

**Allocative Inefficiency and Sectoral Allocation of
Labor: Evidence From US Structural
Transformation**

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Allocative Inefficiency and Sectoral Allocation of Labor: Evidence from U.S. Structural Transformation *

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Abstract

Are productivity differences across producers in an industry a good indicator of allocative inefficiency? If so, what are the welfare consequences of reallocating labor from lesser to more productive producers? This paper addresses these questions in the context of factor specificity, which generates endogenous distribution of total factor productivity across producers, and reallocation of labor *across* sectors, as well as within a sector. The paper builds a multi-sector, multi-region general equilibrium model with land as a region-specific factor, and calibrates it using state-level U.S. data from 1960 to 2004, a period with considerable reallocation of labor out of agriculture. The results show that large and persistent differences in agricultural productivity across U.S. states are consistent with factor specificity due to geoclimatic conditions and do not correspond to economically significant allocative inefficiencies.

JEL classification: O14, O41, O11

Keywords: inefficient allocation of resources; reallocation of labor; agriculture; factor-augmenting technology; United States.

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1 Introduction

Are total factor productivity (TFP) differences across producers in an industry a good indicator of allocative inefficiency? If so, what are the welfare consequences of reallocating labor from lesser to more productive producers? In recent years, there has been a renewed interest among economists on allocative efficiency, and especially toward understanding the implications of inefficient allocation of resources across plants for aggregate productivity.¹ This literature typically starts from the well-documented observation that there are large TFP differences across plants in the manufacturing industry. Using these TFP differences as an indicator of allocative inefficiency, this literature measures the consequences of reallocation of resources for productivity *within* the corresponding manufacturing industry.

However, there are two issues that this literature has not so far satisfactorily addressed. First, reallocation of resources from lesser to more productive producers within a given industry is not the only alternative available to the economy. In an economy consisting of several distinct sectors, reallocation can also take place between sectors.² Accounting for such sectoral factor flows is important because, as resources relocate, there would be endogenous changes in prices and demand, and it would be necessary to account for these general equilibrium effects before one can be definitive about the destination of those resources released by less efficient plants. Existing literature has so far sidestepped this possibility and simply viewed allocative efficiency within the narrow confines of manufacturing industries alone and in a partial equilibrium setting.

Of course, one could argue that at least some of the resources used in manufacturing industries are sector-specific and may not have alternative uses outside that industry. While this argument is probably correct for specialized machinery and equipment, it is less persuasive for labor. Moreover, reallocation of labor across sectors may have non-negligible general equilibrium effects. Thus, given the possibilities that exist outside manufacturing, the focus on allocative inefficiency within manufacturing industries appears unduly restrictive.

The second issue that arises in the allocative efficiency literature is the source of total factor productivity differences across plants. There is widespread agreement that plants are not homogeneous in terms of their productivity levels due to a variety of reasons, including plant-specific factor endowments (Bartelsman and Doms, 2000). Ignoring these plant-specific factors may distort the true magnitude of productivity differences across plants and the economic significance of allocative inefficiency. In fact, one may be even tempted to rationalize all productivity differences across

¹In particular, there is also a growing literature on allocative efficiency using plant level data from U.S. manufacturing industries. See, for instance, Olley and Pakes (1996), Bartelsman and Doms (2000), Foster, Haltiwanger, and Syverson (2008), Petrin, White, and Reiter (2011), and Basu, Pascali, Schiantarelli, and Serven (2010). See also Hsieh and Klenow (2009) for a study of inefficient allocation of resources across manufacturing plants in China and India relative to that in the United States.

²One form of distinctiveness is to classify sectors in accordance with the income elasticity of demand for the products of each sector. Schultz (1945, p. 113), for instance, advocates this view.

plants by appealing to plant-level factor specificity.

Of course, others would argue that if there is indeed such an extensive factor specificity, then we should be able to observe its consequences in factor prices. So, to make a convincing case about the impact of factor specificity on productivity, one should observe physical quantities of factors of production and output, as well as prices of these specific factors. Since most studies on allocative efficiency do not have factor price data, they inevitably treat their factor inputs as homogenous across plants, with largely unexplored implications of factor specificity for resource allocation and efficiency.

It appears then that, to understand the welfare implications of allocative inefficiency, it might be important to allow for sectoral reallocation of labor in the presence of producer-level factor specificity. In this paper, I conduct a quantitative analysis of allocative inefficiency by adopting a framework with two core ingredients. First, I consider a *multi-sector* framework in which labor can be reallocated across sectors. This general equilibrium approach allows me to take into account labor reallocation across sectors in response to allocative inefficiency. Second, I consider a *multi-region* framework which allows for productivity differences in agriculture across regions due to factor-specificity. Agriculture is a natural context to think about specific factors: land is an immobile factor, and the quality of agricultural land and the corresponding climate (geoclimatic conditions) vary substantially even across short distances.³

Starting from such a framework, I develop a general equilibrium model with land as a region-specific factor, and calibrate it using state-level U.S. data. The model captures factor specificity through differences in land-specific (or land-augmenting) productivity across farm regions. These differences in land productivity across regions in turn manifest themselves as differences in farmland rents and in TFP. The necessary data to calibrate this model are total factor productivity estimates and factor prices for farm regions. For productivity data, I use agricultural TFP estimates of Ball, Wang, and Nehring (2010) on 48 contiguous U.S. states from 1960 to 2004. For factor price data, I construct a novel database on farmland rents and farm wages by state covering the same period. In the data, there are substantial differences in farmland rents across regions, there are substantial differences in farmland rents across regions, and there is substantial reallocation of labor out of U.S. agriculture.

Even after factoring in land-specificity into TFP differentials, the calibrated model points to significant deviations from allocative efficiency in U.S. agriculture, and that some states employ “too much” agricultural labor, while others employ “too little” labor. Although both of these cases correspond to inefficient allocation of labor, the results indicate that in terms of quantities, the

³I think of a specific factor as one with limited or no mobility and with inherent characteristics. This definition is consistent with the use of factor specificity in models of international trade (e.g., Dixit and Norman, 1980, chp. 3). It is distinct from factor specificity that arises from relationship-specific investment in an asset with limited outside options.

net benefit of moving to an efficient allocation of labor in agriculture would have amounted to less than 1 percent of total agricultural output per year.⁴ Even after one allows for alternative uses of labor outside agriculture, the welfare costs of inefficient allocation of labor remain low: over the sample period, the welfare costs have amounted to less than 0.25 percent permanent reduction in non-farm consumption. These findings suggest that seemingly large within-sector productivity differences across producers may not necessarily have large aggregate welfare implications, and the U.S. structural transformation of the last 50 years was essentially driven by factors other than responses to inefficient allocation of resources.

Within the recent literature on the economic consequences of productivity differences across plants, the paper by Basu et al. (2010) is the closest to the approach taken here. They also study the welfare implications of resource reallocation using equilibrium modeling. However, their data are from the manufacturing industry, and they do not consider factor specificity. This paper is also related to the literature on the conventional accounts of structural change in the United States that has exclusively focused on between-sector labor reallocation. These accounts emphasize labor reallocation from inefficient to efficient sectors, and sectoral differences in productivity growth and income elasticities of demand. For instance, in a highly influential account of U.S. agriculture, Schultz (1945) defines the “farm problem” as an inefficient allocation of labor *between* agriculture and the rest of the economy.⁵ To allow for these effects, this paper studies the allocation of labor both within-agriculture and across sectors.

The rest of the paper is organized as follows. Section 2 documents the distribution of agricultural TFP across U.S. states from 1960 to 2004. Section 3 presents a multi-sector general equilibrium model which frames the questions of allocative inefficiency relative to a benchmark. Section 4 quantifies the degree of allocative inefficiency both across farm regions and across sectors. Section 5 discusses the possible determinants of allocative inefficiency identified by the model. It considers three possible explanations; policy distortions, regional specialization along product characteristics, and geoclimatic variability and its impact on measures of TFP. Section 6 concludes. Discussion of data sources and several technical issues are contained in three separate appendices. The online Supplementary Material contains detailed information on dataset construction, derivations, and a description of computer codes for replication.

⁴In the model, there is separate demand for amenities provided by land and the corresponding climate, and there is a distinction between farmland productivity and landscape amenities, which jointly determine the allocation of land between farm and non-farm uses. In any case, if there is “too much” agricultural labor due to landscape amenities not accounted for by the model, true economic inefficiency would be even lower, not higher.

⁵Schultz (1945, pp. 47–49, chp. 4) argued that despite persistent differences between agriculture and non-agriculture in their value marginal products of labor, labor reallocation toward non-agriculture was slow due to “barriers” to labor mobility. See Caselli and Coleman (2001) and Dennis and İřcan (2007) for quantitative assessments of the contribution of such channels to agricultural out-migration in the United States. Lee and Wolpin (2006) investigate the contribution of labor mobility across sectors to the growth of service sector employment.

2 The dispersion of farm productivity

Existing productivity dynamics at the plant level has carefully documented the dispersion of productivity across manufacturing plants.⁶ Recent research has used these differences to understand their implications for allocative efficiency. The objective of this section is to document the considerable dispersion of agricultural productivity across 48 contiguous U.S. states from 1960 to 2004.

The agricultural productivity data I use in this study come from the Ball et al. (2010) dataset and are in turn based on a multi-factor productivity estimation method discussed extensively in Ball, Bureau, Nehring, and Somwaru (1997). In the original dataset, all variables are reported as index numbers, and in each case indices are relative to Alabama in 1996 normalized to 1. I document the dispersion of agricultural productivity across states in two ways.

Figure 1 plots the density estimates of log farm productivity levels across 48 contiguous U.S. states for five reference years: 1960, 1970, 1980 (fig. 1A), 1990, and 2000 (fig. 1B). For ease of comparison, the density estimates in each year are centered around that year's mean productivity across states (shown by the vertical line at zero). The estimates indicate considerable dispersion in productivity levels across states, with the ratio of farm productivity in the highest productivity states to the lowest productivity states consistently exceeding 2. For instance, in 2004, farm productivity in California (highest ranked) was higher than that of Wyoming (lowest rank) by a factor of 3. Also, the density estimates suggest that the dispersion of productivity has varied over these reference years, but not in a direction that points to any secular decrease or increase in dispersion.

I document the changes in dispersion of agricultural productivity over time by the coefficient of variation in log productivity across states. Figure 1C shows that the coefficient of variation of log agricultural productivity jumped noticeably in the early 1970s, but since then this measure of dispersion has fluctuated in a narrow band. Overall, then both the density estimates and coefficient of variation indicate that there has been considerable dispersion across U.S. states in agricultural productivity levels, and there does not appear to be a uniform tendency for this dispersion to shrink or expand over the last four decades.

How much of this dispersion simply reflects random movements of individual states within the log agricultural productivity distribution? And, how much of this dispersion is due to persistent, state-specific effects? While it is difficult to be definitive about the transitory versus permanent components of productivity differences across states with 45 observations, there is considerable evidence suggesting that these large differences in productivity are not due to year-to-year random variations. For instance, California, Florida and Iowa rank the highest in terms of productivity

⁶Unless otherwise stated, henceforth productivity refers to total factor productivity.

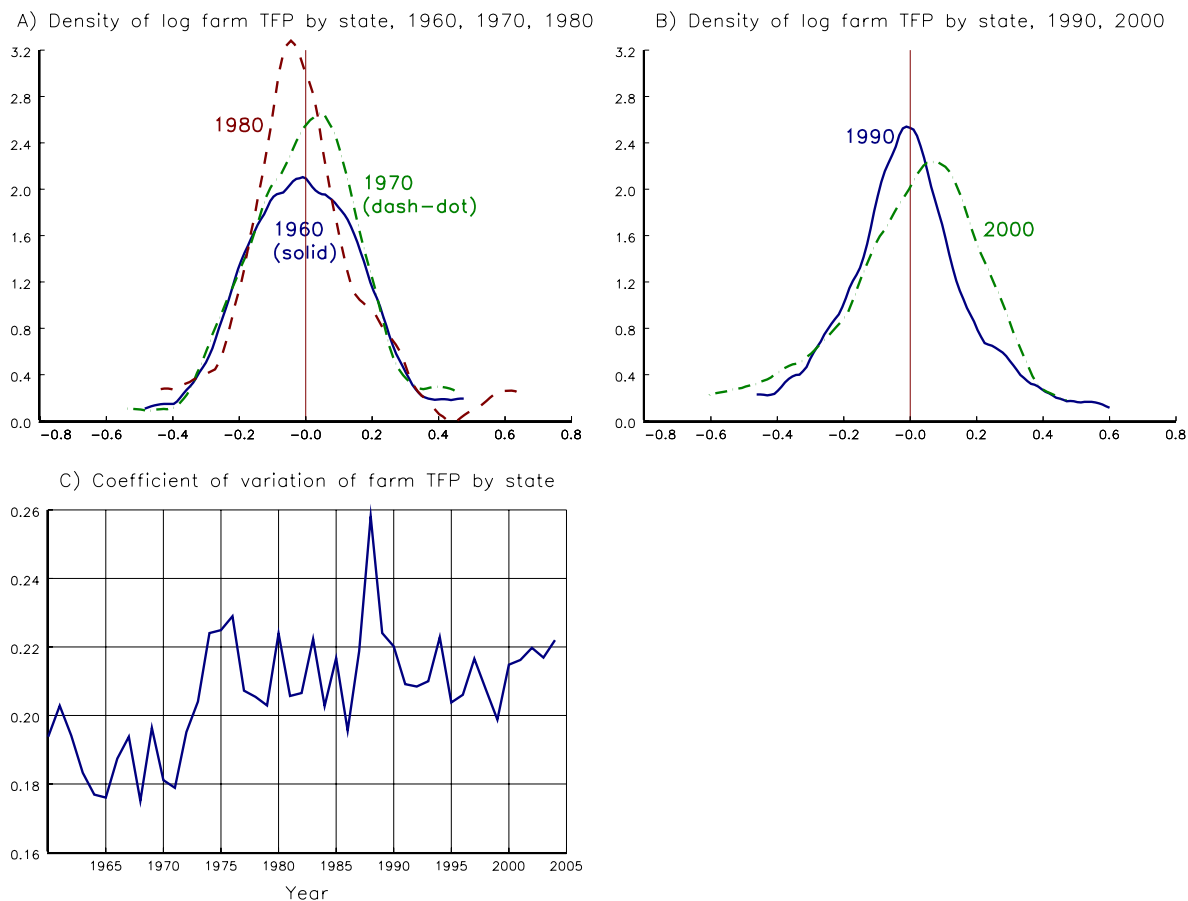


Figure 1: Dispersion of farm productivity levels across U.S. states

Note: **A–B**) The kernel density estimates of farm total factor productivity (TFP) across 48 contiguous U.S. states for selected years. For each year, the density estimates are centered around the mean TFP across states in that year. **C**) The coefficient of variation defined as the across-state standard deviation of TFP in agriculture divided by mean TFP in agriculture. State-level TFP data are from Ball et al. (2010) and cover the period 1960–2004.

in 2004, and their rank orders have changed very little since 1960. Tennessee, West Virginia and Wyoming rank the lowest in terms of productivity in 2004, with both Tennessee and Wyoming exhibiting a fall in their rank orders relative to 1960. The three states which show the most significant relative gains in ranking over time are Indiana (from 27th to 7th place), Rhode Island (from 35th to 8th place), and Oregon (from 46th to 15th place).

In fact, convergence in productivity levels across states is remarkably slow. The online Supplementary Material shows that, although there is a negative correlation between initial productivity level and future productivity growth, the initial productivity accounts for only about 4 percent of the variation in future productivity growth across the states. There is also low persistence of productivity rank orders by state, especially in the mid-productivity range. In the same vein, using *conditional* convergence regressions, Ball, Hallahan, and Nehring (2004) conclude that the convergence rate among U.S. states in agricultural productivity is slow (see also Huffman and Evenson,

1993, p. 203). Thus, while there is evidence for (unconditional) convergence in productivity levels, the magnitude of this convergence is small, with limited upward and downward mobility in rank orders over time. These point to state-specific determinants of productivity in U.S. agriculture, and to the case that factor-specificity would be a fruitful way to think about agricultural productivity differences across states.

3 The model

In this section, I construct a multi-sector model, which allows me to address to what extent agricultural productivity differences across U.S. states correspond to inefficient allocation of resources, and how much welfare gains would in principle be achieved by moving to an efficient allocation of labor. As it will become clear, moving to an efficient allocation would involve both reallocation of labor within agriculture and between sectors. The framework also allows for specificity of geoclimatic conditions in agricultural production.

3.1 Basic elements of the model

Time is discrete and each period is labeled as $t = 0, 1, 2, \dots$. There are three sectors in the model: farm f and non-farm n , and a non-farm landscape h sector that is included to make allowance for non-farm landuse. Let $s \in \{f, n, h\}$ index these sectors. There are three factors of production: labor L , land T , and capital K . Geographically, the economy consists of regions, which are labeled by $j \in \{1, 2, \dots, J\}$. Demographically, the economy features an infinitely-lived representative household whose labor force grows exogenously:

$$\frac{L_t}{L_{t-1}} = n_t. \tag{1}$$

Labour is mobile across sectors and regions. Land is region specific, but otherwise can be used for producing food and non-farm amenities. Production in each sector uses a combination of labor, land, and capital. These factors are linked to value added (output net of intermediate inputs) through sectoral production functions. The farm sector uses L and region-specific T to produce food, non-farm sector uses L and K to produce a non-food consumption good, and non-farm landscape sector uses region-specific T to produce region-specific non-farm landscape amenities. The representative household has preferences over the consumption of food, the non-food good, and non-farm landscape amenities.⁷

Production in each sector also depends on factor-augmenting efficiency. Let $A_{s jt}^K$, $A_{s jt}^L$, and $A_{s jt}^T$ be the efficiency terms corresponding to capital, labor, and land at time t in sector s and region j .

⁷The model links sectors only through factor markets, and does not incorporate intermediate inputs. Thus, in the model, food and non-food consumption originating from farm and non-farm sectors, respectively, do not directly map into their counterparts in the national income and product accounts.

These efficiency terms change over time exogenously. Define G as the growth factor (gross growth rate):

$$G(A_{s jt}^X) = \frac{A_{s jt}^X}{A_{s j, t-1}^X}, \quad X \in \{K, L, T\}. \quad (2)$$

Finally, define the growth rate as $g(A_{s jt}^X) = \ln(G(A_{s jt}^X))$.

In what follows, I describe the demand and supply sides of the economy in detail, and suppress the time variable when this causes no confusion.

3.2 Preferences

The per person instantaneous utility function is Cobb-Douglas $u(C_t, H_t) = \ln(C_t^{\eta^c} H_t^{1-\eta^c})$, where $0 < \eta^c < 1$, the composite consumption good C is constant elasticity of substitution (CES) across good and non-food consumption

$$\left[(1 - \eta^n)^{\frac{1}{\nu}} (C_f - \gamma)^{\frac{\nu-1}{\nu}} + (\eta^n)^{\frac{1}{\nu}} C_n^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}}, \quad 0 < \eta^n < 1, \gamma \geq 0, 0 < \nu < 1, \quad (3)$$

and the consumption of composite non-farm landscape H is CES across region-specific landscape amenities

$$\left[\sum_{j=1}^J (\eta_j^h)^{\frac{1}{\mu}} H_j^{\frac{\mu-1}{\mu}} \right]^{\frac{\mu}{\mu-1}}, \quad \sum_j \eta_j^h = 1, 0 < \eta_j^h < 1, \mu > 0. \quad (4)$$

The instantaneous utility function has unitary elasticity of substitution between C and H , with fixed expenditure shares given by the weight parameters η^c and $1 - \eta^c$, respectively. The composite consumption good is non-homothetic because of subsistence (determined by the parameter γ) nature of food consumption. Food and non-food consumption are gross complements and the degree of complementary depends on the elasticity parameter ν . Expenditure shares of food (net of subsistence food consumption) and non-food depend on the weight parameters $1 - \eta^n$ and η^n , respectively. Preferences for region-specific landscape amenities have a CES structure with weight parameters given by η_j^h , and elasticity parameter given by μ .⁸

The lifetime utility function of the representative household U is additively separable over time

$$\sum_{t=0}^{\infty} \beta^t L_t u(C_t, H_t), \quad 0 < \beta < 1, \quad (5)$$

with a subjective time discount factor β .

⁸For non-farm landscape, the specification allows for different weights in the sub-utility function on different region-specific landscape amenities, and thus allows for preferences for landscape amenities that vary across regions. The elasticity of substitution in amenities across any two pairs of regions, however, is constant.

3.3 Production

Production in each sector is characterized by a constant returns to scale production function. Production in each sector and each region is undertaken by a representative firm. Farm output in region j , Y_{fj} , is CES between labor and region-specific land:⁹

$$\left[\alpha_f^L (A_f^L L_{fj})^{\frac{\sigma_f-1}{\sigma_f}} + \alpha_f^T (A_{fj}^T T_{fj})^{\frac{\sigma_f-1}{\sigma_f}} \right]^{\frac{\sigma_f}{\sigma_f-1}}, \quad \alpha_f^L + \alpha_f^T = 1, \quad \sigma_f > 0. \quad (6)$$

The weights of labor and land in farm production depend on the parameters α_f^L and α_f^T , respectively. The elasticity of substitution between land and labor in farm production is σ_f .

This specification captures two empirically relevant issues. There is a sector-specific component to efficiency of labor in the farm sector (A_f^L), but this labor efficiency term is not region specific; agricultural knowledge and skills are mobile across farm regions. By contrast, land efficiency in agriculture (A_{fj}^T) is not only sector-specific, but is also region specific due to geoclimatic conditions. This is the main factor-specificity captured by the model.¹⁰

Non-farm output Y_n is Cobb-Douglas in labor and physical capital, and does not depend on region-specific inputs:

$$K_n^{\alpha_n^K} (A_n^L L_n)^{\alpha_n^L}, \quad \alpha_n^L + \alpha_n^K = 1. \quad (7)$$

In non-farm production, the elasticity of substitution between capital and labor is unitary, and the corresponding factor weights are α_n^K and α_n^L , respectively. Non-farm labor-efficiency term A_n^L can be expressed as a function of total-factor-augmenting technology, $A_n^L \equiv A_n^{1/\alpha_n^L}$.

The provision of non-farm landscape amenities in region j , Y_{hj} , is linear in region-specific land:

$$A_{hj}^T T_{hj}. \quad (8)$$

The land-efficiency term in non-farm landscape sector A_{hj}^T is region specific; regions offer their idiosyncratic landscape amenities.

The outputs of farm and non-farm landscape sectors are non-durable. Only the output of the non-farm sector can be either consumed or invested in the form of physical capital stock. So, at time t , $Y_{nt} = L_t C_t^n + I_t$, where I is gross investment. Capital stock used in the production of non-farm output changes according to

$$K_{n,t+1} = I_t + (1 - \delta)K_{nt}, \quad (9)$$

⁹Non-farm intermediate inputs are a relatively small fraction of total costs in agriculture. In fact, from 1960 to 1994, feed, seed, and livestock purchases, all originating from agriculture, stand out as the most significant intermediate input into agriculture (23 percent), and the cost shares of physical capital and agricultural chemicals in total agricultural costs were small at 9.4 and 6.3 percent, respectively (Ball et al., 1997). Thus, for modeling purposes, it is reasonable to specify a farm production function net of all intermediate inputs, and one which only uses land and labor.

¹⁰While individual product characteristics in agriculture vary little across state borders (like different wheat and corn varieties), agriculture does not produce a homogenous product. In the data, the limiting factor is availability of TFP estimates at the state-product level. I will return to this issue below.

where $0 \leq \delta < 1$ is the depreciation rate.

3.4 Markets and equilibrium

Product prices and returns to factors of production are determined in competitive markets.¹¹ The representative household owns the land and capital stock, and rents these to firms. The rental rates of capital and region-specific land are, respectively, r^K and r_j^T , $j = 1, \dots, J$. The wage rate is W . Product prices corresponding to farm, non-farm, and region-specific amenities are, respectively, P_f, P_n , and P_{hj} , $j = 1, \dots, J$. The equilibrium concept used in the model is as follows.

Definition 1 *A competitive equilibrium of this economy is a set of non-negative allocations*

$$\mathbf{x}^* = \{C_{ft}^*, C_{nt}^*, H_{1t}^*, \dots, H_{Jt}^*, L_{f1t}^*, \dots, L_{fJt}^*, L_{nt}^*, T_{f1t}^*, \dots, T_{fJt}^*, K_t^*\}_{t=0}^\infty,$$

and prices

$$\mathbf{p}^* = \{P_{ft}^*, P_{nt}^*, P_{h1t}^*, \dots, P_{hJt}^*, W_t^*, r_t^{K*}, r_{1t}^{T*}, \dots, r_{Jt}^{T*}\}_{t=0}^\infty,$$

such that, given the initial conditions for capital stock, the labor force and the technology variables

$$(K_0, L_0, A_{f0}^L, A_{n0}^L, A_{f10}^T, \dots, A_{fJ0}^T, A_{h10}^T, \dots, A_{hJ0}^T) > 0,$$

and the exogenous laws of motion for the labor force and the efficiency terms

$$\{L_t, A_{ft}^L, A_{nt}^L, A_{f1t}^T, \dots, A_{fJt}^T, A_{h1t}^T, \dots, A_{hJt}^T\}_{t=0}^\infty,$$

every representative firm in region $j = 1, 2, \dots, J$, maximizes profits, the representative household maximizes lifetime utility, and all markets clear.¹²

4 Allocation of labor

In the rest of the paper, a calibrated version of the model developed in Section 3 will serve as the benchmark economy with efficient allocation of resources, and these allocations will be numerically computed. In Section 4.1, I discuss the intra-temporal conditions that characterize the efficient allocation of resources in the model economy. The task then is to assess the extent to which realized allocations of resources deviate from the benchmark. Since land is a fixed, region-specific factor, I refine this question by focusing on the allocation of labor, and use the realized values of land input

¹¹Agriculture has traditionally been a highly competitive sector both within and across state borders, with price-taking being the norm rather than exception (Gardner, 2002). So, competitive product markets appear appropriate. The literature exemplified by Schultz (1945) was largely concerned about the barriers to the mobility of agricultural labor, and would put into question the competitive nature of labor markets in the American South. However, competitive labor markets is a reasonable first approximation for the period I study here.

¹²A more complete definition of equilibrium, and its characterization can be found in the Supplementary Material S.2.

in agriculture and non-agriculture. Thus, the model is calibrated to match the allocation of land by state T_{fjt} in the data.

The difference between the model-based benchmark and the realized allocations of labor constitutes a measure of allocative inefficiency.¹³ There are at least two alternative ways to measure inefficiency. First, take as given total agricultural employment, and then compute the difference between the benchmark and the realized allocations of labor across farm regions. Section 4.2 implements this method by computing the total agricultural output loss due to prevailing allocative inefficiency within agriculture. Second, take as given total farm output, and then compute the difference between the benchmark and the realized allocations of labor both between agriculture and non-agriculture, and across farm regions. Section 4.3 implements this method by calculating the total non-agricultural output loss due to economy-wide allocative inefficiency.

4.1 Efficient allocations

According to the model, in equilibrium efficiency-adjusted wages are identical across regions. The direct implication of this equilibrium condition is that efficiency adjusted land-to-labor ratio

$$\tilde{l}_{fj} = \frac{A_{fj}^T T_{fj}}{A_f^L L_{fj}} \quad (10)$$

is uniform across regions $\tilde{l}_{fj} = \tilde{l}_f$. Moreover, the labor market clearing condition implies that the share of agriculture in employment (the left-hand side of equation (11)) is related to the allocation of labor and land across regions (the right-hand side of equation (11)):

$$\frac{L_{ft}}{L_t} = \left(\frac{1}{\tilde{l}_{ft}} \right) \left(\frac{1}{A_{ft}^L L_t} \right) \sum_{j=1}^J A_{fjt}^T T_{fjt}. \quad (11)$$

Expressions similar to equation (10) have been used by Hsieh and Klenow (2009), Petrin and Sivadasan (2011), and others, in both calibration and econometric-based studies of allocative efficiency—but without separate factor augmenting terms for labor A_f^L and land A_{fj}^T .¹⁴ In the absence of factor specificity, there would be a uniform land-augmenting term, and thus in equilibrium land-to-labor ratios in agriculture would be identical across regions.¹⁵ In the current context, these equilibrium conditions require measures of farm sector labor- and land-augmenting terms. These factor augmenting terms are obtained using a method developed by Mundlak (2005) for agriculture. This method first determines the *relative* factor augmenting technology by region,

¹³Using a model-based or empirical benchmark is standard in the literature (e.g., Hsieh and Klenow, 2009). Naturally, this raises the question: how much faith should one have in the model? I will address this question from a variety of angles below. An alternative approach, which is not pursued here, would be to rationalize the data by appealing to a statistical model.

¹⁴In this section, I use “land augmenting” and “land efficiency” terms (and similarly for labor) interchangeably.

¹⁵An identical agricultural land-to-labor ratio across U.S. states is grossly at odds with the data. See Appendix figure A.1.

and then apportions the growth rate of state-level farm sector multifactor productivity into the growth rates of farm sector labor- and land-augmenting technical change. The details are contained in Appendix B.1.¹⁶

The estimates of labor- and land-augmenting terms in agriculture (A_{ft}^L, A_{fjt}^T) depend on the values of the weight of labor in agriculture α_f^L , and the elasticity of substitution between labor and land in agriculture σ_f . In the rest of the paper, I primarily rely on the “base case” parameter values that are the most common estimates available in the empirical literature, but I also check the robustness of the results to alternative parameter values. These base case parameter values are: $\sigma_f = 0.2$ and $\alpha_f^L = 0.654$ (see Appendix A.2 for data sources).¹⁷

The estimates of factor-augmenting efficiency also have implications for the distribution of non-farm landscape amenities across U.S. states—a dimension of the data that is not targeted by the calibration. In Supplementary Material S.3, I derive and demonstrate these implications. Overall, I find that the calibrated model implies that Northeastern states exhibit the highest non-farm landscape productivity A_{hj}^T , congruent with relatively higher population density in these states and intensive agricultural activity. By contrast, the calibrated model implies that Plains and Mountain states have the lowest non-farm landscape productivity, also congruent with their low population densities and relatively extensive agriculture.

Another distinguishing feature of the present framework is equation (11), which accounts for the labor market-clearing condition. Partial equilibrium models typically do not consider such restrictions. Incorporating this condition allows me to discipline the analysis by taking resource constraints into consideration.

4.2 Allocation of labor across U.S. states

The first method I use to assess the degree of allocative inefficiency is based on the actual share of employment in agriculture; thus, the model is calibrated using realized data on the left-hand side of equation (11) and this share is shown in figure 2A. This also pins down \tilde{l}_{ft} in equation (11). Given the share of employment in agriculture, the allocation of labor across U.S. farm regions

¹⁶The empirical implementation of the method uses state-level TFP, labor input, and land input data from Ball et al. (2010), and state-level farm wage and farmland rent data as discussed in the Supplementary Material S.1. One advantage of this method is that it only requires that resources be efficiently allocated within each state, which is consistent with the model.

¹⁷The estimates based on base case parameter values show that, from 1960 to 2004, average labor-augmenting technical change has been roughly 2 percent per year, and land-augmenting technical change has been about 0.86 percent (see Appendix table B.2). These estimates are consistent with the econometric estimates available in the literature (e.g., Binswanger, 1974; Lambert and Shonkwiler, ???), which uniformly finds that technical change in U.S. agriculture has been labor-augmenting (and land-biased) in the second half of the twentieth century. (This is one instance where the model is externally validated.) In general, it is difficult to pinpoint to separate determinants of labor versus land augmenting technical *change*. For instance, although many biological inventions in agriculture have been simultaneously labor- and land-augmenting (Olmstead and Rhode, 2008), there is no compelling reason to think that any such invention would have a proportional impact on labor and land efficiency.

L_{fj}^{model} is calculated using equation (10). The difference between the model-based L_{fj}^{model} and the realized (data) L_{fj}^{data} allocations of labor are a measure allocative inefficiency.

Since there are 45 years of data and $J = 48$ states, I present several complementary statistics to summarize these differences between L_{fjt}^{model} and L_{fjt}^{data} . The first statistics is the root mean squared difference (RMSD) and for $t = 1960, \dots, 2004$ it is defined as

$$\text{RMSD}_t = \left(J^{-1} \sum_{j=1}^J (L_{fjt}^{\text{model}} - L_{fjt}^{\text{data}})^2 \right)^{1/2}. \quad (12)$$

In this expression, L_{fjt}^{data} are indexed—with Alabama in 1996 set equal to one. The calibrated solution of the model requires that $\sum_j L_{fjt}^{\text{data}} = \sum_j L_{fjt}^{\text{model}}$. As a result, the units of measurement of the RMSD in equation (12) do not have a direct economic interpretation. However, changes over time in the RMSD are informative about the dispersion between the model-based and realized allocations of agricultural labor across U.S. states.

Figures 2B presents the RMSD from 1960 to 2004 using the difference for each of the 48 U.S. states between the model-based and realized farm labor. The estimates indicate that the RMSD has declined fairly consistently until 1996, at which time there was a sharp increase. It is instructive to see that similar conclusions emerge both from the base case calibration $\sigma_f = 0.2$, as well as for the alternative calibrated value of the elasticity of substitution between land and labor in agricultural production ($\sigma_f = 0.1$). The main difference is that the RMSDs are consistently lower for $\sigma_f = 0.1$ than those for the base case.

While the RMSD is informative about the time path of allocative inefficiency within U.S. agriculture, it is not informative about the magnitude and economic significance of these inefficiencies at the state level. One way to summarize the magnitude of these inefficiencies is to consider the ratio

$$\frac{L_{fjt}^{\text{model}}}{L_{fjt}^{\text{data}}}, \quad (13)$$

for each $j = 1, \dots, J$ and $t = 1960, \dots, 2004$. This ratio takes the value one when model-based and realized labor input are identical for a given state in a given year.

Figures 2C–D plots the density of the ratio in equation (13) across all 48 states for a given year. I show these densities for five selected years; 1960, 1970, 1980 (fig. 2C), 1990 and 2000 (fig. 2D). Overall, the model is successful in accounting for the main tendencies in the data, and captures the share of employment in agriculture for most states in all periods strikingly well. Also, there is little variation in density estimates from 1960 to 1980, and a tightening of the distribution thereafter. This is consistent with the picture that emerges from the RMSD statistics. Furthermore, these density estimates are suggestive about the *net* magnitude of inefficiency in labor allocation across states. There are many states with 20 percent more farm labor than would have been predicted by

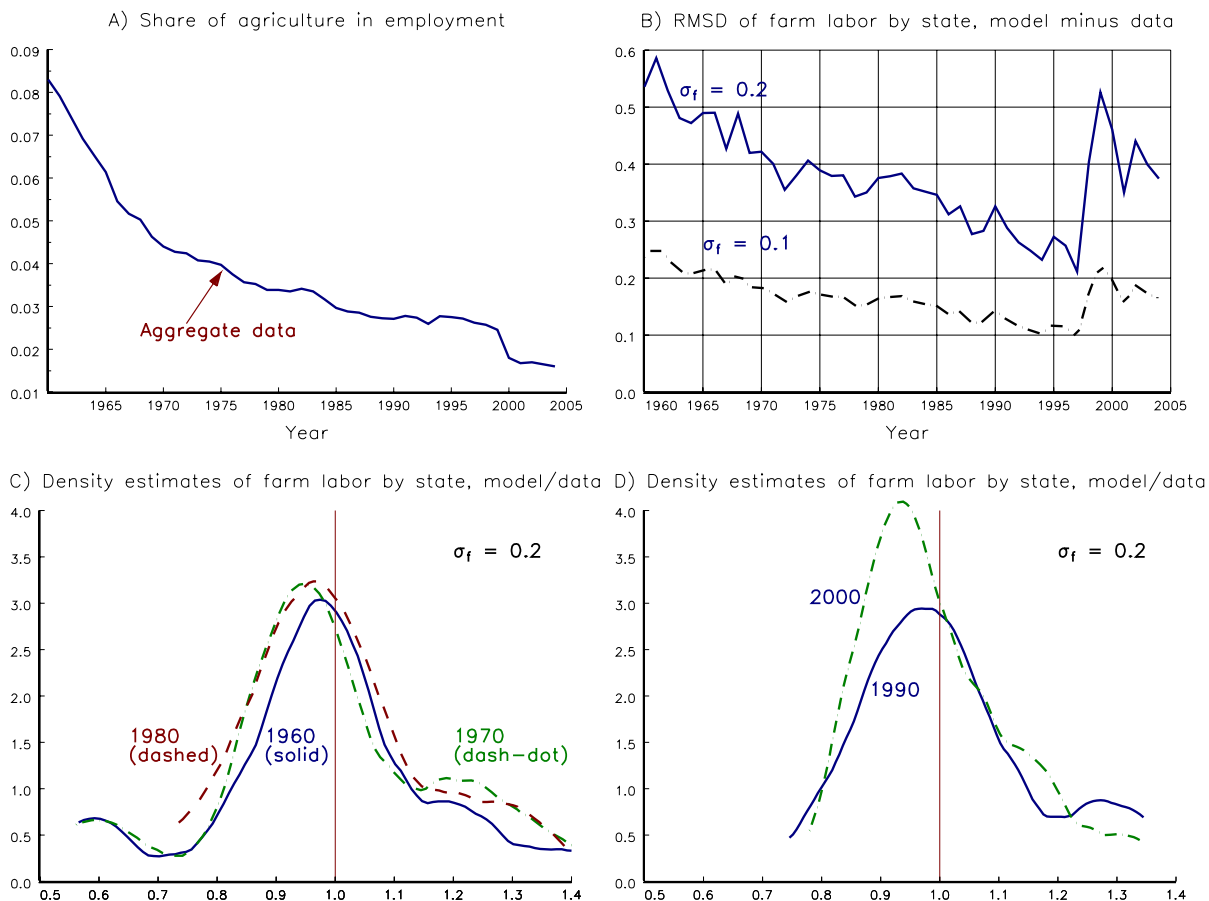


Figure 2: Allocation of agricultural labor across states

Note: A) Share of employment in agriculture. There has been a secular and significant decline in farm employment in the United States, as percent of total employment. The first calibration method matches this data. B) The root mean squared difference between the model-based and realized farm labor from 1960 to 2004 across 48 contiguous U.S. states; see equation (12) in the text. C) and D) The kernel density estimates of model-based farm labor divided by the realized farm labor across 48 contiguous U.S. states for selected years; see equation (13) in the text. Vertical lines indicate the density of the states where model-based and realized data are identical. σ_f is the elasticity of substitution between labor and land in agriculture.

the model. Similarly, there are many states with 20 percent less farm labor compared to the model-based labor allocations. In fact, at least for the period 1960–1980, the density estimates appear symmetric, suggesting that, at the regional level, inefficiencies manifest themselves as under- and over-employment of farm labor with similar frequencies.

What is the economic significance of these differences? This can be addressed by computing the size of the farm output gap that can be attributed to the inefficient allocation of labor across farm regions. In particular, the model-based labor input data can be used in regional farm production functions (6) to compute model-based farm output for each state in each year. Summing across states for each year gives the model-based aggregate farm output that would have been feasible if labor were efficiently allocated across U.S. states. I compare these model-based aggregate farm

output data with the “realized” farm output, which is based on the same regional farm production functions, the same factor-augmenting terms, and the same land input. Thus, the model-based and realized aggregate farm output data differ only to the extent that model-based and realized labor allocations are different across regions, but the aggregate farm labor input is identical in both cases. As such, the comparison quantifies the output effects of within-sector labor reallocation.

For ease of presentation, I report the percentage difference between the model-based and realized agricultural output. Figure 3A contains the results for the base case parameter values. The estimates point to quite minor real output losses on a year-by-year basis. The weight of labor in the farm production function α_f^L has an impact on the implied output gap but the differences are not large enough to qualify the main findings. Figure 3B shows the sensitivity of the allocative-inefficiency-driven output gap in agriculture to the alternative parameter value of the elasticity of substitution between land and labor in agriculture, $\sigma_f = 0.1$. For $\alpha_f = 0.1$ the implied output gap is even smaller, amounting no more than about 0.02 percent of realized output in the 2000s.

Figure 3 also distinguishes across four episodes with distinct policies toward U.S. agriculture. Episodes labeled as “supply control” correspond to policies that tended to restrict agricultural output and increase domestic prices, whereas episodes labeled as “support” correspond to policies that encouraged agricultural production largely in response to rising global food prices. Looking over figure 3, it is difficult to discern a strong correlation between farm policies and aggregate agricultural output gap as measured here. However, in Section 5.1, I will return to the link between allocative efficiency and farm policies using state-level data, and explore the link between inefficient allocation of resources and distortions in more detail.

4.3 Allocation of labor across sectors

The second method I use to assess the degree of allocative inefficiency allows for the possibility of reallocation of labor—relative to the data—between agriculture and non-agriculture. In this case, I calibrate the model to match aggregate farm output in the data. Under an efficient allocation of labor across farm regions, farm output in the data can be produced with fewer farm workers. This gives rise to reallocation of labor from the farm to the non-farm sector, and to higher non-farm output relative to the data. Therefore, this method considers the employment options of labor outside the agricultural sector.

Relative to the first method, this approach comes closer to measuring the general equilibrium ramifications of allocative inefficiency in a multi-sector framework: it allows for the allocation of labor both across farm regions *and* across sectors, after imposing the condition that $Y_{ft}^{\text{model}} =$

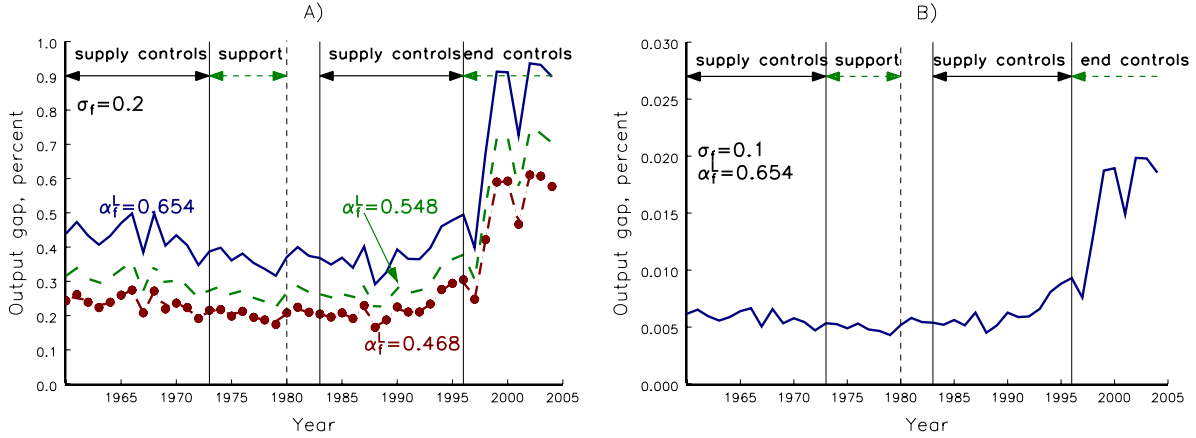


Figure 3: Aggregate farm output gap based on model-based versus realized state level labor inputs

Note: Aggregate farm output gap is the ratio between the model generated output data and realized data minus one, in percent. The model-based aggregate farm output is based on model-based state-level farm labor input. The realized farm output data uses labor input from Ball et al. (2004). Both the model-based and the realized aggregate farm output are based on the regional production functions (6). See the text for details. Policy episodes corresponding to “supply controls” and “support” are discussed in Section 5.1

Y_{ft}^{data} .¹⁸ I then compare the model-based share of employment in agriculture

$$\frac{L_{ft}^{\text{model}}}{L_t} = \frac{\sum_{j=1}^J L_{fjt}^{\text{model}}}{L_t},$$

with the realized (data) share of employment in agriculture

$$\frac{L_{ft}^{\text{data}}}{L_t} = \frac{\sum_{j=1}^J L_{fjt}^{\text{data}}}{L_t}.$$

Figure 4A shows the model-based and realized share of employment in agriculture, and the model-based data are for the base case parameter values. Not surprisingly, the model-based shares are consistently lower than the realized share of employment in agriculture. The gap between the model-based estimates and data is nevertheless not remarkable. It appears that moving to a more efficient allocation of labor both across farm regions and across sectors would have had a negligible influence on the share of employment in U.S. agriculture.

While the gap between the model-based and the realized share of employment in agriculture is negligible, reallocating labor to the non-farm sector would allow the economy to produce more non-farm output, without compromising food consumption. This is a general equilibrium effect:

¹⁸Specifically, this calculation is based on several steps: First, it uses realized farm labor and land input by state in the farm production functions (equation (6)) together with a particular parametrization of the model to determine the implied aggregate farm output. Next, it solves for the model-based agricultural labor input by region, given realized farm land input by region and the aggregate farm output constraint (from step 1). It does so by equating the marginal product of farm labor across regions while ensuring that aggregate farm output constraint is met. Finally, for each year it sums the model-based agricultural labor input by region to arrive at the model-based aggregate farm labor input.

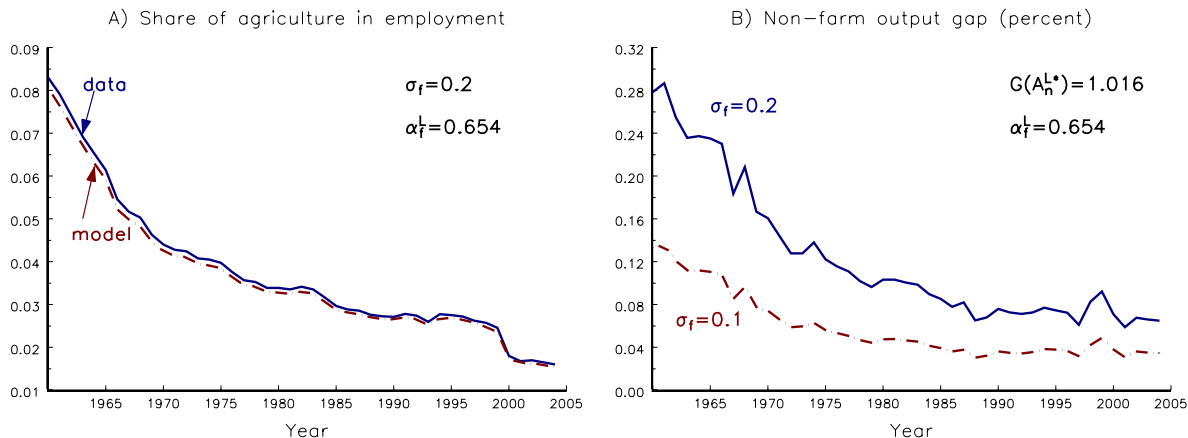


Figure 4: The general equilibrium consequences of inefficient allocation of labor

Note: **A)** The model-based employment data are based on efficient allocation of labor across regions given the constraint that farm value added in the model-based series is identical to the farm value added in the data (see text for details). **B)** Percentage of non-farm output loss due to inefficient allocation of labor across farm regions and across sectors ($\ln(Y_{nt}^{\text{model}}/Y_{nt}^{\text{data}}) \times 100$). σ_f is the elasticity of substitution in agricultural production between labor and land, α_f^L is the weight of labor in agricultural production function, and $G(A_n^{L*})$ is the (gross) long-run growth rate of non-farm TFP.

inefficient allocation of farm labor across regions also corresponds to a loss of potential non-agricultural output. It is possible to quantify this non-agricultural output gap. But this requires solving the dynamic model with endogenous capital accumulation, because the availability of more workers in non-farm production would also affect non-farm production through capital accumulation. As discussed in detail in Appendix C, the dynamic model is solved numerically using a forward-iteration algorithm.

The numerical method uses two distinct series on the employment share of agriculture. The first calibrated series uses the realized agricultural employment, and numerically solves for the implied non-farm output (referred to as Y_{nt}^{data}). The second employment series uses the model-based agricultural employment (from figure 4A) to solve for the implied non-farm output ($\ln(Y_{nt}^{\text{model}})$), but otherwise uses the same parameter values, the same initial capital stock k_0 , and the same steady-state value of the capital stock as in the first simulation. The difference between the model-based non-farm output and the data provides an indication of the welfare loss associated with inefficiencies due to the misallocation of labor both across sectors and across farm regions.¹⁹

Since all the statements about allocative inefficiency that emerge from this study are effectively *relative* to the model, at this point it would be useful to know how well the model performs in those dimensions that have not been targeted by the calibration. One way to do this is to consider

¹⁹To solve the model numerically I use calibrated values of several parameters. These calibrated parameters are discussed in Appendix A.2. In addition, and somewhat different from the standard calibration exercises, the algorithm uses the annual realized and forecasted values of (1) farm and non-farm productivity growth, and (2) population growth. One important choice here is the forecasted (future) gross growth rate of TFP in the non-farm sector, $G(A_n^{L*})$. The simulation results reported below use a *net* annual growth rate of 1.6 percent.

whether the model exhibits realistic farm output dynamics by state. I examine this by considering the covariance between farm output shares and farm productivity at the state level, and comparing model-based and realized covariances. In particular, I implement a method proposed by Olley and Pakes (1996), which decomposes output-share weighted mean productivity in agriculture into average agricultural productivity across states plus an “inefficiency” term:

$$\begin{aligned} A_{ft}^w &\equiv \sum_{j=1}^J w_{jt} A_{fjt} \\ &= \bar{A}_{ft} + \sum_{j=1}^J \left(w_{jt} - \frac{1}{J} \right) (A_{fjt} - \bar{A}_{ft}), \end{aligned} \quad (14)$$

where A_{fjt} stands for agricultural TFP in state j in year t , $\bar{A}_{ft} = (1/J) \sum_{j=1}^J A_{fjt}$ is unweighted mean productivity, and A_{ft}^w is output-share (w_{jt}) weighted agricultural productivity. Here, the weights depend on the farm output in each state divided by the aggregate farm output. In general, the higher the share of output captured by more productive states, the higher is the aggregate agricultural productivity. Dividing both sides of equation (14) by unweighted mean productivity and rearranging these terms gives

$$\frac{A_{ft}^w}{\bar{A}_{ft}} = 1 + \frac{\sum_{j=1}^J (w_{jt} - 1/J) (A_{fjt} - \bar{A}_{ft})}{\bar{A}_{ft}}. \quad (15)$$

In this expression the left-hand side is the ratio of share-weighted mean productivity to unweighted mean, and the right-hand side is the covariance between output shares and productivity at the state level multiplied by J , the number of states. Olley and Pakes (1996) refer to this covariance terms as the “reallocation effect.” I find that the correlation between the model-based reallocation effect and the realized reallocation effect (based on actual output shares) is high: 0.78 for $\sigma_f = 0.2$ and 0.85 for $\sigma_f = 0.1$. So, it appears that the model does a good job in matching the covariance between share of farm output by state and farm productivity by state in the data.

The dynamic solution of the model also allows me to measure the consequences of inefficient allocation of labor across sectors for *non-farm* output. Figure 4B reports the percentage non-farm output gap due to allocative inefficiency across farm regions, as measured by $\ln(Y_{nt}^{\text{model}}/Y_{nt}^{\text{data}}) \times 100$. For the base case parameter values, the percentage differences are relatively small—less than 0.3 percent of the realized non-farm output. The calibration results thus suggest that the general equilibrium ramifications of misallocation of agricultural labor has been small, and has declined considerably over time to negligible levels.

While the deviations in non-farm output from the efficient allocation of labor across sectors have been small, they may nevertheless correspond to a cumulative and significant welfare loss. The utilitarian dimension of the model presents one way to assess these cumulative effects by comparing the consequences of differential non-farm consumption streams from the model-based series and

data. This comparison is facilitated by the fact that consumption of farm goods and composite non-farm landscape are identical in both cases, as the quantitative analysis takes the allocation of land as given and sets agricultural output equal to the data in model-based calibration of efficient allocation of labor. As a result, differences in the lifetime utility originate only from differences in non-food consumption.

I convert these utility differences into “equivalent constant per person consumption” loss (λ), which is defined as the solution to the following equation

$$\begin{aligned}
\sum_{t=0}^T \beta^t u(C_t^d, H_t; \lambda) &= \sum_{t=0}^T \beta^t \left(\eta^c \ln \left[(1 - \eta^n)^{\frac{1}{\nu}} (C_{ft}^d - \gamma)^{\frac{\nu-1}{\nu}} + (\eta^n)^{\frac{1}{\nu}} (C_{nt}^d (1 + \lambda))^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} + (1 - \eta^c) \ln H_t \right) \\
&= \sum_{t=0}^T \beta^t \left(\eta^c \ln \left[(1 - \eta^n)^{\frac{1}{\nu}} (C_{ft}^d - \gamma)^{\frac{\nu-1}{\nu}} + (\eta^n)^{\frac{1}{\nu}} (C_{nt}^m)^{\frac{\nu-1}{\nu}} \right]^{\frac{\nu}{\nu-1}} + (1 - \eta^c) \ln H_t \right) \\
&= \sum_{t=0}^T \beta^t u(C_t^m, H_t),
\end{aligned} \tag{16}$$

where C_n^d is non-food consumption in the data, and C_n^m is non-food consumption computed using model-based agricultural employment. In the utility streams, both food consumption C_{ft}^d , and composite non-farm landscape H_t are identical. The equivalent constant per capita consumption λ is the constant proportionate increase in the realized non-food consumption data that would render at time zero (year 1960) the “lifetime” utility (until year 2004) from the model-based series identical to the lifetime utility obtained from the realized data.

To implement this procedure, for C_{ft}^d and C_{nt}^d , this study uses food and non-food consumption expenditures from NIPAs and the percent gap between the model-based and data series in non-farm consumption to derive the series on C_{nt}^m .²⁰ Figure 4B reports the percent gap between the model-based and data series in non-farm *output*. These output data together with the market clearing in the non-farm goods market yield the calibrated consumption series.

Table 1 reports the equivalent constant non-food consumption loss λ due to inefficient allocation of labor across regions and sectors corresponding to alternative parameter values for the weight of labor in farm production α_f^L , the elasticity of substitution between labor and land in farm production σ^f , and the weight of non-food consumption in food–non-food subutility η^n . Looking forward from 1960 to 2004, all the values of λ emerging from this exercise correspond to welfare losses never exceeding 0.25 percent permanent reduction in non-food consumption.²¹ Overall, the results suggest that the size of the inefficiencies are not likely to be large unless the model is grossly

²⁰To obtain non-food consumption expenditures the procedure deducts gross housing value added and expenditures on food from personal consumption expenditures. See Appendix A for details. The welfare analysis considers the comparison of consumption data from NIPAs and its “scaled” counterpart using the consumption gap between model-based and realized data from the calibration. The model in Section 3 employs value-added functions, while the welfare analysis requires consumption.

²¹Recall that with base case parameters allocative inefficiency has never exceeded 1 percent of total agricultural output.

Table 1: Equivalent constant consumption loss due to labor misallocation (percent)

$\alpha_f^L =$	$\sigma^f = 0.2$			$\sigma^f = 0.1$
	0.654	0.468	0.548	0.654
$\eta^n = 0.850$	0.23	0.25	0.24	0.11
$\eta^n = 0.899$	0.20	0.22	0.21	0.09
$\eta^n = 0.950$	0.19	0.21	0.20	0.09

Note: This table shows the equivalent constant non-food consumption loss due to misallocation of agricultural labor across U.S. states and across farm and non-farm sectors. See equation (16) in the text. The shaded cell contains the value of λ corresponding to the base case parameter values.

understating the marginal utility of non-food consumption since the 1960s. Along similar lines, the welfare costs of any inefficient allocation of farm labor in the early twentieth century in the United States, as well as in contemporary developing countries, are likely to be significantly larger than those reported here.

5 Accounting for allocative inefficiency

One factor that might account for allocative inefficiency is policy “distortions” (Restuccia and Rogerson, 2008). I explore this issue in Section 5.1 below. Of course, agricultural policy distortions are not the only factor that can account for the allocative inefficiency as identified by the model. In fact, it is quite plausible that the model might be misinterpreting the allocation of labor across farm regions as inefficient for a variety of other reasons, including geographic specialization and variability in climate. I address these issues in Sections 5.2 and 5.3.

5.1 Direct farm support programs

How much of the differences in model-based data and realized data can be attributed to distortions introduced into the agricultural markets through farm support policies? One of the major manifestations of policy toward U.S. agriculture has been agricultural land supply control. The policy stance toward agricultural land use has shifted several times over the last 50 years. In the 1960s, the policy objective was to reduce agricultural land use and restrict agricultural supply. The policy objectives moved toward support for production in the 1970s following the run-up in commodity prices. But, by 1983, the policy shifted yet again toward acreage reduction programs, only to be replaced by the 1996 Agricultural Improvement and Reform Act that ended direct supply controls. Figure 5 marks these general tendencies by distinguishing between episodes of “supply controls” and “support” for agricultural production.

Nominal rate of assistance, percent

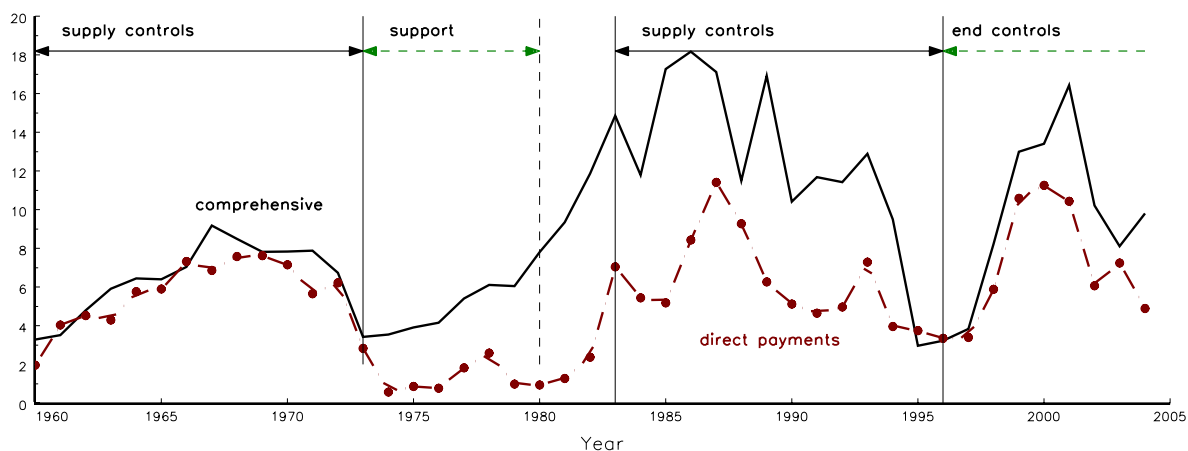


Figure 5: Agricultural land supply control and price-support programs

Note: “Supply controls” refer to episodes of strict agricultural land supply control programs. “Support” refers to episodes during which policies intended to increase agricultural production. The “comprehensive” measure of agricultural price-support programs is from Anderson and Valenzuela (2008) and represents the ratio between farm receipts (including support) and those generated in the market without support (minus one), for covered products. The “direct payments” measure is based on U.S. Department of Agriculture (2011) and represents the ratio between farm receipts (including support) and farm receipts excluding direct government payments to farms minus one.

Parallel to the supply control programs, direct assistance to farmers and subsidies have fluctuated since the 1960s. Figure 5 also presents the nominal rate of assistance toward agriculture in the United States for two alternative measures of assistance. Both the “comprehensive” measure and the measure that only includes direct payments to farmers shows that assistance to farmers tended to decline during periods of supply controls, and have increased during periods without controls. For instance, following the latest elimination of supply controls in 1996, assistance to agriculture rose significantly. Both of these measures are commonly used to measure agricultural distortions at the state level.

These payments effectively increase the rate of return to agricultural land, and as such can be conceptualized as a net subsidy. Since, in agriculture land and labor are gross complements, the subsidy toward land also increases the employment of labor above and beyond the level that would have been observed in the absence of such subsidies. However, since land- and labor-augmenting technology varies across states, it would be best to think of these subsidies in *relative* terms, benefiting those states with lower land-augmenting technology proportionately more than those with higher land-augmenting technology. Moreover, if these subsidies are highly correlated across states, in general equilibrium, such differential effects across states would be even more pronounced: subsidized competition from low efficiency states may even reduce employment in high efficiency states. In fact, in the data, the average of pairwise correlations of farm support between all unique state pairs is 0.62 ($N = 1,128$), which points to significant synchronization of farm subsidies across

states.

In any event, it is still an open question whether and, if so, by how much these policies have distorted the allocation of resources in U.S. agriculture.²² To address this issue, let the ratio between direct government payments and gross receipts of farms at the state level be (τ_{fjt}) . Since τ_{fjt} can be thought of as a rate of subsidy to agriculture, it directly affects the rate of return to land, and the allocation of labor across states. The ratio between the realized allocation of farm labor across states L_{fjt}^{data} and the model-based allocation of farm labor L_{fjt}^{model} gives a measure of allocative inefficiency. Furthermore, a high correlation between $L_{fjt}^{\text{data}}/L_{fjt}^{\text{model}}$ and τ_{fjt} would indicate that farm subsidies have on average increased employment in the farm sector (relative to the model-based data). At the same time, one would expect these correlations to vary across states because of the differences in land-augmenting technology and the general equilibrium effects originating from the synchronized nature of these subsidies across states.

Figure 6 shows the correlation estimates between $L_{fjt}^{\text{data}}/L_{fjt}^{\text{model}}$ and τ_{fjt} by state. While in most cases these correlations are not high, they nevertheless reveal economically interesting insights. The estimates vary substantially across farm regions, with Northwest and Mountain regions exhibiting the largest correlations between subsidies and “excessive” labor use—though Delaware and Montana stand out as exceptions. The correlations are largely negative for the Cornbelt region, which has the highest land-augmenting technology. The Plains states have a mixed profile, with farm labor in South and North Dakota and Oklahoma exhibiting a negative correlation, in contrast to positive correlations in Kansas, Nebraska, and Texas. These correlations suggest that in the absence of highly synchronized farm subsidies across regions, even when aggregate farm labor input were set equal to the realized data, the Cornbelt would have experienced an increase in farm labor, and most likely at the expense of Northwest and Mountain regions. Thus, in the United States, farm subsidies have not only transferred resource from the non-farm sector to the farm sector, they have also resulted in a reallocation of labor across farm regions by non-negligible amounts.²³

²²Of course, farm subsidies primarily transfer resources from the non-farm sector to the farm sector. They also have consequences for the allocation of land across farm regions, and across sectors. A detailed quantitative exploration of these issues is beyond the scope of this paper.

²³In the United States, government policies also target research and development in agriculture. Huffman and Evenson (1993, 2006) provide useful historical accounts of government policies toward agricultural research, as well as extensive evidence on the contributions of government-funded agricultural research to farm productivity growth in the United States. If these public expenditures on research and extension reduce the costs of developing and acquiring state-specific agricultural technology unevenly across states, they may also “distort” resource allocation decisions by farmers. However, Huffman and Evenson (1993, chapter 8) empirically test whether federal agricultural research funds are optimally distributed across states, and do not find evidence for misallocation of funds.

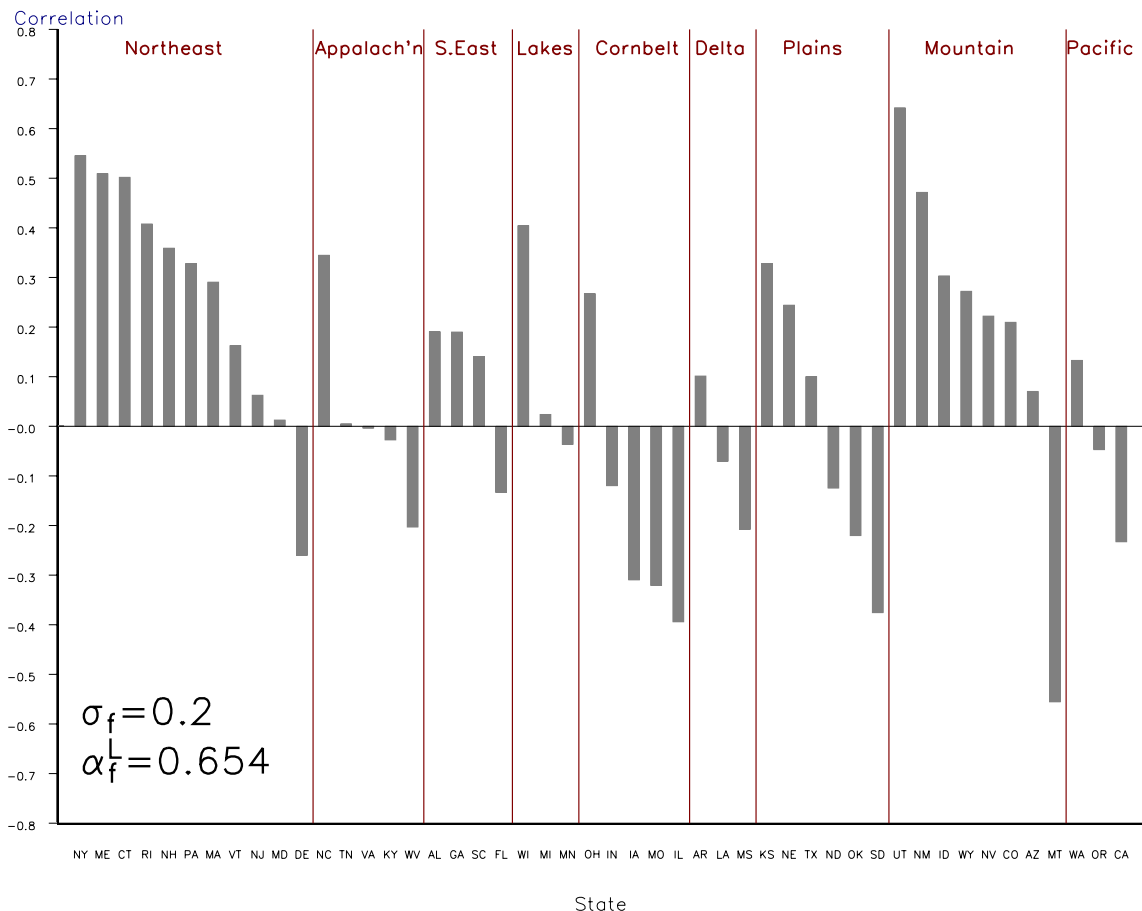


Figure 6: Correlation between employment gap and farm subsidies by state

Note: Employment gap is the ratio between the actual farm labor data by state and its model-based counterpart. Farm subsidy is the ratio between direct government payments to farms and gross receipts of farms by state. The data are from 1960 to 2004. The realized labor input data are from Ball et al. (2010), and farm subsidy data are from U.S. Department of Agriculture (2011). σ_f is the elasticity of substitution in agricultural production between labor and land, and α_f^L is the weight of labor in agricultural production function. See table A.1 for states corresponding to abbreviations.

5.2 Specialization and geographic concentration

The productivity analysis in the paper attributed TFP difference across two farm regions to differences in their land-augmenting efficiencies, and the quantitative analysis attributed observed deviations from identical efficiency-adjusted factor-price ratios to inefficient allocation of labor across regions. This section explores whether differences across regions in specialization may independently account for the observed dispersion of TFP across farm regions and inefficiencies.

The model considers a single agricultural good with the implication that in an efficient equilibrium the ratios of marginal value product of efficiency-adjusted labor and land should be identical across regions. However, if regions specialize in crop versus livestock production, and the prices of these products have evolved differently over time, then these marginal value product ratios

would also depend on the price of crops relative to livestock. Moreover, as relative prices change, producers allocate resources between crop and livestock production. The model does not capture such cross-product reallocations within agriculture.

In fact, in terms of market value of agricultural products sold, there is considerable variation across states in terms of crop and livestock production. In the Supplementary Material S.5, I discuss in detail these geographic concentration patterns for several major livestock products and crops. While there is substantial geographic concentration of agricultural production in any given year, concentration patterns have changed significantly over time in many products, suggesting that this is an additional dimension of resource reallocation worth considering.

Unfortunately, estimates of productivity growth at the product and state level are not readily available. To my knowledge, Huffman and Evenson (1993) is the only study that constructs separate productivity series for crop and livestock farming at the state level, and their data end in 1982. More importantly, there are no state-level data on labor, capital and land inputs to crop and livestock production separately.²⁴ Nevertheless, it is instructive to review the results in Huffman and Evenson (1993), which show that average crop productivity growth exceeded livestock productivity growth from 1950 to 1982, but by a small margin: 2.0 percent per annum versus 1.6 percent, respectively (Huffman and Evenson, 1993, p. 198). But, there was considerable variation across regions over time.

Although we lack productivity growth estimates at the product level, relative price changes provide an (imperfect) indicator of differential productivity growth rates across products. Figure 7 shows prices received and prices paid by farmers for all farm products, as well as for crops and livestock. Over this period there was secular decline in the farm terms of trade (prices received divided by prices paid, figure 7A). Much of this decline in the farm terms of trade was due to faster productivity growth in the farm sector relative to the rest of the economy (Dennis and İřcan, 2007). Figure 7B shows prices received by crop and livestock producers. Over this 45 year period, the price of livestock increased faster than the price of crops, which would indicate that crops had a relatively faster productivity growth. Interestingly, crop prices exhibit no noticeable increase over the last 20 years of the sample.²⁵

A related consideration in this context is whether there are considerable differences in profitability between crops and livestock. The selection mechanism I consider in this paper is based on productivity, but it is possible that selection operates through profitability (e.g., Foster et al., 2008). Figure 7C shows prices received divided by prices paid for crops and livestock separately.

²⁴Because of this data limitation, Huffman and Evenson (1993) allocate inputs to these activities using constant input coefficients based on aggregate studies in certain benchmark years. But, it is not possible to know whether these input coefficients are uniformly applicable across states and over time. In fact, Huffman and Evenson (2006) have not pursued this approach further in the second edition of their book.

²⁵This paper makes no attempt to model the interplay between uncertainty and resource allocation, given the volatility of crop and livestock prices, this may be worth exploring in future work.

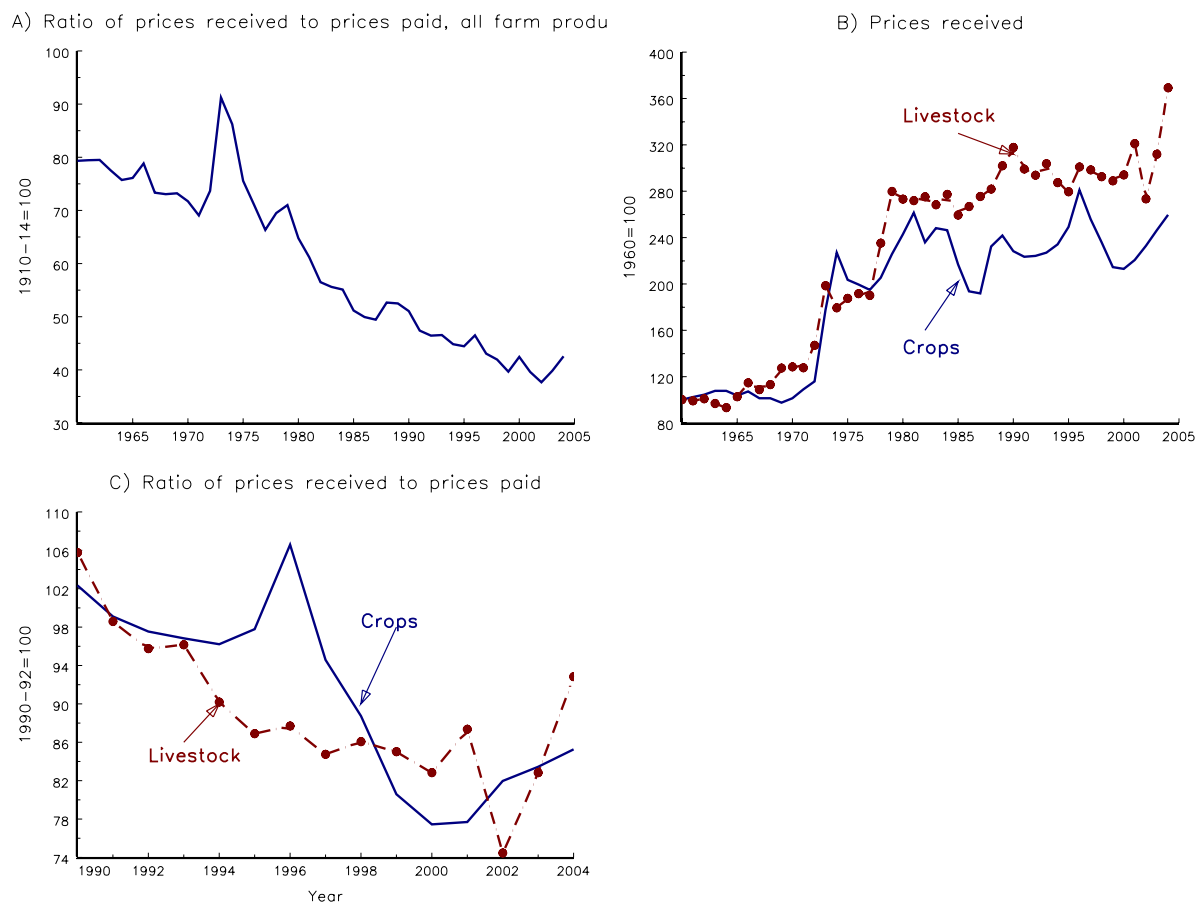


Figure 7: Indexes of prices received and prices paid by farmers

Note: **A)** Prices paid by farmers for commodities, services, interest, taxes and wages. **B)** Prices received by farmers for crops and livestock in are based on index numbers with base year 1910–14=100, and are scaled such that 1960=100. **C)** Prices paid to farmers separately for crop and livestock production are only available since 1990. Source: USDA, Agricultural Statistical Board, NASS. *Agricultural Prices*, various issues available at <http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1002>. **D)** Ball et al. (1997, table 3).

Product-specific prices paid are only available since 1990. A comparison of the ratios of prices-received to prices paid is, of course, only suggestive of the relative profitability in crop and livestock production, but it is a measure that is closely tracked by the USDA. While crop and livestock prices have somewhat diverged during this period, the prices-received-to-paid ratios for crops and livestock have not diverged in any systematic way. So, while livestock prices increased faster than crop prices, so did costs in livestock production—indicating limited differentiation between crops and livestock along profitability.²⁶

²⁶Nevertheless, it is conceivable that prices received and prices paid by, say, crop producers might have varied significantly across states. While factor price differentials across states, once adjusted for quality, appear to be small, I have not been able to conduct a systematic analysis of cross-state variation in the prices paid for other inputs (like fertilizers, pesticides, feed, etc.), and prices received for farm products (after adjusting for quality). State-level data on prices received for individual products and prices paid on several inputs are available in USDA publications, but

Issues related to product and geographic specialization raise legitimate micro-level issues which may affect the allocative inefficiency calculations presented in the paper. Nevertheless, in terms of aggregate agricultural output, the shares of market value of agricultural products claimed by crops and livestock have been relatively stable over time, and since the early 1970s, the share of livestock (including poultry) has been slightly over 50 percent of total market value. This stability suggests that the parsimonious modeling strategy pursued here has a reasonable empirical justification.

5.3 Geoclimatic variability

How much of the allocative inefficiency identified in this paper can be attributed to measurement error in TFP due to geoclimatic variability? To address this issue, I examined whether variations in soil moisture stress *over time* has been correlated with state-level TFP growth rate in U.S. agriculture. In any given period, soil moisture depends on supply of moisture (precipitation) and demand for moisture (like temperature, the amount of moisture in the soil, and evapotranspiration).²⁷ I find that overall geoclimatic variability is not strongly correlated with agricultural TFP in individual states, and there are only a few states with significant correlates.²⁸

6 Concluding remarks

Using state-level data from U.S. agriculture (1960–2004), and a multi-sector model, I demonstrated that despite large agricultural total factor productivity (TFP) differences across U.S. states, the economic consequences of allocative inefficiency have been small. The results suggest that factor-specificity should be taken into consideration in interpreting the ramifications of TFP dispersion across producers for allocative inefficiency.

Some readers may find the message of this study limited given the shrinking size of agricultural labor force, and the fact that the long-run prospects of share of employment in agriculture are highly unlikely to be significantly higher than what they are today. However, in 1960, seven percent of the U.S. labor force was employed in agriculture—a non-negligible share. By comparison, the

not in a machine readable format. If cross-state price variations are prevalent, it would be useful to examine whether these differences are sufficiently significant to swamp cross-state differences in efficiency-adjusted factor-price ratios. At this stage, in the absence of reliable long-term disaggregate productivity data, it is not possible to be definitive about the contribution of specialization at the product level to agricultural transformation.

²⁷To measure geoclimatic variability over time, I used Palmer Drought Severity Index (PDSI), which is a measure of soil moisture based on an environmental demand and supply algorithm. It has been widely used by climatologists, and is available for the contiguous United States (see, Cook, Meko, Stahle, and Cleaveland, 1999).

²⁸Since the 1970s there has been noticeable increase both in precipitation and temperatures in contiguous United States. However, these increases have not been uniform. Whereas states like California, Montana, Wyoming, North Dakota, and parts of Idaho and Texas have had decreases in annual precipitation, the Appalachian and Delta states have had cooling in mean annual temperatures (Karl, Knight, Easterling, and Quayle, 1996). Incidentally, I find a positive correlation between PDSI and agricultural TFP in Montana and North Dakota; see the Supplementary Material S.6 for details.

many studies on allocative inefficiency relies on narrowly defined manufacturing industries with smaller employment shares. Others use the manufacturing sector, which is itself a shrinking sector in terms of its share of employment. In any case, the size of agriculture in most developing countries makes allocative inefficiency in agriculture both relevant and economically significant.

Along similar lines, some readers may find land specificity a specialized context. However, factor specificity can also arise outside agriculture in the form of highly specialized structures, equipment, and machinery, and even across firms in narrowly defined industries. These have been neglected issues in the literature and are worth exploring in future research.

One related topic on which this study is not informative about is *farm-level* productivity dynamics. If evidence from manufacturing establishments offers any guidance on this issues (Bartelsman and Doms, 2000), productivity levels across farms within a state are likely to be quite dispersed as well. Yet, available aggregate data are not informative about farm-level productivity dynamics, including the contribution of entering and exiting farms to observed state-level productivity growth rates.

In any case, even a farm-level study of allocative inefficiency in U.S. agriculture needs to account for the fact that reallocating labor within a sector from less to more productive producers would increase output in that sector, and also change relative prices in a general equilibrium setting. In this paper, I explicitly allowed for alternative uses of resources across sectors. So, the relative merits of using farm-level versus state-level data should be weighted with this general equilibrium approach in mind. In that vein, a promising avenue for future research is paying careful attention to intermediate inputs and input-output table style interactions across and within sectors (e.g., Basu et al., 2010). Such extensions would help align more carefully the model-based consumption and production concepts with their empirical counterparts in national income and product accounts, and would deliver richer channels of resource reallocation.

Appendix

A Data

The data are annual for 48 contiguous U.S. states. In the model, each time period corresponds to a calendar year, and each region corresponds to a U.S. state. State abbreviations are listed in table A.1.

A.1 Variables

Farm and non-farm TFP growth: The data on multifactor productivity A_{nt} in the non-farm sector and regional A_{jnt} in the farm sector are available as index numbers derived using standard

Table A.1: State Abbreviations

State	Abb.	State	Abb.	State	Abb.	State	Abb.
Alabama	AL	Iowa	IA	Nebraska	NE	Rhode Island	RI
Arizona	AZ	Kansas	KS	Nevada	NV	South Carolina	SC
Arkansas	AR	Kentucky	KY	New Hampshire	NH	South Dakota	SD
California	CA	Louisiana	LA	New Jersey	NJ	Tennessee	TN
Colorado	CO	Maine	ME	New Mexico	NM	Texas	TX
Connecticut	CT	Maryland	MD	New York	NY	Utah	UT
Delaware	DE	Massachusetts	MA	North Carolina	NC	Vermont	VT
Florida	FL	Michigan	MI	North Dakota	ND	Virginia	VA
Georgia	GA	Minnesota	MN	Ohio	OH	Washington	WA
Idaho	ID	Mississippi	MS	Oklahoma	OK	West Virginia	WV
Illinois	IL	Missouri	MO	Oregon	OR	Wisconsin	WI
Indiana	IN	Montana	MT	Pennsylvania	PA	Wyoming	WY

productivity measurement techniques, and the data sources are:

A_{nt} : Private non-farm business sector (excluding government enterprises) multifactor productivity are from the U.S. Bureau of Labor Statistics (2011).

A_{ft} : State-level farm sector multifactor productivity estimates are for 48-contiguous states and from the U.S. Department of Agriculture, Economic Research Service. See Ball et al. (2010) for data, documentation, and methods.

State-level labor and land inputs: These data are from Ball et al. (2010). The methodology used by USDA to measure state-level TFP controls for cross-state differences in soil quality in determining land input (Ball et al., 2010). Soil quality assessment is based on Beinroth and Reich (2001), who group land in six quality classes based on a combination of soil performance and soil resilience criteria for grain production. As such, the TFP measures control for state-level fixed effects based on soil quality. Figure A.1 plots the density estimates of farmland-to-labor ratio for five selected years.

State-level farm wage and farmland rent: See the Supplementary Material S.1.

Aggregate sectoral employment: Farm (“agriculture”) and total civilian non-institutional employment are from the Current Population Survey and are based on household surveys (U.S. Bureau of Labor Statistics, Table 1: Employment status of the civilian noninstitutional population, 1940 to date, <http://www.bls.gov/data/home.htm>, accessed 2 May 2011). The government employment data are from the Current Employment Statistics and are based on establishment

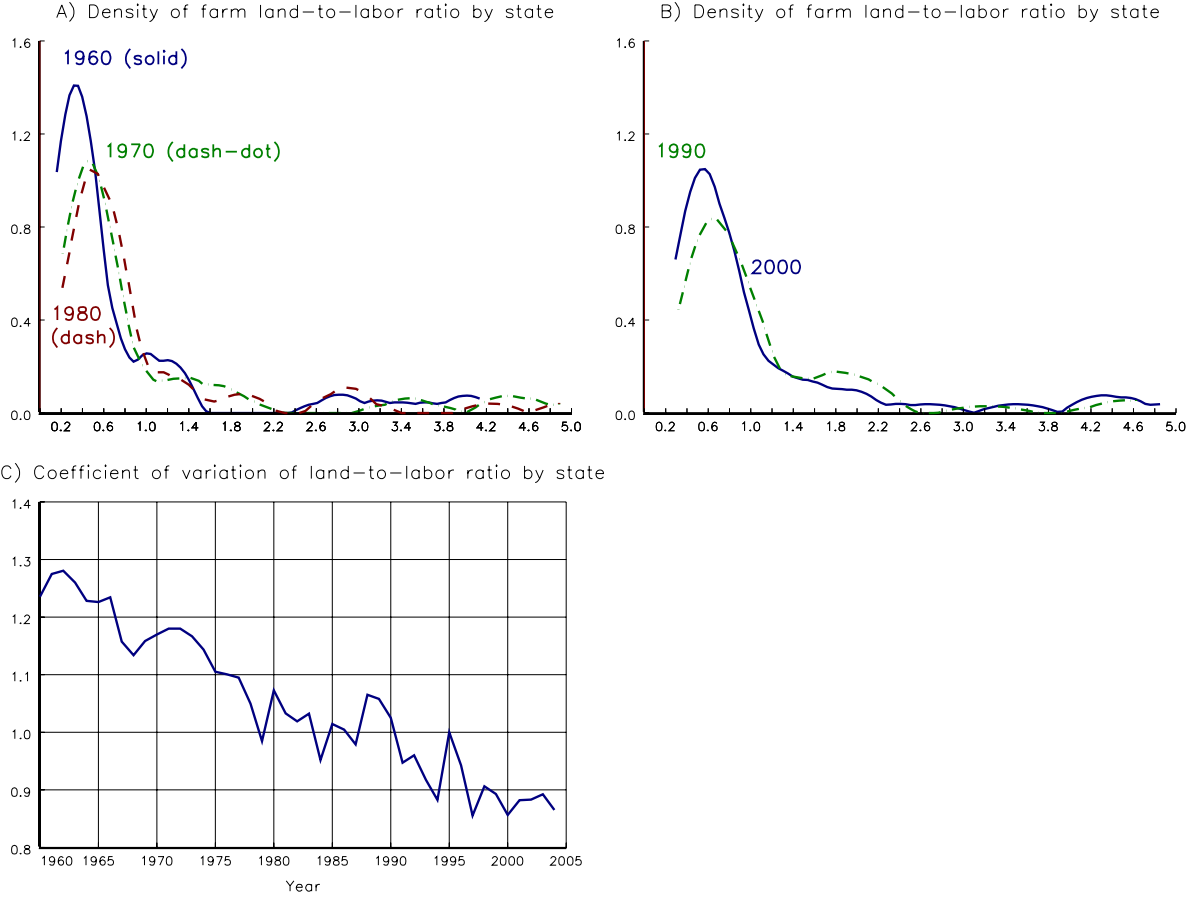


Figure A.1: Dispersion of land-to-labor ratio in agriculture across U.S. states, selected years

Note: **A–B**) The Epanechnikov Kernel density estimates of land-to-labor ratio in agriculture across 48 contiguous U.S. states for 1960, 1970, 1980 (A), 1990, 2000 (B). **C**) The coefficient of variation defined as the across-state standard deviation of land-to-labor ratio in agriculture divided by mean land-to-labor ratio in agriculture. The data source is Ball et al. (2010).

surveys (<http://www.bls.gov/ces/cesbtabs.htm>, accessed 2 May 2011). For forecasts of n_t , $t > T$, I use population projections for ages 16 years and over from the U.S. Census Bureau (2004).

A.2 Calibration

The elasticity of substitution in consumption between farm and non-farm goods is $\nu = 0.1$ (following Dennis and İşcan, 2009). The time discount factor $\beta = 0.943$, and the depreciation rate $\delta = 0.065$ are from Gomme and Rupert (2007). The remaining parameters are calibrated as follows.

Weight of C in consumption η^c : To calibrate the weight of food plus non-food consumption C in total consumption including non-farm landscape η^c , I use the intratemporal optimality condition (S.11), which states that the ratio between consumption expenditures on food plus non-food

and consumption expenditures on non-farm landscape be equal to $\eta^c/(1 - \eta^c)$. Both expenditure items are difficult to map into available data. Expenditures on food and non-food consumption would be best captured by the personal consumption expenditures (PCE) as reported by the U.S. Department of Commerce, Bureau of Economic Analysis (BEA <http://www.bea.gov>, accessed June 6, 2011), in the National Income and Product Accounts (NIPA), Table 2.3.5. But, this includes expenditures on durable goods and housing. Although the model does not tackle the distinct issues related to the consumption of services from durable goods, I include them in non-food consumption expenditures. Expenditures on housing in part capture expenditures on non-farm landscape, so I deduct gross housing value added (NIPA Table 1.3.5) from PCE. Gross housing value added mingles housing services and value of non-farm land, so it overestimates consumption expenditures on non-farm land alone. At the same time, it underestimates expenditures on non-farm landscape, because it does not include the gross value added by all non-farm use of land (such as parks and land reserves). However, making these adjustments would have required extensive and unreliable imputations. Instead, the calibrated model checks the sensitivity of the results to a doubling of gross housing value added.

With these qualifications in mind, the calibrated value of η^c is the sample average of

$$\frac{P_c C}{P_h H + P_c C},$$

where $P_c C$ is personal consumption expenditures minus gross housing value added $P_h H$. The resulting weight of farm and non-farm consumption goods in instantaneous utility is $\eta^c = 0.87$.

Weight of C_f in C and subsistence food consumption γ : Calibrating the weight of non-food consumption in food plus non-food consumption η^n is more complicated, because the underlying preferences are non-homothetic, and the elasticity of substitution between food and non-food is not unitary. As a result the intratemporal optimality condition (S.12) does not immediately link the ratio between consumption expenditures on food and non-food consumption to consumption expenditures to $\eta^n/(1 - \eta^n)$. Moreover, food purchased for on- and off-premises consumption appear as two separate line items in NIPA accounts, but the former is mingled with services associated with on-premise food consumption and accommodation. For this reason, household surveys show higher expenditures on total food, as opposed to food at home—but even then, it is not possible to isolate expenditures on food alone. More importantly, price indexes reported in NIPA are not informative about relative prices in the model. Consequently, it is not possible to use constant price consumption expenditures and combine them with price indexes to calibrate η_n in a model-consistent fashion.

Instead, the calibrated value of η^n is the sample average of

$$\frac{(P_n C_n)/P_f(C_f - \gamma)}{1 + (P_n C_n)/P_f(C_f - \gamma)},$$

where $P_f C_f$ and $P_n C_n$ are, respectively, consumption expenditures on food and beverages purchased for off-premises consumption (“food consumption”), and PCE minus food consumption and gross housing value added from NIPA Tables 1.3.5, 1.5.4, and 2.3.5. The subsistence food consumption underlying this calibration is determined as follows. Using a three sector version of this model, İscan (2010) argues that the most appropriate value of γ/C_f in 1970 is 0.70. Based on this estimate, it is possible to calibrate γ using expenditures on food consumption and food price indexes using the following steps.

Step 1: According to Lebergott (1996) consumption expenditures on food in 1910 was 12,786 million dollars.

Step 2: According to Lebergott (1996), between 1910 and 1929 the price index for food, alcohol, and tobacco increased from 0.079 to 0.141 (1987=1.0), or by 78.5 percent.

Step 3: If subsistence food consumption γ was about 70 percent of food expenditures in 1910, then in 1929 prices this would be equivalent to $.7 \times 12,786 \times 1.785 = 15,974$ million dollars, or about 16 billion dollars.

Step 4: This value of γ can then be inflated using the price index for food consumption (NIPA Table 1.5.4). Based on these calculations, in 1960, γ/C_f was about 45 percent.

Initial non-farm capital stock: Current-cost net stock of private fixed assets and consumer durable goods are from the BEA, Tables 1.1 (Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods) and 2.1 (Current-Cost Net Stock of Private Fixed Assets, Equipment and Software, and Structures by Type). Market capital, K_n , is the sum of nonresidential structures, equipment and software. Since the BEA reports fixed assets on a year-end basis, in the quantitative analysis the value of capital stock for year t is the corresponding value in BEA tables for year $t - 1$. The nominal market output is nominal output (NIPA Table 1.1.5) minus gross housing value added (NIPA Table 1.3.5).

Long-run non-farm labor-augmenting technical change: The calibration uses the sample average so that $g(A_n^L) = 1.634$.

Long-run share of employment in agriculture: The calibration uses the share of employment in agriculture in 2004.

B Farm sector labor- and land-augmenting efficiency

This appendix discusses the method used in the paper to compute labor- and land-augmenting efficiency terms in the farm sector A_{ft}^L and A_{fjt}^T .

B.1 Methodology

To back-out factor-augmenting efficiency variables A_{ft}^L and A_{fjt}^T , I use a two-step method developed by Mundlak (2005). This method has the following requirements: a constant returns to scale production function, a constant elasticity of substitution between land and labor, and competitive factor and product markets in each state. The model builds on these conditions. The first step of the method uses factor-price ratios and relative factor intensities in each region to determine the *relative* factor augmenting technology by region. With this relative factor-augmenting technical change in hand, in the second step, the procedure apportions the growth rate of state-level farm sector multifactor productivity into the growth rates of farm sector labor- and land-augmenting technical change.

In particular, the first step of the Mundlak (2005) method proceeds as follows. Denote the ratio of farm wage rate to land rent in region j by ω_j (the online Supplementary Material S.1 discusses the data sources for ω_j). Competitive factor and product markets implies that ω_j is equal to the ratio of the marginal value product of farm labor to marginal product of pasture rent in physical units:

$$\omega_j = \frac{MP(A_f^L L_{fj})}{MP(A_{fj}^T T_{fj})} \frac{A_f^L}{A_{fj}^T}.$$

Use the regional production function (6) to determine the marginal products, and take logs to obtain

$$\ln l_{fj} = \sigma \ln \left(\frac{\alpha_f^L}{\alpha_f^T} \right) + \sigma \ln \omega_j + (1 - \sigma) \ln a_{fj}, \quad (\text{B.1})$$

where $l_{fj} = T_{fj}/L_{fj}$ is the farmland-to-labor ratio in region j , using land and labor input data from Ball et al. (2010).

Total differentiation of equation (B.1) gives

$$g(l_{fj}) = \sigma g(\omega_j) + (1 - \sigma)g(a_{fj}). \quad (\text{B.2})$$

In this expression, $g(a_{fj}) = g(A_{fj}^L) - g(A_{fj}^T)$ is the measure of relative factor-augmenting technical change in agriculture in region j , and is the variable of interest. For the empirically plausible values of $\sigma < 1$, equation (B.2) therefore links changes in the land-to-labor ratio (land deepening) to a weighted average of changes in wage-to-rental ratio and factor-augmenting technical change with weights determined by the elasticity of substitution between labor and land.

The second step of the Mundlak (2005) method combines the growth rate of total factor productivity $g(A_{fj})$ (from indexes of multifactor productivity in Ball et al. (2010)) and the growth rate of relative factor productivity (from the step above) to determine the growth rates of farm sector labor- and land-augmenting technical change. In particular, with two factors of production, the growth rate of state-level farm sector multifactor productivity $g(A_{fj})$ has two components:

$$g(A_{fj}) = \mu_j g(A_{fj}^L) + (1 - \mu_j) g(A_{fj}^T), \quad (\text{B.3})$$

where μ_j are the elasticities of farm output in region j with respect to labor. Using (B.1) and (B.2), it is immediate to compute $g(A_{fj}^L)$ and $g(A_{fj}^T)$. For a CES production function, the elasticity parameters μ_j in equation (B.3) depend on the weights of labor and land in production (α_f^L and α_f^T), the elasticity of substitution in production (σ), and the ratio of effective land to effective labor (l_{fj}/a_{fj}).²⁹

In the model, A_{ft}^L is common across regions. So, to compute the common growth rates of farm-sector labor augmenting technical change, the calibration uses the cross-regional averages of $g(A_{fj}^L)$, so that $g(A_f^L) = (1/J) \sum_{j=1}^J g(A_{fj}^L)$, and back out region-specific growth rates of farm-sector land-augmenting technical change $g(A_{fjt}^T)$ by $g(A_{ft}^L) - g(a_{fjt})$.³⁰ These calculations can then be combined with particular normalization of productivity levels to determine A_{ft}^L and A_{fjt}^T . The measurements reported below use $A_{f0}^L = 1$ (year=1960), and $A_{f10}^T = 1$ (region=Alabama, year=1960). The following steps summarize the procedure to obtain A_{ft}^L and A_{fjt}^T .

Step 1: Calculate $g(a_{fjt})$ using equation (B.2).

Step 2: Calculate $g(A_{fjt}^L)$ and $g(A_{fjt}^T)$ using equation (B.3).

Step 3: Calculate the cross-regional averages of $g(A_{fjt}^L)$ to obtain $g(A_{ft}^L) = (1/J) \sum_{j=1}^J g(A_{fjt}^L)$.

Step 4: Calculate region-specific $g(A_{fjt}^T) = g(A_{ft}^L) - g(a_{fjt})$.

Step 5: Normalize $A_{f,0}^L = 1$ and $A_{f,1,0}^T = 1$.

Step 6: Calculate for $t = 1, 2, \dots, T$, $A_{ft}^L = A_{f,t-1}^L e^{g(A_{ft}^L)}$, and $A_{fjt}^T = A_{fj,t-1}^T e^{g(A_{fjt}^T)}$.

²⁹Antle and Capalbo (1988) compare the index-number and econometric approaches to the measurement of total factor productivity, and survey the econometric literature on estimating the factor bias of technical change in agriculture. The econometric estimates uniformly show labor-saving technical change in the postwar U.S. agriculture—though they also tend to reject the homogeneity assumption underlying the index-number based decomposition analysis pursued here (e.g., Capalbo and Vo, 1988; Lambert and Shonkwiler, ???). It is interesting to extend the present multi-region framework to one with economies of scale, but such an extension is left for future work.

³⁰Here, the common component of labor-augmenting technical change $g(A_f^L)$ is the cross-sectional averages of state-level $g(A_{fj}^L)$. I also conducted a statistical factor analysis (principle components). For the base case parameters, with one common factor, the average (over time) correlation with mean (across states) $g(A_{fj}^L)$ is 0.815, and with 2 common factors, the correlation is 0.643.

B.2 Estimates

To measure factor-augmenting productivity, this paper uses the following *base case* parameter values. The elasticity of substitution in farm production between labor and land is $\sigma_f = 0.2$ based on Binswanger (1974). The share of labor in the farm sector production $\alpha_f^L = 0.654$ is the sample average (from 1960 to 1974) of the cost share of labor in expenditures on labor and real estate, and are based on Ball et al. (1997, table 4).

To check the sensitivity of the results to alternative parameters, this paper also considers the following ranges for parameter values. The econometric estimates surveyed in Capalbo and Vo (1988) point to even lower elasticities of substitution in farm production between labor and land than the base case $\sigma_f = 0.2$. Thus, the calibration uses $\sigma_f = 0.1$ for sensitivity analysis. The cost share of labor in the farm sector α_f^L has declined slightly over time. After 1975 there was a dramatic run-up in the price of farmland, largely due to the real estate bubble in the late 1970s and early 1980s. This dramatic price movement reduced the imputed share of labor in total costs. So, for sensitivity analysis the simulations consider two alternative values for α_f^L : average cost share of labor from 1960 to 1994, and average cost share of labor from 1975 to 1994. Table B.1 presents the base case parameter values and the ranges considered for sensitivity analysis.

Figure B.1 shows the growth rate of agricultural total factor productivity $g(A_f)$, the growth rate of farm sector labor- relative to land-augmenting technology $g(a)$, and the growth rate of labor-augmenting technology $g(A_f^L)$ for both weighted and unweighted series. Weights are based on the share of each state in total agricultural output. Overall, factor-augmenting growth rates are not particularly sensitive to output-share weights. However, there is considerable variability in the annual growth rates, especially from the mid-1970s to the mid-1990s (figure B.1A).

Relative factor-augmenting technology $g(a)$ and labor-augmenting technology $g(A_f^L)$ (figures B.1B and C) present the main findings of the productivity analysis. These results depend on the elasticity of substitution between labor and land in production σ_f (figure B.1B), and both σ_f and α_f^L , the weight of labor in agricultural production (figure B.1B), and are shown for the *base case* parameter values. The core message of these estimates is that factor- augmenting technical change in U.S. agriculture has on average been labor saving (and land-biased) over this period.

Table B.2 shows the sensitivity of the results to alternative parameter values. The growth rate of relative factor-efficiency is not sensitive to alternative values of α_f^L ; see equation (B.1). However, the growth rates of individual factor-augmenting terms depend on both parameter values and both of these parameters have significant influence on the results. Higher substitutability between labor and land in agricultural production σ_f (.2 versus .1) corresponds to a lower labor-augmenting technical change, and similarly, higher weight of labor in agricultural production α_f^L (.468 versus .654) corresponds to a lower labor-augmenting technical change.

Table B.1: Parameter values used for measuring factor-augmenting technology in agriculture

Description	Mnemonic	Base case	Alternatives
Elasticity of substitution in farm production between labor and land	σ_f	0.2	0.1
Weight of labor in farm production	α_f^L	0.654	0.468 , 0.548
Normalization of factor-augmenting technology			
Farm labor-augmenting technology in 1960	$A_{f,0}^L$	1	
Farm land-augmenting technology, Alabama in 1960	$A_{f,1,0}^T$	1	

Note: “Alternatives” correspond to parameter values considered in the simulations for sensitivity analysis. See the text and Appendix A for details.

C The numerical solution method

The numerical solution is based on a global forward-iteration algorithm (Heer and Maußner, 2005). This algorithm requires a finite time horizon. Let $T_\infty > T > 0$ be the simulation horizon, which is sufficiently “long” so that the numerical solution can be safely assumed to be “close” to the asymptotic steady-state values of the calibrated model. The algorithm solves for the capital stock per worker $\{\tilde{k}_{nt}\}_{t=1}^{T_\infty}$ given the initial capital stock per worker $\tilde{k}_{n0} > 0$, the calibrated parameter values, the share of employment in agriculture $\{\tilde{l}_{ft}\}_{t=1}^{T_\infty}$, population growth $\{n_t\}_{t=1}^{T_\infty}$, the growth rate of non-farm labor-augmenting technology $\{G(A_{nt}^L)\}_{t=1}^{T_\infty}$, and the realized allocation of land between farm and non-farm.

The simulation horizon includes two distinct periods. The first period from $t = 0$ to $t = T$ is the simulation horizon for which there are measures of labor force and factor-augmenting technology terms. The second period from $t = T + 1$ to $t = T_\infty$ is the simulation horizon for which the values corresponding to these terms are set to their forecasted values. The solution algorithm uses both the actual and forecasted values. In particular, for $t = 0, 1, \dots, T - 2$, the algorithm uses actual data. For $t = T - 1, T$, the algorithm uses a mixture of actual and forecasted data, and for $t = T + 1, T + 2, \dots, T_\infty - 1$, it only uses forecasted data. Period $t = T_\infty$ is reserved for the asymptotic-steady state, with the understanding that the numerical discrepancy between the solution of the model at $T_\infty - 1$ and the asymptotic-steady state values is relatively “small.”

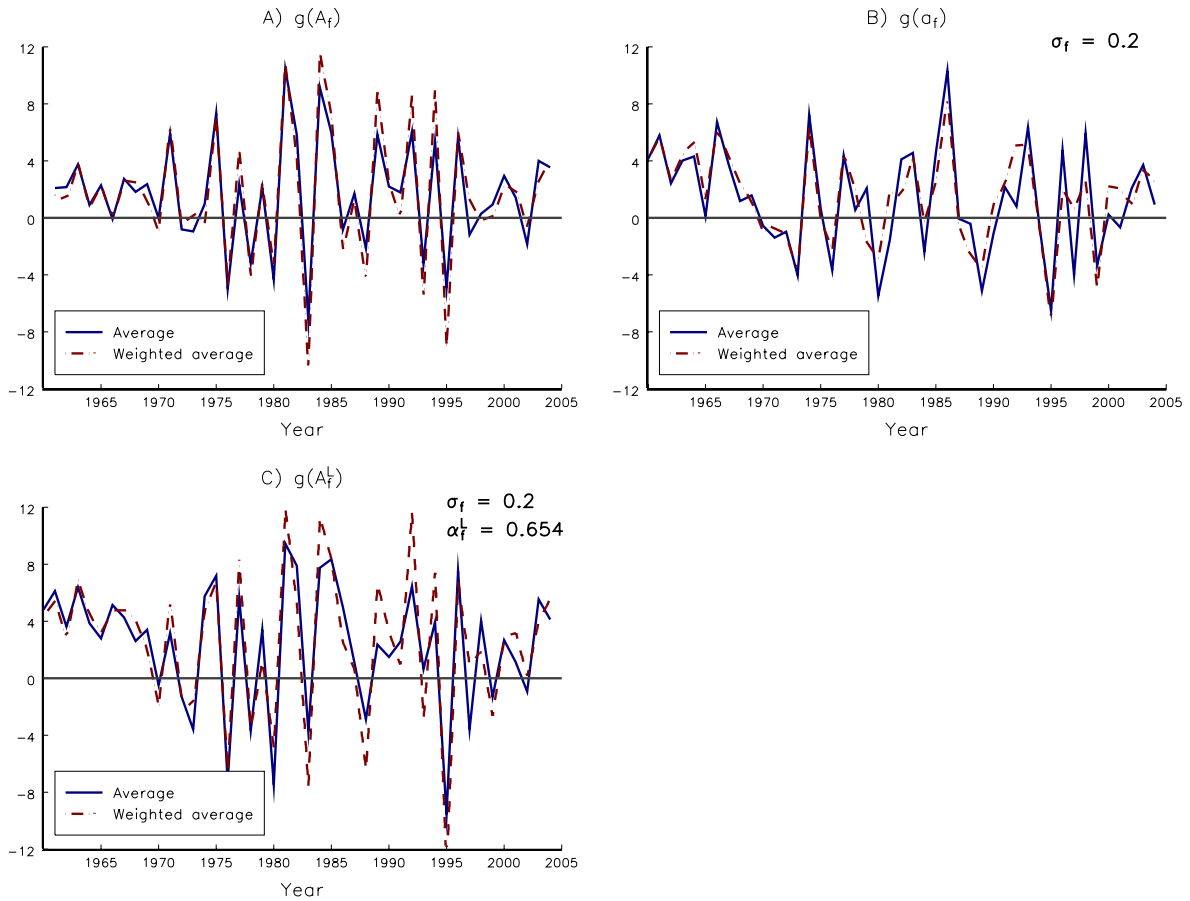


Figure B.1: Technical change in U.S. agriculture, 1960–2004

Note: A) Total factor productivity growth averaged over 48 contiguous states $g(A_f)$ based on Ball et al. (2010). B) The growth rate of relative (labor-to-land) factor-augmenting technology averaged across states $g(a_f)$ based on equation (B.2) in the text. C) The growth rate of labor-augmenting technology averaged across states $g(A_f^L)$ based on equation (B.3) and for the base case parameter values in table B.1. All growth rates are in percent.

Table B.2: Average growth rate of factor-augmenting technology

Parameters	$g(a_f)$		$g(A_f^L)$		$g(A_f^T)$	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
$\sigma_f = 0.2, \alpha_f^L = 0.654$	1.11	1.35	1.96	1.99	0.84	0.60
$\sigma_f = 0.2, \alpha_f^L = 0.468$	1.11	1.35	2.32	2.46	1.20	0.96
$\sigma_f = 0.1, \alpha_f^L = 0.654$	1.28	1.47	2.41	2.51	1.13	0.94
$\sigma_f = 0.1, \alpha_f^L = 0.468$	1.28	1.47	2.22	2.29	0.95	0.76

Note: This table shows the average annual growth rates of relative (labor-to-land) factor-augmenting technology $g(a_f)$ in agriculture, labor-augmenting technology $g(A_f^L)$, and land augmenting technology $g(A_f^T)$ computed in 48 contiguous U.S. states from 1960 to 2004. See the text for the methodology, which is based on Mundlak (2005). Weights are based on the share of each state in output over a given period. α_f^L is the weight of labor in agriculture, and σ_f is the elasticity of substitution between labor and land in agriculture. All growth rates are in percent. Consistent with the model, both the weighted and unweighted averages over time and across states of $g(A_{fjt}^T)$ reported in this table depend on the assumption of a common, unweighted average across states $g(A_f^L)$. The shaded row contains the base case parameter values and the corresponding productivity estimates.

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