

Why is Measured Productivity so Low in Agriculture?

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Abstract

In poor countries, labor productivity in agriculture is considerably lower than in the rest of the economy. We assess whether this well known fact implies that labor is mis-allocated between the two sectors. We make several observations that suggest otherwise. First, the same fact holds for US states where severe mis-allocation is implausible. Second, the gaps between the marginal value products of agriculture and non-agriculture are considerably smaller when measured through wages than through labor productivities. Third, labor productivity in agriculture is severely mis-measured in the US.

Keywords: mis-allocation of labor; productivity gaps; wage gaps.

JEL classification: O1.

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1. Introduction

One of the biggest challenges in economics is to understand why cross-country differences in output per worker are so large. A promising explanation is that distortions in poorer countries lead to the mis-allocation of production factors, and that this has quantitatively important detrimental consequences for aggregate labor productivity. A growing recent literature assesses how far this explanation can go. One strand of the literature focuses on the mis-allocation of production factors among firms of a given broad sector; see for example Restuccia and Rogerson (2008) and Guner et al. (2008). Another strand of the literature focuses on the mis-allocation of production factors among broad sectors. Of particular interest in the second context is whether labor is mis-allocated between non-agriculture and agriculture. The reason for suspecting this is that poorer countries have large parts of their labor forces in agriculture although labor productivity is much lower there; see Caselli (2005) and Restuccia et al. (2008) for detailed evidence. Several authors have therefore argued that the reallocation of workers from agriculture to non-agriculture would substantially increase output per worker. Vollrath (2009) and McMillan and Rodrik (2011) are two recent examples.

In this paper, we question whether productivity gaps paint an accurate picture of the mis-allocation of labor between non-agriculture and agriculture. We begin by pointing out that taking the logic from the first paragraph at face value, one would expect labor productivities to be roughly equalized between non-agriculture and agriculture in the US where severe mis-allocation of labor is implausible. We document that, in contrast, there are large productivity gaps also across US states. To establish this, we measure labor productivity in each sector as value added in current dollars per hour worked using data from the BEA's regional accounts for value added and the Current Population Survey (CPS) for hours worked. We find that during the period 1980–2009, productivity was considerably higher in non-agriculture than in agriculture in most US states. Specifically, the median productivity gap was around a factor of two and the maximum productivity gap was around a factor of six. Surprisingly, these numbers are not too different from those typically found in developing countries, which suggests that it is necessary to revisit to what extent productivity gaps indicate a mis-allocation of labor.

We start to answer this question by observing that productivity gaps are about average value products per unit of labor, whereas mis-allocation is about marginal value products per unit of labor where labor refers to either workers or hours worked. Our main contribution is to provide two measures of the marginal value product of an hour worked in each sector. The first measure uses labor productivity adjusted for the share of labor income in value added (“productivity method”) and the second measure uses average wages (“wage method”). It is important to realize that the two measures are linked by a simple identity: by definition average labor productivity times the labor share equals the average wage. This identity will serve as a useful consistency check on the estimates that we obtain from each of the two methods.

To implement the productivity method, we start with measuring the labor shares in the two

sectors. Using the method of Gollin (2002), we find 0.67 for non-agriculture and 0.44 for agriculture in the US during 1980–2009, implying that the labor share in non-agriculture is larger than in agriculture. There is ample additional evidence that confirms this finding; see Gollin et al. (2014) for a summary of that evidence. In our context, this means that not only is agriculture less productive than non-agriculture, but also a lower share of agriculture’s value added goes to labor. As a result, the gaps in the marginal value products exceed the gaps in labor productivity, which were large to begin with. This finding has potentially stark implications, and so it warrants an independent plausibility check through the wage method of measuring marginal value products.

Calculating wages in current dollars from the CPS, we find that there are sizable gaps in the average wages per worker between agriculture and non-agriculture in US states. However, the implied gaps in the marginal value products are considerably smaller than those measured via the productivity method. To be concrete, while the median gap in the marginal value product according to the productivity method equals three, it equals only two according to the wage method. One might be inclined to take this as good news, as gaps of two are easier to rationalize than gaps of three. However, our accounting identity says that the marginal value products measured in both ways must be equal, and so the finding that they are different implies that at least one of the following statistics is systematically mis-measured in at least one of the two sectors: labor productivity; the labor share; the average wage.

Given the detailed and well-documented data that are available for US states, we are able to go further and show that there is a measurement problem with agricultural value added. Specifically, it turns out that the BEA under-estimates value added in agriculture along two dimensions: it does not include some factor payments that conceptually belong to agriculture, an example being land rents that it counts as value added in real estate instead of value added in agriculture; it does not correct sufficiently for under-reporting of proprietors’ income in agriculture. We show that making the appropriate corrections for these flaws reduces the measured productivity gaps by so much that the implied gaps in marginal value products become roughly equal to those implied by the wage method. We emphasize that this does not imply that the allocation of labor between non-agriculture and agriculture is efficient, but that the median gap in marginal value products is only two instead of three. In a follow up paper, Herrendorf and Schoellman (2014), we explore the role of sectoral differences in human capital in explaining gaps of two and find that a broad measure of human capital accounts for them in the US.

A natural question to ask is whether our findings for the US generalize to other countries. To answer this question, we collect census data for 13 countries during 1990–2010. The selection criterion for including a country in our analysis is that there is sufficiently detailed information in its census so that we are able to calculate wages at the sectoral level. The resulting sample covers 30% of the world population in 2010 and contains four of the five most populous countries (namely, India, US, Indonesia, Brazil). The GDP per capita variation in this sample is sizable: for example,

the Penn World Table 8.0 reports that during 1990–2010 US GDP per capita was between 12 and 17 times that of India.

We first establish that the usual stylized facts about agriculture hold for these countries: the poorer countries tend to have larger employment shares in agriculture and larger productivity gaps between non-agriculture and agriculture; the poorest countries have around two-thirds of their employment in agriculture and large productivity gaps larger than a factor of four. We then establish that our two key findings from US states also hold for this group of countries. First, the wage method implies considerably smaller gaps in marginal value products than the labor productivity method, but the gaps calculated according to the wage method are still sizable. Second, there appears to be a measurement problem in agriculture. As in US states, the identity linking the marginal value products calculated via the two methods holds outside of agriculture but not in agriculture where it turns out that again average labor productivity times the labor share considerably exceeds the average wage in agriculture. In contrast to US states, we do not have sufficient information for the other countries in our sample to precisely identify where in agriculture the measurement problem is. We leave this as an important task for future research.

Our work is related to Gollin et al. (2014), who use the productivity method to calculate marginal value products. They then ask how much of sectoral gaps in marginal value products can be rationalized by sectoral human capital, which they construct from the observed years of schooling and off-the-shelf Mincer returns for the aggregate economy. They find that sectoral differences in human capital leave a sizable part of the marginal value products unexplained. Our work suggests that the wage method consistently estimates smaller gaps in marginal value products than the productivity method so that there is less to explain.

Our work is related to a large literature that compares productivity in agriculture and in the rest of the economy; see Capalbo and Antle (1988) for a review of the earlier literature and Rao (1993) and Restuccia et al. (2008) for subsequent contributions to this literature. This literature is mostly concerned with measuring *real output* by industry over time and with attributing changes in real output to changes in the input factors and to technological progress. While this is an important task, here we focus on the gaps in *nominal value added per hour* between non-agriculture and agriculture at a point in time. The reason is that the gap in nominal marginal value products is the natural statistic to look at in the context of mis-allocation. Despite the difference in focus, our finding that there is a measurement problem in agriculture should be of interest also to scholars whose goal is to measure real output in agriculture.

The remainder of the paper proceeds as follows. Section 2 measures productivity gaps in US states. Section 3 measures wage gaps in US states and compares them to productivity gaps. Section 4 shows that there is mis-measurement of agricultural value added in US states. Section 5 extends the previous analysis to other countries. Section 6 concludes. An appendix contains a detailed description of our data sources. All figures and tables are at the end of the paper.

2. Measuring Productivity Gaps for US States

In this section, we document that measured productivity in agriculture is lower than in non-agriculture in most US states, and that the difference is often large quantitatively. We follow the FAO and define the agricultural sector as the farm industries crop and livestock production. Non-agriculture comprises all industries other than agriculture. We exclude the military from non-agriculture because for US states we do not have employment data by state for it. We use the standard definition of (labor) productivity, i.e., value added in current dollars per worker or per hour. We call the ratio between the productivity in non-agriculture and in agriculture the *productivity gap*. We will first measure productivity gaps using the conventional data sources that are typically available for cross sections of countries. We will then improve the measurement by using better data on hours worked than are typically available.

2.1. Measurement for 2000

To take a first look at the data, we start with the census year 2000 and standard data sources, namely the BEA's regional accounts (which form the basis of NIPA) and the Population Census. We obtain the Census numbers from the public-use version made available through Ruggles et al. (2010). The Appendix contains a detailed discussion of the data sources and how we construct agriculture and non-agriculture.

<Figure D.1 about here>

Figure D.1 shows the productivity gaps for 2000.¹ Agricultural value added per worker is depicted on the x-axis and non-agricultural value added per worker is depicted on the y-axis. For almost all states, productivity is higher in non-agriculture than in agriculture. Moreover, the resulting productivity gaps are sizable: the median gap equals 1.7, the gap at the 90th percentile equals 2.8, and the maximum gap is larger than 3. The gap for the aggregate US economy is 1.6, similar to the median gap across states.

It is surprising to us that there were such large sectoral productivity gaps in some US states in 2000. In the next subsection, we explore whether these gaps are robust to improved measurement.

2.2. Improved measurement

2.2.1. Value added

The BEA measure of value added by state does not include subsidies and taxes. This is potentially important here because agriculture receives higher than average subsidies.² It turns out

¹All figures are collected in Appendix E.

²The BEA is not explicit about whether or not it includes net subsidies in sectoral value added. We established that it does not do this at the state level by personal communication with people in the BEA who are familiar with the relevant NIPA procedures.

that the vast majority of US farm subsidies go to large farms in the few states that have relatively productive agricultural sectors. In contrast, agriculture in most states tends to pay similar taxes as subsidies, implying that the net transfers from the government tend to be small. For this reason, productivity gaps at the median, the 90th percentile, and the maximum, as well as for the aggregate US economy, are very similar whether or not we include subsidies and taxes. More detailed results are available upon request.

2.2.2. *Hours worked*

Since census employment in the US refers to bodies in the first job, the question arises whether our results change if we use hours worked and take into account multiple jobs. To assess whether this is the case, we measure sectoral hours worked using the monthly data from the *Current Population Survey (CPS)*, which we access through the National Bureau of Economic Research. The CPS is a rotating panel survey administered by the BLS to a sample of households. The survey contains questions about the identity of the main jobs and about total hours worked. From 1994 onwards, the survey also asks workers in outgoing rotation groups about the identity of their first two jobs and their hours worked at each. Before 1994, the CPS included supplements for the month of May in 1979, 1980, 1989, and 1991 that collected similar information. We use the monthly files in combination with the information from outgoing rotation groups and earlier supplements to estimate the hours worked in agriculture and non-agriculture for each state, month, and year, accounting as well as we can for first and second jobs. The details are available in the Appendix.

To get a sense about the size of the difference between the employment from the Population Census and the CPS, we start with the national level. CPS employment is full-time equivalent employment that we calculate on the basis of hours worked in first and second jobs under the assumption that a full-time job amounts to 48 weeks per year and 40 hours per week. We find that CPS employment exceeds Census employment in both sectors. Since the CPS is deemed to be a very reliable source of US employment data, this implies that the Population Census underestimates sectoral employment. We also find that the relative discrepancy between the Population Census and the CPS numbers is considerably larger in agriculture than in non-agriculture. There are two reasons for this. First, the Population Census records only primary jobs, and so it underestimates employment in both sectors. It turns out that it is more important in agriculture than in non-agriculture because relatively more jobs in agriculture are second jobs. Second, the Population Census is taken during the month of March, which is not necessarily representative of the other months. As Figure D.2 shows, this is more important in agriculture than non-agriculture, because employment in agriculture is very seasonal and March is a month with below average activity in agriculture; in contrast, employment in non-agricultural is hardly seasonal.³

³Note that hours worked and usual hours worked in agriculture show similarly strong seasonal variation.

<Figure D.2 about here>

An additional issue with the employment numbers from the Population Census is that they refer to workers instead of hours worked. If hours per worker are roughly the same in both sectors, then using workers instead of hours worked does not affect the calculations of productivity gaps. The information on hours worked by sector from the CPS allows us to assess whether this is the case for the United States. We find that it is not, and that workers in agriculture tend to work more hours. Restricting attention to workers with only one job, the average farmer works 40.4 hours per week whereas the average non-farmer works just 37.2 hours. Not taking the sectoral difference in hours worked into account leads to an underestimate of sectoral productivity gaps.

2.2.3. Averages by decade

Our results for the year 2000 raise the obvious question whether 2000 was an unusually bad year for US agriculture. To address this question, we extend our measurement to 1980–2009 and group the data in three non-overlapping ten-year bins: 1980–1989, 1990–1999, and 2000–2009, which we refer to as the 1980s, 1990s, and 2000s. All numbers that we will report are the ten-year averages of the sectoral productivity gaps by state within the respective bin.⁴ While using ten-year bins increases the number of observations underlying each statistic that we calculate, the CPS still contains only a few agricultural workers in states with small agricultural sectors. To make sure that our results are not driven by these states, we require that for all states in our sample the CPS have complete hours information for at least 90 agricultural workers in each decade. This leads us to exclude Alaska, Connecticut, Massachusetts, Rhode Island, and West Virginia.

<Figure D.3 about here>

Panel (a) of Figure D.3 shows the new measures of productivity gaps in the form of a histogram. With the improved measurement and thirty years of data, the stylized fact of Subsection 2.1 survives; in most states and years, there is a sizable productivity gap between non-agriculture and agriculture. Panel (b) of Figure D.3 shows that the productivity gaps do not decline over time.⁵ This, and the fact that we average over ten-year bins, addresses the concern that our initial results reflected a bad harvest during the year 2000. Table D.1 gives the summary statistics for the productivity gaps: the median gap is 1.9, the gap at the 90th percentile is 3.0, and the maximum gap is 5.7.

<Table D.1 about here>

It is remarkable that the summary statistics for US states come out very close to those in developing countries. For example, Gollin et al. (2014) document for a set of 112 developing countries that the median productivity gap is 3 and the 95th percentile is 8.8. In the next section,

⁴Note that although the CPS started before 1980, only since 1978 does it have information for each individual state, which is crucial here. We start in 1980 because this allows us to form natural ten-year bins.

⁵It is also the case that the identities of the states with the largest productivity gaps remains the same across decades.

we start to address the question whether productivity gaps of this size imply mis-allocation. To this end, we connect labor productivity to the marginal value product of labor and bring to bear additional evidence from wages. We first derive a key identity that links the different statistics.

3. From Gaps in Productivity to Gaps in Marginal Value Products

3.1. A key identity

We use the following notation: Y denotes value added, L hours worked, W the average wage per hour (i.e. average earnings divided by hours worked), and LS the labor share (i.e., the payments to labor divided by value added). Both Y and W are measured in terms of current dollars. The indexes a and n indicate agriculture and non-agriculture.

To derive a relationship between productivity gaps and wage gaps, we recall the definition of the labor share:

$$LS \equiv \frac{WL}{Y} = \frac{W}{Y/L}. \quad (1)$$

We stress that this is an accounting identity that must hold without further assumptions on the market structure or the technology. Dividing the identities for non-agriculture and agriculture by each other and rearranging, we obtain a second identity that connects gaps in productivity and wages:

$$\text{Gap}(Y/L) \cdot \text{Gap}(LS) = \text{Gap}(W), \quad (2)$$

where the gap of variable X is defined as:

$$\text{Gap}(X) \equiv \frac{X_n}{X_a}.$$

Under the standard assumption of perfect competition, the average wage in a sector equals the marginal value product of labor. Identity (2) therefore offers two ways of measuring the marginal value product: as the product between labor productivity and the labor share and as the average wage. While data limitation typically imply that one can only pursue the former way of measuring the marginal value product, here we are able to pursue both ways.

Measuring the two sides of (2) therefore offers two different ways of assessing how different the marginal value products of labor are at the sectoral level. We emphasize that since (2) is an identity, both ways of measuring the marginal value product must should give the same answer in the absence of measurement error.

3.2. The productivity method

In order to measure the marginal value products through productivities, we need to estimate the labor shares in non-agriculture and agriculture. Since agricultural value added amounts to only around a percentage point of US GDP, non-agriculture comprises almost the whole economy. Hence, we can use a standard value for the aggregate labor share also for non-agriculture. We choose 0.67 as a compromise value between the two most widely used sources: Gollin (2002) quotes 0.66–0.77 for the US economy whereas Cooley and Prescott (1995) quote a lower value of 0.60.

A natural conjecture about the labor share in agriculture is that agriculture is less labor intensive than non-agriculture, in part because agriculture is more land intensive. Using the value added data from the BEA and the methodology of Gollin (2002), we find a value of 0.44 for the average labor share in US agriculture during 1980–2009. Two additional pieces of evidence show that 0.44 is indeed a reasonable estimate in agriculture. First, Mundlak (2005) pointed out that sharecropping arrangements in different countries and periods all allocate around half of the harvests to the sharecropper. Since sharecroppers tend to use some capital they own, this implies a labor share in agriculture that is smaller than 0.5. Second, using data on value added and factor inputs, Griliches (1964) directly estimated a production function for agriculture for the 1950s and found labor shares in the range of 0.4–0.5. This result was confirmed by Kislev and Peterson (1987) for the 1980s.

With labor shares of 0.67 in non-agriculture and of 0.44 in agriculture, $\text{Gap}(LS) = 1.52$. Substituting this into equation (2) gives:

$$\text{Gap}(Y/L) \cdot 1.52 = \text{Gap}(W) \implies \text{Gap}(Y/L) < \text{Gap}(W). \quad (3)$$

(3) implies that on average wage gaps should be one-and-a-half times larger than average productivity gaps. Moreover, as long as $LS_a < 0.67$, wage gaps should certainly be larger than productivity gaps. We view (3) as staking out a reasonable ballpark for the measured gaps in wages and productivity. Next, we will measure wage gaps by state and check whether they are in the ballpark.

3.3. The wage method

The CPS Matched Outgoing Rotation Groups contain information on hourly nominal wages, age, education, gender, state and sector. We use this information to calculate average wages in current dollars in each sector–state pair. While doing this is straightforward in principle, an issue arises because the self-employed (proprietors) and non-wage workers do not report hourly wages.⁶ Although the share of the individuals with missing wage information among agricultural workers

⁶Alternative data sources do collect the farm and business income of such individuals. However, this information is not useful for our purposes because it measures the income residually claimed by the proprietor, which is both a payment for their labor and the use of their capital.

declined from 62 percent in 1980 to 44 percent in 2009, these numbers are too large to ignore and so we will impute the wages of the self-employed and non-wage workers.⁷

A naive approach to imputing wages would be to take the average wage of those workers who report wages. We eschew this approach because proprietors in each sector differ systematically in their observable characteristics from wage workers: they have higher levels of schooling and experience than wage workers. Moreover, the differences between the observable characteristics of proprietors and wage workers are more pronounced in agriculture. To take this into account, we impute the missing wages of proprietors under the assumption that a proprietor earns the same hourly wage as a wage worker who has the proprietor’s observable characteristics. This means, for example, that the imputed wage for a 40-year old farm proprietor from Alabama with a high school degree equals the wage of a 40-year old farm worker from Alabama with a high school degree.⁸ To implement the imputation, we regress log hourly-wages on state fixed effects and age, education, and gender for the individuals who report this information; we use the estimated regression coefficients and the observable characteristics of the individuals with missing wage information to impute their wages. We choose to run the log-wage regressions separately for each sector and decade, which allows us to capture differences in the wage structure and in the return to observed factors over time and across sectors. One reason why this may matter is that the market return to skills may have risen over time or it may be higher in one sector than in the other.

<Figure D.4 about here>

<Table D.2 about here>

Figure D.4 plots the productivity gaps against the wage gaps and Table D.2 reports the summary statistics. We can see that there are relatively large differences between average wages in non-agriculture and agriculture at the state level. Moreover, the summary statistics of the wage and the productivity distributions are surprisingly similar. In fact, for the states at the median of each distribution, the gap in productivity and nominal wages equals 1.9. This means that in the median state, an average worker in non-agriculture receives almost twice the nominal wage of an average worker agriculture. The gaps at the 90th percentile and the maximum are even larger.⁹ In a companion paper, Herrendorf and Schoellman (2014), we calculate average hourly wages for wage workers in non-agriculture and agriculture also from two different data sources, namely, the Census and from the March demographic oversample of the CPS. The aggregate statistics are remarkably similar to what we find here. This gives additional credibility to our findings for wages.

Figure D.4 and Table D.2 also show that the wages are not in the ballpark staked out by (3),

⁷To be precise, the shares refer to individuals who list farm as their main job in which they work most hours.

⁸This approach does not correct for the differences in unobservable characteristics between proprietors and wage workers. Below, we will argue that differences in unobservable characteristics are unlikely to overturn our results.

⁹Note that in Table D.2 the states for which a given summary statistic of nominal wages are reported may not be the same.

which suggests that the productivity gaps should be smaller than the wage gaps. Instead, the productivity gaps come out much larger than the wage gaps in many states. Put differently, the labor share gap that is implied by the gaps in productivity and wages that we find is considerably smaller than the ballpark figure 1.5 in almost all states and is smaller than 1 in the median state. Since the relationship (2) between wage and productivity gaps is an identity that must hold, this implies that there must be a measurement problem with wages or productivity, or with both of them.

Since we can only take the observed characteristics of proprietors into account in our wage imputation, one may think that selection along unobserved characteristics could be behind our results. We have performed two consistency checks that suggest that proprietors are not driving our analysis. First, proprietorships are declining sharply in agriculture: whereas only 38% of agricultural workers worked for wages in 1980, by 2009 56% are working for wages. Despite this sharp decline, our gaps in average wages show no trend. Second, the following back-of-the-envelope calculation shows that to overturn our results the imputed proprietors' income would have to take extreme values that seem unreasonable to us. Specifically, suppose that selection along unobserved characteristics implies that the median wage gap and the median productivity gap match up and that the labor share gap that links the two is still equal to 1.52. Since the median productivity gaps equals 1.9, this implies that the median wage gap must equal 2.7, instead of the measured 1.9. To see what this means, it is useful to decompose the wage gap into the parts due to proprietors and wage workers:

$$\text{Gap}(W) = \frac{W_n}{(L_{aw}/L_a)W_{aw} + C(L_{ap}/L_a)W_{ap}}.$$

Here, W_{aw} and W_{ap} are the wages of wage workers and proprietors in agriculture, L_{aw} and L_{ap} are their labor, and C is the correction factor to the wages of agricultural proprietors for unobserved characteristics. For which C would we get $\text{Gap}(W) = 2.7$? The answer turns out to be for $C \approx 0.5$. This means that if selection along unobserved characteristics explained our results, then proprietors would have to make about half of what we imputed. To put this into context, note that the standard deviation of the residual log-wage inequality of wage workers in agriculture is around 0.5. Since $\ln(0.5 \cdot W_{ap}) = -0.7 + \ln(W_{ap})$, average wages of proprietors would have to be about $0.7/0.5 = 1.4$ standard deviations below the average wages of wage workers with the same characteristics. Given that proprietors are positively selected along observable characteristics, such a huge degree of negative selection along unobservable characteristics appears to be implausible.

3.4. Locating the measurement problem

While the previous evidence implies that there must be a measurement problem, it does not imply in which sector the problem is. We now use additional information to show that the measurement problem is in agriculture. We do this by calculating the labor shares at the sectoral level

that follow when we plug the measured wages and productivities into identity (1). The left panel of Figure D.5 shows the implied decadal averages of the labor shares for non-agriculture. They fall into the relatively tight range $0.59 - 0.64$, which is roughly consistent with the standard values for labor shares. We conclude that the implied labor shares for non-agriculture are plausible.

<Figure D.5 about here>

The right panel of Figure D.5 shows the implied labor shares in agriculture. The average by decade is $0.60 - 0.61$, which is considerably larger than what the existing evidence for the labor shares for agriculture suggests. Moreover, they are much more dispersed and many observations on the right panel are close to one or even larger than one. Given that the underlying wages and productivities are averages over decades and states, this is not plausible. We conclude that the implied labor shares in agriculture are implausibly large and that the measurement problem is in agriculture. Reinspecting (1), we also conclude that given that the measurement problem is in agriculture, either agricultural wages must be overestimated and/or agricultural productivity must be underestimated. If agricultural productivity is underestimated, then this may be due to agricultural value added being underestimated, agricultural hours being overestimated, or both.

4. Re-measuring Agricultural Productivity

In this section, we establish that agricultural productivity is mis-measured in US states. Showing this requires us to show that either the numerator or the denominator of agricultural productivity is mis-measured.

4.1. Hours

To assess whether sectoral hours worked are mis-measured, we compare hours worked in the CPS with those in American Time Use Survey (ATUS).¹⁰ ATUS data are collected from time use diaries in which the participants record their activities by minute for a 24-hour period. ATUS data are deemed very reliable. We focus on the period 2003–2010 during which the ATUS and the CPS overlap. Given that ATUS does not have many observations in agriculture, we only calculate hours at the national level. We find that there are only small differences between ATUS and CPS estimates of hours worked: while ATUS hours are 6.7% lower than CPS hours in agriculture, they are 4.3% lower in non-agriculture.¹¹ This suggests that in the US mis-measurement of hours worked is not an important factor behind the implausibly large productivity gaps that we found above. In the following subsections, we will establish that instead mis-measurement of agricultural value added is the key factor behind them.

¹⁰Accessed online through Hofferth et al. (2013).

¹¹Note that the fact that ATUS hours are smaller than CPS hours is expected because ATUS uses a strict definition of time spent at work. For example, ATUS does not count time spent at business meals or commuting, while respondents in the CPS may implicitly include such time in their responses.

4.2. Farm value added

Above, we have used farm value added from the BEA’s regional accounts. Although these data underlie the construction of NIPA, it turns out that they have a crucial shortcoming when it comes to measuring agricultural value added at the state level. The shortcoming comes from the fact that the BEA follows the System of National Accounts (SNA) and views agricultural value added as the value added that is produced by *farmers*, i.e., persons who operate a farm or who are employed on a farm, instead of the value added that is produced on *farms*. To appreciate the significance of using farmers instead of farms, an example may be helpful. Consider the payments that are received by farm contractors or the rental payments that are received by land owners who are not farmers. Clearly, these are factor payments that are generated on farms, and conceptually they belong to the value added produced on farms. However, the BEA does not report them as part of agricultural value added because they do not lead to income of farmers. Instead it reports the payments to farm contractors as value added in agricultural services and the payments to land owners as value added in real estate.

To see how much this shortcoming matters for measuring productivity gaps, we construct a new measure of value added that includes all factor payments generated on farms irrespective of who they accrue to. To this end, we use the State–Net–Value–Added Accounts provided by the USDA, which is the original data source of the BEA. Since these accounts include a detailed breakdown of the receipts, expenses, and factor payments in the farm sector at the state level, they have sufficient information to make the required adjustments. The Appendix describes in detail how we use this information to calculate the value added produced on farms. We obtain non–agricultural value added as the difference between state GDP and state agricultural value added.

<Figure D.6 about here>

Figure D.6 plots on the x-axis the agricultural value added from the BEA, which we used above, and on the y-axis the agricultural value added from the USDA, which includes all factor payments. All value added numbers in the figure are for the year 2000 and per CPS hour worked. As expected, most observations are above the 45 degree line, that is, value added per hour worked based on the USDA is larger than value added per hour worked based on the BEA. Moreover, for states with low agricultural productivity the difference can be large quantitatively. This suggests that using the BEA numbers for value added leads to a downward bias in the calculation of productivity in agriculture, and thereby biases upwards the measured productivity gaps between non–agriculture and agriculture.

Since BEA value added is similar to the standard data sources that are available for developing countries, this suggests that part of the large productivity gaps that people find for developing countries may be the result of mis–measurement due to the practise of counting some agricultural value added in non–agriculture. In the next subsection, we identify a further source of mis–measurement of agricultural value added, which arises because proprietors tend to under–report their income

severely.

4.3. *Proprietors' income*

<Table D.3 about here>

The Internal Revenue Service (IRS) periodically conducts tax audits to assess the degree of tax compliance. These audits find that proprietors severely under-report their income. Table D.3 lists the ratio of actual proprietors' income (as determined by tax audits) to reported proprietors' income for the two studies that fall into our period of investigation, Internal Revenue Service (1996) and Internal Revenue Service (2007). The estimates range from 1.4 to 3.6, suggesting under-reporting on a massive scale. Moreover, the degree of under-reporting appears to be more severe in agriculture than in non-agriculture. Potentially this is a serious issue for calculations of agricultural productivity because proprietorships are much more common in agriculture than in non-agriculture; during 1980–2009 the average share of proprietors' income in value added was 37% in agriculture and 8% in non-agriculture.

In non-agriculture, the BEA reacts to the evidence of under-reporting by taking the IRS estimates into account. As a result, it roughly doubles the reported income of proprietors. In agriculture, the BEA follows the production approach to estimate value added as the difference between revenues and expenses. Since the production approach does not directly feature the income of proprietors, it is not clear in principle whether the BEA should make any adjustment for the under-reporting of farm proprietors' income.¹² In practise, however, it turns out that the BEA should adjust for the under-reporting of farm proprietors' income, because the value added of farm proprietors under the production approach only modestly exceeds the reported income of farm proprietors. We establish this for 2002 and 2007 by comparing proprietors' revenue minus costs calculated from the Census of Agriculture with proprietors' income calculated from the March supplement to the Current Population Survey.¹³ We find that at the national level the ratios of the value added of farm proprietors under the production approach and the reported income of farm proprietors equal 1.2 and 1.1 in 2002 and 2007, whereas the IRS estimates indicate that a much larger correction is warranted.

<Figure D.7 about here>

If under-reporting of proprietors' income in agriculture is part of the reason why we have such large productivity gaps in some states, then states in which proprietors' income constitutes a larger share in agricultural value added should have larger productivity gaps. Figure D.7 shows that this is indeed the case (the regression coefficient is significantly different from zero at the 99% significance level). This suggests that under-reporting of proprietors' income should account for

¹²The preceding paragraph draws on Bureau of Economic Analysis (2009), which contains details on how the BEA actually constructs state-industry value added.

¹³Accessed online through King et al. (2010).

part of the large measured productivity gaps. It is impossible to be more specific though. To begin with, over the years the IRS studies found fairly different degrees of under-reporting. Moreover, we have no information on whether the degree of under-reporting in agriculture is uniform or varies by state. The latter is a possibility because the type of agriculture varies across US states. For example, coastal states like California and Florida specialize in fruit and vegetable production, the Great Plains specialize in grain production, and Texas and the Western states specialize in livestock production. Since these types of agriculture have different production structures, e.g. in terms of the degree of mechanization and the reliance on intermediate inputs, the scope for under-reporting of proprietors' income may well differ.

<Table D.4 about here>

We start by experimenting with the range 40 – 260% under the assumption that the adjustment factor is the same in all states.¹⁴ The productivity gaps after the corrections for missing value added and for under-reporting of proprietors are listed in Table D.4 for three different correction factors: 1.5 is the average over the range 1.4 – 1.5, whereas 2.3 and 3.6 are the suggested adjustment factors for non-agriculture and agriculture in 2001. We have highlighted the third column, because it adjusts farm proprietors' income by the same factor of 2.3 that the BEA uses for non-farm proprietors' income. Intuitively, this column asks how far we can get simply by performing the BEA's adjustment from the non-farm sector also in the farm sector. It is reassuring that for the median state the third column produces a corrected productivity gap of 1.3, which is exactly the value required to resolve the productivity puzzle. To see why, recall that the wage gap for the median state was 1.9, so with a corrected productivity gap of 1.3 the ratio of the two gaps equals $1.9/1.3 = 1.5$, which is what equation (3) suggested it should be. While this works at the median, at the maximum the corrected productivity gaps are still larger than the wage gaps. However, this is not necessarily implausible anymore, because the differences between the two gaps are largely reduced and it is perfectly possible that in some US states agriculture is more labor intensive than non-agriculture (think of fruit picking and vegetable farming in the coastal states).

In sum, we have established two reasons why the BEA under-estimates agricultural value added at the level of US states: the SNA classifies some of the value added generated on farms in other industries; the BEA does not properly adjust for under-reporting of proprietors' income in agriculture. We have shown that this implies that the productivity gaps between non-agriculture and agriculture that are based on BEA value added data are artificially large.

¹⁴Note that adding missing proprietors' income does not affect the capital share estimates that we use, because they are obtained either by measuring capital and labor income in the part of value added that is not proprietors' income or by estimating production functions.

4.4. Accounting for the gaps in marginal value products in US states

The previous discussion suggests that a value around two is a reasonable estimate of the gaps in marginal value products between non-agriculture and agriculture in US states. This raises the question what might explain such sizable gaps in the US. While the analysis so far does not rule out the possibility of mis-allocation between non-agriculture and agriculture, standard explanations from the literature are geared toward developing countries with large shares of the labor force in agriculture. For example, Adamopoulos and Restuccia (2014) and Donovan (2014) point to the scale or risk of farming; Restuccia et al. (2008) and Herrendorf and Teixeira (2011) to barriers of moving workers or intermediate goods between agriculture and non-agriculture; and Lagakos and Waugh (2013) to selection of the workers in the two sectors.

In our view, the most promising explanation for gaps in marginal value products in US states is sectoral differences in human capital. The evidence provided so far followed the literature in that sectoral averages of value added or wages were calculated per worker or per hour worked. Therefore, these calculations do not take into account that workers in non-agriculture might have more human capital than workers in agriculture. The interesting question that arises is how much of the gaps in marginal value products is accounted for by sectoral differences in human capital. In a follow up paper, Herrendorf and Schoellman (2014), we show that human capital broadly defined can account for the gaps in average wages in US.

5. Cross-country Evidence

5.1. Preliminaries

In the previous section we documented that the two methods to calculate marginal value products do not agree with each other. We then documented that mis-measurement of value added in agriculture was the key problem. In this section we consider to what extent the same conclusion applies also to the measurement of productivity gaps internationally. We consider a sample of countries for which we have access to population censuses with the detailed data required for our analysis. We calculate the marginal value products through both the productivity method and the wage method and we assess whether the results agree with each other. We find that they do not, which implies that at least one of the three terms in identity (2) must be mis-measured: productivity gaps, wage gaps, or labor share gaps.

In order to enter our sample a country needs to satisfy two criteria: for at least one year during the period 1990–2009 the UN data base reports NIPA information on value added in agriculture as a share of GDP and IPUMS reports employment by sector and earned income from population censuses. We insist on information from population censuses because we want data sets that are large and representative. The following country–year pairs satisfy these criteria: Brazil (1991,2000);

Canada (1991,2001); India (1993,1999); Indonesia (1995); Israel (1995); Jamaica (1991,2001); Mexico (1990,2000); Panama (1990,2000); Puerto Rico (1990,2000); Uruguay (2006); United States (1990,2000); Venezuela (1990,2001). The resulting sample of countries covers 30% of the world population in 2009. Moreover, it contains four of the five most populous countries, namely, India, US, Indonesia, and Brazil, with China as the most populous country missing.

<Table D.5 about here>

Table D.5 reports several summary statistics for our sample of country–year pairs: at the median, the gap in GDP per capita (in international prices) with the US is a factor of 4.5, agriculture has an employment share of 17 percent, and the productivity gap between non–agriculture and agriculture is 2.6; at the maximum, these statistics grow considerably to a GDP gap of 22, an employment share of agriculture of 62 percent, and a productivity gap of 4.4. The correlation in our sample between GDP per capita relative to the US and the employment share in agriculture is -0.71 and the correlation between GDP per capita relative to the US and the productivity gaps is -0.65. In addition to rich countries like Canada and the US, our sample comprises relatively poor countries that have large workforces in the sector in which they are very unproductive, agriculture. India and Indonesia are two examples. One shortcoming of our sample is that it does not contain African countries which have even larger GDP gaps relative to the US than a factor 22. The reason for this is that IPUMS does not report sufficiently detailed census information about wages by sector for African countries.¹⁵

5.2. Labor share gaps

Having established that there are large productivity gaps between non–agriculture and agriculture in our sample of countries, we now conduct the same analysis as for US states to the extent possible. We start by calculating wage gaps and comparing them to the productivity gaps. As above, the labor shares in value added of agriculture and non–agriculture are crucial in this context. Above, we worked with labor shares in value added of agriculture and non–agriculture equal to 0.44 and 0.66, respectively, and an implied ratio of the labor shares in non–agriculture to agriculture of 1.5. This meant that on average wage gaps were predicted to be 50% higher than productivity gaps. There is substantial evidence that similar numbers apply also across countries, which implies that we should see considerably larger wage gaps than productivity gaps also across countries.

A first piece of evidence comes from the classic study by Hayami and Ruttan (1970), who estimated agricultural production functions for a sample of 38 countries. The advantage of this way of proceeding is that it does not require an imputation of the labor share of proprietors’ income. Hayami and Ruttan (1970) found that depending on the estimation method the average agricultural

¹⁵South Africa has the best information among all African countries, but that information is still not sufficient to conduct our exercise.

labor share falls into the range 0.34 – 0.49. Subsequent studies that directly estimated agricultural production functions have found that, if anything, the average agricultural labor share is smaller; see for example Fulginiti and Perrin (1993) and Craig et al. (1997). A second piece of evidence is that share-cropping arrangements allocate around half of the harvests to the land owner, which leaves at most the other half for labor (Mundlak, 2005). Importantly, this evidence is from different time periods and different countries. A third piece of evidence comes from specific studies which imputed the labor shares in agriculture for the countries in our sample: Echevarria (1998) found an agricultural labor share of 0.41 for Canada during 1971–93; Schultz (1964) found 0.4 for India during 1918–19; Mundlak et al. (2002) found less than 0.33 for Indonesia during 1980–98; Fishelson (1974) found 0.44 for Israel in the late 1960s. We conclude that the existing evidence for our sample of countries suggests that agricultural labor shares are smaller than 0.5, and are therefore smaller than the typical value of 0.67 for the labor share in non-agriculture.

One might think that the evidence that labor shares are smaller in agriculture than in non-agriculture contradicts the evidence of Gollin (2002) that the labor share in aggregate GDP is uncorrelated with GDP per capita. After all, poorer countries tend to have larger agricultural sectors, which would seem to imply that they should have smaller labor shares in aggregate GDP. There are two reasons why this way of thinking is flawed. First, Gollin’s method effectively calculates the labor share in non-agriculture, instead of the labor share in the aggregate economy. For rich countries, the reason is that the share of agriculture in total value added is only a few percentage points. For poor countries, the reason is that agriculture is dominated by proprietors (often subsistence farmers) and that Gollin’s method calculates the labor share only for the part of value added that is not produced by proprietors. Second, even if Gollin’s method correctly calculated the labor share for the aggregate economy, the evidence of lower labor shares in agriculture would not necessarily contradict the evidence that aggregate labor shares are uncorrelated with GDP per capita. The reason is that the other sectoral labor shares are likely to be correlated with GDP per capita as well. A simple example may be instructive: Suppose that all countries had the same labor shares as the US both in agriculture and in aggregate GDP. To be consistent with the stylized fact that labor shares in aggregate GDP are uncorrelated with GDP per capita, poorer countries would then just have to have larger labor shares in non-agriculture than richer countries. Since the share of agricultural value added in total GDP is relatively small even in poor countries the required variation across countries in the labor share of non-agriculture would remain modest.¹⁶

5.3. *Wage gaps*

To calculate wage gaps, we follow the same principles as before to the extent possible. We use only information from individuals who are at least 10 years old and have valid information for our

¹⁶The share of agricultural value added in total value added remains below 0.33 in all countries in our sample.

key variables: sex, education, employment by sector and so on.¹⁷ We again face the problem of missing wages for proprietors and some workers. As before, we use wage regressions to impute the missing wages. The characteristics that we include in these regressions are the geographic region, education, potential experience, and sex. As before, we run the wage regressions separately for agriculture and non-agriculture.

We face two challenges when imputing wage information for our sample countries. First, in some countries a sizable fraction of workers list their status as unpaid workers. We take these reports seriously and enter a zero wage income for all such workers. Since agriculture has a higher fraction of unpaid workers than non-agriculture, this may bias our calculated wage gaps upwards. Since we will find that the calculated wage gaps are still too small compared to the productivity gaps, this way of proceeding is conservative and does not invalidate our conclusions. Second, although we have information on earnings from population censuses for all countries in our sample, the level of detail of the employment information differs across countries. In some countries (including the US), we have information on hours worked so that we can calculate the hourly wage for wage workers. We use that wage in our imputations of the annual earnings of proprietors (which equals the hourly wage of a wage worker with the same characteristics as the proprietor times the number of hours worked by the proprietor). In some other countries, we have less detailed information but can calculate daily or weekly wages. Using these wages for the imputation amounts to assuming that proprietors work the same number of daily or weekly hours as wage workers. In yet some other countries, we know nothing about hours worked so that we are forced to work with monthly income. Using these wages for the imputation amounts to assuming that proprietors work the same number of monthly hours as wage workers. We emphasize that all three methods lead to an estimate of the annual labor income of proprietors. The reason why the first method is preferred to the second one and the second method is preferred to the third one is that the required assumptions increase when going from method one to three. We also emphasize that while not taking into account differences in hours worked between proprietors and wage workers may bias our calculations of the wage gaps, the difference in hours worked between wage workers and proprietors would have to be very large to overturn our results. For the US, we don't find anything close to such large differences in hours worked between proprietors and wage workers.¹⁸

<Figure D.8 about here>

<Table D.6 about here>

Figure D.8 plots and Table D.6 reports the results for wage gaps in comparison to productivity gaps. We can see that again the productivity gaps exceed the wage gaps for most country-year pairs. Moreover, at the maximum the productivity gap comes out as twice the wage gap. To

¹⁷For the US, we started with 18 years because hardly anyone younger than 18 years works full time.

¹⁸More details on the wage imputation are in the Appendix.

reconcile this with identity (2), we would have to believe that agriculture is more labor intensive than non-agriculture in most countries and that in one country it is twice as labor intensive. This is implausible and suggests that again there is a measurement problem in at least one of the three components of identity (2): productivity gaps, wage gaps, or labor share gaps.

5.4. Locating the measurement problem

<Table D.7 about here>

The next step is to show that, as before, the measurement problem is located in agriculture. Since the population censuses do not contain information about non-wage income (like benefits), we cannot follow the same steps as for US states and directly calculate the implied sectoral labor shares by combining census information with information about benefits. We therefore go down a different path and calculate the labor shares implied by productivity gaps and wage gaps vis the identity:

$$LS = (Y_a/Y)LS_a + (Y_n/Y)LS_n.$$

Solving for the labor shares in agriculture and non-agriculture, we find:

$$LS_a = \frac{LS}{(Y_a/Y) + (Y_n/Y)(LS_n/LS_a)},$$

$$LS_n = \frac{LS}{(Y_a/Y)(LS_a/LS_n) + (Y_n/Y)}.$$

For the right-hand variables of a particular country, we use the standard value of 0.67 for the aggregate labor share LS , the NIPA values for the sectoral value added shares Y_i/Y , and the ratios implied by the previous analysis for the labor-share gaps LS_n/LS_a . Table D.7 reports the summary statistics of the results. We can see that the implied labor shares in non-agriculture are close to the standard aggregate value of 0.67, which is plausible. In contrast, the implied labor share in agriculture at the median is already larger than in non-agriculture and at the 90th percentile it considerably exceeds 1. This is not plausible and suggests that there is a measurement problem in agriculture also for the sample of countries.¹⁹

Unfortunately, for our sample of countries we cannot establish which exact nature the measurement problem takes. One possibility is that farmers in poor countries also underestimate production and acreage to avoid being taxed, which has been a worry in the literature (Berry, 1984; Ngen-

¹⁹One might think that our claim that Gollin's method effectively calculates the labor share for non-agriculture implies that we should have proceeded differently by setting $LS_n = 0.67$ and then calculating the implied labor share in agriculture as $0.67 \times (LS_a/LS_n)$. It is straightforward to show that if $LS_a/LS_n > 1$, then this procedure produces even larger labor shares in agriculture than our procedure above. So proceeding with $LS = 0.67$ is conservative in the current context.

dakumana, 2001). But we cannot establish this conclusively here because the descriptions of data for poor countries are much less detailed than for the US for which we had precise references to other documents and to multiple sources for the same statistic. In addition, the data collection in many poor countries is rather opaque. Missing data are often filled in by international groups such as the World Bank or the Food and Agriculture Organization, which don't make publicly available the data available to them and the process they use to compile totals (Jerven, 2013). We therefore draw a somewhat more cautious conclusion than for US states: the accounting identity (2) does not hold for our sample of countries, which suggests a measurement problem; additional consistency checks imply that the measurement problem again in agriculture; this suggest that at least one of the following three statistics is mis-measured in agriculture: labor productivity, average hourly wages, or labor shares.

Our results suggest that gaps in wages between 2–4 are a reasonable estimate of the median gaps in marginal value products in our sample of selected countries. While these numbers are sizable still, they are considerably smaller than the productivity gaps that are usually quoted. This leaves the question what may account for wage gaps between 2–4. In a follow up paper, Herrendorf and Schoellman (2014), we show that human capital broadly defined can account for most of the wage gaps in a similar sample of countries. Specifically, we find that the residual wage gaps after accounting for sectoral differences in human capital are of a size that can be reconciled with rather benign explanations such as differences in the costs of living.

6. Conclusion

In this paper, we have assessed whether the commonly observed large productivity gaps between non-agriculture and agriculture imply that labor is mis-allocated between the two sectors. We have established three facts that suggest otherwise. First, there are also sizable productivity gaps in US states where severe mis-allocation is implausible. Second, the gaps between the marginal value products of agriculture and non-agriculture are considerably smaller when measured through wages than through labor productivities. Third, labor productivity in agriculture is mis-measured in the US. We take these facts to mean that we are not yet clear about how large the gap is that many people are attempting to explain.

Acknowledgements

For helpful discussions and comments, we thank the editor Matthias Doepke, several anonymous referees, Roozbeh Hosseini, Moritz Kuhn, Patrick Minford, Diego Restuccia, Kerry Smith, Ákos Valentinyi, Gustavo Ventura, and the audiences at Arizona State University, the Canadian Macro Study Group, the Cologne Workshop on Macroeconomics, the Federal Reserve Banks of Minneapolis and St. Louis, the Free University of Berlin, the Growth and Development Conference at Toronto,

the HKUST Macroeconomics Conference, the Midwest Macroeconomics Meetings, the Meetings of the Society for Economic Dynamics, the Helsinki Center of Economic Research, Simon Fraser University, the Universities of California at Santa Barbara, Konstanz, Laval, Mannheim, Toronto, and Western Ontario. For financial support, Herrendorf thanks the Spanish Ministry of Education (grants ECO2009-11165 and ECO2012-31358).

Appendix A. Data Appendix: Sectoral Value Added

In this part of the Appendix, we explain in more detail how we construct our measures of agricultural value added at the state level. Given these measures, it is straightforward to obtain measures of nonagricultural value added by subtracting agricultural value added from state GDP as reported by the BEA.

Appendix A.1. BEA

The BEA numbers for sectoral value added are taken straight from the BEA’s regional economic accounts. In particular, for value added in agriculture, we use item 10010 (value added of farms) for years with the SIC classification and item 4 (value added of crop and animal production) for years with the NAICS classification; for GDP at the state level we use item 0 in the SIC and item 1 in the NAICS, minus value added in the military (item 112000 in the SIC and item 80 in the NAICS).

Appendix A.2. USDA

To construct a measure of agricultural value added from USDA data, we use the USDA’s value-added spreadsheets at the state level.²⁰ We construct income produced on farms as follows:

- The value of crop production is farm income. The USDA reports values for eight types of crops, as well as total values for home consumption and inventory adjustment.
- The value of livestock production is farm income. The USDA reports values for four types of livestock, as well as values for home consumption and inventory adjustment.²¹
- Revenues produced from miscellaneous farm activities may or may not be counted as farm income. Considering each in turn:
 - The value of machine hire and customwork is farm income, because it includes payments for providing services closely related to the farm. Examples are planting, plowing, spraying, or harvesting for others.

²⁰The spreadsheets are available at http://www.ers.usda.gov/Data/FarmIncome/Zip_filesXls.htm.

²¹Note that NAICS uses animal production and USDA uses livestock production for the same industry.

- The value of forest products sold from the farm is farm income. Ideally we would exclude this revenue from agriculture and include it in forestry. However, some of the expenses of farms and some of the labor on farms are devoted to generating this revenue. Since we cannot isolate the relevant expenses and labor, we include the revenue as farm income.
- Other income is farm income, because it is closely related to farm operations. Examples include animal boarding, breeding fees, and energy generated on the farm.
- The gross imputed rental value of farm dwellings is not farm income, because it is not closely related to farm operations.

We construct expenses for intermediate inputs used by farms as follows:

- Farm-origin expenses are farm expenses. The USDA reports feed purchased, livestock and poultry purchased, and seed purchased in this category.
- Manufactured inputs are farm expenses. The USDA includes fertilizers and lime, pesticides, petroleum fuel and oils, and electricity in this category.
- Other purchased inputs may be farm expenses or factor payments, in which case they are not counted as farm expenses. In particular:
 - Repair and maintenance of capital items are farm expenses, in line with usual NIPA procedures.
 - Expenses for machine hire and custom work are farm expenses.
 - Marketing, storage, and transportation expenses are farm expenses.
 - Contract labor is a factor payment to contractors or crews that provide labor to farms, and so is counted as a factor payment and not as farm expenses.
 - Miscellaneous expenses are farm expenses. Examples include the costs of animal health care and insurance.

In addition to a “raw” value added measure, we also construct a value added measure that includes subsidies and property taxes. To do so we take value added and add the line “net government transactions”. Note that the government also provides indirect support for farmers through price supports and similar programs; the effects of these indirect supports are already counted in value added.

Appendix B. Data Appendix: Sectoral Labor Inputs

This section provides the details of how we construct sectoral labor inputs. It also explains how we define agricultural and nonagricultural workers, hours worked, wages, and so on.

Appendix B.1. Population Census

To calculate labor input from the US Population Census, we use the public-use census data made available through the IPUMS data service, Ruggles et al. (2010). We use the 5 percent sample for 1980, 1990, and 2000, which is the largest publicly available sample for these years. We impose as little sample selection as possible. We require that workers be in the labor force and employed ($\text{empstat} = 1$). The Census asks about the employment status of those aged 16 and older, so we restrict our sample to this age group. We exclude workers with invalid or missing industry codes.

To assign workers to agriculture and non-agriculture, we need to construct a crosswalk from workers' self-reported industry to our agriculture/nonagriculture classification. One potential complication is that the US Census uses a different coding scheme for industry in every year. Fortunately, however, the agricultural definitions are fairly clear throughout. In particular, we define agriculture as the crop and animal production industries, which corresponds exactly to codes 010 and 011 of "ind" in 1980 and 1990, and to codes 017 and 018 in 2000. We construct non-agriculture as the residual, that is, non-agricultural workers are all workers with valid industry reports that do not work in an agricultural industry or in the military.

As a robustness check on our results, we also experiment with two alternative methods of defining workers in the agriculture sector. First, we tried taking a somewhat broader view of the industries that should be included in agriculture. However, these attempts yield a larger estimate of the agricultural labor force and consequently lower agricultural labor productivity figures, only adding to the productivity puzzle. Second, we tried using workers' reported occupations rather than their industries. In this case, we identify workers who report being farmers, ranchers, farm managers, or farm laborers rather than those who report being in the animal and crop production industries. Again, we generally found that this method led to higher levels of employment in agriculture. Results are available upon request.

After dividing the population into agricultural and non-agricultural workers, we calculate employment and hours worked by state and sector. For all calculations, we restrict the samples to individuals with valid responses. We use the reported state of residence (statefip) and weight all variables with individual weights (perwt). We compute sectoral employment as the number of workers in each sector.

Appendix B.2. Current Population Survey

The Current Population Survey (CPS) administered by the BLS is our principal data source for the number of workers and hours worked and the wages and earnings received.²² We restrict our attention to those workers in the CPS who have a job and valid occupation and industry

²²Data are available at http://www.nber.org/data/cps_basic.html.

codes. We use information about age, education, employment, gender, and state of residence from the CPS Basic Monthly Data, which we take from the NBER’s CPS data repository. We also use information about hours worked in primary and secondary jobs by industry, which is available in the May supplements of the 1979, 1980, 1989, and 1991 CPS (again taken from the NBER’s CPS data repository) and in the Outgoing Rotation Groups during 1994–2009. Lastly, we use information about wages and earnings from the NBER Matched Outgoing Rotation Groups (MORG) during 1980–1993 and the Outgoing Rotation Groups during 1994–2009.

To measure the number of workers, we use the CPS Basic Monthly Data. The CPS uses the coding schemes from the Population Censuses for both first and second jobs. The codes for agriculture are 017 during 1980–1982, 010–011 during 1983–2002, and 0170–0180 during 2003–2009. We assign each worker to the sector of his primary job, which the CPS defines as the job with most hours worked. We then count the total number of hours worked by this worker in all jobs, regardless of the sector. We cap total hours worked at 99 (consistent with earlier CPS procedures and a reasonable limit on the work week), and weight using the provided weight (pwsswgt). This gives us a measure of hours worked by primary workers in each sector, state, month, and year. We multiply this figure by 4.33 to generate monthly hours worked.

This measure of hours worked does not account for the time allocation of workers who have secondary jobs in a different sector than their primary job. In other words, these data are analogous to what we would find in the US Population Census, which does not distinguish between primary and secondary jobs. To account for secondary jobs in a different sector, we draw on data on primary and secondary jobs from the CPS from 1994 onward, and from the May supplements of the 1979, 1980, 1989, and 1991 CPS. We use this information in the following way:

1. For the months where the data are available, we calculate the fraction of the total hours worked that is devoted to agriculture by workers whose first jobs are in agriculture and non-agriculture. We aggregate this information to the state–month–year level.
2. We use a regression with state and month fixed effects as well as a linear time trend to predict the time allocation of the workers with a primary job in agriculture and non-agriculture for years in which the data are not available.
3. We combine our information on the hours worked by those with primary jobs in agriculture and non-agriculture with our predicted time allocations of hours to calculate labor in agriculture and non-agriculture.²³

We measure wages per hour using CPS data to be consistent with our other work. We perform wage regressions using the wage data from the NBER Matched Outgoing Rotation Group (MORG) during 1980–1993 and from the outgoing rotation groups in the CPS Basic Monthly Data during

²³Note that this means that we use the predicted hours also when we actually have hours in the CPS. We do this for logical consistency and to smooth the data in states with small agriculture samples.

1994–2009. We again use the outgoing rotation group weights and we multiply top-coded wages by 1.4 as suggested by the CPS. As is standard, we run the wage regressions for a selected sample of workers who meet the following criteria:

- They work for wages and salaries (the reason for this restriction is that the reported wages of self-employed or unpaid workers are considered unreliable, and are usually not even collected).
- They have a valid hourly wage, that is, they either report a positive hourly wage or a positive weekly wage and provide a positive estimate of their usual weekly hours worked; in the latter case we compute the hourly wage as weekly wage/hours per week.

We use the following controls in our wage regression: the state of residence, gender, potential experience, and education. We transform potential experience into 5-year bins (0–4 years, 5–9 years, and so on) and run wage regressions with dummy variables for each potential experience group. Education data are straightforward except that there is a shift in the coding scheme for education in the middle of this period. Until 1991 the scheme counted years in school (such as four years of college), while from 1992 onward it measured degree attainment (such as bachelor’s degree). We run wage regressions with dummies for years before 1991 and with dummies for degree from 1992 onwards.

One final issue to address is that monthly CPS wage data do not include all the compensation that labor receives. First, they do not include irregular compensation, such as bonuses. This type of income is better captured in retrospective questions, such as the question in the March CPS supplement on total labor income earned in the last year. We construct the ratio of retrospective March CPS income to the sum of all monthly income in the prior year, and use this ratio as a correction for irregular compensation. The second component of labor compensation missing is benefits. Fortunately, NIPA includes information on wages and on total compensation (wages plus benefits) by state, year, and industry. We correct CPS wages by the ratio of NIPA total compensation to NIPA wages to adjust for benefits. This correction is generally slightly larger for the non-agricultural sector, indicating that benefits are more generous there. All our figures on wages in the paper include both of these corrections so that they represent total labor compensation.

Appendix C. Data Appendix: Proprietors’ Income

Appendix C.1. Census of Agriculture

We calculate revenues minus costs for farm proprietors using the 2002 and 2007 Censuses of Agriculture. The Census of Agriculture distinguishes between family or individual farms, partnerships, corporations, and other farms (which includes cooperatives, trusts, institutional farms, and other unusual arrangements). We calculate farm proprietor income as farm income less farm expenses and factor payments for family or individual farms and partnerships. In theory, the result

should be identical to farm income from the March CPS, which measures the income from owning and operating one's own farm, unless one is incorporated. In practice, it is quite close.

We construct income produced on farms as follows:

- The value of total sales is farm income. This includes the sales of crops and livestock of many types.
- The value of government payments is farm income. This category captures subsidies from the federal government.
- The revenue from several services is farm income:
 - The value of machine hire and customwork is farm income, because it includes payments for providing services closely related to the farm. Examples are planting, plowing, spraying, or harvesting for others.
 - The sale of forest products is farm income, for the same reasons as it is counted in the USDA.
 - Patronage dividends and refunds from cooperatives are farm income, which occur when farmers paid for inputs through cooperatives but price realizations come out lower than expected.
 - Agri-tourism payments, insurance payments, and payments from state and local government programs are farm income.
 - Other farm-related income is farm income.
- We do not count one other type of farm income, namely gross cash rent or share payments, which should be reported as a factor payment elsewhere.

We construct expenses for intermediate inputs used by farms as follows:

- The purchases of products produced in the farm sector (including seeds, livestock, and feed) are farm expenses.
- The purchases of manufactured inputs (including fertilizer, lime, chemicals, gasoline and other fuels, and utilities) are farm expenses.
- We count repair and maintenance of capital items, machine hire and custom work, and miscellaneous expenses as farm expenses.
- We do not count as farm expenses several items that are factor payments, such as rental payments for land and machinery; payments to landlords; interest payments; and payments to workers.

Finally, we take the measure of property taxes directly from the line “property taxes paid”. Our measure of revenues minus costs of proprietors then is farm income minus farm expenses, farm factor payments, and property taxes paid.

Appendix C.2. March Supplement to the CPS

The March supplement to the Current Population Survey asks about the pre-tax income of farmers who own and operate their own farm or are self-employed on their own farm. It does not contain information on the income of those who work as salary or wage employees, including those who work on their own incorporated farm; this information is collected elsewhere. Moreover, it does not contain information on the earnings of owner non-operators, such as those with shares in a farm corporation. Thus the pre-tax income of farmers from the March supplements corresponds closely to the figure computed from the Census of Agriculture above.

We download the relevant data from the IPUMS data service, Ruggles et al. (2010). The relevant variable is `incfarm`. We add this income to the national total using the provided weights (`wt supp`).

Appendix D. Data Appendix: Sectoral Labor Inputs for Countries

Our data for sectoral labor inputs for countries comes from Minnesota Population Center (2014). The data consist of a number of population censuses or similar data sets, collected and harmonized in a single repository. The data are ideal for our purposes because they represent large, nationally representative samples, allowing us to construct reliable aggregate estimates of sectoral labor inputs. Further, the substantial work done by IPUMS to harmonize the data is useful for generating comparable results across countries. We select from the repository all country-year pairs that are taken during or since 1990, and that contain the necessary variables (wage or earned income, education, age, gender, industry of employment and so on). The primary limiting constraint for us is the availability of wage or earned income; most countries do not collect these data in their censuses.

We perform some selection on these samples: we drop anyone less than ten years old; anyone who is out of the labor force; those with negative or missing weights; and those with missing values of our key variables. We divide workers into agriculture and non-agriculture on the basis of the provided, pre-harmonized variable “`indgen`”. Fortunately, the underlying censuses of most countries include a distinct industry code for agriculture, making this step fairly reliable. We aggregate the number of workers by sector using the provided weights to produce the sectoral labor force.

The second object we construct is the annual labor income per worker for each sector and country. IPUMS classifies workers into three basic type: those employed for wages; the self-employed (proprietors); and unpaid workers. Unlike in the CPS, some countries collect earned or wage income for all three types. We choose to ignore such income when provided, because it is not clear how to interpret the positive wage income of a worker who claims to be unpaid; likewise, the

earned income of a self-employed worker may represent both labor and capital income. For unpaid workers we impute annual labor income of 0. For proprietors, we impute their labor income.

The imputation process is conceptually similar to what we do for the CPS, explained in the text. We use log-wage regressions to measure the market return to observed characteristics in each sector and country. We then use the regression to impute the labor income for proprietors. Our measures of observable characteristics include potential experience (grouped into 5-year bins, with a full set of dummy variables); education categories (we use each country's original education variable, with a full set of dummy variables); sex; and a regional geographic control, typically state or province. The latter variable is intended to help capture regional price or cost of living differences.

The main difference between our samples is in the information on the intensive margin of labor supply. For some countries we have enough information to construct annual hours worked, but for a few we have no information at all. As explained in the text, we can construct a measure of annual labor income per worker for any of these types of information. However, we prefer more detail because it allows us to make fewer assumptions when imputing the annual labor income of proprietors. For example, if we have annual income and annual hours worked then we can construct hourly wages for wage workers; impute the hourly wages of proprietors; and then multiply by annual hours worked of proprietors to find the annual labor income of proprietors. In this case our assumption is that the hourly wage of proprietors and wage workers (with the same observable characteristics, in the same sector) is the same. For some other countries we have only monthly labor income. In these cases we have to directly impute the monthly labor income of proprietors using the monthly labor income of wage workers. When we do so, we are making the additional assumption that proprietors and wage workers (with the same observable characteristics, in the same sector) work the same hours per month.

In our sample of countries there are actually six different ways of reporting labor income and labor supply. Each differs in the assumption implied by our imputation process. Listed in order of increasingly strong assumptions:

1. Annual income and annual hours worked: Canada 1991 and 2001; Jamaica 1991 and 2001; Puerto Rico 1990 and 2000; US 1990 and 2000; Venezuela 2001. The only assumption is that proprietors and wage workers earn the same hourly wages. This assumption also applies for each of the following five ways of reporting.
2. Monthly income and hours worked per week: Brazil 1991 and 2000; Indonesia 1995; Israel 1995; Mexico 1990 and 2000. The assumption is that proprietors and wage workers work the same number of weeks per month.
3. Weekly income and days per week: India 1993. The assumption is that proprietors and wage workers work the same hours per day.
4. Monthly income and days per week: Uruguay 2006. The assumption is that proprietors and wage workers work the same hours per day.

5. Weekly income: India 1999. The assumption is that proprietors and wage workers work the same hours per week.
6. Monthly income: Panama 1990 and 2000; Venezuela 1990. The assumption is that proprietors and wage workers work the same hours per month.

Two countries change the level of detail at which they report labor supply within our time frame: India and Venezuela. India's information became less detailed over time. If we return to Figure 9, we see that this had essentially no change on our key result. India's measured productivity was too large compared to its measured wage gap in both years, and by roughly the same amount. Venezuela's information became more detailed over time. Again, if we return to Figure 9 we see that increasing the level of detail actually increased our results: productivity gaps are even less plausible in 2001 than in 1990, as judged by wage gaps. These two comparisons offer suggestive evidence that our imputations do not drive our results.

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Table D.1: Productivity Gaps with CPS Hours for US States 1980–2009

Aggregate Economy	2.0
State-Level Distribution ^a	
Median	1.9
90 th Percentile	3.0
Maximum	5.7

^a Distribution of labor productivity gaps (non-agriculture relative to agriculture) at the state-decade level, excluding five states with small samples: Alaska, Connecticut, Massachusetts, Rhode Island, and West Virginia.

Table D.2: Wage Gaps for US States

	Gap(Y/L)	Gap(W)
Aggregate Economy	2.0	2.0
State-Level Distribution ^a		
Median	1.9	1.9
90 th Percentile	3.0	2.2
Maximum	5.7	2.8

^a Distribution of the relevant gaps (non-agriculture relative to agriculture) at the state-decade level, excluding five states with small samples: Alaska, Connecticut, Massachusetts, Rhode Island, and West Virginia.

Tables and Figures

Table D.3: Actual divided by Reported Proprietors' Income for US States

	Non-farm	Farm
1980s	1.4 – 1.5	1.4 – 1.5
2001	2.3	3.6

Table D.4: Corrected Productivity Gaps for US States 1980–2009

Correct. Factor	1.5	2.3	3.6
Aggregate Economy	1.6	1.4	1.2
State-Level Distribution ^a			
Median	1.5	1.3	1.1
90 th Percentile	2.5	2.0	1.7
Maximum	4.8	3.6	2.9

^a Distribution of labor productivity gaps (non-agriculture relative to agriculture) at the state-decade level, excluding five states with small samples: Alaska, Connecticut, Massachusetts, Rhode Island, and West Virginia.

Table D.5: Summary Statistics for Characteristics of Sample Countries

	GDP pc Gap (US rel. to country)	Agric. Empl. Share (in %)	Prod. Gap (non-ag. rel. to ag)
Median	4.5	17	2.6
90 th Percentile	11	44	4.3
Maximum	22	62	4.4

Table D.6: Summary Statistics for Gaps in Sample Countries

	Gap(Y/L)	Gap(W)
Median	2.6	2.0
90 th Percentile	4.3	3.6
Maximum	4.4	4.1

Table D.7: Summary Statistics for Implied Labor Shares in Sample Countries

	LS_n	LS_a
Median	0.67	0.75
90 th Percentile	0.67	1.08
Maximum	0.70	1.25

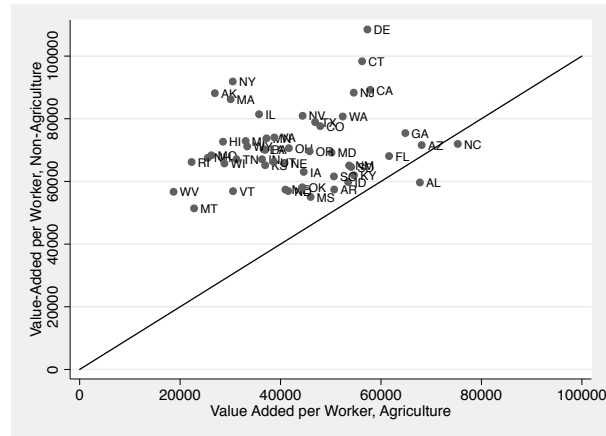


Figure D.1: Sectoral Value Added per Worker for US States in 2000

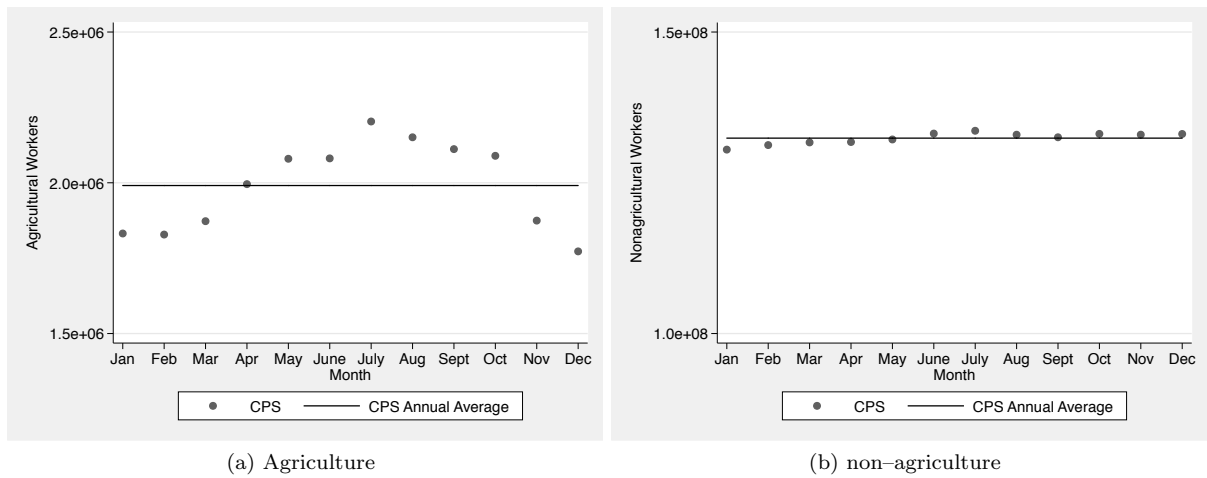


Figure D.2: Sectoral employment for US States in 2000

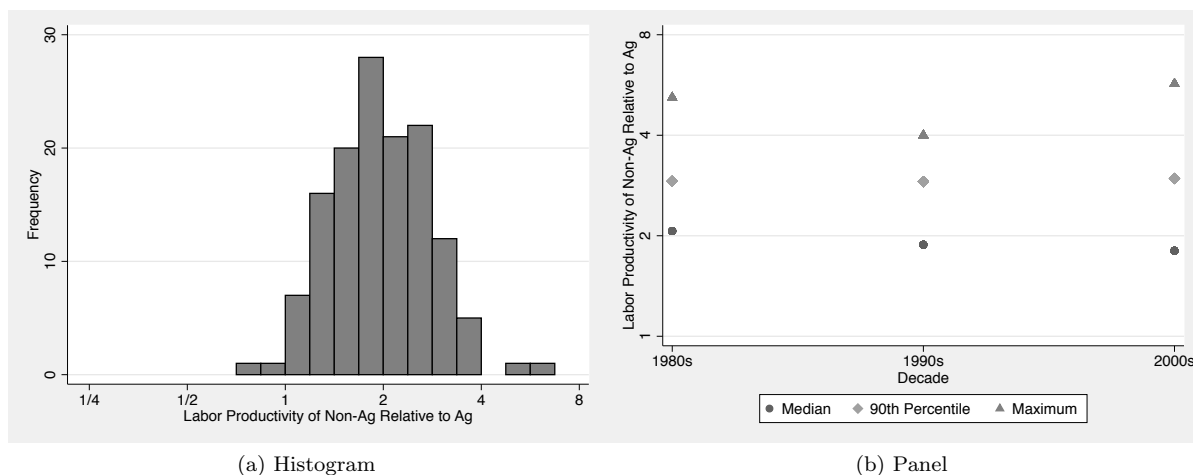


Figure D.3: Improved Measurement of Labor Productivity Gaps for US States 1980–2009

Figure D.4: Comparing the Estimates of the Gaps in Marginal Value Products for US States

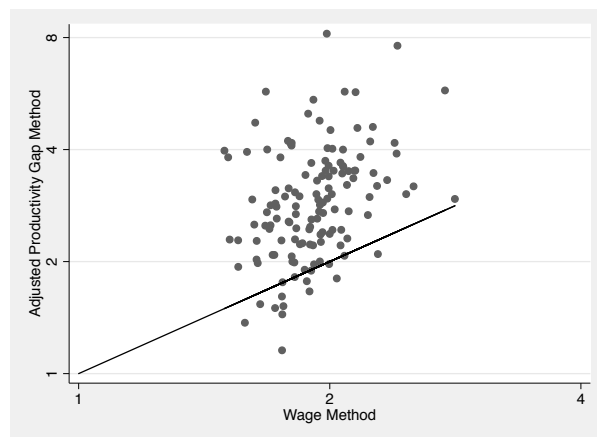


Figure D.5: Implied Labor Shares for US States

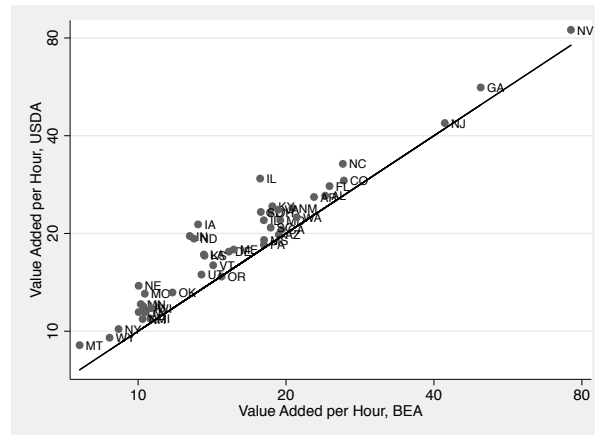
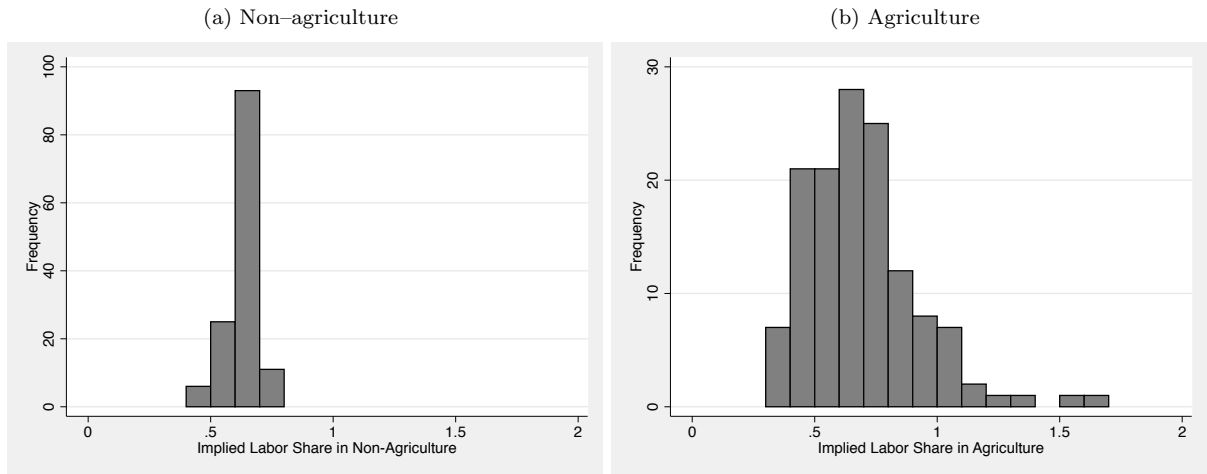


Figure D.6: Agricultural Value Added for US States in 2000 from Different Data Sources

Figure D.7: Proprietors' Share in Agricultural Value Added versus Productivity Gaps for US States (averages over 1980–2009)

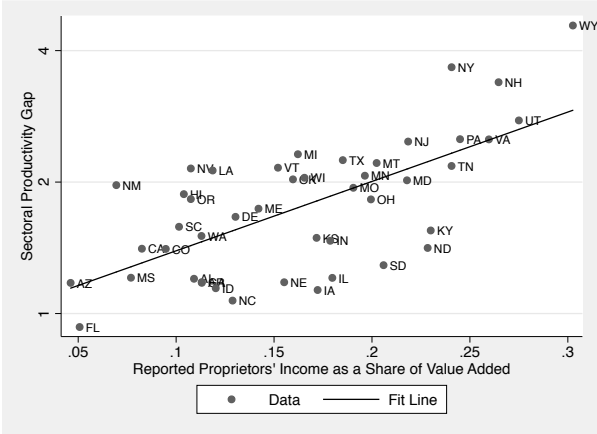


Figure D.8: Comparing Wage Gaps to Value Added Gaps across Different Countries

