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Public Expenditure and Agricultural Growth: The Case of Social Protection in Asia

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Abstract

This paper has the double aim of analyzing the impacts of government expenditure in social protection on agricultural growth in Asia and their stabilizing role on growth by acting as a buffer against weather shocks. We exploit a cross-country longitudinal dataset of standardized and homogeneously measured fiscal variables covering the whole of Asia to estimate the elasticities of agricultural Gross Domestic Product to several measures of social protection. We find that government expenditure in social protection for the poor stimulates agricultural Gross Domestic Product and counters the negative impacts of extreme weather shocks. Impacts are heterogeneous and vary according to the income level of countries.

Keywords: public expenditure, agricultural growth, social protection, fixed effects, instrumental variables.

JEL classification numbers: E6, H3.

1. Introduction

Public expenditures are a large share of aggregate demand and constitute an important instrument to pursue growth and equity (Barro, 1990; Bailey, 1995). In recent years, especially in developing countries, the focus seems to have shifted towards equitable growth, which can benefit the largest possible share of the population, especially those at the bottom of the income distribution. However, for several types of public spending, pursuing growth often comes at the expense of equity and vice versa. This has been a widely held view for social protection expenditure too. In fact, while there is agreement that minimal social protection measures are necessary to guarantee social cohesion and equity through income redistribution, further expansion of social protection has been traditionally opposed on the grounds of a trade-off between equity and growth due to its supposed discouraging effects on aggregate labor supply and savings (Arjona et al., 2001).

Nonetheless, there are solid theoretical reasons why social protection might also be good for growth, for example, by providing a temporary and partial remedy for missing markets for credit and insurance, especially in rural areas (de Janvry et al., 2008). A large body of household level evidence, mostly from rural contexts, shows almost unanimously that social protection programs can boost farm production by easing liquidity or risk constraints, allowing smallholders to make new investments in inputs or technologies, or by altering labor allocation decisions (Phimister 1995; Hennessy, 1998; Karlan et al., 2014; Prifti et al., 2017; Daidone et al., 2019). Macro level evidence around the effects of social protection expenditure on economic growth is scant and focuses on the effects of social protection on total GDP growth in developed countries (Arjona et al., 2001; Barrientos, 2008; Alam et al., 2010).

This paper covers both developed and developing countries and, to the best of our knowledge, is the first to take a sectoral approach by focusing on how social protection expenditure impacts agricultural GDP, in an attempt to test empirically whether the proven effects at the farm-household level show up also at the macro level. Besides looking into the ability of social protection to support growth in good times, we study whether it can act as a source of increased resilience in bad times. To this end, we test whether social protection can act as a shock absorber by mitigating the negative effects of extreme weather events on agriculture production.

We use a recently released cross-country longitudinal dataset that covers 38 Asian countries during the 2008-2015 period and contains standardized and homogeneously measured aggregate variables on social protection indicators (ADB, 2019). Agriculture employs large shares of the population across Asia and contributes between 8 per cent (Malaysia) and 50 per cent (Myanmar) of total GDP. Rural areas host the vast majority of the extreme poor (75 per cent), who live mostly off agriculture (65-99 per cent) and are the recipients of large shares of social protection expenditure (Lowder et al., 2017; ADB, 2019). Social protection expenditure, as a share of GDP per capita in Asia, increased from 3.4 per cent in 2009 to 4.2 per cent in 2015. Social protection is becoming the preferred instrument to pursue inclusive growth, not only by redistributing its fruits from top to bottom but also by opening up economic opportunities for those at the bottom and further fueling the growth process. This study sheds light on the latter aspect and on the debate of a growth-equity trade-off around social protection, i.e., whether it can promote equity without hampering growth, but actually sustaining it through the economic inclusion of the poor.

We use a linear model to estimate how aggregate agricultural production growth reacts to changes in public expenditure on social protection. To address concerns that the expansion of social protection can itself be influenced by overall economic growth due to the counter cyclical nature of the former and lead therefore to reverse causality we take several measure. First, we use the lagged and contemporaneous values to measure the effects social protection expenditure. Lagged explanatory variables are commonly used to partially circumvent endogeneity concerns (Baccini and Urpelainen, 2014; Reed, 2015). Secondly, we follow previous literature and use a fixed effects estimator which addresses time-invariant sources of endogeneity Furceri and Zdzienicka, 2012. Finally, we combine the fixed effects estimator with an innovative instrumental variables approach which is the most general approach to correcting the possible endogeneity bias (Lewbel, 2012). Fixed effects estimates show that a one percent increase in total social protection spending leads to 0.02 percent increase in agriculture GDP. This is a sizable impact considering that, in reality, the average compound growth rate of social protection expenditure at constant prices was 5.8 per cent a year during the period covered by our data. The effects are driven by upper-middle income and high-income countries, while in terms of spending components social assistance and expenditure targeted to the poor play a crucial role. We also find that social protection spending mitigates the negative effects on agricultural growth of extreme weather shocks.

2. Literature review

There are several channels through which social protection spending can boost economic activity in rural areas. At the micro level, social protection alleviates bottlenecks and improves allocative efficiency of resources that prevent groups of households from participating in and benefiting from the market economy, causing a loss of potential output for society as a whole.

Social protection can ease credit constraints both directly, by providing liquidity to cash-starved households, and indirectly, by acting as collateral and improving their chances of accessing formal loans (Karlan et al., 2014). This can lead to investments in human capital that increase labor productivity in the medium-to-long run, or in productive assets (seeds, fertilizers, mechanized services, bikes) that provide an immediate stimulus to farm production. Secondly, households may engage in risk avoidance in the face of incomplete insurance markets, opting for low-risk low-return production technologies that put a cap on production and productivity growth (Hennessy, 1998; Mendola, 2007). By providing income security, social protection can push individuals to get into riskier investments with higher earning potential (Serra et al., 2006). Third, social protection can affect the allocation of resources and time in the household (Barrientos, 2008). Access to social transfers, for instance, allows them to smooth consumption and manage vulnerability to shocks better, by avoiding negative coping strategies and loss of productive assets (Dercon, 2002). Moreover, households can pull out of occasional paid jobs, thus freeing up labor that can be used on their own farm to increase production.

The empirical literature has documented positive impacts on direct indicators of crop production, farm income, asset accumulation and livestock holdings for several developing countries (Miller et al., 2008; Todd et al., 2010; Boone et al., 2013; Evans et al., 2014; Banerjee et al. 2015; Hidrobo et al., 2018; Prifti et al., 2019). The literature on the effect of unconditional government transfers on labor supply highlights the absence of disincentive effects (Baird et al., 2018). Banerjee et al. (2017) analyze seven cash transfer programs in developing countries, finding no systematic evidence that cash transfer programs discourage family labor, neither on the farm nor in paid employment.

At the community (meso) level, public work programs help build up community infrastructure and assets that increase local productive capacity (Berhane et al., 2014). Social transfers can generate multiplier effects in the local economy, when spent on goods produced in the community, if the supply is sufficiently elastic to accommodate the extra demand and avoid local price increases. Research on seven different social transfers programs in Africa revealed that each US dollar transferred to poor households generated an extra USD 0.27-1.52 in local income (Thome et al., 2016).

At the macroeconomic level, first order effects on growth flow through increased consumption. The stimulus to aggregate demand will be higher when social protection expenditure is targeted to the poor, who have a higher propensity to consume. Second order effects are channeled through increased labor productivity of a healthier and more educated work force. On the downside, part of the literature has highlighted that social protection may create negative incentives to supply labor by increasing the attractiveness of the outside option (Krueger and Meyer, 2002). Social insurance may also crowd out private savings by creating the expectation of a reliable retirement income, although this may be a greater concern for the better off and sectors with a lower degree of informality than agriculture (Barrientos, 2017; Alderman and Yemstov, 2012).

The empirical literature has found contradicting results on the relationship between social protection and aggregate demand (Mathers and Slater, 2014). A strand of studies in developed countries have found that social transfers (McCallum and Blais, 1987; Cashin, 1994), social insurance (Korpi, 1985; Baldacci et al., 2010), active labor market programs (Arjona et al. 2001) and several components of social spending (Furceri and Zdzienicka, 2012; Alper et al. 2008) have a positive impact on GDP growth, private investment and aggregate consumption. Other studies find evidence of a negative impact of social protection spending on GDP (Arjona et al., 2001; Arjona et al., 2002). Lopez (2005), focusing on ten Latin American countries, finds that a 10% increase in government expenditure for the provision of public goods to the rural economy (infrastructure, education, health and social protection programs) financed by an equal reduction of private goods expenditure, leads to a 2.3 percent growth in agricultural value added.

Our work relates also to the literature on the impacts of extreme weather events on agriculture (Lesk at al., 2016; Burke et al., 2015). Poor rural households rarely have the resources to adapt their production systems to meet the challenges of extreme weather shocks. Social protection has the potential for reducing the vulnerability of farm households to extreme weather shocks by offering an alternative to negative coping strategies (distress asset sales, child labor) and by reducing risk avoidance, which hinders the uptake of improved technologies that facilitate adaptation (Asfaw and Davis, 2018; Hansen et al., 2019). For instance, social assistance in Zambia has been found to help rural farmers reduce the negative impacts of droughts and floods on welfare indicators (consumption expenditure) and on negative coping strategies (Asfaw et al., 2017; Lowder et al., 2017). A cross-country synthesis from Sub-Saharan Africa found that social assistance programs reduce the impact of weather shocks on ex-post risk management and food security (Asfaw and Davis, 2018). We found no studies on the relationship between social protection, weather shocks and agriculture at the macro level.

3. Data and descriptive statistics

We used panel data from 38 Asian countries running over the period 2008 to 2015. We combined several sources. The Asian Development Bank (ADB) database provides detailed information on total social protection expenditure (SPE), classified under three main headings: social assistance (ESA), social insurance (ESI), and labor market programs (ALMP) (Asian Development Bank, 2019). The first component includes cash transfers, in-kind transfers, health assistance (free access to medicines and health services). The second component comprises old age pensions, health insurance and unemployment benefits. Finally, labor market programs include skills development and public works programs. Since some of the programs are poverty targeted, the ADB database offers a split of total social protection expenditure between poor and non-poor households (SPEP). The time dimension of the panel used in the analysis is constrained by the availability of reliable data on social protection expenditure, limited to yearly figures from 2008 to 2015. Macroeconomic data on agricultural GDP (AGDP) debt to GDP ratio, population growth, interest rates and trade openness come from the World Development Indicators (World Bank, 2019). Real interest rate is the lending interest rate adjusted for inflation. Trade openness is the sum of exports and imports of goods and services measured as a share of gross domestic product and population growth is just the annual percentage change in the total population of a country. Data on extreme temperatures come from the Emergency Events database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters in Belgium (CRED, 2019). EM-DAT is an open-access database recording disasters on a country-level base. To be classified as a disaster, an event needs to fulfil at least one of the following four conditions: (i) 10 or more people dead, (ii) 100 or more people affected, (iii) a declaration of a state of emergency, or (iv) a call for international assistance. An extreme temperature event concerns cold or heat waves and severe winter conditions (frost, snow) caused by atmospheric situations that last from minutes to days.

We divided countries into a "higher-income" and a "lower-income" subgroup based on the World Bank's income level classification. The former group includes low and low-middle income countries, while the latter includes upper-middle-income and high-income countries[1].

Table 1 in the appendix shows the composition of SPE for the whole sample and for income subgroups in the first and last year of our data. Each cell is the average of the GDP shares over all countries. In 2015, lower-income countries spent 4.2 per cent of their GDP in social protection against almost 6 per cent in higher-income countries. The composition of SPE is similar in the two subgroups. Lower-income (higher-income) countries allocate 30 per cent (25 per cent) of SPE to social assistance and 64 per cent (71 per cent) to social insurance. In higher-income countries, most of the SPE goes for the poor (SPEP = 4.8 per cent of GDP), while in lower-income countries social protection for the poor accounts for 0.3 per cent of GDP.

The top-left graph in figure 1 in the appendix shows total social protection expenditure for all countries by year in constant 2010 dollars. Between 2008 and 2015, the yearly compound growth rate of total social protection expenditure for all countries was 5.8 per cent. Over the

[1] Lower-income: Afghanistan, Armenia, Bangladesh, Bhutan, Cambodia, India, Indonesia, Kiribati, Kyrgyzstan, Lao, Micronesia, Mongolia, Nepal, Pakistan, Papua New Guinea, Philippines, Samoa, Solomon Islands, Sri Lanka, Tajikistan, Timor-Leste, Tonga, Uzbekistan, Vanuatu, Vietnam. Higher-income: Azerbaijan, Fiji, Georgia, Japan, Korea, Malaysia, Maldives, Marshall Islands, Nauru, Palau, Singapore, Thailand.

same period, the compound growth rate of total agricultural GDP of all countries was 4.3 per cent against an overall economic growth of 4.5 per cent. We take the log of these two variables and show their co-variation over time using the pooled data (bottom left graph). Each data point refers to a combination of SPE and AGDP in a given year. When both the within- and between-country variation is considered, there is a clear pattern of these variables growing together. However, we adopt a fixed effects estimation strategy, which exploits only the "between variation". We show in the bottom right graph that a positive association remains even when getting rid of the "within variation" by plotting country level averages of SPE and AGDP. This provides only suggestive evidence that there might be a positive effect of social protection on agriculture production. In the next section, we look more formally into the relationship in a regression framework, taking into account the influence of other confounders and addressing possible reverse causality issues.

4. Empirical methodology

We follow a dynamic growth equation approach to estimate the impact of social protection expenditure and its subcategories on aggregate agricultural production (Furceri and Zdzienicka, 2012):

$$\Delta y_{it} = a_i + b_t + \sum_{j=0}^{1} \delta_j \Delta SPE_{i,t-j} + \gamma' X_{it} + \varepsilon_{it} \qquad (1)$$

We derive the corresponding impulse response functions from the estimated δ_j. In Eq. (1), y is the log of value of agricultural production, SPE is the log of total social protection expenditure (or its subcategories), a_i are country-fixed effects and b_t are time-fixed effects. X is a vector of control variables that can affect growth in the short term, such as the log of openness, population growth, real interest rate, and debt to GDP. Trade openness can contribute to increased growth by facilitating technology transfer as well as greater economies of scale associated with access to the larger international markets. Growth accounting suggests that population growth is one of the sources of growth for the value of production. In agriculture, population growth can impact the extensive margin, leading to expansion into new land, and the intensive margin, i.e., the more intensive cultivation of the existing fields, raising crop yields by through better weeding, draining and other land preparation activities (Boserup, 1991). Interest rates influence the availability of credit in the economy and can affect investments in agriculture. As a monetary policy instrument, interest rates used counter-cyclically by cutting them when economic growth is sluggish and vice-versa (Bonilla, 2015).

Equation (1) can also be modified to correct for possible autocorrelation by including the lagged dependent variable (Δy_{t-1}) on the right-hand side.

$$\Delta y_{it} = a_i + b_t + \beta \Delta y_{t-1} + \sum_{j=0}^{1} \delta_j \Delta SPE_{i,t-j} + \gamma' X_{it} + \varepsilon_{it} \quad (1a)$$

In order to estimate the mitigating role of social protection expenditure on the value of agricultural production, we augmented equation (1) with an indicator of climate shock and its interaction with social protection expenditure:

$$\Delta y_{it} = a_i + b_t + \beta \Delta y_{t-1} + \sum_{j=0}^{1} \delta_j \Delta SPE_{i,t-j} + \mu Shock_t + \lambda \Delta SPE_t \cdot Shock_t + \gamma' X_{it} + \varepsilon_{it} \quad (2)$$

The parameter μ is likely to be negative, as growing evidence (Dell et al. 2012; Lee et al. 2016) shows that climatic shocks have negative effects on agricultural production. The parameter λ could be in principle positive or negative, depending on whether social protection expenditure is effectively playing a mitigating role or not, respectively. Positive values of λ and such that the combined effect of the shock and of social expenditure is smaller than the main effect of the shock (i.e. $(\mu + \lambda \Delta \overline{SPE}_t) < |\mu|$) would suggest that social protection expenditures mitigate the negative consequences of a climate-related shock.

Ordinary least squares estimates of δ and λ *in* equations (1) and (2) can suffer from endogeneity bias, since macroeconomic effects can go both ways, with social protection contributing to a broader domestic source of economic growth and a growing economy providing more resources for social spending. Reverse causation can be formally expressed as $\Delta SPE_{it} = \theta\Delta y_{it} + \xi_{it}$, where θ is likely to be negative. Indeed, empirical economics literature shows that several categories of social spending may respond to the economic cycle and work as automatic stabilizers. Darby and Melitz (2008) analyzed the cyclicality of social spending, finding that several components (such as unemployment benefits, health, retirement and incapacity-related spending) are countercyclical. Assuming positive values for δ and negative for θ, simple OLS estimates of δ in equation (2) could be biased downward.

We address endogeneity concerns in two steps. First, we exploit repeated measurement and use a fixed effects estimator as our benchmark estimator, which gets rid of time-invariant sources of endogeneity. Time varying common factors that cause co-movements of social protection and agricultural production can still lead to endogeneity bias, which is usually handled through instrumental variables. However, in a macroeconomic setting it is hard to find exogenous instruments, i.e., variables that are strong determinants of social protection, but exert no influence on agricultural production other than through social protection. We combine the fixed effects estimator with the approach proposed by Lewbel (2012), which allows to identify structural parameters in regression models with endogenous regressors in the absence of external instruments. In this approach, identification comes from having included regressors uncorrelated with the product of heteroscedastic errors ($\varepsilon v'$), which is a feature of many models in which error correlations are due to an unobserved common time-varying factor, such as growth drivers in our case.

Let Z include some or all of the elements of X so that $Cov(Z, \varepsilon v')$=0. The latter assumption means that $(Z - \bar{Z})v$ is a valid instrument for ΔSPE_{it} since it is uncorrelated with ε. It is generated by multiplying the mean-centered included exogenous regressors with the vector of residuals from the 'first-stage regression' of each endogenous regressor on all exogenous regressors. The strength of the instrument will be proportional to the covariance of $(Z - \bar{Z})v$ with v, which corresponds to the degree of heteroscedasticity of v with respect to Z, i.e, on how far from zero $Cov(Z, v^2)$ is. Finally, since the number of generated instruments is higher than the number of endogenous variables, we can also perform tests of over-identifying restrictions on instrument validity.

5. Results

5.1 Direct effects of social protection on agricultural production

Table 2 shows fixed effect (FE) estimates of the effect of total social protection expenditure and its components on agricultural production in the full sample (equation 1). Total social protection expenditure has a weakly significant but positive impact on agricultural GDP while its lagged value is statistically insignificant. A one percent increase in SPE is associated with a contemporaneous increase of almost 0.02 percentage points of agricultural growth. This is six times smaller than the coefficient found by Furceri and Zdzienicka (2012) for the impact of social spending on GDP in OECD countries. However, social spending in the latter includes health and other items on top of social protection and amounts to 21 per cent of GDP, while SPE accounts for less than 5 per cent of GDP in our study. None of the SPE components taken alone has any effect on agricultural growth and neither do their one-year lagged values.

Table 3 in the appendix shows the impact estimates for lower- and higher-income subgroups. For poorer countries, total social protection expenditure or any of its components has no impacts on agricultural growth neither at time *t* nor at time *t-1* (upper panel). Impacts in the full sample are clearly driven by richer countries (lower panel), where a one percent increase in SPE is associated with a contemporaneous 0.06 percent increase in agricultural production. The growth effect of the social protection stimulus persists one year after the increase with a similar magnitude, as shown by the coefficient on the lagged SPE. This is reassuring since lagged variables are more immune than current ones to the risks of bias from reverse causality that plague macroeconomic models (Baccini and Urpelainen, 2014). The expansionary effects of social protection for the subgroup of richer countries are closer to those found for OCED countries in Furceri and Zdzienicka (2012), probably due to similar levels of income and social protection spending.

Of all three components of social protection expenditure, only social assistance contributes to growth in the higher-income group both through its current and lagged changes. Social insurance spending has no impact on agricultural output, despite being the largest component and absorbing three times as many resources as social assistance. ESI provides generous benefits to a small share of the population, while it fails to reach most workers in the informal and rural economy. On the other hand, a large part of social assistance programs is poverty-targeted, making this component more likely to reach rural areas, where the poor live, and to stimulate the agricultural economy (Lowder et al., 2017). In fact, social assistance spending was evenly split between the poor and non-poor, while ESI was five times more likely to go to the non-poor than to the poor (ADB, 2019). Further, ALM is too small to produce impacts and is more likely to affect the urban economy. For the same set of reasons, social protection expenditure for the poor (SPEP) also has a positive but stronger impact on agricultural production with a one year lag. The delayed effect may be due to the fact that public transfers to poor smallholders promote growth by stimulating investment in higher-risk higher-return activities and reallocation of resources (land and labor), both of which may require time. The rest of regressors exert mostly no influence on growth, with some exceptions for population growth and trade openness.

There can be two reasons why positive impacts are significant only for the higher-income countries. First, higher-income countries spend considerably more in components that are more likely to reach the rural economy, namely SPEP. Furthermore, SPEP is comparable to the size of the agricultural economy in higher-income countries (4.8 per cent vs 5.8 per cent), but it makes up only a fraction of it in the lower-income subgroup (0.3 per cent vs 18 per cent) (Table 1). Secondly, there could be an issue of endogenous covariation, in virtue of which richer countries grow more and spend more in social protection. To address this concern more rigorously, we present fixed-effect instrumental variable (FE-IV) estimates in tables 4-5.

Table 4 shows FE-IV estimates of equation (1) for the full sample. The sign and magnitude of coefficients are in line with those of the FE estimates in table 1, but the weakly significant impact of SPE is lost. This is unsurprising, since instrumental variable methods are notoriously less efficient due to generated regressors in the first stage. Table 5 shows FE-IV estimates for the subgroup analysis. For lower-income countries, FE-IV estimates are similar to the FE results in table 3, confirming the lack of influence of social protection on agriculture production for this subgroup. For higher-income countries, the FE-IV estimates partially confirm results in table 3. In fact, while the same-year effect of social protection is insignificant, total social protection expenditure and expenditure for the poor stimulate agricultural production with a one-year lag. We consider the FE-IV impact estimates of the one-year lagged expenditure on social protection for the poor and on social assistance to be the most reliable, as they embody all the corrections for reverse causality bias. Finally, the positive effect of population growth and trade openness is clearer in the IV-FE approach.

For the IV identification strategy to be valid, it is necessary that the generated instruments be strongly correlated with the social protection variable, but uncorrelated with the shock in Equation (1). When instruments are weak, even the slightest correlation between the instrument and the shock in Equation (1) might induce a large inconsistency in the IV estimate, possibly exceeding the inconsistency of the corresponding FE estimate. Further, weak instruments can generate inflated standard errors in the second stage (Wooldridge, 2002). We find limited evidence for symptoms of weak instruments in our estimates. Moreover, the first stage F statistics is considerably high in all specifications, rejecting the null hypothesis that all regressors jointly have no explanatory power on social protection (p value of the test provided in tables 4-5). Only in one case (Table 5, column 1, lower panel) test results provide some support to the weak instruments hypothesis. We also perform a test of over-identifying restrictions to provide support to the assumption of uncorrelated instruments with the unobserved determinants of economic growth in Equation (1). Failure to reject the exclusion of the instruments as a group, as shown by the high p values of the Sargan test (tables 4-5), indicates that the FE-IV estimates are consistent. Hence, the expansionary effects of social protection spending on agriculture GDP are largely confirmed for the higher-income group after addressing endogeneity concerns.

5.2 Mitigating the impacts of weather shocks on agricultural production

We now show results for the hypothesis that social protection expenditure can boost agriculture GDP and mitigate the negative impacts of extreme weather shocks. To support this claim, statistically significant estimates of the main effects of the shock (μ) and social protection (δ) as well as of their interaction (λ) are necessary.

Table 6 shows fixed effects estimates of the coefficients μ, δ and λ from Equation (2) for the full sample. We find no significant effects of social protection or of extreme temperatures on agricultural GDP. Similarly, we find no significant relationships for the lower-income subgroup (Table 6). In higher-income countries, extreme temperature shocks reduce agricultural GDP growth by 0.09 percentage points. However, considering the stimulus to the rural economy from SPE, the negative impacts of the shocks are reduced by nine times ($\mu + \lambda\Delta\overline{SPE}_t$=0.01). The mitigating effect of social protection works through social assistance, which in higher-income countries stimulates agriculture (δ≈0.001) and attenuates the negative growth impact of weather shocks from -0.07 (μ) percentage points to -0.03 ($\mu + \lambda\Delta\overline{SPE}_t$) percentage points.

We then estimate Equation (2) using instrumental variables (Table 7). Results show that the magnitude of the estimated impacts of social protection and of extreme temperature shocks are similar to those from table 6. However, a lot of statistical precision is lost and, with it, the mitigating effect of social protection.

We are now only able to confirm the positive impact of social protection on growth (column 1 higher-income countries) and the negative impact of weather shocks (column 2 higher-income countries). First stage and over-identification diagnostic statistics are not included to save on space, but they confirm the overall strength and validity of the instruments.

Overall, our estimates lend support to the view that social protection has expansionary effects on the rural economy, especially when targeted to the poor, and that it can attenuate the dip in agriculture GDP caused by extreme weather shocks as is the case of heat or cold waves. Effects are heterogeneous and are driven by richer countries, even after addressing the issue of endogeneity stemming from reverse causality from agricultural growth to public expenditure for social protection. This could point to the existence of threshold levels of income or expenditure above which the growth impacts of social protection show up at the macroeconomic level. We leave the study of these aspects for future research.

6. Discussion and conclusions

This paper provided evidence on the short-term effects of social protection expenditure on growth in the agricultural sector. We found that fiscal stimulus channeled through social protection programs could stimulate the rural economy and cushion the negative impacts of extreme temperature on sectoral growth. However, impacts are heterogeneous across countries and are driven by specific types of social protection interventions.

We used fixed effects and instrumental variables estimators to avoid the endogeneity bias from the possible reverse causality relationship from agricultural growth to social protection expenditure. The latter estimator allows for more general forms of endogeneity, although this comes at the price of stronger identifying assumptions. Test diagnostics confirmed the overall validity of these assumptions and the consistency of the estimates.

Fixed effects estimates show that social protection has a significant positive impact on agricultural output. A one percent increase in total social protection expenditure is associated with a contemporaneous increase of almost 0.02 percentage points of agricultural growth in the full sample. Impacts in the full sample are driven by richer countries, where a one percent increase in the current and the one-year lagged SPE is associated with a 0.06 percent increase in agricultural production. For poorer countries, total social protection expenditure or any of its components has no impacts on agricultural growth. In terms of types of expenditure, only social assistance contributes to growth in the higher-income group. In addition, larger shares of social protection expenditure targeted to the poor translate into higher growth rates in agriculture. The reason might be that these types of expenditure are the ones that more likely reach the rural economy. In fact, social insurance and active labor market programs, which mostly target urban areas, have no impact on agricultural output. The instrumental variables approach largely confirmed the expansionary effects of social protection spending on agriculture GDP, with a similar pattern of impacts across subgroups and spending components.

Social assistance plays an important role in terms of limiting the negative growth impacts of weather shocks and increasing the overall resilience of the rural economy. This is particularly true for the poor, whose livelihoods are disproportionately affected by weather shocks but rarely have the resources to adapt their production systems to meet the challenges posed by climate change.

The fact that positive relationships are valid only for richer countries might indicate that the expansionary effects of social protection show up at the aggregate level only above a minimum level of expenditure. As countries grow richer, they can rely on more resources to allocate to social protection and the poor, who are most likely to engage in agricultural livelihoods. Higher-income countries also have a smaller agriculture sector relative to the rest of the economy. These circumstances make it more likely for the injected liquidity to affect the overall agricultural growth process, instead of being too dispersed with limited effects concentrated in small groups of households.

Social protection spending and its share to the poor are on an increasing trend in the window covered by our data for both lower-income and higher-income subgroups. The former subgroup is 8-10 years behind in terms of spending volumes and could be expected to experience a significant impact of social protection on agricultural production in a decade's time. For this to materialize, as lower-income countries grow richer, they must stay on a positive trajectory of social protection spending, by investing bigger shares of GDP in this area of the public budget.

Data Availability Statement

Data derived from public domain resources

The data that support the findings of this study are available in the public domain at:

Asian Development Bank at https://guides.lib.umich.edu/c.php?g=282964&p=3285995.

World Bank at https://databank.worldbank.org/source/world-development-indicators

CRED at https://www.emdat.be/emdat_db/

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Appendix

Table 1: Social protection expenditure and agricultural production

	Share of GDP (%)	
All Asia	2008	2015
ESI	2.13	3.32
ESA	0.95	1.34
ALMP	0.08	0.21
SPEP	2.26	2.15
AGDP	15.32	14.04
Lower-income		
ESI	1.13	2.71
ESA	1.06	1.29
ALM	0.10	0.24
SPEP	0.12	0.29
AGDP	19.92	18.18
Higher-income		
ESI	3.71	4.28
ESA	0.79	1.52
ALMP	0.05	0.15
SPEP	4.30	4.80
AGDP	6.15	5.83

Table2: Effects of social protection expenditure: all Asia, FE

	SPE	**SPEP**	**ESA**	**ESI**	**ALM**
Social spending$_t$	0.0196*	0.00256	-0.00361	0.00275	0.00109
	(1.81)	(0.30)	(-0.85)	(0.54)	(0.15)
Social spending$_{t-1}$	0.00694	0.0107	-0.00213	-0.00361	-0.00196
	(0.53)	(1.41)	(-0.69)	(-0.54)	(-0.29)
Agricultural production$_{t-1}$	-0.105	-0.102	-0.101	-0.0781	-0.113
	(-1.67)	(-1.51)	(-1.54)	(-1.10)	(-1.14)
Population growth$_t$	0.0932	0.0968	0.0990*	0.0779	0.0987
	(1.64)	(1.69)	(1.79)	(1.39)	(1.46)
Openness$_t$	0.206*	0.208*	0.0266	-0.0307	-0.0370
	(1.84)	(1.83)	(0.39)	(-0.69)	(-0.67)
Real interest rate$_t$	0.00273	0.00284	0.00239	0.00140	0.000910
	(0.74)	(0.78)	(0.61)	(0.35)	(0.48)
Debt-to-GDP	0.0417	0.0493	-0.0110	0.0248	0.0292
	(0.83)	(1.00)	(-0.17)	(0.45)	(0.52)
N	128	128	127	127	102

Notes: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effects of social protection expenditure: FE

	SPE	SPEP	ESA	ESI	ALM
Lower-income					
Social spending$_t$	0.0169	0.00210	-0.00897	0.00132	-0.000107
	(1.59)	(0.15)	(-1.22)	(0.26)	(-0.01)
Social spending$_{t-1}$	0.00342	0.00903	-0.00769	-0.00204	-0.00314
	(0.29)	(0.91)	(-1.08)	(-0.33)	(-0.36)
Higher-income					
Social spending$_t$	0.0581**	0.0186	0.00689***	0.00414	0.0406
	(2.38)	(1.54)	(3.54)	(0.34)	(0.91)
Social spending$_{t-1}$	0.0638**	0.0380*	0.00792*	0.00405	-0.00610
	(2.61)	(3.00)	(2.35)	(1.99)	(1.91)

Notes: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effects of social protection expenditure: all Asia, FE-IV

	SPE	SPEP	ESA	ESI	ALM
Social spending$_t$	0.0356	0.00839	-0.00397	0.00870	-0.0104
	(1.01)	(0.34)	(-0.58)	(0.34)	(-0.63)
Social spending$_{t-1}$	0.0146	0.0124	-0.00227	-0.000706	-0.00807
	(0.68)	(0.92)	(-0.44)	(-0.05)	(-0.75)
Agricultural production$_{t-1}$	-0.113	-0.108	-0.101	-0.0829	-0.113
	(-1.40)	(-1.30)	(-1.25)	(-0.98)	(-1.14)
Population growth$_t$	0.0961**	0.0964**	0.0993**	0.0813*	0.0987
	(2.20)	(2.22)	(2.26)	(1.68)	(1.46)
Openness$_t$	0.235**	0.220**	0.0268	-0.0269	-0.0370
	(2.16)	(2.11)	(0.55)	(-0.69)	(-0.67)
Real interest rate$_t$	0.00257	0.00276*	0.00241	0.00140	0.000910
	(1.56)	(1.68)	(1.46)	(0.86)	(0.48)
Debt-to-GDP	0.0472	0.0541	-0.0113	0.0181	0.0292
	(0.96)	(1.01)	(-0.26)	(0.37)	(0.52)
F-test (p value)	0.0007	0.0003	0.0000	0.0731	0.0003
Sargan test (p value)	0.7335	0.9681	0.3778	0.8391	0.7576
N	128	128	127	127	102

Notes: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of social protection expenditure: FE-IV

	SPE	SPEP	ESA	ESI	ALM
Lower-income					
Social spending$_t$	0.0228	0.0302	-0.0145	-0.00541	-0.00428
	(0.87)	(1.00)	(-1.26)	(-0.50)	(-0.26)
Social spending$_{t-1}$	0.00641	0.0133	-0.00931	-0.00513	-0.00548
	(0.33)	(0.80)	(-1.23)	(-0.57)	(-0.49)
F-test (p value)	0.0000	0.0028	0.0000	0.0000	0.0062
Sargan test (p value)	0.5717	0.8246	0.0026	0.0173	0.5421
Higher-income					
Social spending$_t$	0.107	0.0362	0.00855	-0.000454	-0.0308
	(1.52)	(1.09)	(1.01)	(-0.06)	(-0.55)
Social spending$_{t-1}$	0.0887*	0.0470*	0.00885	0.00223	-0.0138
	(1.84)	(1.67)	(1.15)	(0.10)	(-0.56)
F-Test (p value)	0.2222	0.0041	0.0000	0.0000	0.3891
Sargan test (p value)	0.5797	0.3470	0.4546	0.1917	0.3518

Notes: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Mitigating effects of social protection expenditure: FE

All Asia	**SPE**	**SPEP**	**ESA**	**ESI**	**ALM**
Social spending$_t$	0.0168*	0.000850	-0.00303	0.00466	0.00971
	(1.72)	(0.08)	(-0.66)	(1.00)	(1.30)
Extreme Temperature	-0.0338	-0.0365	-0.0290	-0.0138	-0.0275
	(-1.15)	(-1.19)	(-1.05)	(-0.55)	(-0.86)
Extreme Temperature Social spending$_t$*	0.0329	0.0338*	-0.00255	-0.00323	-0.0224*
	(0.80)	(2.01)	(-0.42)	(-0.35)	(-1.86)
Lower-income					
Social spending$_t$	0.0149	0.00155	-0.00742	0.00645	0.0118
	(1.66)	(0.12)	(-0.83)	(1.51)	(1.24)
Extreme Temperature	-0.0247	-0.0340	-0.0232	0.0420	-0.0361
	(-0.62)	(-0.75)	(-0.63)	(0.37)	(-0.83)
Extreme Temperature Social spending$_t$*	0.00189	0.175	-0.00347	-0.000109	-0.0215
	(0.04)	(1.11)	(-0.48)	(-0.02)	(-1.26)
Higher-income					
Social spending$_t$	0.0500*	0.0207	0.00643**	0.00172	0.0418
	(2.00)	(1.89)	(3.35)	(0.16)	(0.92)
Extreme Temperature	-0.0973***	-0.155***	-0.0686***	-0.423***	0.0526
	(-7.79)	(-12.94)	(-4.22)	(-14.18)	(1.12)
Extreme Temperature Social spending$_t$*	0.582***	0.970***	0.202***	4.417***	0
	(4.39)	(11.81)	(7.37)	(13.11)	(.)

Notes: *t* statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Mitigating effects of social protection expenditure: FE-IV

All Asia	**SPE**	**SPEP**	**ESA**	**ESI**	**ALM**
Social spending$_t$	0.0138	0.00604	-0.00109	-0.00131	0.0247
	(0.44)	(0.24)	(-0.16)	(-0.07)	(1.06)
Extreme Temperature	-0.0343	-0.0368	-0.0290	-0.0145	-0.0277
	(-1.43)	(-1.58)	(-1.24)	(-0.63)	(-1.07)
Extreme Temperature Social spending$_t$*	0.0349	0.0289	-0.00415	0.00182	-0.0344
	(0.36)	(0.65)	(-0.35)	(0.09)	(-1.54)
Lower-income					
Social spending$_t$	0.0111	0.0331	-0.00657	-0.00113	0.0353
	(0.44)	(1.11)	(-0.39)	(-0.07)	(1.54)
Extreme Temperature	-0.0254	-0.0315	-0.0230	-0.0206	-0.0446
	(-0.83)	(-0.97)	(-0.82)	(-0.71)	(-1.37)
Extreme Temperature Social spending$_t$*	0.00232	0.181	-0.00427	-0.0117	-0.0408*
	(0.02)	(0.77)	(-0.22)	(-0.58)	(-1.83)
Higher-income					
Social spending$_t$	0.119**	0.0351	0.00994	0.0503	-0.0235
	(2.18)	(1.19)	(1.27)	(1.23)	(-0.43)
Extreme Temperature	-0.0892	-0.156**	-0.0699	-0.405	0.0430
	(-1.58)	(-2.20)	(-1.25)	(-1.63)	(0.49)
Extreme Temperature Social spending$_t$*	0.468	0.963	0.195	4.233	0
	(0.91)	(1.45)	(1.18)	(1.36)	(.)

Notes: t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.