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Two Blades of Grass: The Impact of the Green Revolution*

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Abstract

This paper examines the impact of the Green Revolution on aggregate economic outcomes during the second half of the 20th century in a sample of 85 developing countries. We restrict our attention to the agricultural-productivity shock coming from the adoption of modern-variety crops. Our estimation strategy exploits time variation in the development and diffusion of modern varieties of 10 major crops, and spatial variation in agroclimatically suitability for growing them, to identify the causal effects of adoption. According to our baseline estimate, a 10 percentage-points increase in adoption of modern varieties increases GDP/capita by 15 percent. This effect is fully accounted for by a combination of the direct effect on crop yields, factor adjustment in agriculture, and structural transformation. The analysis also reveals that the shock reduced fertility and this was only partly offset by decreasing mortality rates, so that the net effect on population growth was negative.

Keywords: Green Revolution; Productivity Shock; Macroeconomic Development.

JEL: N50; O11; O13; O50; Q16.

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“Whoever makes two ears of corn, or two blades of grass, to grow upon a spot of ground where only one grew before, would deserve better of mankind, and do more essential service to his country, than the whole race of politicians put together.”

Jonathan Swift in Gulliver’s Travels

1 Introduction

How important is agricultural productivity growth in development? Early views of development assumed that most of the impetus for development and economic growth would necessarily come from the industrial sector, which was thought to offer the potential for rapid rates of productivity growth. In contrast, the agricultural sector in most developing countries was seen as backward and stagnant, with limited potential for growth (e.g., Lewis (1951)). In recent years, agriculture’s potential significance has been a theme in a renewed literature on structural transformation and growth. A new literature has offered theoretical models in which agricultural productivity growth may prove important for subsequent industrialization and in which agricultural productivity differences may play a role in explaining cross-country disparities in income. However, it has proved difficult to assess the overall importance of agriculture’s contributions to growth, and a lively policy debate remains on whether (and when, where, and how) governments should focus their development efforts on agriculture.

This paper takes advantage of new data sources that make it possible to examine the impacts of what is arguably the most important episode of agricultural innovation in modern history – the Green Revolution that began in the 1960s. As Evenson and Gollin (2003a) argued, the Green Revolution is best understood as an increase in the rate of growth of agricultural productivity, based on the application of modern crop breeding techniques to the agricultural challenges of the developing world. The Green Revolution emerged from philanthropic efforts – arguably shaped by geopolitical interests – to address the challenges of rural poverty and agrarian unrest in the late 1950s and early 1960s, and it involved a concerted effort to apply scientific understandings of genetics to the development of improved crop varieties that were suited to the growing conditions of the developing world. The Green Revolution delivered a massive and nearly immediate impact in some locations in the developing world – particularly in the irrigated rice-growing areas of Asia and the wheat-growing heartlands of Asia and Latin America. These were the focal points for the greatest initial research efforts, and they were also the easiest places in which to develop widely adapted new varieties. Other parts of the developing world received little benefit, however, from these early efforts – for reasons that will be discussed in detail below.

How much did the Green Revolution matter? Did the agricultural productivity increases generate large and long-lasting benefits? Answering this question has been difficult, because of the obvious challenges to causal identification. Because growth in one sector of an economy will inevitably link (positively and/or negatively)

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1 See, for example, Caselli and Coleman (2001); Caselli (2005); Córdoba and Ripoll (2009); Gollin et al. (2002, 2007); Restuccia et al. (2008); Vollrath (2011).
to growth in other sectors, it is challenging to find compelling evidence at the national level for the causal impacts of agricultural productivity growth. It is easier to find evidence of such impacts at the micro level, and several recent papers have made use of natural experiments (e.g., Bustos et al. (2013) and Hornbeck and Keskin (2011)) or structural estimation (e.g., Foster and Rosenzweig (2004), Foster and Rosenzweig (2007)) to look at the cross-sectoral impacts of shocks to agricultural productivity. However, these localized effects can be difficult to generalize to full general equilibrium impacts on aggregate economies. The local movements of people across sectors are only a relatively small part of the transformation process. In particular, for poor countries with large fractions of their workers initially in agriculture, the main mechanisms of structural transformation are not played out within local labor markets. Instead, they involve large-scale movements of people across locations – from rural to urban or from one region to another. Studies that emphasize the local movements of people will miss these broader and more secular changes.

This paper models the impact of the Green Revolution on national economies, rather than on local labor markets. The main idea is to use exogenous variation in geography, combined with the essentially exogenous (to individual countries) timing of agricultural research successes, to instrument for the timing and magnitude of agricultural productivity shocks received by countries. This allows us to trace the impact of agricultural productivity increases across a large set of countries. We observe strong and robust impacts of these Green Revolution productivity shocks. Most striking is the impact on per capita GDP. Depending on the specification, we find that a 10-percentage point increase in the share of area under modern varieties in 2000 is associated with a 10-15 percentage point increase in per capita GDP. Moreover, we find no evidence that the Green Revolution was offset substantially by Malthusian effects; the increased availability of food was not eroded by population increases. Instead, population appears to have declined, if anything, in response to the growth in agricultural productivity. Our paper also sheds light on a concern often expressed in the literature about the potential for agricultural productivity improvements to pull additional land into agriculture at the expense of forests and other environmentally valuable land uses. We find that, to the contrary, increases in the area under improved varieties has tended to reduce the amount of land devoted to agriculture – consistent with what has been termed the “Borlaugh hypothesis.” Under this hypothesis, improvements in the productivity of food crops leads to intensification of agriculture on a smaller land area, preventing expansion on the extensive margin.\(^2\)

We further show that the impact of the Green Revolution on per capita GDP comes from effects on total factor productivity (TFP) beyond those simply derived from increases in crop yields – including, for instance, changes in the quality of land, labor, and capital. Our analysis also finds that per capita GDP rises due to factor adjustments of various kinds. Likewise, we can look at the channels through which the Green Revolution appears to have altered population size. Our analysis suggests that the main effect occurs through an effect of the Green Revolution on lower birthrates. In the data, this effect is only partly offset by an increase in life

\(^2\)Norman Borlaug (1914-2009) was a wheat scientist closely associated with the early years of the Green Revolution. Borlaug won the Nobel Peace Prize in 1970 for his work in developing and promoting the Green Revolution, most notably through his efforts in wheat breeding for yield and rust resistance. Borlaug argued forcefully that improved varieties and higher agricultural productivity would lead to reduced pressure on land resources, as higher production would be achieved through intensification rather than extensive expansion of agricultural area. This argument was dubbed the “Borlaugh hypothesis” by Angelsen et al. (2001), p. 3.
expectancy; the net result is a negative effect of the Green Revolution on population growth.

A large literature considers the social, economic, and environmental impacts of the Green Revolution; it would be too ambitious to review this literature here. Recent surveys include Renkow and Byerlee (2010) and Pingali (2012). Our paper addresses some of the same macro-scale questions that have previously been considered using different methods by Evenson and Rosegrant (2003), Perez and Rosegrant (2015), and others. These studies have used a range of models of varying structures and with differing assumptions. A recent survey of these models can be found in Godfray and Robinson (2015). In contrast to these approaches, our analysis is based on econometric evidence from a panel of countries. As noted above, our identification approach uses agroecology as an instrument for technology change, a method that has been used previously to look at the impact of plantation agriculture on long-run development patterns (Easterly (2007)); the effects of the adoption of potatoes in Europe following the Columbian Exchange (Nunn and Qian (2011), the impact of agricultural productivity improvements on local non-agricultural development (Bustos et al. (2013)); and the impact of irrigated agriculture on political outcomes (Bentzen et al. (forthcoming)). This paper is also related to an even larger literature has considered the impact of agricultural science or research on economic and social outcomes at a more geographically limited scale. This literature has been surveyed by Maredia and Byerlee (2000); other important contributions include Fan et al. (2002); Meinzen-Dick et al. (2003); Thirtle et al. (2003); Pingali and Kelley (2007); Dalrymple (2008); Raitzer and Kelley (2008); Rusike et al. (2010).

In the remainder of this paper, we begin in Section 2 by documenting the historical context in which the Green Revolution unfolded, including the institutional background for the scientific research that gave rise to the Green Revolution. Section 3 presents data on the diffusion of modern varieties that were at the core of the Green Revolution. Section 4 describes the estimation strategy including a detailed discussion of our identifying assumptions. Section 5 presents our estimates of the long-term and large-scale consequences of the Green Revolution. In Section 6, we explore the potential channels for these impacts; Section 7 concludes with implications for long-term strategies of growth and development.

## 2 Background: The Green Revolution

Although formal programs of scientific research on crop improvement in developing countries can be traced back into the nineteenth century and before, the Green Revolution of the 20th century can be dated fairly precisely. Following some early exploratory work in the 1940s and 1950s, the major efforts can be traced to the creation in 1960 of the International Rice Research Institute (IRRI), located near the town of Los Banos in the Philippines, and in 1967 of a sister institution, the International Center for Maize and Wheat Improvement (CIMMYT), with headquarters near Texcoco, Mexico. These two research centers were funded by a group of aid donors, including the Ford and Rockefeller Foundations as well as a number of national aid agencies. CIMMYT grew out of an ongoing program of wheat research that the Rockefeller Foundation had been funding in Mexico since the late 1940s, under the leadership of Norman Borlaug, a plant pathologist and wheat breeder who went on to win.
the Nobel Peace Prize in 1970 for his efforts. The history of the early Green Revolution has been documented previously in a number of sources, e.g., Dalrymple et al. (1974); Dalrymple (1978, 1985, 1986); Barker et al. (1985). Breeding efforts at these institutions were subsequently extended to other crops and other research centers, as discussed below.

For the purposes of this paper, it is important that the timing of the initial Green Revolution and its subsequent patterns of diffusion were largely exogenous to individual countries. The argument we will make is based on two claims. The first is that the timing of the initial research was driven by a mixture of humanitarian and geopolitical concerns and coincided with the birth of the international aid community; in this sense, it was not driven by an assessment of the subsequent growth prospects of any particular country or set of countries. The second is that the principal initial research behind the Green Revolution in rice and wheat diffused rapidly from the locations where the research was initially carried out. Diffusion took place very rapidly in similar agroecological areas and more slowly in areas with less favorable geographies. The research targeted specific phenotypic problems thought to have widespread relevance rather than focusing on specific countries. And in spite of the rapid success of research on rice and wheat, it took much longer for the Green Revolution to be extended to other crops, reflecting large differences in the initial stock of scientific knowledge as well as the greater heterogeneity of growing environments. On all counts, we argue that the differential impact of agricultural research on developing economies reflected factors largely exogenous to those countries.

2.1 The Timing of the Green Revolution

Evenson and Gollin (2003a) argue that the Green Revolution should be understood as the application of modern agricultural science to the problems of developing countries. In this sense, the start of the Green Revolution can be defined quite precisely. Although many developing countries had some indigenous and colonial programs of crop improvement, it is a reasonable generalization to say that few developing countries had large or systematic programs of crop improvement before 1950. Colonial programs of agricultural research tended to focus on non-food crops, such as sugar, that provided raw materials for industry or were consumed in the colonial heartland. Food crops tended to receive a low priority. To the extent that there were active programs of research on food crops, as in India, in the first half of the twentieth century, they tended to focus on identifying vigorous strains of existing varieties rather than developing new lines. According to De Datta (1981), rice research in the developing world in the early 20th century tended to consist of little more than selection of high-performing varieties from farmers’ fields, along with some efforts to introduce materials from other geographies and to select them for local adaptation. Very little cross-fertilization was attempted – essentially the effort to create new genetic mixes through deliberate breeding of one variety to another – because of the relative technical difficulty of this process and perhaps also because of the limited familiarity with the principles of Mendelian genetics that are required to make sense of cross-fertilization.\(^3\)

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\(^3\)Rice and wheat are self-pollinating crops in which each small flower on a stalk tends to pollinate itself. Cross-fertilization is a painstaking process that (in the 1960s) required emasculating certain stalks by carefully removing the male portion of the flower with a tweezers so that it will be unable to pollinate itself and can then be pollinated from another source chosen by the scientist.
For rice and wheat, the first large-scale programs of cross-fertilization (henceforth, “breeding”) were those carried out by IRRI and CIMMYT (including the precursor Rockefeller program on wheat in Mexico), beginning in the 1950s and early 1960s. In both crops, these early efforts reflected an emerging view that rich countries had both obligations and opportunities to encourage development in the newly independent countries of Africa and Asia, in the wake of the Second World War. This view coincided with geostrategic concerns triggered by the Cold War. The threat of agrarian revolutions in Asia and Latin America seemed to call for efforts to promote rural development – and in turn to focus on agricultural productivity. (For a detailed discussion, see Perkins (1997).) It was presumably not a coincidence that the United States, being pulled steadily into a war in Indochina and fearing a domino effect, chose to support investments in rice research; nor that it would support a wheat research program that was based in Mexico.

Against this backdrop, rice breeding began at IRRI in 1965, several years after the founding of the institute, and within the first weeks of breeding effort, scientists made a cross that gave rise to what would eventually prove to be the first “mega-variety” of rice. For wheat, it is similarly possible to identify a zero-date for the Green Revolution: the first successful crosses from the Rockefeller wheat program took place in 1955, and the first varieties were released in Mexico in 1961.

The sections below will describe the diffusion of improved varieties of rice, wheat, and other crops; a key point is that the diffusion patterns were initially shaped largely by the extent of research effort and by agroecological similarity to the locations where the initial research was carried out. Diffusion of high-yielding rice and wheat to less favorable areas was more gradual and reflected the time required to address geographies and agronomic problems of narrower significance. Similarly, the eventual development and spread of improved varieties of maize, sorghum, millet, root crops, and legumes was driven in significant measure by the timing and scale of the international research efforts. These efforts can be identified in large degree with the creation of new research centers and programs. Thus, in the wake of the successes of IRRI and CIMMYT, two additional centers were created in 1967, the International Institute for Tropical Agriculture (IITA) in Ibadan, Nigeria, and the International Center for Tropical Agriculture (CIAT) in Cali, Colombia. These institutions were assigned mandates for additional crops and different agroecologies; the subsequent rolling out of additional centers provides a valuable tool for identification in our analysis. There are now fifteen such institutions that carry out agricultural research on subjects ranging from aquaculture to livestock science to climate adaptation.4

To a degree, adaptive breeding – the effort to tailor high-yielding varieties to specific agroecological niches and to address problems of local importance – has been carried out by national governments through agricultural

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4 These centers operate collectively as an entity known as the CGIAR (formerly known as the Consultative Group on International Agricultural Research). CGIAR defines itself today as a “worldwide partnership addressing agricultural research for development.” Its research is funded by national and multilateral development agencies, non-governmental organizations, private philanthropies, and other donors, with an annual budget approaching $1 billion in 2015.
research systems, university-based research programs, and other local research. A concern for our identification strategy is that this effort may thereby reflect institutional capacity, raising the possibility that the diffusion curves for different countries are related to general institutional factors that might lead to growth through other channels. But what is clear is that even for the most advanced developing countries, adaptive breeding has continued even to the present day to rely heavily on research emerging from the CGIAR. Many or most improved crop varieties in the developing world continue to use genetic material that can be traced to the CGIAR, and almost all national research programs in the developing world maintain close connections to CGIAR institutions. In that sense, the research products of the CGIAR continue to play a significant role in shaping the diffusion of modern varieties. The role of the CGIAR and of international research institutions through the late 1990s is documented fully in Evenson and Gollin (2003b); a more recent study by Walker and Alwang (2015) describes the continuing importance of international research for the diffusion of improved crop varieties in sub-Saharan Africa.\(^5\)

Beyond the institutional role of the CGIAR in the development of improved varieties, an additional source of exogeneity is the sheer difficulty of achieving research success in different crops. The rapid progress of varietal improvement in rice and wheat for favorable environments turned out to be a happy accident. As discussed below, it turned out that in both crops, substantial yield gains could be achieved through the introduction of a single gene for dwarfism. But an additional underlying reason for the rapid successes in these crops was that research built on a large stock of scientific knowledge. Both crops had been heavily researched prior to the 1960s in advanced countries, and scientists could work with elite breeding lines. Moreover, they had a good understanding of the extent of genetic diversity and the sources of useful genes. The situation was very different for tropical root crops such as cassava and sweet potato; it was also quite different for crops that were quite minor in rich countries, such as millet and sorghum. These differing initial stocks of knowledge and improved genetic materials create another source of exogenous variation in the timing and extent of the Green Revolution. Evenson and Gollin (2003a) argued that the slow diffusion of improved varieties in sub-Saharan Africa reflected the differences in crop mix and agroecology relative to Asia. Because crop varieties can be highly location specific, there were limited spillovers of crop varieties from Asia to Africa. The Green Revolution varieties of rice proved poorly suited to Africa; maize varieties that had performed well in Mexico also proved disappointing under farmers’ conditions in Africa.

### 2.2 History of the Green Revolution in Rice

This section considers the detailed case of the Green Revolution in rice in South and Southeast Asia. We argue here that genetic and agroecologic factors created a strong element of exogeneity to the diffusion of Green Revolution varieties of rice.

As noted by Dalrymple (1979), varietal improvement efforts in rice and wheat can be dated well back into

\(^5\)A chapter (Pandey et al. (2015)) in the book also by Walker and Alwang (2015) discusses international research impacts in recent times in South Asia.
the 19th century and beyond; but the distinctive feature of the early Green Revolution was the development and introduction of short semi-dwarf varieties of rice and wheat that were adapted to tropical and semi-tropical environments. These short varieties were well suited to intensive cultivation. In particular, they responded well to heavy doses of fertilizer. For both rice and wheat, traditional varieties tended to be substantially taller; it was not uncommon for tropical Asian rice varieties to be two meters tall, whereas the semidwarfs were closer to one meter tall. The taller varieties suffered from two disadvantages. First, a large amount of the plant’s energy was devoted to the production of leaves and stalks, with a relatively small fraction of the plant biomass being allocated to grain. Second, the tall varieties were subject to an architectural design flaw; since grain grows near the top of a rice plant or wheat plant, heavy grain yields would make the plants top-heavy and would induce them to fall over – a problem known as “lodging.” For rice, Barker et al. (1985) note that lodging was a constraint on crop yields in tropical Asia: “Particularly in the irrigated areas, fields of lodged rice (with stalks bent over and panicles lying flat on the ground) were a familiar sight at harvest-time. Fertilizer was not used because the application of nitrogen to tall indica varieties weakened the stalks, advancing the date of lodging and further reducing yields” (Barker et al. (1985)).

The architecture of rice and wheat plants thus implied that chemical fertilizers were little used in tropical production of these crops through the 1950s. As reported by Barker et al. (1985) (Table 6.2, p. 77), NPK fertilizer use on rice in India in the 1956-60 period was approximately 2 kg/ha, compared with over 200 kg/ha in Japan or Taiwan. Essentially zero fertilizer was used on rice in Bangladesh, Indonesia, Thailand, or other countries in the global heartland of rice cultivation. Crop yields were correspondingly low, as plants were starved for nutrients: in 1965, Indian rice yields were 1.3 t/ha, and similarly low levels prevailed in Cambodia (1.1 t/ha), Indonesia (1.8 t/ha), Bangladesh (1.7 t/ha), Pakistan (1.4 t/ha), and the Philippines (1.3 t/ha). By contrast, in northern Asia and in rich countries, yields were commonly 4.5-6.5 t/ha (FAOSTAT).

The rice and wheat scientists involved in forming the nascent IRRI and CIMMYT were clear that one of their first research challenges was to develop shorter varieties of these crops, with stiffer straw, that would tolerate more intensive use of fertilizer. They also sought shorter duration varieties with broad adaptability to different environments. Short varieties of rice and wheat were known and had been cultivated in northern Asia, possibly for many centuries, although Dalrymple (1979) writes that the agronomic potential of these varieties did not become clear until the 20th century and the advent of chemical fertilizers. These varieties were not well suited to tropical and semi-tropical conditions, however. As a result, the earliest breeding efforts at IRRI involved focusing on crosses of these semi-dwarf varieties with sturdy and well adapted tropical rice varieties. The eighth cross made, in the first weeks of IRRI’s existence, was of an Indonesian variety (Peta) with a semi-dwarf from Taiwan (Dee-Geo-Woo-Gen, or DGWG). The resulting cross, known as IR8, was arguably one of the most successful innovations in human history. IRRI released seed of IR8 in 1965, and by 1969 approximately 10 percent of Asia’s rice area was planted in IR8 or other varieties, most of them derived from IR8 or closely related to it (Herdt and Capule (1983)). By 1980, about 16 million ha, accounting for around 40 percent of Asia’s rice area, was planted in what were known as high-yielding rice varieties (HYVs or HYRVs, also referred
Diffusion of rice MVs was extraordinarily rapid in those areas where the varieties were well adapted. Although at the micro level, adoption was associated with a variety of individual farmer characteristics such as education, land tenure, and farm size, the aggregate patterns suggested very large disparities within and across countries based on agroclimatic and agroecological factors. The reliable availability of water and effective control of water proved to be an important determinant of the diffusion of the MVs. In the most favorable agroecologies, diffusion was rapid and pervasive. In less favorable ecologies (e.g., in areas characterized by cold temperatures, short growing seasons, flooding, or drought, among other challenging conditions), the profitability of the new seeds was far more marginal and seems to have been much more localized.

These patterns are evident in both national and sub-national statistics. Some countries with favorable agroecology – especially those with extensive irrigation and/or lowlands with reliable rainfall – saw very rapid adoption of the MV rices. For example, Sri Lanka introduced MV seeds in 1968-69; by 1973-74, 48 percent of the rice area was planted in MVs, a figure that rose to 71 percent by 1980-81, a mere twelve years after the introduction of the new seeds. In the Philippines, MV seeds were introduced in 1965-66, and by 1970-871, over 50 percent of the national rice area was planted in MVs. But other countries with less ideal conditions (e.g., Bangladesh, Cambodia, Nepal) saw much slower diffusion. Similar disparities in diffusion arose within countries. For instance, across Indian states, by 1975-76, a mere decade after the introduction of MVs, adoption was recorded at over 99 percent in Punjab and nearly as high in Haryana (both relatively minor producers of rice), but closer to 50 percent in Tamil Nadu and Andhra Pradesh. And in the rainfed states of eastern India (West Bengal, Orissa, and Bihar), which accounted for the largest shares of national rice cultivation, adoption rates averaged around 25 percent, based on Indian statistics reported in Barker et al. (1985), Table 10.4, p. 149.

2.3 History of the Green Revolution in Wheat

The Green Revolution in wheat followed a similar pattern to that in rice. The research effort began with the Rockefeller Foundation’s program on wheat improvement based in Mexico and with the effort to develop shorter varieties that would respond better to chemical fertilizer. As described in Dalrymple (1978), semi-dwarf wheats were reported by international agricultural experts traveling in Japan in the 19th century. Over the succeeding decades, a number of semi-dwarf wheat varieties from Japan entered breeding programs in Italy and other countries; at the same time, a reciprocal flow of varieties brought a number of American improved varieties to Japan, where eventually the variety Norin 10 was developed in the 1930s. Dalrymple (1978) writes that Norin 10 was brought to the United States in 1946. It entered breeding programs in the United States and also formed one of the key ingredients of the Rockefeller breeding program in Mexico. By 1961, the first semi-dwarf varieties were released from the Rockefeller program, based on a cross of Norin 10 with the variety Brevor. Within a year, these varieties were taken to India for trial; by 1965, two semi-dwarf varieties originating from the Mexican program had been released in India; more or less concurrently, semi-dwarf varieties were released in Pakistan.
By 1970, nearly 10 million ha of MV wheat had been planted in Bangladesh, India, Nepal, and Pakistan; by 1977-78, the area planted to MVs had reached 20 million ha, accounting for approximately two-thirds of the wheat area in those countries (Dalrymple (1985)).

As was the case in rice, the MV wheat varieties diffused somewhat more gradually to countries outside the Indo-Gangetic plane. By 1997, CIMMYT estimated that nearly 50 million ha globally were planted in wheat varieties developed at CIMMYT or based on varieties that had a CIMMYT parent. An additional 17 million ha were planted with varieties derived from CIMMYT grandparents or other CIMMYT ancestors, accounting for 62 percent of total world wheat area (Pingali (1999)).

The major determinant of diffusion for MV wheat was the water regime. By 1977, just fifteen years after the development of the first semi-dwarf wheat varieties, 83 percent of the wheat area defined as “favorable production environments” (i.e., having good rainfall or irrigation) was planted to semi-dwarfs Byerlee and Moya (1993). Diffusion of MVs in dryland areas was much lower – possibly only about 20-25 percent Byerlee and Moya (1993). This pattern resulted was evident within countries as well as across countries: by 1983, adoption of wheat MVs in North Africa and the Middle East was only 31 percent, compared to 79 percent in South Asia. As for rice, the pre-existing patterns of irrigation and climate were primarily responsible for the differing patterns of diffusion.

2.4 History of the Green Revolution in Other Crops

Patterns of diffusion in other crops were similarly shaped by the starting date of modern research, the stock of knowledge and improved genetic material, the extent of the research effort, and the heterogeneity of the farming ecologies for those crops. For some crops (e.g., barley), international research targeted at developing countries did not begin until 1975. For others, such as cassava, the initial stock of scientific knowledge was essentially nil. Evenson and Gollin (2003b) concluded that these factors essentially explained the differential levels of adoption and the patterns of diffusion across crops and countries. In this view, the low rates of adoption of improved crop varieties in sub-Saharan Africa reflect the late starting date of research; the relative importance of crops for which research progress came late and slow; the heterogeneity of production environments and the complexity of farming systems (i.e., the lack of large tracts of agroecologically similar land, comparable to the irrigated lowlands of Southeast Asia or the Indo-Gangetic plane of South Asia). Given these challenges, we can defend the claim that Africa’s delayed and weak Green Revolution was largely exogenous – and that more generally, the timing and intensity of the Green Revolution is largely due to exogenous differences across geographies and agroecologies.

3 Data

Our empirical analysis is based on data from 85 developing and middle income countries (as of 1960) for which we have data on our key variables in the period 1960-2000. A list of the countries in our sample can be found in
the appendix to this paper. The key variables capture actual adoption of modern varieties, the agroclimatically attainable yields we use to construct our instrument, and a range of outcome variables. We discuss these in turn below.

3.1 The Diffusion of MV Crops

Evenson and Gollin (2003b) provide approximate MV adoption rates 11 major crops in developing and middle income countries since the onset of the Green Revolution in the 1960s. The 11 crops are: barley, cassava, dry beans, groundnut, lentils, maize (corn), millet, potatoes, rice, sorghum, and wheat. We do not have data on agroclimatically attainable yields for lentils, so we focus on the remaining 10 crops in our analysis. Combined, these 10 crops account for about 60 percent of the total harvested area in the 85 countries we are analyzing. The remaining 40 percent is mostly cash crops, such as sugar and cotton, and crops used for fodder, so our 10 crops give us a reasonable proxy for total non-meat food production.

The adoption rate of modern-variety (MV) crops are defined as the area planted with modern varieties of a given crop relative to the total area planted with either modern or traditional varieties of the specific crop. Figure 1 depicts the average adoption rate in the sample for four selected crops. Wheat is the crop where the adoption of MVs has been fastest. Starting from zero in 1960 — before MVs of wheat were available — adoption gradually increased to about 40 percent in 2000. Adoption of MVs of other crops were slower, partly because research into crop improvement started earlier for wheat and MVs of wheat were for that reason commercially available decades before, e.g., MVS of cassava. This heterogeneity in introduction and adoption provides us with both spatial and temporal variation in the diffusion of MV crops.

The heterogeneity is also visible when looking at individual countries. For example, Figure 2 shows the aggregate adoption rate for four countries in four different regions: Brazil, India, Turkey, and Nigeria. The three former countries are big producers of wheat and, except Turkey, rice. That made them early adopters of MVs because new varieties of wheat and rice were commercially available relatively early on. Nigeria, on the other hand, relies more on Cassava and Sorghum, which are crops where new high-yielding varieties were developed later. This is an important reason why MV crops first became important much later in Nigeria than in the three other countries.

Income, investment, human capital, and agricultural policies, of course, also matter for adoption, so Nigeria may have adopted MV crops later than India simply because India was more developed in 1960. To avoid such endogeneity in our empirical analysis, we use geographical determined suitability measures for MV crops as a source of exogenous variation in adoption rates, along with the timing of the global breakthrough of MVs.

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6 Source: calculations based on FAO data.
7 The average adoption rates for each crop are only calculated across countries where the crop in question is actually grown.
**Figure 1:** Adoption of modern varieties for selected crops

**Figure 2:** Adoption of modern varieties for selected countries
3.2 Attainable yields and MV adoption

The backbone of our empirical analysis is agro-climatically attainable crop yields computed by FAO.\textsuperscript{8} The agro-climatically attainable yield of a given crop in a given geographical location is the highest possible yield which the local climate permits. Sorghum, for example, requires a certain combination of temperature, moisture, and sunlight in order to thrive. Moreover, the optimal combination of these climatic factors varies over the growing season. Deviations from the optimal climate reduce agro-climatically attainable yields.

The agro-climatically attainable sorghum yields are depicted in Figure 3. Green areas indicate high yields, whereas hues going toward orange signify progressively low yields. White areas are completely unsuitable for sorghum. As it can be seen on the map, sorghum thrives in warm and arid climates, whereas attainable yields are lower in the temperate zones and in the tropics.\textsuperscript{9}

The cost of purchasing seeds of modern high-yielding varieties is independent of climate, so the net return of adopting them is larger when the agro-climatically attainable yield is high. This prediction is supported by the data. For example, only 20 percent of the area planted with sorghum in humid Thailand was of MVs in year 2000, whereas it was 87 percent in arid Iran. In the next section, we statistically show that this pattern of adoption holds for all crops in our sample.

We refer the reader to the FAO GAEZ webpage for all the technical details of the computation of agro-climatically attainable yields. A few of them should be noted here, however. FAO computes agro-climatically attainable yields under different assumptions about the agricultural technology in use, or, in the FAO terminology, the input level. In our analysis, we use the agro-climatically attainable yields calculated under the assumption that a high input level is used. A high input level corresponds to modern farming techniques: fully mechanized agriculture, use of synthetic fertilizer and, crucial for our analysis, modern crop varieties. Moreover, we assume that irrigation systems are in place such that countries like Egypt do not appear to be unsuitable for agriculture. These assumptions about input levels and irrigation are independent of the production methods actually in use. Instead, the agro-climatically attainable based on these assumptions reflect the potential yields if modern farming techniques are adopted. Changing one or both of these assumptions does not influence our findings.

3.3 Outcome variables

The two main outcome variables examined in the empirical analysis are income, measured as log GDP per capita, and log population size. These data are taken from The Maddison-Project (2013), but we obtain similar results if we use alternative data sources, such as Penn World Tables or Word Development Indicators. We use the The Maddison-Project (2013) data in our main empirical analysis, as they are available before 1960. This allows us to do a falsification check where we ask whether the adoption of MV crops after 1960 is statistically related to income growth before 1960. As we demonstrate in Section 5.2, it turns out not to be the case, and we

\textsuperscript{8} The data can be downloaded from http://www.fao.org/nr/gaez/en/.

\textsuperscript{9} The corresponding maps for the remaining crops can be found on the FAO GAEZ website.
conclude that our estimated coefficients of MV adoption in our empirical analyses do not pick up unobserved pretrends. Table 1 displays the initial means by subsamples which are separated on the basis of the median MV crop share in 2000. We find that countries with above median adoption rate in 2000 had larger populations, and were more densely populated and slightly richer in 1960 than countries below the median.

For the period 1960–2000, we also study the effect of the adoption MV crops on (in logs): yield per agricultural worker, harvest area, agricultural population, agricultural employment share, life expectancy, infant mortality, adult mortality, and the rate of natural population increase. These data are from FAO and World Development Indicators. The descriptive statistics for all the outcome variables are reported in Table 2.

[Tables 1 and 2 about here]

4 Estimation Strategy

The overall goal of our empirical analysis is to estimate the effects of the adoption of MV crops on measures of economic development. Our identification strategy exploits the interaction of two sources of variation: the time variation arising from the breakthrough of MV crops in the late 1960s and the cross-sectional variation in a country’s climatic suitability for growing MVs.\(^\text{10}\) The baseline estimation equation has the following form:

\[
y_{it} = \beta_0 + \beta_1 \text{mvs}_{it} + \sum_{k=1970}^{2000} \gamma_k \text{year}_k^{it} + \sum_{c=2}^{N} \delta_c \text{country}_c^{it} + \epsilon_{it},
\]

\(^{10}\)In this way, the spirit of our estimation strategy is close related to Nunn and Qian (2011). However, since data on actual adoption are available in our case, the current analysis goes one step further and exploits their basic reduced-form approach to obtain climatic-driven predicted adoption rates, which should be free of various biases when estimated.
where \( y_{it} \) is the outcome of interest (e.g., log GDP/capita, log population size, etc.) in country \( i \) at time period \( t \), which are 1960, 1970, ..., 2000.\(^{11}\) Time and country fixed effects are given by \( \sum_k y_{it}^k \) and \( \sum_{c} c_{tryt}^c \), and \( \varepsilon_{it} \) is an error term. The main explanatory variable, \( mvs_{it} \), is the actual adoption rate of MV crops, defined as the harvested area of MVs of the 10 crops in our data set, relative to the total harvested area of the 10 crops (i.e., of both MVs and traditional varieties). We estimate the coefficient of interest, \( \beta_1 \), by OLS as well as 2SLS using the first-stage strategy outlined below.

There are some caveats to our measure of MV adoption. Our data on MV adoption is limited to 10 crops, and adoption of MVs of all other crops therefore becomes an omitted variable in our estimating equation. This is a problem for our identification strategy if this omitted variable is correlated with the observed adoption of MVs. Our 2SLS strategy partly solves this problem by removing all co-variation between the two variables that is unrelated to climatic variation across countries. Moreover the development of MVs of cash were driven by commercial rather than philanthropic considerations, and their diffusion followed a different pattern than MVs of the food crops in our data set. We, therefore, expect any potential omitted variable bias of our estimates should be relatively small. And this is indeed what we find when we address this issue empirically in Section 5.3.3 by including reduced-form versions of our instrument for the most important cash crops (cotton, soybeans, and sugar).

A related caveat arises from our choice of denominator in the definition of the actual adoption rate. By using only the harvested area of the 10 crops in our MV data set, we are essentially capturing the adoption rate of MVs of food crops. This is a reasonable choice, as scientific effort behind the Green Revolution in developing countries was mostly aimed at food security. However, the share of food production in total agricultural production varies from country to country. In most countries, food production is the main activity, but a small number of countries in our sample rely heavily on cash crops, such as sugar in the Caribbean.

These caveats to our definition of \( mvs_{it} \) are only relevant for the interpretation of the point estimate of \( \beta_1 \). According to our definition, it should be interpreted as the effect on our outcome variables in the average country in our sample from full adoption of MVs of the 10 crops in our data, including potential spill-over effects to adoption of MVs of other crops. By implication, when we later in the paper calculate the growth contribution of MVs in the average country in our sample as the estimated \( \beta_1 \) multiplied by the average MV adoption rate in year 2000, we get the correct magnitude.

The adoption of MV crops is likely to be a function of a number of factors, including the level of economic development. To remove this endogenous component, we construct an instrument for the actual adoption rate of MV crops in equation (1) in two steps. First, exploiting the fact that we have data on the adoption of each MV crop \( j \), we estimate the following equation:

\[
mvs^j_{it} = \sum_{k=1970}^{2000} \alpha_k^j potential_{i}^k \times year_{it}^k + \sum_{k=1970}^{2000} \theta_k year_{it}^k + u^j_{it},
\]  

\(^{11}\) The Appendix to this paper also reports results from specification starting in 1940, but due to missing data for some countries, these samples are unbalanced.
where \( mvs_{jt} \) is the area planted with MV crop \( j \) as a share of total land planted with this crop type.\(^{12}\) The principal idea by estimating equation (2) is to exploit an exogenous measure for the potential of adopting a given MV crop. We use potential\(_i^j\) for this purpose, defined as the average agro-climatically attainable yield for a given crop across all land suitable for agriculture within a country.\(^{13}\) This variation is then interacted with a full set of time-period fixed effects, \( \sum year_t^k \), to exploit that the timing of the global diffusion of MV crops as well. Because some of the new crop types were developed earlier than others, we interact potential\(_i^j\) with time-period fixed effects in the baseline model instead of an indicator function (equal to one after 1960), for example. This is to allow the effect of the climatic determined potential of growing MV crops on the actual adoption to vary over time. Finally, the unexplained part in this regression is \( u_{it} \).

In the second step, we multiply the predicted adoption rates for individual crops from equation (2) by the crops’ share of harvested land in 1960. We then sum across crops to arrive at the aggregate to country-level predicted adoption rate of MVs:

\[
pmvs_{it} = \frac{\sum_{j=1}^{J} \hat{mvs}_{jt} \times harvested\ area_{1960}^j}{\sum_{j=1}^{J} harvested\ area_{1960}^j},
\]

This predicted adoption rate is going to be our instrumental variable for the actual adoption of MVs in equation (1). We thereby concentrate on the exogeneous factors behind MV adoption, namely that some countries were more climatically suitable for MV crops, and that the timing of their development was driven by international efforts rather than concerns for individual countries. The relationship between the actual and the predicted MV shares is shown in Figure 4 for the year 2000 (or equivalently, the change in adoption rate between 1960 and 2000, as MV adoption wase zero for all countries in 1960). There is a strong positive correlation (p-val=0.00). The correlations in 1970, 1980 and 1990 are similarly strong. In 1960, both variables are zero for all countries.

From the figure it is noteworthy that some Asian and South American countries have higher adoption rates than predicted by their climatic suitability for growing them. These discrepancies partly reflect some of the endogeneity we are facing as, for instance, rapid growth in South-East Asia may be a cause for rapid MV adoption rather than vice versa. By using the predicted MV share as an instrument, we avoid that such effects show up as a bias to our empirical estimates.

With our instrumental variable at hand, we estimate the following first-stage equation:

\[
mvs_{it} = \lambda_0 + \lambda_1 pmvs_{it} + \sum_{k=1970}^{2000} \lambda_k year^k_t + \sum_c \lambda_c country^c_i + u_{it},
\]

where \( pmvs_{it} \) is the predicted adoption rate, which is the excluded instrument for actual adoption rate in equation (1). The remaining variables are as defined above. When estimated by 2SLS – using first-stage equation (4) – the coefficient of interest \( \beta_1 \) in equation (1) reflects a one-unit, natural-endowments driven

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\(^{12}\)If, for instance, a country has 60 percent of its rice fields planted with modern varieties, then \( mvs^i = 0.6 \).

\(^{13}\)FAO computes agro-climatically attainable yields under different assumptions about the technology in use. We use the agro-climatically attainable yields based on high input levels, which corresponds to modern post Green Revolution farming techniques, and consequently to a situation when modern varieties are used.
increase in the share of land with MVs on the outcome of interest. Contrary to regressions with generated regressors, parameter estimates in 2SLS regressions with generated instruments are asymptotically distributed as in standard 2SLS regressions. The standard errors of the 2SLS estimate of $\beta_1$ are, therefore, asymptotically valid.

In addition to our baseline 2SLS specification, represented by equation (1) and (4), we perform a number of robustness checks. In particular, we add control variables to the regressions by including $\sum_{k=1970}^{2000} X_i' \times \text{year}_i^k \rho_k$ on the right hand sides of the equations. $X_i'$ is a vector of, e.g., geographical characteristics or initial values of outcome variables. They are interacted with the time-period fixed effects, $\sum \text{year}_i^k$, to pick up potential trends in the outcomes related to the specific controls.

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14Wooldridge (2010), p117.
5 The long-run impact of MV crops

5.1 Baseline results: income and population

We begin by documenting the relationship between the actual MV adoption rate and income and population. Income is a natural outcome variable in our analysis, as it is closely related to economic development and human welfare. We also look at the effect on the size of the population to test whether there is a Malthusian drag on income growth when it is driven by agricultural productivity.

As shown in column 1 of Table 3, controlling for country and time-period fixed effects, the OLS estimate of the impact of MV adoption, $\beta_1$ in equation (1), is 0.99 and statistically significant at the one percent level. This result suggests that countries with higher rates of adoption grew faster in terms of income. The point estimates can be interpreted as the effect on the outcome variables of full adoption of MVs. However, this is an out of sample prediction since no country in our sample achieved full adoption in year 2000; the average adoption rate in year 2000 is 27 percent. In what follows, we therefore discuss the quantitative implications of our estimates in the context of a hypothetical 10 percentage points increase in the share of land planted with MV crops (i.e., adoption rate). That also has the benefit that for such small values, the estimated effects on log GDP/capita, and later other outcomes, are approximately equal to percentage changes in levels. Using this interpretation, the OLS estimate suggest that a 10 percentage points increase in adoption of MVs causes GDP/capita to rise by circa 10 percent.

The OLS estimate is, however, possibly a biased estimate of the causal impact of adoption of MV crops since the decision to adopt new crops is endogenous. According to Boserup (1965), for example, population pressures influence the rate of technological progress in the agricultural sector, and we actually see in our data that initially more densely populated countries, measured by population density in 1960, have higher rates of adoption (see Table 1). Population pressures may also prompt governments or international institutions to initiate programs aimed at increasing agricultural productivity through new technologies. Adoption may similarly be affected by income levels.

In the light of such potential endogeneity issues, we follow the above mentioned strategy and estimate $\beta_1$ in equation (1) by 2SLS using equation (4) as the first stage. The point estimate, reported in column 2 of Table 3, is 1.46. While it is about 50 percent larger than the corresponding OLS estimate, the difference is not significant in a statistical sense. Nevertheless, the point estimate implies that a 10 percentage points increase in adoption of MVs leads to an increase in GDP/capita of 15 percent. In column 3, we report the reduced-form estimate, regressing income directly on predicted MV adoption (along with the country and time period fixed effects) and, unsurprisingly, we also find a large and statistical significant effect of the predicted adoption of MVs on income.

Column 4-6 report OLS, 2SLS and reduced-form estimates of the effect of MV adoption on population size. All estimates are negative and statistically significant. The 2SLS estimate is numerically larger than the OLS counterpart, but, as in the income regressions, the difference is not statistically significant at conventional
levels. The 2SLS point estimate is -0.40, indicating that a 10 percentage point increase in MV adoption reduces population size by four percent. It is notable how relatively small the impact on population is compared to income. In section 6.2, we demonstrate that this finding is explained by counteractive effects from falling mortality and fertility rates, where the later effect dominates weakly.

[Table 3 about here]

We regard the 2SLS estimates in Table 3 as our baseline estimates. Such panel estimates do not lend themselves to simple graphical illustration, so in Figure 5, Panel A, we depict partial correlation plots between income and predicted MV adoption in a long-difference specification for the years 1960 and 2000. A similar correlation plot is depicted in Panel B. The long differences specification provide readable figures, while still holding time-period fixed effects constant and are, in this way, equivalent to the baseline reduced-form estimates from the 10-year panel models reported in Table 3. Well-known growth success stories, such as Botswana, Mauritius, and China, and war-torn growth disasters, such as Sierra Leone, Liberia, and Iraq, are clearly visible in Panel A. Yet, at also appears that our results for GDP/capita are not driven by such outliers. The same is true for our results for population size, as it is evident from Panel B.

5.2 Falsification tests

Our identification strategy allows us to carry out a falsification exercise which looks at changes in the economic outcomes in the period 1940-1960, i.e., before the possibility of growing MV crops was present, and check if they correlated with post-1960 changes in predicted MV adoption (i.e., in our instrument). The estimation results from this falsification test are reported in Table 4. Columns 1 and 3 use the pre-period years 1940, 1950,
and 1960, while Columns 2 and 4 make use of the pre-period years 1950 and 1960. There is no evidence of any relationships like those presented in the previous table, suggesting that $\hat{\beta}_1$ is not contaminated by some preexisting trends in income or population, that is, countries with predicted higher MV adoption were not on a different growth path before the introduction of MVs. These results provide evidence of the internal validity of our research design.

[Table 4 about here]

5.3 Robustness

5.3.1 Locations of international research centers

The MV crops, we analyze in this paper, were – as discussed in Section 2 – developed at international research centers, of which nine were located in a country of our sample. If the location of these research centers were correlated with both the climatic variables used in the development of our instrumental variable and economic variables, such as subsequent foreign aid or trade agreements; and if MV adoption were higher in countries with a research center, then the exclusion restriction of our instrument would be violated. These are a lot of ifs, and based on our reading of the historical evidence, we find it implausible. We nevertheless do a series of robustness checks to our baseline 2SLS estimates in order to check this possibility.

In Column 1 of Table 5, we include a dummy for whether a country is the host of a research center in our baseline GDP/capita regression. The dummy is interacted with time dummies, to make it comparable to our time-varying MV adoption variable (any constant effects of being host to a research center is captured by the country fixed effects). Controlling for the location of research centers in this way does not change our baseline result: the coefficient on actual MV adoption is virtually unchanged compared to our baseline 2SLS specification in Table 3. The same is true in column 2, where we include distance to nearest research center as a control variable (also interacted with time dummies), and in column 3, where we exclude the nine countries with research centers from the regression.

We obtain similar results in Columns 4-6 of Table 5, where we perform the same robustness test for our baseline population estimate. The only difference is that the point estimate on MV adoption falls slightly when the nine countries with research centers are excluded in Column 6.

[Table 5 about here]

5.3.2 Asian influence

We now probe into how the economic development of East- and South-Asian countries influence our findings. This region is, on average, more suitable for MV crops than elsewhere, and their economic performance has been exceptional compared to other regions in the sample, particularly Sub-Saharan Africa. Table 6 checks whether our baseline 2SLS estimates are driven by East and South Asia alone.
Columns 1–4 show the effect of MVs on income continues to be positive and statistically significant when controlling for the variation occurring between East- and South-Asian countries and the remaining countries of our sample over time. In particular, column 1 includes a region dummy for East Asia interacted with a full set of time-period fixed effects, column 2 replaces it with a South-Asian region dummy, while column 3 combines both regions into one. Finally, column 4 drops the 14 countries altogether from the baseline sample. The estimated coefficient is slightly smaller when an East-Asia dummy is included, and slightly larger in the three other cases. The differences are insignificant, however, and our baseline results do not appear to be driven by time-varying region effects between Asia and the remaining countries in our sample.

We do the same exercise for population size in columns 5–8. All the points estimates are negative and relatively close to the baseline.

[Table 6 about here]

5.3.3 Time-varying geographical changes

This section investigates whether our 2SLS estimates pick up time-varying geographical effects unrelated to the Green Revolution. Such effects could arise if other technological advancements disproportionately benefit countries with certain geographical characteristics that correlate with our instrument. Table 7 reports the robustness of our findings when different geographical controls (all interacted with a full set of time-period fixed effects) are included. Column 1 adds absolute latitude and absolute longitude to our baseline income regression. These basic geographical variables capture anything from climate to colonial history, and they are widely used as control variables in the growth literature. In Column 2, we control for the suitability of cotton, sugar and soybeans interacted with their 1960 share of total harvested area. This specification roughly corresponds to a reduced-form version of the generated instrument, and serves to control for omitted variable bias coming from MV adoption for these important cash crops. Column 3 controls for mean temperature and precipitation, which are both important variables used to construct our instrument, and may be related to, for instance, the disease environment. In Column 4, we control for additional geographical variables widely used in the literature (arable land, elevation and distance to waterways), and in Column 5 we include all the control variables from Columns 1–4 simultaneously.

The estimated effect of MV adoption on income remains significant across all five columns. The point estimate for MV adoption falls compared to the baseline when we control for absolute latitude and longitude, and for the climatic variables, and it increases slightly in the other specifications. When all controls are included, the point estimate is slightly larger than in our baseline regression, but the difference is highly insignificant. Note also that our instrument remains strong (Kleibergen-Paap=16.36) in column 5 even if we include ten geographical control variables interacted with time dummies.

In column 6–10 of Table 7, we perform the same robustness checks for our baseline population regression. The estimated effect of MV adoption on population size is generally less robust to the geographical control variables than our income regressions in terms of statistical significance. However, the point estimate remains
negative across all specifications.

5.3.4 Further robustness checks

We report additional robustness checks in the Appendix to the paper. Firstly, we show the robustness of our baseline findings using alternative specified predicted MV adoption rates. In particular, we obtain the same results if country fixed effects are included in equation (2) or if the time fixed effects, in the interaction term with the potential of growing MVs, are replaced with an indicator equal to one after 1960 (i.e., the initial dating of the global diffusion of MVs). Secondly, the baseline estimates are hardly affected by stopping the analysis in 1980, implying that only exploiting the first wave of diffusion of MVs gives rise to similar findings. Moreover, starting the analysis in 1940, which produces an unbalanced panel, but has the advantage of considering more years prior to the Green Revolution for comparison, also gives rise to the same conclusions. Thirdly, the inclusion of the interaction between institutional quality, as measured by the average constraint on the executive in 1950, 1960, and 1970, and a full set of time fixed effects has little effect on the overall conclusion that MVs have a positive effect on income and a negative effect on population size. Finally, controlling for initial values of income, population density (or size), and trade share – interacted with a full set of year fixed effects – has little effect on our baseline estimates, suggesting that they are not contaminated with, e.g., processes of convergence in the outcomes of interest which are unrelated to the Green Revolution.

6 Channels

6.1 Decomposing the income effect

Our baseline estimate implies that a 10 percentage points higher adoption rate of MV crops increases GDP per capita in developing countries by circa 15 percent. A naive partial equilibrium calculation would suggest a substantially lower effect. MVs have roughly 50 percent higher yields than their traditional counterparts (Evenson and Gollin (2003b)), and agriculture, on average, accounted for less than 50 percent of GDP in our sample of countries in 1960. Combining these two statistics would suggest that GDP per capita should increase by 2.5 percent.

The naive calculation is, of course, naive because it does not take factor adjustment, sectorial shifts and potential spill-over effects into account. The question is, then, whether such general equilibrium effects can account for the gap between the naive estimate of 2.5 percent and our econometric estimate of around 15 percent. We address this question in two steps. First, we look at agricultural productivity, as measured by yields per agricultural worker, and then we proceed to look at structural transformation.
6.1.1 The effect on agricultural productivity

To structure the discussion of the effect on agricultural productivity, we assume that agricultural production, \( Y_a \), is a constant-returns-to-scale Cobb-Douglas function of land, \( X \), agricultural capital, \( K \), and agricultural labor, \( L \):

\[
Y_a = ZAX^\alpha K^\beta L^{1-\alpha-\beta}, \quad 0 < \alpha + \beta < 1, \quad \alpha, \beta > 0.
\] (5)

We omit \( a \)-subscripts on the inputs for simplicity. \( K \) is defined broadly to cover everything from tractors to fertilizer. We abstract from human capital here, but we will return to it briefly below. \( Z \) is the component of total factor productivity that depends directly on the variety of crops grown. The introduction of MVs during the Green Revolution should be interpreted as a shock to \( Z \). The parameter \( A \) is all other components of total factor productivity that are indirectly affected by the introduction of MV crops.

We divide by the labor input to obtain the production function for yields per worker:

\[
y_a = ZAx^\alpha k^\beta.
\] (6)

The optimal level of capital determined by profit maximization leads to the following first-order condition for capital:

\[
\beta ZAx^\alpha k^{\beta-1} = r \Leftrightarrow k = \left( \frac{\beta}{r} ZAx^\alpha \right)^{\frac{1}{1-\beta}},
\] (7)

where \( r \) is the real interest rate, which we assume to be exogenous and constant in the long run. By taking logs of the per worker production function and substituting the first-order condition for capital for \( k \), we get:

\[
\ln y_a = \frac{1}{1-\beta} \ln Z + \frac{1}{1-\beta} \ln A + \frac{\alpha}{1-\beta} \ln x + \frac{1}{1-\beta} \ln \frac{\beta}{r}.
\] (8)

To evaluate the consequences of the introduction of MV crops, we differentiate with respect to the share of MVs grown, denoted by \( m \):

\[
\frac{\partial \ln y_a}{\partial m} = \frac{1}{1-\beta} \left[ \frac{\ln Z}{\partial m} + \frac{\ln A}{\partial m} + \frac{\alpha \ln x}{\partial m} \right].
\] (9)

This equation shows that MVs can affect yields per worker through the direct effect on yields \( \ln Z/\partial m \), the indirect effects on TFP, \( \ln A/\partial m \), which we return to below, and through adjustments of the land to labor ratio, \( \ln x/\partial m \). Each of these three channels are magnified by capital adjustment, which is a fourth channel and captured by the \( 1/1-\beta \) in front of the bracket.

We estimate the total effect on yields per worker, \( \partial \ln y_a/\partial m \), by the same empirical approach as we used to estimate the effect on GDP per capita and population in the previous section. Our yield per worker variable is based on data on produced quantities and harvested area for a large number of crops. To compute a measure of yields that resemble a quantity index without having access to crop-specific prices, we normalize yields of each crop to their average level in 1960.15 For a given year and country, we then weigh them together with their 1960 area shares multiplied by the actual extent of harvested land in that country during that year. The results

\[15\]We do not have data for yields and the harvested area before 1961, so for 1960, we assume the level of these variables were as in 1961.
reported in column 1 of Table 8 show that a 10 percentage points higher MV adoption rate increases yields per worker measured in this way by about 20 percent.\(^\text{16}\)

We use Equation (9) to decompose this effect into its parts. We know from prior studies that $\beta \approx \frac{1}{3}$ in agriculture, so one third of the 20 percent productivity increase comes from capital adjustment, leaving 13 percentage points to be explained by what is inside the bracket.\(^\text{17}\) As mentioned above, MVs have, on average, 50 percent higher yields than traditional varieties, implying that the direct TFP effect of a 10 percentage points higher MV adoption rate is 5 percent. The estimated effect on yields is, however, based on the ten crops for which we have data on MV adoption. The area share of these crops were 65 percent in 1960 in the average country in our sample, so we set so we set $\ln Z_{\partial m} = 0.5 \cdot 0.65$. That leaves about 10 percentage points of the effect on yield per worker to be explained by the two other terms inside the bracket.

The effect on land per worker can be decomposed into an effect on total agricultural land, and an effect on the total number of agricultural workers, i.e., $\ln x_{\partial m} = \ln X_{\partial m} - \ln L_{\partial m}$. We report the estimates of the two right-hand terms in Columns 2 and 3 of Table 8. The introduction of MVs is associated with significantly less land use and significantly fewer agricultural workers.\(^\text{18}\) The effect on workers is largest, so the net effect $\ln x_{\partial m}$ is 0.1. The higher land-to-labor ratio has a relatively modest effect on yields per worker, however, as $\alpha$, the output elasticity of land, is around 0.2; see Valentinyi and Herrendorf (2008).

As it always is the case with total factor productivity, $\ln A_{\partial m}$ is not observed. But since we have pinned all other terms in the equation down statistically (or by evidence from earlier studies), we can infer that $\ln A_{\partial m} \approx 0.8$, meaning that a 10 percentage points increase in MV adoption increases total factor productivity by 8 percentage point beyond the higher yields per plant they offer.

Before we discuss whether this magnitude is plausible, we should note that it is not statistically different from zero, given the statistical uncertainty on the estimates in Columns 1–3 used in the calculation. Yet, there are reasons to believe $\ln A_{\partial m}$ to be both large and positive. First, the direct income effect from adopting MVs allows farmers to invest more in health and human capital, and gives them better access to markets. Foster and Rosenzweig (2004), for instance, show that the Green Revolution has increased both demand and supply of schooling in India, and that better educated individuals adopted new productivity enhancing agricultural technologies faster. The experience with MVs of the ten crops in our sample may likewise make farmers more inclined to adopt MVs of other crops, and new agricultural methods more generally. Improved health will also increase agricultural productivity. We return to health effects in Section 6.2, where we show that the introduction of MVs reduced mortality. All these mechanisms related to human capital and health are not part of the accounting framework above, and are therefore captured by $\ln A_{\partial m}$. Moreover, since we are looking at a 40 year period, these effects have had a long time to accumulate.

Changes in average soil quality is also reflected in changes in $A$. We assume constant returns to scale in the

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\(^{16}\)Due to missing data, we have three fewer observations in the regressions in Table 8 than in our baseline regressions. We therefore report estimates of the effects on GDP/capita and population size in this smaller sample in the two rightmost columns of Table 8.

\(^{17}\)See, e.g., Valentinyi and Herrendorf (2008).

\(^{18}\)We compute the number of agricultural workers as the agricultural employment share multiplied by total population. Differences in participation rates across sectors are implicitly controlled for in our regressions by the fixed effects.
production function, which implies that there are no productivity gains from reducing the extent of crop land. In reality, marginal lands are likely to be abandoned first, or brought into use last. The negative coefficient of total agricultural land in Column 2 of Table 8 implies that countries that successfully went through Green Revolution expanded agricultural land less rapidly, and that the average soil quality of their crop lands therefore is likely to be higher. The negative coefficient is also consistent with the Borlaug hypothesis.

Based on our data set, we cannot say whether these effects can account for the entire induced coefficient \( \ln A \approx 0.8 \), but the estimate does seem plausible given the statistical uncertainty in our regressions. It is consequently also plausible that a 10 percentage points higher MV adoption rate can increase yields per worker by 20 percent, as both factor adjustment and indirect TFP effects compound the direct 5 percent increase in yields.

6.1.2 Structural change and nonagricultural productivity

Agriculture accounted for 69 percent of employment in 1960 in our sample, and, since productivity is relatively low in agriculture, a substantially smaller fraction of GDP. Since we find almost identical impacts on agricultural productivity and on GDP per capita, there has to be a substantial contribution to GDP per capita from structural transformation, from spill-over effects on nonagricultural productivity, or both.

The estimated negative coefficient of the log of agricultural employment share in Column 4 of Table 8 indicates that the introduction of MV crops has initiated a structural shift of economic activity towards nonagricultural sectors. On average, nonagricultural sectors are substantially more productive than agriculture in developing countries, so such a shift could provide a significant boost to GDP per capita. A shift to nonagriculture may also cause aggregate productivity to grow faster if economic growth is driven by learning-by-doing or scale effects in the nonagricultural sector.

To assess the implications of the MVs for GDP per capita more formally, we use the following relationship:

\[
gdp = AES y_a + (1 - AES) y_n ,
\]

where \( gdp \) is GDP per capita, AES is the agricultural employment share, and \( y_a \) and \( y_n \) are average labor productivity in agriculture and nonagriculture, respectively. Taking logs and differentiating with respect to the share of MV crops, we get:

\[
\frac{\partial \ln gdp}{\partial m} = \frac{1}{gdp} \left\{ \frac{\partial y_a}{\partial m} AES + \frac{\partial y_n}{\partial m} (1 - AES) + \frac{\partial AES}{\partial m} (y_a - y_n) \right\}
\]

\[
\approx \frac{\partial \ln y_a}{\partial m} \frac{Y_a}{GDP} + \frac{\partial \ln y_n}{\partial m} \left(1 - \frac{Y_a}{GDP}\right) - \frac{\partial \ln AES}{\partial m} \frac{y_n - gdp}{gdp} .
\]

To arrive at the last expression, we use that \( \frac{\partial \ln x}{\partial x} \approx \frac{\partial x}{x} \). The effect on log GDP per capita can be decomposed into direct productivity effects in agriculture and nonagriculture (\( \frac{\partial \ln y_a}{\partial m} \) and \( \frac{\partial \ln y_n}{\partial m} \)), weighted by their respective
shares of GDP, and structural transformation. By how much structural transformation, $\frac{\partial \ln AES}{\partial m}$, affects GDP per capita depends on the productivity gap between nonagriculture and the general economy, $\frac{y_n - gd_p}{gd_p}$.

We assess the relative importance of the three channels for the average country in our sample. The average country had an agricultural employment share of 0.7 in 1960. We do not have comprehensive data on relative sectorial productivity levels for 1960, but contemporary data suggest that countries with agricultural employment shares around 0.7 have nonagricultural sectors that are between three and 10 times more productive than agriculture.\(^{19}\) We choose $y_n = 3y_a$ to be on the conservative side. These numbers imply that our average country has $\frac{Y_a}{GDP} = 0.44$ and $\frac{y_n - gd_p}{gd_p} = 0.88$. Combined with the estimates of $\frac{\partial \ln y_a}{\partial m}$ and $\frac{\partial \ln AES}{\partial m}$, reported in Table 8, we have that:

\[
\frac{\partial \ln y_a}{\partial m} \frac{Y_a}{GDP} = 2 \cdot 0.44 = 0.88, \tag{12}
\]

\[
-\frac{\partial \ln AES}{\partial m} \frac{y_n - gd_p}{gd_p} = -(-1.0) \cdot 0.88 = 0.88. \tag{13}
\]

According to these calculations, higher agricultural productivity (including productivity gains from factor adjustment) and structural change, coincidentally, both contribute by approximately 8.8 to the economic growth caused by a ten percentage points higher adoption rate of MVs. Taken together, these two effects increase GDP per capita by 17.6 percent, which is somewhat higher than our estimated GDP effect of 15 percentage points. When statistical uncertainty is taken into account, however, these estimates are essentially of the same magnitude. This suggests that $\frac{\partial \ln y_n}{\partial m}$ is close to zero. In other words, we do not need to look for spill-over effects on nonagricultural productivity to rationalize the relatively large effect of the introduction of MVs on GDP per capita we find in our empirical analysis. In fact, we may be looking for moderate negative spill-over effects, a realistic possibility since the average migrant out of agriculture is unlikely to obtain the nonagricultural average productivity level immediately, if ever.

### 6.2 Decomposing the population effect

Our baseline results suggest that the introduction of MVs had a significant negative impact on population size. In this section, we decompose the total effect of MVs on population into its effects on mortality and fertility.

The estimates, reported in the first four columns, document the impact on various measures of mortality. According to Column 1, adoption of MVs had a positive, but only borderline statistically significant effect on life expectancy at birth, suggesting that a 10 percentage points increase in MV adoption increases life expectancy by 1.25 percent. In comparison, the average increase in the actual share of MV 1960–2000 was 21 percentage points and life expectancy increased with 26 percent over the same time period. Columns 2–4 show negative and statistically significant effects on infant mortality and adult mortality (for both sexes). The lack of significance of the coefficient of life expectancy, therefore, seems to be a statistical artifact rather than an indication that life expectancy was unaffected by the Green Revolution. Moreover, the improvement in life expectancy were driven by mortality decreases of all ages and for both sexes, albeit the adult mortality impact for females (compared to

\(^{19}\)Calculations based on data from Gollin et al. (2014).
males) are somewhat larger in magnitude. Since morbidity and mortality are highly correlated, the documented decrease in mortality also suggests that adoption of MVs improved health, which may further contribute to the higher TFP level we observe in agriculture.

The negative impact on mortality would in itself increase population growth. Thus, in order for the mortality results to be consistent with the fact that MV adoption reduces population growth (see column 7), the impact on fertility (or migration) needs to negative and sufficiently large to offset the positive contribution from the decreasing mortality rate. Columns 5 reveals that we indeed find a large negative impact on the fertility rate. Moreover, the impact is larger than the mortality effect, as the estimate, reported in Column 6, shows that the effect on the rate of natural population increase (crude birth rates minus crude death rates) is negative and statistically significant. Moreover, the magnitude is very similar to effect on population growth demonstrating that our baseline finding is not picking up net migrational responses.

[Table 9 about here]

7 Lessons and future perspectives

We have in our empirical analysis so far concentrated on getting the right point estimate for the effects of adopting MV crops. We have used an instrumental variable based on spatial variation in the climatic suitability for growing MVs and the time variation from their introduction in the late 1960s to avoid endogeneity. We have then subjected our baseline estimates to numerous robustness tests to make sure that they are not contaminated by confounders, or other statistical problems. Finally, in the case of income, we have used an accounting framework to show that while our estimated effect of MV adoption seems rather large, it is consistent with a standard production function and the magnitudes of general equilibrium effects that we should expect from the results of previous research. Based on these checks, we feel confident in using our estimates to evaluate the actual effect of the introduction of modern crop varieties in developing countries.

We do so simply by multiplying our point estimates with the actual adoption rates in year 2000, and transform them into growth contributions by taking the exponential, i.e., by computing $\exp(\hat{\beta}_1 mvs_{2000}) - 1$. Since adoption is correlated with country size, we calculate this expression for both the average country in our sample, and for the developing world as a whole. The results are reported in Table 10.

The average country had a MV adoption rate of 27 percent in 2000, which translates into a 48 percentage points contribution to growth in GDP/capita in the period 1960-2000. By comparison, the actual growth in the average country during the 40-year period was 56 percent. Our results, naturally, are surrounded by statistical uncertainty, but they nevertheless strongly indicate that the Green Revolution has been a very important source of economic growth in developing countries. Perhaps even the most important one.

Turning to the developing world as a whole, defined as the 85 countries in our sample, MV adoption was 59%. Combined with our point estimate, it implies a whopping 137 percentage points growth contribution. Nonetheless, due to rapid GDP growth in the largest countries, this is a somewhat smaller fraction of actual
growth than in the average country.

Compared with the GDP/capita effect, the relative impact of MV adoption on population size is rather modest. In the average country it has reduced the population size by 10 percentage points compared to a counterfactual with no MV adoption. For developing world as a whole, the contribution is minus 21 percentage points. These numbers should be compared to actual population growth of 164 percent in the average country, and 129 percent in total. Yet, a 21 percent reduction in population size can still give a substantial boost to incomes in economies facing Malthusian constraints. It will also have substantial positive effects on the climate and the environment in general, since our results indicate that the developing world would have contained more than one billion more people in 2000 if the Green Revolution had not happened. This estimate, of course, is based on the assumption that one billion more people could be fed without the new crop varieties. While this may be doubtful, the result nevertheless dispels the pessimistic Malthusian view that improvements in agricultural productivity in the poorest countries of the world results in growing populations rather than rising incomes.

[Table 10 about here]

The Green Revolutions is often associated with the 1960s and 1970s, but rather than slowing down, the rate of adoption and the number of new crop varieties released increased in the 1980s and 1990s, and the acceleration seems to have continued to the Present day. Scattered evidence from sub-Saharan Africa suggests that the MV adoption rate has increased by as much in the 2000s as in the four preceding decades.20 Coincidentally, the 2000s has also been a decade of extraordinary high growth in Africa.

Yet, there is still a huge potential for improving living standards in developing countries through new crop varieties. Adoption is far from universal, and agriculture is still a crucial sector most places. Moreover, genetic engineering of some crops has already increased their yields beyond what traditional cross breeding has achieved, and the technology therefore has a huge potential for improving incomes in the poorest places on our planet. Indeed, our results suggests that the investments in the development of MV crops by far have been the most successful form of foreign aid to developing countries in the past half of a century. This fact should be recognized when the merits of GM crops are publicly debated.

20Source: Calculations based on DIIVA data.
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Maredia, M. K., Byerlee, D. R., January 2000. Efficiency of research investments in the presence of international spillovers: wheat research in developing countries. Agricultural Economics of Agricultural Economists 22 (1).
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URL http://dx.doi.org/10.1007/s10887-011-9074-1


Table 1: Initial Differences in Outcomes by Actual MV adoption in 2000

<table>
<thead>
<tr>
<th>Actual MV adoption in 2000, Median:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>above</td>
<td>below</td>
<td>(-2) - (1)</td>
<td></td>
</tr>
<tr>
<td>Log GDP p.c. 1960</td>
<td>7.301</td>
<td>7.000</td>
<td>0.040**</td>
</tr>
<tr>
<td>(0.711)</td>
<td>(0.629)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log population 1960</td>
<td>9.317</td>
<td>7.845</td>
<td>0.000***</td>
</tr>
<tr>
<td>(1.495)</td>
<td>(0.981)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP p.c. growth 1950-1960</td>
<td>0.199</td>
<td>0.201</td>
<td>0.959</td>
</tr>
<tr>
<td>(0.154)</td>
<td>(0.170)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population growth 1950-1960</td>
<td>0.242</td>
<td>0.215</td>
<td>0.062*</td>
</tr>
<tr>
<td>(0.063)</td>
<td>(0.067)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log population density 1960</td>
<td>4.321</td>
<td>3.552</td>
<td>0.013**</td>
</tr>
<tr>
<td>(1.442)</td>
<td>(1.340)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># Countries</td>
<td>43</td>
<td>42</td>
<td></td>
</tr>
</tbody>
</table>

Notes. This table reports initial differences (in 1960) by the actual adoption rate in 2000. In particular, column 1 provides means and standard errors for the group of countries above (or equal to) the median value of the actual MV adoption in 2000, and column 2 provides means and standard errors for the group of countries below the median value of the actual MV adoption in 2000. Column 3 report whether the means are statistically significant from each other.

Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>mean</td>
<td>sd</td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>(in logs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Life Expectancy</td>
<td>555</td>
<td>3.904</td>
<td>0.232</td>
<td>3.292</td>
<td>4.340</td>
</tr>
<tr>
<td>Population</td>
<td>542</td>
<td>8.954</td>
<td>1.514</td>
<td>5.603</td>
<td>14.05</td>
</tr>
<tr>
<td>GDP p.c.</td>
<td>540</td>
<td>7.349</td>
<td>0.789</td>
<td>5.667</td>
<td>9.494</td>
</tr>
<tr>
<td>Harvest Area</td>
<td>425</td>
<td>14.19</td>
<td>1.659</td>
<td>8.189</td>
<td>18.73</td>
</tr>
<tr>
<td>Agri. Population</td>
<td>524</td>
<td>8.408</td>
<td>1.529</td>
<td>4.904</td>
<td>13.43</td>
</tr>
<tr>
<td>Agr. Employment share</td>
<td>567</td>
<td>-0.589</td>
<td>0.512</td>
<td>-2.797</td>
<td>-0.0513</td>
</tr>
<tr>
<td>Yield p.w.</td>
<td>410</td>
<td>4.570</td>
<td>0.885</td>
<td>2.776</td>
<td>7.848</td>
</tr>
<tr>
<td>Fertility rate</td>
<td>425</td>
<td>1.655</td>
<td>0.358</td>
<td>0.412</td>
<td>2.196</td>
</tr>
<tr>
<td>Adult Mortality Female</td>
<td>425</td>
<td>5.519</td>
<td>0.477</td>
<td>4.256</td>
<td>6.497</td>
</tr>
<tr>
<td>Adult Mortality Male</td>
<td>425</td>
<td>5.760</td>
<td>0.352</td>
<td>4.775</td>
<td>6.501</td>
</tr>
<tr>
<td>Infant mortality</td>
<td>386</td>
<td>4.306</td>
<td>0.668</td>
<td>1.872</td>
<td>5.410</td>
</tr>
<tr>
<td>(in levels):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual MV Adoption</td>
<td>595</td>
<td>0.114</td>
<td>0.186</td>
<td>0</td>
<td>0.927</td>
</tr>
<tr>
<td>Pred. MV Adoption</td>
<td>595</td>
<td>0.082</td>
<td>0.097</td>
<td>0</td>
<td>0.558</td>
</tr>
<tr>
<td>GDP p.c. Growth</td>
<td>485</td>
<td>0.120</td>
<td>0.253</td>
<td>-0.996</td>
<td>1.606</td>
</tr>
<tr>
<td>Population Growth</td>
<td>489</td>
<td>0.234</td>
<td>0.0765</td>
<td>-0.0587</td>
<td>0.488</td>
</tr>
<tr>
<td>Rate of Natural Increase</td>
<td>425</td>
<td>0.251</td>
<td>0.0660</td>
<td>-0.0457</td>
<td>0.400</td>
</tr>
</tbody>
</table>
Table 3: The effect of MVs GDP/capita and population size

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GDP/capita</td>
<td>Population</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual MV adoption</td>
<td>0.992***</td>
<td>1.456***</td>
<td>-0.206***</td>
<td>-0.397**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.177)</td>
<td>(0.322)</td>
<td>(0.0705)</td>
<td>(0.162)</td>
<td></td>
</tr>
<tr>
<td>Predicted MV adoption</td>
<td>1.831***</td>
<td>-0.499***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.504)</td>
<td>(0.186)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>425</td>
<td>425</td>
<td>425</td>
<td>425</td>
<td>425</td>
</tr>
<tr>
<td>Countries</td>
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<td>85</td>
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<td>85</td>
</tr>
<tr>
<td>Estimator</td>
<td>OLS</td>
<td>2SLS</td>
<td>OLS</td>
<td>OLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Kleibergen-Paap</td>
<td>.</td>
<td>29.67</td>
<td>.</td>
<td>.</td>
<td>29.67</td>
</tr>
</tbody>
</table>

Notes: The table reports OLS and 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable are: Actual MV adoption, which is the actual share planted with MV crops and Predicted MV adoption, which is the predicted share of MV crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Falsification test

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
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<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GDP/capita</td>
<td>Population</td>
<td></td>
</tr>
<tr>
<td>Predicted MV adoption, leaded 2 periods</td>
<td>-0.272</td>
<td>-0.0129</td>
<td>-0.0884</td>
</tr>
<tr>
<td></td>
<td>(0.310)</td>
<td>(0.310)</td>
<td>(0.139)</td>
</tr>
<tr>
<td># Observations</td>
<td>200</td>
<td>170</td>
<td>202</td>
</tr>
<tr>
<td># Countries</td>
<td>85</td>
<td>85</td>
<td>85</td>
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<tr>
<td>Estimator</td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
</tr>
</tbody>
</table>

Notes: The table reports OLS estimates based on a falsification exercise, checking if changes in the outcome during the pre-period (i.e., 1940-1960 or 1950 and 1960) correlates with future values of our instrumental variable from Table 3. Thus, the dependent variables are measured in the pre-period 1940–1960 (odd numbered columns) or 1950 and 1960 (even numbered columns), while the explanatory variable is measured in the post-period 1960–1980 (odd numbered columns) or 1970 and 1980 (even numbered columns). The explanatory variable is predicted MV adoption as defined in equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1.
Table 5: Robustness to research centers

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable (in logs):</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP/capita</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Actual MV adoption</strong></td>
<td>1.473***</td>
<td>1.528***</td>
<td>1.569***</td>
<td>-0.406**</td>
<td>-0.414**</td>
<td>-0.299**</td>
</tr>
<tr>
<td></td>
<td>(0.315)</td>
<td>(0.302)</td>
<td>(0.316)</td>
<td>(0.172)</td>
<td>(0.164)</td>
<td>(0.146)</td>
</tr>
<tr>
<td>Controls ( (\times \sum yr) )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hosting research center dummy</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Distance to research center</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Excluding countries with research center</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
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<tr>
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<td>425</td>
<td>425</td>
<td>380</td>
</tr>
<tr>
<td># Countries</td>
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<td>76</td>
<td>85</td>
<td>85</td>
<td>76</td>
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<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>Kleibergen-Paap</td>
<td>27.21</td>
<td>30.28</td>
<td>37.74</td>
<td>27.21</td>
<td>30.28</td>
<td>37.74</td>
</tr>
</tbody>
</table>

Notes: The table reports 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable is Actual MV adoption, which is the actual share planted with MV crops, which is then instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.
### Table 6: Robustness to East and South Asian Countries

<table>
<thead>
<tr>
<th></th>
<th>Full Sample w.o East/ South Asian countries</th>
<th>Full Sample w.o East/ South Asian countries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6) (7) (8) (9)</td>
<td></td>
</tr>
<tr>
<td>Dependent Variable (in logs):</td>
<td>GDP p.c</td>
<td>Population</td>
</tr>
<tr>
<td>Actual MV adoption</td>
<td>1.325***</td>
<td>1.521***</td>
</tr>
<tr>
<td></td>
<td>(0.378)</td>
<td>(0.343)</td>
</tr>
<tr>
<td>Controls ($\sum yr$)</td>
<td>East Asian region Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>South Asian region No</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>East &amp; South Asian regions No</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td># Observations 425</td>
<td>425</td>
</tr>
<tr>
<td></td>
<td># Countries 85</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>Estimator 2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td></td>
<td>Kleinbergen-Paap 29.76</td>
<td>31.05</td>
</tr>
</tbody>
</table>

Notes: East Asia is China, Indonesia, Cambodia, Lao PDR, Myanmar, Malaysia, Philippines, Thailand, and Vietnam. South Asia is Bangladesh, India, Sri Lanka, Nepal, and Pakistan. The table reports 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable is Actual MV adoption, which is the actual share planted with MV crops, which is then instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>GDP p.c</td>
<td>1.079**</td>
<td>1.579***</td>
<td>1.327***</td>
<td>1.528***</td>
<td>1.555***</td>
<td>-0.254</td>
<td>-0.475***</td>
<td>-0.309*</td>
<td>-0.274</td>
<td>-0.193</td>
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<tr>
<td></td>
<td>(0.450)</td>
<td>(0.330)</td>
<td>(0.470)</td>
<td>(0.413)</td>
<td>(0.488)</td>
<td>(0.193)</td>
<td>(0.166)</td>
<td>(0.175)</td>
<td>(0.199)</td>
<td>(0.204)</td>
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<td><strong>Controls (×∑yr)</strong></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Absolute latitude and longitude</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
</tr>
<tr>
<td>Suitability for cash crops (cotton, sugar, soybeans)</td>
<td>-</td>
<td>Yes</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>-</td>
<td>Yes</td>
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<tr>
<td>Mean temperature and precipitation</td>
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<td>-</td>
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<td>-</td>
<td>-</td>
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<tr>
<td>Arable land, distance to waterway and elevation</td>
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<td>-</td>
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<td>Yes</td>
<td>-</td>
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<tr>
<td>All geographic controls</td>
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<td>425</td>
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<td><strong># Countries</strong></td>
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<tr>
<td><strong>Estimator</strong></td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
</tbody>
</table>

Notes: The table reports 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable is Actual MV adoption, which is the actual share planted with MV crops, which is then instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1
Table 8: The Agricultural Sector

<table>
<thead>
<tr>
<th>Dependent Variable (in logs):</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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</thead>
<tbody>
<tr>
<td>Yield p.w.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Harvest Area</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Agri. Population</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agri. Employment Share</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP p.c.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual MV adoption</td>
<td>2.042***</td>
<td>-0.504</td>
<td>-1.468***</td>
<td>-1.048***</td>
<td>-0.420**</td>
<td>1.522***</td>
</tr>
<tr>
<td></td>
<td>(0.423)</td>
<td>(0.339)</td>
<td>(0.396)</td>
<td>(0.298)</td>
<td>(0.168)</td>
<td>(0.333)</td>
</tr>
<tr>
<td># Observations</td>
<td>410</td>
<td>425</td>
<td>410</td>
<td>410</td>
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<tr>
<td># Countries</td>
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<td>82</td>
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<td>82</td>
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<td>82</td>
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</table>

Notes: The table reports 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable is Actual MV adoption, which is the actual share planted with MV crops, which is then instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>(in logs)</td>
<td>(in levels)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Life expectancy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infant mortality</td>
<td>-0.125</td>
<td>-1.984***</td>
<td>-1.598***</td>
<td>-0.943***</td>
<td>-1.432***</td>
<td>-0.281***</td>
<td>-0.262***</td>
</tr>
<tr>
<td></td>
<td>(0.0789)</td>
<td>(0.355)</td>
<td>(0.274)</td>
<td>(0.223)</td>
<td>(0.254)</td>
<td>(0.0583)</td>
<td>(0.0798)</td>
</tr>
<tr>
<td># Observations</td>
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<td>386</td>
<td>425</td>
<td>425</td>
<td>425</td>
<td>425</td>
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<tr>
<td># Countries</td>
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<td>85</td>
<td>85</td>
<td>85</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td>Kleibergen-Paap</td>
<td>29.67</td>
<td>22.43</td>
<td>29.67</td>
<td>29.67</td>
<td>29.67</td>
<td>29.67</td>
<td>29.67</td>
</tr>
</tbody>
</table>

Notes: The table reports 2SLS estimates based on estimation equations (1) and (4). The observations are reported at the country level every decade over the period 1960-2000. All regressions include country and time fixed effects. The dependent variables are in logs and indicated at the top column. The main explanatory variable is Actual MV adoption, which is the actual share planted with MV crops, which is then instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops according to equation (3). Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1
Table 10: The impact of MV adoption 1960-2000

<table>
<thead>
<tr>
<th></th>
<th>Average developing country</th>
<th>Developing world total</th>
</tr>
</thead>
<tbody>
<tr>
<td>MV adoption rate year 2000</td>
<td>21 %</td>
<td>48 %</td>
</tr>
<tr>
<td>MV’s contribution to GDP/capita growth 1960-2000</td>
<td>47 pp</td>
<td>137 pp</td>
</tr>
<tr>
<td>Actual GDP/capita growth 1960-2000</td>
<td>56 %</td>
<td>171 %</td>
</tr>
<tr>
<td>MV’s contribution to population growth 1960-2000</td>
<td>-7 pp</td>
<td>-16 pp</td>
</tr>
<tr>
<td>Actual population growth 1960-2000</td>
<td>164 %</td>
<td>129 %</td>
</tr>
</tbody>
</table>
A Countries in the Sample


B Addtional Robustness Results

B.1 Alternative Predicted MV shares

This section reports the main results for income and population using alternative specified predicted MV adoption rates as instruments for the actual adoption rate. In particular, the baseline estimates, reported in the paper, is based on the following estimation equation for the predicted MV adoption rate:

$$ mv_{jt}^i = 2000 \sum_{k=1970}^{2000} \beta_j^k \text{potential}_i^k \times yr_k^i + 2000 \sum_{k=1970}^{2000} \gamma_k yr_k^i + \varepsilon_{jt}^i, $$

(14)

where we, conservatively, exclude country fixed-effects, even though they are controlled for when estimating the effect of MVs on the economic outcomes later on. Thus, as a check of robustness, Panel A of Table 1a shows the results when controlling for the country fixed effects in deriving the predicted MV adoption rate, that is, we use a model where country fixed effects, $\sum \delta c ctry_c^i$, have been added:

$$ mv_{dt}^i = 2000 \sum_{k=1970}^{2000} \beta_j^k \text{potential}_i^k \times yr_k^i + 2000 \sum_{k=1970}^{2000} \gamma_k yr_k^i + \sum c \delta c ctry_c^i + \varepsilon_{dt}^i, $$

(15)

while panel B reports the results using this prediction equation:

$$ mv_{dt}^i = \beta \left( \text{potential}_i^k \times 1[\tau > 1960] \right) + \sum_{k=1970}^{2000} \gamma_k yr_k^i + \sum c \delta c ctry_c^i + \varepsilon_{dt}^i, $$

(16)

where we have replace the time-period fixed effects, in the first term on the RHS, with an indicator which equals one after 1960 (i.e., the dating of the global diffusion of modern varieties).

As seen from Table 1a both procedures lead to the same conclusion as the baseline estimates did in the paper. In fact, when the predicted MV adoption is based on equation (15), the results become even stronger than in the paper. Therefore, this section establishes that our findings are robust to choice of specification in predicting the MV adoption rate and that we, in the paper, use a more conservative approach.
B.2 Start and Ending Year

This section reports the baseline 2SLS results when starting the analysis in 1940, which, due to missing data, give rise to an unbalanced panel and when stopping the analysis in 1980, implying that these estimates would only capture variation in the first diffusion wave of MV crops. As seen from Table 2A, we obtain similar 2SLS estimates, both in the extended sample (columns 1 and 4) and reduced sample (columns 2, 3, 5, and 6).

B.3 Initial characteristics

Table 3a controls for initial log GDP per capita, initial population density, initial institutions, and initial trade share—where initial refers to the year 1960—interacted with a full set of year fixed effects. This type of check takes into account the possibility that, for example, initial income could be correlated with our measure for the potential for growing MVs and we, therefore, with our baseline estimate unintentionally captures possible convergence in income over the considered period. However, as seen from the 2SLS estimates, reported Table 4a, our findings for income are robust both in magnitude and statistical significance, while the 2SLS estimate in column 4 for population, which controls for initial population density, loses some precision, we also conclude that our findings for populations are robust.

21 As measured by the average constraint on the executive (from the Polity IV dataset) in 1950, 1960, and 1970.
Table 1A: Alternative Predicted MV adoption rates

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual MV adoption</td>
<td>1.496***</td>
<td>-0.629***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(Dependent Variable (in logs): GDP/capita)</td>
<td>(0.444)</td>
<td>(0.184)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Predicted MV adoption I</td>
<td>3.334***</td>
<td>-1.401***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.944)</td>
<td>(0.371)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimator</td>
<td>2SLS</td>
<td>OLS</td>
<td>2SLS</td>
<td>OLS</td>
</tr>
<tr>
<td>Kleibergen-Paap</td>
<td>22.47</td>
<td>.</td>
<td>22.47</td>
<td>.</td>
</tr>
</tbody>
</table>

Panel A: Alternative Prediction: with country FE

|                  | Actual MV adoption | 1.456***  | -0.520***  |
|                  | (Dependent Variable (in logs): Population) | (0.413) | (0.168) |
|                  | Predicted MV adoption II | 3.836***  | -1.370***  |
|                  | (1.052) | (0.408) |
| Estimator        | 2SLS  | OLS   | 2SLS  | OLS   |
| Kleibergen-Paap  | 25.68 | .     | 25.68 | .     |

Panel B: Alternative Prediction: Indicator with country FE

Notes: The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables indicated at the top column. The main explanatory variable is: Predicted MV adoption I and Predicted MV adoption II, which are the predicted share of modern-variety crops according to equation (15) and (16), respectively. Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1.
Table 2a: Start and Ending Year

<table>
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<td></td>
<td>(1)</td>
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<thead>
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<tr>
<td>GDP/capita</td>
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<tr>
<td>Actual MV adoption</td>
</tr>
<tr>
<td>Estimator</td>
</tr>
<tr>
<td>Kleibergen-Paap</td>
</tr>
<tr>
<td># Observations</td>
</tr>
<tr>
<td># Countries</td>
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<table>
<thead>
<tr>
<th>Actual MV adoption</th>
<th>1.345***</th>
<th>1.167***</th>
<th>1.019***</th>
<th>-0.370**</th>
<th>-0.141</th>
<th>-0.167</th>
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<tbody>
<tr>
<td></td>
<td>(0.323)</td>
<td>(0.394)</td>
<td>(0.391)</td>
<td>(0.172)</td>
<td>(0.133)</td>
<td>(0.172)</td>
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</tr>
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<td>372</td>
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</tr>
<tr>
<td>85</td>
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<tr>
<td>85</td>
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</tbody>
</table>

Notes: The table reports 2SLS estimates. The observations are reported at the country level every decade over the periods: 1940–2000, 1960–1980, and 1940–1980 (see the top row). All regressions include country and time fixed effects. The dependent variables are indicated at the top column. The main explanatory variable is actual MV adoption instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops. Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1.
<table>
<thead>
<tr>
<th>Actual MV adoption</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP/capita</td>
<td>-0.368**</td>
<td>-0.313</td>
<td>-0.422***</td>
<td>-0.374**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>1.633***</td>
<td>1.472***</td>
<td>1.558***</td>
<td>1.574***</td>
<td>0.334</td>
<td>0.374</td>
<td>0.307</td>
<td>0.310</td>
</tr>
</tbody>
</table>

**Controls** (\( \times \sum_{yr} \))

- **log GDP/capital_{1960}**
  - Yes
  - No
  - No
  - No
  - Yes
  - No
  - No
  - No

- **Log Population density_{1960}**
  - No
  - Yes
  - No
  - No
  - No
  - Yes
  - No
  - No

- **Initial Institutions**
  - No
  - No
  - Yes
  - No
  - No
  - Yes
  - No
  - No

- **Trade share_{1960}**
  - No
  - No
  - No
  - Yes
  - No
  - No
  - No
  - Yes

- **Estimator**
  - 2SLS
  - 2SLS
  - 2SLS
  - 2SLS
  - 2SLS
  - 2SLS
  - 2SLS
  - 2SLS

- **Kleibergen-Paap**
  - 26.87
  - 23.57
  - 24.79
  - 29.54
  - 26.87
  - 23.57
  - 24.79
  - 29.54

- **# Observations**
  - 425
  - 425
  - 370
  - 380
  - 425
  - 425
  - 370
  - 380

- **# Countries**
  - 85
  - 85
  - 74
  - 76
  - 85
  - 85
  - 74
  - 76

Notes: The observations are reported at the country level every decade over the period 1960–2000. All regressions include country and time fixed effects. The dependent variables indicated at the top column. The main explanatory variable is actual MV adoption instrumented with Predicted MV adoption, which is the predicted share of modern-variety crops. Standard errors (in parentheses) account for arbitrary heteroskedasticity and are clustered at the country level.

*** p<0.01, ** p<0.05, * p<0.1.