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Structural change accounting with labor market distortions

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ABSTRACT

This paper quantifies the relative importance of sectoral productivity and labor market distortions for structural change in the U.S., India, Mexico and Brazil between 1960 and 2005. I use census data to compute human capital by sector and infer labor market distortions as sectoral gaps in wage per unit of human capital. I incorporate these distortions into a model of structural change, and calibrate the model to reproduce the time paths of sectoral shares of labor and value added for each country. Counterfactuals reveal that (1) TFP growth in agriculture drives most of the decline in its share of labor; (2) the role of labor market distortions is limited.

1. Introduction

An extensively documented feature of economic development is continued decline in the share of labor employed and value added produced in agriculture, commonly referred to as structural change. Perhaps less well known is that employment in agriculture declines at a much lower rate relative to value added. A direct implication is that value added per worker measured at domestic prices is lower in agriculture than in manufacturing and services. These features of the data are possibly symptoms of distortions to labor migration across sectors (Buera and Kaboski, 2009).[1]

In this paper, I construct a model of structural change that incorporates this kind of labor market distortion. The model can simultaneously account for the dynamics of employment and value added in the data. I use the model to quantitatively evaluate the importance of (1) productivity growth in agriculture vis-à-vis non-agriculture and (2) labor market distortions for structural change.

In doing so, this paper bridges two literatures. The macroeconomic literature on structural change typically assumes that labor can freely move across sectors, e.g., Kongsamut et al. (2001), Ngai and Pissarides (2007), and Acemoglu and Guerrieri (2008). While these models could generate the broad patterns of structural change observed in the data, they often have difficulty explaining the fact that employment and value added have markedly different dynamics. Another literature utilizes micro data to measure differences in wage and labor productivity across broad economic sectors, e.g., Hnatkovska and Lahiri (2013), Gollin et al. (2014) and Herrendorf and Schoellman (2014). These papers find that individual characteristics such as age and education cannot fully account for sectoral differences in wage or labor productivity,

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[1] Often cited examples are the *hukou* system in China and labor regulations in India manufacturing (Besley and Burgess, 2004).

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especially in poorer countries. To the extent that these observations are at odds with a frictionless labor market, there is suggestive evidence of distortions to inter-sectoral labor migration. This paper combines approaches from these two literatures: I use census data to measure labor market distortions and, in addition, evaluate their importance for structural change in a standard model. I apply the model to the growth experience of the U.S., India, Mexico, and Brazil over the period 1960–2005. The U.S. is a useful benchmark as it is commonly regarded as a frictionless economy. The rest are developing countries that account for 22 percent of world population in 2005; these countries experienced fast economic growth and significant structural change over the reference period. Another selection criterion is to have sufficiently detailed census data available from IPUMS.

The model economy has three sectors: agriculture, manufacturing, and services. Preferences are non-homothetic. Production technology in each sector is a linear combination of total factor productivity (TFP) and labor in efficiency units. I model labor market distortions as taxes on labor earnings. These taxes differ across sectors, thereby generating wedges in sectoral wages in equilibrium. The model is very parsimonious; it has six preference parameters and two exogenous sequences: TFP and wage wedges.

Wage wedges are computed as sectoral differences in wage per unit of human capital in the data. I construct measures for years of schooling and experience from census data of individual countries that are harmonized by IPUMS. I estimate country- and sector-specific Mincer returns by running wage regressions for each sector and for each country, and use these returns to translate years of schooling and experience to human capital. For the U.S., wage differences across sectors are mostly accounted for by human capital differences. As one might expect, there is little friction in the U.S. labor market. For other countries, human capital accounts for much less of the wage gaps between sectors – controlling for human capital, the average wage is 20 percent lower in agriculture compared to non-agriculture in India and as much as 50 percent in Mexico.

Given wage wedges, TFP for each sector is chosen such that the model reproduces time paths of sectoral shares of labor and real aggregate GDP per worker in the data.[2] As implications, the model also matches the shares of value added in the data. In addition, the model generates changes in relative prices of output that are quantitatively consistent with those in the data. Therefore, the model replicates the process of structural change for each country.

Next I use the model to answer two questions. First, in the presence of labor market distortions, what is the relative importance of TFP growth in agriculture versus non-agriculture for structural change? I provide answers to this question through two counterfactual experiments. Consider first a counterfactual economy in which TFP for agriculture is held constant at the initial value. I find that in this case labor migration out of agriculture either occurs at a much reduced pace or completely stops. This is true for all countries despite substantial differences in their initial share of labor in agriculture and per capita income. This result suggests that the decline of labor in agriculture is mostly driven by productivity growth in agriculture. To confirm this, consider another counterfactual economy in which TFP for non-agriculture is held constant at the initial level. The absence of productivity growth in non-agriculture has little effect on labor allocation – the share of labor in agriculture in this case looks nearly identical to the actual one. Therefore, a broad conclusion from these counterfactual experiments is that TFP growth in agriculture is the more important driver of structural change.

The second question asks the opposite: Given technological process, how important are labor market distortions for structural change? If these distortions have diminished over time, how much has the improvement in labor market efficiency contributed to structural change? If these distortions have not relaxed over time, what are the gains from policies that aim at reducing such distortions? I answer these questions by considering two counterfactual economies: one in which wage wedges are constant at their initial values and another one in which wage wedges are converging to zero. The findings are two-fold. On one hand, in countries where labor market efficiency has improved over time (as measured by the decline in wage wedges), such improvement has accelerated labor migration out of agriculture, but only by a small margin. On the other hand, in countries where labor market distortions have not diminished much historically, potential gains from further improvement in labor market efficiency is also limited. To provide a quantitative handle on this, consider the case of Mexico. If wage wedges have not declined as in the data, Mexico would have had a 2 percent higher share of labor in agriculture by 2005. Alternatively, if Mexico has a continually improving labor market and eventually a frictionless one, its share of labor in agriculture would have been lower by 2 percent by 2005.

Perhaps it is not surprising that wage wedges do not play a quantitatively important role for the U.S. For other countries, measured wage wedges suggest that their labor markets are far from frictionless, yet the counterfactual experiments suggest current allocations are not far from those in a frictionless economy. Why? First, this iterates the previous result that TFP growth in agriculture is the main driver of structural change. Wage wedges distort the allocation of labor across sector, but do not affect TFP. Therefore, labor market distortions play a secondary role relative to TFP. Second, while removing the wage wedges leads to more efficient allocation of labor (more precisely, human capital) across sectors, the gain in aggregate output is small.[3] I further show that the limited role of labor market distortions is robust to alternative ways of measuring wage wedges and different specifications of preferences.

This paper is broadly related to the literature on structural change, see Herrendorf et al. (2013a) and reference therein. It adds to papers that seek to identify determinants of structural change. For a set of industrialized countries, Alvarez-Cuadrado and Poschke (2011) find that productivity growth in agriculture is the more important factor for structural change

[2] These variables in the data are converted to ones expressed in efficiency units.

[3] Vollrath (2014) establishes a similar result by means of a development accounting exercise.

after 1960. Duarte and Restuccia (2010) use a similar model to gauge the importance of structural change in explaining the convergence of income per worker between late starters and the United States. The current paper complements these papers by considering the role of labor market distortions.

Several other papers also incorporate inter-sectoral distortions in a model of structural change. Cai and Pandey (2013) focus specifically on the size-dependent labor regulations in India's manufacturing sector. They find that while these regulations are crucial for the "missing middle" feature of the establishment size distribution, their impact on sectoral employment and aggregate output are small. Swiecki (2013) incorporates inter-sectoral distortions and international trade into a model of structural change, and finds that distortions play a secondary role relative to sectoral productivity growth. Restuccia et al. (2008) find that wage wedges, measured as differences in average wage across sectors, could significantly slow the process of structural change. Cheremukhin et al. (2013) use a neoclassical growth model to study industrialization of Russia. They find that labor market distortions are less important relative to distortions in the product market. The current paper differs from these papers in its use of census data to construct measures for human capital and wage wedges.

The remainder of this paper is organized as follows. Section 2 introduces the model. Section 3 presents the quantitative results. Section 4 concludes.

2. Model

Environment: The economy has a stand-in household composed of measure one identical members. The household's utility function is given by

$$U(c_a, c_m, c_s) = \left[\lambda_a^{1/\rho}(c_a - \overline{c_a})^{(\rho-1)/\rho} + \lambda_m^{1/\rho}(c_m)^{(\rho-1)/\rho} + \lambda_s^{1/\rho}(c_s + \overline{c_s})^{(\rho-1)/\rho}\right]^{\rho/(\rho-1)},$$

where c_a, c_m, c_s are the consumption goods produced in agriculture, manufacturing, and services, respectively. Preferences are non-homothetic given that $\overline{c_a} > 0$ and $\overline{c_s} > 0$. The weights on consumption goods are such that $0 < \lambda_i < 1$, and $\sum \lambda_i = 1$. The parameter ρ governs the elasticity of substitution between consumption goods.

Output in each sector, y_i, is produced by a representative firm using a linear technology $y_i = A_i N_i$, where A_i is the total factor productivity (TFP) and N_i is the labor in efficiency units.

There are competitive labor markets where firms hire labor. There are also competitive goods market where output is bought and sold. There is a government that levies taxes on labor earnings and rebates tax proceeds to the household via lump-sum transfers.

Optimization: The representative firm in sector i hires labor N_i to maximize profit

$$\max_{\{N_i\}} p_i y_i - w_i N_i, \tag{1}$$

where p_i is the price of output produced in sector i and w_i is the wage per efficiency worker.

The household chooses allocation of labor across sectors (n_a, n_m, n_s) and consumption allocations (c_a, c_m, c_s) to maximize utility, i.e.,

$$\begin{aligned} &\max_{\{c_a, c_m, c_s, n_a, n_m, n_s\}} U(c_a, c_m, c_s) \\ &\text{s.t.:} \sum p_i c_i = w_a n_a + (1-\tau_m) w_m n_m + (1-\tau_s) w_s n_s + TR, \\ &\sum n_i = 1, \end{aligned} \tag{2}$$

where τ_m and τ_s are taxes on labor earnings from manufacturing and services, respectively. For agriculture, the tax is normalized to zero. TR is transfer from the government.

The goods market clearing conditions are

$$c_a = A_a N_a, \quad c_m = A_m N_m, \quad c_s = A_s N_s. \tag{3}$$

The labor market clearing conditions are

$$n_a = N_a, \quad n_m = N_m, \quad n_s = N_s. \tag{4}$$

The government balances budget, i.e.,

$$TR = \tau_m w_m n_m + \tau_s w_s n_s. \tag{5}$$

Equilibrium: *A competitive equilibrium is a set of prices* $\{p_a, p_m, p_s, \ w_a, w_m, w_s\}$, *allocations for the household* $\{c_a, c_m, c_s, n_a, n_m, n_s\}$, *and allocations for the firm* $\{N_a, N_m, N_s\}$ *such that (i) given prices,* $\{N_a, N_m, N_s\}$ *solve the firm's profit maximization problem in* (1); *(ii) given prices,* $\{c_a, c_m, c_s, n_a, n_m, n_s\}$ *solve household's optimization problem in* (2); *and (iii) markets clear and government balances budget*: (*Eqs.* (3)–(5)) *hold.*

The first order conditions for the household's optimization implies

$$w_a = (1-\tau_m), \quad w_m = (1-\tau_s) w_s.$$

That is, the after tax wage is equated across sectors in equilibrium. Therefore, these taxes generate differences in wages across sectors. I refer to these differences as wage wedges through out the paper. The firm's profit maximization implies

$w_i = p_i A_i$. These conditions together yield the following expressions for the relative prices of output:

$$\frac{p_a}{p_m} = \frac{(1-\tau_m)A_m}{A_a}, \quad \frac{p_s}{p_m} = \frac{(1-\tau_m)A_m}{(1-\tau_s)A_s}. \tag{6}$$

The optimal consumption demand is given by the following equations:

$$\frac{c_a - \overline{c_a}}{c_m} = \left(\frac{\lambda_a}{\lambda_m}\right)\left(\frac{p_m}{p_a}\right)^{\rho},$$
$$\frac{c_s + \overline{c_s}}{c_m} = \left(\frac{\lambda_s}{\lambda_m}\right)\left(\frac{p_m}{p_s}\right)^{\rho}.$$

Using (6) and the market clearing conditions (3) and (4), the optimal consumption allocation can be written as

$$\frac{A_a n_a - \overline{c_a}}{A_m n_m} = \left(\frac{\lambda_a}{\lambda_m}\right)\left(\frac{A_a}{(1-\tau_m)A_m}\right)^{\rho}, \tag{7}$$

$$\frac{A_s n_s + \overline{c_s}}{A_m n_m} = \left(\frac{\lambda_s}{\lambda_m}\right)\left(\frac{(1-\tau_s)A_s}{(1-\tau_m)A_m}\right)^{\rho}. \tag{8}$$

The two equations above, together with the resources constraint $n_a + n_m + n_s = 1$, yield the share of efficiency labor in agriculture

$$n_a = \frac{1 + \frac{\overline{c_s}}{A_s} - \frac{\overline{c_a}}{A_a}}{1 + \left(\frac{\lambda_m}{\lambda_a}\right)(1-\tau_m)^{\rho}\left(\frac{A_a}{A_m}\right)^{1-\rho} + \left(\frac{\lambda_s}{\lambda_a}\right)(1-\tau_s)^{\rho}\left(\frac{A_a}{A_s}\right)^{1-\rho}} + \frac{\overline{c_a}}{A_a}. \tag{9}$$

Eq. (9) reveals mechanisms driving structural change that are standard in the literature. Other things equal, TFP growth in agriculture shifts labor towards manufacturing and services through two channels: an *income effect* that operates through the term $(\overline{c_a}/A_a)$ and a *relative price effect* that operates through the terms $(A_a/A_m)^{1-\rho}$ and $(A_a/A_s)^{1-\rho}$, provided that $0 < \rho < 1$. Eq. (9) also indicates that labor migration out of agriculture could be sped up through reductions in wage wedges. That is, the share of labor in agriculture increases with τ_m and τ_s. Note that the quantitative importance of wage wedges depends entirely on the elasticity of substitution ρ. Since labor taxes in the model are reimbursed back to the household, there is no loss in household income. Instead, these taxes change the relative prices of output – see Eq. (6), thereby affecting consumption allocations and consequently labor allocations. The importance of this mechanism depends on the complementarity of consumption goods. Consider the extreme case of $\rho = 0$. In this case, taxes have no impact on labor allocation at all because consumption allocation is independent of relative prices.

3. Quantitative analysis

Annual data on employment and value added by sector from 1960 to 2005 are from the GGDC 10-sector database (Timmer, 2009).[4] I map the 10 industries in the data to the three sectors in the model as follows. The agriculture sector is the sum of agriculture, forestry, and fishing. The manufacturing sector is the sum of mining, quarrying and manufacturing. And the services sector comprises of all remaining industries.

Human capital: To compute human capital, I use microdata from censuses of individual countries that are harmonized in IPUMS-International (2014). The minimum requirement for a sample is to have information on class of worker (employees or self-employed), hours of work, industry, core demographics, and educational attainment. For each country, it is further required that at least one sample has data on reported wage or earnings.

I follow the procedures in Herrendorf and Schoellman (2014) to calculate human capital by sector. This calculation involves two steps. First, I regress the logarithm of wage on years of schooling, years of experience, and gender. Note that (1) these wage regressions involve only employees in each sector, because self-employed do not report wage; (2) for each country, these wage regressions are run separately for agriculture, manufacturing and services. Hence, the Mincer returns to schooling and experience are country- and sector-specific. In this case, the sectoral differences in human capital come from both differences in educational attainment and differences in returns to education. In fact, the wage regressions suggest that the Mincer returns to schooling are systematically lower in agriculture than in manufacturing and in services. Second, I use the estimated Mincer returns to translate observed characteristics to human capital for all individuals, both employees and self-employed. The implicit assumption is that a self-employed with characteristics that are the same as an employee within a sector would have earned the same wage. It is critical that self-employed are included in the calculation of average human capital because they typically make up more than half of the labor force in agriculture, even in developed countries like the U.S. Further detail on human capital calculation is delegated to Section Appendix A of the Appendix.

[4] For Brazil, value added shares are from the World Development Indicators.

Table 1
Sectoral human capital.

Country	Average human capital	
	Manu./agri.	Serv./agri.
India	2.56	4.17
Mexico	1.96	2.17
Brazil	2.44	3.23
US	1.49	1.72

These sectoral human capital estimates are extended into an annual series using cubic-spline interpolation. Table 1 shows average human capital in manufacturing and services relative to that in agriculture. Agriculture is consistently the sector with the least average human capital and the gap is quite large – average human capital in non-agriculture is three times that in agriculture for India and Brazil. Even for the U.S., average human capital is close to twice larger in non-agriculture.

Wage wedges: In the model, wage wedges are sectoral differences in wage per efficiency worker. Therefore, a straightforward and consistent way to compute these wedges in the data is to calculate the residual differences in wage across sectors after adjusting for human capital. However, this calculation requires wage data at the sector level. This is not an issue for the U.S. since wage is available annually from the Current Population Survey (King et al., 2010). For other countries, wage data is much less frequent. For India, each of the five census samples contains wage information. For Mexico and Brazil, only one sample has income variables that could be used to compute wage.

I proceed as follows. For the U.S., I calculate wedges as $\tau_m = 1-(\hat{w}_a/h_a)/(\hat{w}_m/h_m)$ and $\tau_s = 1-(\hat{w}_a/h_a)/(\hat{w}_s/h_s)$, where $\hat{w}_i$ is the average wage and h_i is the average human capital for sector i.[5] For other countries, I take advantage of the linear production technology and the property that wage equates value added per worker in equilibrium. Therefore, I calculate wedges as $\tau_m = 1-(\widehat{vapw}_a/h_a)/(\widehat{vapw}_m/h_m)$ and $\tau_s = 1-(\widehat{vapw}_a/h_a)/(\widehat{vapw}_s/h_s)$, where $\widehat{vapw}_i$ is the value added per physical worker at current prices for sector i.

Admittedly, value added per worker is a noisy proxy for wage. For the purpose of this paper, however, it suffices that the ratio of value added per worker between sectors is a good proxy for the ratio of wage. This is true if labor income share is roughly the same across sectors. It should also be noted that this measure of wage wedges is subject to measurement errors if value added is mis-measured. In fact, Herrendorf and Schoellman (2015) and Cai and Pandey (2015) show that in many countries under-reporting of self-employment income could lead to agricultural value added that is substantially under-measured. In this case, the computed wage wedges are likely inflated as well. In Section 3.4 I provide a further discussion on alternative ways of measuring wage wedges.

With the limitations in mind, Table 2 presents for each country summary statistics for the imputed wage wedges. For the U.S., the differences in wage across sectors are mostly accounted for by differences in human capital. Also note that the average wage wedge between agriculture and non-agriculture (manufacturing and services) is practically zero. This is consistent with the finding in Herrendorf and Schoellman (2014). Outside the U.S., the wage wedges are generally fairly substantial. Holding human capital fixed, an average worker that moves from agriculture to manufacturing would experience a reduction in earnings that ranges from 24 percent in India to 61 percent in Brazil. Moving from agriculture to services, the reduction in earnings ranges from 13 percent in India to 58 percent in Mexico.

Efficiency units: The process of structural change is typically described by changes in the following variables in the data: the share of labor by sector, the share of value added by sector, and aggregate income per worker. The model is described with labor expressed in efficiency units. Therefore, mapping the model to data requires converting the relevant variables in the data into efficiency units as well. I observe from data the share of physical labor L_i and average human capital h_i. Therefore, I calculate the share of efficiency labor for sector i as

$$\frac{L_i h_i}{\sum L_i h_i}.$$

Note that the share of value added is independent of how labor is denominated and hence requires no conversion. Finally, I observe from data real GDP per physical worker *gdpwok*, which is converted to real GDP per efficiency worker as

$$\frac{gdpwok}{\sum L_i h_i}.$$

[5] Wage for self-employed is imputed as in Herrendorf and Schoellman (2014).

Table 2
Imputed wage wedges.

Country	(τ_m)		(τ_s)	
	Mean	Std.	Mean	Std.
US	0.14	0.06	−0.12	0.08
India	0.24	0.08	0.13	0.08
Mexico	0.47	0.06	0.58	0.10
Brazil	0.61	0.09	0.19	0.26

3.1. Calibration

In this section I describe how model parameters are determined. I set consumption weights as follow: $\lambda_a = 0.1, \lambda_m = 0.15, \lambda_s = 0.75$. For the elasticity of substitution, I set $\rho = 0.5$, roughly the mid-point of values estimated in Herrendorf et al. (2013b) under different specifications. This is also the preferred value in Buera and Kaboski (2009) for studying structural change in the U.S. dating back to 1870. These parameter values are also similar to those in Betts et al. (2013) and Uy et al. (2013).

There remains two preference parameters $(\overline{c_a}, \overline{c_s})$ to be determined. A common strategy in the literature is to choose values for these preference parameters to match sectoral shares of labor. Looking forward, this approach is not followed here. The reason is that sectoral shares of labor will later on be used to pin down the sequence of TFP. As a result, these moments in the data cannot be used to discipline the values for $\overline{c_a}$ and $\overline{c_s}$.

Instead, I calibrate these two parameters to relative prices of output in 1980 India. I proceed as follows. For a given choice of $\overline{c_a}$ and $\overline{c_s}$, I pick levels of TFP such that the model exactly matches the sectoral shares of labor observed in 1980 India data. The model then implies a particular set of relative prices of output: that between agriculture and manufacturing and that between services and manufacturing. The program then searches for combinations of $\overline{c_a}$ and $\overline{c_s}$ such that the model also matches these relative prices in the data. The calibration yields $\overline{c_a} = 878.6$ and $\overline{c_s} = 1552.7$.

In principle, the calibration could be applied to any country with relative price data. India is a convenient case for two reasons. First, India has the largest share of labor in agriculture in 1980. For such an economy, the calibration produces a tighter estimate for $\overline{c_a}$ and $\overline{c_s}$, because when income is low the share of labor in agriculture in the model is quite sensitive to the values for $\overline{c_a}$ and $\overline{c_s}$. This would not be the case if, for example, these values are calibrated to the U.S., where agriculture is almost a negligible component of the aggregate economy. Second, there is data for India to discipline other implications from the model that are not targeted in the calibration. Rosenzweig and Wolpin (1993) and Atkeson and Ogaki (1996) report that the subsistence consumption share of income is about 33 percent for India. The calibration of $\overline{c_a}$ produces a subsistence share of income that is 30 percent. This approach of using expenditure data to discipline the subsistence parameter is also used in Lagakos and Waugh (2013).

3.2. Accounting for structural change

The last exogenous variable is TFP for each sector: $\{A_a, A_m, A_s\}$. I use the model to infer these sequences. The basic idea is to pick these sequences such that the model reproduces the time paths of sectoral shares of labor and real aggregate GDP per worker observed in the data (both converted to efficiency units). Therefore, the model by construction replicates the process of structural change in the data.

How about sectoral shares of value added? It turns out that for India, Mexico and Brazil, matching labor shares in the data implies also that the model matches the value added shares in the data. This is by the virtue of the way wage wedges are computed for these countries.[6] For the U.S., the model matches value added shares well in the data by implication (see Section Appendix B of the Appendix). Therefore, in the counterfactual exercises that follow I could restrict my attention to only the labor allocation aspect of structural change.

With the inferred sequence of TFP, the model generates testable implications about the relative prices of output. Table 3 presents the annual percentage change of the price of output in agriculture and services relative to that in manufacturing, both in the data and in the model. To derive the price level of output by sector in the data, I divide value added in current prices by the value added in constant prices.[7] These price levels are then used to calculate the relative prices and their growth rates. It is reassuring that the model delivers changes in relative prices that are quantitatively consistent with those in the data. For example, the relative price of services has been increasing in all countries and that of agriculture has been increasing in all countries except Mexico. The model generates both observations.

[6] To see this, let $\hat{x}$ denote the data counterpart of variable x. Consider share of value added in agriculture in the model $v_a = \frac{p_a A_a n_a}{p_a A_a n_a + p_m A_m n_m + p_s A_s n_s}$. Using Eq. (6) and the fact that $1-\tau_m = \frac{\hat{p}_a \hat{y}_a / \hat{n}_a}{\hat{p}_m \hat{y}_m / \hat{n}_s}$ and $1-\tau_s = \frac{\hat{p}_a \hat{y}_a / \hat{n}_a}{\hat{p}_s \hat{y}_s / \hat{n}_s}$, we have $v_a = \frac{\hat{p}_a \hat{y}_a}{\hat{p}_a \hat{y}_a + \hat{p}_m \hat{y}_m \left(\frac{n_a}{n_m}\right)\left(\frac{\hat{n}_m}{\hat{n}_a}\right) + \hat{p}_s \hat{y}_s \left(\frac{n_a}{n_s}\right)\left(\frac{\hat{n}_s}{\hat{n}_s}\right)}$. Therefore, if $n_i = \hat{n}_i$ then $v_a = \hat{v}_a$ and similar arguments could establish also that $v_m = \hat{v}_m$ and $v_s = \hat{v}_s$.

[7] Data on value added in current prices are not available for Brazil until 1990. This precludes Brazil from the calculation of relative prices.

Table 3
Annual percentage changes of relative prices.

Country	Agr./man.		Ser./man.	
	Data	Model	Data	Model
India	1.27	0.88	1.35	1.86
Mexico	−0.88	−3.6	0.56	0.41
US	0.34	0.44	2.02	5.08

3.3. Counterfactual experiments

In this section I use the model to answer two broad questions of interest. The first question is to quantify the relative importance of TFP in agriculture versus outside agriculture for structural change, given distortions that prevail in the labor market. Rostow (1960) argues that productivity growth in agriculture is central to transition to modern growth. Recent quantitative investigations into this question reiterates this view, e.g., Gollin et al. (2007) and Duarte and Restuccia (2010). But these studies typically assume a frictionless labor market. The question I ask is which channel dominates in the presence of labor market distortions.

To isolate the importance of TFP in agriculture and non-agriculture, I perform two counterfactual experiments. In the first one, I keep agricultural TFP constant at the initial level. In the second one, I keep TFP for non-agriculture constant at the initial level. In each case, variables other than the ones described remain the same. Fig. 1 plots the share of labor in agriculture in the counterfactual economies along with actual one.

To the extent that the decline in the share of labor in agriculture is synonymous with structural change, a clear message from Fig. 1 is that in every country structural change is driven almost exclusively by TFP growth in agriculture. That is, once TFP growth in agriculture is shut down, labor barely moves from agriculture to the rest of the economy. In contrast, keeping TFP in manufacturing and services constant has minimal impact on the share of labor in agriculture. The mechanisms at work are standard. Reducing TFP in agriculture has two effects: (1) lower aggregate income, and therefore a higher share of labor in agriculture because income elasticity of agricultural consumption is less than unity; and (2) higher relative price of agricultural goods, and since consumption goods are complements, labor moves to a sector with increasing relative price. Hence, both the income effect and the relative price effect are working in the direction of “pulling” labor into agriculture.

On the other hand, reducing TFP growth in manufacturing and services drives labor into agriculture through an income effect, which is countered by higher relative price of non-agricultural output that draws labor out of agriculture. Quantitatively, the two effects off-set each other, leaving minimal changes to labor allocations. This is a property of the preferences formulation, in particular the fact that consumption goods are gross complements. Similarly, Herrendorf et al. (2013b) also find for the U.S. that the income effect and the relative price effect are equally important for structural change under the consumption value added specification.

The second question asks the opposite. That is, given technological progress, how important are labor market distortions for structural change. If these distortions have diminished over time, how much has the improvement in labor market efficiency contributed to structural change? If these distortions have not relaxed over time, what are the gains from policies that aim at reducing such distortions? Examples of policies that distort inter-sectoral labor movements are abundant. The size-dependent labor regulations derived from the Factory's Act in India restrict the manufacturing sector's ability to absorb labor from agriculture. The *Hukou* system in China has been often cited as an example of policies that restrict inter-sectoral labor movement. Answering these questions helps shed light on the costs of these policies (and the benefits from reverting them) in the context of structural change.

Specifically, I consider two counterfactual economies: one in which the wage wedges remain constant over time and another in which they gradually decline to zero. Again, exogenous variables other than the ones described remain unchanged. Fig. 2 plots the share of labor in agriculture in these two counterfactual economies along with actual ones. For India and the U.S., the measured wage wedges show little trend over time. Consequently, the labor allocations in the first counterfactual economy look nearly identical to actual ones. For Mexico and Brazil, the measured wage wedges have declined considerably over the sample period. The reduction in labor market distortions contributes to faster decline in the share of labor in agriculture by roughly 2 percent in Mexico and 1 percent in Brazil. Quantitatively, improving labor market efficiency contributes little to structural change.

In the second counterfactual economy, wage wedges were forced to gradually converge to zero. Relative to the data, the reallocation of labor out of agriculture is faster in the counterfactual economy. This is true for all countries but the magnitude differs across countries. For India, Brazil and the U.S., labor allocation in the counterfactual economy looks indistinguishable from the actual one. The most visible differences are observed in the case of Mexico: the share of labor in agriculture is 2 percent lower in the counterfactual economy along the path of structural change. Put differently, Mexico's share of labor in agriculture declines from 37 percent in 1960 to 8 percent in 2005; the same decline would have happened by 1996 in the counterfactual economy.

It is perhaps not surprising that for the U.S. wage wedges do not matter for allocations, because its labor market is close to frictionless after all. The more demanding question is why labor market distortions have limited effects on structural

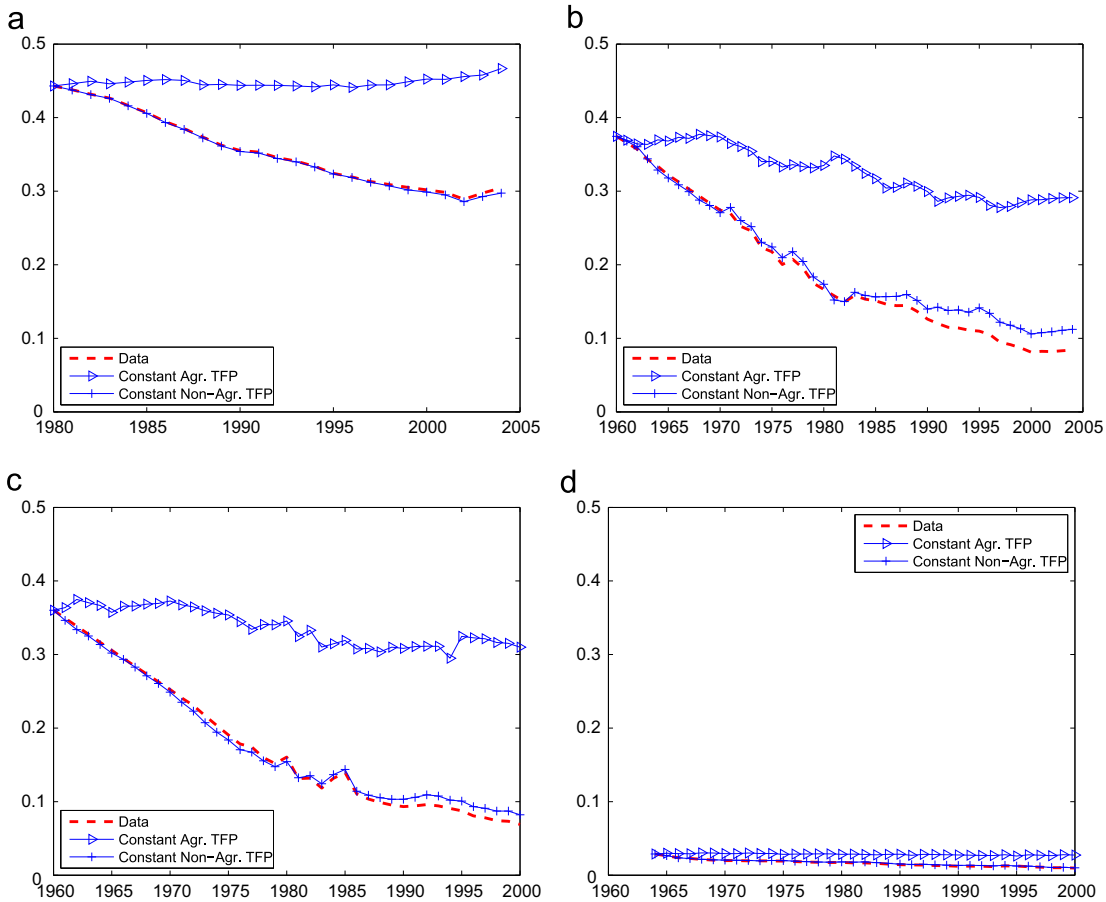

Fig. 1. Share of labor in agriculture with counterfactual TFP. (a) India. (b) Mexico. (c) Brazil. (d) United States.

change in other countries, despite sizeable wage wedges and a much larger initial share of labor in agriculture in these countries? The reasons are as follows. First, labor market distortions in the model do not affect sectoral TFP in equilibrium. As shown previously, TFP growth in agriculture is the dominant force behind structural change. Instead, the wage wedges in the model impact allocations through a *relative price effect*. Declining wage wedges, for example, render goods produced in manufacturing and services less expensive relative to agriculture – see Eq. (6). Therefore, expenditures shift away from goods produced in agriculture and labor moves out of agriculture. Furthermore, these adjustments are limited by the extent of complementarity between consumption goods. Consider the extreme case where consumptions are perfect complements, in which case expenditure would not adjust to changes in relative prices at all and those wedges would have no effect on labor allocations. This is most clearly seen in Eq. (9) by setting $\rho = 0$.

To see this in a different way, in the model the wage wedges lead to misallocation of labor across sectors. Removing the wage wedges, thus, leads to gains in aggregate output, thereby reducing the share of labor in agriculture because of the non-homothetic preferences. Quantitatively, such gains are small, e.g., removing wage wedges yields a 1.8 percent increase in output for Mexico. Since labor is denominated in efficiency units, in other words, the gain in aggregate efficiency through better allocation of human capital across sectors is limited. A similar conclusion is reached in Vollrath (2014) by means of development accounting and for a larger set of countries.

The broad conclusions from these counterfactual experiments are two-fold: (1) TFP growth in agriculture is the most important force behind structural change; (2) the role of labor market distortions is limited. The first conclusion concords with the consensus in the literature. The second one is subject to a few qualifications. First of all, the role of labor market distortions is evaluated in this paper using a very parsimonious model of structural change. This simple model might fail to capture other important margins, in particular, the possible interaction between distortions and TFP in agriculture. For example, labor market distortions in the framework Lagakos and Waugh (2013) could endogenously reduce TFP for agriculture through distorting self-selection of individuals. Second, the conclusion is about the role of labor market distortions in structural change. Obviously, reducing these distortions will have a first-order effect on the relative wage between agriculture and the rest of the economy. Therefore, labor market distortions could be important, qualitatively and quantitatively, for other aspects of the economy such as inequality and welfare.

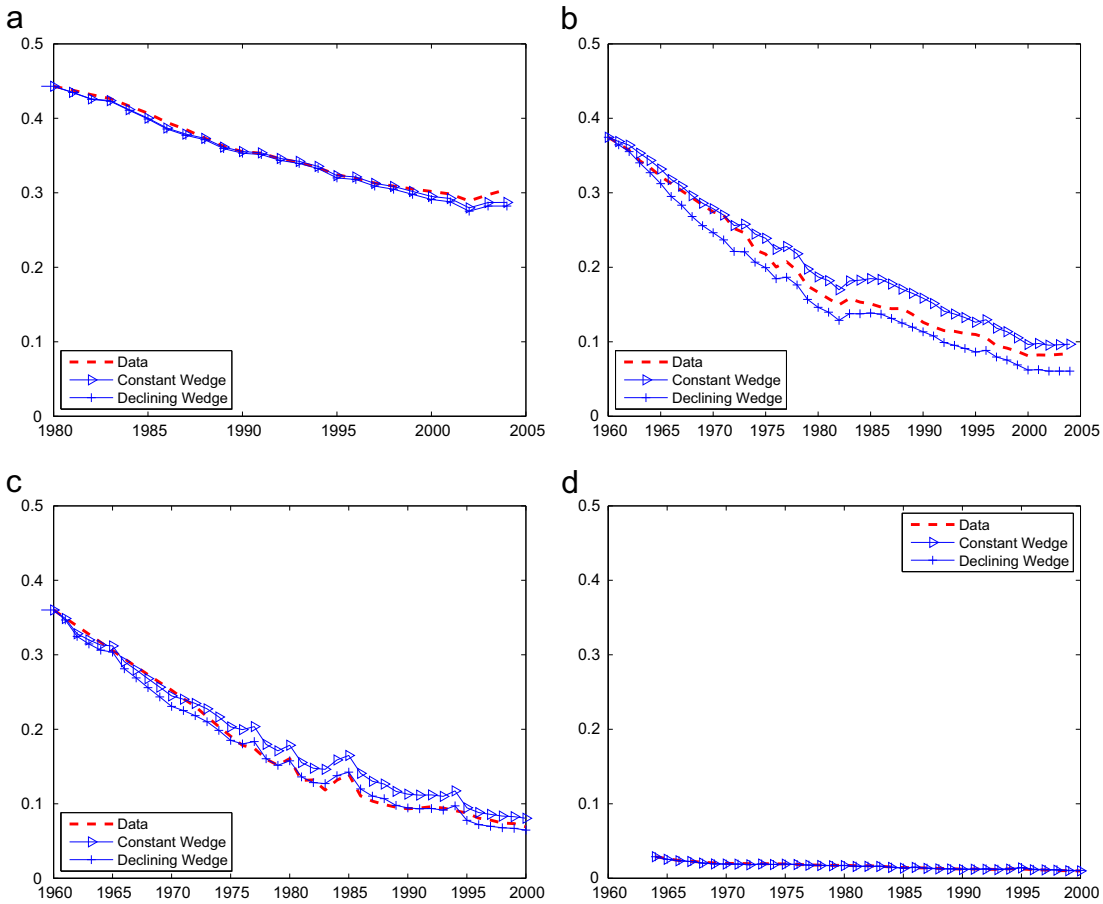

Fig. 2. Share of labor in agriculture with counterfactual wage wedges. (a) India. (b) Mexico. (c) Brazil. (d) United States.

Table 4
Wage wedges under alterative methods.

Sample	τ_m		τ_s	
	Wage	Value added	Wage	Value added
India 1983	0.22	0.27	0.01	0.11
India 1987	0.40	0.32	0.17	0.17
India 1993	0.29	0.20	0.11	0.05
India 1999	0.26	0.13	0.17	0.10
India 2004	0.24	0.36	0.16	0.34
Mexico 1990	0.07	0.36	0.12	0.43
Brazil 1991	0.03	0.56	−0.23	0.03

3.4. Robustness

In this section, I provide evidence that the results are robust to different ways of measuring wage wedges and different elasticities of substitution in preferences.

Alternative measures of wedges: The limited importance of wage wedges could be an artifact of mismeasuring these wedges. For countries other than the U.S., wage information is scarce in census data; and value added per worker is used as a proxy for wage. One possibility is that value added per worker is a poor proxy for wage, therefore under-estimates the true wage wedges. To verify this hypothesis, I focus on censuses in which wage data is available: India (1983, 1987, 1993, 1997, 2004), Mexico (1991) and Brazil (1990). For these samples, I compute wage wedges the same way I did for the U.S. Then I compare the resulting wage wedges against ones computed using value added data from the same year. Table 4 shows the wedges computed under these two different methods.

For India, different methods yield wedges that are similar in magnitude. For Mexico and Brazil, using wage data yields wedges that are significantly smaller. In this case, the quantitative importance of wedges for structural change would further reduce. Therefore, I conclude that the limited role played by wage wedges in structural change is not due to mismeasuring these wedges.

Different elasticity: Eq. (9) suggests that the quantitative importance of wage wedges increases when consumption goods are more substitutable (high values for ρ). There is considerable variation in the values for the elasticity in the literature. For the U.S., Herrendorf et al. (2013b) propose a range between 0 and 0.85 depending on whether the appropriate notion is final consumption expenditure or value added components of final consumption. Buera and Kaboski (2009) suggest a value of 0.5 in their analysis of U.S. structural change that covers a longer period of time. Adopting the methodology in Herrendorf et al. (2013b) and Uy et al. (2013) estimate an elasticity of 0.75 using Korea consumption data. Like in this paper, Betts et al. (2013) adopt a value of 0.5 in their analysis of structural change in Korea.

From the papers above, a reasonable upper bound for the elasticity is 0.75. Therefore, I repeat the accounting exercise using $\rho = 0.75$ for Mexico, for which the wage wedges appear to matter the most. I find that the results barely change with a higher elasticity. Therefore, for elasticity within a empirically feasible range, wage wedges are unlikely to have a large impact on structural change.

4. Conclusion

One of the fundamental questions in economics is why some countries are richer than others. The main reasons for low income in developing countries are high employment and simultaneously low productivity in agriculture (Caselli, 2005). Hence, understanding the determinants of structural change, and in particular that of labor migration from low-productivity agriculture to high-productivity manufacturing and services, is a key step towards understanding cross-country income difference. It is further observed that labor markets in many developing countries are subject to distortions that act as barriers to labor moving out of agriculture. These observations motivate the question asked in this paper: What is the relative importance of sectoral productivity and labor market distortions for structural change?

I first use census data to establish that for several developing countries labor market distortions, in the form of wedges in wage per unit of human capital across broad economic sectors, are systematic. Yet contrary to expectation, these wedges play a quantitatively limited role in structural change. Instead, most of the movement of labor from agriculture to non-agriculture is driven by improvement of productivity in agriculture. Furthermore, removing these labor market distortions yields positive but small gains in aggregate output. Therefore, the overall effects of labor market distortions are not quantitatively significant.

The analysis in the current paper is limited by the assumption that labor market distortions are orthogonal to TFP in agriculture. It is perceivable that labor market distortions could interact with other facts highlighted in the literature that are important for agricultural productivity such as technological adoption in Donovan (2013), self-selection as in Lagakos and Waugh (2013), and farm size in Adamopoulos and Restuccia (2014). This is left for future research.

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Appendix A. Sectoral human capital

Census data for India, Mexico and Brazil is from IPUMS-International (2014), and for the US IPUMS-CPS (King et al., 2010). There are five samples for India (1983, 1987, 1993, 1999, 2004) , six for Mexico (1960, 1970, 1990, 1995, 2000, 2010) and five for Brazil (1960, 1970, 1980, 1991, 2000). For the U.S., samples are March supplements to current population survey from 1964 to 2013.

Samples are further restricted to include individuals between age 18 and 65 with non-negative wage and salary income, non-negative hours of work, and information on age, gender, and educational attainment. Individuals are identified as employees or self-employed by their "class of workers".[8] Generally only employees report wage or income. Self-employed either do not report income or their reported income is hard to interpret and is thus ignored. If not reported, hourly wage is computed as total income divided by hours of work. Years of schooling are either directly observed or imputed using information provided in IPUMS. I calculate years of experience as min{age – 18, age – years of schooling – 6}.

I run OLS regression of the logarithm of wage for employees on their years of schooling, years of experience, years of experience squared, and gender. These wage regressions are run separately for each sector and for each country. Thus, the estimated Mincer returns are country- and sector-specific. These Mincer returns are then used to translate individuals characteristics to human capital for both employees and self-employed. It is important to include self-employed in the

[8] Self-employed include those who run their own business as well as unpaid family members.

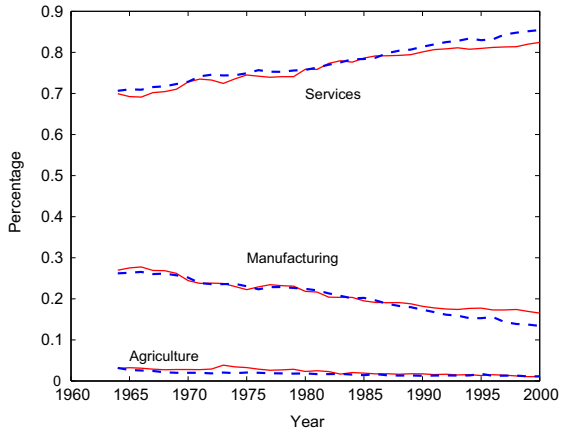

Fig. B1. US value added share by sector data (solid line). Model (dotted line).

calculation of average human capital because they make up more than half of the labor force in virtually every country, and a significant share of the labor force in services in low income countries.

The availability of wage and income variable in census varies across countries. For the U.S. and India, income information is available in each sample. In this case, the wage regression is run using pooled samples with year dummy to control for inflation. For Mexico, income information is available only in the 1990 sample, and for Brazil the 1991 sample. In this case, the wage regression uses only the referenced sample.

Appendix B. U.S. value added shares in the model

See Fig. B1.

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