Resource Allocation, Technology Adoption, and Productivity: A Quantitative Analysis with Panel Farm-Level Data*

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Abstract

We examine how resource allocation across production units shapes technology adoption and productivity growth, combining a unique panel dataset of the universe of Canadian farms spanning 1986 to 2006 with a quantitative model of heterogeneous producers. The period features the advent and rapid diffusion of a major new seeding technique, zero tillage, whose use expanded from zero percent of cultivated land in 1986 to 60 percent by 2006. We document substantial technology adoption, land consolidation, and productivity growth, facilitated by an economic environment characterized by relatively high allocative efficiency, whereby more productive farms operate at a larger scale. Empirically, we find that adopting zero-tillage raises farm-level productivity. Through quantitative analysis, we estimate that zero-tillage adoption accounts for roughly 35 percent of the near doubling of agricultural productivity over the period and 45–70 percent of the observed structural transformation. Our counterfactual experiments show that high allocative efficiency was crucial for the widespread adoption of technology, which would have nearly disappeared with correlated distortions commonly documented in developing countries. We also show that technological progress can be a powerful driver of catch-up growth in developing economies with low correlated distortions.

Keywords: Farms, productivity, size, distortions, technology, growth, panel data.
JEL classification: O11, O14, O4.

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1 Introduction

An essential research question in the economics of growth and development is what accounts for the great disparities in aggregate productivity across countries, which are at the core of international differences in income per capita (Klenow and Rodriguez-Clare, 1997; Prescott, 1998; Jones, 2016). There are two broad explanations for lower aggregate productivity in developing countries. First, due to a variety of distortions and frictions, factors of production are less efficiently allocated across firms in developing countries, depressing aggregate productivity (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Second, developing countries feature substantial gaps relative to developed countries in the adoption and diffusion of new technologies (Comin and Hobijn, 2010; Comin and Mestieri, 2018; Ayerst, 2025). We examine the role of resource allocation across production units for technology adoption and productivity following a recent literature linking distortions to technology decisions by firms (Restuccia and Rogerson, 2017; Ayerst, 2025; Ayerst et al., 2024).

We provide direct empirical evidence and a quantitative assessment of the role of resource allocation across production units on technology adoption by exploiting a unique panel dataset of the universe of Canadian farms spanning a period during the advent of a new seeding technology in agriculture, its adoption and diffusion by Canadian farms. While the share of employment and output in agriculture nowadays is low in developed countries, agriculture plays a disproportionate role in the aggregate outcomes of developing countries (Gollin et al., 2002; Restuccia et al., 2008), as a result, technology gaps in agriculture are essential in understanding low aggregate productivity in the developing world.

Using panel data from the Canadian Census of Agriculture during the period between 1986 and 2006, we characterize misallocation and technology diffusion of the zero-tillage technology. Zero-tillage is a new seeding technique developed in the 1970s that enables the preparation of soil and the planting of seeds in one operation with minimum soil disruption, saving on time and resources in addition to a more efficient use of land. Consistent with the historical experience on the decline in the number of farms in Canada and the process of land consolidation into larger farms, between 1986 and 2006, the number of farms declined by 43% and average farm size increased by 46%. During the period, there was widespread diffusion of zero-tillage among Canadian farms, from 0% of the land cultivated in 1986 to around 60% by 2006. The process of land consolidation and technology diffusion during the period is associated with a substantial increase in the agricultural yield of 70% and agricultural output per farm of 149% (4.7% annual growth). At the farm level, the adoption of the zero-tillage technology had a significant positive effect on farm productivity, a result robust to many controls. Moreover, more productive farms adopted the zero-tillage technology in greater proportion, by 1996 the adoption rate among the most productive farms was double the rate of the least productive farms.

An important context in the process of land consolidation and technology adoption among Canadian farms, is the relatively high allocative efficiency in agriculture, the ratio of actual to efficient agricultural output, which is relatively constant during the period at 83-85% nationwide, 87-88% within narrow Census subdivisions, and 95% both nationwide and within narrow Census subdivisions when using the panel to control for potential measurement error in the data. High allocative efficiency results from a strong positive relationship between farm operational size and productivity, which is summarized by a relatively high elasticity of farm land and capital with respect to farm productivity. This feature of resource allocation contrasts markedly with the evidence of substantial resource misallocation of land and other factors of agricultural production in developing countries where farm size and productivity are much less aligned (Chen et al., 2023; Adamopoulos et al., 2022; Aragón et al., 2024).

To quantify how resource allocation across production units shapes technology adoption, productivity growth, and structural transformation, we develop a two-sector model of agriculture and non-agriculture, where individuals make occupational (sector) choices and farmers decide on scale, operation, and technology adoption in agriculture. In this framework, distortions affect the allocation of factors across farms and their operation decision (selection), which in turn act as an effective tax on technology adoption (technology). These effects work to lower agricultural productivity and to hinder structural transformation. We calibrate the model to Canadian data in 1986 and 2006. Of particular interest is the parameter determining the cost of zero-tillage adoption. We then conduct counterfactual experiments to assess the quantitative effect of zero-tillage technology on structural transformation and agricultural productivity growth during the period. We also examine the quantitative effect of higher distortions for technology diffusion, agricultural productivity, and structural transformation.

Our quantitative analysis reveals that the adoption of the zero-tillage technology in Canada between 1986 and 2006 contributed to 35% of the substantial growth in agricultural productivity, between 45 to 70% of the reallocation of employment out of agriculture (structural transformation), and all the increase in average farm size in the data. We also find that a relatively high allocative efficiency in Canada (in particular the relatively low correlated distortions), was essential in supporting the adoption and diffusion of zero-tillage. In a counterfactual experiment where we only change the correlated distortion parameter as documented in developing countries (high distortions), the adoption of zero-tillage technology would have been only 5% of cultivated land in 2006 instead of 60% in the data and would have dampened the increase of agricultural productivity to 5%, one sixth of the actual agricultural productivity growth. We also show that correlated distortions, as opposed to lower economy-wide and sectoral productivity, are key in dampening technology adoption and growth since the same technological progress has much larger effect in a developing economy with low distortions than in the same economy with high distortions. Moreover, technological progress alone in a low-distortions developing economy generates a substantial process of convergence in productivity, structural transformation, and farms size relative to the advanced economy.

We contribute to three broad branches of the literature. First, we relate to a large literature on production heterogeneity and misallocation (Restuccia and Rogerson, 2008; Guner et al., 2008; Hsieh and Klenow, 2009) and more specifically misallocation in agriculture (Adamopoulos and Restuccia, 2014; Chen et al., 2023; Ayerst et al., 2020). We contribute to this literature by examining empirically and in a quantitative model the effect of misallocation on technology adoption and productivity. Second, we relate to the literature on technology adoption and productivity in agriculture (Yang and Zhu, 2013; Caunedo and Keller, 2021; Chen, 2020). We contribute to this literature by analyzing an episode of adoption and diffusion of technology using micro-level data and a quantitative model. Third, we connect to the literature linking misallocation with effects on selection and technology (Pavcnik, 2002; Bustos, 2011; Khandelwal et al., 2013; Yang, 2021; Majerovitz, 2023; Ayerst et al., 2024). We contribute to this literature by analyzing a specific episode of technology adoption.

The remainder of the paper proceeds as follows. In the next section, we provide details of the data we use and empirical findings on allocative efficiency and the adoption and productivity effect of zero-tillage technology. In Section 3, we describe the model and section 4 calibrates the model to Canadian data for 1986 and 2006. We perform quantitative experiments to assess the effect of the adoption of zero-tillage technology in the Canadian economy and in counterfactual alternative developing economies. We conclude in Section 5.

2 Empirical Findings

We focus on the period between Census years 1986 and 2006 for which we have access to a panel data of farms in Canada. We describe the data and present a number of facts related to farm productivity, resource misallocation, and the adoption of the zero-tillage technology.

2.1 Data

We use the Canadian Longitudinal Census of Agriculture (L-CEAG) that provides information on all operating farms in Canada every 5 years between 1986 and 2006. Our analysis focuses on the cropping sector, which accounts for most of the output and land in Canadian agriculture. The data include information on farm characteristics, such as output, land, capital, and input use. We construct farm-level total factor productivity (TFP) and distortions using the data and a standard structural framework. Below we provide details on the data and variables used in our analysis. All the real variables are reported in 1986 Canadian dollars.

Real gross output. We measure output using the real gross output of crop farms. Nominal gross farm receipts are deflated using the farm-level output price index obtained from the Census of Agriculture.

Real capital. We measure capital using the real capital stock of crop farms. The reported market value of farm machinery and equipment is deflated using the Machinery and Motor Vehicles Price Index from the Canada Farm Input Price Index provided by Statistics Canada.

Land input and by crops. We measure land input using the total cultivated area of farms in acres. We also measure the total area of cultivated land by major crops in acres, including wheat, barley, canola, and rye.

Zero-tillage and other farm characteristics. We measure the total area of cultivated land using the zero-tillage technology in acres. We also use information on farm characteristics, including farm identification for the panel, age of farm operators, and location by Census Consolidated Subdivision (CCS), henceforth census subdivision or CCS for short.

Sample selection. We restrict our sample to crop farms. We exclude farms with missing values for output, land, or capital. We also exclude farms with zero output, land, or capital. Following Brown et al. (2020), to focus on grain farms of sufficient scale and to exclude hobby or lifestyle operations, we restrict the sample to farms with gross farm income of at least 10,000 CAD (in constant 1986 dollars). To limit the influence of outliers, we trim the top and bottom 1% of the farms based on farm-level measured productivity.

2.2 Aggregate Statistics

Table 1 presents aggregate statistics for Canadian farms producing crops during the period 1986-2006.

Table 1: Aggregate Statistics - Canadian Agriculture from 1986 to 2011

Year	Output	Farms	Land	Capital	TFP	Average Farm Size
1986	6.69	107,980	86.29	10.91	1.00	800
1991	7.72	90,685	79.44	10.75	1.15	876
1996	5.78	81,185	78.10	12.83	0.91	961
2001	7.35	69,670	71.94	13.74	1.23	1,033
2006	9.50	61,665	72.11	15.19	1.62	1,169
Ratio (06/86)	1.42	0.57	0.84	1.39	1.62	1.46

Notes: Output and capital are reported in real terms (1986 prices) in billions of Canadian dollars. Total land is reported in unit of millions of acres. Average farm size is reported in acres.

During this period, real agricultural crop output increased by 42%, rising from 6.69 billion in 1986 to 9.50 billion in 2006. Meanwhile, the total number of farms declined by 43%, dropping from 107,980 in 1986 to 61,690 in 2006. Despite a slight decline in the total amount of cultivated land by around 16%, the substantial decline in the number of farms associated with a process of land consolidation resulted in a substantial increase in average farm size by approximately 46%. Additionally, the total amount of capital increased by 39%, from 10.91 billion in 1986 to 15.19 billion in 2006.

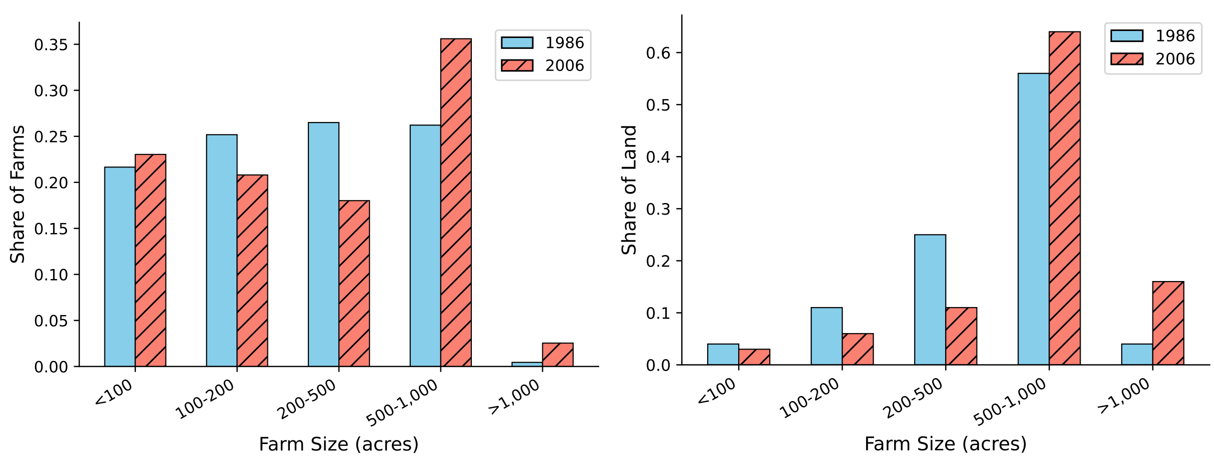
Agricultural total factor productivity (TFP) is measured as a residual assuming the following aggregate production function:

$$Y = AM^{1-\gamma} \left(K^{\alpha} L^{1-\alpha}\right)^{\gamma},$$

where Y is agricultural output, M is number of operating farms, L is land, K is capital and A is measured agricultural TFP. Parameters γ and α are set to 0.54 and 0.67. The TFP index represents measured TFP relative to 1986, which increases 60% between 1986 and 2006 (an annualized growth rate of 2.38%). We note that the number of farms in Canada is closely linked to agricultural employment. On average, there were approximately 1.5 workers per farm during the period from 1976 to 2021.

Figure 1 documents the distribution of farms by land size in 1986 and 2006. As noted earlier with the average farm size, there is a substantial shift in the size distribution of farm during this period. In panel A, while most farms were smaller than 500 acres in 1986, the share of farms larger than 500 acres increased substantially by 2006. Specifically, the share of farms larger than 500 acres rose from 27% in 1986 to 38% in 2006, while the share of farms smaller than 500 acres decreased from 73% to 62%. Panel B documents the share of land by farm size. The proportion of land held by farms larger than 500 acres increased from 60% in 1986 to 80% in 2006. Conversely, the share of land held by farms smaller than 500 acres decreased from 40% in 1986 to 20% in 2006.

Figure 1: Farm Size Distribution



(a) Share of farms by size

(b) Land share by farm size

Notes: Distribution of farms by size in 1986 and 2006. Panel (a) shows the share of farms by size. Panel (b) shows the share of land by farm size.

2.3 Farm-level Productivity and Resource Misallocation

We consider a standard framework for evaluating productivity and misallocation in agriculture following Lucas (1978) and Adamopoulos and Restuccia (2014). We document key facts about the distribution of farm-level productivity and resource misallocation across Canadian farms from 1986 to 2006. Our findings indicate that resources are allocated close to efficient levels among Canadian farms. We identify a strong positive correlation between input factors (land and capital) and farm productivity, contrasting with prior studies in developing countries that report weak or negligible relationships Adamopoulos et al. (2022); Chen et al. (2023); Aragón et al. (2024).

Over the sample period, we observe minimal changes in the efficiency of resource allocation among Canadian farms. The majority of improvements in agricultural TFP at aggregate level are driven by enhancements in the distribution of farm-level productivity.

Basic framework. We consider a standard framework to evaluate the extent of resource misallocation in Canadian agriculture using micro-level farm data. The framework and data are employed to measure farm-level total factor productivity (TFP) and to quantify the potential agricultural productivity gains that could be achieved from factor reallocation across farms.

We consider M farms and measure farm-level productivity s_i as the residual from the following farm-level production function,

$$y_i = s_i^{1-\gamma} \left(k_i^{\alpha} \ell_i^{1-\alpha} \right)^{\gamma}, \ \alpha, \gamma \in (0,1), \tag{1}$$

where y_i is real output, k_i is capital, ℓ_i is the amount of operated land, and (α, γ) are input elasticities. Following Valentinyi and Herrendorf (2008), we choose $\alpha = 0.67$ and $\gamma = 0.54$ to match the capital and land income share in agriculture in advanced economies such as the United States and Canada.

Farm-level total factor productivity (TFP) is computed as the residual from equation (1), using farm-level output and input data. We define farm-level distortions as the average product of factor inputs,

$$\text{distortion}_i = \frac{y_i}{k_i^{\alpha}\ell_i^{1-\alpha}}.$$

which should equalize across farms in the absence of frictions or distortions. This measure of average products is proportional to the marginal product given our production function specification. Our measure of farm distortions relates to revenue productivity (TFPR) in Hsieh and Klenow (2009) in that it is the object that equalizes across production units in the absence of distortions.

We characterize the efficient allocation of capital and land across a fixed set of M producers with different productivity s_i as the allocation that maximizes aggregate output subject to the resource constraints:

$$Y^e = \max_{\{k_i,\ell_i\geq 0\}} \quad \sum_i s_i^{1-\gamma}\left(k_i^{\alpha}\ell_i^{1-\alpha}\right)^{\gamma},$$

subject to

$$K = \sum_i k_i, \quad L = \sum_i \ell_i.$$

The efficient allocation equates the marginal product of capital and land across farms and is characterized as

$$k_i^e = \frac{s_i}{\sum_{j-1}^{M} s_j}K, \quad \ell_i^e = \frac{s_i}{\sum_{j=1}^{M} s_j}L.$$

Note that the efficient allocation implies a strong positive relationship between farm-level productivity and size where more productive farms operate more inputs. However, previous studies examining resource misallocation in agriculture in less developed countries (Adamopoulos et al., 2022; Chen et al., 2022) document that this positive relationship is weak or nonexistent, providing evidence of severe misallocation of resources in agriculture in less developed countries. To the best of our knowledge, no such analysis has been conducted for the agricultural sector in developed countries. Hence, our analysis of Canadian farms provides a first opportunity to assess systematic evidence of resource misallocation in a developed country.

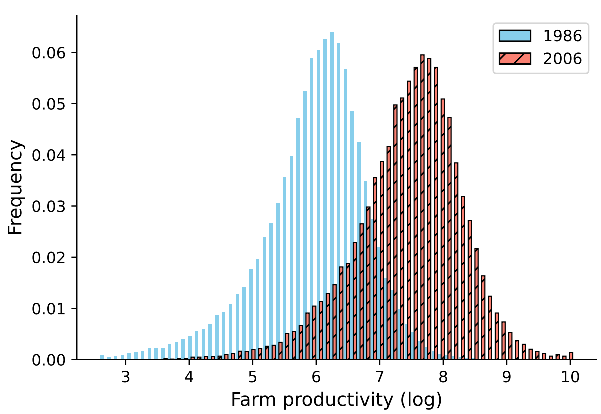
We assess the extent of misallocation by allocative efficiency, a standard measure widely used in the misallocation literature. Allocative efficiency (AE) is defined as the ratio of the actual output (Y) in the distorted economy to the aggregate output given the efficient allocation (Y^e):

$$AE = \frac{Y}{Y^e}.$$

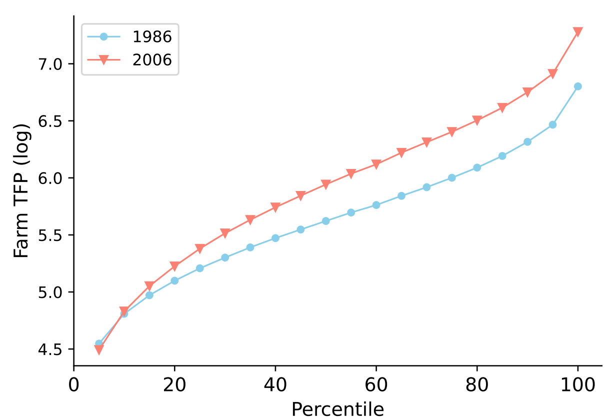
Allocative efficiency ranges from 0 to 1, with 1 representing perfect resource allocation across producers, while values closer to 0 indicate greater inefficiencies in resource allocation. Previous studies on resource misallocation in low-income countries have found low allocative efficiency values, indicating a great extent of misallocation.

Farm-level productivity. We document the evolution of farm-level TFP distribution over time. Figure 2 plots the distribution of farm-level TFP in 1986 and 2006. There is a substantial improvement in the distribution of farm productivity during this period. On average, farm-level TFP increased by 67% (0.51 log-points) from 1986 to 2006.

Figure 2: Distribution of Farm TFP



(a) Histogram of log(TFP)



(b) log(TFP) by percentiles

Notes: The distribution of farms by TFP in 1986 and 2006.

Table 2: Dispersion of Farm-level TFP

Dispersion Measures	1986	1991	1996	2001	2006
Standard deviation of log	0.55	0.57	0.53	0.62	0.64
Ratio of p90 to p10	4.53	4.76	4.31	5.70	6.82

Notes: Dispersion in farm TFP measured by the standard deviation (std) of log farm TFP and by the ratio of percentile 90 to percentile 10 farm TFP.

Table 2 reports a summary of farm-level productivity and distortions for the period 1986-2006. The measures on the standard deviation of the log and the inter-decile difference indicate that TFP dispersion across farms has increased over time: the standard deviation of log TFP rises from 0.55 to 0.64, and the 90–10 percentile difference grows from 1.51 to 1.92.

Resource misallocation. Table 3 presents a summary of key measures of resource misallocation across Canadian farms over time. The dispersion of distortions remains relatively stable throughout the sample period (1986–2006), with both the standard deviation and the 90–10 percentile difference showing little change. The elasticity of farm distortions with respect to farm TFP, another common measure of misallocation, is 0.76 in 1986 and declines slightly to 0.68 in 2006.

Table 3: Measures of Resource Misallocation

	log(distortion)		Distortion	Allocative Efficiency	
Year	std	p90-p10	Elasticity	Nationwide	Within CCS
1986	0.56	1.65	0.76	0.83	0.88
1991	0.56	1.56	0.73	0.83	0.87
1996	0.52	1.49	0.68	0.85	0.88
2001	0.57	1.63	0.66	0.83	0.87
2006	0.59	1.64	0.68	0.83	0.87

Notes: The first two columns report the standard deviation (std) and the difference between the 90 and 10 percentile of log distortions. Distortion Elasticity refers to the elasticity coefficient from regressing log(distortion) on log(TFP).

We examine resource allocation among Canadian farms and study the agricultural implications of reallocation at different levels of aggregation: nationwide, within Census Consolidated Subdivisions (CCS), and across time during our sample period. To ensure the results are not driven by outliers, we follow standard practices in the misallocation literature and trim our sample by the top and bottom 1% of farm-level TFP and farm-level distortion measures. However, the results are robust to different trimming thresholds, such as 2% or 5%.

Table 3 reports allocative efficiency at both the nationwide and within CCS levels. During this period, allocative efficiency remained around 0.83-0.85 at the nationwide level and around 0.87-0.88 at the CCS level. These results indicate that there is little misallocation across CCS locations, instead the bulk of nationwide misallocation stems from misallocation across farms within CCS.

Our findings indicate that resource allocation among Canadian farms is close to the efficient allocation and remains stable throughout the sample period from 1986 to 2006. The substantial increase in aggregate agricultural TFP during this time is primarily driven by shifts in farm-level productivity distribution rather than improvements in resource allocation efficiency.

Measurement error. The measures of TFP and distortions (TFPR) may reflect measurement error, transitory output or input shocks, and unobserved location-specific characteristics, which can impact the measures of misallocation. Following Adamopoulos et al. (2022), as a robustness exercise, we address these concerns by estimating permanent farmer fixed-effect measures of TFP and distortions. In particular, we decompose the logarithm of farm-level TFP and distortions,

$$\log(\mathrm{TFP}_{ict}) = \mu_t^{TFP} + \mu_i^{TFP} + e_{ict}^{TFP},$$

$$\log(\mathrm{distortion}_{ict}) = \mu_t^{distortion} + \mu_i^{distortion} + e_{ict}^{distortion},$$

where μ_t^{TFP} and $\mu_t^{distortion}$ are a year fixed effect component that captures the common shocks to all farms at time t, μ_i^{TFP} and $\mu_i^{distortion}$ are a farm's fixed-effect components that do not vary over time; e_{ict}^{TFP} and $e_{ict}^{distortion}$ capture the idiosyncratic shocks specific to the farmer in a given year t.

Table 4: Measures of Misallocation Based on Farm Fixed-Effect Components

	(1) Nationwide	(2) Within CCS
Standard deviation		
log TFP	0.33	0.26
log distortion	0.28	0.26
Elasticity		
Distortion to TFP	0.59	0.57
Land to TFP	0.96	1.04
Capital to TFP	0.85	0.87
Allocative Efficiency	0.95	0.95

Notes: In efficient allocation, elasticity of distortion to TFP is 0 while elasticity of inputs (land and capital) to TFP is $1/(1-\gamma) = 2.17$. Statistics for column (1) are computed based the fixed effect estimation of the permanent components of farm productivity and distortions. Statistics for column (2) are derived by removing CCS location fixed effect from the farm-level fixed effect, following the approach of Adamopoulos et al. (2022).

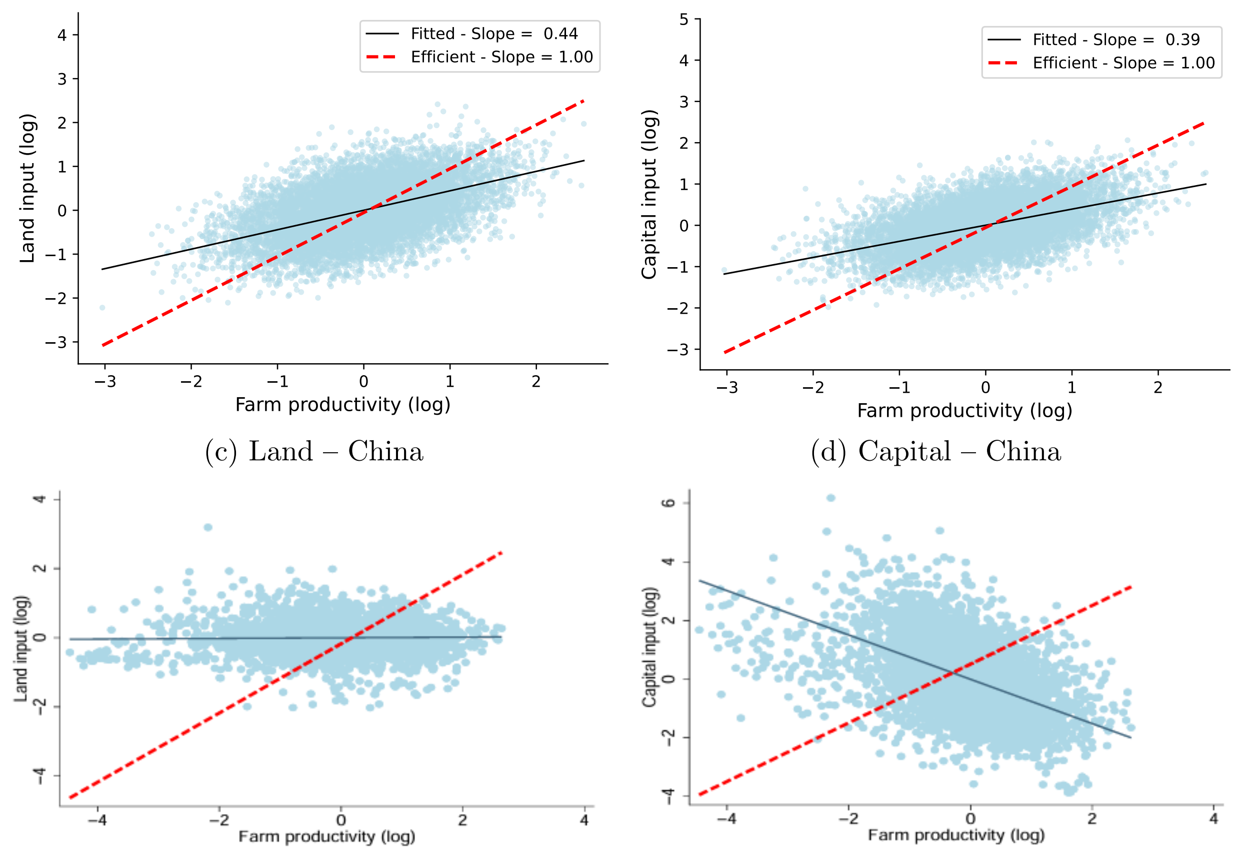
We next examine resource allocation among Canadian farms using farm-level fixed-effect estimates of productivity and distortions. Our analysis considers factor allocation at two levels: (1) across the entire country and (2) within Census Consolidated Subdivisions (CCS). Table 4 reports summary statistics for productivity, distortions, and measures of resource misallocation among Canadian farms.

The estimates in Table 4 show a substantial decline in the dispersion of both log TFP and distortions when moving from cross-sectional to fixed-effects estimates. The standard deviation of log TFP is 0.33 for the permanent component of farm productivity (μ_i^{TFP}), and further declines to 0.26 when CCS location fixed effects are removed. Similarly, the standard deviation of log distortions is 0.28 for the permanent component of distortions ($\mu_i^{\text{distortion}}$), falling to 0.26 after controlling for CCS fixed effects.

Figure 3: Factor Allocations by Farm Productivity in Canada and China

(a) Land – Canada (b) Capital – Canada

(c) Land – China (d) Capital – China



Notes: The data on inputs and productivity refer to the panel farm fixed effect. The data for Canada are generated from simulations of 10,000 farms using estimated moments, whereas the data for China are from Adamopoulos et al. (2022). The solid dark-blue line is the estimated relationship between inputs and farm productivity whereas the dashed red line is the efficient allocation associated with each level of farm productivity.

The elasticity of distortions with respect to productivity is estimated to be 0.59 and 0.57. In contrast, the elasticities of land and capital with respect to farm TFP are high and significantly positive. Specifically, the elasticity of land to TFP is estimated at 0.96 and 1.04, while the elasticity of capital to TFP is 0.85 and 0.87. These estimates indicate a much stronger relationship between productivity and size at the farm level than those documented for low-income countries in previous studies.

Measuring productivity and distortions using farm fixed effects yields higher implied allocative efficiency. In both the national and CCS-level analyses, allocative efficiency is estimated at 0.95, suggesting an allocation very close to the efficient allocation. This implies potential gains from reallocation are only slightly above 5 percent $(1/0.95 - 1)$.

Figure 3 plots farm inputs (land and capital) against farm-level productivity for two countries: Canada and China. Due to data confidentiality restrictions, we do not report the raw Canadian data. Instead, using the estimated moments, we simulate 10,000 farms to visually represent the factor allocation among Canadian farms. These results are compared to the corresponding figures for China reported in Adamopoulos et al. (2022).

Under efficient allocation, there should be a strong positive relationship between farm inputs and productivity, with an expected elasticity of one. For Canada, we find that both land and capital are more intensively allocated to more productive farms, as indicated by a significantly positive slope. In contrast, Adamopoulos et al. (2022) report that in China, there is little to no correlation between land inputs and productivity, and in the case of capital, the relationship is even negative. These findings suggest substantial deviations from an efficient allocation in China, while providing strong evidence of a more efficient resource allocation among Canadian farms.

2.4 Adoption of Zero-Tillage Technology

The 1990s saw the widespread adoption of a new seeding technique known as zero tillage in Canada (Brown et al., 2020). This technology enabled the preparation of the seedbed and the planting of seeds in a single operation, while minimally disturbing the soil. Traditional seeding involves multiple tilling passes, which dries the soil and removes previous crop residue, leading to erosion issues, especially under windy conditions. Zero tillage offers numerous benefits, including reduced fuel consumption, soil moisture conservation, decreased soil erosion, and lower labor requirements. Zero-tillage is an advancement over "minimum tillage" technology, which involves less tillage than conventional methods but still disturbs the soil more than zero tillage.

The moisture conservation benefits of zero tillage allows farms to plant crops annually, rather than leaving fields fallow every second or third year, a practice known as ”summer-fallowing.” Summer-fallowing was traditionally used to conserve moisture for future crops and to control weeds through tillage. By enabling annual planting, zero tillage helps farmers utilize their land more efficiently. However, zero tillage also requires the application of more fertilizer, as leaving the soil idle increased plant-available nitrogen levels through the natural process of mineralization. In addition, zero tillage relies on herbicides for weed control, which was traditionally managed by conventional tillage.

Zero tillage gradually became the dominant seeding technology in Canada, increasing from 0 percent of cultivated land in 1986 to around 60 percent of cultivated land in 2006. The share of farms utilizing zero tillage technology increased from 0 percent in 1986 to around 45 percent in 2006.

We next examine the relationship between the adoption of the zero-tillage technology and farm-level productivity. Table 5 reports the impact of zero-tillage adoption on farm-level productivity by regressing the change in log farm TFP on a dummy variable indicating zero-tillage technology adoption. The regressions control for log farm TFP in the initial period, changes in the share of cultivated land by crop type, as well as time and CCS location fixed effects.

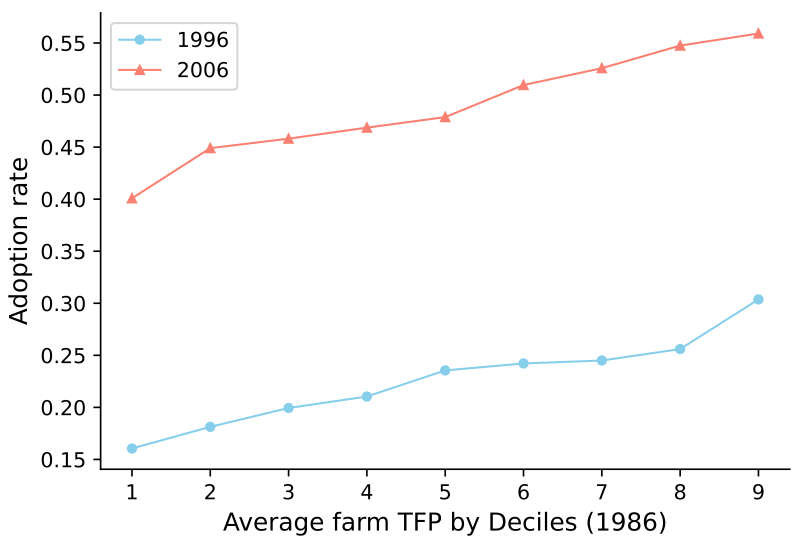
Table 5: Zero-Tillage Adoption and Farm TFP Growth

	$\Delta \log(\text{TFP})$
$ZTAdopt_{2006}$	0.24***
	(0.0087)
Controls	✓
Observations	18,275
Adj. R-squared	0.28

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variables is the 20-year changes in farm log(TFP) defined as $\Delta \log(\text{TFP}) \equiv \log(\text{TFP}_{2006}) - \log(\text{TFP}_{1986})$. The key explanatory variable $ZTAdopt_{2006}$ is the dummy indicating whether the farm adopted the technology in the later period (2006). Controls include initial $\log(\text{TFP}_{1986})$, changes in land shares by crop types (wheat, canola, barley, and rye), and location (CCS) fixed effects.

To capture the longer-run impact of the zero-tillage technology, we focus on the change in farm-level TFP over the available 20-year period. In particular, we restrict the sample to farms observed in both the initial period (1986) and the final sample period (2006), allowing us to examine changes over the 20-year horizon. Since no farms had adopted zero-tillage technology in 1986, we compare the outcomes in 2006 between farms that adopted the technology and those that did not. We find that the change in log TFP is 0.24 log points higher for adopters relative to non-adopters.

Figure 4: Adoption Rate by Deciles of Initial TFP in 1986



Notes: Adoption rate is computed as the share of farms adopting zero-tillage technology in each decile of intial TFP in 1986. The blue line shows the adoption rate in 1996 and the red line shows the adoption rate in 2006.

It is important to note that this result should not be interpreted as causal, as the decision to adopt the technology may be endogenous and correlated with unobserved farm-level characteristics. Nevertheless, the findings provide suggestive evidence that farms adopting zero-tillage technology tend to experience significantly higher TFP growth.

Figure 4 presents the average adoption rates of zero-tillage across deciles of farm-level TFP in 1986. The figure reveals a positive relationship between initial productivity and subsequent adoption: farms with higher TFP in 1986 were more likely to adopt zero-tillage technology in both 1996 and 2006. Among farms in the bottom 10% of the initial TFP distribution, only about 16% had adopted by 1996 and 40% by 2006. In contrast, adoption rates were substantially higher among farms in the top 10% of the initial TFP distribution—approximately 30% in 1996 and 56% in 2006.

Table 6: Determinants of Zero-Tillage Adoption

	(1) OLS $ZTAdopt_{t+5}$	(2) Logit $ZTAdopt_{t+5}$
log(TFP$_t$)	0.17***	1.13***
	(0.0045)	(0.0291)
log($distortion_t$)	-0.11**	-0.68***
	(0.0046)	(0.0305)
Age of operators	-0.002***	-0.01***
	(0.0001)	(0.0008)
Controls	✓	✓
Observations	72,090	72,090
Adj. R-squared	0.12	

Notes: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Dependent variable is the dummy whether the farm first adopt zero-tillage technology in the later period ($t+5$). Independent variables include the farm-level log(TFP), log(distortion), and the age of operators in the initial period t. Sample includes only farms that do not adopt zero-tillage technology in initial period t. Controls include land shares by crop types (wheat, canola, barley, and rye), as well as time and location (CCS) fixed effects.

Table 6 presents the relationship between farm characteristics and the adoption of zero-tillage technology. The regression analysis examines the adoption of zero-tillage technology between 1986 and 2006, considering initial farm-level TFP, distortion, and the age of operators in 1986. The results indicate that more productive farms adopt the zero-tillage technology to a greater extent. Farms facing greater distortions and those farm managed by older operators show lower adoption rates of the zero-tillage technology.

3 Model

We develop a model of structural transformation between agriculture and non-agriculture building on Gollin et al. (2002) and Restuccia et al. (2008). Production in agriculture takes place among heterogeneous farms as in Adamopoulos and Restuccia (2014). Farmers make a technology adoption decision in addition to the farm size operation. We examine how distortions and technological progress affect the operation (selection) and adoption (technology) decisions of farms and their implications on agricultural productivity, structural transformation, and aggregate productivity.

3.1 Economic Environment

Technologies. At each date, a homogeneous agricultural good is produced by farms indexed by i. The production function of farm i is given by

$$y_i = A\kappa\nu_i a_i^{1-\gamma}\ell_i^{\gamma},\ \gamma \in (0, 1),$$

where y_i is agricultural output, ℓ_i is the land input, A is economy-wide productivity, κ is agricultural specific productivity, and $\nu_i a_i^{1-\gamma}$ is the farm's idiosyncratic productivity. The term $a_i^{1-\gamma}$ is a permanent component of total factor productivity while ν_i is a transitory component of total factor productivity with $\mathbb{E}\nu_i = 1$ that is drawn each period from an iid cumulative distribution function $H(v)$ after production decisions are made (Boar et al., 2022). We note that the transitory component ν_i could also capture measurement error in the data which similarly leads to a disconnect between the reported output and labor inputs. Farm idiosyncratic productivity a_i is determined by two components: farm's ability s_i and a technology adoption choice z_i as follows:

$$\log(a_i(s_i, z_i)) = \log(s_i) + \log(z_i).$$

Adopting technology z_i faces a convex cost in units of labor. We describe in detail below the technology adoption decision.

Non-agricultural output is produced by a representative firm using labor as the only input according to the following constant returns to scale production function:

$$Y_n = AN_n,$$

where A is economy-wide productivity and N_n is the labor input.

Preferences and endowments. There is a representative household of measure one comprising of individuals with different farm operating ability s_i drawn from a distribution $F(s)$ and endowed with one unit of time each period supplied inelastically for production. The household owns L units of land also supplied inelastically to farms for agricultural production. The household has Stone-Geary preferences over agricultural and non-agricultural goods:

$$u(c_a, c_n) = a \log(c_a - \bar{a}) + (1 - a) \log(c_n),$$

where c_a and c_n are consumption of agricultural and non-agricultural goods, respectively. The parameter $\bar{a}$ represents the minimum consumption (subsistence) of agricultural goods and a is a weight parameter.

Market structure. We assume competitive markets in both sectors and normalize the price of agriculture to one (numeraire). We denote by p_n the relative price of non-agriculture, q the rental rate of land, and w the wage rate in non-agriculture. Farms face idiosyncratic distortions which we model as proportional revenue taxes τ as in Restuccia and Rogerson (2008). Following Bento and Restuccia (2017) and Ayerst et al. (2024), we parameterize idiosyncratic distortions as a function of farm-level productivity and a random component in order to capture the relationship between farm land size and farm productivity observed in the data. Specifically, we assume that the farm-level distortion $\tau(a, \epsilon)$ is given by

$$\log(1 - \tau(a, \epsilon)) = (1 - \gamma) \left[-\rho \log a - \log \epsilon \right],$$

where ρ is the elasticity of farm distortions with respect to farm productivity and ϵ is drawn from $G(\epsilon)$, which we assume is log normal with zero mean and standard deviation σ_ϵ.

Occupational choice. Individuals with farm operating ability $s_i \sim F(s)$ and random distortions $\epsilon_i \sim G(\epsilon)$, choose whether to operate a farm or to work in the non-agricultural sector. Income in agriculture is determined by the value from operating a farm given by $V(s_i, \epsilon_i)$. Income in the non-agricultural sector is given by wage w. Individuals choose to operate a farm if the income from operating a farm is greater than the income from working in the non-agricultural sector. Denote the occupational choice of operating a farm by an indicator function $o(s, \epsilon)$ given by

$$o(s,\epsilon) = \begin{cases} 0 & \text{if } V(s,\epsilon) < w, \\ 1 & \text{if } V(s,\epsilon) \geq w. \end{cases}$$

We denote the income of individual i as $I(s_i, \epsilon_i)$:

$$I(s_i,\epsilon_i) = o(s_i,\epsilon_i)V(s_i,\epsilon_i) + (1 - o(s_i,\epsilon_i))w.$$

The household's total income is given by

$$I = \int_s \int_\epsilon I(s,\epsilon) dF(s) dG(\epsilon) + qL.$$

Household's consumption. The household chooses consumption of agricultural and non-agricultural goods to maximize utility subject to the budget constraint:

$$\max_{c_a, c_n} \quad u(c_a, c_n) \quad \text{s.t.} \quad c_a + p_n c_n = \int_s \int_\epsilon I(s,\epsilon) dF(s) dG(\epsilon) + qL + T,$$

where p_n is the relative price of the non-agricultural good and T is a total transfer from the government.

3.2 Equilibrium

The model is static and we consider a competitive equilibrium in which households, farms, and firms take prices as given, and prices clear the markets.

Incumbent farms. An incumbent farm i is characterized by idiosyncratic productivity a_i and distortions τ_i. The farm's expected per-period profit is given by

$$\begin{aligned}\pi(a_i, \tau_i) &= \max_{\ell \geq 0} \quad \mathbb{E}_\nu \left[(1-\tau_i) A\kappa\nu a_i^{1-\gamma}\ell^\gamma - q\ell\right], \\ &= \max_{\ell \geq 0} \quad (1-\tau_i) A\kappa a_i^{1-\gamma}\ell^\gamma - q\ell.\end{aligned}$$

The optimal land choice and output of an incumbent farm is given by

$$\begin{aligned}\ell(a_i, \tau_i) &= \left(\frac{\gamma}{q}\right)^{\frac{1}{1-\gamma}} ((1-\tau_i)A\kappa)^{\frac{1}{1-\gamma}} a_i, \\ y(a_i, \nu_i, \tau_i) &= \left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} (1-\tau_i)^{\frac{\gamma}{1-\gamma}} (A\kappa)^{\frac{1}{1-\gamma}} \nu_i a_i.\end{aligned}$$

The optimal expected profit of an incumbent farm is given by

$$\pi(a_i, \tau_i) = (1-\gamma)\left(\frac{\gamma}{q}\right)^{\frac{\gamma}{1-\gamma}} ((1-\tau_i)A\kappa)^{\frac{1}{1-\gamma}} a_i.$$

Technology choice. The farm chooses the adoption of technology level z_i to maximize its value net of technology adoption cost:

$$\begin{aligned}V^{adopt}(s_i, \epsilon_i) &= \max_{z_i \geq 0} \left[\pi(a_i, \tau(a_i, \epsilon_i)) - p_n \psi z_i^\phi\right], \\ \text{s.t.} \quad & \log(a_i) = \log(s_i) + \log(z_i),\end{aligned} \tag{2}$$

where ψ is a parameter that determines the level of adoption costs and $\phi > 1$ is the elasticity of technology adoption cost with respect to technology adoption level.

If the farm chooses not to adopt technology (equivalent to $z = 1$), the value of the farm is given by

$$V^{not\ adopt}(s_i, \epsilon_i) = \pi(a_i, \tau(a_i, \epsilon_i)), \qquad \text{s.t.} \quad \log(a_i) = \log(s_i). \tag{3}$$

The optimal value of an entering farm is given by

$$V(s_i, \epsilon_i) = \max\left\{V^{adopt}(s_i, \epsilon_i), V^{not\ adopt}(s_i, \epsilon_i)\right\}.$$

We generically denote the optimal farm technology adoption level by $z(s_i, \epsilon_i)$ with the convention that $z = 1$ is no technology adoption.

Definition of equilibrium. A competitive equilibrium comprises prices $(p_n,\ w,\ q)$; decision functions for farms: land demand $\ell(a, \tau)$, output $y(a, \nu, \tau)$, expected profits $\pi(a, \tau)$, technology adoption $z(s, \epsilon)$, net value of farm $V(s, \epsilon)$, farm operating decision $o(s, \epsilon)$; mass of non-agricultural workers N_m; household's consumption (c_a, c_n) and income I; and lump-sump transfer T such that:

(i) Given prices, household's income I and transfer T, the allocation (c_a, c_n) solves the household's problem.

(ii) Given w and q, decision function $\ell(a, \tau)$ solves the incumbent farm's problem, determining expected farms' profit $\pi(a, \tau)$ and realized output $y(a, \nu, \tau)$.

(iii) Given w and q, farms choose technology adoption $z(s, \epsilon)$ to maximize the value of the farm $V(s, \epsilon)$.

(iv) Given w and q, farm operating decision $o(s, \epsilon)$ solves the individual occupational choice problem.

(v) The government's budget is balanced:

$$T = \int_s \int_\epsilon \int_\nu o(s, \epsilon)\tau\left(a, \epsilon\right) y\left(a, \nu, \tau(a, \epsilon)\right) dH(\nu) dG(\epsilon) dF(s),$$
$$\text{where} \quad a = a(s, z(s, \epsilon)).$$

(vi) The agricultural and non-agricultural goods markets clear:

$$c_a = \int_s \int_\epsilon \int_\nu o(s,\epsilon) y\left(a, \nu, \tau(a,\epsilon)\right) dH(\nu) dG(\epsilon) dF(s),$$

$$\text{where} \quad a = a(s, z(s,\epsilon)),$$

and

$$c_n + \int_s \int_\epsilon o(s,\epsilon) \mathbb{1}_{z(s,\epsilon)>1)} \psi z(s,\epsilon)^\phi dG(\epsilon) dF(s) = AN_n.$$

(vii) The land and labor markets clear:

$$\int_s \int_\epsilon o(s,\epsilon) \ell\left(a, \tau(a,\epsilon)\right) dF(s) dG(\epsilon) = L,$$

$$\text{where} \quad a = a(s, z(s,\epsilon)),$$

and

$$\int_s \int_\epsilon o(s,\epsilon) dF(s) dG(\epsilon) + N_n = 1.$$

4 Quantitative Analysis

We calibrate a distorted benchmark economy in two periods: before and after zero-tillage technology adoption to match data for Canada in 1986 and 2006. We then use the calibrated economies to perform experiments in order to assess the contribution of the zero-tillage technology on productivity and structural transformation; and to assess the potential role of distortions on technology diffusion and other aggregate outcomes.

4.1 Calibration

We first calibrate a distorted benchmark economy to micro, sectoral, and aggregate data for the Canadian economy in the initial period 1986. We parameterize the distributions of ability s and random distortions ϵ to be independently log normal with normalized means and standard deviations σ_s and σ_ϵ, respectively. There are 12 parameters to calibrate: the decreasing returns to scale γ, the dispersion in farming ability σ_s, the level and curvature parameters of the innovation cost function ϕ and ψ, the productivity elasticity of distortions ρ, the dispersion of the random component of distortions σ_ϵ, the dispersion of transitory productivity σ_ν, the agricultural consumption weight a, the subsistence level of agricultural consumption $\bar{a}$, relative productivity in agriculture κ, economy-wide productivity A, and the aggregate land endowment L.

A set of 5 parameters are either normalized or assigned values from outside evidence. We set the decreasing returns to scale to $\gamma = 0.65$ based on factor income shares in agriculture from Valentinyi and Herrendorf (2008) commonly used in the agricultural misallocation literature for advanced economies, the curvature of the investment cost function to $\phi = 2$ (Acemoglu et al., 2018). We assume that the zero-tillage technology is not available or profitable in the 1986 economy ($\psi_0 = \infty$) based on the fact that no farm in Canada had adopted the technology at this time. Aggregate productivity terms (A_0, κ_0) are each normalized to 1.

We jointly calibrate the remaining 7 parameters $(\rho, \sigma_s, \sigma_\epsilon, \sigma_\nu, a, \bar{a}, L_0)$ to match 6 moments from the 1986 data plus an assumed long-run share of employment in agriculture of 1.5%. The six moments we target from the 1986 data are: (1) the measured elasticity of distortions with respect to farm productivity, (2) the standard deviation of log land, (3) the standard deviation of log farm distortions, (4) the standard deviation of log farm TFP, (5) the agricultural employment share, and (6) the average farm size.

Table 7: Calibration of Benchmark Economy in 1986 (Initial Period)

Parameter	Value	Targeted moments	Model	Data
ρ	0.27	Elasticity of distortions	0.76	0.76
σ_s	4.10	Sd log land	0.94	0.93
σ_ϵ	2.20	Sd log farm distortions	0.53	0.54
σ_ν	0.05	Sd log farm TFP	0.56	0.55
$\bar{a}$	19.10	Agricultural employment share	0.04	0.04
L_0	31.96	Average farm size (acres)	800	800
a	0.10	Long-run agricultural employment share	0.015	0.015

We note that the resulting calibrated distortions parameter $\rho = 0.27$ implies a measured elasticity of distortions of 0.76, hence there is a substantial gap between the model parameter and the measured elasticity due to strong operation selection of farms, a feature discussed in detail in Ayerst et al. (2024) using a similar model of misallocation featuring selection and technology channels across production units.

We then calibrate the same distorted benchmark economy in the later period to Canadian data in 2006 where the zero-tillage technology has been adopted by many Canadian farms ($\psi_1 < \infty$). We keep all parameter values the same as in the initial period benchmark economy except we jointly calibrate 4 parameters $(A_1, \kappa_1, \psi_1, L_1)$ to match 4 moments in 2006: (1) the growth in non-agricultural labor productivity from 1986 to 2006, (2) the agricultural employment share, (3) the fraction of cultivated land operated under zero-tillage technology, and (4) the average farm size. We note that these moments are informative in identifying the parameters of interest. For instance, the technology cost shifter, ψ_1, has a first order effect on the share of land operated under the zero-tillage technology, total cultivated land L_1 implies a change in the agricultural land per labor between 1986 and 2006, and the exogenous technology components (A_1, κ_1) have first-order implications on productivity growth in non-agriculture and structural transformation during the period.

Table 8: Calibration of Benchmark Economy in 2006 (Later Period)

Parameter	Value	Targeted moments	Model	Data
A_1	1.30	Non-agricultural labor productivity (2006/1986)	1.30	1.30
κ_1	1.20	Agricultural employment share	0.02	0.02
ψ_1	2.20	Fraction of land using zero-tillage	0.60	0.60
L_1	23.38	Average farm size	1,169	1,169

We validate the calibrated economy by examining other important moments that are not targeted in the calibration. Table 9 reports three relevant moments: allocative efficiency, agricultural TFP growth, and the impact on farm-level TFP of adopting the zero-tillage technology.

Regarding allocative efficiency, which is the ratio of actual to efficient agricultural output,

Table 9: Model Validation in Untargeted Moments

Untargeted moments	Model	Data
Allocative efficiency in 1986	0.83	0.83
Agricultural TFP growth 1986-2006	94%	94%
Regression $\Delta \log$(farm TFP) on farm adoption dummy	0.36	0.24

we find that the model matches quite closely the allocative efficiency in the Canadian data in 1986 even though the model uses simple parametric assumptions on farm ability and distortions. The model also matches agricultural TFP growth between 1986 and 2006, even though the model only targeted the agricultural employment share, the aggregate land endowment, and non-agricultural labor productivity. This alignment is not mechanical, as the model's implied changes in agricultural output could diverge from the actual data. Similarly, even though the curvature parameter of the adoption cost function ϕ was set at the outset from the literature, we find that the farm-level impact of technology adoption on TFP is quite close to our empirical finding.

These results suggest that our calibrated economy provides a reasonable abstract representation of the Canadian data and, as a result, is useful for quantitative analysis assessing economic forces of variation over time. In the next section, we implement relevant counterfactual experiments to asses the contribution of technology adoption and distortions for aggregate outcomes.

4.2 Experiments

We examine the aggregate impact of the adoption of zero-tillage technology in the Canadian economy. We use the calibrated model to measure the contribution of zero-tillage technology adoption on agricultural productivity and other outcomes. Table 10 reports the results for the benchmark economies in 1986 and 2006 on the agricultural employment share, agricultural TFP, and average farm size. Recall that these two benchmark economies differ only on four parameters (A, κ, ψ, L).

To decompose the sources of variation, we conduct two counterfactual experiments. First, we consider the benchmark economy in the initial period 1986 and change only the cost of the zero-tillage technology ψ to that calibrated in the later period (2006), hence we change ψ_0 to ψ_1 in the benchmark economy in 1986, reflecting the technological progress associated with the zero-tillage technology. We find that the technological progress associated with the adoption of zero-tillage technology between 1986 and 2006 in isolation accounts for 70% of the structural change observed in the data ((4%-2.6%)/(4%-2%)), about 35% of the actual growth in agricultural TFP (log(1.26)/log(1.94)), and more than the observed increase in the average farm size.[1]

Table 10: Impact of Zero-Tillage Technology 1986-2006

	Agricultural Emp. Share (%)	Agricultural TFP	Average Farm Size (acres)
Benchmark economy:			
1986 $(A_0, \kappa_0, \psi_0, L_0)$	4.0	1.00	800
2006 $(A_1, \kappa_1, \psi_1, L_1)$	2.0	1.94	1,132
Experiments:			
(1) $(A_0, \kappa_0, \psi_1, L_0)$	2.6	1.26	1,294
Contribution (%)	*70*	*35*	–
(2) $(A_0, \kappa_0, \psi_1, L_1)$	3.1	1.26	791
Contribution (%)	*45*	*35*	–

Recall that total land per capita L declined by 27 percent between 1986 and 2006. To assess the relevance of this decline when measuring the contribution of the zero-tillage technology, we conduct a second experiment, where in addition to the change in zero-tillage technology we also change the total amount of land from L_0 to L_1 as calibrated for the benchmark economies in the two periods. We find that the decrease in total agricultural land diminishes the effect of technology adoption on structural transformation, with the overall effect accounting for 45 percent of the decline in the share of employment in agriculture compared with 70 percent

[1] We note that agricultural TFP in the model is defined as $\text{TFP}_a \equiv Y/(L^{\gamma} N_a^{1-\gamma})$ since we abstract from capital. We find that the increase in agricultural TFP in the model of 94% is consistent with the agricultural TFP increase in the data when measured in the same way.

when the land input is constant in the previous experiment. However, the contribution of technology adoption to the increase in agricultural TFP remains the same, accounting for 35 percent of the increase in agricultural TFP in the data. We note that in this experiment the implied change in average farm size is negative, highlighting the role of other factors on the increase in farm size during the period, such as residual productivity growth in agriculture (A, κ) and its effect on agricultural employment.

We also use the calibrated model to examine the impact of distortions on technology adoption. To do so, we assess the aggregate impact of the zero-tillage technology in hypothetical economies with varying idiosyncratic distortions. We focus on differences in the systematic component of distortions ρ a prevalent form of distortions in developing countries and known to effectively discourage investment (Ayerst, 2025; Ayerst et al., 2024). We consider $\rho = 0.80$ (instead of $\rho = 0.29$ in the benchmark economy), which generates a productivity elasticity of distortions of around 0.90 consistent with measured elasticity of distortions in developing countries (Adamopoulos et al., 2022; Chen et al., 2022). Table 11 reports the results of the zero-tillage technology (the change in ψ_0 to ψ_1) in the benchmark economy ($\rho = 0.27$), and contrasts these results with those of an economy facing higher distortions ($\rho = 0.80$).

Table 11: The Effect of Distortions (Higher ρ) on Technology Adoption

	Adoption Rate (%)	Agricultural TFP	Agricultural Share of Employment (%)	Average Farm Size
Benchmark $\rho = 0.27$				
1986 $(A_0, \kappa_0, \psi_0, L_0)$	0.0	1.00	4.0	800
2006 $(A_0, \kappa_0, \psi_1, L_0)$	63.0	1.30	2.5	1,294
Change (%)	–	*30*	*−38*	*62*
Experiment $\rho = 0.80$				
1986 $(A_0, \kappa_0, \psi_0, L_0)$	0.0	0.39	29.0	111
2006 $(A_0, \kappa_0, \psi_1, L_0)$	5.0	0.41	25.0	130
Change (%)	–	*5*	*−14*	*17*

Notes: Results of isolating technology adoption in more distorted economies. We consider an increase in ρ from 0.27 in the benchmark economy to 0.80. The adoption rate refers to the fraction of land operated under zero-tillage.

In the initial period, the more distorted economy ($\rho = 0.80$) features higher agricultural employment (29% versus 4% in the benchmark economy), lower agricultural TFP (39% of the benchmark economy), lower average farm size (14% of the benchmark economy), and lower aggregate productivity (75% of the benchmark economy), even though the only difference between these economies is the value of correlated distortions ρ. These effects of idiosyncratic distortions on aggregate outcomes are well studied in the misallocation literature. What is novel is the effect of distortions on technology adoption. When we apply the same change across these economies in the cost of zero-tillage associated with technological progress (ψ_0 to ψ_1), we find that higher distortions dampen substantially the rate of technology adoption in agriculture, an adoption rate of only 5% in the more distorted economy compared with 63% in the benchmark economy. Even with the same technological progress on zero-tillage technology, distortions dampen the growth of agricultural TFP, an increase between 1986 and 2006 of 5% compared with 30% in the benchmark economy; slows down the process of structural transformation whereby the share of employment in agriculture falls only by 14% in the more distorted economy compared with 38% in the benchmark economy; and slows down the growth in average farm size, an increase in average farm size of 17% compared with 62 percent increase in the benchmark economy.

We can also evaluate the impact of technological progress in less developed economies more generally. In particular, we consider two counterfactual economies that both feature low relative aggregate productivity (31% of the benchmark economy in the initial period and a high share of employment in agriculture (70% in the initial period relative to 4% in the benchmark economy). But the two counterfactual developing economies differ on the drivers of variation relative to the benchmark economy. In counterfactual economy 1, the high employment share in agriculture relative to the benchmark arises from high distortions $\rho = 0.80$ and relatively low agricultural productivity $A\kappa = 0.875$. In counterfactual economy 2, distortions are the same as in the benchmark economy so the high employment share in agriculture arises from much lower agricultural productivity $A\kappa = 0.60$. In each of these developing economies, we study technological progress through a reduction in the cost of zero-tillage technology, from ψ_0 to ψ_1.

Table 12: Technological Progress in Alternative Developing Economies

	Agriculture Share of Employment (%)	Adoption Rate (%)	Agricultural TFP	Average Farm Size
Counterfactual 1: $\rho = 0.80$				
$(A = 0.30, \kappa = 2.92)$				
Initial $\psi_0 = \infty$	70	0.0	0.28	46
Later $\psi_1 = 1.85$	48	7.6	0.32	66
Change (%)	*−22*	–	*14*	*43*
Counterfactual 2: $\rho = 0.27$				
$(A = 0.30, \kappa = 1.98)$				
Initial $\psi_0 = \infty$	70	0.0	0.28	45
Later $\psi_1 = 1.85$	8	60.2	0.62	395
Change (%)	*−62*	–	*121*	*778*

The results of these experiments are reported in Table 12. We find that the counterfactual developing economy with higher distortions experiences much less technological diffusion and as a result much less agricultural and aggregate productivity growth and structural transformation than an equivalent developing economy with low distortions. In particular, the same technological progress (a reduction in ψ) implies an adoption rate of zero-tillage in the later period of 8% in the more distorted economy compared to 60% in the developing economy with lower distortions. The higher diffusion of zero-tillage in agriculture translates into a much lower share of employment in the less distorted economy in the later period (8% versus 48%), faster convergence in agricultural TFP relative to the benchmark in the less distorted economy (0.62 versus 0.32), and a substantial catch up in average farm size relative to the distorted economy in the less distorted economy (growth in average farm size of 778% versus 43% in the more distorted economy).

Underneath these aggregate results, there are important differences in the micro moments between the high and low distortion economies worth discussing. Whereas dispersion in farm-level TFP remains roughly the same in the high distortion economy after zero-tillage technology, in the low distortion economy, technology adoption substantially changes the productivity distribution and land consolidation across farms. For instance, the percentile 10 farm TFP increases from 0.24 in the initial period to 1.47 in the later period, illustrating the effect of stronger selection at the bottom of the productivity distribution; and the percentile 90 farm TFP increases from 3.8 to 8.3, reflecting the effect of increased productivity investment by farms at the top of the productivity distribution. Stronger selection and higher productivity investment generate an overall reduction in productivity dispersion (p90/p10 ratio falls from 16-fold to 5.6-fold) and a shift to the right in the productivity distribution accounting for the substantial 121% increase in agricultural TFP in the less distorted economy.

These results suggest that distortions, especially distortions that are correlated with producer productivity, substantially mitigate the aggregate impact from the same technological progress in less developed countries. The results are consistent with empirical evidence from policy reforms that find reductions in misallocation are accompanied by changes in the productivity distribution through improved selection of operating units and technology upgrading (Pavcnik, 2002; Bustos, 2011; Khandelwal et al., 2013).

5 Conclusions

Using a unique panel dataset of the universe of Canadian farms between 1986 and 2006 and a standard framework of production heterogeneity, we find a relatively high level of allocative efficiency compared to other agricultural contexts in developing countries, and even relative to other advanced countries in the manufacturing sector. Specifically, allocative efficiency in Canadian farms is roughly constant across time between 1986 and 2006, measuring around 82% nationwide, 85% within Census subdivisions, and 95% when using the panel to control for potential measurement error in the cross-section of farms.

We document that between 1986 and 2006 Canadian agriculture featured the adoption and diffusion of a new seeing technique, the zero-tillage technology, from zero percent of the cultivated land in 1986 to 60 percent in 2006. We use the data together with a quantitative model of agricultural production and structural transformation to measure the contribution of technology adoption on agricultural productivity and structural transformation. We find technological progress alone associated with the adoption of the zero-tillage technology contributed to 35 percent of the growth in agricultural productivity, leading also to important changes in structural transformation and land consolidation among farms.

We also used the model to quantify the importance of distortions for technology adoption. In Canada, the rapid adoption of zero-tillage was supported by a strong institutional environment where more productive farms and farms adopting the technology could grow their size. We find that distortions, in particular distortions that constrain the size of more productive farms, substantially affect the rate of technology adoption, dampening the impact of technological progress on agricultural productivity and structural transformation. In particular, in a counterfactual Canadian economy featuring high distortions (a high productivity elasticity of distortions) as widely documented for developing countries, the adoption rate of zero-tillage would have only been 5 percent instead of 63 percent and growth in agricultural productivity growth only one sixth of that in an economy with low distortions. This result suggests that correlated farm distortions are effectively a barrier to the diffusion of new technologies, an effect which we find is quantitatively important. We also show that technological progress can be a powerful driver of catch-up growth in developing economies with low correlated distortions.

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