Capital Obsolescence and Agricultural Productivity*

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Abstract

This paper studies the role of capital quality in accounting for agricultural productivity differences across countries. We construct a novel dataset of agricultural equipment prices and make three contributions. First, we document that economies with higher labor productivity in agriculture display lower relative prices of old-to-new equipment. Second, we link these relative price differences to the path of capital quality, using a model that features endogenous quality adoption via capital vintages. Our model generates an identification restriction that links the growth rate of capital quality in an economy to the slope of the age-price profile, and the quality of the best capital vintage operated to the intercept of the profile. Third, using this identification restriction, we build a measure of the quality of the capital stock in a sample of high- and middle-income countries. We find that capital quality explains half of the agricultural productivity growth differences and a third of the differences in the level of productivity in the sample.

JEL codes: O11, O13, O40, E00.
Keywords: Agricultural productivity, capital-embodied technology adoption, vintage capital.

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"*...Improvements in technology affect output only to the extent that they are carried into practice either by net capital formation or by the replacement of old-fashioned equipment by the latest models...*"

Solow (1959)

1 Introduction

In this paper, we examine the role of capital-embodied technology adoption for cross-country disparities in agricultural productivity, a key driver of world income inequality (Caselli, 2005; Herrendorf and Valentinyi, 2012). We start by documenting a new empirical regularity that is informative as of the speed of adoption of capital-embodied technology: the relative price of old-to-new equipment varies with development and it is higher in less productive economies. Absent distortions, there are two reasons why the price of a good might decay with age: physical depreciation and the availability of higher quality goods in the market, which induces economic obsolescence. To formally link the observed variation in the price of old-to-new equipment, i.e. the age-price profile, with the availability of higher quality goods in the economy we write down a novel and parsimonious model of vintage capital. Through the lens of such model, the slope of the age-price profile of a durable good is proportional to the degree of economic obsolescence. Moreover, the intercept of the age-price profile corresponds to the marginal product of capital and, under minimal assumptions, identifies the average quality of the stock of capital. Equipped with this identification strategy and a newly built dataset of new and old equipment prices, we infer the average quality of the capital stock and its growth rate across high- and middle-income countries. Then, we quantitatively assess the role of capital quality for productivity differences via growth and development accounting exercises.

We construct a novel dataset of multiple cross-sections of prices for new and used agricultural equipment across countries. We focus on tractors, which are, arguably, the most important agricultural equipment good used in the modern agricultural sector.[1] Our benchmark dataset covers 15 high- and middle-income countries between 2007 and 2016. Importantly, it provides detailed measures of equipment characteristics, such as horsepower, hours of use, model, brand and age. This level of detail allows us to price a synthetic piece of equipment of comparable characteristics across countries using hedonic techniques (as in the seminal work of Griliches, 1961). We construct country-specific age-price profiles by following the

[1] One-third of world trade in farm machinery is accounted for by tractors alone Mehta and Gross (2007). Additionally, tractors are also complementary to many other capital goods, such as harvesters and tillage equipment.

decay in the price of this synthetic piece of equipment with age. We find that the slope of the profile varies with development: older pieces of agricultural equipment are relatively more expensive than newer ones in countries with lower labor productivity. For example, in countries with 20% of the agricultural labor productivity of the US, a 15-year-old piece of equipment is 67% as valuable as a new one. At the same time, in the US, a 15-year-old piece of equipment is only 52% as valuable as a new one. The disparities we report are sizeable, systematic, and robust to controlling for time effects, the cost (wages) of repair workers as well as the type of cultivated crops. To the best of our knowledge, this is the first study to document the variation in age-price profiles of agricultural equipment across countries.

Next, we argue that this empirical regularity embeds information about the disparities in the rate of capital-embodied technology adoption across countries. To do it, we write down a novel and parsimonious growth model of vintage capital. In the model, households consume and invest in alternative vintages of capital which are rented to local farmers in a spot market. Alternative vintages are perfect substitutes in farm production and are retired following an exogenous shock.[2] The technological frontier is determined by new vintages that become available to all countries at a common rate, and adoption of better quality vintages is costly. The cost of adoption depends on the quality of the goods used in a country, the pace of improvement of the frontier technology and a country-specific wedge, which is a reduced form for various barriers that disincentivize adoption. Our cost structure allows for divergence in the growth rates of quality and output per worker across countries. The equilibrium path of adoption in the economy trades off induced obsolescence on installed (older) equipment with gains in productivity from higher quality.

We analytically show that the path of capital quality is identified by regressing the logarithm of equipment prices on age and additional controls. In particular, the slope and the level of the model predicted cross-sectional age-price profile map into the rate of embodiment and a measure of average quality of installed stocks, respectively. We implement this finding empirically to recover the path of capital quality in our sample of high- and middle-income countries. First, we infer the rate of capital-embodied technology adoption from the country-specific age coefficients (i.e. the price elasticity to age) and physical depreciation rates, which we derive from the price decay of a synthetic piece of equipment with hours of use. Then, we combine our measured rate of embodiment with USDA-ERS data on factor shares to additionally infer the level of average quality of the capital stock from country-specific

[2]Both these assumptions make the model tractable and are not fundamental to the identification strategy proposed in the paper. The latter is robust to allowing for (a) endogenous investment in the pace of vintage retirement, as discussed in the online appendix; and (b) an arbitrary substitution pattern across vintages.

regression intercepts. We find that, on average, richer countries have both higher growth rates and higher levels of agricultural equipment quality. For example, equipment quality in the agricultural sector grows by 3.4% per year in the US compared to 1.4% in Brazil. The average quality of capital in the US is about 10 times larger than that in Brazil.

We quantify the importance of our measured path of capital quality for agricultural productivity via growth and development accounting exercises. On average across countries, 32% of growth rate of agricultural value added that is unaccounted for by observable factors (labor, capital stocks and intermediate goods) can be attributed to capital quality. Moreover, disparities in agricultural productivity growth across countries halve once we account for capital quality disparities. We also find that about a third of the cross-country disparities in agricultural value added per worker in 2013 can be explained by differences in the average quality of agricultural equipment.

The role of capital quality for agricultural productivity is heterogeneous across countries. In particular, capital quality growth is more important for productivity growth at the top of the distribution of income per worker. In the US, capital quality accounts for approximately one-third of the growth rate of TFP; in Brazil and Italy, it accounts for close to 10%. The source of this heterogeneity is that, on average, countries with higher value added per worker have also a higher share of physical capital in production. In our analysis, we abstract away from the capital intensity decision, differently from the diffusion literature that considers the advancement of certain factors of production over others (Manuelli and Seshadri, 2014).[3] Our rationale for this abstraction is the salient characteristic of the capital stock dynamics of the countries in our sample: the quantity of capital (the number of tractors) is relatively constant over time.[4] Still, if different vintages of capital are interpreted as different goods, capital-embodied technology adoption ultimately leads to the retirement of these older vintages and, potentially, stronger intensity in the use of capital services. We therefore believe that our growth and development accounting results are a lower bound to the potential gains from capital-embodied technology adoption.

Our benchmark identification restriction stems from cross-sectional age-price profile. But, in principle, both cross-sectional and longitudinal age-price profiles can be used to infer the quality of installed capital stock. There are two main advantages of using the cross-sectional age-price profile. First, the average growth rate of capital-embodied technology adoption can be inferred using the slope of the profile even when the economy displays a non-trivial

[3] Chen (2017) studies the decision of capital intensive technologies in agriculture, while Comin and Hobijn (2010) study the diffusion process for various types of equipment across countries and time.

[4] In our sample, the number of tractors in each country decreases by 0.05% on average from 1990 to 2013.

transition dynamic for the path of quality. As we discuss in section 4.1, this is not possible when using the longitudinal profile as movements in interest rates and the rate of adoption show up non-separably in the slope of the profile. Second, when using the cross-section of prices, the intercept of a regression of log-prices on age always delivers a measure of the best available quality in the economy. Differently, when using the longitudinal profile, this intercept yields a measure of the quality of the good that is being priced and, in general, it is not informative of the quality of the stock installed in the economy.

Through the lens of our model, cross-country differences in the path of quality reflect differences in adoption costs. Countries with lower value added per worker measure higher adoption costs (as in Sunding and Zilberman, 2001, Hoff *et al.*, 1993, Sims and Kienzle, 2009). A theory studying the sources of cross-country heterogeneity in adoption costs exceeds the scope of our accounting exercise. However, towards the end of the paper, we discuss alternative mechanisms that might explain these disparities and the robustness of our identification strategy to such mechanisms. To start, disparities in adoption costs may be partially a reflection of trade tariffs. Higher import tariffs may disincentivize the adoption of technology and generate slower improvement in quality. Or, by protecting local producers from competition, may encourage production of lower quality goods.[5] For a subsample of our main dataset we are able to trace the country of origin of each piece of equipment and use this information to build separate measures of quality for imported and locally produced equipment. We find that the slope of the age-price profiles are different for three countries in our subsample: the US, Germany and Mexico. In the last two countries, quality growth is higher for imported goods than for locally produced ones, and the opposite is true in the US. We also show that measures of average quality based on imported goods overestimate cross-country differences in the quality of the capital stock relative to our benchmark estimates.

Disparities in adoption rates may also arise due to differences in the stock of equipment available in the second-hand market or in the economies of scale in production, across countries.[6] We consider an extension of the model where a farmer's valuation for equipment is heterogenous and a secondary market endogenously arises. We show that this heterogeneity does not affect the slope of the age-profile. We conclude that the inferred quality growth

[5]Indeed, Eaton and Kortum (2001) show that most capital goods are produced by a handful of countries. Mutreja *et al.* (2017) show that the fraction of locally produced goods is still significant in poor countries.

[6]There is an extensive literature on the welfare and allocative implications of markets for used durable goods. Stolyarov (2002) focuses on the volume of trade in cars in different years. Additionally, looking at the market for used cars (in France and the US), Gavazza *et al.* (2014) study the role of heterogeneity in willingness to pay and transaction costs in welfare. In addition, Jovanovic (1998) shows how the presence of a frictionless secondary market may increase inequality in a world where capital goods are indivisible.

is robust to various sources of farm heterogeneity, including distortions on farm-level productivity. We reach the same conclusion when allowing for economies of scale through fixed operating costs. Both mechanisms, however, may be relevant in explaining differences in the average quality of the stock of capital as identified from the intercept of the age-price profile.

Finally, the adoption of better quality capital goods might be complementary to other factors of production and to the technology operated by farmers. Hence, high (Hicks-neutral) productivity might be correlated with the adoption of higher quality capital stocks. We discuss an extension of our benchmark identification where we allow for cross-country disparities in (Hicks-neutral) productivity. We show how to separately identify the growth rates of capital-embodied and -disembodied technology, as well as cross-country disparities in the level of productivity and the quality of the capital stock. This identification has additional data requirements: the slopes of the cross-sectional and longitudinal profiles identify growth rates; while the intercept of the cross-sectional profile and the ratio of the price of a good of arbitrary quality across different economies separately identify the levels of productivity and capital quality. This identification is empirically implementable given the richness of our dataset.

Literature review. Our paper relates to the macroeconomic literature that studies the determinants of agricultural productivity differences across countries. These differences may arise, for example, due to market distortions that generate inefficient production scales or prevent factor reallocation. Alternatively, distortions in returns to investment may discourage physical and human capital accumulation, as well as technology adoption. An extensive literature examines the role of some of these mechanisms for agricultural productivity: Restuccia *et al.* (2008) and Donovan (2014) study the role of disparities in the intensity of intermediate input use across countries, Lagakos and Waugh (2013) study the role of sectorial differences in hours and human capital levels, Herrendorf and Schoellman (2015) study the role of disparities in the returns to human capital across sectors, and Adamopoulos and Restuccia (2014) study the disparate incidence of size-dependent distortions on farms across countries. Disparities in the adoption patterns of capital-embodied technology, and hence, in the quality of physical capital used in production, remain unaccounted for.[7] This paper fills the gap.

[7] Most cross-country analyses of agricultural productivity of which we are aware use Food and Agriculture Organization (FAO) capital stock data. According to the FAO Statistical Database (FAOSTAT), "the gross fixed capital stock is the value, at a point of time, of assets held by the farmer with each asset valued at "as new" prices, regardless of the age and actual condition of the assets". The FAO also provides data in 40-CV tractor-equivalent machinery units, a measure of the metric horsepower on the farm. It does not directly control for factors such as the quality of the stock or hours.

Our paper also relates to the literature that studies the link between technology adoption and capital obsolescence in models of vintage capital (Benhabib and Rustichini, 1991; Jovanovic and Rob, 1997; Greenwood and Jovanovic, 2001; Jovanovic and Yatsenko, 2012).[8] Our main contribution is to present a tractable framework that links the age-price profile of equipment prices to technology adoption and quality levels and that, under minimal assumptions, can be mapped into the standard two-sector economy as in Greenwood *et al.* (1997).

The main identification restriction that stems from our framework allows us to provide a methodological contribution to the literature that infers quality from equipment prices. We use the cross-section of equipment prices to back out the rate of embodiment and, a novelty, the level of quality. The seminal work of Hulten (1992a) and Greenwood *et al.* (1997) show how to recover changes in the quality of capital equipment from changes in the relative price of investment (see also Gordon, 1990; Hulten, 1992b; Cummins and Violante, 2002). Under minimal assumptions, we show that the rate of embodiment inferred from their methodology is proportional to the one proposed in this paper (with a factor of proportionality that depends on the share of capital).[9] Empirically, these alternative measures are very close to each other. When we apply their methodology to the US data, we find an average growth rate in agricultural capital quality of between 1.2 and 2.5% for the period 1990-2000, close to our measure of 3.4% using more recent data.[10]

The closest paper to ours in terms of identification of the rate of embodiment is Gort, Greenwood and Rupert (1999). The authors use the cross-section of *rental rates* of commercial buildings to infer the rate of improvement in quality of structures. In our paper, we use the cross-section of *prices*, which includes the present discounted value of expected equipment services. Distinctively, we are able to infer not only the rate of quality improvement, but also the level of quality of the stocks from the intercept of the model-predicted age-price profile. An alternative method to measure the quality of the stock can be found in Caselli and Wilson (2004), who infer quality from the import composition of capital investment across seven categories. Their identifying assumption is that categories of investment with higher R&D expenditure entail higher quality. Compared to their study, we restrict our analysis to the agricultural sector and provide a measure of the quality of the capital stock that relies on relative prices instead of R&D content. In addition, we build a measure that

[8] Boucekkine *et al.* (2011) build an extensive review of this literature.

[9] Krusell *et al.* (2000) offer estimates of quality-adjusted prices for various types of equipments in the US. Unfortunately the series of prices for agricultural equipment, tractors, has been discontinued.

[10] Bahk and Gort (1992) and Gort *et al.* (1991) also measure a higher growth rate of quality in the US manufacturing sector using cross-sections, compared to those produced by Gordon (1990), using time-series.

covers all installed capital rather that imported capital. Our measure of quality correlates at 80% with one based on R&D content of imported equipment.

The remainder of the paper is organized as follows. Section 2 presents our empirical evidence; Section 3, the model; Section 4, the identification and estimation strategies; Section 5 the growth and income accounting exercises. Section 6 discusses alternative frameworks that may generate disparate adoption rates across countries. Section 7 concludes.

2 Empirical evidence

In this section, we document the evolution of agricultural tractor prices with age across countries (i.e. the age-price profiles). We first show that age-price profiles for agricultural tractors of a given set of observable characteristics are steeper in more productive countries. Then, we present robustness checks on our findings that control for two dimensions of cross-country heterogeneity: 1) cultivated crops and 2) wages of repair workers.

2.1 Data sets

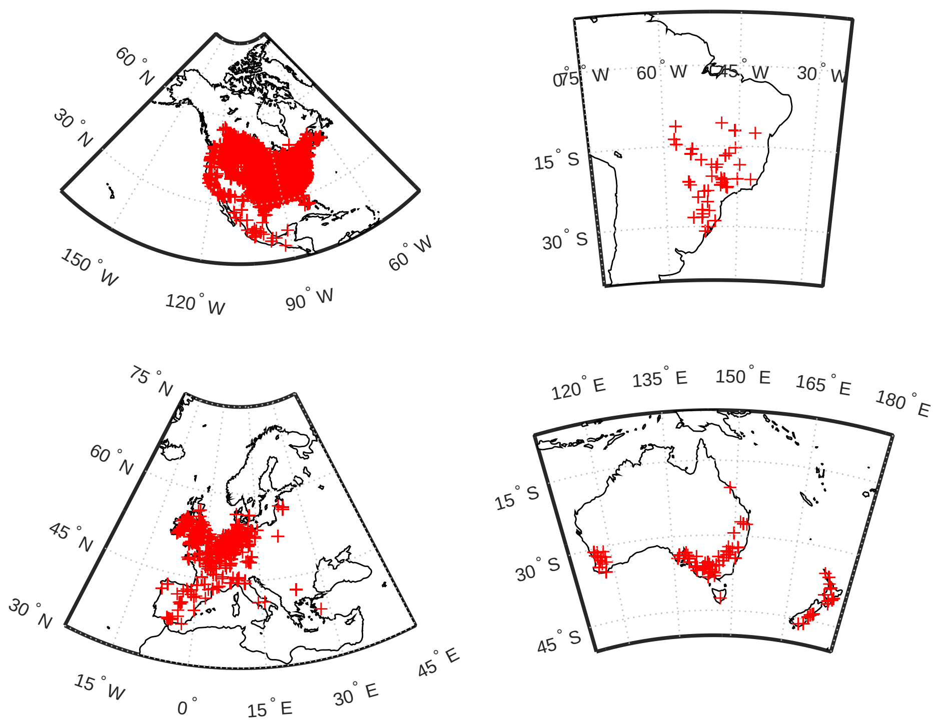
Our dataset consists of new and old agricultural tractor prices compiled using information provided by a major data publisher. This company gathers information on the characteristics and prices of various types of agricultural equipment available around the world.

Our main dataset consists of a total of 373,997 observations for retail "ask" prices across 15 countries over different years between 2007 and 2016 (see Table C.I for the list of countries and summary statistics). It covers high- and middle-income countries. For example, Brazil and Bulgaria, among the least productive countries in our sample, feature levels of agricultural value added per worker equal to 19% and 11% of the US value in 2013 (FAOSTAT), respectively.[11] We also observe equipment prices for more productive economies such as Canada, whose agricultural value added per worker is 89% of the US value, or France, which is 78% as productive as the US. For some countries, like the US (Canada), we observe repeated cross-sections from 2007 (2008) to 2016, whereas for some other countries, we observe a single cross-section of data, like Ireland (2015) and Belgium (2016). Figure I shows the geographical coverage of a subsample of our dataset (132,688 observations) for which location data is accurate enough to allow us to geolocate it.

[11] Agricultural value added is computed by multiplying the value of gross agricultural production per worker by 1 minus the sum of intermediate input factor shares.

For each transaction recorded in our dataset, we observe the price, age, model, horsepower, use hours and location of the tractor sold. We impute hours of use for those observations with missing information; details on the imputation method can be found in the online appendix. The average tractor in the sample is 12 years old and the oldest one is 46 years old. Our dataset contains information across all the age and horsepower brackets considered by the Census in US, Canada, Mexico and Brazil, although it tends to over-sample among tractors with high horsepower.[12]

Figure I: Geographical distribution



Geographical distribution of retail "ask" prices matched via geolocation (132,688 observations).

We complement our main dataset with three additional series that we use for robustness checks. First, we collect retail "sale" prices (i.e., transaction prices) for a subsample of our main dataset consisting of 250,000 observations. Second, we gather information on the crops cultivated at each of the quote locations. For those observations where we have full information on the country, state and city where the price quote was reported, we are able to match high-resolution microdata recording crop yields. We use the EarthStat dataset constructed by Ramankutty *et al.* (2008), which consists of agricultural census and survey

[12] Detailed comparisons to Census data can be found in the online appendix.

information on crop land areas and yields for 175 crops measured at the smallest political units reasonably obtainable for 206 countries.[13] EarthStat data are available for grid sizes of 5-arc min (which is roughly equivalent to an area of 10 km by 10 km). We search for the crop with the highest recorded yield produced in a 20-mile-wide grid around each sale location and match this information with our tractor price data. Third, we complement the main dataset with wages of repair workers in each country. We use the NBER "Occupational wages around the world" dataset, which provides occupational wage data for 161 occupations in 171 countries from 1983 to 2008 by calibrating observed wages into a normalized wage rate for each occupation. Wages are deflated using the purchasing power parity deflators from the Penn World Tables 7.0.

2.2 Analysis

The objective of our analysis is to describe the age-price profiles for an agricultural tractor of comparable characteristics across countries. Our econometric strategy consists of implementing hedonic pricing techniques as in Griliches (1961), Gordon (1987) and Hulten and Wykoff (1981). We allow for alternative profile shapes (i.e., concave, convex) and incidences of equipment characteristics. This flexibility makes the empirical analysis comparable to other studies that estimate economic depreciation for durable goods.[14] Additionally, it allows us to assess the pertinence of our theory-based accounting framework which hinges, as discussed later, on a logarithmic shape for the age-price profile.

We incorporate a Box-Cox type power transformation on a standard hedonic pricing model:

$$\frac{p_{i,c,t}^{\theta_1}-1}{\theta_1}=\gamma_{1,c,t}+\gamma_{2,c}a_{i,c,t}+\frac{X_{i,c,t}^{\theta_2}-1}{\theta_2}\beta+\epsilon_{i,c,t}, \tag{1}$$

where i indicates a quote at time t in country c. The dependent variable is a tractor's quoted price, while the regressors include a tractor's age as the number of years since it was built, a, and a matrix of equipment characteristics, X, excluding age – that is, horsepower, manufacturer and use hours. Turning to the coefficients, $\gamma_{1,c,t}$ is a country- and time- specific effect, β is the vector of coefficients associated with each characteristic in X, while θ_1 and θ_2 are the shape parameters associated with prices and equipment characteristics, respectively.

[13] Further details on the EarthStat dataset, in particular on yields computations, are available in the online appendix.

[14] There is extensive work in the national accounts literature that estimates measures of economic depreciation using prices of used equipment. For the US, see Fraumeni (1997), for Canada, see Gellatly *et al.* (2002). In addition, there is some research comparing profiles of economic depreciation across countries for a limited number of car models, see Storchmann (2004).

The coefficient γ_2 shapes the relation between price and age. When the estimated θ_1 is not significantly different than zero, the left-hand side of equation 1 corresponds to a logarithmic transformation, $\log(p)$, and the estimated parameter γ_2 is the price elasticity with respect to age. On the other end, when the estimated θ_1 is positive (negative), the age-price profile of a tractor with characteristics X is convex (concave).[15]

Our estimation set-up allows for two sources of cross-country heterogeneity in the age-price profile: the coefficient on age $\gamma_{2,c}$ and the country- and time-specific effect, $\gamma_{1,c,t}$. This last term allows for country-specific intercepts in our pricing equation that evolve over time at different rates across countries. It captures country-specific characteristics that may affect the overall price level, such as the institutional characteristics of the market for used equipment, and time trends specific to each country. The coefficient on age is assumed time-invariant in our benchmark estimation, but our results are robust to allowing for time variation, i.e. cohort effects in the slope of the age-price profile (see online appendix). Finally, we assume that the shape parameters are identical across countries and over time.[16]

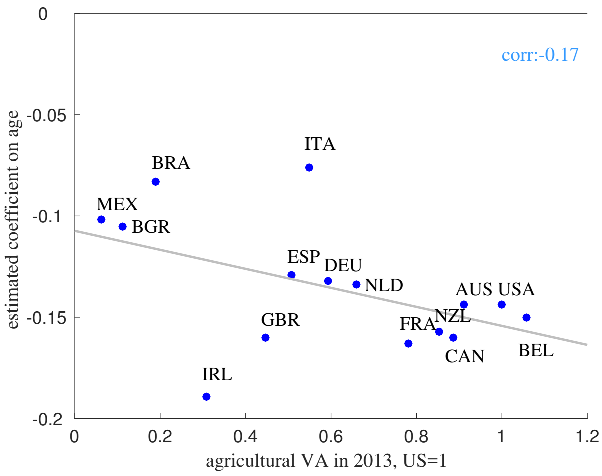
We estimate equation 1 in a pooled regression by including year dummies, country dummies, an interaction country-year dummy and an interaction of country dummies with age. Details of the empirical implementation can be found in the online appendix. The estimation is conducted via maximum likelihood. We first find the maximum likelihood estimates of the Box-Cox transform parameters, θ_1 and θ_2. The procedure, as outlined in Box and Cox (1964), consists of estimating a linear model for each possible transformation of the transform variables and maximizing the likelihood over them. To estimate standard errors for the coefficients of interest, $\gamma_{1,c,t}$, $\gamma_{2,c}$ and β (clustered by countries), we transform the data using the estimated Box-Cox parameters and run a least square estimation.

Appendix C, Table C.II columns (1) and (2), presents the results of our estimation. As expected, the predicted prices decrease in age and hours of use, and they increase in horsepower. The shape parameter in prices θ_1 is significantly different from zero and positive at 0.103. Hence, the age-price profile is convex but only slightly more so than a logarithmic profile, as predicted by the theory on which our accounting exercises hinge (see section 4). The estimated shape parameter for horsepower and hours θ_2 is significant at 0.104. The

[15] Omitted variables among tractor characteristics, such as the degrees of sophistication and computerization, may, in principle, bias our estimates. Including tractor model among the regressors in matrix X could prevent this bias. We observe the model of each tractor sold and find that, in our dataset, combinations of manufacturer, production year and horsepower exhaust the information provided by model (model is co-linear), and therefore, we omit it.

[16] Our main results do not change when we allow for country-specific shape parameters and estimate equation 1 separately for each country. These estimates are available upon request.

Figure II: Price decay with age



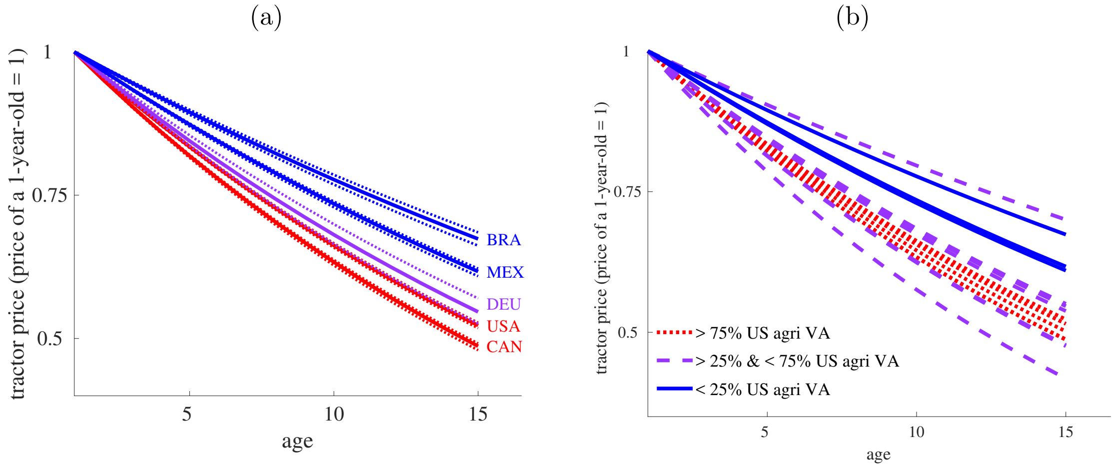
The figure shows the estimated coefficient $\gamma_{2,c}$. Agricultural value added in 2013 is computed from the USDA-ERS dataset by multiplying the value of gross agricultural production per worker by 1 minus the sum of intermediate input factor shares. Source: FAOSTAT and own computations based on price quotes from a major publisher.

estimated coefficients for hours and horsepower are -0.176 and 4.588, respectively, which are both significant at the 5% level. A total of 188 dummies associated with different manufacturers in the sample are included to control for brand-specific differences in prices. Our statistical model generates 89.8% of the variation observed in the data.[17]

The estimated coefficients associated with age, $\gamma_{2,c}$, are all significantly different from zero and negative. For any shape parameter θ_1, we can describe the price elasticity with respect to age as $\gamma_2 \frac{a}{p^{\theta_1}}$. Therefore, the ratio of price elasticities between two countries computed at a given age and price is the ratio of estimated γ_2s in the two countries. Our estimates suggest that prices are more elastic to age in high-productivity countries than they are in low-productivity ones. Indeed, the correlation between the price elasticity and the net value added of agricultural production across countries is negative at -0.48, with a p-value of 0.070 (see figure II). A least squares regression of the estimated γ_2s on net value added of agricultural production indicates that for a country with half the agricultural value added of the US, such as Spain, the price decay per year is 0.054 points lower than that of the US.

[17] A large portion of our sample stems from observations in Canada and the US. In the online appendix, we present estimation results when we exclude pricing data for these two countries. We find that the estimates for the country-specific coefficient on age become smaller. However, the relative magnitude of the slopes across countries is maintained. This implies that the relative size of our inferred quality improvement measures is robust.

Figure III: Age-price profiles



Panel (a) plots the predicted age-price profiles (continuous line) and confidence intervals (dotted line) for five countries in our sample, while Panel (b) plots the same profiles for all the countries in our sample. The colors of the lines in both panels reflect the country's rankings with respect to agricultural value added per worker in 2013 from the lowest in blue (below 75% the US value) to the highest in red (above 75% the US value). Source: FAOSTAT and own computations based on price quotes from a major publisher.

Moreover, the R^2 of such a regression is 0.23, indicating that a significant fraction of cross-country variation in agricultural value added is accounted for by cross-country heterogeneity in price elasticities with respect to age.

To construct comparable age-price profiles across countries, we use our estimated econometric model to predict the decay of prices with age for a given tractor in each country. Because not all tractors are used in all countries, we consider a "synthetic" tractor with the average equipment characteristics of our sample. This tractor has manufacturer John Deere (for which we have observations in all countries), 3170 hours of use in a year and 167 horsepower, corresponding to the average in the sample. Figure III panel (a) plots this profile for five countries in our sample with confidence intervals, while panel (b) plots the profiles for all countries in the sample, color-coding by the level of agricultural value added per worker in 2013. First, notice that the shape of the profiles are non-linear, reflecting an estimate for the shape parameter θ_1 that is positive and statistically different from one. Second, poorer countries tend to show flatter profiles. The cross-country correlation between the price of a tractor with average characteristics at age 15 relative to that at age 1 and agricultural value added per worker in 2013 is negative, at -0.46.[18]

[18]Relative prices predicted using the results from an estimation conducted without controlling for tractor

Robustness checks. First, we test the robustness of our empirical findings to a different category of "prices". The empirical results presented above focus on retail "ask" prices because these are available for a larger set of countries and years, but we find that our conclusions are robust to using transaction prices instead. Quantitative details are presented in section 5.3.

Second, we examine the robustness of the estimated coefficients characterizing the age-price profile, γ_2, with respect to two dimensions of cross-country heterogeneity: 1) cultivated crops and 2) wages of repair workers. First, the degree of a tractor's mechanical wear may depend on the type of crop it was used for. For example, some locations produce much more wear and tear on machinery than others and their geographical characteristics may also be associated with specific types of crops. Second, the resale price of a piece of equipment may be negatively related to the relative cost of repairs, a large component of which is the labor cost (i.e., the wages of repair workers).[19]

We estimate equation 1 using two additional sets of regressors: dummies for the main crop cultivated in each of the sale locations, and interaction terms between hours of use and PPP wages of repair workers. The sample we use for this estimation (matched dataset) covers 15 countries and approximately 96,500 retail observations.[20] Appendix C, Table C.II columns (3)–(6), present these results. For comparison, we also re-estimate equation 1 using this smaller sample (column (3)). We conclude that introducing crop and wage controls does not change the main empirical findings on the relation between age and price. The correlation between the estimates of γ_2 controlling for crops and wages (column (6) in Table C.II) and the baseline estimates (column (3) in Table C.II) is 0.92.

3 A model of capital obsolescence

This section presents a general equilibrium model of vintage capital that links the cross-country variation in the age-price profiles of agricultural equipment and value added per

characteristics – that is, without including the matrix X in equation 1, display a downward bias. Hence, age-price profiles are steeper in all countries. Had we use these estimates, we would have inferred higher rates of capital-embodied technology adoption than the ones documented in this paper.

[19]Equipment parts also contribute to the cost of repairs. Unfortunately, direct measures of them are unavailable to us. However, we expect that the cost of parts and that of overall equipment to be correlated. If parts are relatively more expensive in poorer economies, that would shift the relative price of used to new equipment down. Hence, after controlling for the cost of parts we would expect even flatter age-price profiles.

[20]The reduction in the size of the sample occurs due to missing location data that prevents us from matching prices to crops. In addition, wage data by occupation are not available for France and Spain.

worker to patterns of capital-embodied technology adoption and the composition of the capital stock.

We study an infinite-horizon economy populated by a continuum of homogeneous households and farms. Households consume and invest. Investment can be directed to accumulate capital of varying quality. Quality is not directly observable but, as in Manuelli and Seshadri (2014), we assume there is a mapping from observable characteristics X to quality $q(X)$. Capital quality indexes vintages j through a one-to-one mapping. The highest available quality at time t is $q(X_{J_t})$ with vintage J_t.

Farms produce final output using a constant returns technology that employs capital services, labor n, and land l. The share of capital (labor) in production is α_k (α_n), and the share of land is α_l. Capital services are the product of the number of machines of a particular vintage and their corresponding quality $q(X_j)k_j$ (to ease notation, define $q_j = q(X_j)$). Capital of varying quality is perfectly substitutable in production, and we call the (endogenous) set of vintages used in production $A_t \equiv \{j \leq J_t : k_{j,t} > 0\}$.[21] The production function is:

$$y_t = (\sum_{j \in A_t} q_j k_{j,t})^{\alpha_k} l_t^{\alpha_l} n_t^{\alpha_n}.$$

The supplies of labor and land are inelastic at N and L, respectively, while the supply of each vintage of capital is determined by households.

We assume that the world frontier for capital quality changes at a constant exogenous growth rate $\overline{\mu}$:

$$Q_{J_{t+1}} = Q_{J_t}(1 + \overline{\mu}).$$

The rate of adoption in each country is endogenous. The cost of adopting capital of improved quality q_j when the best operated technology in the economy is $q_{\bar{j}}$ is $C(q_j, q_{\bar{j}}, \overline{\mu})$ per unit of new capital,

$$C(q_j, q_{\bar{j}}, \mu) = \begin{cases} \frac{q_j}{q_{\bar{j}}} \left(\frac{1+\tau}{1+\overline{\mu}} \right) & \text{if } q_j > q_{\bar{j}}, \\ 1 & \text{otherwise.} \end{cases}$$

This cost increases with the improved quality level, decreases with the quality of the best technology adopted in the country and decreases with the speed of innovation – that is,

[21] This assumption can also be found in Hulten (1992b). It implies that x machines of quality $2q$ yield the same services as $2x$ machines of quality q. Our framework can be generalized to allow for a common elasticity of substitution across vintages through a CES aggregator. A similar problem is studied in Jovanovic and Yatsenko (2012) to explain adoption lags, but the authors do not focus on the implications of those patterns for the pricing of old and new equipment. In terms of our quantitative exercise, allowing for arbitrary elasticities would require direct measures of them in each country, which are not available to us at the moment.

improvements in quality around the world. The reason for which the cost of adoption depends on the speed of innovation is that as the latter increases, any piece of equipment becomes economically obsolete at a faster rate. The key parameter in the cost function is τ, which is reduced form for various adoption costs (i.e. market power on equipment providers which induces positive markups, trade barriers, taxation, etc.). In general, τ can be interpreted as a country-specific wedge that makes adoption relatively more expensive in a particular country relative to others. In the accounting framework of our quantitative analysis, this wedge is the main driver of differences in adoption rates across economies.

The problem of technology adoption has been widely studied in the literature. The seminal work of Parente and Prescott (1994) analyzed this problem by assuming that adoption costs depend on the level of local technology relative to that of the world technology. This assumption imposes tight restrictions on the growth rate of technological improvement along the the balanced growth path (BGP). In particular, while levels of productivity are allowed to differ across countries, there is a common rate of technological improvement.[22] The cost assumed in this paper allows us to construct economies where the rate of quality improvement differs across countries. To the extent that adoption costs are heterogenous across countries quality growth will differ. As adoption costs converge across economies, so will the rates of endogenous quality adoption and long run output growth.

3.1 Households

Households rent capital and labor to farms at market prices. Given the arrival rate of new capital, households decide how much to invest in capital of each quality $x_t^{q_j}$. Let A_t^h be the set of vintages that the household holds in its portfolio, $A_t^h \equiv \{j \leq J_t : k_{j,t} > 0\}$. The stock of capital of a given vintage has a physical depreciation of rate δ, each period. A particular vintage is retired at random with the realization of a shock χ, which is distributed Poisson with intensity $\lambda > \delta$.[23] The random variable χ takes two values $\chi = \{1, 0\}$, where 0 corresponds to retirement and occurs with probability $1 - \exp(-\lambda)$ each period. Hence, the expected lifetime of a stock of vintage j is $T(j) = \frac{1}{\lambda}$. The price of a new piece of equipment of vintage j at time t is $p_{j,t}$.

[22] We study a similar set up to theirs in our online appendix, when discussing the incidence of non-trivial transition dynamics in quality growth.

[23] Alternatively, we could allow households to choose their optimal retirement rate λ at the moment of investment, given some cost of maintenance. If this cost is proportional to the quality of the vintage of goods being maintained q_j, our identification results for capital quality hold. The online appendix discusses this case extensively.

The problem of the representative household is:

$$\max_{c_t,\{x_{j,t},k_{j,t+1}\}_{j\in A^h_{t+1}}} \sum_{t=0}^{\infty} \beta^t U(c_t),$$

subject to:

$$c_t + \sum_{j\in A^h_{t+1}} C(q_j, q_{\bar{J}_t}, \overline{\mu}) p_{j,t} x_{j,t} \leq \sum_{j\in A^h_t} r_{j,t} k_{j,t} + w_t n_t + r_{l,t} l_t,$$

$$(k_{j,t+1} - k_{j,t}(1-\delta)\chi) = x_{j,t} \quad \text{for all} \quad j \in A^h_{t+1},$$

where $r_{j,t}$ is the rental rate for vintage j capital at time t, w_t is the wage rate, and $r_{l,t}$ is the rental rate for land.

3.2 Farms

Each farm in the economy seeks to maximize profits by choosing its amounts of land, labor and capital (of different vintages). Let A_t be the set of vintages that the farm rents, $A_t \equiv \{j \leq J_t : k_{j,t} > 0\}$. The farmer's problem is static and corresponds to:

$$\max_{\{k_{j,t}\}_{j\leq J}, l_t, n_t} (\sum_{j\in A_t} q_j k_{j,t})^{\alpha_k} l_t^{\alpha_l} n_t^{\alpha_n} - w_t n_t - r^l_t l_t - \sum_{j\in A_t} r_{j,t} k_{j,t},$$

subject to:

$$q_j \leq Q_{J_t} \quad \text{for all } j \in A_t,$$

$$Q_{J_{t+1}} = Q_{J_t}(1+\overline{\mu}).$$

Hence, the farm can use vintages of quality lower or equal to the best-available technology. Demand for capital of vintage i, k_i, is characterized by the optimality condition:

$$\alpha_k y_t \frac{q_i}{\sum_{j\in A_t} q_j k_{j,t}} \leq r_{i,t}.$$

If $r_{i,t} > \alpha_k y_t \frac{q_i}{\sum_{j\in A_t} q_j k_{j,t}}$ then $k_i = 0$. Otherwise, capital demand is positive. The equilibrium quantity of capital services used in production is fully determined by the households supply. Due to the assumption of perfect substitutability across capital vintages, none is strictly necessary for production. In particular, the marginal product of capital of a particular vintage j is positive and bounded away from infinity as the quantity of capital goes to zero, i.e., $\lim_{k^{q_i}\to 0} \alpha_k \frac{q_i y_t}{\sum_{j\in A_t} q_j k_{j,t}} < \infty$, except when only one vintage is used in production.

3.3 Adoption and capital stock dynamic

The return to any vintage of capital corresponds to its marginal product plus its resale value. The euler equation of the households implies that it should satisfy:

$$\frac{r_{j,t+1}}{p_{j,t}} = \frac{R_{t+1}}{(\exp(-\lambda))} - \frac{p_{j,t+1}}{p_{j,t}}(1-\delta), \quad \text{if } j \leq \bar{j}_t,$$

and

$$\frac{r_{j,t+1}}{p_{j,t}} = C(q_j, q_{\bar{j}_t}, \overline{\mu})\frac{R_{t+1}}{(\exp(-\lambda))} - \frac{p_{j,t+1}}{p_{j,t}}(1-\delta), \quad \text{if } j > \bar{j}_t,$$

where R_{t+1} is the interest rate in the market, i.e., the value of the return to a unit of consumption foregone today, $R_{t+1}^{-1} = \beta\frac{U'(c_{t+1})}{U'(c_t)}$; and $\bar{j}$ is the best vintage used in production.

Because the marginal product of capital for any vintage used in production is the same except through differences in quality (which are fully accounted for by equilibrium prices), arbitrage implies:

$$C(q_{j_{t+1}}, q_{\bar{j}_t}, \overline{\mu}) \geq 1, \qquad j_{t+1} \geq \bar{j}_{t+1}. \tag{2}$$

In other words, if $C(q_{j_{t+1}}, q_{\bar{j}_t}, \overline{\mu}) > 1$ quality j_{t+1} is not adopted. In equilibrium, the return to capital equalizes across vintages, $\frac{r_{\bar{j},t+1}}{p_{\bar{j},t}} = \frac{r_{j,t+1}}{p_{j,t}}$. Hence, the marginal quality adopted is such that the cost of adoption equals one,

$$\frac{q_{j_{t+1}}}{q_{\bar{j}_t}}\frac{1+\tau}{(1+\overline{\mu})} = 1.$$

When adoption costs are the same across economies, as indicated by $\tau = 0$, the quality of the next available technology adopted is proportional to the current technology and the rate of improvement of the frontier technology, $q_{j+1} = (1+\overline{\mu})q_{\bar{j}_t}$. Economies wherein the cost of adoption is relatively high, i.e. $\tau > 1$, display a rate of adoption in quality that is lower than the improvement in frontier quality. Changes in the institutional environment (for example, changes in taxation) will shift τ, induce changes in the rate of adoption and have the potential to shift equilibrium adoption rates closer to the frontier innovation rate.

Proposition 1 *The equilibrium stock of capital services, $\sum_{j\in A_{t+1}} q_j k_{j,t+1}$ is determined by*

$$1 = \frac{(1-\lambda)}{R_{t+1}}\left[\alpha_k(\sum_{j\in A_{t+1}} \frac{q_j}{q_{\bar{j}_{t+1}}} k_{j,t+1})^{\alpha_k - 1} l_{t+1}^{\alpha_l} n_{t+1}^{\alpha_n} + (1-\delta)(\frac{q_{\bar{j}_{t+1}}}{q_{\bar{j}_{t+2}}})^{1-\alpha_k}\right] \tag{3}$$

Proof. The proofs to all propositions can be found in Appendix A ■

The total stock of capital services is determined by the optimality of the households' capital accumulation policy. However, due to the assumption of perfect substitutability, the distribution of capital across vintages is indeterminate. Still, as we describe in the next section, the shape of the age-price profile, which is the main object of our analysis, is independent of the vintage composition.

Definition: *A feasible allocation is a set of sequences of investment and capital stocks of different vintages, labor, land and household consumption*

$[\{[x_{\underline{j},t},....,x_{\overline{j},t}]\}_{t=0}^{\infty},\{[k_{\underline{j},t+1},....,k_{\overline{j},t+1}]\}_{t=0}^{\infty},\{n_t\},\{l_t\},\{c_t\}]$ *such that markets clear, i.e.*

$$n_t = N \qquad l_t = L,$$

$$c_t + \sum_{j\in A_{t+1}^h} C(q_j, q_{\overline{j}_t}, \overline{\mu}) p_{j,t} x_{j,t} \leq (\sum_{j\in A_t} q_j k_{j,t})^{\alpha_k} l_t^{\alpha_l} n_t^{\alpha_n},$$

$$(k_{j,t+1} - k_{j,t}(1-\delta)\chi) = x_{j,t} \quad \textit{for all} \quad j \in A_{t+1},$$

where $p_{j,t}$ is the present discounted value of capital services for vintage j.

3.4 Balanced growth path

In this section, we show that there exists a balanced growth path (BGP) and characterize equilibrium allocations.

Definition: *A BGP is a feasible allocation wherein output and efficiency units of capital grow at a constant rate and the vintage composition of the capital stock, labor, land and the expected distance between the best- and worst-available vintage used in production, $(\overline{j}_t - \underline{j}_t)$, are constant.*

Given that all farms are identical, it is possible to describe the aggregate production function of this economy as:

$$Y_t = (\sum_{j\in A_t} q_j k_{j,t})^{\alpha_k} N^{\alpha_n} L^{\alpha_l},$$

where N is the aggregate labor supply, and L the aggregate land supply. Without loss of generality, we normalize the labor supply to one, $N = 1$. Hence, output per worker is:

$$y_t = (\sum_{j \in A_t} q_j k_{j,t})^{\alpha_k} l^{\alpha_l}.$$

Before characterizing the BGP, it is useful to define the effective growth rate of capital quality, μ, as

$$1 + \mu = \frac{1 + \overline{\mu}}{1 + \tau}.$$

Also, let $\widetilde{k}_t$ be the aggregate stock of capital per worker in efficiency units of the best available technology, i.e., $\widetilde{k}_t \equiv \sum_{j \in A_t} \frac{q_j}{q_{\bar{j}_t}} k_{j,t}$; and let $\widetilde{x}_t$ be the aggregate level of investment $\widetilde{x}_t \equiv \sum_{j \in A_t} \frac{q_j}{q_{\bar{j}_t}} x_{j,t}$.

Proposition 2 *There exist a BGP in which consumption, c_t, output per worker, y_t, and the price of capital for the best-available technology, $p_{\bar{j},t}$, grow proportionally to the quality of the best-available vintage in the market, at rate*

$$g_y = g_c = g_p = \alpha_k \mu.$$

Investment in the stock of capital, $\widetilde{x}_t$, and the stock of capital per worker, $\widetilde{k}_t$, measured in efficiency units of the best technology available are constant. The bounds for the best- and worst-available vintages used in production, $\underline{j}_t$ and $\overline{j}_t$ respectively, grow proportionally to the growth rate of the best-available quality in the market, $g_{q_{\bar{j}_t}} = \mu$.

A constant vintage composition along the BGP allows us to be consistent with a constant normalized investment, $\widetilde{x}$. To pin down the level of normalized investment we take a stand on the actual vintage composition of the capital stock (the BGP characterization is silent about it) and focus on the case of positive investment in the top available technology only. Note that the vintage composition is irrelevant for the identification of the rate of embodiment and our growth accounting exercises. But assuming a particular vintage composition allows us to separately identify the contribution of capital quality and capital quantity in our development accounting exercise.

Let the aggregate stock of capital per worker be $k_t \equiv \sum_{j \in A_t} k_{j,t}$; and the aggregate level of investment be $x_t \equiv \sum_{j \in A_t} x_{j,t}$. Define the effective discount rate as $\widehat{\delta} = \frac{(1-(1-\lambda)(1-\delta))}{(1-((1-\lambda)(1-\delta))^{T_j})}$; and summarize the efficiency units of stock of capital along the BGP by $\widetilde{q}_{\bar{j}} \equiv \sum_{j \in A} \frac{q_j}{q_{\bar{j}}}(1-\delta)^{\bar{j}-j}$, so that $\widetilde{q}_{\bar{j}} = \frac{\widetilde{k}}{k_{\bar{j}}}$.

Corollary 1 *If the capital accumulation policy is*

$$k_{\bar{j}_{t+1},t+1} = x_t$$

and for $j < \bar{j}_{t+1}$

$$k_{j,t+1} = \begin{cases} k_{j,t}(1-\delta) & \text{if } \chi = 1, \\ 0 & \text{otherwise,} \end{cases}$$

the total stock of capital in the economy is

$$k = \frac{1}{\widetilde{q_{\bar{j}}}\widehat{\delta}} \left(\frac{\alpha_k l^{\alpha_l}(1-\lambda)}{R - (\frac{(1-\lambda)(1-\delta)}{(1+\mu)^{1-\alpha_k}})} \right)^{\frac{1}{1-\alpha_k}},$$

and aggregate investment follows

$$x = k\widehat{\delta}.$$

The share of capital of older vintages decays geometrically with depreciation and the likelihood of the retirement shock, following the assumption of positive investment in the top available technology only.[24] Note that if λ equals 1, the full stock of capital is retired every period and investment equals the total stock of capital. Alternatively, when $\lambda \to 0$ and the expected time to retirement goes to infinity, investment corresponds to the depreciated part of the aggregate stock each period, $x = \delta k$. The equilibrium capital stock raises with the land endowment and falls with the rate of arrival of better quality capital, μ. Intuitively, the faster the adoption of better quality stocks, the faster installed stocks become obsolete. Hence, it is optimal to economize on stocks and take advantage of the more efficient vintages that become available.

Although different equilibrium vintage structures have different implications for the aggregate stock of capital in the economy, k, and total investment, x, all generate the same stock of capital services , $\sum_{j \in A} q_j k_j$, (see Proposition 1). Hence, they generate the same marginal product of capital and aggregate output.

[24]When the elasticity of substitution across goods is non-unitary, but vintages are substitutes in production, the optimal capital accumulation strategy implies that the relative stock of capital of each vintage is proportional to their quality. In economies where goods are more substitutable, the vintage composition of the capital stock tilts towards (newer) vintages of higher quality.

3.4.1 Predicted prices

The price of a piece of equipment of vintage j and age a at time t is:

$$p_{j,t}(a) = \sum_{s=t+1}^{\infty} \frac{(1-\lambda)^{s+a-t}(1-\delta)^{s+a-(t+1)}}{\prod\limits_{h=0}^{s-t+1} R_{t+1+h}} \frac{\alpha_k q_j y_s}{\sum_{j \in A_s} q_j k_{j,s}}. \tag{4}$$

Conditional on the quality of a given good, the price of older equipment is lower than the price of newer equipment. The rate of decay of the price with age depends not only on the structural parameters of the model, such as the physical depreciation rate and the exogenous retirement rate, but also on equilibrium outcomes, such as the optimal choice of the vintages used in production, A_s, and the speed of adoption.

We characterize the relationship between the prices of new and old equipment with the rate of arrival of the best quality in the market μ and the stock of capital services along the BGP. The interest rate and growth rate of quality are constant at R and μ, respectively. Let $p_{\bar{j}_{t+1},t}(0)$ be the price of a new piece of equipment of quality $q_{\bar{j}_{t+1}}$ at time t. This price corresponds to the present discounted value of capital services throughout its expected life:

$$p_{\bar{j}_{t+1},t}(0) = \frac{\frac{(1-\lambda)}{R}}{1-\psi} q_{\bar{j}_{t+1}} \frac{\alpha_k l^{\alpha_l}}{(q_{\bar{j}_{t+1}} \widetilde{k}_{t+1})^{1-\alpha_k}}, \tag{5}$$

where $\psi = (\frac{1}{1+\mu})^{1-\alpha_k} \frac{(1-\lambda)(1-\delta)}{R} < 1$ is an effective discount rate. Note that there is a mapping between the price of a new piece of equipment and the relative price of investment to consumption as presented in Greenwood *et al.* (1997): we refer the reader to the Appendix A.1 for a description of such a mapping.

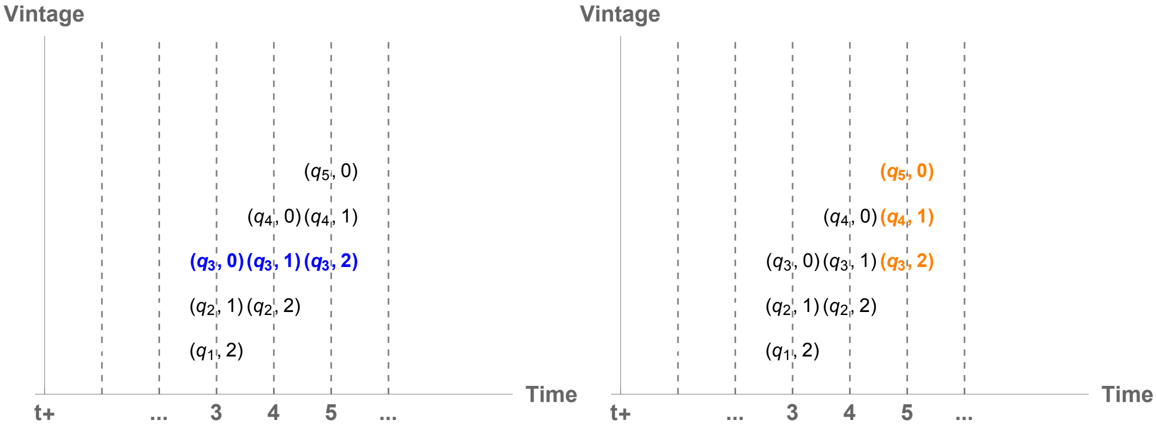
Age-price profiles can be constructed longitudinally, following a piece of equipment with time; or in the cross-section, looking at different vintages of capital at the same point in time (see figure IV).

If a years elapse, the piece of equipment priced in equation 5 has a trading price of:

$$p_{\bar{j}_{t+1},t+a}(a) = (1-\delta)^a \left(\frac{1}{1+\mu}\right)^{(1-\alpha_k)a} p_{\bar{j}_{t+1},t}(0). \tag{6}$$

This condition characterizes the longitudinal age-price profile. The degree of economic obsolescence induced on the good is the inverse of $\left(\frac{1}{1+\mu}\right)^{(1-\alpha_k)a}$. Hence, it is proportional to the improvement in quality as time elapses, μ, and negatively related to the share of capital

Figure IV: Price profiles



(a) Longitudinal (b) Cross-sectional

In the longitudinal profile we follow a particular vintage, i.e. one with quality q_3, as it ages. In the cross-sectional profile we compare prices of different vintages (and qualities) at a given point in time, i.e. $t = 5$.

in production, α_k.

To characterize the cross-sectional age-price profile, we look at the price of an a-year-old tractor in the current period. This piece of equipment has a quality level $j = \bar{j}_{t-a+1}$, and corresponds to the best available technology a years ago. By arbitrage:

$$p_{\bar{j}_{t-a+1},t}(a) = (1-\delta)^a \left(\frac{1}{1+\mu}\right)^a p_{\bar{j}_{t+1},t}(0), \tag{7}$$

where $p_{\bar{j}_{t-a+1},t}(a)$ is the price of an a-year-old piece of equipment of quality $q_{\bar{j}_{t-a+1}}$. The slope of the cross-sectional profile is proportional to capital quality improvement, $\frac{1}{1+\mu}$, and it is a combination between economic obsolescence and changes in the cross-sectional quality composition of the stock of capital. Along the balanced growth path, the range of vintages in operation is pinned down by the rate of adoption of higher quality vintages, μ. Therefore, a regression of equation (7) in logs would yield an estimate of economic obsolescence, up to a country-specific depreciation rate. We discuss and use this identification restriction in the quantitative exercises that follows.

4 The path of capital-embodied technology

In this section, we outline our identification strategy for recovering the path of capital-embodied technology from prices of old and new equipments. Then, we describe our estimation of the cross-country path of capital quality in the agricultural sector for 15 countries between 1990 and 2013.

4.1 Identification

We identify the paths of the best-available technology and total capital services from prices of old and new equipments through the lens of our model. Two key model ingredients allow us to do so: i) the balanced growth assumption and ii) competitive rental markets for capital of different vintages, both of which validate the price characterization in equations 6 and 7.

Our main identification restriction is the cross-sectional age-price profile, characterized by the logarithm of equation 7:

$$\ln(p_{\bar{j}_{t-a+1},t}(a)) = \ln\left(\frac{\Gamma_t}{1-\psi}\right) + a\ln\left(\frac{1-\delta}{1+\mu}\right), \tag{8}$$

where Γ_t is a constant corresponding to the present value of the services associated with a piece of equipment of the best vintage at time t, $\Gamma_t = \frac{\alpha_k q_{\bar{j}_{t+1}}^{\alpha_k} l^{\alpha_l}}{(\widetilde{k}_{t+1})^{1-\alpha_k}} \frac{(1-\lambda)}{R}$. The price elasticity to age identifies the rate of adoption, μ, up to a value for the rate of physical depreciation. This rate of adoption and equation 3 further pin down the level of capital services in terms of the best available quality, $\widetilde{k}$. Finally, these two measures and the intercept of the age-price profile identify disparities in the level of the top quality used in production, $q_{\bar{j}}$.

Notice that our theory-informed age-price profile, equation 8, imposes a log-linear relation between the price of a tractor and its age. This is an implication of two assumptions: (a) a geometric decay of physical depreciation and (b) a constant hazard of vintage retirement. Differently, in Section 2, we let the data speak about the shape of the age-price profile and refrained from imposing any a-priori structure. The estimation results implied a shape that was only slightly more convex than the one implied by the logarithmic transformation. We read this result as an attestation of the sensibility of our two modelling assumptions.

In identifying the path of quality we could alternatively had used the longitudinal age-price profile, equation 6. Two caveats challenge this approach. First, as we describe next, identifying the level of capital quality in the economy is problematic. Second, whereas the identification strategy for the rate of embodiment in the cross-sectional age-price profile is robust to allowing for transitional dynamics in the rate of quality improvement, it is not in the case of the longitudinal age-price profile.

On the first caveat, equation 6 makes clear that the intercept of the longitudinal age-price profile depends on the quality of each piece of equipment being priced. Hence, it requires the flexibility of a vintage-specific intercept. If we were to regress prices of particular vintages through time and allow for a common intercept, this would pick up some combination of the prices of the vintages in our sample when new. Differently, in the cross-sectional price equation, 7, the intercept always corresponds to the price of the best available vintage at a point in time, independently of the piece of equipment being priced. Hence, combined with our balanced growth assumption, this intercept identifies the best quality in the economy. Still, we can use the longitudinal profile to identify the growth rate of capital quality. In section 6, we exploit the multiple cross-section structure of our dataset and construct a synthetic panel to identify quality growth with the longitudinal age-price profile.

On the second caveat, note that our benchmark model is such that equipment quality always grows at a constant rate, irrespective of whether the economy is on a transition path or on its BGP.[25] This feature stems from the assumed functional form of the adoption cost function. Alternatively, we could have posed a cost function along the lines of Parente and Prescott (1994), such that all economies share the same BGP but differences in adoption costs yield differences in the steady state levels of income as well as differences in the path of quality along the transition path.[26] Whereas the slope of the cross-sectional age-price profile still pins down the average rate of embodiment, this is not the case in the longitudinal profile. The reason is that, along the transition path, equipment prices fall non-linearly with the rate of embodiment but also with the interest rate. These two effects cannot be separated from each other.

We analyze these non-trivial transition dynamics for the capital quality path in the online appendix. Here, we want to note that our estimates for cross-country disparities in adoption costs and associated paths of quality under balanced growth might be a lower bound to those we would have obtained when analysing an economy with non-trivial transitional dynamics for equipment quality. The reason is that, when convergence to the BGP is monotonic, we should observe higher average growth rates of quality along the transition path than in steady state. If the economies under analysis are approaching the same steady state and

[25] Following a change in τ, the stock of capital services may deliver a non-trivial dynamic as in the standard two-sector economy with investment-specific technical change.

[26] This non-trivial dynamics for quality can be micro-founded through a theory of endogenous diffusion across countries, as in Barro and Sala-I-Martin (1997); Benhabib and Spiegel (2005).

we aim at generating flatter age-price profiles in poorer economies, adoption costs in these economies should be relatively higher than those inferred under a constant arrival rate.

4.2 Estimation

We use our identification strategy to infer the path of capital-embodied technology in the agricultural sector from prices of new and old agricultural tractors traded in each country. We consider 15 middle- an high-income countries between 1990 and 2013: Australia, Belgium, Bulgaria, Brazil, Canada, Spain, France, Great Britain, Germany, Ireland, Italy, Mexico, the Netherlands, New Zealand and the US. We use two main data sources: FAOSTAT and our own dataset of equipment prices described in Section 2.

We start by assuming that countries differ from one another on four exogenous dimensions: 1) factor shares, α_k, α_l and α_n; 2) endowments of land per worker in the agricultural sector, l; 3) depreciation of physical capital, δ; and 4) adoption costs, τ, which induces differences in the path of capital quality, as described by the arrival rate of the best-available technology μ and the highest level of quality operated in a given year $q_{\bar{j}}$. Differences in the arrival rate of the best-available technology and the level of the highest quality technology adopted imply differences in the average quality of installed capital at each point in time.

We augment our model-implied regression with measures of observable characteristics for each tractor and estimate:

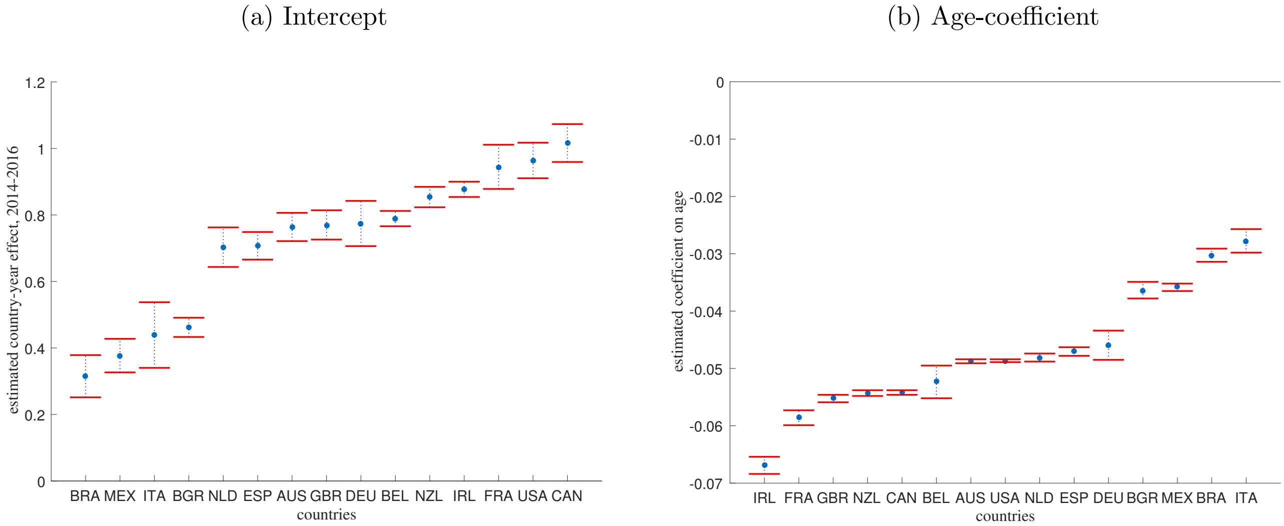
$$\ln(p_{i,c,t}) = \gamma_{1,c,t} + \gamma_{2,c} a_{i,c,t} + \frac{X_{i,c,t}^{\theta_2} - 1}{\theta_2}\beta + \epsilon_{i,c,t}, \tag{9}$$

where i is a quote, c is country, t is a year, $\gamma_{1,c,t}$ is a country- and time-specific effect, $\gamma_{2,c}$ is a country-specific coefficient on age, X is a matrix of equipment characteristics excluding age, β is a vector of coefficients associated with each of these characteristics, and ϵ is an error term that is assumed to be normally distributed. Given the assumed sources of cross-country heterogeneity, we include country-year effects and country-specific coefficients on age.[27]

Among the regressors, we include a matrix of equipment characteristics, X, which includes horsepower, use hours per year and manufacturer. We control for observable characteristics as our model embeds a one-to-one mapping between age and quality (i.e. all goods of a given age share the same quality). This is certainly not the case in the data as a

[27]Equation 8 dictates that country-specific μ and δ imply country- and time-specific coefficients on age. We do not allow the coefficient on age to change over time, consistently with the balanced growth assumption. As a robustness, we estimate equation 9 year by year and measure negligible changes in the coefficient associated to age. These results are available in the online appendix.

Figure V: Estimation results



Panel (a) shows estimated country-specific intercepts as averages between the years 2014 and 2016, $\gamma_{1,c,2014-2016}$, (solid line) with confidence intervals (dashed lines). The intercepts are relative to country Bulgaria and year 2015. Panel (b) shows estimated country-specific coefficients for age, $\gamma_{2,c}$, (solid line) with confidence intervals (dashed lines).

variety of equipment of different characteristics is introduced to the market each a year. By controlling for this within-age variation we build the data analog to model vintages.

We estimate equation 9 using our main dataset, covering multiple cross-sections between 2007 and 2016. Although this equation could be estimated, and the path of capital quality inferred, with a single year of data, we additionally exploit time variation in order to estimate the parameters more precisely. The estimation is conducted via maximum likelihood and results are shown in Appendix C, Table C.IV. Figure V plots (a) the estimated country dummies as averages between the years 2014 and 2016, $\gamma_{1,c,2014-2016}$, and (b) country-specific coefficients for age, $\gamma_{2,c}$, alongside their confidence intervals. There is significant variation in both estimates across countries. The price elasticity to age corresponds to the slope parameter reported in panel (b) of figure V. The coefficient of variation (standard deviation) of this elasticity is 0.23 (0.01) across countries, and estimates go from 2.8% in poorer economies to about 6.7% in richer ones. Similarly, the coefficient of variation (standard deviation) of the estimated country effects is 0.31 (0.22), with estimates going from 0.31 to 1.01.

4.2.1 Growth of capital-embodied technology

Our identification strategy indicates that the growth rate of capital quality, μ, can be inferred from the coefficient associated to age in regression 9, γ_2, and a value for the depreciation rate of physical capital, δ.

We measure physical depreciation from the price decay of a piece of equipment with hours of use. Consider two tractors of identical quality but differing hours of usage. Tractors A and B are both a-year old, but only tractor B was used in production and has positive hours of usage. The price difference between the two tractors reflects physical depreciation:

$$p_B = p_A \Theta(u_B),$$

where u_B is the number of hours tractor B was operated for and $\Theta(u_B)$ is the wear and tear induced by these hours. Assume, as we do in our model, that $\Theta(u)$ has an exponential decay in hours and is a function of a single parameter that is not vintage specific, δ. Let avg(u) be the "usual" number of hours a tractor is operated in a given year. We can specify physical depreciation as $\Theta(u) = (1-\delta)^{u/\text{avg}(u)}$. For example, if tractor B is operated at twice the average hours in a year, its physical depreciation will equate that of a tractor which was used for two years at the average hours. Therefore,

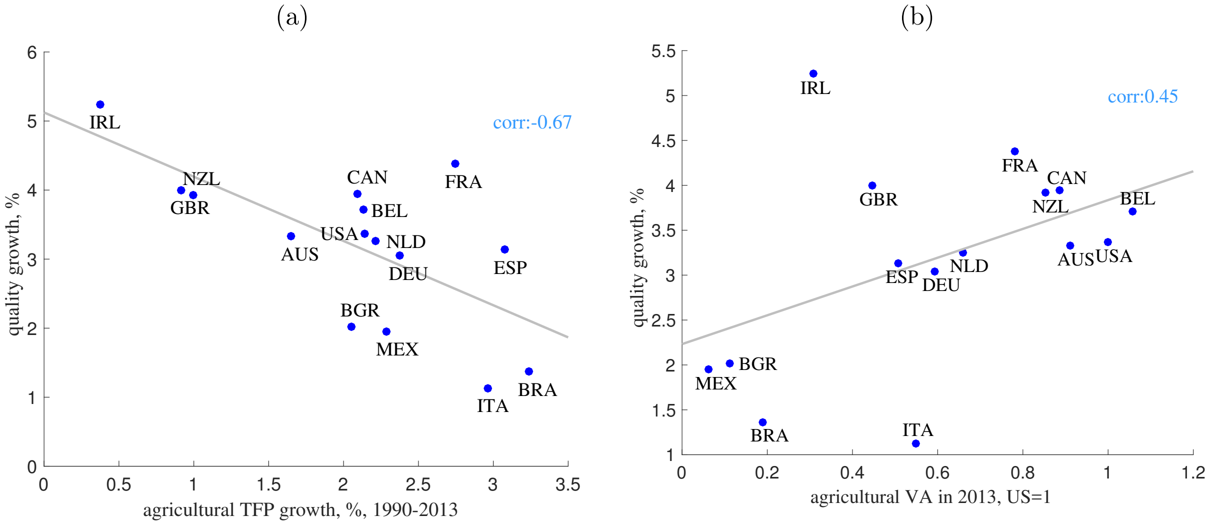
$$\delta = 1 - \left(\frac{p_B}{p_A}\right)^{\frac{1}{u_B/avg(u)}}. \tag{10}$$

When we implement this insight empirically, we use the baseline estimates from section 2 to predict the price of a synthetic tractor with average characteristics (comparable across countries) at different hours of usage for each country. We then measure the rate of depreciation in country c as the average depreciation rate resulting from evaluating equation 10 for a set of hours $u \in U = \{u_1, u_2, \ldots, u_{12}\}$:

$$\delta_c = \frac{1}{11}\sum_{j=1}^{11}\left(1 - \frac{\hat{p}_c(u_{j+1})}{\hat{p}_c(u_j)}\right),$$

where $u_1 = 0$, avg(u) is the average yearly hours of usage in the US and $\hat{p}_c(u)$ is the predicted price for country c of the tractor with average characteristics, average age and u hours of

Figure VI: Inferred growth rate of capital quality μ.



usage, as predicted by our estimation in Table C.II, column (1).[28]

The cross-country estimates of the depreciation rate are shown in Appendix B.2, Table B.II. The sample average of these depreciation rates is 1.59%.[29] Figure B.I in Appendix B.2 shows a negative correlation between physical depreciation and value added per worker in 2013 of -0.74 with a p-value of 0.0014. On the one hand, as poorer countries face a lower labor cost of tractor maintenance, one would expect a lower rate of physical depreciation in these countries. On the other hand, as richer countries adopt better tractor qualities, which may be more robust to wear and tear, one would expect a lower rate of physical depreciation in these economies. In our sample, the second effect prevails.

With our depreciation measures at hand, we use the cross-sectional age-price profiles predicted by the model, equation 8, and the estimates of the slope of the age-price profile to infer country-specific arrival rates of improved quality, μ (Figure VI).

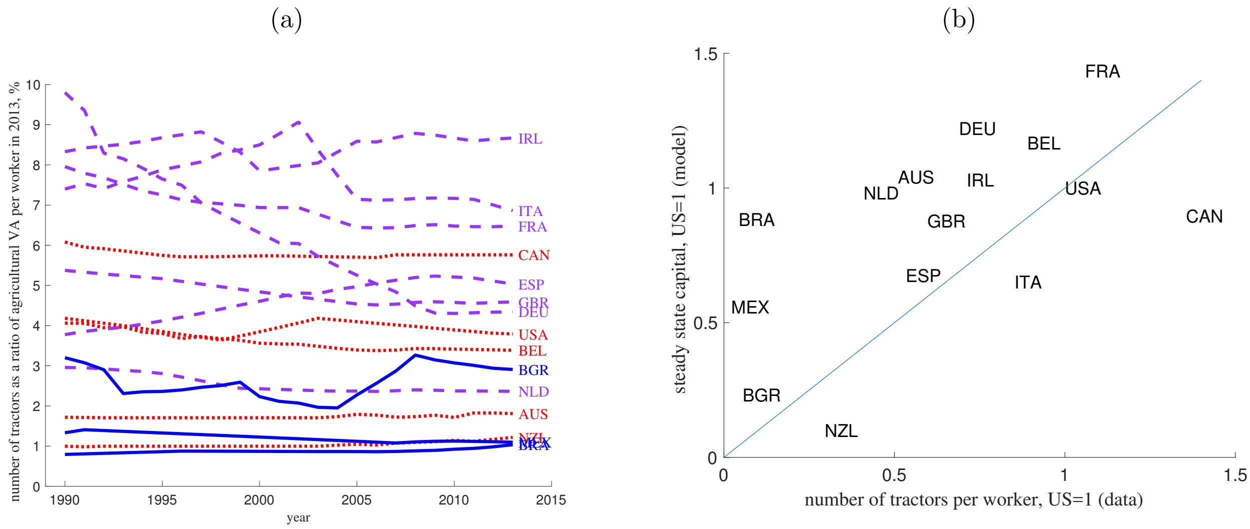
[28]Given the results of the baseline estimation in Section 2, for each country c we predict:

$$\hat{p}_c(u) = \left(\hat{\theta}_1 \hat{\gamma}_{1,c,2015} + \hat{\theta}_1 \hat{\gamma}_{2,c} \bar{a} + \hat{\theta}_1 \hat{\beta}_{\text{hours}} \frac{u^{\hat{\theta}_2} - 1}{\hat{\theta}_2} + \hat{\theta}_1 \frac{\bar{X}_{c,-\text{hours}}^{\hat{\theta}_2} - 1}{\hat{\theta}_2} \hat{\beta}_{-\text{hours}} + 1 \right)^{\frac{1}{\hat{\theta}_1}},$$

where the bar operator indicates sample averages, the hat operator indicates sample estimates and β is a vector of coefficients on tractor characteristics other than and hours, $X_{-\text{hours}}$.

[29]The cross-country coefficient of variation in physical depreciation is 0.022. One of the possible reasons why we infer heterogenous rates of physical depreciation is cross-country differences in the repair behavior.

Figure VII: Observed number of tractors used vs. steady state quantity of tractors



The colors of the lines in panel (a) reflect the country's rankings with respect to agricultural value added per worker in 2013 from the lowest in blue (below 75% the US value) to the highest in red (above 75% the US value).

On average, we infer higher growth rates of capital quality in richer countries. This is the result of little variation in the estimates for physical depreciation rates across countries and a negative correlation between the slope of the age-price profile and income per worker. We find that capital quality in the agricultural sector grows by 3.4% per year in the US compared to 1.4% in Brazil, a country that measures a value added per worker in agriculture that is 20% of that in the US. Overall, our inferred growth in capital quality has a correlation of 0.45 with agricultural value added per worker.

To understand the plausibility of the inferred growth of agricultural capital quality, we study the implications of our model for a non-targeted moment, the stock of capital per worker. We specify steady state quantity of capital per worker in our model, k, from corollary 1 – that is, when there is positive investment in the top available technology only. Differences in the steady state capital across countries are a function of the arrival rate of quality μ (controlling for the depreciation rate, factor shares and land endowments, which we take from the data). As shown in Figure VII panel (a), the number of tractors is relatively stable in time across the countries in our sample. We compare the model-implied differences in the steady state quantity of capital per worker to differences in the average number of tractors per worker observed in the data over the 1990–2013 period. Figure VII panel (b) plots the model and data moments, which have a correlation of 0.58. As a measure of fit we use Asker, Collard-Wexler and Loecker (2014)'s statistics, which is an un-centered R^2:

$$S^2 = 1 - \frac{(\mathbf{x} - \hat{\mathbf{x}})'(\mathbf{x} - \hat{\mathbf{x}})}{\mathbf{x}'\mathbf{x}},$$

where $\mathbf{x}$ is a vector of data moments, $\hat{\mathbf{x}}$ is a vector of model moments, and S^2 indicates the proportion of the observed data captured by the model's prediction. The S^2 of our model for capital per worker is 66.9%.

We also test the predictions of our model in terms of the findings in Nelson (1964). He shows that the average age of capital should be negatively related to the gap between the average quality of the capital stock and the quality of newly installed capital. In our sample, countries with higher quality growth have, on average, lower average age for the stock.

Comparison to the literature. We compare our findings to alternative measures of capital quality growth available in the literature. Hulten (1992a) and Greenwood *et al.* (1997) show how changes in the quality of capital equipment can be measured by changes in the price of consumption relative to that of quality-adjusted investment in capital equipment, g_{p_c/p_i}. This relationship holds in our model with an elasticity proportional to the share of capital equipment in output (see equation 6 under zero physical depreciation):

$$\mu = \frac{g_{p_c/p_i}}{1 - \alpha_k},$$

For the US, Krusell *et al.* (2000) offer estimates of quality-adjusted prices for various types of equipments. We use their estimates for the price of tractors and that of farms' capital equipment between 1980 and 2000.[30] The quality-adjusted price of tractors relative to consumption decreased by 1.9% per year on average between 1990 and 2000 and by 2.2% per year between 1980 and 2000. Similarly, the quality-adjusted price of farms' capital equipment relative to consumption decreased by 1% per year between 1990 and 2000 and by 2.1% per year between 1980 and 2000. Through the lenses of our model and given a 24% capital share for the US, these relative price growths translate into an estimated average growth rate in capital quality between 2.8 and 2.9% for the period 1980-2000 and between 1.2 and 2.5% for 1990-2000. Our estimate of quality growth based on age-price profiles is 3.4% per year for the US, which is very close to these alternative measures.

[30] Estimates are not available for later years as the NIPA's category "Tractors" has been discontinued. NIPA used to have these three categories: "Tractors", "Agricultural machinery, except tractors", "Construction machinery, except tractors", whereas now it has only two categories: "Agricultural machinery", "Construction machinery".

4.2.2 Level of capital-embodied technology

The highest level of capital quality operated in a given year, $q_{\bar{j}_{t+1}}$, can be recovered, according to our identification strategy from the country-time effects estimated in regression 9, γ_1, given data for factor shares, land and output per worker relative to the US.

We take factor shares from FAO-based datasets published by the United States Department of Agriculture Economic Research Service (USDA-ERS) in relation to the study by Fuglie (2015). Fuglie (2015) uses estimates of 19 studies for nationally or regionally representative cost shares or production elasticities for agricultural inputs. For the areas where direct estimates are not available, they assign the values from regions with resembling agricultural sectors (usually within the same geographical region).[31] However, among the poorer countries in our sample, Brazil and Mexico have available estimates (Appendix B.1). The USDA-ERS also publishes total agricultural land in hectares of "rainfed cropland equivalents." This is the sum of rainfed cropland (weight equals 1.00), irrigated cropland (weight varies from 1.00 to 3.00, depending on the region) and permanent pasture (weight varies from 0.02 to 0.09, depending on the region). We divide these estimates by the number of agricultural workers and use this figure as our measure of land endowment. We normalize land per worker to 1 in the US. In 2013, Australia had approximately 2 times the US land endowment, while the Netherlands had approximately 10% of the US land endowment.[32]

We measure the highest level of capital quality operated in a country relative to the US over the period 2014-2016, as these are the years for which our dataset on tractor prices clusters most observations. In addition, we assume log utility and a discount factor β equal to 0.95.[33] Without loss of generality, we normalize output per worker and the highest level of capital quality operated in the US in a given year to 1. Details and derivations are presented in Appendix B.3.

Figure VIII, panel (a) plots the top quality operated in a country relative to the US as an average for the 2014-2016 period:

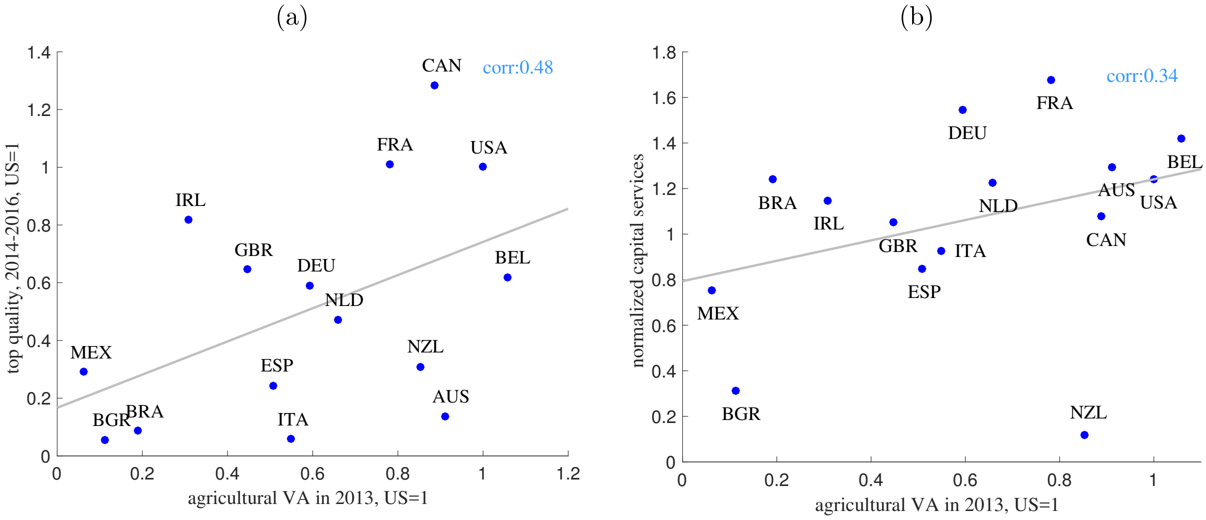
$$\frac{q_{\bar{j}_{c,2014-2016}}}{q_{\bar{j}_{US,2014-2016}}} = \frac{1}{3} \sum_{t=\{0,1,2\}} q_{\bar{j}_{c,2014+t}}.$$

[31] Fuglie (2015) shows that imputed shares represent only one-quarter of world agricultural output.

[32] The correlation between rained cropland equivalent and cropland measures is 0.95 in our sample in 2013. Canada and Australia are the only two countries for which these two measures of land per worker differ slightly.

[33] These two assumptions identify a country-specific interest along the balanced growth path R_c: $R_c = \frac{(1+\alpha_{k,c}\mu_c)}{\beta}$.

Figure VIII: Inferred level of capital quality, 2014-2016



The left panel shows the inferred top capital quality between 2014 and 2016, $q_{\bar{j}_{2014-2016}}$. The right panel shows the inferred level of capital services normalized by the top capital quality in each year, $\tilde{k}$.

Moreover in panel (b), we show the total level of capital services normalized by the top quality operated in a year, $\tilde{k}$ in our model. We measure a higher top quality of agricultural capital in richer countries than in poorer countries. For example, the top quality of agricultural capital in the US is 12 times larger that in Brazil for the period 2014-2016. Our inferred top capital quality has a correlation of 0.48 with agricultural value added per worker across countries. Finally, normalized capital services also correlate positively with agricultural value added per worker. In addition, the richer countries in our sample show a wider range of qualities for installed capital, on average. This is a consequence of their faster growth in quality adoption and higher share of capital in production as in Jovanovic and Rob (1997).

Comparison to the literature. Using import data, Caselli and Wilson (2004) show large disparities in the composition of equipment investment across countries, and argue that the latter are relevant for differences in productivity across economies. Relevant to our analysis, they show that equipment types coming out of high R&D industries are more complementary with factors that are relevant for the adoption of newer technologies. Here, we use this findings to build an alternative measure of capital quality based on the R&D composition of equipment investment. We use the 2005 R&D expenditure in non-electrical equipment (ANBERD dataset compiled by the OECD) to build an index of the quality of equipment produced in a country. Next, using 2015 COMTRADE data on the composition

Table I: R&D content of capital

	Model	R&D content
	Average quality	
Australia	0.138	0.251
Canada	1.243	0.828
Spain	0.247	0.199
France	0.953	0.331
Great Britain	0.620	0.327
Germany	0.601	0.593
Italy	0.066	0.200
Netherland	0.473	0.353
United States	1.000	1.000
	Top quality	
United States	1.000	1.000
Bulgaria	0.056	0.245
Brazil	0.086	0.595
Mexico	0.291	0.708

The table compares our inferred quality of agricultural capital from that inferred using R&D content of investment (domestic and imported).

of imports by country of origin and 2005 NIOT data on home-trade shares in equipment, we measure a country's composition of its capital stock by country of origin. Last, we build a quality index for the stock of capital in each economy as the average of our R&D-based quality index weighted by the composition of the capital stock by country of origin.

This measure is shown in Table I, panel *Average quality*, for the countries in our sample that have information on R&D expenditures. We compare this alternative measure to our measure of average capital quality computed under corollary 1 in our model.[34] The two measures correlate at 80.0%. Both of them are also broadly consistent on the ordering of countries by quality of their capital stock: Australia, Spain and Italy are at the bottom, while USA and Canada are at the top.

Measures of R&D expenditures are not available for the poorer countries in our sample. However, we are still able to measure the R&D content of their imports. We work under the assumption that the quality of imports in these countries is at least as good as that of locally-produced capital and compare the R&D content of their imports to the R&D content of nationally produced capital in the US. We consider this exercise as a cross-country comparison of the top quality of operated machines, $q_{\bar{j}}$. Table I, panel *top-quality*, reports

[34]Under the assumption that there is positive investment in the top available technology only, average quality weighted by the quantity of capital of each operated vintage reads: $q_{\bar{j},c}\left(\sum_{i=1}^{1/\lambda}\left(\frac{1-\delta_c}{1+\mu_c}\right)^{i-1}\right)^{1-\alpha_K}$.

this R&D-based measure of $q_{\bar{j}}$ along with our measure. The two measures deliver the same relative order of countries. However, the R&D-based measure vastly underestimates the magnitude of the differences with respect to the US.

Lastly, our working hypothesis in the previous exercise is that imported and locally-produced goods have similar quality. A subsample of our dataset allows us to track the country of origin of the piece of equipment being traded. Hence, we can test this hypothesis directly. We do this in section 6. We find that the average quality of installed capital is higher for imported equipment in Mexico, Great Britain and Germany, but lower for the United States, France and Canada.

5 The role of capital-embodied technology in agricultural productivity

In this section, we use our inferred path of quality of the capital stock to examine its role for the disparities in agricultural labor productivity across countries. We conduct standard accounting exercises to quantify: (i) the role of capital-embodied technology in labor productivity growth over the 1990–2013 period, and (ii) the role of cross-country disparities in the average quality of capital in the agricultural sector for agricultural value added per worker in 2013. To conclude, we show the robustness of our findings to using sale prices rather than ask prices in our capital quality inference.

5.1 Growth accounting

We examine the role of adoption patterns of capital-embodied technology in agricultural productivity growth via a growth accounting exercise along the lines of Solow (1957) and Jorgenson and Griliches (1967). Given our production function and the assumption of balanced growth, we can relate the growth rate (g) of total factor productivity (TFP) to the path of capital embodied technology adoption:

$$\underbrace{g^d_{y,c} - \alpha_{k,c} g^d_{k,c} - \alpha_{l,c} g^d_{l,c}}_{g_{TFP,c}} = \alpha_{k,c} g_{q_{\bar{j}},c} + g_{Res,c}, \tag{11}$$

where the LHS is the growth rate of TFP, i.e., value added per worker in the data (d) corrected by capital stock and land. This growth rate can be decomposed in two parts, one

Table II: Growth accounting exercise

	g_{TFP}	$\alpha_k\mu$
Australia	1.65	0.33
Belgium	2.14	1.14
Bulgaria	2.05	0.35
Brazil	3.23	0.34
Canada	2.09	0.73
Spain	3.07	0.59
France	2.75	1.35
Great Britain	0.91	1.47
Germany	2.37	0.94
Ireland	0.37	1.62
Italy	2.96	0.21
Mexico	2.29	0.86
Netherland	2.22	1.00
New Zealand	1.00	0.39
United States	2.14	0.80
$R^2(g_{\text{TFP}}, \alpha_k\mu)$	13.8%	
$\sigma(\log(g_{\text{TFP}} - \alpha_k\mu))$	1.20	
$\sigma(\log(g_{\text{TFP}}))$	0.57	

The table reports the growth rates of TFP over the 1990-2013 period and the growth rates of capital quality multiplied by the capital share. The bottom panel reports the R^2 of regressing TFP growth on capital quality growth multiplied by its factor share along with the standard deviation of the logarithm of TFP growth when the capital quality component is not considered ($\sigma(\log(TFP - \alpha_k\mu))$) and when it is ($\sigma(\log(TFP))$).

related to capital quality, $g_{q_{\bar{j}},c}$, and a residual, $g_{Res,c}$. This last part measures our model's ignorance: when the modeled growth rate of output per worker exactly matches the observed growth rate of TFP, i.e., $g_{Res,c} = 0$, the model attributes the growth rate in TFP to capital quality.[35]

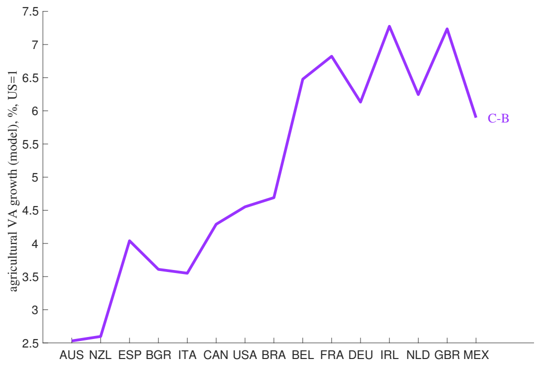
Table II compares the growth rate of TFP to the growth rate of capital quality multiplied by the capital share for the period 1990-2013. We measure the growth rate of TFP from FAO-based data published by the USDA-ERS on the growth rate of agricultural output per worker net of the growth rate of observed intermediate inputs, capital and land multiplied by the corresponding factor shares. Given the identity in equation 11, we compute the fraction of TFP growth explained by the quality of capital services: $\frac{\alpha_{k,c}\mu_{q,c}}{g_{TFP,c}}$. On average, in each country, capital quality explains 32% of the growth rate of TFP between 1990 and 2013.[36] Capital quality accounts for about one-third of the growth rate of TFP in the US and half of

[35] Notice that our model implies constant level of normalized capital services and land per worker along the BGP, so that the growth rate of value added and productivity are the same.

[36] This average excludes Great Britain and Ireland, for which the contribution of capital quality growth to TFP is 161% and 434%, respectively

Figure IX: Counterfactual exercise

(a)



2013-2023 growth rates of model-predicted agricultural output per worker under the baseline path of capital quality ("B") and under the counterfactual path of quality ("C"). Countries are ordered by ascending capital shares. Agricultural value per worker is normalized to equal 1 in the US in each period in both the baseline and the counterfactual scenarios.

that in France and Belgium. On the other hand, it accounts for close to 10% of the growth rate of TFP in Brazil and Italy. How much of the dispersion in TFP growth across countries is explained by capital quality? The dispersion in the logarithm of TFP growth halves when we include capital quality (see Table II). In particular, this dispersion goes from 1.20 without the contribution of quality to 0.57 with its contribution. We conclude that capital quality accounts for 47.8% of the cross-country dispersion in TFP growth between 1990 and 2013.

Overall, quality disparities in capital stocks across countries are sizeable and contribute substantially to the disparate behavior of productivity growth observed in the agricultural sector. Measured quality growth, μ, is a combination of the common arrival of technology in the world, $\overline{\mu}$, and country-specific distortions, τ – that is, $1+\mu = \frac{1+\overline{\mu}}{1+\tau}$. The latter are a reduced form for various adoption costs of agricultural equipment as well as polices that discriminate between new and old equipment. To close this section, we study the implications for agricultural output per worker of varying country-specific distortions.[37]

We start by setting the growth rate of the frontier technology to the growth rate of quality of the country with the fastest arrival of technology (highest μ), Ireland. This gives

[37]Notice that the level of quality pinned down from the constant in equation 8 depends on the identified growth rate of quality, μ. Therefore, when running counterfactuals on the measure of distortions, and hence the rate of adoption, we keep the steady state level of quality constant and assume that the movement in the rate of adoption is fully absorbed by a change in the constant of the pricing equation.

us a measure of distortions, τ, in each country: the average cross-country distortion is 2%. Now, consider a policy that reduces distortions in each country by 2%, so that the average distortion across countries is zero. How would agricultural output per worker look like 10 years into the future, along the new BGP? Figure IX plots the ten-year growth rate (2013-2023) of agricultural output under the counterfactual scenario net of that under the estimated path of quality growth, across countries. While all countries improve their value added, the gains differ across countries and these disparities are related to the share of capital in production. In the figure, countries are ordered by ascending capital share. Countries that are relatively more capital intensive benefit more from reduced distortions, and their productivity gains are larger. If different vintages of capital are interpreted as different goods, capital-embodied technology adoption ultimately leads to retirement of these older vintages and, potentially, stronger intensity of use of capital goods. As our growth accounting exercise assumes a constant capital share, we believe the results are a lower bound of the potential gains from capital-embodied technology adoption.

5.2 Development accounting

Our model specifies output per worker in a country, c, as a function of capital quantity, capital quality and land. Under the balanced growth assumption, this reads:

$$y_c^d = Res_c q_{\bar{j},c}^{\alpha_{k,c}} \tilde{k}_c^{\alpha_{k,c}} l_c{}^{\alpha_{l,c}},$$

where Res is the Solow residual – that is, $Res = 1$ when our model exactly replicates the value added per worker observed in the data. Further, the specification of corollary 1 allows the decomposition of capital services in its quantity and quality components so that:

$$y_c^d = Res_c (q_{\bar{j},c} \widetilde{q}_{\bar{j},c})^{\alpha_{k,c}} \hat{\delta}_c^{\alpha k,c} k_c{}^{\alpha_{k,c}} l_c{}^{\alpha_{l,c}}, \tag{12}$$

where $q_{\bar{j}} \widetilde{q}_{\bar{j}}$ is the average quality of the capital stock and k is its quantity. Using equation 12, we quantify the contribution of capital quality for income differences in agricultural value added across countries in 2011-2013 via two standard development accounting exercises. We choose this period because these are the most recent years for which FAO data are currently available and we inferred the level of capital quality using data over three years.

First, we measure the success of our model in explaining cross-country agricultural income differences. As in Caselli (2005), this amounts to asking the following question: Suppose

Table III: Development accounting: decomposition

	$\frac{y^d_{US,2011-2013}}{y^d_{c,2011-2013}}$	% AGRICULTURAL VA DIFFERENTIAL WRT US EXPLAINED BY:				
		$q_{\bar{j}}$	$\widetilde{q}_{\bar{j}}$	k	l	TOTAL
Bulgaria	9.6	22.5%	2.9%	10.2%	41.5%	69.9%
Brazil	5.4	37.9%	-9.0%	2.0%	18.7%	60.5%
Mexico	16.3	19.2%	-20.5%	11.1%	41.0%	99.9%

The table reports the percentage contribution of each income component to country differences in agricultural value added per worker with respect to the US. The results are reported for countries in the bottom quartile of the agricultural income distribution. Factor shares and land endowments are imputed from the data as 2011–2013 averages.

all countries had the same level of residual efficiency Res; how would the distribution of agricultural income per worker in our sample look like compared to the actual distribution? We measure the observed agricultural value added per worker in 2011-2013 by multiplying the value of gross agricultural production per worker by 1 minus the sum of intermediate input factor shares, as published by the USDA-ERS.[38] We compute the proportion of observed agricultural value added per worker, y^d, captured by our model's predictions, y, using our adjusted R^2, $S^2(y_{2011-2013}, y^d_{2011-2013})$. Our model explains 77.1% of the cross-country variation in agricultural value added per worker. If we were *not* to account for cross-country differences in capital quality – that is, if we were to set $q_{\bar{j},c}\widetilde{q}_{\bar{j},c} = 1$ in each country, our adjusted R^2 would decrease to 44.9%. We conclude that capital quality accounts for 32.2% of cross-country variation in agricultural value added per worker in our sample, holding capital per worker fixed. Capital quality has an additional indirect effect that is not captured in our accounting exercise: when capital quality improves, the return per unit of investment increases and generates additional incentives for capital accumulation. Hence, we believe our result is a lower bound for the role of capital-embodied quality in producing disparities in agricultural labor productivity.

Second, using equation 12, we decompose the difference in agricultural value added per worker in a given country with respect to the US into four main components, capital quality,

[38] Intermediate inputs include crops materials (fertilizers, pesticides, seeds), animal materials (pharmaceutical, feeds) and livestock capital.

capital quantity, capital replacement rate and land per worker, plus a residual term:

$$\begin{aligned}\log(y^d_{US,t}) - \log(y^d_{c,t}) \quad = \quad & \underbrace{\alpha_{k,US}\log(q_{\bar{j}_t,USA}) - \alpha_{k,c}\log(q_{\bar{j}_t,c}) + \alpha_{k,USA}\log(\widetilde{q}_{\bar{j},USA}) - \alpha_{k,c}\log(\widetilde{q}_{\bar{j},c})}_{\text{capital quality}} + \\ & \underbrace{\alpha_{k,US}\log(k_{USA,t}) - \alpha_{k,c}\log(k_{c,t})}_{\text{capital quantity}} + \underbrace{\alpha_{k,US}\log(\hat{\delta}_{USA,t}) - \alpha_{k,c}\log(\hat{\delta}_{c,t})}_{\text{replacement rate}} \\ & \underbrace{\alpha_{l,US}\log(l_{USA,t}) - \alpha_{l,c}\log(l_{c,t})}_{\text{land}} + \log(Res_{USA}) - \log(Res_c).\end{aligned}$$

The contribution of capital quality can be further divided into two components: differences in the highest quality and in the average quality of capital operating in a country.

Across the countries in our sample, land is the most important driver of differences in agricultural value added per worker with respect to the US, on average. Quality, in its two components, comes second, with an average contribution that is only slightly below that of land. To ease the exposition, we present a detailed decomposition only for the countries in the bottom quartile of the agricultural income distribution in our sample. Table III shows that in these countries the two most important drivers of differences in agricultural value added per worker are i) the highest quality of operated equipment and ii) land endowments. The former accounts for between 20% and 40% of the percentage differences in agricultural value added per worker with respect to the US in Bulgaria, Brazil and Mexico. The total contribution of capital quality for the income per worker differential with respect to the US is 25% for Bulgaria, 29% for Brazil and -1% for Mexico. This implies that the contribution of the range of capital qualities operated in the country, $\widetilde{q}_{\bar{j}}$, is negative for Brazil and Mexico and positive for Bulgaria. In other words, a faster arrival rate of the best-available technology μ results in a wider gap in quality between the best and worst technologies operating in the US compared to Brazil, Mexico and Bulgaria. At the same time, the higher capital intensity of agricultural production in the US, increases the role of capital quality for production compared to the other three countries. The arrival rate effect outweighs the capital intensity effect in Brazil and Mexico, while the opposite is true for Bulgaria. On average, capital quality accounts for 17.7% of the difference in agricultural value added per worker between these three countries and the US.

5.3 Robustness

The results presented above rely on a measure of quality inferred from retail ask prices. In this section, we test the robustness of these results to using sale, transaction, prices instead.

We observe sale prices for a subsample of our dataset. This subsample covers 250,000 observations across 10 countries, over the period 2007-2016.[39] We apply the methods described in section 4 on this subsample to infer the cross-country paths of quality. The yearly average growth rate of quality inferred from sale prices is 3.8% compared to 3.3% from ask prices, for the same set of countries. The growth rate of capital quality in the US increases of 0.3 percentage points when inferred using sale rather than ask prices. Two outliers stand out for their deviations between inferences: Spain and the Netherlands. In these two countries, our estimates based on sale prices are 1.7-points below and above the corresponding estimates based on ask prices, respectively. To note that Spain and the Netherlands have the smallest sample sizes (less than 100 observations in the subsample). Overall, the correlation between the two inferences of the growth rate of capital quality is 0.79. We find an even higher correlation between the inferences of the quality of the top operated technology, at 0.974. The top capital quality in the US is inferred to be 11 times larger than that of Brazil when using estimates based on sale prices, compared to 12 times larger when using estimates from ask prices.

We input these alternative paths of quality in our growth and development accounting exercises, as above. We find that irrespective of the definition of prices used to infer the path of quality, capital quality explains 37% of the dispersion in TFP growth across the countries in our subsample. On average, in each country, estimates based on sale prices attribute 48.6% of the growth rate of agricultural TFP between 1990 and 2013 to capital quality compared to 32.5% when using estimates from ask prices. Again, Spain and the Netherlands account for the difference.

Turning to disparities in agricultural value added per worker in our subsample, the model captures 77.7% of the observed disparities in 2013 when estimates from sale prices are used. Moreover, capital quality explain 40.3% of such disparities. This is in comparison to using estimates from ask prices, when the fraction captured by the model amounts to 72.5% and the one attributable to capital quality is about half.

6 Discussion

Given the relevance of capital-embodied technology adoption for differences in agricultural productivity across countries, in this section, we discuss deviations from our benchmark

[39]Specifically, the countries are Australia, Brazil, Canada, Spain, France, Great Britain, Mexico, Netherlands, New Zealand and United States.

model that would potentially affect the identification of the rate of adoption and weaken or strengthen our income accounting results.

Technology: heterogeneity and economies of scale. The benchmark model is one in which disparities in adoption rates are induced by barriers or costly adoption. It is possible that disparities in adoption rates are also related to the incidence of a) increasing returns in production (associated to fixed operating costs) or b) heterogeneity in returns to investment. The latter is of particular interest in view of the extensive literature that studies the role of revenue productivity dispersion for agricultural productivity (Adamopoulos and Restuccia, 2014, Restuccia and Santaeulalia-Llopis, 2015). We study these extensions (a-b) in the online appendix of the paper.

We show that dispersion in productivity across farms explains differences in the level of prices of the same quality goods across countries. However, the only determinant of the cross-sectional decay of prices with age is the arrival of newer (and higher quality) vintages into the economy. In other words, differences in production heterogeneity (or farm-level distortions) cannot explain differences in the age-price profiles once we control for observable characteristics. Production heterogeneity generates the same elasticity of prices to age that we derived in equation 8 of the benchmark economy and, hence, the same implied path of best-available quality from the data, μ. A similar effect has the presence of fixed operating costs in production. These costs induce cross-country disparities in the level of prices of a particular quality, but they do not affect the slope of the cross-sectional age-price profile.

Aggregate productivity. Disparities in adoption rates might be induced by complementarities with other factors of production, i.e. fertilizers, which improve the quality of the harvested land. It is likely that capital-embodied technology adoption is complementary to land quality and the size of plots operated (Restuccia and Santaeulalia-Llopis, 2015).[40] If technologies that are more productive require higher quality capital goods, higher total factor productivity is likely to correlate with the adoption of higher quality vintages of capital. In our benchmark model, productivity growth is only associated to the adoption of better quality goods. However, differences in institutional capacity or human capital, can induce differences in overall productivity and adoption incentives. In our accounting exercises, these productivity differences are considered a residual (Res).

Alternatively, we could have explicitly modelled the dynamic of a country-specific Hicks

[40] To the extent that plot sizes generate increasing returns in production, the discussion in the previous subsection is relevant.

neutral productivity term. We describe this alternative environment in the online appendix. We show that cross-sectional differences in the prices of goods of different age still pin down the rate of quality improvement. Hence, our identification of quality growth is invariant to such a modelling assumption. In addition, we show how to combine the rate of embodiment obtained from the cross-sectional profile with the slope of the longitudinal age-price to build a measure of the growth rate of Hicks neutral productivity.

To give a quantitative bite to this statements, we exploit the multiple cross-section structure of our dataset to infer capital quality growth and productivity growth from the cross-sectional and longitudinal profiles (details are in Appendix B.4). The cross-country average decay in prices (after controlling for physical depreciation) is 5.0% per year, compared to 2.8% for the inference based on the cross-sectional profile. Hence, a 2.14% (1.34%) per-year growth in Hicks neutral technology, on average (for the US) is consistent with the estimated growth rate of capital quality from the cross-sectional profile.

The identification of the quality level of the stock of capital is slightly more challenging than in our benchmark exercise, but empirically implementable. To be able to identify separately differences in the level of Hicks neutral productivity and the quality of the best available vintage used in the economy, we need an additional price equation. As we describe in the online appendix, we use the ratio of the price of a good of arbitrary quality, q_j, in different economies. Our measures of (normalized) capital services and the ratio of output per worker measured in the data allow us to identify differences in the quality of the best available technology from the ratio of prices of vintage j across economies. With this measure at hand, we can use the intercept of the age-price profile to infer the relative level of Hicks neutral productivity across countries.

Factor supply and capital intensity. For the countries in our sample, the land supply in rainfed cropland equivalents has been fairly constant during the period under analysis, and hence we do not think of it as a mayor source of bias in our estimates of capital quality. This margin is likely to be relevant when analyzing the role of capital quality in lower income economies, as we discuss in the next subsection.

The number of agricultural workers has been declining though, in accordance with structural movements as these economies develop. The macroeconomic impact of such labor flows is analyzed in Lagakos *et al.* (2015). A priori, the adoption of better quality equipment goods can have two counteracting effects. On the one hand, better quality equipment improve the marginal product of labor, increasing equilibrium salaries and inducing workers to remain in the farms. On the other hand, the arrival of better quality equipment goods can be overall labor saving, and in particular may replace the work of low skilled workers while being complementary to high skill ones (Acemoglu, 1998 and the extensive literature on skill-biased technological change). These movements generate incentives of out-migration for low skilled workers and increase capital intensity in the agricultural sector.

Whereas these considerations are absent in our benchmark accounting, we consider an exercise in which we give each country the path of capital quality of the US along with the US relative composition of labor and capital after controlling for the share of land.[41] On average, the gains in value added per worker relative to the US split about 2/3 for the change in the path of quality and 1/3 for the change in capital intensity. These results suggest that for the countries in our sample, improvements in quality of the capital stock are first order to understanding productivity differences.

A low-income economy. In our benchmark exercises, we study the role of capital quality for a sample of high- and middle-income economies. Cross-country disparities in agricultural productivity widen as we move down the development spectrum, towards low-income economies. One of the challenges of applying our methodology in low-income countries is that the extensive margin of capital adoption (which we do not model directly) is arguably very relevant in explaining low levels of labor productivity. Still, we can perform our analysis to build a lower bound to the potential gains of capital-embodied technology adoption. To do this, we extend our main dataset to include data for a country that is substantially poorer and less productive than any one in our sample: India. We gather 130 observations of equipment price quotes in 2016.

Our methodology to recover the path of capital quality for India follows the one outlined and applied in section 4. Indeed, and to make our estimates consistent across different exercises, the sample used in the benchmark estimation presented in section 4 already includes these observations. We find that India's slope coefficient is among the smallest similarly to middle-income countries in the sample (Brazil, Bulgaria, and Mexico). That is, equipment prices decay slowly with age. In addition, the intercept of the age-price profile is the smallest in the sample, below the level of the normalizing country, Bulgaria.

We infer a growth rate of capital quality for India of 1.8%, which is in line with that inferred for middle-income countries. To check how sensible this measure is, we look at the

[41] It is likely that the share of land in production depends among others, on the quality of the land and the farming characteristics in each country. We abstract away from the effect that technology adoption may have on shifting the intensity of land use.

model fit on capital per worker: the model implies a level of capital per worker in India that is about 7.2% that in the US, compared to 1.1% in the data. The undershooting of the model is to be expected as India is a country that is still adopting the "tractor" technology at the extensive margin (i.e. transitioning from labor and animal power intensive production to capital intensive production). Indeed, the number of tractors per worker has been raising at 7.8% per year in India, compared to an average in our sample of -0.3%.

Our accounting exercises imply that capital quality explains 7.4% of the growth rate of agricultural productivity in India between 1990 and 2013. This is similar to our conclusions for Brazil and Bulgaria, but different from the case of Mexico, where capital quality growth explains 1/3 of agricultural productivity growth. In 2013, agricultural value added in the US is about 60 times that in India. The model explains 66.1% of this differential, and capital quality accounts for 57.1% (with differences in the level of the top technology alone accounting for roughly half of it).

Open economy. In the analysis of this paper we assume economies are in autarky, abstracting away from the allocation of production across countries and the pattern of trade across them. Eaton and Kortum (2001) document that equipment goods are produced in a handful of developed countries and exported to others. In our data, 35% of the low-HP tractors (less than 40hp) is manufactured in Japan and 75% of high-HP tractors (100hp - 175hp) is manufactured in the US and Germany. Our model describes a closed economy, but the inferred adoption rates μ should be interpreted as a measure of the goods that become available to consumers in an economy. When markets are integrated and the law-of-one-price holds, the introduction of a good to a particular economy can induce obsolescence in goods in a different economy.[42] Hence, economies that are more open to trade with economies that adopt rapidly could experience faster obsolescence in their own capital stocks. However, for foreign adoption to become relevant for domestic obsolescence, goods adopted elsewhere need to be available to some consumers in the domestic economy.

Studies in the trade literature show evidence of pricing-to-market effects whereby the same good is sold at different prices in different countries even after adjusting for exchange rates, purchasing power and transportation costs. In our dataset there is some evidence, despite weak, of such pricing patterns.[43] Our inference of the level of capital quality relies on

[42] As pointed out by Mutreja *et al.* (2014), barriers to trade can be consistent with price equalization across economies.

[43] We restrict our sample to consider only a subset of tractors sold in each country and run a regression specification as in section 2. This sub-sample covers 828 observations and 10 countries, Australia, Canada, France, Great Britain, Germany, Ireland, Mexico, the Netherlands, the United States and Spain. The corre-

Table IV: Imported and locally produced tractors

	Age coefficient		*Intercepts*		*Quality growth*		*Quality level*	
	$\gamma_{2,c}$	$\gamma_{2,c}^{\text{IMP}}$	$\gamma_{1,c,2014-2016}$	$\gamma_{1,c}^{\text{IMP}}$	local	imported	top	average
Brazil	-0.038		0.287		2.14%	2.14%	1.00	1.00
Canada	-0.051		1.151	-0.011	3.58%	3.58%	0.94	0.94
France	-0.071		1.198	-0.222	5.65%	5.65%	0.50	0.50
Great Britain	-0.064		0.941	0.009	4.89%	4.89%	1.02	1.02
Germany	-0.047	-0.016	0.914	0.056	3.14%	4.84%	1.19	1.08
Mexico	-0.019	-0.083	0.287	0.981	0.20%	8.82%	9.50	5.84
United States	-0.049	0.008	1.148	-0.152	3.37%	2.56%	0.48	0.51

In columns 2 and 3, the table shows the estimated country-specific coefficients for age $\gamma_{2,c}$ and for the interaction term between the import dummy and age, $\gamma_{2,c}^{\text{IMP}}$. In columns 4 and 5, the table shows the estimated country-specific intercepts $\gamma_{1,c,2014-2016}$ and the country-import specific intercepts, $\gamma_{1,c}^{\text{IMP}}$. Empty cells imply the estimates were not statistically different from zero. The last four columns report the path of quality for imported and locally produced goods. In particular, columns 6 and 7 show the growth rate of quality while 8 and 9 report the level of quality of imported goods as a percentage of that of locally produced goods.

residual price variation across countries (i.e. after controlling for observable characteristics) reflecting variation in quality. Hence, we test the robustness of our inference on the level of quality and its implications for development accounting, to the presence of pricing-to-market effects of the magnitude estimated in the literature (Simonovska, 2015). We find that the average quality of agricultural equipment accounts for 27.5% of the cross-country disparities in agricultural value added per worker in 2013, 3pct points less than in the baseline. Details of the exercise are available in Appendix B.5.

The richness of our data also allows us to trace back the location of the plant where a tractor was produced. Hence, we are able to compare the quality of locally produced and imported tractors for a subsample of our main dataset.[44] To implement the measurement, we augment our baseline regression 9 to include a dummy that takes value one if the good is imported and zero otherwise along with its interaction with age and their respective coefficients $\gamma_{1,c}^{\text{IMP}}$ and $\gamma_{2,c}^{\text{IMP}}$. Results are reported in table IV along with the inferred path of capital quality. The coefficient on age differs between locally-produced and imported goods only for three countries: in Germany and Mexico the slope of the age-price profile is steeper for imported goods compared to locally produced whereas the opposite is true in the United

lation of the estimated country dummies with income per worker is positive, at 0.5713, but not statistically different from zero, p-value at 0.184. These results are robust to various specifications of the regression equation, including the log-transformation on the price and the set of controls included.

[44] The subset of our dataset covers 95,953 observations across seven countries.

Sates. This implies a path of quality growth that is higher for imported goods in Germany (a 1.71% increase) and Mexico (a 8.62% increase) and for locally produced goods in the US (a 0.81% increase). The country dummies are higher for imported goods in Mexico, Great Britain and Germany, but lower for the United States, France and Canada. Therefore, focusing on imported goods would magnify inferred differences in adoption. United States and France measured quality of imported tractors is about half of that of locally produced ones. The case of Mexico is remarkable. The top quality of imported tractors in Mexico is 9 times that of locally produced ones. However, because the growth rate of quality has been so high for imported tractors, the average quality of the stock of imported capital is only 6 times that of the locally produced one.

7 Conclusions

In this paper, we explore the implications of disparate patterns of capital-embodied technology adoption for agricultural productivity differences across countries. To do so, we construct a novel dataset of prices for second-hand equipment (tractors) in middle- and high-income countries that allows us to control for differences in observable characteristics. Through the lenses of our model and using our dataset, we infer the path for the highest available quality of installed capital from the age-price profile of tractors of a given vintage under a balanced growth assumption. On average, richer countries have both higher growth rates and higher levels of capital quality.

We study the role of capital-embodied technology in the labor productivity of the agricultural sector via standard growth and income accounting exercises. We conclude that 32% of the growth in agricultural value added per between 1990 and 2013 that is unaccounted for by observable factors can be attributed to capital quality disparities. In addition, the dispersion in the logarithm of TFP growth in the agricultural sector halves when capital quality is taken into account. When each country is assigned an installed capital stock of identical quality to that of the US, our model explains only 45% of the variation in output per worker across countries compared to 77% in our benchmark.

It is likely that disparities in adoption patterns and in age-price profiles across countries reflect partially differences in the availability and characteristics of secondary markets. Understanding their relationship is a promising avenue for future research.

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A Model representation and proofs

A.1 Alternative representation of the model

In this subsection we describe how our model maps into the standard framework of Greenwood *et al.* (1997).
The euler equation that describes prices in our model is

$$p_{\bar{j}_{t+1},t} = \frac{(1-\lambda)}{R_{t+1}} \left[\alpha_k q_{\bar{j}_{t+1}} \Big(\sum_{j \in A_{t+1}} q_j k_{j,t+1} \Big)^{\alpha_k - 1} l_{t+1}^{\alpha_l} n_{t+1}^{\alpha_n} + (1-\delta) p_{\bar{j}_{t+1},t+1} \right]. \tag{13}$$

Define the efficiency units of capital at any point t as $k_{e,t} = \sum_{j \in A_{t+1}} q_j k_{j,t}$. The household's euler equations imply that the price of the best available technology is an operator homogeneous in the efficiency of the best vintage available adjusted by the share of capital, i.e. $p_{\bar{j},t} \propto q_{\bar{j}}^{\alpha_k}$. In addition, the price of any good is homogeneous in its quality and hence the price of a good relative to that of the best available vintage is the ratio of their productivities, $\frac{p_{j,t}}{p_{\bar{j},t}} = \frac{q_j}{q_{\bar{j}}}$. Hence, equation 13 can be rewritten as

$$\frac{q_{\bar{j}_{t+1}}^{\alpha_k}}{q_{\bar{j}_{t+1}}} = \frac{(1-\lambda)}{R_{t+1}} \left[\alpha_k (k_{e,t+1})^{\alpha_k - 1} l_{t+1}^{\alpha_l} n_{t+1}^{\alpha_n} + (1-\delta) \frac{q_{\bar{j}_{t+2}}^{\alpha_k}}{q_{\bar{j}_{t+2}}} \right],$$

which is the optimality condition in the benchmark model of Greenwood *et al.* (1997) if the quality of the stock in their model, q, is proportional to the quality of the best technology in our model $q = q_{\bar{j}}^{1-\alpha_k}$. The optimality condition is consistent with a relative price of investment to consumption equal to $\frac{1}{q_{\bar{j}}^{1-\alpha_k}}$. This is also the decay in our longitudinal age-price profile.

A.2 Proofs

Proof. (Proposition 1)

The homogeneity of the operators describing equilibrium prices implies that for the best available vintage, $p_{\bar{j},t} \propto q_{\bar{j}}^{\alpha_k}$, and for any other vintage, prices are proportional to the best available technology, $p_{j,t} = \frac{q_j}{q_{\bar{j}}} p_{\bar{j},t}$.

Using the euler equation of the households, equation 3.3, we obtain

$$1 = \frac{(1-\lambda)}{R_{t+1}} \left[\alpha_k \Big(\sum_{j \in A_{t+1}} \frac{q_j}{q_{\bar{j}_{t+1}}} k_{j,t+1} \Big)^{\alpha_k - 1} l_{t+1}^{\alpha_l} n_{t+1}^{\alpha_n} + (1-\delta) \Big(\frac{q_{\bar{j}_{t+1}}}{q_{\bar{j}_{t+2}}} \Big)^{1-\alpha_k} \right]$$

which, given the set of vintages available for production, A_{t+1}, pins down the level of capital services $\sum_{j \in A_{t+1}} q_j k_{j,t+1}$. ■

Proof. (Proposition 2)

Guess: *The quality of the bounds for the best and worst vintages used in production,* $\underline{j}_t$ *and* $\bar{j}_t$ *respectively, grow proportionally to the growth rate of the best-available quality in the market,* $g_{q_{\bar{j}_t}} = \mu$. *The growth* *rate of output per capita is proportional to the growth rate of the quality of the best-available vintage, i.e.,* $g_y = \alpha_k \mu$.

Under our guess, we can de-trend output by $(q_{\bar{j}_t})^{\alpha_k}$ to obtain:

$$\frac{y_t}{(q_{\bar{j}_t})^{\alpha_k}} = (\sum_{j \in A_t} \frac{q_j}{q_{\bar{j}_t}} k_{j,t})^{\alpha_k} l^{\alpha_l},$$

which is a constant if $\sum_{j \in A_t} \frac{q_j}{q_{\bar{j}_t}} \frac{k_{j,t}}{k_t}$ is a constant. We have guessed that the bounds of A_s grow at rate μ.[45] Combining our guess with proposition 1 , $\widetilde{k}$is a constant since it satisfies

$$1 = \frac{(1-\lambda)}{R} \left[\alpha_k (\widetilde{k})^{\alpha_k - 1} l^{\alpha_l} + (1-\delta)(\frac{1}{1+\mu})^{1-\alpha_k} \right] \tag{14}$$

By definition, total investment corresponds to

$$\widetilde{x}_t = \sum_{j \in A_{t+1}} \frac{q_j}{q_{\bar{j}_t}} (k_{j,t+1} - (1-\delta) k_{j,t})$$

The expected distance between the best and worst vintages in production to be constant, i.e., $\underline{j}_t = \bar{j}_t - u$ for some $u > 0$. This is true because the expected time for which a vintage of capital remains in the market is $T_j = \frac{1}{\lambda}$, so $u = T_j$ is consistent with the bounds growing at a constant rate:

$$\widetilde{x}_t = \widetilde{k}_{t+1} - (1-\delta)(\widetilde{k}_t - \frac{q_{\underline{j}_t}}{q_{\bar{j}_t}} k_{\underline{j},t+1}).$$

Given that the vintage composition is constant along the BGP, $k_{\underline{j},t+1}$ is constant. In addition, $\frac{q_{\underline{j}_t}}{q_{\bar{j}_t}} = \frac{1}{(1+\mu)^{T_{\underline{j}}}}$. Therefore, total investment is constant along the BGP. The price of the best-available technology increases at rate $g_{p_{\bar{j}}} = \alpha_k \mu$ due to its homogeneity in the quality of the best available technology. Hence, the value of investment, $p_{\bar{j}_{t+1}} \widetilde{x}$, grows proportionally to the growth rate of the best available quality, μ^{α}. Using the production function, and the constant capital in efficiency units, output should grow at rate $\alpha_k \mu$. From the feasibility condition of the economy, consumption should then also grow at rate $\alpha_k \mu$. ■

Proof. (Corollary 1) If the accumulation policy is such that there is only positive investment in the top technology, the share of total capital accounted for by a vintage that is n lags away from the best-available capital in a given period is constant. Hence, the total amount of capital in any period is described as:

$$\sum_{\underline{j}_t}^{\bar{j}_t - 1} ((1-\lambda)(1-\delta))^{\bar{j}_t - 1 - j} x = k.$$

The quality values of the best and worst technology operating are proportional to each

[45]Alternatively, one could have assumed away the random retirement of capital (at rate λ). In this case, there are infinitely many vintages operating at each point in time. Given the optimal investment strategy for capital , the BGP is preserved, as $\sum_{j=-\infty}^{\bar{j}_t} \frac{q_j}{q_{\bar{j}_t}} \delta (1-\delta)^{\bar{j}_t - j}$ is a geometric series with infinitely many terms.

other, with $q_{\underline{j}_t} = \frac{q_{\bar{j}_t}}{(1+\mu)^{\frac{1}{\lambda}}}$.

Solving for the optimal investment level, we obtain:

$$x = k \frac{(1-(1-\lambda)(1-\delta))}{(1-((1-\lambda)(1-\delta))^{T_j})},$$

which is a constant.

To pin down the level of capital in steady state, notice that in the detrended economy, the relative price of capital of the best available technology to consumption in period $t+1$ should equal 1. Hence,

$$\frac{p_{\bar{j}_{t+1},t}}{q_{\bar{j}_{t+1}}^{-\alpha_k}} = 1$$

which pins down the stock of capital per worker, k, as a function of land per worker, the quality of the stock in operation and the parameters:

$$k = \frac{1}{\widetilde{q}_{\bar{j}_{t+1}} \widehat{\delta}} \left(\frac{\alpha_k l^{\alpha_l}(1-\lambda)}{R - (\frac{1}{1+\mu})^{1-\alpha_k}(1-\lambda)(1-\delta)} \right)^{\frac{1}{1-\alpha_k}},$$

■

B Details of the quantitative analysis

B.1 Factor shares

Factor shares are computed from the shares published by the USDA-ERS by assuming constant returns to scale in labor, land, and capital. Table B.I shows the factor shares for the countries in our sample as averages for the 1990–2013 period.

B.2 Physical depreciation

Robustness on λ. We conduct our income exercises under the assumption that the expected lifetime of a tractor is the same across countries and set it at the average age of tractors in our sample. Alternatively, one could allow for country-specific expected lifetimes – that is, country specific λ's in our model. We consider this alternative specification of the model as a robustness check on our results and calibrate the country-specific λ to match average tractor age in our sample for each country. The correlation between the two sets of estimates is 98.4%. Moreover, the fit of the model decreases of about 1 percentage point, settling at 75.7%.

Table B.I: Factor shares

	α_n	α_l	α_k
Australia	12%	78%	10%
Belgium	51%	18%	31%
Bulgaria	37%	46%	17%
Brazil	60%	15%	25%
Canada	78%	3%	18%
Spain	64%	17%	19%
France	51%	18%	31%
Great Britain	25%	39%	37%
Germany	51%	18%	31%
Ireland	51%	18%	31%
Italy	64%	17%	19%
Mexico	19%	37%	44%
Netherland	51%	18%	31%
New Zealand	12%	78%	10%
United States	40%	36%	24%

B.3 Best technology

We identify the best technology operated in each country from the country-year specific effect as predicted by our model in equation 9. Here we show how we recover the best technology operated in a country in a given year, $q_{\bar{j}_{t+1,c}}$, form the country-year specific dummy for that year, $\gamma_{1,c,t}$. Dropping the time subscript, we can write:

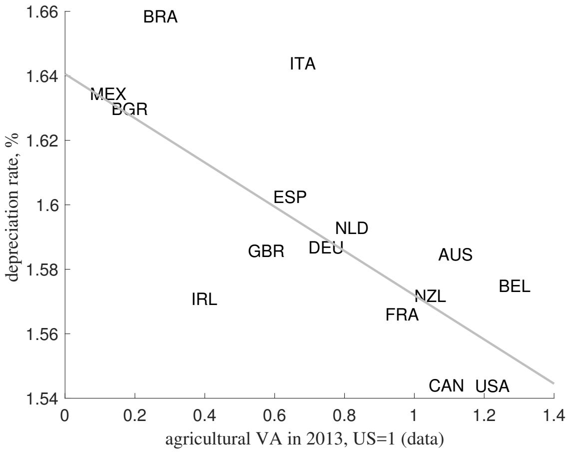
$$e^{\gamma_{1,c}} = \frac{\alpha_{k,c} q_{\bar{j}_{t+1},c}^{\alpha_{k,c}} {l_c}^{\alpha_{l,c}}}{\tilde{k}_c^{1-\alpha_{k,c}}} \frac{(1-\lambda)}{R_c} \left(\frac{1}{1 - \frac{(1-\lambda)(1-\delta_c)}{R_c} \left(\frac{1}{1+\mu_c}\right)^{1-\alpha_{k,c}}} \right).$$

Note that under balanced growth, normalized capital services, $\tilde{k}$, can be computed as a function of the growth rate of the best technology and other parameters (land per worker, capital share, physical depreciation rate, land per worker and expected lifetime of a tractor, see equation 14). The best technology operating in country c in a given year relative to that of the US is:

$$\frac{q_{\bar{j}_{t+1},c}}{q_{\bar{j}_{t+1},US}} = \left(\frac{D_c}{D_{US}} (\tilde{k}_{USA} q_{\bar{j}_{t+1},US})^{\alpha_{k,US}-\alpha_{k,c}} \left(\frac{\tilde{k}_c}{\tilde{k}_{USA}} \right)^{1-\alpha_{k,c}} \right)^{\frac{1}{\alpha_{k,c}}}, \tag{15}$$

for $D_c = e^{\gamma_{1,c}} \left(1 - \frac{(1-\lambda)(1-\delta_c)}{R_c} \left(\frac{1}{1+\mu_c}\right)^{1-\alpha_{k,c}}\right) \left(\frac{R_c}{1-\lambda} \frac{1}{l_c^{\alpha_{l,c}} \alpha_{k,c}}\right)$. We normalize the best technology, land and output per worker in agriculture to one in the US, $q_{\bar{j}_t,US} = 1$, $l_{US} = 1$, $y_{US} = 1$. For a given tractor's expected lifetime $T = \frac{1}{\lambda}$, which we set to 15 years, we can identify cross-country differences in the best technology operating in a given year from equation

Figure B.I: Physical depreciation



Physical depreciation and value added per worker. Agricultural value added in 2013 is computed from the USDA-ERS dataset by multiplying the value of gross agricultural production per worker by 1 minus the sum of intermediate input factor shares. Source: FAOSTAT and own computations based on price quotes from a major data publisher.

Table B.II: Physical depreciation

	δ
Australia	1.58%
Belgium	1.57%
Bulgaria	1.63%
Brazil	1.66%
Canada	1.54%
Spain	1.60%
France	1.57%
Great Britain	1.59%
Germany	1.59%
Ireland	1.57%
Italy	1.64%
Mexico	1.63%
Netherland	1.59%
New Zealand	1.57%
United States	1.54%

Inferred physical depreciation. The table shows inferred physical depreciation, δ, for the countries in our sample. Source: Own computations based on quotes from major data publisher.

15.[46]

B.4 Identification in the longitudinal age-price profile

We exploit the repeated time-series structure of our dataset to infer capital quality growth from the longitudinal profile.

The longitudinal age-price profile for a tractor of vintage $\bar{j}_{t+1}$, introduced in the market in year t, can be expressed as:

$$\ln(p_{\bar{j}_{t+1},t+a}(a)) = a \ln\left(\frac{(1-\delta)}{(1+\mu)^{1-\alpha_k}}\right) + \ln(p_{\bar{j}_{t+1},t}(0)),$$

[46] Our results are robust to a value for the tractor's expected lifetime. When we set T to 9.3 years, which is the sample average age, our model explains only 1% more of the cross-country variance of the logarithm of output per worker in agriculture. Further details are available upon request.

Table B.III: Quality growth in the longitudinal profile

	μ_{long}	$\mu - \mu_{long}$
Australia	3.65%	-1.37%
Bulgaria	4.42%	-1.95%
Brazil	5.56%	-2.08%
Canada	4.11%	-1.30%
Spain	6.60%	-1.89%
France	7.99%	-3.98%
Great Britain	6.30%	-3.28%
Germany	2.02%	-1.09%
Italy	3.95%	-1.19%
Mexico	7.67%	-5.13%
Netherland	4.07%	-1.30%
New Zealand	4.91%	-1.98%
United States	3.38%	-1.34%

The table shows the inferred growth of capital quality in the longitudinal profile. Column (A) reports the inferred quality growth while column (B) reports the deviations from the baseline in pp.

where, recall, $p_{\bar{j}_{t+1},t}(0)$ is the price of the tractor when new and is a function of the best available quality in the year the tractor was introduced, $q_{\bar{j}_{t+1}}$. When we allow the path of quality to differ across countries, regressing the price of a vintage on its age with country-specific age coefficients as well as vintage- and country-specific intercepts identifies the growth rate of quality, μ, across countries.

We construct synthetic vintages defined by a triplet of characteristics: year built, model and manufacturer (for example, a 1970 8430 John Deere tractor). In total, we observe 17,882 of such vintages for 13 countries between 2007 and 2016 for a total of 62,006 observations.[47] On this dataset, we run a random effects regression for the following specification:

$$\ln(\widehat{p}_{j,c,t}) = \gamma_{3,j,c} + \gamma_{4,c} a_{j,c} + \epsilon_{j,c,t}, \tag{16}$$

where j is a vintage, c is a country, $\gamma_{3,j,c}$ is a vintage and country fixed effect, $\gamma_{4,c}$ is a country-specific coefficient on age and ϵ is an error term that is assumed to be normally distributed.

The estimated coefficients on age have a correlation of 74.2% with the baseline estimates based on the cross-sectional profile. Table B.III shows the inferred growth rate of capital quality: the cross-country average is 5.0% per year, compared to 2.8% in the baseline for the same set of countries. In the US, the growth rate of capital quality is 3.38%, 1.37 percentage points higher than in the baseline. The most sizeable deviations from the baseline come for France, Great Britain and the Mexico with the new estimates being more than 3 percentage points higher than the baseline. On the opposite end, Germany and Italy have estimates

[47] The 13 countries for which we are able to build this vintages are Australia, Bulgaria, Brazil, Canada, Spain, France, Great Britain, Germany, Italy, Mexico, the Netherlands, New Zealand, and US. We compare cross-sectional results on the same dataset.

about 1% higher in the longitudinal profile.

Our accounting exercises measure that capital quality explains on average 50.9% of the growth rate of agricultural productivity, compared to 27.4% in the baseline for the same countries.[48] The 23 percentage points increase in the measured contribution of capital quality may be explained by the slope of the longitudinal profile picking up forces that are un-related to capital quality.

B.5 Pricing to market

We adjust our estimation procedure to take into account the possibility of there being pricing-to-market effects in such that the same good is sold at different prices in different countries even after adjusting for exchange rates, purchasing power and transportation costs.

We start by specifying the observed price of a tractor in our dataset ($p^o_{i,c}$) as the product of two components: the discounted value of rental flows evaluated at the market rate ($p_{i,c}$, as before) and a pricing-to-market factor (PTM):

$$\ln(p^o_{i,c}) = \ln \mathrm{PTM}(y_c) + \ln(p_{i,c}),$$

where the pricing to market factor depends on the per capita income of the country where the tractor is sold, c. Our pricing equation therefore reads:

$$\ln(p^o_{i,c}) = \ln \mathrm{PTM}(y_c) + \ln\left(\frac{\Gamma_c}{1-\psi}\right) + a \ln\left(\frac{1-\delta}{1+\mu}\right).$$

Simonovska (2015) measures that doubling a country's per capita income results in an 18% increase in the price of identical items sold there. We use her estimate and the normalization of PTM $= 1$ for the US in each year to parameterize the pricing to market factor. Notice that, since the price elasticity is positive and Simonovska (2015) attributes at most a third of it to shipping costs, we believe the differences in capital quality we measure are a lower bound for actual differences in that all the unexplained part is taken as unrelated to capital quality.

The results of the development accounting exercise are robust to the presence of pricing-to-market effects of the magnitude estimated in the literature in the pricing of tractors in our dataset. The fit of the model on the cross-country variation in agricultural value added per worker in 2013 is 72.5%, 5 percentage points below the baseline, and the contribution of capital quality is 27.3%. Focusing on middle-income countries, the fit on the agricultural value added differential with respect to the US decreases only slightly (on average, 8 percentage point). Overall, we measure that the average quality of agricultural equipment accounts for 9.8% of the cross-country disparities in agricultural value added per worker in 2013, 8pct points less than in the baseline.

[48] Great Britain is excluded from this average as the fraction of agricultural productivity growth explained by capital quality is above 100% in both cross-sectional and longitudinal estimates.

C Estimation results

Table C.I: Summary statistics

Country	Observations	Cross-sections	Price	Age	Hours p/year	Horsepower
Australia	1281	2014-2016	51102	11	478	182
Belgium	72	2015	58366	11	647	172
Bulgaria	90	2014-2015	61632	10	750	242
Brazil	1253	2013-2015	25814	14	669	120
Canada	23817	2008-2016	76443	10	375	173
Spain	315	2013-2016	31494	17	546	123
France	1543	2012-2015	38924	13	460	129
Great Britain	2993	2011-2015	52298	9	638	148
Germany	3007	2013-2015	52660	13	574	164
India	129	2016	4248	10	474	44
Ireland	185	2015	36613	11	772	123
Italy	207	2014-2015	22768	16	279	99
Mexico	633	2013-2016	33716	13	450	127
Netherlands	544	2013-2015	34166	15	474	123
New Zealand	715	2015-2016	50795	9	604	133
United States	337342	2007-2016	72525	12	303	168
Total	**374126**		**71813**	**12**	**317**	**167**

Benchmark dataset of tractor retail ask quotes.

Table C.II: Estimation results for retail prices

	Raw data	Imputed data	Imputed & matched Data			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Country Dummy * age						
Australia	-0.0499	-0.144	-0.112	-0.114	-0.111	-0.113
	(0.000420)	(0.000578)	(0.000494)	(0.000481)	(0.000488)	(0.000498)
Belgium	0.0101	-0.150	-0.174			
	(0.0131)	(0.00401)	(0.00114)			
Brazil	-0.114	-0.0832	-0.0721	-0.0737	-0.0780	-0.0794
	(0.00322)	(0.00133)	(0.000381)	(0.000353)	(0.000876)	(0.000886)
Bulgaria		-0.105	-0.0776			
		(0.00189)	(0.00595)			
Canada	-0.136	-0.160	-0.107	-0.109	-0.106	-0.108
	(0.000282)	(0.000591)	(0.000766)	(0.000770)	(0.000728)	(0.000741)
Spain	-0.120	-0.129	-0.0537			
	(0.00125)	(0.000838)	(0.000426)			
France	-0.151	-0.163	-0.111			
	(0.00263)	(0.00169)	(0.000648)			
Great Britain	-0.118	-0.160	-0.121	-0.123	-0.120	-0.122
	(0.000936)	(0.000821)	(0.000413)	(0.000408)	(0.000391)	(0.000398)
Germany	-0.152	-0.132	-0.0968	-0.0983	-0.0954	-0.0970
	(0.00257)	(0.00344)	(0.00118)	(0.00117)	(0.00111)	(0.00113)
Italy		-0.0762	-0.0533	-0.0543	-0.0500	-0.0509
		(0.00242)	(0.00137)	(0.00134)	(0.00103)	(0.00104)
Ireland	0.202	-0.189	-0.125			
	(0.100)	(0.00195)	(0.000693)			
India	-0.0812	-0.0894				
	(0.000108)	(0.000243)				
Mexico	-0.0833	-0.102	-0.184	-0.187	-0.182	-0.185
	(0.000934)	(0.000779)	(0.000916)	(0.000867)	(0.000703)	(0.000717)
Neatherlands	-0.186	-0.134	-0.0862	-0.0877	-0.0879	-0.0894
	(0.00103)	(0.000930)	(0.000208)	(0.000209)	(0.000782)	(0.000799)
New Zealand	-0.136	-0.157	-0.126			
	(0.000585)	(0.000754)	(0.000702)			
United States	-0.122	-0.144	-0.0905	-0.0921	-0.0899	-0.0916
	(0.000117)	(0.000306)	(0.000402)	(0.000396)	(0.000337)	(0.000343)
Controls						
Horsepower	2.561	4.588	1.949	1.986	1.930	1.966
	(0.00558)	(0.0222)	(0.0149)	(0.0152)	(0.0134)	(0.0136)
Hours	-0.156	-0.176	-0.0877	0.276	0.289	0.294
	(0.00212)	(0.00460)	(0.00434)	(0.0126)	(0.00756)	(0.00770)
Wage*hours				0.336		0.264
				(0.0125)		(0.00485)
Crops	N	N	N	N	Y	Y
Shape parameters						
θ_1	0.0949	0.103	0.0632	0.0649	0.0624	0.0641
	0.00106	0.000835	0.00176	0.00177	0.00176	0.00177
θ_2	0.103	0.104	0	0	0	0
	0.00246	0.00177	0.00326	0.00327	0.00327	0.00327
Observations	214,278	366,125	96,770	95,964	95,964	95,964
R^2	0.887	0.898	0.906	0.906	0.907	0.907
Likelihood	-2.343e+06	-4.028e+06	-1.104e+06	-1.095e+06	-1.104e+06	-1.095e+06

All regressions include country-year and manufacture dummies. Horsepower is measured in hundred units of horse power, and hours per year are measured in ten thousand hours of usage. All regressions allow for right-hand side (hours and horsepower) transformation with coefficient θ_2 and left-hand side transformation with coefficient θ_1. Columns (1) and (2) use raw and imputed retail data. Columns (3)–(6) use retail data matched with information on crop production. Other Controls stands for crops controls as described in the data appendix. Standard errors in parentheses.

Table C.III: Estimation results for retail prices, ctn'd.

	2007	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Country-year dummy										
Australia								2.390	2.195	2.296
								(0.029)	(0.031)	(0.025)
Belgium									2.400	
									(0.054)	
Brazil							1.404	1.205	0.672	
							(0.043)	(0.038)	(0.035)	
Bulgaria								1.403	1.246	
								(0.053)	(0.036)	
Canada		2.825	2.437	3.035	3.161	3.191	3.150	3.229	3.038	3.094
		(0.045)	(0.043)	(0.039)	(0.040)	(0.039)	(0.037)	(0.042)	(0.041)	(0.041)
Spain							2.391	2.356	1.816	1.985
							(0.028)	(0.030)	(0.025)	(0.025)
France						2.365	2.913	2.889	2.609	
						(0.038)	(0.035)	(0.054)	(0.045)	
Great Britain					2.343	2.318	2.477	2.589	2.221	2.208
					(0.032)	(0.029)	(0.037)	(0.039)	(0.038)	(0.031)
Germany							2.101	2.470	2.121	
							(0.050)	(0.058)	(0.058)	
Italy								1.702	0.910	
								(0.074)	(0.019)	
Ireland									2.590	
									(0.035)	
India										-2.394
										(0.022)
Mexico							1.225	1.155	1.153	1.137
							(0.021)	(0.021)	(0.019)	(0.022)
Neatherlands							2.421	2.135	2.011	
							(0.032)	(0.025)	(0.025)	
New Zealand								2.481	2.704	
								(0.034)	(0.021)	
United States	2.248	2.406	2.436	2.515	2.635	2.745	2.845	3.064	2.997	2.868
	(0.041)	(0.040)	(0.038)	(0.040)	(0.041)	(0.041)	(0.041)	(0.043)	(0.042)	(0.040)

Estimates of country-year coefficients for retail data when hours have been imputed (Column (2) in table C.II). Standard errors in parentheses.

Table C.IV: Model-based estimation results for retail prices

	Benchmark (1)	Panel Sample (2)
Country Dummy * age		
Australia	-0.0487	-0.0377
	(0.000163)	(0.00130)
Belgium	-0.0523	-0.0122
	(0.00134)	(0.00492)
Brazil	-0.0364	-0.00768
	(0.000676)	(0.00533)
Bulgaria	-0.0303	-0.0302
	(0.000537)	(0.00147)
Canada	-0.0542	-0.0398
	(0.000206)	(0.000339)
Spain	-0.0470	-0.0388
	(0.000347)	(0.00259)
France	-0.0586	-0.0490
	(0.000601)	(0.00229)
Great Britain	-0.0552	-0.0391
	(0.000296)	(0.00119)
Germany	-0.0460	-0.0377
	(0.00118)	(0.00171)
Italy	-0.0669	
	(0.000710)	
Ireland	-0.0278	-0.0115
	(0.000966)	(0.00422)
India	-0.0360	
	(7.37e-05)	
Mexico	-0.0358	-0.0320
	(0.000311)	(0.00108)
Neatherlands	-0.0481	-0.0364
	(0.000340)	(0.00138)
New Zealand	-0.0543	-0.0398
	(0.000236)	(0.00215)
United States	-0.0487	-0.0387
	(0.000103)	(0.000263)
Controls		
Horsepower	-0.0332	-0.0815
	(0.00101)	(0.00336)
Hours	0.987	0.897
	(0.00465)	(0.00435)
Shape parameter		
θ_2	0.00990	0
	0.00163	
Observations	366,125	64,471
Panel observations		17,137
R^2	0.893	
Likelyhood	-151842	

Column (1) presents our benchmark estimate using the logarithm of the price as the dependent variable. The regression allows for a Box-Cox transformation on the right-hand side (hours and horsepower) with coefficient θ_2 and manufacturer controls. Column (2) presents estimates of a panel regression with random coefficients. Standard errors in parentheses.

Table C.V: Benchmark estimation results, ctn'd.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
Country-year dummy										
Australia								0.800	0.732	0.760
								(0.011)	(0.012)	(0.010)
Belgium									0.789	
									(0.019)	
Brazil							0.468	0.411	0.219	
							(0.016)	(0.014)	(0.013)	
Bulgaria								0.488	0.436	
								(0.016)	(0.011)	
Canada		0.931	0.798	0.992	1.034	1.043	1.027	1.051	0.990	1.007
		(0.017)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)
Spain							0.822	0.817	0.631	0.675
							(0.009)	(0.011)	(0.009)	(0.009)
France						0.802	0.994	0.992	0.897	
						(0.013)	(0.011)	(0.018)	(0.015)	
Great Britain					0.781	0.773	0.812	0.861	0.736	0.712
					(0.011)	(0.010)	(0.013)	(0.014)	(0.014)	(0.011)
Germany							0.705	0.834	0.715	
							(0.017)	(0.019)	(0.019)	
Italy								0.572	0.306	
								(0.022)	(0.006)	
Ireland									0.877	
									(0.013)	
India										-1.044
										(0.009)
Mexico							0.401	0.381	0.373	0.368
							(0.007)	(0.007)	(0.006)	(0.007)
Neatherlands							0.800	0.711	0.694	
							(0.012)	(0.010)	(0.010)	
New Zealand									0.815	0.892
									(0.012)	(0.008)
United States	0.736	0.785	0.789	0.816	0.855	0.890	0.920	0.990	0.971	0.930
	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)

Estimates of country-year coefficients for our benchmark estimation (Column (1) in table C.IV). Standard errors in parentheses.

Table C.VI: Estimation results, subsample tracking country of origin

	β_{age}	$\beta_{age,imp}$	**Country dummy**	**Country dummy*imp**
Brazil	-0.0379	-0.00228	-0.0212	0.00142
	(0.00600)	(0.00886)	(0.0726)	(0.105)
Canada	-0.0507	-0.00406	0.919	-0.0109
	(0.00310)	(0.00319)	(0.0484)	(0.0483)
France	-0.0707	0.0141	0.911	-0.222
	(0.0106)	(0.0116)	(0.101)	(0.113)
Great Britain	-0.0637	0.00133	0.709	0.00903
	(0.00501)	(0.00552)	(0.0489)	(0.0505)
Germany	-0.0469	-0.0164	0.627	0.0557
	(0.00193)	(0.00304)	(0.0225)	(0.0327)
Mexico	-0.0185	-0.0825		0.981
	(0.000875)	(0.0155)		(0.274)
United States	-0.0487	0.00783	0.916	-0.152
	(0.000190)	(0.000306)	(0.00731)	(0.00415)
Controls				
Horsepower			-0.0192	
			(0.00105)	
Hours			0.544	
			(0.00167)	
Shape parameter				
$theta_2$			-0.127	
			0.00338	
Observations			95,951	
R^2			0.893	
Likelyhood			-33811	

Estimates of country-year coefficients for our benchmark estimation (Column (1) in table C.IV). Standard errors in parentheses.