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Does Agricultural Growth Cause Manufacturing Growth?

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The role of agricultural development for industrialization is central to several theories of economic development and policy. However, empirically assessing the impact of agricultural growth on manufacturing growth is challenging because of endogeneity concerns. To address the identification challenge, I use random weather variations to instrument agricultural growth. The instrumental variable estimations show that agricultural growth has a significant positive impact on manufacturing growth. I discuss the empirical implications for efficiency of the manufacturing sector and the role of agriculture in Africa's industrialization.

Introduction

The role of agricultural development for industrialization has been an important issue in both economic theory and development policy, gaining prominence as early as the 1950s with the seminal work by Lewis (1954). Many developing countries tried to promote industrialization at the expense of agricultural growth through a transfer of resources from their vast agricultural sector to the manufacturing sector by imposing high agricultural taxes and subsidizing the manufacturing sector (Schiff and Valdés 2002; Krueger 1996). On the other hand, the development of the manufacturing sector may benefit substantially from agricultural growth due to various potential channels through which agricultural growth may enhance manufacturing growth (e.g. supply of raw materials and increased demand for manufacturing products). Thus taxing the agricultural sector with the aim of subsidizing the manufacturing sector and promoting industrialization may actually end up reducing manufacturing growth because high taxes on the agricultural sector may discourage agricultural growth (Anderson and Brückner 2012), which may indirectly reduce manufacturing growth. Such a view underlies another policy approach where agricultural development is assumed to be the fundamental driver of industrialization and countries put more emphasis on investing in the agricultural sector (as opposed to imposing high taxes on the agricultural sector).[1]

These two divergent policy approaches illustrate the stark choices that countries face regarding resource allocations between the agricultural and the manufacturing sectors in order to speed up industrialization. Central to the two policy prescriptions is the perceived impact of agricultural growth on manufacturing growth. However, empirically identifying the actual impact has been a challenge since the observed correlations between the two growth rates do not necessarily capture the causal effects.

In this paper, I attempt to address this identification challenge by using random variations in the weather to instrument for agricultural growth. Using country-level panel data, I exploit the within-country variations in the weather (temperature and precipitation) to instrument for within-country variations in agricultural growth. Agriculture is heavily dependent on the weather, and this is also visible in the strong correlation between agricultural growth and weather variations in the data. The significant dependence of agriculture on the weather provides a useful opportunity to instrument agricultural growth—a feature that has recently been exploited by a number of other studies too (see, for example, Miguel *et al.* 2004; Burke and Leigh 2010; Brückner and Ciccone 2011; Brückner 2012).

According to the instrumental variable (IV) regressions, the impact on manufacturing growth of a 1 percentage point increase in agricultural growth is around 0.4 percentage points. Figure 1 highlights the benchmark pattern in the data. The scatterplot covers 3582 observations (from 136 countries) on agricultural and manufacturing growth.[2] Both of the variables are expressed as deviations from country— and year—specific means. There is a significant positive correlation between agricultural and manufacturing growth—even after taking away the country and year fixed effects. The IV curve is estimated using the weather instruments (discussed in Section II) to instrument agricultural growth. We see that the IV curve is steeper than the OLS curve, suggesting that the actual effect of agricultural growth could be larger than what the OLS estimates indicate.

The estimates for the whole sample can mask potential heterogeneities across subsamples. A possible factor that may affect the impact of agricultural growth is the efficiency of the manufacturing sector in the reallocation of factors. For example, suppose that agricultural growth affects manufacturing growth through a cheaper (or more abundant) supply of agricultural inputs for the manufacturing sector. Then whether firms in the manufacturing sector take advantage of the increased supply of agricultural inputs can depend on their efficiency in mobilizing inputs. Thus if there are distortions that limit the manufacturing sector's efficiency in reallocation of factors, the impact of agricultural growth may be less pronounced. I look at two possible sources of such distortions—trade closedness and restrictiveness of the business regulatory environment. I use the World Bank's *Ease of Doing Business* index as a proxy for the efficiency of business environment. The impact of agricultural growth tends to be higher in economies that are ranked as having a better business environment as well as in

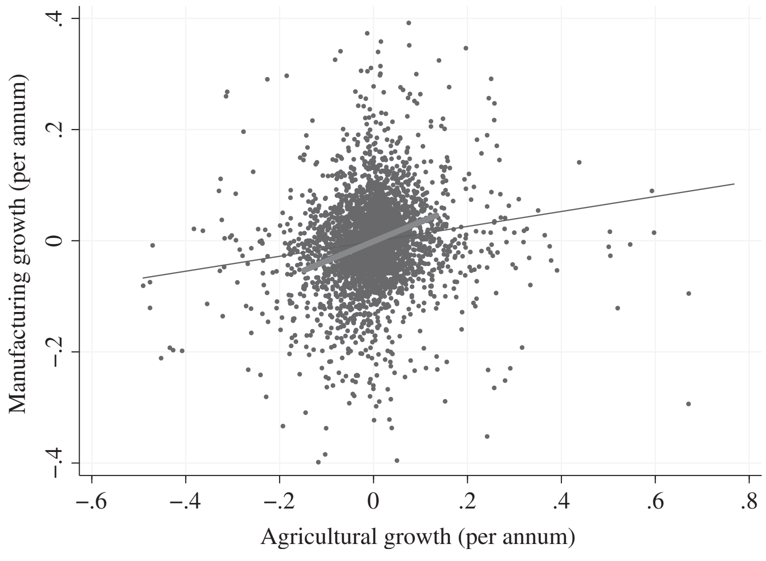

FIGURE 1. OLS (thin) and IV (thick) estimates of the impact of agricultural growth on manufacturing growth.

Notes: This graph shows the relationship between agricultural and manufacturing growth. Both of the variables are expressed as deviations from country- and year-specific means.

economies that are more open to trade. These findings suggest that the competitiveness of the manufacturing sector is indeed important for translating agricultural growth into a higher growth in the manufacturing sector. This result is consistent with Chanda and Dalgaard (2008) who emphasize distortions across sectors as important determinants of total factor productivity differences across countries.

I also look at the impact of agricultural growth for the sub-Saharan Africa (SSA) subsample. One may reasonably expect—given the dominant share of agriculture in SSA economies—agricultural growth to have a relatively larger impact in SSA. However, the estimated impact of agricultural growth in the SSA region is not larger than the average impact for the whole sample, possibly pointing to a weaker linkage between agriculture and manufacturing in SSA.

This paper is related to several studies. The focus on manufacturing growth distinguishes this study from a number of other empirical papers that study the impact of agricultural growth: Tiffin and Irz (2006) on overall GDP, Christiaensen *et al*. (2011) on non-agricultural GDP and poverty rate, and Brückner (2012) on urbanization in SSA. Tiffin and Irz (2006) and Christiaensen *et al*. (2011) find that an increase in agricultural output increases overall GDP and reduces the poverty rate, respectively. The benchmark result in this paper (i.e. the positive effect of agricultural growth on manufacturing) is consistent with the results in Tiffin and Irz (2006) and Christiaensen *et al*. (2011) in the sense that the effect of agriculture on manufacturing can contribute to the effect of agriculture on overall GDP (through manufacturing value added) and poverty rate (e.g. through higher household income from manufacturing employment).

The link between agriculture and manufacturing sectors is interesting for several reasons. First, agriculture typically constitutes a dominant portion of the economies in developing countries. For example, at least half of the total labour force is engaged in agriculture in nearly half of the low and lower middle income countries. Second, as has been experienced by the East Asian economies, growth in the manufacturing sector can make an important difference in the growth prospect of overall GDP in a developing country (Page 2012). Thus from a policy perspective, the extent to which agricultural development should be seen as an integral part of industrialization policies partly depends on the expected impact of agricultural growth on manufacturing growth. The link between agricultural development and manufacturing growth also underlies several models of structural change. Murphy *et al*. (1989) present a model where an increase in agricultural productivity leads to industrialization by increasing the demand for industrial products. The role of agricultural development for generating a market for the manufacturing sector is also noted by several earlier works (see, for example, Nurkse 1953; Lewis 1954; Johnston and Mellor 1961; Mellor and Johnston 1984). The provision of labour for the manufacturing sector is the core element of the seminal work by Lewis (1954) and many other models of structural change (see, for example, Fleming 1955; Ranis and Fei 1961; Jorgenson 1961; Harris and Todaro 1970; Matsuyama 1992; Laitner 2000; Gollin *et al*. 2002; Hansen and Prescott 2002; Lucas 2004).

Another strand of the literature examine the impact of weather variations on various economic and political outcomes. The presumed dependence of agriculture on the weather also underlies the instrumental variable approach adopted by several other studies. For example, to study the impact of income shocks on the likelihood of the survival of leaders, Burke (2012) uses weather variations to instrument shocks to GDP. On the other hand, Jones and Olken (2010), Hsiang (2010) and Dell *et al*. (2012) estimate the direct impact of weather variations on economic outcomes such as GDP growth, industrial value added and exports. Dell *et al*. (2014) provide a detailed review of the literature.

Although the use of instrumental variable regression is an appealing element of the estimates in this paper, the results are not without limitations. One may notice that weather variations are essentially short-run variations. Thus the impact of such short-run variations could differ from long-term shifts in productivity due to, say, improved seed varieties or shifts in government policies. Hence the estimated impacts in this paper are more likely to come from short-run effects such as increased consumption demand for manufacturing products (due to improved farm incomes) and a more abundant supply of agricultural inputs than from long-run effects like the release of labour from agriculture to manufacturing. This is also confirmed by the insignificant effect of the lag of agricultural growth in the instrumental variable estimations.

Even though the instruments are plausibly exogenous to factors that may also affect other sectors (like overall economic policies and technological changes), they should also satisfy the exclusion restriction in the sense that they affect manufacturing growth only through agricultural growth. However, one can think of alternative mechanisms through which the instruments can potentially affect manufacturing growth. To the extent that the data allow us to examine the exclusion restriction, the instruments do not seem to affect manufacturing growth via channels other than agricultural growth. First, controlling for potential confounding factors does not change the results. Second, comparison of coefficients from separate regressions where each instrument is included one at a time yields very similar results. These results help to minimize the concern about violation of the exclusion restriction. Of course, the data do not allow us to completely rule out all potential channels through which the instruments affect manufacturing growth, and the results need to be interpreted with this precaution in mind.

The next section presents the data. This will be followed by discussion of the empirical results. Section III concludes.

I. DATA

Table 1 presents summary statistics of the variables included in the analysis. The data on agricultural growth, manufacturing growth, the weather instruments and the control variables include 3604 observations (from 136 countries) spanning the period 1970–2010. Agricultural value added includes the sum of value added in the sectors corresponding to divisions 1–5 in the UN's International Standard Industrial Classification (ISIC), revision 3. Manufacturing refers to industries belonging to ISIC divisions 15–37. The source for precipitation and temperature data is Harris *et al*. (2014).[3] The data on agricultural growth, manufacturing growth, population growth, share of rural population and mineral and energy depletions as a percentage of gross national income (GNI) are from the *World Development Indicators* by the World Bank.[4] Data on the number of anti-government demonstrations (variable 'Number of protests') are from Databanks International. The level of democracy (variable 'Polity2'), ranging from −10 for the least democratic to 10 for the most democratic regimes, is the Polity2 variable in the Polity IV dataset.

Average agricultural and manufacturing growth rates for the whole sample are 2.7% and 4.3% per annum, respectively. The whole sample consists of diverse groups of countries.[5] This indeed masks substantial heterogeneity across subsamples. Six high-performing East Asia (HPEA) economies—namely, Cambodia, China, Indonesia, Malaysia, Thailand and Vietnam—experienced a rapid industrialization during the

TABLE 1
SUMMARY STATISTICS

Variable	Mean	SD	Observations	Countries
Agricultural growth (% per annum)				
Whole sample	2.7	9.0	3604	136
SSA	3.0	10.9	1064	38
HPEA	3.5	3.5	201	6
Manufacturing growth (% per annum)				
Whole sample	4.3	9.8	3604	136
SSA	4.3	12.0	1064	38
HPEA	9.9	7.2	201	6
Manufacturing value added (% of GDP)				
Whole sample	15.5	7.6	3387	136
SSA 1970	10.3	5.1	24	24
SSA 2000	11.4	7.5	32	32
HPEA 1970	18.1	10.7	4	4
HPEA 2000	26.6	7.2	6	6
Rural population (% of total)				
Whole sample	52.0	22.6	3604	136
SSA 1970	81.7	11.0	24	24
SSA 2000	66.8	15.5	33	33
HPEA 1970	79.5	6.6	6	6
HPEA 2000	64.3	15.3	6	6
Population growth (% per annum)				
Whole sample	1.8	1.3	3604	136
SSA	2.7	1.2	896	38
HPEA	1.7	0.7	201	6
Number of protests (per annum)	0.58	1.6	3604	136
Polity2	2.8	7.1	3604	136
Energy depletion (% of GNI)	4.0	10.2	3604	136
Mineral depletion (% of GNI)	0.8	2.3	3604	136
Precipitation (mm)	1201.1	803.6	3604	136
Temperature (°C)	19.6	7.7	3604	136

sample period, with 10% annual growth in the manufacturing value added.[6] On the other hand, SSA experienced a relatively slow growth in the manufacturing sector despite having a substantial room for further industrialization (as measured by the low level of industrialization in 1970). The manufacturing growth gap between SSA and HPEA economies is also somehow mirrored in the agricultural growth gap. Annual agricultural growth averaged at 3.5% per annum in HPEA, which exceeds that of SSA by 0.5 percentage points. Compared to SSA, HPEA experienced a larger reduction in the rural population (as a share of the total population) and a slower population growth. Thus the higher agricultural output growth in HPEA is largely driven by increased agricultural output per capita (i.e. the growth happened despite a relatively slower growth in the rural population).[7] Note also that HPEA started out with a higher share of the manufacturing sector (at 18.1% of GDP) in 1970, as compared to SSA, whose manufacturing value added was only 10.3%. The manufacturing sector continued to keep a relatively small share in SSA until the year 2000, while it increased substantially in HPEA, constituting nearly a third of GDP in the year 2000.

II. Empirical Results

The regression model under consideration is

$$(1)\qquad Manu\_g_{i,t} = \sum_{l=0}^{L} \beta_l Agri\_g_{i,t-l} + \Gamma X_{i,t} + \alpha_i + \kappa_t + \varepsilon_{i,t},$$

where $Manu\_g_{i,t}$ denotes growth in manufacturing value added (in country i, year t), $Agri\_g_{i,t-l}$ denotes growth in agricultural value added (in country i, year $t-l$), $X_{i,t}$, α_i and κ_t are control variables, country effect and year effect, respectively, and $\varepsilon_{i,t}$ is the error term.

Regression results

Table 2 presents estimation results from the fixed effects regression of equation (1). Year and country fixed effects are included in all of the regressions. The fixed effects estimates have the advantage of controlling for country-specific factors that do not vary over time, such as geography, initial conditions and historical legacies. For example, compared to SSA, the initial level of industrialization is substantially larger in the high-performing East Asian economies. The effect of such differences would be accounted for by country-specific dummies in the fixed-effect regressions. The year effects control for variations at a global level that may possibly affect both agricultural and manufacturing growth (such as global recessions/booms).

The first two columns of Table 2 present the results without including the control variables. Current and lagged agricultural growths are significantly correlated with manufacturing growth. The correlation is the highest with current growth in agriculture and tends to fall for further lags. The correlation with current agriculture shows a slight increase as I control for the lags. This is because current agricultural growth is negatively correlated with lagged agricultural growth in the data (with a correlation coefficient of -0.18). Hence dropping the lagged agricultural growth reduces the coefficient on current agricultural growth if the lagged growth is positively correlated with manufacturing growth, which is the case here. The exclusion of year dummies (not reported here) slightly increases the coefficient on current agricultural growth, suggesting that part of the correlation is driven by global trends in both manufacturing and agricultural growth.

The last two columns of Table 2 report the estimation results controlling for a wide variety of variables. Both agricultural growth and manufacturing growth could be jointly affected by a number of factors. Availability of labour could be one of them. The population growth rate and the share of agricultural population are meant to control for growth in the total labour force and changes in its composition. One observes that manufacturing growth is positively correlated with population growth and the share of agricultural population. A positive and significant coefficient on the rural population share suggests that economies with a higher share of rural population have greater scope for further industrialization, possibly through structural transformation. Another set of factors that could affect both agricultural and manufacturing growth rates are policies and institutions. There is some empirical evidence that large income shocks are

TABLE 2
REGRESSION RESULTS: DEPENDENT VARIABLE IS MANUFACTURING GROWTH (% PER ANNUM)

	(1)	(2)	(3)	(4)
Agri_g (% per annum)	0.12***	0.13***	0.11***	0.13***
	(0.03)	(0.04)	(0.03)	(0.04)
L.*Agri_g*		0.10***		0.10***
		(0.03)		(0.03)
L2.*Agri_g*		0.07**		0.06**
		(0.03)		(0.03)
L3.*Agri_g*		0.03		0.03
		(0.02)		(0.03)
L4.*Agri_g*		0.05**		0.05**
		(0.02)		(0.02)
Rural population (% of total)			0.18***	0.13**
			(0.07)	(0.06)
Population growth (% per annum)			0.57	0.57
			(0.35)	(0.37)
Polity2			0.04	0.06
			(0.05)	(0.05)
Number of protests (per annum)			−0.31**	−0.33***
			(0.12)	(0.12)
Energy (% of GNI)			0.11**	0.13***
			(0.05)	(0.05)
Mineral (% of GNI)			−0.02	−0.12
			(0.11)	(0.14)
Country and year effects	Yes	Yes	Yes	Yes
Observations	3604	3179	3604	3179
Countries	136	133	136	133
R-squared	0.01	0.02	0.02	0.03

Notes
The variable *Agri_g* is agricultural growth per annum. Robust standard errors clustered by country are in parentheses.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

associated with political protests, violence and democratization (see, for example, Burke and Leigh 2010; Miguel *et al*. 2004; Brückner and Ciccone 2011). Thus I also control for the number of anti-government demonstrations and the level of democracy.

An abundance of natural resources can also affect both agricultural and manufacturing growth through the classic Dutch-disease effect and the potential erosion of institutional quality (Sachs and Warner 1995). On the other hand, availability of energy can help to boost manufacturing growth. The two measures of natural resource abundance—the share of mineral depletion and energy depletion in GNI—control for such effects. The coefficients on agricultural growth and its lags are more or less stable for inclusion of the control variables.

Even though they take into account country- and time-specific effects, the above estimates can potentially be inconsistent for several reasons. Technically speaking, such a bias can occur if the error term $\varepsilon_{i,t}$ is correlated with agricultural growth. One potential source of bias is reverse causality, whereby manufacturing growth affects agricultural growth (instead of the other way round). For example, a higher manufacturing growth can lead to an increased demand for agricultural goods and a more abundant (or cheaper) supply of inputs from the manufacturing sector to the agricultural sector. In the presence of such reverse causality, the coefficients in Table 2 may overestimate the impact of agricultural growth. On the other hand, the coefficients may underestimate the impact of agricultural growth if manufacturing growth has a negative impact on agricultural growth. For example, growth in the manufacturing sector may go hand in hand with a structural transformation where labour resources are moved from the agricultural sector to the manufacturing sector, as in Lewis (1954). For a given level of agricultural productivity, this could reduce the total output produced in the agricultural sectors.

Another plausible source of bias is the possibility that the observed correlation between manufacturing and agricultural growth is driven by a set of other factors that cause both variables to co-move, but that are not included in the regression. In the presence of such factors that are not controlled for in the regressions and that can jointly affect both agricultural and manufacturing growth, the estimated coefficients may not be consistent due to the classical omitted variable problem. Yet another source of bias is measurement error in the agricultural growth data. This is of a particular concern for developing countries where the data quality is likely to be less reliable. The instrumental variable estimation reported in the next subsection attempts to address the potential bias in the above regressions arising from one or more of the possible sources of bias.

Instrumental variable estimates: main results

In order to address the concern that the above regressions are likely to suffer from various sources of bias, I estimate equation (1) instrumenting agricultural growth by variations in the weather. I report estimates using the Fuller 1 estimator since it is more robust to potential bias arising from weak instruments (Fuller 1977; Stock and Yogo 2005). The first-stage regression is

$$Agri\_g_{i,t} = \psi_1 Prec_{i,t} + \psi_2 Prec_{i,t-1} + \pi Temp_{i,t} + \Phi X_{i,t} + \theta_i + \chi_t + \mu_{i,t},$$

where $Prec_{i,t}$ and $Temp_{i,t}$ are the precipitation and temperature instruments. Following Burke and Leigh (2010), $Prec_{i,t}$ is the annual percentage change in precipitation interacted with the average share of agricultural GDP during the years 1990–2000. Interacting the annual percentage changes in precipitation with a measure of the size of the agricultural sector in the economy provides a stronger identification. $Temp_{i,t}$ measures the annual change in temperature.[8] The ψ terms are expected to have a positive sign, whereas π is expected to be negative. Robustness checks using the weather variables in levels (rather than in differences as in the above specification) yield similar results, although the identification is typically stronger in the specification with differences.

Table 3 summarizes the first-stage regressions. Country and year fixed effects are included in all of the regressions. The first four columns include the precipitation (columns (1) and (2)) and temperature (columns (3) and (4)) instruments separately. The last two columns include both instruments. In all specifications, agricultural growth responds significantly to the instruments. The coefficients on the instruments have the expected signs. The instruments jointly explain more than 2% of the variation in agricultural growth, and the *F*-statistic on the excluded instruments is well above the Stock–Yogo critical value for 5% maximal Fuller relative bias at the 5% significance level.

TABLE 3
FIRST-STAGE REGRESSIONS: DEPENDENT VARIABLE IS AGRICULTURAL GROWTH (% PER ANNUM)

	(1)	(2)	(3)	(4)	(5)	(6)
$Precip_{i,t}$	0.64***	0.64***			0.59***	0.58***
	(0.13)	(0.13)			(0.12)	(0.13)
$Precip_{i,t-1}$	0.40***	0.39***			0.38***	0.37***
	(0.10)	(0.10)			(0.10)	(0.10)
$Temp_{i,t}$			−1.73***	−1.74***	−1.44***	−1.44***
			(0.40)	(0.40)	(0.37)	(0.37)
Controls	No	Yes	No	Yes	No	Yes
Country effect	Yes	Yes	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3604	3604	3604	3604	3604	3604
Countries	136	136	136	136	136	136
F-statistic on excl. instruments	18.20	17.08	18.97	19.15	14.45	13.95
Stock–Yogo critical values	13.46/ 7.49	13.46/ 7.49	24.09/ 12.71	24.09/ 12.71	9.61/5.60	9.61/5.60
Partial R^2 of excl. instruments	0.016	0.016	0.008	0.008	0.021	0.021

Notes
The dependent variable is agricultural growth. $Precip_{i,t}$ and $Precip_{i,t-1}$ are the precipitation instrument and its lag, respectively. $Temp_{i,t}$ is the temperature instrument. The first two columns include only the precipitation instruments, columns (3) and (4) include only the temperature instrument, and the last two columns include both instruments. The control variables (not reported) are the share of agricultural population, population growth, number of anti-government protests, Polity2, and energy and mineral income as a share of GNI. Robust standard errors clustered by country are in parentheses. The Stock–Yogo critical values reported in the table are the weak instrument test critical values (of 5% significance level) for 5%/30% maximal Fuller relative bias. *F*-statistic larger than the critical value implies rejection of the null of weak instrument.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

Table 4 presents the estimated impact of agricultural growth using the instrumental variables regression. In all of the columns, only current agricultural growth is included.[9] The first two columns present results using the precipitation instrument only. According to the results in columns (1) and (2), a 1 percentage point increase in agricultural growth increases manufacturing growth by 0.37 percentage points. Note that the estimates from the IV regressions are substantially larger than those from the fixed effects regressions reported in Table 2, where the estimated coefficients are in the range 0.11–0.13. This suggests that the endogeneity sources that may cause a downward bias (such as measurement errors and structural transformation) outweigh those that may cause an upward bias.

Columns (3) and (4) of Table 4 report estimation results using the temperature instrument only. Comparison of the coefficients from the two instruments provides a useful diagnosis of the exclusion restriction. Even though the instruments are plausibly exogenous to factors that may also affect other sectors (like overall economic policies and technological changes), they should also satisfy the exclusion restriction in the sense that they affect manufacturing growth only through agricultural growth. If both temperature and precipitation affect manufacturing growth only through agricultural growth, then one would expect the coefficients estimated using the two instruments to be more or less

TABLE 4
RESULTS FROM INSTRUMENTAL VARIABLE ESTIMATION: DEPENDENT VARIABLE IS MANUFACTURING GROWTH (% PER ANNUM)

	Precipitation		Temperature		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Agri_g	0.37**	0.37**	0.36**	0.35**	0.38***	0.37***
(% per annum)	(0.17)	(0.17)	(0.14)	(0.14)	(0.13)	(0.13)
Rural population		0.17***		0.17***		0.17***
(% of total)		(0.06)		(0.06)		(0.06)
Pop. growth		0.38		0.40		0.38
(% per annum)		(0.36)		(0.33)		(0.34)
Polity2		0.04		0.04		0.04
		(0.05)		(0.05)		(0.05)
Number of protests		−0.30**		−0.30**		−0.30**
(per annum)		(0.12)		(0.12)		(0.12)
Energy		0.11**		0.11**		0.11**
(% of GNI)		(0.06)		(0.05)		(0.06)
Mineral		−0.04		−0.04		−0.04
(% of GNI)		(0.12)		(0.12)		(0.12)
Country and year effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3604	3604	3604	3604	3604	3604
Countries	136	136	136	136	136	136
F-statistic on excl. instruments	18.20	17.08	18.97	19.15	14.45	13.95
Stock–Yogo critical values	13.46/ 7.49	13.46/ 7.49	24.09/ 12.71	24.09/ 12.71	9.61/ 5.60	9.61/ 5.60
p-value of *C*-statistic for null of orthogonality of temp. instrument	—	—	—	—	0.69	0.69

Notes
The variable *Agri_g* is agricultural growth. The first four columns include the precipitation instruments (columns (1) and (2)) and the temperature instrument (columns (3) and (4)) separately. The last two columns include both instruments. Robust standard errors clustered by country are in parentheses. The Stock–Yogo critical values reported in the table are the weak instrument test critical values (of 5% significance level) for 5%/30% maximal Fuller relative bias. *F*-statistic larger than the critical value implies rejection of the null of weak instrument.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

the same. For example, if the coefficients estimated using the temperature instrument are larger than the ones using precipitation, then this would indicate that temperature may affect manufacturing growth on top of its effect through agricultural growth (assuming that precipitation satisfies the exclusion restriction).[10] In our case, the coefficients estimated from the precipitation instrument (columns (1) and (2)) and the temperature instrument (columns (3) and (4)) are very similar—providing no indication that the exclusion restriction is violated.

Columns (5) and (6) of Table 4 report estimation results where both the precipitation and temperature instruments are jointly included in the second-stage regression. Once again, the estimated impact of agricultural growth is very similar to the estimates where the instruments are included separately. According to the *p*-value for the *C*-statistic, the orthogonality of the temperature instrument cannot be rejected (conditional on orthogonality of the precipitation instrument). Note that the coefficient on agricultural growth stays stable when the control variables are included. The stability of coefficients for the inclusion/exclusion of alternative instruments and control variables is quite reassuring since it gives further credence to the exogeneity of the instruments.

An issue of concern for the exclusion restriction with the temperature instrument, as highlighted by Hsiang (2010), is that in countries with relatively hotter seasons, temperature increases may have a direct effect on labour productivity through thermal stress. Thermal stress is less of a concern for the precipitation instrument. Moreover, a number of previous studies generally find that, unlike temperature, precipitation does not appear to have direct effect on industrial output (see, for example, Jones and Olken 2010; Dell *et al*. 2012,, 2014). In Table 4, we have seen that the estimated impact of agricultural growth from the temperature instrument is very similar to that from the precipitation instrument, suggesting that the estimate from the temperature instrument does not seem to have captured the effect of thermal stress (on top of temperature's effect through agricultural growth). To further check the sensitivity of the temperature instrument for this exclusion concern, I also run the regression excluding the top third of the countries in the distribution of temperatures in hottest months (not reported).[11] If the results from the temperature instrument are driven by thermal stress, then the effect should diminish when countries with relatively hot seasons are dropped. I find that the impact of agricultural growth is still significant (and the coefficient does not decrease) after excluding the countries with relatively hotter seasons, suggesting that the results from the temperature instrument are not driven primarily by thermal stress. Another concern for the exclusion restriction, which pertains to the precipitation instruments, is that precipitation may affect manufacturing growth through hydroelectricity supply. A robustness check through controlling for hydroelectricity production does not change the estimated impact (not reported).[12]

Table 5 includes the lag of agricultural growth. Both current and lagged agricultural growth are instrumented, with the lags of the instruments as an additional set of instruments. Including further lags makes inference difficult because the identification becomes weaker as the number of endogenous variables increases (with the number of lags of agricultural growth). Note also that the F-statistic on the excluded instruments decreases substantially when the lagged agricultural growth is included in the regression. Current agricultural growth remains significant. It is also interesting that lagged agricultural growth, which is significant in the fixed effects regressions (see Table 2), is no longer significant. A potential reason is that the correlation in Table 2 is spurious. However, it could also be due to the nature of the instruments. Weather variations are typically not expected to last long. Thus the coefficients are effectively capturing the impact of short-lived variations in agricultural growth that do not alter expectations about future productivity.

Sub-Saharan Africa

We now look at results focusing on sub-Saharan Africa (SSA). SSA is a particularly interesting subsample. First, it is heavily dependent on agriculture—over two-thirds of the population live in rural areas. Second, despite the availability of a vast and cheap labour force in SSA, the kind of low-skill manufacturing growth experienced by the East Asian countries did not happen in SSA. The share of manufacturing value added in SSA's GDP is stagnant at the level of the 1970s. Third, parallel to the dismal performance in the manufacturing sector, SSA experienced the least growth in agricultural per-capita incomes as compared to many other regions.[13]

TABLE 5
RESULT FROM INSTRUMENTAL VARIABLE REGRESSION: DEPENDENT VARIABLE IS MANUFACTURING GROWTH (% PER ANNUM)

	Precipitation		Temperature		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Agri_g (% per annum)	0.47*	0.49*	0.48**	0.48**	0.45**	0.46**
	(0.25)	(0.26)	(0.19)	(0.19)	(0.18)	(0.18)
L.*Agri_g*	−0.10	−0.11	0.19	0.19	−0.03	−0.02
	(0.15)	(0.16)	(0.16)	(0.16)	(0.11)	(0.12)
Rural population (% of total)		0.17***		0.16***		0.17***
		(0.06)		(0.05)		(0.06)
Pop. growth (% per annum)		0.36		0.10		0.30
		(0.51)		(0.46)		(0.48)
Polity2		0.04		0.03		0.03
		(0.06)		(0.05)		(0.05)
Number of protests (per annum)		−0.34**		−0.30**		−0.33**
		(0.13)		(0.13)		(0.13)
Energy (% of GNI)		0.11**		0.11*		0.12**
		(0.05)		(0.06)		(0.05)
Mineral (% of GNI)		−0.08		−0.09		−0.09
		(0.12)		(0.14)		(0.12)
Country and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3320	3320	3462	3462	3320	3320
Countries	135	135	136	136	135	135
Kleibergen–Paap *F*-statistics	7.72	7.72	6.56	6.60	6.98	6.89
Stock–Yogo critical values	8.53/ 5.10	8.53/ 5.10	15.50/ 8.03	15.50/ 8.03	6.24/ 3.98	6.24/ 3.98
p-value of *C*-statistic for null of orthogonality of temp. instrument	—	—	—	—	0.32	0.32

Notes
The variable *Agri_g* is agricultural growth. Both agricultural growth and its lag are instrumented (with the lags of the instruments as an additional set of instruments). The first four columns include the precipitation instruments (columns (1) and (2)) and the temperature instruments (columns (3) and (4)) separately. The last two columns include both instruments. Robust standard errors clustered by country are in parentheses. The Stock–Yogo critical values reported in the table are the weak instrument test critical values (of 5% significance level) for 5%/30% maximal Fuller relative bias. *F*-statistic larger than the critical value implies rejection of the null of weak instrument.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

Table 6 presents the estimates for the SSA subsample. An alternative specification, instead of splitting the sample, would have been to include an interaction term for SSA in a regression where all the observations are included. However, the sample splitting is adopted here (and in the regressions below) due to the fact that since the interaction term enters as an extra endogenous variable, it is typically difficult to obtain a strong identification for the specification with an interaction term. The estimates in Table 6 are reported for alternative sets of instruments. According to the *F*-statistic on the excluded instruments, both the temperature and precipitation instruments provide a fairly strong identification for this subsample.

Given the dominant share of agriculture in SSA economies, one may reasonably expect an additional percentage point increase in SSA's agricultural growth to have a larger impact on manufacturing growth. However, the overall pattern from the regressions in Table 6 is that the impact of agricultural growth in the SSA region does not seem to be larger than the average impact for the whole sample (see Table 4). The fact that the coefficient for SSA is more or less similar with the coefficient for the whole sample, despite agriculture having a larger share in SSA, possibly points to a weaker linkage between agriculture and manufacturing in SSA.

Comparing HPEA to SSA, the growth rate of manufacturing output is 10.1% per year in HPEA while it is 4.3% in SSA, implying a gap of 5.7 percentage points in the

TABLE 6
IMPACT OF AGRICULTURAL GROWTH IN SSA

	Precipitation		Temperature		Both	
	(1)	(2)	(3)	(4)	(5)	(6)
Agri_g (% per annum)	0.32 (0.22)	0.31 (0.23)	0.30 (0.19)	0.30 (0.19)	0.33** (0.15)	0.32** (0.15)
Rural population (% of total)		0.05 (0.13)		0.05 (0.13)		0.05 (0.13)
Pop. growth (% per annum)		0.67 (0.41)		0.68** (0.29)		0.66** (0.32)
Polity2		0.10 (0.06)		0.10* (0.06)		0.10* (0.06)
Number of protests (per annum)		−0.59*** (0.22)		−0.59*** (0.19)		−0.60*** (0.20)
Energy (% of GNI)		0.18*** (0.06)		0.18*** (0.06)		0.19*** (0.06)
Mineral (% of GNI)		0.25* (0.15)		0.25* (0.15)		0.25* (0.15)
Country and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1023	1023	1023	1023	1023	1023
Countries	38	38	38	38	38	38
F-statistic on excl. instruments	12.89	11.35	15.65	15.72	13.38	12.48
Stock–Yogo critical values	13.46/7.49	13.46/7.49	24.09/12.71	24.09/12.71	9.61/5.60	9.61/5.60
p-value of *C*-statistic for null of orthogonality of temp. instrument	—	—	—	—	0.97	0.92
p-value for null that coeff. on *Agri_g* for SSA subsample equals coeff. for whole sample	0.68	0.63	0.75	0.75	0.72	0.70

Notes
This table presents the instrumental variable estimation results for the SSA subsample. The dependent variable is manufacturing growth. The variable *Agri_g* is agricultural growth. The first four columns include the precipitation instruments (columns (1) and (2)) and the temperature instrument (columns (3) and (4)) separately. The last two columns include both instruments. Robust standard errors clustered by country are in parentheses. The Stock–Yogo critical values reported in the table are the weak instrument test critical values (of 5% significance level) for 5%/30% maximal Fuller relative bias. *F*-statistic larger than the critical value implies rejection of the null of weak instrument.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

manufacturing growth rates between HPEA and SSA (see the descriptive statistics in Table 1). Similarly, the agricultural growth is 3.5% per annum in HPEA while it remained at 3.0% per annum in SSA. Given that the coefficient for the impact of agricultural growth on manufacturing growth is about 0.32, the 0.5 percentage point gap in agricultural growth between the two regions implies a 0.16 percentage point gap in the manufacturing growth rate (0.32×0.5). Thus the slow agricultural growth in SSA does not appear to be the major factor for the low manufacturing growth in SSA as the gap in agricultural growth between the two regions explains no more than 3% of the 5.7 percentage point gap in manufacturing growth.[14]

Impact of agricultural growth and competitiveness

A possible factor that affects the impact of agricultural growth is the efficiency of the manufacturing sector in the reallocation of factors. It has become increasingly evident that inefficiencies in factor reallocation are important determinants of total factor productivity (see, for example, Chanda and Dalgaard 2008; Hsieh and Klenow 2009). For example, a potential channel through which agricultural growth affects manufacturing growth is a cheaper (or more abundant) supply of agricultural inputs for the manufacturing sector. Thus whether firms in the manufacturing sector take advantage of the increased supply of agricultural inputs may depend on their efficiency in mobilizing inputs. If there are various constraints that limit the efficiency of the manufacturing sector in the reallocation of factors, then the impact of agricultural growth may be less pronounced. I look at two possible sources of such distortions—trade closedness and restrictiveness of the business regulatory environment. Openness to trade can drive out less efficient firms and reallocate resources to more efficient ones through increased competition (Melitz 2003). Thus in more open economies, one may expect the manufacturing sector to be relatively more efficient in responding to agricultural productivity. Similarly, one can plausibly expect the manufacturing sector to be more efficient in economies where the business regulatory environment is less distortionary.

The first four columns of Table 7 compare the impact of agricultural growth between two sets of countries that differ with respect to the share of trade in GDP. The first two columns report the estimation results for countries with low trade share (below the median country), while columns (3) and (4) include countries with higher trade share (above the median country). The data for trade share are from Frankel and Romer (1999). I use the constructed trade share in Frankel and Romer (1999) since it is less susceptible to endogeneity concerns than the actual trade share.[15] There are countries that do not have the constructed trade share data in Frankel and Romer (1999). Thus the number of observations (countries) in Table 7 falls to 2890 (100), leaving us with 80% of the whole observations. Notice that the instruments are relatively weaker for the estimations in columns (3) and (4). For the first two columns, the F-statistic on the excluded instruments is above the Stock–Yogo critical value for 5% maximal Fuller relative bias (at the 5% significance level). However, for columns (3) and (4), the F-statistic is below (above) the critical value for 5% (30%) maximal Fuller relative bias. The impact of agricultural growth in countries with higher trade is significant and about three times larger than the impact in countries with lower trade (i.e. 0.46 versus 0.13). The null hypothesis that the coefficient on agricultural growth for countries with low trade share equals the coefficient for countries with high trade share is rejected with p-value 0.11.

TABLE 7

IMPACT OF AGRICULTURAL GROWTH, TRADE SHARE AND BUSINESS ENVIRONMENT: DEPENDENT VARIABLE IS MANUFACTURING GROWTH (% PER ANNUM)

	Share of trade in GDP				Business environment			
	Low		High		Better		Worse	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agri_g (% per annum)	0.12	0.13	0.45**	0.46**	0.58*	0.58*	0.12	0.12
	(0.11)	(0.11)	(0.21)	(0.22)	(0.30)	(0.30)	(0.13)	(0.13)
Rural population (% of total)		0.03		0.20**		0.16***		0.15
		(0.14)		(0.08)		(0.06)		(0.12)
Pop. growth (% per annum)		0.75		−0.34		0.42		0.51
		(0.84)		(0.30)		(0.47)		(0.57)
Polity2		−0.02		0.23**		−0.02		0.05
		(0.06)		(0.10)		(0.08)		(0.06)
Number of protests (per annum)		−0.41***		−0.37		−0.07		−0.58***
		(0.10)		(0.34)		(0.20)		(0.13)
Energy (% of GNI)		0.10*		0.25***		0.23**		0.08
		(0.06)		(0.10)		(0.09)		(0.06)
Mineral (% of GNI)		−0.04		−0.08		0.05		−0.17
		(0.15)		(0.21)		(0.15)		(0.19)
Country and year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1422	1422	1458	1458	1749	1749	1799	1799
Countries	44	44	56	56	70	70	64	64
F-statistic on excl. instruments	5.99	5.98	11.79	11.09	4.71	4.52	7.23	7.28
Stock–Yogo critical values: 9.61/5.60								
p-value for null that coeff. on *Agri_g* for countries with high trade share (better business environment) is equal to corresponding regression for countries with low trade share (worse business environment)	—	—	0.11	0.11	0.07	0.07	—	—

Notes The variable *Agri_g* is agricultural growth. The first four columns compare the impact of agricultural growth between economies with high versus low trade share. The last four columns compare the impact between economies with better versus worse business environment. Robust standard errors clustered by country are in parentheses. The Stock–Yogo critical values reported in the table are the weak instrument test critical values (of 5% significance level) for 5%/30% maximal Fuller relative bias. *F*-statistic larger than the critical value implies rejection of the null of weak instrument. Agricultural growth is instrumented by precipitation and temperature instruments.
***, **, * indicate significant at the 1%, 5%, 10% level, respectively.

Using the the World Bank's *Ease of Doing Business* index as a measure of the business regulatory environment, columns (5)–(8) of Table 7 compare the impact of agricultural growth in countries that have a relatively better business regulatory environment with the impact in those that have more restrictive regulations. I use the index data from 2012.[16] The index ranks economies based on their regulatory environment that affects firms (like regulations toward starting a business, registering property, getting credit, paying taxes, enforcing contracts and resolving insolvency). The instruments tend to be relatively weak for estimates in columns (5) and (6), with the F-statistic on the excluded instruments below the critical value for 30% maximal Fuller relative bias. Thus the results need to be interpreted with caution.[17] The impact of agricultural growth is large and significant in countries with better business regulatory environment (ranked as better than the median). The coefficient for countries with better business environment is about six times larger than for countries with worse environment. The null hypothesis that the impact is the same across the two groups of countries is rejected with p-value 0.07.

To summarize, the impact of agricultural growth appears to be higher in economies that are ranked as having better business environment as well as in economies that are more open to trade. These findings suggest that the competitiveness of the manufacturing sector is indeed important for translating agricultural growth into a higher growth in the manufacturing sector. This result is consistent with Chanda and Dalgaard (2008), who emphasize distortions across sectors as important determinants of total factor productivity differences across countries.

III. Conclusion

The role of agricultural development for industrialization has been an important issue in both economic theory and development policy. However, empirically identifying the actual impact has been a challenge since observed correlations between the two growth rates do not necessarily capture the causal effects. In this paper, I attempt to address this challenge by estimating the impact of agricultural growth on manufacturing growth using random variations in the weather as instruments for agricultural growth. I find that the impact on manufacturing growth of a 1 percentage point increase in agricultural growth is within the neighborhood of 0.4 percentage points. The coefficients estimated from the IV regressions are generally greater than the ones from the fixed effects regressions.

The estimated impact of agricultural growth tends to be larger in economies that are more open to trade and that have better business regulatory environment. These results suggest that a more competitive environment for the manufacturing sector may indeed be important for translating agricultural growth into more success in the manufacturing sector. I also look at the impact of agricultural growth for the SSA subsample, and assess the extent to which SSA's low agricultural growth explains the poor performance in the manufacturing sector. The empirical findings point to a weak linkage between agricultural growth and manufacturing growth in SSA. And partly because of the weak linkage, the slow agricultural growth in SSA does not appear to be the major factor behind SSA's weak manufacturing growth.

A final caveat is in order. Although the use of reasonably exogenous instruments is an appealing element of the estimates in this paper, the instruments are not without limitation. One also has to bear in mind that weather variations are essentially short-run variations. Thus the impact of such short-run variations could differ from long-term shifts in productivity due to, say, improved seed varieties or shifts in government policies. Hence the estimated impacts in this paper are more likely to come from short-run effects such as increased consumption demand for manufacturing products (due to improved farm incomes) and a more abundant supply of agricultural inputs than from long-run effects like the release of labour from agriculture to manufacturing. This is also confirmed by the insignificant effect of lagged agricultural growth in the instrumental variable estimations.

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NOTES

1. For example, Ethiopia followed the so-called Agricultural Development Led Industrialization (ADLI) where the development of agriculture is assumed to lead to industrialization and the government provides active support for the agricultural sector in the form of rural infrastructure and extension services.
2. The whole sample consists of 3604 observations. 22 outlier observations (i.e. less than 1% of all observations) are dropped from the scatterplot to enhance readability; this does not affect the results (the curves) since the curves are estimated using the entire set of observations.
3. The country-level temperature and precipitation data, produced by the Climatic Research Unit at the University of East Anglia, are derived from monthly series on high resolution (0.5×0.5 degree) grids. The high-resolution data are constructed based on an archive of weather data provided by more than 4000 weather stations distributed around the world. The country-level data are constructed by aggregating these high-resolution data where each grid is weighted by the size of its area.
4. See http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=world-development-indicators (as at 26 February 2012).
5. In the whole sample, 19% of the observations are from high income groups (according to the World Bank classification). The shares of observations from upper middle income, lower middle income and low income countries are 32%, 29% and 20%, respectively.
6. Other authors have considered different sets of countries as HPEA (see, for example, Page 1994; Weeks 2000). The HPEA list in this paper includes East Asian countries that have experienced a relatively high manufacturing growth (above 8% per annum) during the sample period and that are not high income countries (according to World Bank classification). The latter criterion is meant to consider countries that are relatively comparable to SSA in terms of the level of development.
7. Note that the calculated figures are not weighted by the relative size of each observation. Thus the means reported here, for example, are not meant to calculate the mean values at the regional level.
8. Following Burke and Leigh (2010), the temperature change is multiplied by -1 if the 1960–70 average temperature is below 12°C because an increase in temperature can be conducive for agriculture in cold areas.
9. Results with lag of agricultural growth are presented in Table 5.
10. Similarly, if one instead assumes that temperature satisfies the exclusion restriction, then a larger coefficient from the precipitation instrument would indicate that precipitation may affect manufacturing growth on top of its effect through agricultural growth.
11. The cross-country distribution of hottest month is constructed as follows. First, for each country, the hottest month and the temperature in that month are defined based on the average temperature for each month over the sample period in the country. The month with the highest average temperature is considered as the hottest month for the country. Then countries are ranked according to the average temperature in their hottest month. The top third of the countries in this ranking are excluded in the regression for the sensitivity analysis.
12. About a thousand observations have to be dropped due to limited availability of data on hydroelectricity production. The hydroelectricity data are from the World Development Indicators online database, accessed in February 2012.
13. *World Development Report 2008*, World Bank, p. 53.
14. Notice that this computation abstracts from the general equilibrium effects.
15. The data are reported in Table A1 of Frankel and Romer (1999, pp. 394–8). A country can appear in only one of the subsamples. The constructed trade share data are based on the correlation between actual trade share in 1985 and geographic characteristics of countries (such as country size and distance to potential

trading partners). See Frankel and Romer (1999) for a detailed discussion on the construction of the trade share variable.
16. The indices are available only for years 2012 and 2013.
17. However, the weak identification seems to be driven by a small set of countries with very low agricultural GDP. For example, when I exclude countries whose agricultural GDP share during the 1990s is below 2.5% of the overall GDP, I get a stronger identification (with the *F*-statistic being above the Stock–Yogo critical value for 30% maximal Fuller relative bias) and the results in columns (5) and (6) of Table 7 are still robust.

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