy.

Finally, and most importantly, our identification strategy remains observational. The credibility of the estimated effects therefore relies on the validity of the underlying assumptions, which, although plausible and empirically supported by multiple robustness checks, cannot be fully verified. Overall, although these limitations call for cautious interpretation, the consistency of results across different specifications and the coherence of heterogeneity patterns suggest that the observed associations are meaningful and provide insights into how local contexts shape policy impacts.

Our findings are particularly relevant given the wide scope of the 80-euro bonus. While not a universal transfer, it is less targeted and practically unconditional compared to typical poverty-focused programs. As noted by Shahidi et al [4], "social assistance is increasingly conditional on a range of punitive, work-related obligations that compel entry into precarious employment conditions". This conditionality may affect the health outcomes of monetary transfers, as any potential positive effects may be offset by the negative impact of precarious employment conditions on beneficiaries' health [47]. The exclusion of the lowest income groups from the set of beneficiaries may also prevent the aggregate measure of the health impact being affected by risky behaviors, more common within these groups, which could be exacerbated by the additional money received through the transfer [4].

Our results are consistent with a growing body of evidence from high-income countries showing that cash transfers, particularly those targeting middle-income or near-poor households, can improve a range of health outcomes. For instance, studies on the Canada Child Benefit [14], the U.S. Earned Income Tax Credit [12,13], and the UK income support reforms among the others point to positive effects on physical and mental health, healthcare access, and food security. By documenting similar effects in the Italian context, our study contributes to this literature and extends its external validity [11]. At the same time, we recognize that generalizing these findings beyond Italy requires caution. Institutional factors - such as the structure of the healthcare system, labor market regulations, and the baseline level of social protection - are likely to shape both the magnitude and channels of impact. Future research should explore these dimensions more explicitly to understand under what conditions income support policies yield the strongest health benefits.

Finally, our findings also have some policy relevance. While the Renzi bonus was not explicitly designed to improve health, our findings suggest that income support programs of this kind can be associated with modest improvements in population-level health indicators. The relative simplicity of the policy – automatic delivery through payroll systems and limited conditionality – may have facilitated its reach and effectiveness. Although the specific institutional and economic context of Italy plays a role in shaping these outcomes, similar programs in other high-income settings could yield comparable effects, particularly where financial barriers to healthcare and other essential services persist. Further research is needed to better understand the conditions under which such transfers produce the strongest health-related impacts.

5. Conclusion

We study the impact of a nationwide cash transfer program introduced in Italy in 2015 on municipal-level mortality, using panel data from 2010 to 2019. Exploiting cross-municipality variation in treatment intensity, we find that greater program exposure is significantly associated with reduced all-cause mortality. While not explicitly health-focused, the program's broad coverage and simple delivery may have supported modest population health improvements. These results, consistent with international evidence, highlight the potential of income support to affect health outcomes. Our findings also suggest that contextual factors – such as education and healthcare access – mediate effectiveness. Further research is needed to unpack the underlying mechanisms and identify the conditions under which income support most effectively translates into health gains.

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CRediT authorship contribution statement

Stefania Fontana: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Calogero Guccio:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Giacomo Pignataro:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Domenica Romeo:** Writing – review & editing, Writing – original draft, Conceptualization.

Declarations of competing interest

none

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