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CHASING AFTER THE FRONTIER IN AGRICULTURAL PRODUCTIVITY

Jules-Daniel WURLOD, Derek EATON

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Abstract

This paper explores international productivity patterns in agriculture. We test whether countries higher productivity growth has been experienced by countries that were initially further from the technological frontier. Based on a panel of 84 countries at various levels of development, we find support for convergence among OECD countries but divergence in our sample at large over the period 1960-2010. We then test whether technological catch-up is conditional on absorptive capacities and domestic investments in R&D. While agricultural research intensity has a significant effect on labor productivity growth, the size of this effect decreases the further the country is from the frontier. We calculate a threshold level for the effectiveness of research intensity: increased R&D contributes to catching up to the frontier for those countries with a distance to the frontier less than 22. We also test for additional factors affecting productivity growth, and find that secondary education plays a strong role in less developed countries, while trade openness appears to have had a positive effect on productivity in middle income countries. On the other hand, there is little evidence of much effect, either positive or negative from IPR protection. Of perhaps greater interest is the apparent impact of economic growth outside of agriculture in driving agricultural productivity improvements.

Keywords: agriculture, productivity, convergence, R&D, IPR, education.

JEL classification: O13, O33, Q11, Q16, Q18.

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1 Introduction

Productivity growth in agriculture has recently been of renewed concern from a food security perspective. First, while productivity growth has historically been high in developing nations since World War II, the rate of increase of productivity improvements appears to have slowed while demand for food and agricultural products is expected to continue growing (Pardey et al., 2013, 2014). Secondly, sustainability concerns imply that agricultural production needs to be increased on existing agricultural lands, to halt further conversion of natural lands. Thirdly, episodes of food price volatility in the first decade of this century posed challenges to how developing economies dependent on food imports can ensure affordable access to foodstuffs. Maintaining and enhancing productivity growth in agriculture, particularly among countries that are currently much less productive, is therefore an urgent policy matter (Alston and Pardey, 2014).

There are two sources of productivity growth: technical change, or movement of the technology frontier, and a catch-up effect, or efficiency change, whenever countries are moving closer to the frontier. A longstanding conjecture in growth theory is that countries with less productive technologies can catch-up with frontier countries by leapfrogging on early stages of technological development, affording them with higher productivity growth (important contributions include Gerschenkron, 1962; Barro and Sala-i Martin, 1997; Howitt, 2000; Acemoglu and Zilibotti, 2001). Furthermore, simply by assuming some form of public good nature of knowledge, productivity convergence becomes a natural outcome, with economies further behind the frontier tending to grow faster (Fare et al., 1994; Abramovitz, 1990). However, technology diffusion might not be automatic, and there might also be conditions necessary in order to benefit from the advantage of 'backwardness'. Nelson and Phelps (1966), and more recently Benhabib and Spiegel (1994) and Islam et al. (2014), have highlighted that absorptive capacities, determined primarily by human capital, might be a condition for the transfer of technologies. This is distinct from the primary role of human capital in technological change that is acknowledged in modern endogenous growth models (see for example Howitt, 2000; Acemoglu and Zilibotti, 2001).

As emphasized by Pardey et al. (2010), the agricultural sector presents specific characteristics and circumstances that could impact the likelihood of technology diffusion to less productive economies. First, production units in agriculture are generally quite numerous and atomistic, which can slow or complicate the process of technology adoption in primary production, particularly for multi-faceted technologies combining a range of inputs with tacit knowledge. Second, uncontrolled factors, such as agricultural pests, and changing weather and climatic conditions, require investments in maintenance research to prevent the erosion of past productivity gains. More importantly, technologies developed in a given agro-ecological and socioeconomic context may not necessarily suitable in others without some form of adaptation (Eberhardt and Teal, 2012). This could imply that technology transfer in agriculture is conditional on domestic R&D investments to adapt inputs (e.g. seeds, machinery, chemicals) and production techniques to local specificities (Pardey et al., 2010).

In terms of empirics, several studies have tested the convergence hypothesis for total factor productivity (TFP) in agriculture. Martin and Mitra (2001) found that technology catch-up occurs faster in agriculture than in the manufacturing sector, using a sample of 50 countries at different stages of development from 1967 to 1992. In contrast Suhariyanto and Thirtle (2001) find no evidence of convergence in agriculture among 18 Asian countries over the period 1965-1996. Schimmelpfennig and Thirtle (1999), as well as Rezitis (2010), find mixed evidence of productivity convergence in agriculture between the United States and European countries using time series tests. Rao and Coelli (2004) and Coelli and Rao (2005) have shown partial evidence of TFP convergence: countries that were less efficient in 1980 have a higher TFP growth rate than countries that were at the frontier in 1980, and conclude that these results indicate both a degree of catch-up due to improved technical efficiency along with technical change at the frontier. Ludena et al. (2007) have found that the frontier in agriculture advanced more rapidly over 1960–1970s than individual TFP, thereby leading to divergence, or negative technical efficiency growth, but convergence, or catching up to frontier, in the 1980–1990s.

More recent evidence, such as that of Fuglie et al. (2012), points towards robust but highly uneven productivity growth in agriculture across countries. One argument for these differences might be investments in research and development. Although the empirical literature on the benefits from R&D at the macro level is limited and fragmentary (Pingali and Heisey, 1999), evidence seems to point towards a statistically significant impact (for example Pardey and Beintema, 2001; Alene, 2010; Fuglie et al., 2012), though much smaller than suggested by the micro 'case-study' literature.[1] Other authors come to less equivocal conclusions. Wang et al. (2013) find that R&D

[1] The rates of return of R&D measured in the micro case-study literature can be very skewed, but are usually high: the mean and the mode of all studies combined are respectively 81 and 44 percent (Alston et al., 2000). The micro literature on the impact of R&D and innovation on agricultural productivity emerged in the 1960's. The first paper to add R&D in a production function approach to measure its impact on productivity is Griliches (1964). Since then, numerous contributions have been made – around 300 studies – a third published in peer-reviewed journals (see Alston, 2010, for a complete review of these studies). In all cases, heterogeneity in estimates on the productivity effect of R&D can be caused by modeling challenges, arising because benefits are spread both across economic agents and through time. These are identified in the literature as 'temporal' and 'spatial' attribution problems (Alston, 2010). Temporal attribution problems are caused by the time lag between costs and benefits, a sum of the 'gestation' or 'invention' lag (the time required to develop new technologies), and the 'adoption' lag, the time required for the technology to reach

affects agricultural productivity only over the long term, as only research stocks, or accumulation of several years of expenditure, have a statistically significant impact on agricultural TFP growth. In a study including both absorptive capacities (education/extension) and capacities of scientists to innovate and adapt foreign technologies in a single econometric framework, Evenson and Fuglie (2010) find that marginal increases in technology capital, given minimum levels of education and/or extension, have an impact on productivity growth. On the other hand, marginal increases in education and/or extension, even given miminum levels of technology capital, do not seem to have much impact.

One contribution of our paper is to re-examine the convergence hypothesis (as formulated by Nelson and Phelps (1966) and Howitt (2000)) in the case of the agricultural sector over a longer timeframe and using panel data techniques. We use the cross-country dataset of inputs, outputs and productivity measures over 1960-2010 developed by Fuglie (2012), starting from FAOSTAT but with adjustments for differences in input quality. After first testing whether the unconditional convergence hypotheses holds for the agricultural sector, we test whether convergence occurs conditional on investments in R&D and on absorptive capacities. We combine data on R&D expenses for both OECD and developing countries from various sources, and follow an empirical framework and specification recently suggested by Madsen et al. (2010) for aggregate productivity growth (including manufacturing and services). In contrast with Evenson and Fuglie (2010), who use two discrete composite indexes of invention-innovation and technology mastery, we use a continuous variable for R&D expenditure, as well as for education. There are advantages and disadvantages to each approach which should probably be viewed as complementary to each other. Our approach allows us to assess the effects of marginal changes in R&D and other variables, without making assumptions about thresholds or cutoffs. But the dataset is not large enough to allow us to explore such features with, for example, semiparametric techniques. The panel data approach does allow us to control for country-specific unobservable factors through the inclusion of country fixed effects, so far absent in most of the studies measuring productivity growth rates in agriculture (see for example Headey et al., 2010). We also consider the issue of temporal attribution problems by varying the number of lags in our estimates.

Our results suggest that research intensity has a positive impact on productivity growth in all income groups, with the exception of LDCs. Furthermore, we find that the observed effect is lower the further a country is behind the technological frontier. In other words, R&D seems to

farmers in the field (Pardey et al., 2010). The spatial attribution problem is due to the non-excludable and non-rival nature of technology, as the number of agents benefitting from technological improvements can be large, making it harder to identify the range and to account for other factors. (Alston, 2010).

be more effective in more productive countries, in contrast with the general predictions from the macroeconomic literature on productivity convergence. Overall, our findings suggest a more nuanced picture of the productivity impacts of R&D than usually found in the literature (for example in Pardey et al., 2013). We do not conclude that R&D necessarily should be less effective but offer possible explanations for this observed result in our discussion. In addition, our estimates of the impact of education are also differentiated by income level: education appears to be more important for enhancing agricultural productivity growth in less developed countries than for lower and upper middle income countries (UMI/LMI).

In a second step, in light of the findings of heterogeneity across countries and income groups, we test for additional determinants of productivity growth by sequentially incorporating various regressors in a fixed effects model, building on the earlier work of Headey et al. (2010).[2] We include policy and institutional factors found to affect productivity growth in the literature. Specifically, we measure the impact of 1) trade openness, as in Madsen et al. (2010): increased trade openness is expected to facilitate the inflow of foreign technologies; 2) intellectual property rights, which can stimulate or hinder technological change and diffusion (Evenson and Swanson, 2010); 3) rural infrastructure and road density, potentially reducing transport costs and supporting market integration; 4) support to the agricultural sector, which can distort relative prices and stimulates less efficient use of resources (Headey et al., 2010); 5) growth in non-agricultural sectors, elaborating on recent findings by Lagakos and Waugh (2013) and Gollin et al. (2014) and 6) civil conflicts, considering that many country/periods exhibit negative productivity growth rates. We find that trade openness, IPR protection and economic growth in the non-agricultural sector have a statistically significant positive impact on productivity growth, and that these impacts seem stronger for middle income countries than in LDCs. Civil conflicts are also found to have a negative impact on productivity growth.

Our paper is structured as follows. In the next section, we describe the dataset used in our study. Section 3 and 4 present some descriptive statistics on global patterns of productivity and research intensity, while Section 5 describes our empirical specification. Sections 6 and 7 present our main results, and Section 8 concludes.

[2] A major difference though is that we use the productivity estimates of Fuglie (2012).

2 Data Sources

Data on inputs and outputs are from Fuglie (2012), published by the Economic Research Service of the U.S. Department of Agriculture. This dataset includes yearly estimates of all major input categories – labor, area harvested, machinery, fertilizers, livestock input and animal feed consumption – for 170 countries at all income levels, from 1961 to 2010. The data originates from FAOSTAT, and in some cases, is supplemented with data from national statistical sources. A major advantage of this dataset is that some attempts are made to correct measures of various inputs for differences in quality, which greatly improve productivity measurement (Craig et al., 1997). In the case of land, for example, estimates are weighted by irrigation type, i.e. whether agricultural land is rainfed, irrigated or used for pasture.[3]

In this paper, we choose to focus on labor productivity. First, because recent contributions in the literature has shown that the measurement of cross-country TFP in agriculture presents challenges in generating robust and plausible estimates in levels for cross-country comparisons (Alston and Pardey, 2014), and that estimates of Total Factor Productivity (TFP) growth rates can vary greatly with the methodology used. To illustrate this, Figure A1 in the Annex plots the estimates for annual TFP growth rates from three major studies: Fuglie et al. (2012), Headey et al. (2010) and Coelli and Rao (2005). Each study uses a different methodology to estimate TFP growth. Fuglie et al. (2012) use a Solow decomposition method, Headey et al. (2010) use both a stochastic frontier approach (SFA) and a data envelopment analysis (DEA), while Coelli and Rao (2005) use a Malmquist index.[4] In Figure A1, each point off the 45 degree line indicates a difference between the TFP growth rates calculated by each study, for a given country in a given period.[5] We see

[3]Our measures of inputs include: Labor: number of economically active persons in agriculture; livestock: number of cattle-equivalent head of livestock on farms; machinery: number of 40-CV tractor-equivalent machinery units in use; fertilizers: Sum of N, P2O5, and K2O fertilizers in tons of 'N-fertilizer equivalents'; animal feed consumption: Metric energy-equivalents (1000 Mcal)

[4]From a methodological point of view, these are the 3 different families of models prevalent in the literature. Each of those methodologies have pros and cons. DEA consists in a linear optimization of combinations of inputs and outputs, with the advantage to remain a non-parametric approach, making results less sensitive to choices of functional forms. SFA models allow to account for the stochastic nature of production that can be caused by statistical noise, distinguishing between efficiency and the error term, but needs assumptions on a function functional form for production, such as Cobb-Douglas or the more general translog production function, and needs assumptions on the distribution of the inefficiency parameters. Residual Approaches specify a production function and simply regress the value of output on the different inputs. This approach suffers the same caveat as DEA methods, imputing distance from the production frontier strictly to differences in efficiency, without considering the stochastic dimension of agricultural production, and also needs an assumption on the functional form of the production function.

[5]Due to data aggregation issues, we can only compare studies providing growth rates for similar periods. Furthermore, we need to aggregate annual growth rates into rates by decade. To this end, because the aggregation method chosen might create self-generated differences, we use two alternative approaches. First, a simple arithmetic mean of annual growth rates over the period under consideration. This methodology was chosen by Headey et al. (2010) to aggregate growth rates by decade. Second, we use a regression approach to estimate the growth rates out of the TFP levels provided by the authors. The TFP growth rate over the period will be equal to the coefficient on a time trend

that the assessment of TFP growth rates in agriculture is not necessarily consistent across studies, leaving significant room for improvement in further research, confirming the argument made by Alston and Pardey (2014).

It is known that partial productivity measures have important shortcomings as proxies for productivity. Using partial productivity measures at face value does not account for input substitution (Capalbo and Antle, 1988). For example, if increased output per worker is obtained by an increase in land use, despite the apparent impact on our partial productivity measure, TFP would remain unchanged (Ludena et al., 2007). Although recent studies have shown that labor productivity and TFP growth tend to follow a similar pattern (see for example Madsen and Timol, 2011), we control for input substitution by including other available inputs as control variables in all our specifications, as in Dowrick and Nguyen (1989).

Our dataset for Research and Development comes from various sources. First, for developing countries, we compile data from the Agricultural Science and Technology Indicators (ASTI) by IFPRI, covering most low and middle income countries. To recover estimates of R&D expenditure for previous periods, we rely on data from the ISNAR Agricultural Research Indicators Series, edited by Pardey and Roseboom (1989), providing data on R&D expenditure based on surveys for the period 1960–1986. For OECD countries, our main data source comes from Pardey et al. (1997) for 1981 to 1993. For more recent periods, we complement our dataset with estimates from OECD Stat, who provide gross domestic expenditure on R&D by sector of performance. Following the literature (see for example Beintema and Stads, 2006), R&D expenses are normalized to account for differences in the size of the agricultural sector. Because our production data does not provide directly usable estimates of value added, we normalize our R&D figures by estimates of value added by the World Development Indicators (WDI) of the World Bank. To measure education, we use the Barro and Lee index of the average number of years of schooling of the population over 25 years old (Barro and Lee, 2013). Section 7 requires additional data. The real rate of assistance (RRA) data come from the "Database of Global Distortions to Agricultural Incentives" from Anderson and Valenzuela (2008). Trade openness is measured as the sum of imports and exports over GDP from WDI. Intellectual property rights data come from Ginarte and Park (Ginarte and Park, 1997). Economic growth in the non-agricultural sectors are proxied by two variables. First the non-agricultural GDP, calculated from agricultural and total GDP from WDI, and second the percentage of rural population not employed in agriculture from FAOSTAT. Our road density net-

variable generated simply by regressing TFP levels on a constant and a time trend. For brevity purposes, only the results using the arithmetic method are presented in the Annex, as results are not very sensitive to the aggregation method

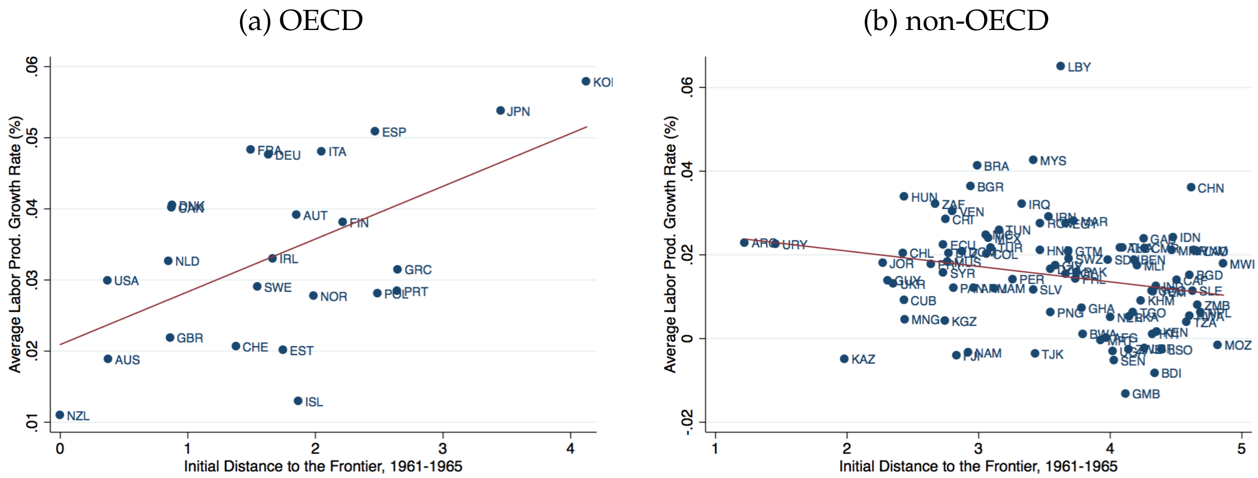


Figure 1: Labor Productivity Convergence

work estimates are borrowed from Calderon and Serven (2004). Finally, data for armed conflicts come from UCPD (Gleditsch et al., 2002). We select only high intensity conflicts, i.e. conflicts causing more than 1,000 deaths cumulatively.

3 Productivity Convergence

Figure 1 plots the initial distance to the frontier with the average productivity growth rate throughout the rest of the sample period, for OECD and non-OECD income groups.[6] Important differences are evident. There seems to be convergence among OECD countries, where initially less productive countries tend to grow faster, while this does not seem to be the case for non-OECD countries. In other words, technology advances at the frontier seem to diffuse among OECD countries, but not to all countries in our sample. Figure 2 shows Box-whisker plots of the distribution of distance to the frontier, by income level and through time. This allows to test the findings of Ludena et al. (2007), who find divergence in TFP during the 1960s – 1970s and convergence during the 1980s–1990s, as well as to differentiate between income groups. In case of convergence, the average distance to the frontier should decrease through time. As can be seen, the average distance to the frontier decreased in the 1960s and 1970s for all income groups but LDCs, but, since the 1980s, it increased for all income groups but the OECD, suggesting that the agricultural sector in middle- and low-income economies is lagging behind, with productivity growth rates below those at the technological frontier. Figure 3 shows average productivity growth rates by income level

[6]Income groups are defined using the World Bank definition for the year 1961. The list of countries and income groups can be found in Table A1 in the Annex.

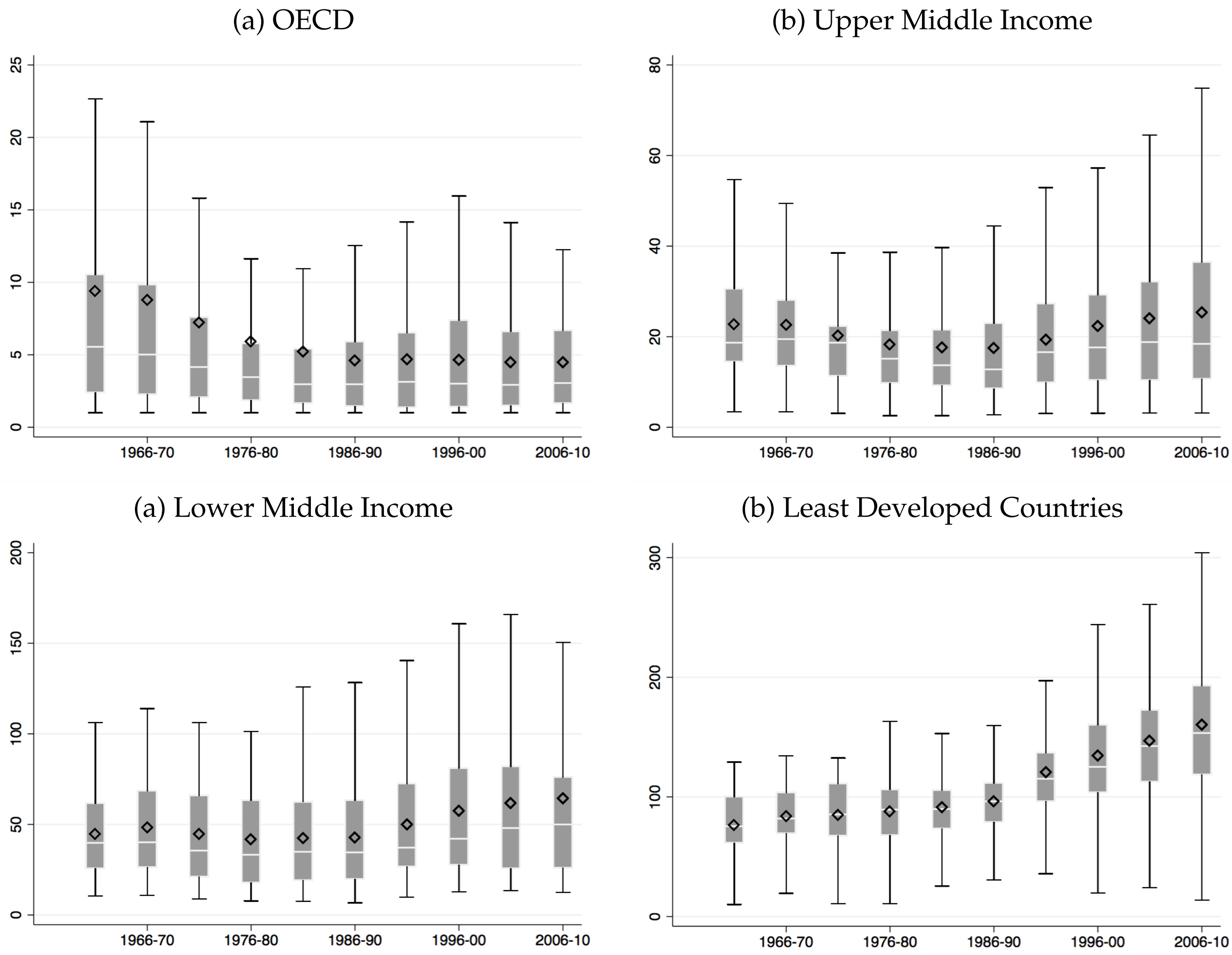


Figure 2: Distance to the Frontier by period (1961-2010) and income level

through time, and also suggests that the gap in productivity across income levels keeps widening, as the average growth rate in labor productivity is higher for higher income groups. This tendency seems to be weaker in the most recent periods in the sample, where productivity growth rates seem to converge. However, convergence in growth rates does not imply convergence in levels, which would require a sustainably higher growth rates for less productive countries.

To test the convergence hypothesis formally, we follow Bernard and Jones (1996) and run a simple regression of the average growth rate of labor productivity on a constant, the initial distance to the frontier, and the growth rate of other inputs as control variables:

$$\frac{\dot{A}_{it}}{A_{it}} = \alpha + \beta \left(\frac{A_{it0}^{MAX}}{A_{it0}} \right) + \gamma C_{it} + \epsilon_{it} \qquad (1)$$

We vary the initial period, as estimates are sensitive to the choice of initial period. Table 1

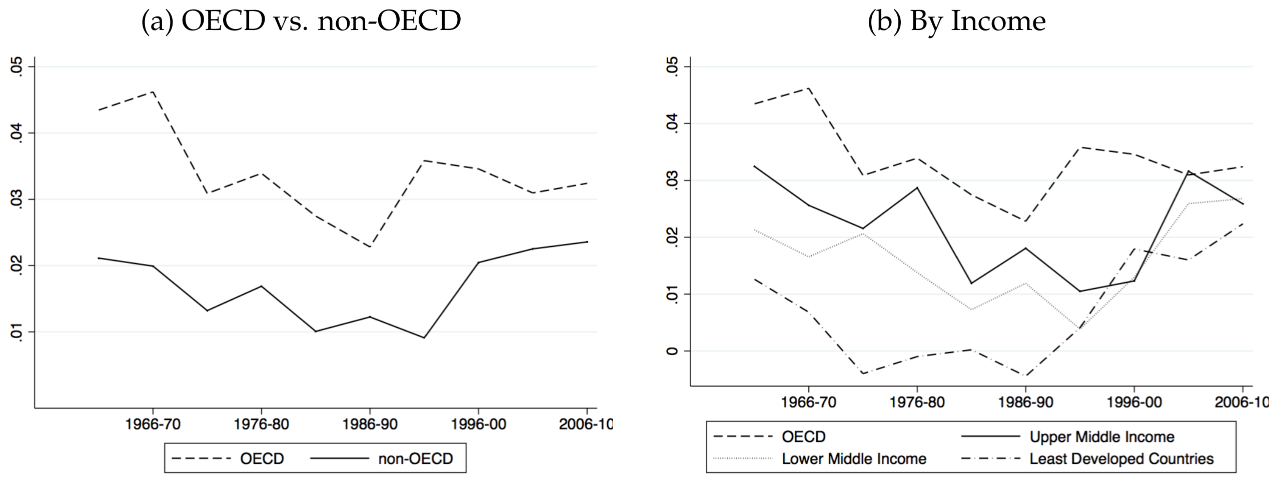


Figure 3: Average Labor Productivity Growth

shows the estimated coefficients. Results confirm the patterns suggested graphically. For OECD countries, the initial distance to the frontier is positively correlated with the growth rate in subsequent periods. However, when considering other income groups, or our sample as a whole, there seems to be evidence of divergence in productivity. Overall, this section has shown that our data does not seem to exhibit strong sign of convergence in productivity when taking our sample as a whole, a result in contrast with the findings of Martin and Mitra (2001), Rao and Coelli (2004) and Coelli and Rao (2005). The remaining of this study aims at measuring causes for (the absence of) convergence for some income groups.

Table 1: Labor Productivity Convergence

	(1a) 1961-65	(1b) 1966-70	(2a) 1961-65	(2b) 1966-70	(3a) 1961-65	(3b) 1966-70	(4a) 1961-65	(4b) 1966-70	(5a) 1961-65	(5b) 1966-70
	Full sample		OECD		non-OECD		UMI/LMI		LDCs	
DTF_{it0}	-0.00681***	-0.00678***	0.0115***	0.0112**	-0.00613***	-0.00595***	-0.00288	-0.00445*	-0.00517	-0.00541
	(0.000)	(0.000)	(0.002)	(0.037)	(0.001)	(0.001)	(0.284)	(0.086)	(0.375)	(0.310)
Landg	-0.208	-0.207	0.865*	0.699	-0.194	-0.207	-0.0120	-0.0529	0.336	0.249
	(0.183)	(0.166)	(0.071)	(0.215)	(0.226)	(0.182)	(0.953)	(0.792)	(0.205)	(0.379)
Fertg	0.00568	0.0244	0.154	0.0985	0.0295	0.0538	0.0541	0.105**	0.0182	0.0281
	(0.867)	(0.495)	(0.220)	(0.479)	(0.397)	(0.159)	(0.167)	(0.042)	(0.720)	(0.574)
Machg	0.193***	0.219***	-0.187	-0.138	0.153**	0.157**	0.0906	0.0786	0.0541	0.0857
	(0.000)	(0.000)	(0.104)	(0.415)	(0.012)	(0.011)	(0.248)	(0.334)	(0.491)	(0.331)
Liveg	0.188*	0.169	0.883***	0.746*	0.190*	0.176	-0.0155	0.0977	0.196	0.276
	(0.077)	(0.122)	(0.003)	(0.053)	(0.082)	(0.127)	(0.917)	(0.560)	(0.381)	(0.182)
Feedg	-0.0248	-0.0434	-0.367**	-0.300	0.00471	-0.0201	0.0601	0.0551	-0.0241	-0.0233
	(0.664)	(0.459)	(0.028)	(0.158)	(0.935)	(0.740)	(0.411)	(0.466)	(0.754)	(0.799)
Countries	124	124	24	24	100	100	61	61	28	28

Notes: *Dependent variable: Average labor prod growth, 1966-2010 for spec. (a) and 1971-2010 for spec. (b). p-values in parentheses: $p^{***}\leq 0.01$, $p^{**}\leq 0.05$, $p^{*}\leq 0.1$*

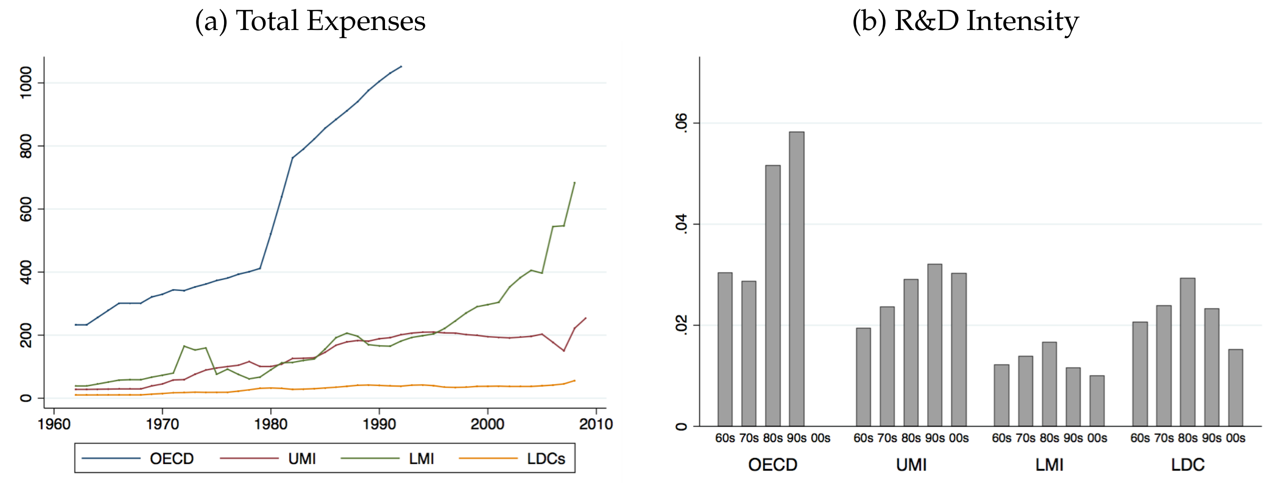


Figure 4: R&D expenses and intensity, by income group, 1960–2010

Notes: Total expenses are in Mill. 2005 PPP $ and presented in 3-year moving average. R&D intensity is defined as total expenses over agricultural GDP. Data for OECD countries for 1990–2010 available only for a subset of countries, and are therefore not presented to keep the sample unchanged

4 Research and Development

This section describes R&D expenses – both public and private – across countries and time.[7] FIgure 4 shows R&D expenses and research intensity, as defined by total expenses over agricultural GDP, averaged by income group. As can be seen, OECD countries still account for the major share of world expenses in agricultural research and development. The average expenses for middle income countries increased since the early 2000s, mostly pulled by China and India, to an average annual of 600 million 2005 PPP $ per country. As a share of agricultural GDP, OECD countries are still leading, with annual expenses reaching almost 6% of GDP in the 90s. On average, countries invest between 1–6% of agricultural GDP in research and development.[8]

Figure 5 shows Box-Whisker plots of intensities by decade and by income group. Furthermore, even if the spread of observations is relatively high, the average intensity remains highest for OECD countries. Furthermore, the average intensity in lower-middle income and low income countries tends to decrease since 1990, whereas numbers for higher income groups tends to remain stable or increase.

Table 2 shows the most and least productive countries, by period subsample, with their cor-

[7]For more comprehensive studies on patterns of R&D spendings, refer to Pardey et al. (2013), Beintema and Stads (2006) or Pardey et al. (2006).

[8]These figures are slightly higher than intensities reported in the literature, for example, in James et al. (2008). However, our dataset also includes private R&D spending, which accounts for almost half of total spendings in recent periods in high income countries (Pardey et al., 2006)

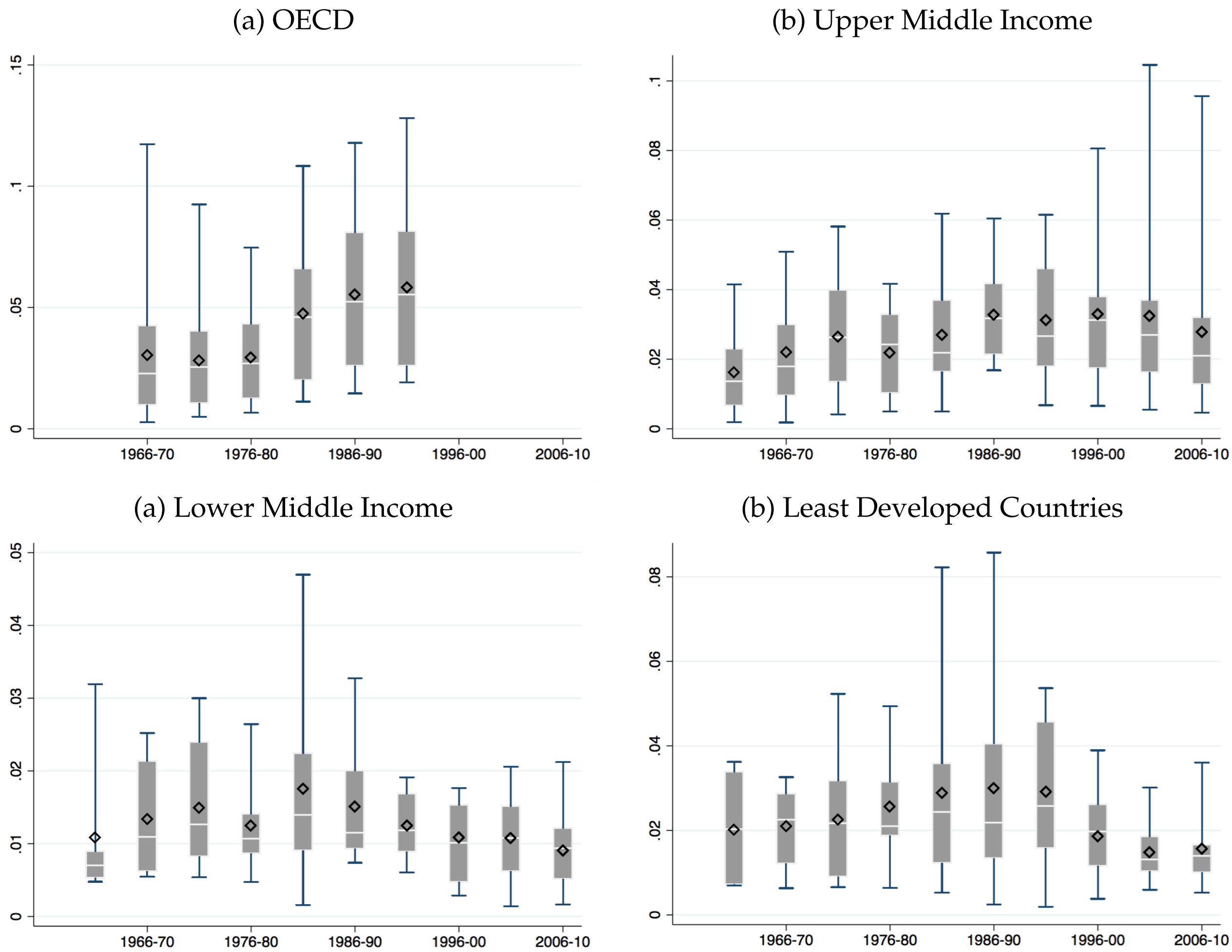


Figure 5: R&D expenses and intensity, by income group, 1960–2010

Notes: Total expenses are in Mill. 2005 PPP $ and presented in 3-year moving average. R&D intensity is defined as total expenses over agricultural GDP

responding growth rate in productivity and their R&D expenses. From 1961 to 1980, the most productive country was New Zealand, a country well endowed in land. Since 1980, the most productive country is the US. The sample of most productive countries includes a range of countries who all belong to the OECD income group.

On the other side of the spectrum, least productive countries are mostly SSA countries, but also Vietnam during the war, Cambodia and Nepal. For these countries, the productivity growth rates are on average lower than growth rates at the frontier, in contrast with predictions from the convergence literature. Many countries/periods also present negative productivity growth.

One advantage of our dataset is to allow for a continuous measure of R&D expenses and intensities. In contrast with Evenson and Fuglie (2010), who use a categorical variable for both

R&D expenses and education level, we do not need to determine arbitrarily discrete thresholds that we expect to be associated with higher productivity growth. However, this also comes at a cost, as many observations can be missing for some countries/periods. Particular attention thus needs to be paid to the size of the sample for each regression.

Table 2: Avg. prod. growth, R&D expenses by productivity level

Period		Frontier	Prod. growth (%)	R&D exp.	Least productive	Prod. growth (%)	R&D exp.
1961-1965	1	New Zealand	2.7	64	Zambia	1.1	N/A
	2	United States	4.3	1730	Nepal	0.0	6.8
	3	Australia	4.6	229	Mozambique	0.6	12.3
	4	Netherlands	4.5	148	Malawi	2.1	4.5
1966-1970	1	New Zealand	2.8	93	Vietnam	0.5	N/A
	2	United States	5.2	2186	Nepal	0.4	6.8
	3	Australia	3.3	332	Mozambique	2.1	13.1
	4	Netherlands	8.1	260	Malawi	1.9	5.2
1971-1975	1	New Zealand	-1.4	174	Malawi	1.9	6.1
	2	United States	1.8	2169	Vietnam	-0.2	N/A
	3	Australia	2.2	382	Nepal	0.7	18.5
	4	Netherlands	3.4	267	Mozambique	-2.6	14.4
1976-1980	1	New Zealand	1.1	185	Lao PDR	4.3	N/A
	2	United States	2.1	2522	Nepal	0.1	24.7
	3	Australia	1.1	436	Mozambique	-4.0	N/A
	4	Netherlands	4.2	333	Cambodia	2.9	N/A
1981-1985	1	United States	0.9	5332	Malawi	-0.4	29.4
	2	New Zealand	-0.7	227	Zambia	-0.9	30.3
	3	Netherlands	2.9	645	Cambodia	3.5	N/A
	4	Australia	1.1	537	Mozambique	-2.9	N/A
1986-1990	1	United States	1.8	6359	Zambia	-0.1	27.4
	2	New Zealand	0.7	215	Malawi	-0.4	33.8
	3	Netherlands	-0.7	744	Gambia	-0.6	N/A
	4	Australia	0.9	599	Mozambique	0.2	N/A
1991-1995	1	United States	4.2	7062	Zambia	0.0	21.0
	2	Canada	5.9	918	Malawi	2.9	23.7
	3	Denmark	5.7	172	Gambia	-0.4	5.0
	4	Australia	3.6	705	Mozambique	2.1	N/A
1996-2000	1	United States	2.9	N/A	Tanzania	1.4	38.0
	2	Canada	3.4	N/A	Zambia	0.8	20.7
	3	Denmark	4.6	N/A	Mozambique	2.0	N/A
	4	Australia	3.5	N/A	Gambia	5.4	3.2
2001-2005	1	United States	3.4	N/A	Senegal	-1.5	25.4
	2	Denmark	4.1	N/A	Burundi	-1.5	6.0
	3	Canada	3.7	N/A	Mozambique	-0.3	19.9
	4	Australia	-1.3	N/A	Gambia	-1.8	2.4
2006-2010	1	United States	3.3	N/A	Lesotho	0.8	N/A
	2	Denmark	3.8	N/A	Burundi	-1.2	10.0
	3	Canada	2.1	N/A	Mozambique	1.0	18.5
	4	France	4.4	N/A	Gambia	4.8	2.9

Notes: R&D Expenditure is in Mill. 2005 PPP $. N/A are missing observations. Frontier countries and Least productive countries are resp. the 4 most and least productive countries in each sample period

5 Empirical Framework

Following Madsen et al. (2010), our empirical framework combines two broad streams of the literature on conditional convergence. First, it elaborates on the hypothesis by Nelson and Phelps (1966), where convergence occurs conditional on absorptive capacities measured by the education level. In this framework, the relationship between the growth rate of productivity and educational attainment is given by:

$$\frac{\dot{A}_{it}}{A_{it}} = \beta SCH_{it}\left(\frac{A^{MAX}_{it-1}}{A_{it-1}}\right) \tag{2}$$

Where $\frac{A^{MAX}}{A_i}$ is the distance of country i from the frontier, i.e. the technology gap. In this equation, the further a country is from the frontier, the higher its growth rate will be in the next period, provided it has an adequate level of absorptive capacities to benefit from the advantage of backwardness (Gerschenkron, 1962). The rationale is that a more educated labor force will be more able to absorb and master foreign technology. Second, we also include the hypothesis formulated by Howitt (2000), where research intensity and its interaction with distance to the frontier will be a driver of productivity growth. To test this hypothesis, Griffith et al. (2003) suggest an empirical specification as follows:

$$\frac{\dot{A}_{it}}{A_{it}} = \alpha\frac{RD_{it-1}}{AgGDP_{it-1}} + \beta\frac{A^{MAX}_{it-1}}{A_{it-1}} + \gamma\left(\frac{RD_{it-1}}{AgGDP_{it-1}}\right)\left(\frac{A^{MAX}_{it-1}}{A_{it-1}}\right) \tag{3}$$

This equation suggests that R&D in countries off the frontier does not only stimulate productivity growth per se, but also facilitates the adoption of foreign technologies. Combining both hypotheses yields (Madsen et al., 2010):

$$\begin{aligned}\frac{\dot{A}_{it}}{A_{it}} &= \alpha_i + \beta_1\frac{A^{MAX}_{it-1}}{A_{it-1}} + \beta_2\frac{RD_{it-1}}{AgGDP_{it-1}} + \beta_3\left(\frac{RD_{it-1}}{AgGDP_{it-1}}\right)\left(\frac{A^{MAX}_{it-1}}{A_{it-1}}\right) + \beta_4 SCH_{it}\\ &+ \beta_5\left(SCH_{it}\right)\left(\frac{A^{MAX}_{it-1}}{A_{it-1}}\right) + \gamma C_{it} + \epsilon_{it}\end{aligned} \tag{4}$$

Where C_{it} is a vector of control variables. The first set of control variables is directly required by the use of a partial productivity measure, and thus includes the growth rate of other inputs – land, fertilizers, machinery, livestock, feed for cattle. Second, we also include a measure of trade openness. In addition to being potentially correlated with institutional characteristics favoring entrepreneurship, and to foster the equalization of prices by reducing the friction with international markets, this variable also captures the potential to acquire knowledge embedded in imported goods (Madsen et al., 2009).

6 Regression Results

This section presents the results of the fixed effects estimation of the conditional convergence equation (4) in Section 5, with Table 3 showing estimates for all countries and then three different subsamples: OECD countries, middle-income countries (both upper and lower) and less developed countries (LDCs). The difference with the results in Table 1 are clear. The estimated coefficients on distance to the frontier (DTF) are statistically significant and positive for both the entire sample as well as the UMI/LMI subsample of developing countries. This finding, in line with the results of Griffith et al. (2003), Kneller (2005), Kneller and Stevens (2006), and Madsen (2007, 2008) for the manufacturing sector, suggests that conditional on both the level of research intensity and educational attainment, when productivity increases at the frontier in one period, off-frontier countries will grow faster in the next period. In other words, labor productivity growth seems to occur as a result of autonomous transfer of foreign technology in developing countries, irrespective of investments in R&D and the education level. This effect is not observed though for the LDCs, taken as a subsample, suggesting that there may be further barriers or impediments to the use of foreign technology. At the same time the sample size is also considerably reduced for this group (19 countries with an average of 6 out of the 10 five-year time periods).

Table 3: Panel Regressions of Labor Productivity Growth

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
	All countries (83)		OECD (21)		UMI/LMI (44)		LDCs (19)	
ln DTF_{it-1}	0.0379***	0.0358***	0.0174	0.0419	0.0543***	0.0594***	0.0217	0.0251
	(0.000)	(0.000)	(0.193)	(0.117)	(0.000)	(0.000)	(0.294)	(0.170)
$R\&D_{it-1}$	0.618***	0.563***	0.452**	0.438*	1.578**	1.487**	-4.247	-3.859
	(0.000)	(0.000)	(0.021)	(0.051)	(0.012)	(0.030)	(0.110)	(0.102)
(ln DTF x R&D)$_{it-1}$	-0.180***	-0.183***	-0.101	-0.126	-0.444***	-0.459**	0.825	0.755
	(0.000)	(0.000)	(0.366)	(0.386)	(0.006)	(0.014)	(0.146)	(0.133)
ln Sch_{it}		0.00649		0.0366		0.0137**		-0.0117*
		(0.137)		(0.148)		(0.029)		(0.065)
ln DTF_{it-1} x ln Sch_{it}		-0.00000748		-0.000272		-0.0000881		0.000190
		(0.921)		(0.455)		(0.370)		(0.117)
TOg_{it}	0.00786	0.00714	0.0369***	0.0321***	0.00871	0.00505	0.00257	0.00253
	(0.102)	(0.126)	(0.000)	(0.002)	(0.122)	(0.333)	(0.822)	(0.812)
$Landg_{it}$	0.216***	0.215***	0.1000	0.148	0.123*	0.130*	0.267***	0.282***
	(0.000)	(0.000)	(0.543)	(0.330)	(0.082)	(0.062)	(0.005)	(0.003)
$Fertg_{it}$	0.00309	0.00519	0.0310	0.0375	-0.00593	0.000614	0.00506	0.00433
	(0.587)	(0.369)	(0.611)	(0.549)	(0.703)	(0.971)	(0.373)	(0.451)
$Machg_{it}$	0.0173	0.0386**	0.138	0.172	0.0285	0.0530**	0.0322	0.0153
	(0.305)	(0.015)	(0.537)	(0.476)	(0.337)	(0.024)	(0.263)	(0.608)
$Liveg_{it}$	0.0944**	0.102**	-0.0411	0.000261	0.149***	0.161***	0.0685	0.0529
	(0.029)	(0.020)	(0.746)	(0.998)	(0.007)	(0.006)	(0.461)	(0.569)
$Feedg_{it}$	0.0470**	0.0499**	0.0193	0.00509	0.0166	0.0268	0.0938***	0.0955***
	(0.031)	(0.024)	(0.826)	(0.956)	(0.568)	(0.386)	(0.003)	(0.001)
Observations	454	454	110	110	244	244	97	97
Countries	83	83	19	19	44	44	19	19
R^2	0.54	0.55	0.51	0.54	0.49	0.52	0.62	0.64

Notes: Fixed effects regressions. Coefficients are reported with p-values in brackets, with robust standard errors. *,**, *** indicates significance at the 10%, 5%, and 1% levels.

The coefficient on agricultural research intensity (R&D) is positive and statistically significant for the whole sample and also for subsamples, with the exception of the LDCs. This suggests that R&D does have an impact on the growth rate of productivity, which is consistent with most of the empirical evidence found in the literature (see for example Pardey et al., 2013). The partial effect of R&D appears much stronger for middle-income countries than for OECD countries but it is necessary to take account of the interaction term with DTF as well, which provides a direct estimate of the impact of research intensity at different levels of technological development. In contrast with the macroeconomic literature on conditional convergence suggesting an advantage from "backwardness" (Gerschenkron, 1962), investments in R&D seem to have a lower impact the further a country is from the technological frontier, all else equal. In other words, R&D investments are more effective for more productive countries. Using the coefficient in specification (1a), we can calculate the partial effect of research intensity, and the break-even point in terms of DTF at which R&D starts to lose its impact on the growth rate of productivity. Given our coefficients, the impact of research intensity disappears when the distance to the frontier is greater than about 22, (25 when using only the UMI/LMI subsample).[9] These results suggest a more nuanced picture of the productivity impacts of R&D than usually found in the literature.

Various explanations can be suggested for the decreasing effectiveness of R&D as one is further from the frontier. One is that there might be some threshold level of R&D intensity necessary to see substantial effectiveness. Looking at Figure 4, it is clear that since the 1980s, the research intensity of OECD countries has been considerably higher than any of the developing countries, where this intensity has actually even declined in recent decades (for LMI countries and LDCs). This suggests an additional explanation related to the growth in private agricultural R&D in OECD countries, which accounts for most of the overall growth. The dataset does not capture private R&D for other groups of countries though this certainly much lower. It may therefore be the case that this private R&D has driven most of the advancement of the frontier, while public R&D has possibly been less effective. Although there is plenty of micro evidence of the returns to public agricultural research in some OECD economies, especially in the U.S. (as noted above), this evidence is less widespread for developing countries. Furthermore, concerns have been raised in the past about the effectiveness of public agricultural research and extension services in developing countries, from both efficiency and priority-setting perspectives (Kiers et al., 2008). Thus our results, in failing to find an overall positive effect from R&D across income groups, may reflect these various effects.

[9] The DTF in our sample averages approximately 6 for OECD countries, 21 for UMI, 50 for LMI and 108 for LDCs

One additional factor to consider is the introduction of modern biotechnology and, in particular, genetically modified (GM) crops, in a number of OECD countries in the 1990s. A considerable portion of the increase in R&D expenses in the U.S. and some other countries, especially by the private sector have led to the development of a range of GM crop varieties, with consequent increases in agricultural productivity. Regulatory regimes have differed though between countries and meant that this new technology has not diffused to the large majority of countries in the sample. This could be interpreted as also accounting for a seemingly perverse result on the impact of R&D. In particular, it makes it more difficult for countries to benefit from backwardness if they are constrained by regulations from using one of the predominant technologies moving the frontier forward. It is not possible to identify the extent of such an effect and it is important to recall that we are here looking at aggregate agricultural productivity. It is also worth recalling that some middle income countries in the sample, such as China, Argentina, and Brazil, have adopted a number of GM crops with consequent productivity benefits.

To address the potentially long gestation period inherent to the R&D process (Alston, 2010; Pardey et al., 2014), we also include 2 period-lags for R&D, suggesting that benefits are expected to occur within a 5-10 year time span. Although anecdotal evidence from the biotech technology suggest the time lag between the commercial release of a new technology and adoption occurs within 10-13 years, and accounting for the 10-20 years necessary for the production of knowledge to turn research input into output and regulatory approval could require a 20-30 years time lag. To test this, we also include estimates of 2 and 3 lags, 3 and 4 lags, and 4 and 5 lags (20-25 years) with results in the Appendix. However, the statistical significance of the impact or R&D on labor productivity growth disappears when considering more than 2-period lags. This could be due to the fact that most countries off the technology frontier invest in adaptive R&D, requiring a shorter knowledge production period. Also, regulatory issues might not be as important in many countries. But these additional lags also considerably reduce the number of observations in our sample, implying that the results should be interpreted with caution.

The coefficient for the education variable also suggests nuanced conclusions. The level of education in the country is often cited as a precondition for mastering technology (Evenson and Fuglie, 2010). More educated farmers may be more efficient managers and also more likely to adopt newer technologies. Our results suggest that increasing the proportion of the population with some amount of secondary schooling has a positive impact on productivity growth for upper middle income and lower middle income countries. While one might not expect to see an impact in OECD countries, it is noteworthy that the coefficient for education for the sub-sample of 19 least developed countries is negative (and significant at a 10 percent level). This might reflect a type of urban bias among such countries, assuming that the increases in access to secondary education might have benefitted primarily urban populations and that this is correlated with general policy bias against agriculture and rural areas (Kydd and Dorward, 2001).

Trade openness is included as a control as in Madsen et al. (2010). Greater trade openness can be expected to facilitate the inflow of foreign technologies, particularly through imports. In the agricultural sector, one can think of imports of various inputs such as farm machinery, agrochemicals, or plant seeds and animal genetic stock. Trade openness might also be a proxy for licensing and technology imported through increased foreign direct investment. The results indicate that overall trade openness is not related to agricultural productivity. It does appear to play a positive role though among the OECD countries, which have the highest level of productivity growth. In and of itself though, it does not appear to play a strong role among developing countries. It is important to note though that this is an aggregate measure of trade openness and it may not apply as much to agricultural goods for which tariff reduction has been much less than for manufactured goods.

Among the other inputs, the coefficient on land is significant and positive in developing countries, though not in OECD. It is important to recall that this variable accounts for differences between irrigated and non-irrigated land. Thus the results likely reflect the increase in irrigation among both middle income and least developed countries over this period.

7 Explaining Productivity Growth in Developing Countries

The results above of the conditional convergence analysis point to a number of unanswered questions concerning why productivity-enhancing technology fails to generally flow from advanced economies to developing countries. This section explores further potential causes for observed variation in the growth rates of productivity for developing countries. We now dispense with the Madsen et al. (2010) specification of technological diffusion, based on distance to the frontier, and sequentially incorporate various regressors in a simple fixed effects model to explain labor productivity growth. This approach builds on the work of Headey et al. (2010), and Evenson and Fuglie (2010), by using the updated Fuglie dataset and by controlling for unobserved hetereogeneity. The sequential progression of specifications is partly determined by data availability, which becomes quite limited for certain variables of interest.

We are primarily interested in institutional and policy factors that have been identified in the literature as important determinants of agricultural productivity growth through improvements in the efficiency of production using current technologies or the development and diffusion of new technologies. These include R&D, education, trade openness, intellectual property rights, infrastructure, support to the agricultural sector, growth in non-agricultural sectors, and the incidence of conflict. Results are presented for middle income countries and LDCs in Tables 4 and 5 respectively.

The education level of farmers is expected to influence their capacity or inclination to master new agricultural techniques (Evenson and Fuglie, 2010) and the mechanism is similar to its inclusion in the original Nelson-Phelps model. Data on education levels among farmers or even rural areas is limited. We therefore resort to using standard population-wide measures of education, specifically the proportion of the population that has some amount of secondary education (Barro and Lee, 2013). There is more variation in secondary education than in primary education, as the latter has become more widely available.[10]

Education appears to be more important for less developed countries than for lower and upper middle income countries (UMI/LMI). For the latter group, the coefficient on education is not significant for specifications including multiple explanatory variables. On the other hand, for LDCs, education remains significantly positive through all specifications, suggesting that it influences agricultural productivity particularly when both existing productivity and availability of education is lower. For less developed countries, the elasticity of productivity growth with respect to the proportion of the population benefitting from secondary education is approximately 0.5-0.6. Although the specification we use is different from Evenson and Fuglie (2010), our results are consistent.[11]

Trade openness (TO) still does not appear to play much of a role in productivity growth. Some specifications yield significant results for the coefficient on this variable but this is not generally robust to different configurations of explanatory variables. For example, for UMI/LMI countries this, statistical significance on the coefficient of trade openness disappears when we also control for R&D, non-agricultural growth or for the rate of assistance to agriculture and a similar result is seen in LDCs. This suggests that trade openness itself is not necessarily an important factor for agricultural productivity growth but that in other specifications, it may be correlated with and capturing the effects of general non-agricultural sector growth, discussed below.

[10] Evenson and Fuglie (2010) use the average years of schooling from Barro and Lee (2013). We found more significant results by using the proportion of the population with secondary schooling.

[11] The approach of Evenson and Fuglie does not though immediately distinguish between the effects of education from those of extension services as these are combined in a 'Technology Mastery' index.

Next, we reconsider the role of R&D together with intellectual property rights (IPRs) as a related institutional factor. The role of IPRs in stimulating or hindering technological change and diffusion has been the subject of considerable debate and some analysis (see for overviews Moser, 2013; Eaton and Graff, 2014; Evenson and Swanson, 2010). IPRs such as patents, plant variety rights, trademarks and trade secret protection, may stimulate innovation, by internalizing knowledge externalities, and may also stimulate technology transfer through imports, licensing and foreign direct investment. On the other hand IPRs might inhibit international technological diffusion where imitation is relatively easy, if their introduction and enforcement increases prices in countries where previously such technologies could be copied at little cost. Their importance in this regard, relative to other factors affecting innovation and diffusion of new technologies, appears mixed, varies by sectors and is clearly an empirical issue. In our analysis, we use lagged values of the Ginarte and Park index to reduce the chance of endogeneity and also to allow for improvements in this institutional variable to take effect. Any effects from policies or regulatory changes to extend IPRs or improve their enforceability cannot be expected to work instantaneously. Given the expected relationship between R&D and IPRs, we also include an interaction term.[12]

We find that R&D seems to have no effect on agricultural productivity growth in middle-income countries. At first this seems inconsistent with the findings from the convergence specifications. However the partial effect of R&D in the earlier analysis also needs to take account of the interaction term with the distance to frontier, which will yield estimates that are negative. In Table 5 the coefficient estimate on R&D for LDCs is significantly negative across all specifications in which it is included. The partial effect for R&D is not though statistically different from zero given the size and standard errors of the coefficient on the interaction between R&D and IPRs.

The results appear to indicate that IPRs have a somewhat positive effect on labor productivity growth for UMI/LMI countries but a negative effect in less developed countries. The first of these two findings would seem plausible and in line with the conclusions of others that IPRs are not likely to have much effect at low levels of economic development where other factors constitute more important constraints on innovation or adoption of existing technologies. Once a country has reached a certain level of economic development, then some of these other constraints, such as general education and technological capability among firms, may have been eased and IPRs can, for example, facilitate access to newer technologies. Similarly as the level of technological sophistication increases, technologies closer to the frontier, which are more likely to be protected

[12]The results with the interaction term are reported for LDCs only (see Table 5) as they were considerably different. In the case of middle income countries, the inclusion of the interaction term did not alter the results substantially and so these are not included in Table 4 in the interest of brevity.

by IPRs in other countries, may become more relevant or appropriate.

The significance of the coefficient on IPRs for middle income countries is however not robust across all specifications, and varies considerably in size, suggesting misspecification issues. The Ginarte and Park index, composed of five sub-indices, includes only a few dimensions that may be directly relevant for the agricultural sector. These include plant variety rights. It may be argued that general patent protection promotes the licensing and importing of a range of technologies in chemicals and machineries that can be relevant for agriculture. It is possible though that this IPR variable is correlated with and capturing the effects of other aspects that are favorable to technological diffusion and that are not captured in our regressions. One might be the overall regulatory environment and ease of investment and doing business. In particular, the Ginarte and Park index is likely to be correlated with the quality of the contracting environment.

The negative coefficient on IPRs for LDCs might at first suggest that the implementation of such regimes actually serves to restrict the unlicensed or unauthorized flow of foreign technologies into those countries. However once the interaction with R&D is taken into account, the total partial effect of IPRs is not statistically different from zero. Although the specification is clearly not satisfactory, we posit that the evidence is not pointing towards an important role for IPRs in promoting innovation and technology diffusion in LDCs, nor in middle income countries. It would be interesting to include other explanatory variables for aspects of the business and contracting environment that may be confounding the specific effects of IPRs. We were though unable to find such variables available for sufficient periods and leave this to future work.

Given the substantial number of observations with negative growth rates, especially in LDCs, it seems relevant to control for the incidence of civil or international conflict and its negative effects on agricultural production, as was done by Headey et al. (2010).[13] Whereas their analysis was essentially cross-sectional, our panel data approach estimates the effects of the onset of conflict on agricultural productivity. Furthermore we recognize the long-term effects that conflict is reputed to have on agricultural productivity by lagging this variable (C), which also helps reduce potential endogeneity concerns. We screen out low intensity conflicts and select only conflicts which caused more than 1,000 deaths cumulatively. Somewhat surprisingly the results are not as strong as might be expected. The significance of the conflict variable is not robust across specifications for UMI/LMI countries. For LDCs, its negative effect is significant (in the most complete specification), although the sample then consists of only 18 countries.

We also examine the effects of including nonagricultural productivity growth through two ad-

[13]See also Fulgitini and Perrin (1998).

ditional explanatory variables, the proportion of the rural population engaged in non-agricultural activities (Non-Ag Pop) and the growth in non-agricultural GDP (Non-Ag GDP). This has not generally been included in previous studies on agricultural productivity growth on which we build, but does have a longer tradition in the development economics literature, going back at least as far as the work of Lewis (1954), and the concept of surplus, underemployed labor in agriculture. Recently Gollin et al. (2014) have noted and examined how labor productivity is systematically higher in the nonagricultural sector than in agriculture, even after accounting for potential measurement errors in effective labor and in value added. Related literature has looked at the greater amount of cross-country variation in physical productivity in agriculture than in the nonagricultural sector (Caselli, 2005; Restuccia et al., 2008; Chanda and Dalgaard, 2008). Proposed explanations of this misallocation of labor across sectors include distortions that reduce farm size, low intermediate usage in agriculture (Restuccia et al., 2008), selection of lower-ability workers into agriculture (Lagakos and Waugh, 2013), and institutional frictions to labor mobility out of agriculture (Gollin et al., 2014).

Under any of these scenarios, one would expect nonetheless that growth in the nonagricultural economy would induce some labor reallocation and consequent productivity effects. Growth, and increases in labor productivity, in other sectors can increase their relative return to labor and wage rates, thus drawing labor out of agriculture and stimulating increases in productivity of labor use in agriculture. There may also be a demand-side effect operating through output markets, as nonagricultural growth increases the demand for final agricultural products.There is not sufficient data to distinguish between these two different effects. We see that nonagricultural growth has a significantly positive effect on agricultural productivity growth in middle income countries but not in LDCs. We interpret these results with caution however, as there is potentially also an element of reverse causality, with agricultural productivity growth releasing labor for use in other sectors. This push vs pull relationship between agricultural and nonagricultural sector growth has been the subject of considerable analysis and discussion in agricultural development literature (Gardner, 2005; Dorward, 2013). To try to reduce the potential for reverse causality, we also used lagged nonagricultural growth (results non shown), but this generally did not lead to significant coefficients. The relative importance of nonagricultural employment in rural areas also yields a significant coefficient estimate, though for reduced sample size. Thus even the development of the rural non-farm sector may play a role in driving agricultural labor productivity.

For UMI/LMI countries we also assess the importance of two other factors related to policy: infrastructure and agricultural support policy. Rural infrastructure, in particular roads, are expected to be important for supporting agricultural growth, by reducing transport costs and supporting market integration. The coefficient for the density of the road network (ROAD) is however not significant. It may be though that UMI/LMI countries already have achieved reasonable levels of infrastructural development, at least in terms of roads. The importance of roads may be stronger in LDCs. Unfortunately there is insufficient data available to assess this.

Protectionist agricultural policy is reflected by the real rate of assistance to agriculture (RRA) in terms of protection from world prices for farm output. Conventional theory posits that this support distorts relative prices and stimulates less efficient use of resources. The results presented do not find any evidence that an increase in such support affects agricultural productivity, though in some specifications we tried the coefficient was statistically significant and positive. The inclusion of RRA however reduces the sample size to only 24 countries. All the same the role of shielding producers from world markets may deserve further analysis. One conjecture could be that such measures are serving in part to reduce output price volatility facing farmers.

Table 4: Explaining Labor Productivity Growth

	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)	(1h)	(1i)
	UMI/LMI								
ln Sch_{it-1}	0.00685***	0.00760***	0.00200	0.00467	0.00467	0.00652	0.00708	0.00528	0.00828
	(0.002)	(0.001)	(0.415)	(0.302)	(0.303)	(0.101)	(0.102)	(0.488)	(0.110)
TOg_{it}		0.0117**	0.0129**	0.00844	0.00875	0.0105*	0.00122	0.0106*	0.00604
		(0.046)	(0.024)	(0.138)	(0.127)	(0.088)	(0.851)	(0.085)	(0.341)
IPR_{it-1}			0.00900***	0.00499**	0.00500**	0.00261	0.00225	0.00899*	0.00305
			(0.000)	(0.022)	(0.021)	(0.243)	(0.335)	(0.052)	(0.171)
$R\&D_{it-1}$				-0.152	-0.150	-0.0687	-0.107	-0.00377	-0.155
				(0.251)	(0.257)	(0.764)	(0.456)	(0.982)	(0.634)
C_{it-1}					-0.00279	-0.00538	-0.00247	-0.00319	-0.00517
					(0.500)	(0.266)	(0.509)	(0.503)	(0.348)
Non-Ag Pop_{it}						0.0520***			
						(0.007)			
Non-Ag GDP_{it}							0.134**		
							(0.021)		
$ROAD_{it-1}$								-0.00293	
								(0.615)	
RRA_{it-1}									0.00721
									(0.594)
$Landg_{it}$	0.162***	0.167***	0.176***	0.101	0.0989	0.0653	0.110*	0.137*	0.0854
	(0.006)	(0.004)	(0.010)	(0.113)	(0.126)	(0.429)	(0.079)	(0.098)	(0.268)
$Fertg_{it}$	0.0373**	0.0227	0.0117	0.00159	0.00143	0.00753	-0.00611	-0.0187	0.00706
	(0.023)	(0.113)	(0.453)	(0.926)	(0.933)	(0.665)	(0.711)	(0.403)	(0.694)
$Machg_{it}$	0.0476**	0.0494**	0.0470***	0.0574**	0.0571**	0.0533*	0.0607**	0.0445	0.0411
	(0.020)	(0.016)	(0.006)	(0.023)	(0.026)	(0.056)	(0.015)	(0.178)	(0.141)
$Liveg_{it}$	0.283***	0.242***	0.200***	0.185***	0.188***	0.212***	0.173***	0.195***	0.194***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
$Feedg_{it}$	0.0519**	0.0427**	0.0480**	0.0462	0.0468	0.0364	0.0440	0.0658*	0.0315
	(0.042)	(0.045)	(0.015)	(0.149)	(0.146)	(0.345)	(0.158)	(0.091)	(0.466)
Observations	525	467	405	246	246	145	240	191	139
Countries	61	61	50	45	45	24	44	38	24
R^2	0.23	0.26	0.27	0.32	0.31	0.41	0.34	0.33	0.37

Notes: Fixed effects regressions. Coefficients are reported with p-values in brackets, with robust standard errors. *,**, *** indicates significance at the 10%, 5%, and 1% levels.

Table 5: Explaining Labor Productivity Growth

	(1a)	(1b)	(1c)	(1d)	(1e)
			LDCs		
ln Sch_{it-1}	0.00597***	0.00605***	0.00808*	0.00859**	0.00964**
	(0.003)	(0.005)	(0.057)	(0.030)	(0.014)
TOg_{it}		0.0116**	0.0128	0.0149	0.0109
		(0.045)	(0.260)	(0.163)	(0.384)
IPR_{it-1}			-0.0120*	-0.0118*	-0.0158**
			(0.060)	(0.072)	(0.049)
$R\&D_{it-1}$			-1.125***	-1.111**	-1.125**
			(0.009)	(0.013)	(0.024)
$(IPR \times R\&D)_{it-1}$			0.545**	0.534**	0.589**
			(0.014)	(0.020)	(0.020)
C_{it-1}				-0.00937	-0.0180**
				(0.332)	(0.018)
Non-Ag GDP_{it}					0.166
					(0.107)
$Landg_{it}$	0.219**	0.236***	0.276*	0.270*	0.294**
	(0.012)	(0.009)	(0.053)	(0.064)	(0.030)
$Fertg_{it}$	0.0161**	0.00826**	0.00316	0.00206	0.00637
	(0.023)	(0.047)	(0.627)	(0.768)	(0.350)
$Machg_{it}$	0.0264	0.00937	0.0218	0.0158	-0.00737
	(0.232)	(0.687)	(0.514)	(0.682)	(0.842)
$Liveg_{it}$	0.201***	0.144***	0.117	0.122	0.109
	(0.000)	(0.006)	(0.244)	(0.246)	(0.287)
$Feedg_{it}$	0.0978***	0.0871***	0.0944**	0.0973**	0.0753*
	(0.008)	(0.002)	(0.018)	(0.018)	(0.063)
Observations	246	210	98	98	89
Countries	28	28	20	20	18
R^2	0.42	0.42	0.36	0.36	0.38

Notes: Fixed effects regressions. Coefficients are reported with p-values in brackets, with robust standard errors. *,**, *** indicates significance at the 10%, 5%, and 1% levels.

8 Summary and Conclusion

This paper has explored international productivity patterns in agriculture, re-examining evidence for convergence across countries. The results highlight the differentiated impact of R&D and education at different levels of technological development. We find that R&D has a statistically significant impact on labor productivity growth, but that this impact is lower the further a country is from the technological frontier, in contrast with predictions from the macroeconomic literature on productivity convergence. The productivity-enhancing effect of research intensity is therefore less clear for LDCs.

Our results on convergence, both unconditional and conditional, contrast with some earlier findings, most notably those of Martin and Mitra (2001). Three salient differences may account for this: two based on the dataset and the third on our specification. One is the longer dataset, although if anything, there is more evidence towards converging growth rates in the additional 1995-2010 period included in the Fuglie (2012) dataset (see Figure 3). The second difference is the adjustments made for the quality of inputs in the productivity estimates by Fuglie. These seem to affect developing countries more than OECD countries, and most of the sample period is characterized by clear gaps in productivity growth rates between groups of countries according to overall income levels.

The third difference is our conditional convergence specification, which draws on recent macroeconomic literature and controls for the influence of R&D, as well as its interaction with the distance to the frontier. Given the limited and imperfect data, we are reticent to draw unequivocal policy recommendations from our analysis. We do though see the as potentially uncovering interesting aspects deserving further investigation. For example, our results do support previous analysis that has questioned the effectiveness of agricultural R&D in developing countries, highlighting institutional biases and constraints (Kiers et al., 2008). Our results do not necessarily imply that such investments should be assigned lower priority. If anything, our findings highlight the importance of considering both quantity and quality of investments in national agricultural research systems. Much of the current literature concentrates on the arguments for increasing the quantity, such as those by Alston and Pardey (2014); Pardey et al. (2010, 2013), with good reason given observed declines in agricultural R&D over the longer term in many countries.

We also estimated a relatively straightforward regression of labour productivity growth on a range of explanatory variables in an attempt to update the results of Headey et al. (2010). One difference is that we now control for unobserved heterogeneity as well as using the Fuglie productivity dataset. These results are generally far from satisfactory. Nonetheless they do point to a strong role for education in promoting productivity growth in LDCS, though not necessarily in middle income countries. Trade openness also appears to have had an effect on productivity in middle income countries. IPRs do not seem on the other hand to be as relevant and further analysis could find ways to disentangle the effects from the influence of other aspects of the legal environment that can influence business and investment opportunities. More interestingly, ours is the first paper to consider the possible role of growth in the nonagricultural sector. We suggest that this may also warrant further analysis, given the role such growth might have played in driving agricultural productivity growth in middle income countries.

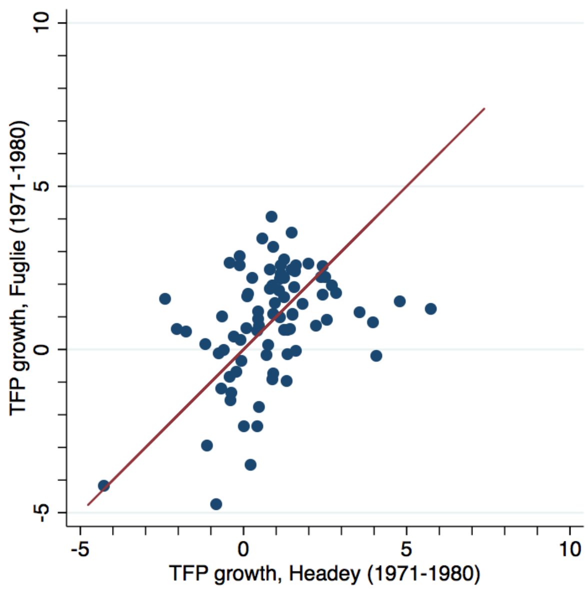
Appendix A Sample

Table A1: Country Sample

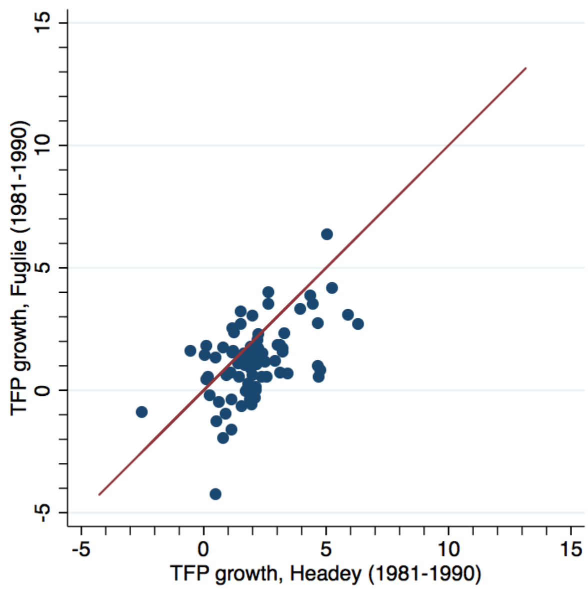
Country	Inc. group	Country	Inc. group	Country	Inc. group
Australia	OECD	Bulgaria	UMI	Pakistan	LMI
Austria	OECD	Chile	UMI	Papua New Guinea	LMI
Canada	OECD	Colombia	UMI	Paraguay	LMI
Denmark	OECD	Costa Rica	UMI	Philippines	LMI
Estonia	OECD	Cuba	UMI	Sri Lanka	LMI
Finland	OECD	Dominican Republic	UMI	Sudan	LMI
France	OECD	Fiji	UMI	Swaziland	LMI
Germany	OECD	Gabon	UMI	Syrian Arab Republic	LMI
Greece	OECD	Hungary	UMI	Tajikistan	LMI
Iceland	OECD	Iran, Islamic Rep.	UMI	Thailand	LMI
Ireland	OECD	Jamaica	UMI	Tunisia	LMI
Italy	OECD	Jordan	UMI	Ukraine	LMI
Japan	OECD	Kazakhstan	UMI	Yemen, Rep.	LMI
Korea, Rep.	OECD	Libya	UMI	Zambia	LMI
Netherlands	OECD	Malaysia	UMI	Afghanistan	LDC
New Zealand	OECD	Mauritius	UMI	Armenia	LDC
Norway	OECD	Mexico	UMI	Bangladesh	LDC
Poland	OECD	Namibia	UMI	Benin	LDC
Portugal	OECD	Panama	UMI	Burundi	LDC
Spain	OECD	Peru	UMI	Cambodia	LDC
Sweden	OECD	Romania	UMI	Central African Republic	LDC
Switzerland	OECD	South Africa	UMI	Congo, Rep.	LDC
United Kingdom	OECD	Turkey	UMI	Gambia, The	LDC
United States	OECD	Uruguay	UMI	Ghana	LDC
Bahrain	High Inc.	Venezuela, RB	UMI	Guyana	LDC
Brunei Darussalam	High Inc.	Bolivia	LMI	Haiti	LDC
Cyprus	High Inc.	Cameroon	LMI	Kenya	LDC
Israel	High Inc.	China	LMI	Lao PDR	LDC
Kuwait	High Inc.	Cote d'Ivoire	LMI	Liberia	LDC
Latvia	High Inc.	Ecuador	LMI	Malawi	LDC
Lithuania	High Inc.	Egypt, Arab Rep.	LMI	Mali	LDC
Malta	High Inc.	El Salvador	LMI	Mozambique	LDC
Qatar	High Inc.	Guatemala	LMI	Myanmar	LDC
Russian Federation	High Inc.	Honduras	LMI	Nepal	LDC
Saudi Arabia	High Inc.	India	LMI	Niger	LDC
Trinidad and Tobago	High Inc.	Indonesia	LMI	Rwanda	LDC
United Arab Emirates	High Inc.	Iraq	LMI	Senegal	LDC
Albania	UMI	Kyrgyz Republic	LMI	Sierra Leone	LDC
Algeria	UMI	Lesotho	LMI	Tanzania	LDC
Argentina	UMI	Mauritania	LMI	Togo	LDC
Belize	UMI	Mongolia	LMI	Uganda	LDC
Botswana	UMI	Morocco	LMI	Vietnam	LDC
Brazil	UMI	Nicaragua	LMI	Zimbabwe	LDC

Appendix B TFP growth rates

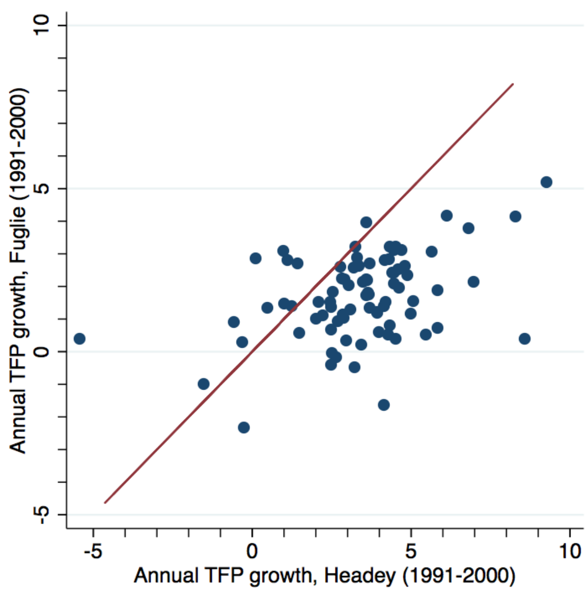
(a) Headey (2010) vs. Fuglie (2012), 1971-1980



(b) Headey (2010) vs. Fuglie (2012), 1981-1990



(c) Headey (2010) vs. Fuglie (2012), 1991-2000



(b) Headey (2010) vs. Coelli and Rao (2005), 1981-2000

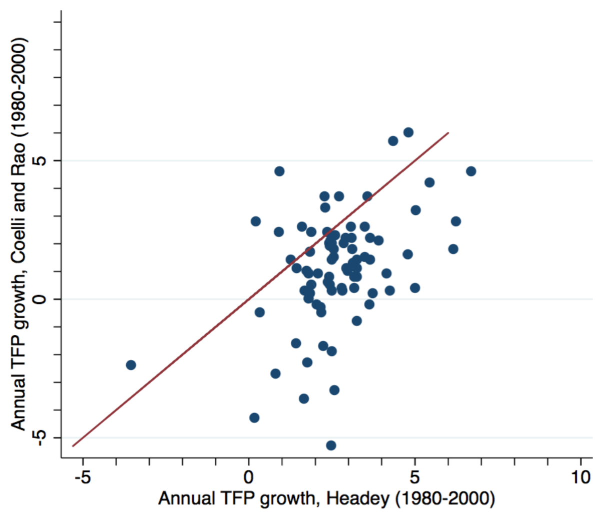


Figure A1: Annual TFP growth comparison of studies

Appendix C Additional lags for R&D

Table A2: Additional Lags

	(1a)	(1b)	(1c)	(1d)
	Whole sample			
ln DTF_{it-1}	0.0546***	0.0686***	0.0734***	0.0766***
	(0.000)	(0.001)	(0.001)	(0.000)
$\text{R\&D}_{it-1}$	0.364*			
	(0.052)			
ln DTF_{it-1} x $\text{R\&D}_{it-1}$	-0.124**			
	(0.012)			
$\text{R\&D}_{it-2}$	0.357**	0.573***		
	(0.034)	(0.001)		
ln DTF_{it-1} x $\text{R\&D}_{it-2}$	-0.0834	-0.114		
	(0.315)	(0.119)		
$\text{R\&D}_{it-3}$		-0.110	0.00944	
		(0.506)	(0.954)	
ln DTF_{it-1} x $\text{R\&D}_{it-3}$		0.00654	-0.0327	
		(0.894)	(0.673)	
$\text{R\&D}_{it-4}$			-0.0223	-0.0813
			(0.844)	(0.532)
ln DTF_{it-1} x $\text{R\&D}_{it-4}$			0.000259	-0.0160
			(0.996)	(0.779)
$\text{R\&D}_{it-5}$				0.112
				(0.454)
ln DTF_{it-1} x $\text{R\&D}_{it-5}$				0.0108
				(0.898)
ln Sch_{it}	0.0167	0.0295**	0.0382**	-0.00610
	(0.111)	(0.028)	(0.047)	(0.760)
ln DTF_{it-1} x ln Sch_{it}	-0.000747	-0.00173	-0.00213	-0.000754
	(0.392)	(0.138)	(0.177)	(0.598)
Landg_{it}	0.221***	0.152**	0.0761	0.0977
	(0.000)	(0.024)	(0.337)	(0.350)
Fertg_{it}	0.000140	0.00566	0.00579	0.00574
	(0.984)	(0.464)	(0.528)	(0.478)
Machg_{it}	0.0594***	0.0361	0.0248	0.0583*
	(0.006)	(0.112)	(0.533)	(0.090)
Liveg_{it}	0.0929*	0.0882	0.0806	0.110**
	(0.087)	(0.243)	(0.294)	(0.047)
Feedg_{it}	0.0572**	0.0354*	0.0346	0.0150
	(0.014)	(0.068)	(0.126)	(0.575)
N	352	299	253	206
Countries	76	73	66	63
R^2	0.51	0.51	0.46	0.57

Notes: p-values in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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