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DISTORTIONS, PRODUCER DYNAMICS, AND AGGREGATE PRODUCTIVITY: A GENERAL EQUILIBRIUM ANALYSIS

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Distortions, Producer Dynamics, and Aggregate Productivity: A General Equilibrium Analysis
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ABSTRACT

In less developed economies the allocation of factor inputs to more productive farms is often hindered. To analyze how distortions to factor reallocation affect farm dynamics and agricultural productivity, we develop a model of heterogeneous farms that make cropping choices and invest in productivity improvements. We calibrate the model using detailed farm-level panel data from Vietnam, exploiting regional differences in agricultural institutions and outcomes. We focus on south Vietnam and quantify the effect of higher measured distortions in the North on farm choices and agricultural productivity. We find that the higher distortions in north Vietnam reduce agricultural productivity by 41%, accounting for 61% of the observed 2.5-fold difference between regions. Moreover, two-thirds of the productivity loss is driven by farms' choice of lower productivity crops and reductions in productivity-enhancing investment, which more than doubles the productivity loss from static misallocation.

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1 Introduction

The reallocation of resources across businesses is a salient feature of the growth process in developed economies: successful businesses expand, while unsuccessful businesses contract and even exit (Baily et al., 1992; Davis et al., 1998; Foster et al., 2001), contributing to a more efficient allocation of resources across producers. Business dynamism is also observed in the agricultural sector in developed countries where land consolidation and farm exit are important drivers of productivity (Key, 2019). In sharp contrast, the allocation of resources across producers is hindered in less developed countries by a variety of regulations, policies, and institutions (Adamopoulos and Restuccia, 2014; Restuccia and Rogerson, 2017). In this paper, we examine how distortions to factor allocation affect farm growth and the level of agricultural productivity in the context of a model of farm heterogeneity and dynamics. Exploiting detailed farm-level panel data from Vietnam and regional differences in agricultural institutions, we find substantial differences in agricultural productivity, farm dynamics, and crop choice across regions, most of which can be accounted for by measured differences in distortions.

Vietnam offers a valuable context to study these issues. Since the late 1980s, the country has undergone major reforms—including decentralizing farm production to the household and liberalizing output and input markets—that led to substantial improvements in productivity and growth. Reflecting unique historical legacies, institutional change has been uneven across north and south Vietnam, allowing us to focus on regional differences in the cost of misallocation.

We start by showing differences in factors related to productivity in north and south Vietnam, where measured productivity is over twice as high in the South. First, we show that farm inputs tend to be more correlated with farm productivity in the South than in the North. The elasticity of land and labor use with respect to productivity is three to four times higher in the South than in the North, indicating a more efficient resource allocation among farms in the South. Second, we show that crop productivity and selection into crops differs across the regions. While farms in both regions primarily grow rice, farmers in the South are much more likely to grow more productive perennial cash crops, such as coffee. Third, the productivity of young farmers in the South grows faster than that of young farmers in the North. Additionally, the productivity of the typical farmer in the South grows over twice as fast as in the North.

We then develop a model of farm dynamics to understand productivity differences between south and north Vietnam. The model's structure follows Lucas (1978) in which heterogeneous farm managers hire land and labor in order to produce output using a decreasing returns to scale production technology. This leads to a non-degenerate distribution of farms in equilibrium where farm size and labor use depend on the productivity distribution. Our main departure from the existing literature is to endogenize the productivity process of farms.

Farm productivity depends on four components that reflect empirical differences observed in the data. The first is a permanent farmer-specific productivity component. The second is a random productivity component that varies between periods. The third is an ability component that depends on endogenous investments that farmers make to improve productivity, reflecting evidence that less distorted farmers invest more in farm improvements and experience faster productivity growth. Finally, there is a crop-specific productivity component that depends on the farmer's endogenous crop choice. Following Adamopoulos and Restuccia (2020), this component captures factors that affect the relative profitability of farms growing different crops. Farmers select crops upon entry based on the expected value of each crop and an idiosyncratic preference across crops, which allows us to match the substantial overlap in farm productivity across different crops in the data (Appendix A.2).

We follow Restuccia and Rogerson (2008) by modeling institutional distortions as idiosyncratic output wedges at the farm level. The farm-level distortions capture institutional factors (e.g., land sale or rental restrictions, or insecure property rights) that affect farmers' input choices relative to their first best. Institutional distortions depend on farmer productivity, farmer crop choice, and a random stochastic component that varies over time. In addition, government land-use regulations, such as restrictions on crop choice, force farmers to grow a crop independent of its relative profitability or the household's idiosyncratic preferences. This constraint on household choices is motivated by government restrictions on crop choice captured by our data (see also, Le, 2020).

In the stationary equilibrium, aggregate productivity depends on both the extent of static misallocation caused by farm-level distortions as well as the endogenous distribution of farm-level productivities, which reflects farmers' investment in ability and crop selection. To understand the quantitative importance of these factors, we calibrate the model to data on south Vietnam from the Vietnam Access to Resources Household Survey (VARHS), a rich household-level panel dataset covering 2006 to 2016. In the data, we group farms into three types: Rice, Perennial, and Other Crop farms based on the farm production value in each of these crops. We discipline the model's parameters to match moments related to the productivity distribution across farms, productivity growth, and differences across crop types. A novel feature of our calibration is that we explicitly allow for measurement error in farm-level output and inputs and use the model to examine the impact of measurement error on our quantitative conclusions.

Our main experiment involves adjusting distortion parameters in the benchmark economy, which is calibrated to south Vietnam, to match measured distortions in north Vietnam. Relative to the South, distortions in the North are more highly correlated with farm-level productivity, implying the allocation of factors is less sensitive to farm productivity; perennial crops are more distorted compared to rice and other crops; and a higher share of farms face government-imposed crop restrictions. Imposing the North distortions on the benchmark economy leads to: 1) productivity falling by 41% relative to the benchmark economy, representing over 60% of the observed TFP gap between the North and the South; 2) a reduction in the average TFP growth rate of farmers by 1.6 percentage points, just under half of the observed gap between the North and the South; 3) a reduction in farm TFP dispersion of 8 points, more than half the 14 percentage points lower dispersion in the North compared to the South; and 4) a drop in the share of perennial farmers from 33% to 9%, which is similar to the observed 5% in the North. In our quantitative analysis, the key institutional feature is the larger elasticity of distortions with respect to farm productivity in the North, consistent with historical institutions placing more restrictions on the accumulation of land in the North.

To understand the channels through which larger measured distortions in the North account for the North-South productivity gap, we examine the separate contributions of factor misallocation, the endogenous farm productivity distribution, and crop choice. We find that all channels are important, with factor misallocation accounting for one-third of the productivity loss, and the remaining two-thirds arising from the reallocation of economic activity to lower-productivity crops (crop choice) and, more importantly, the shift in the within-crop farm productivity distribution due to lower investment. The channels of dynamic misallocation (crop choice and farm productivity) are the source for two-thirds of the productivity loss in the model, more than doubling the impact of static factor misallocation.

Regarding measurement error, empirically we find a limited amount of measurement error in our data using the methodology in Bils et al. (2021), at least comparatively with estimates for the manufacturing sector using the same methodology. Our result, however, is consistent with estimates for the agricultural sector in other contexts (Adamopoulos et al., 2022; Aragón et al., 2022), partially reflecting that our analysis makes within-country and within-survey comparisons, where measurement error is less likely to be a factor. Nevertheless, while the impact of measurement error in our main result is limited due to our focus on differences in misallocation between north and sound Vietnam, we note that measurement error does have a more substantial impact on the level of misallocation when comparing reallocation gains associated with an economy without distortions. In our framework, the relatively small impact of measurement error on static misallocation is amplified through endogenous productivity dynamics.

Our work connects with several strands in the literature. We relate to the broad literature on resource misallocation across production units for understanding aggregate productivity (Restuccia and Rogerson, 2008; Guner et al., 2008; Hsieh and Klenow, 2009), particularly in agriculture (Adamopoulos and Restuccia, 2014) where important aspects of land institutions are associated with the misallocation of land and other productive inputs, hampering agricultural productivity (Adamopoulos et al., 2022; Bolhuis et al., 2021; Chen et al., 2022, 2023). We contribute to this literature in three important dimensions. First, we take advantage of Vietnam's unique historical context to quantify differences in misallocation between north and south Vietnam, rather than quantifying the level of misallocation relative to a hypothetical undistorted economy. Second, to our knowledge, we provide the first assessment of the broader impact of misallocation on producer dynamics in the agricultural sector, through crop choice and farm investment. In this regard, our work joins a recent literature studying the role of producer dynamics on aggregate outcomes (Hsieh and Klenow, 2014; Bento and Restuccia, 2017; Guner et al., 2018; Akcigit et al., 2021; Da-Rocha et al., 2023; König et al., 2022), and a literature in microeconomics studying the channels of firm-level upgrading in developing countries (Verhoogen, 2021). Third, incorporating farm dynamics into our model produces a number of falsifiable predictions about the impact of distortions on farm dynamics and the farm distributions. Importantly, this provides a test to the model that is often missing in static models of misallocation. We show that not only do distortions explain a large share of the North-South productivity gap, but also differences in average farm TFP growth, the distribution of farm productivities, land holdings, and cropping decisions. We also contribute to a growing literature investigating economic growth and regional convergence in Vietnam (Benjamin and Brandt, 2004; Le, 2020; Ayerst et al., 2020).

The paper is organized as follows. Section 2 summarizes the institutional context. Section 3 summarizes the data, construction of key moments, and differences between the north and south Vietnam. Section 4 describes the model. Section 5 calibrates a benchmark economy with distortions to panel farm-level data from the South, discussing the model's quantitative properties and goodness of fit. Section 6 presents the quantitative analysis where the main experiment involves applying measured distortions in the North to the benchmark economy, and discusses the extent to which this counterfactual economy resembles key features of the North. Section 7 concludes.

2 Institutional Context

Our analysis begins in 2006, nearly two decades after the start of economic reform in Vietnam. Central to these efforts was the return to family farming. In the late 1980s, production rights to land reverted to households, and over time expanded to include rights to transfer, exchange, lease, inherit, and mortgage. Titling of land began in 1994 with the passing of the 1993 Land Law and by 1997 Land Use Certificates had been issued to approximately one-half of all cultivated land (Benjamin and Brandt, 2004). By 2004, coverage extended to three-quarters of all cultivated land (Brandt et al., 2006) but subsequently stalled (Markussen, 2017).

Property rights' reforms were accompanied by liberalization of product markets, especially for rice, and input markets such as those for fertilizer (Benjamin and Brandt, 2004). Restrictions on the volume of rice exports were relaxed, as were internal product market barriers. Similarly, restrictions on fertilizer imports were removed. Prices came to be largely market-determined. Geographic mobility barriers were also relaxed.

Often neglected in discussions of agricultural development in Vietnam are important regional differences in land institutions. Vietnam was under Chinese rule until 968 CE when an independent kingdom was established in the north. Over time, control spread south. Historically, the state played an important role in determining land rights. Land was both privately- and state-owned, with state ownership more prevalent in the north and in some of the more densely populated regions in the south (Ho, 2023). State-owned land was largely used for redistributive purposes, and assigned to landless households. This land could not be traded however, and households retained usufruct rights only if they farmed the land themselves.

By contrast, privately-owned land could be bought, sold and inherited.

These differences were reinforced by institutional changes following the division of Vietnam into two countries in 1954. In the north, rural households were organized into communes and agriculture collectivized for more than three decades until the reforms in the late 1980s. By contrast, land in the south remained private, and farming continued to be carried out at the household level, including during the short inter-regnum between reunification in 1975 and the agricultural reforms.[1] Reflective of these differences, nearly two-thirds of the farmland currently held by households in the north was obtained directly from the commune during the decentralization of land rights to households. In the south, inheritance, land sales, and rental exert a much larger influence on patterns of landownership. We observe an especially sharp contrast between the Red River Delta in the north, where 82.8% of agricultural land of households was allocated by the state, and the Mekong River Delta in the south, where only 4.7% was (Brandt et al., 2006).

Regional differences appear in other forms and are also likely a legacy of institutions and the more important role of the state in the North prior to reform. Restrictions persist on crop choice, largely related to rice production and national food security, and are more prominent in the North (Markussen et al., 2011; Markussen, 2017). Risk of land expropriation remains, with these risks negatively related to informal ties to local officials and cadres (Markussen and Tarp, 2014). Land titling has expanded but in sub-regions in the north remains well below national levels. Households in the north also are much more likely to report issues with respect to access to water for irrigation, and problems of flooding.

Farm households in Vietnam carry out productivity-augmenting investments in land and irrigation and acquire information on new technologies and markets through agricultural extension services. We examine the effect of these investments on farm productivity growth, and their correlation with measures of market distortions discussed in the next section. In

[1] After the reunification in 1975 until the start of reforms in 1986, efforts to collectivize the south were resisted and largely failed. For example, only 6% of farmers in the Mekong Delta joined cooperatives by 1986 (Pingali and Xuan, 1992).

both the North and the South, more productive and less-distorted farmers invest significantly more time and resources in improving farm productivity. However, the benefits of these investments are much weaker in the North, with only participation in extension services positively correlated with farm productivity growth. By contrast, in the South investments in cash and in-kind (labor) in land and water, as well as acquisition of new knowledge through extension services are positively correlated with farmer productivity growth.

3 Productivity in North and South Vietnam

We provide an overview of our dataset and construction of the main variables used in our analysis. We use the constructed dataset to examine productivity differences between north and south Vietnam in (*i*) the misallocation of factors of production, (*ii*) crop productivity and selection into crops, and (*iii*) farm dynamism. In Appendix A.1, we show that the empirical comparisons between the north and the south hold if we restrict focus to the rice-growing delta regions—the Mekong Delta in the South and the Red River Delta in the North—where technology and geographic differences are less likely to be a concern. These empirical differences act as the foundation for the model that we develop in the next section.

3.1 Data and Variable Construction

We use data from the Vietnam Access to Resources Household Survey (VARHS) that covers households from 12 provinces in north and south Vietnam surveyed biennially between 2006 and 2016. We focus on a sub-sample of 2,118 households that are included in all six biennial surveys from 2006 to 2016. We provide a brief overview of the data construction, a more detailed documentation is provided in Ayerst et al. (2020). Our variables of interest are output (value added) $y_{f,t}$, land $l_{f,t}$, and labor $n_{f,t}$ at the farm-year (f, t) level.

Farm-level output is measured as the sum of crop production, valued using a common price for each crop, net of intermediate input expenditure. To construct the common price, we first calculate the median price for each crop, as reported by households. We then construct the common price as the weighted sum of the median price across years, where weights are the relative total quantity of that crop's production for the year. We use crop sales and quantities, when available, to compute prices and reported values and quantities when sales are unavailable.[2] Finally, we set observations with negative value added to zero, which account for around 2.5% of our sample and are primarily in the North.

Production inputs are land and labor. Land is constructed as the cultivated area of plots owned and rented by households excluding land used for activities unrelated to crop production (e.g., forestry, animal husbandry), left fallow for more than 48 months, or rented out. Labor is constructed as the sum of hired labor and the labor supplied by household members. Using information on family members that hire out in agriculture, we construct wages controlling for individual characteristics (e.g., age, education, sex), the year of work, and regional differences that we use to convert household expenditure on hired labor into a quantity of hired labor.

Following Hsieh and Klenow (2009), we construct the farm-level TFP and the farm-level wedge for farm f as:

$$\text{TFP}_{f,t} = \frac{y_{f,t}}{(\ell_{f,t}^{\alpha} n_{f,t}^{1-\alpha})^{\gamma}}, \qquad \text{and} \qquad \text{Wedge}_{f,t} = \frac{y_{f,t}}{\ell_{f,t}^{\alpha} n_{f,t}^{1-\alpha}}. \tag{1}$$

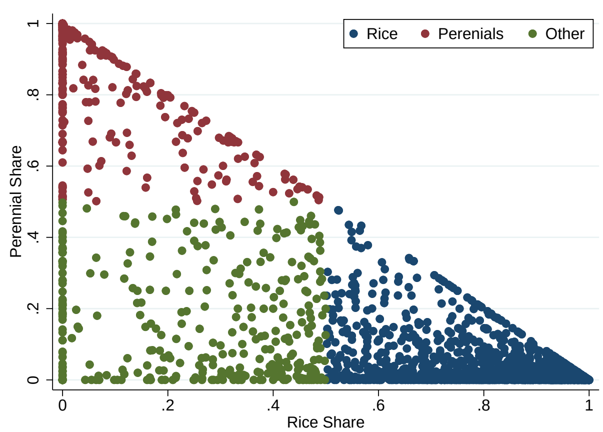
We use the term wedge, instead of TFPR (total factor revenue productivity), to highlight that the wedge is a model-based measure of misallocation of land and labor across producers. In an undistorted economy, marginal products and hence wedges are equalized across producers. The variables in (1) are consistent with the model that we develop in the next section. We

[2] We make two adjustments to the output data for missing data and survey changes. First, the 2006 survey only asks for the total value of a crop produced by the household for some crop categories. For most crops, households are still asked to report both value and quantity. We regress crop prices on region, year, and crop fixed effects and then use the estimated fixed effects to construct predicted prices for the crops with missing quantity data. This allows us to impute a quantity for these crops in the 2006 survey. Second, the survey treats potatoes, cassava and sweet potatoes as a single crop in 2006 and as unique crops in 2008 and later surveys. For 2006, we treat this category as potatoes, noting that it only accounts for around 2.7% of total production value and all three crops fall into the 'Other Crop' farmer type (see below).

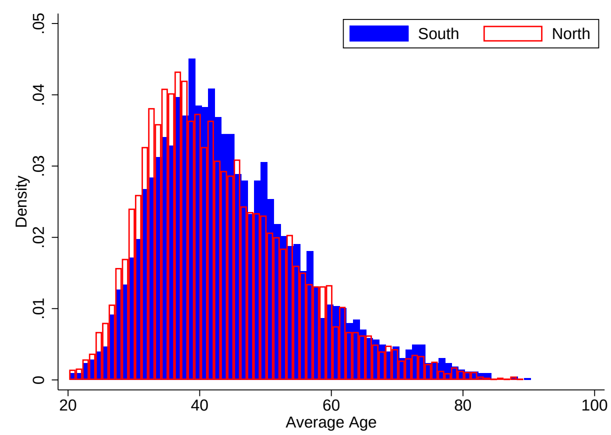
allow for measurement error in output and inputs in the quantitative analysis and show how this impacts our main results.

We categorize households as either rice farms, perennial farms, or other (annual) crop farms based on their most valuable crop grown over the survey.[3] We categories farmers as a rice or perennial farmer if more than 50% of their output value, across all years, is in rice or perennial crops. We do not impose strict annual cutoffs because of inter-cropping, crop-rotation, and the fact that farms may devote some of their land to other crops. However, cropping tends to be concentrated in these categories.[4]

Figure 1: Farm Crop Type and Age Distribution



(a) Crop Composition



(b) Age Distribution

Figure 1a summarizes the empirical distribution of households across farm types. Unsurprisingly, most households are classified as rice farms as this is the most widely produced crop in Vietnam. The remaining households are split between perennials and other crop farms. Other crop farms grow, on average, around 30% of value in rice, but have a higher

[3]In the survey, perennials include: fruits, coffee, tea, cocoa, cashew nuts, sugarcane, pepper, rubber, medicinal trees and plants, and other perennial crops. Other crops include maize, potatoes, sweet potatoes, cassava, peanuts, soybeans, vegetables, and other annual crops. Farmers for whom more than half of their average yearly crop output is from rice (perennials) are rice (perennial) farmers while the remainder are "other crop" farmers.

[4]For example, over two-thirds of rice farmers have a rice share over 75% and just under half of rice farmers have a rice share over 90%. For perennials, these numbers are slightly higher at 70% and 50% of farmers for the same thresholds. In addition, more than 90% of rice and perennial farm-year observations would have the same classification if classified year by year. Differences are more common in the case of other crop farmers.

production value in other annual crops.

We construct a measure of farm age for each household. Farm age is taken as an average of individual household member age weighted by the number of days working in crop production. Figure 1b reports the histogram of constructed farm ages in the North and South. Most farms are between 20 and 60 years old and the South is slightly older than the North.

Finally, to minimize the influence of outliers, we winsorize the final set of variables at the top and bottom 2% for both the North and South in each year.[5]

Land quality differences. The productivity gap between the North and South is unlikely to be explained by differences in land suitability. Appendix A.4 examines the potential role of land quality differences between the South and the North using potential yield data from the Global Agro-Ecological Zones (GAEZ) analyzed in Adamopoulos and Restuccia (2022). We find minimal differences in land quality between the two regions; if anything, land quality is slightly higher in the North than the South.

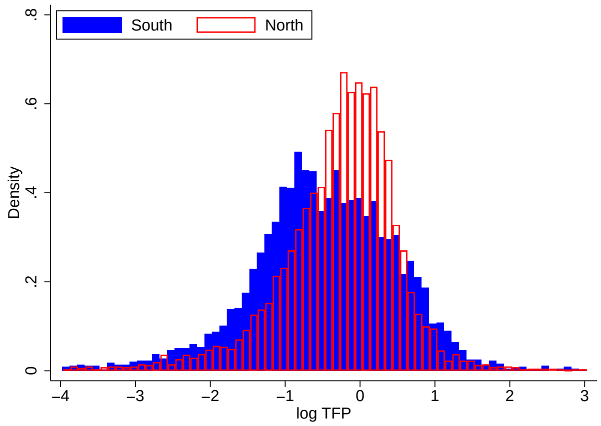
3.2 Misallocation

The first source of productivity differences between north and south Vietnam that we examine is the misallocation of factors of production. Figure 2 plots histograms of the TFP and the wedge distributions, where both variables are normalized by the mean in each region (North / South) year. Both TFP and wedges tend to be more dispersed in the South, as documented in Ayerst et al. (2020).

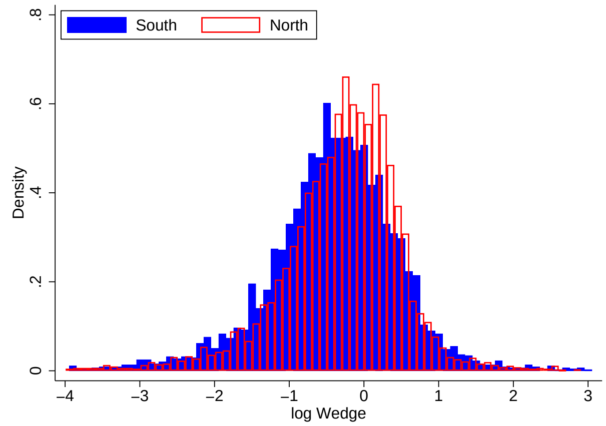
Wedges are important because of their impact on the allocation of resources in the economy. In an undistorted economy, resource allocation is proportional to farm-level TFP. As a simple measure of misallocation, we regress farm-level land and labor inputs on measured TFP to examine the allocative efficiency in each region. Table 1 reports the results.

[5] We winsorize rather than trim the data since trimming disproportionately affects the share of perennial farmers in the final dataset. Other than for the crop share, trimming the data implies similar moments compared to winsorizing.

Figure 2: TFP and Wedge Distribution



(a) TFP Distribution



(b) Wedge Distribution

Notes: Histogram of TFP and wedges for farm-year observations in north and south Vietnam. TFP and wedges are normalized by the mean in each region (North / South) year. We calculate TFP and wedges according to (1) with $\gamma = 0.70$ and $\alpha = 0.50$.

Table 1: Farm Allocations

	(1) log Land	(2) log Labor
log TFP (South)	0.554***	0.382***
	(0.0312)	(0.0228)
log TFP (North)	0.152***	0.122***
	(0.0200)	(0.0169)
North FE	Yes	Yes
R^2	0.208	0.132
Observations	10526	10526

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. All regressions include fixed effects for the region (North/South) of the household.

The results show that a one log point higher TFP results in three-to-four times more factors allocated to a farm in the South compared with the North, pointing to substantially larger misallocation in the North. It is also important to note that while the allocative efficiency of the South is much higher than that in the North, both economies face severe misallocation. In the hypothetical undistorted economy, the elasticity between land or labor and TFP is $1/(1-\gamma) = 3.33$ based on the model and calibrated parameters.

3.3 Crop Productivity Differences

The second source of productivity differences between north and south Vietnam that we examine is crop selection. Table 2 provides summary statistics by farm type for north and south Vietnam. An observation is a farm-year and only includes farm-years where TFP can be calculated. Farm-level TFP and wedges are normalized to one in each region-year such that reported values capture relative productivity and distortions within regions.

There are stark differences within regions between crops. In the South, perennials tend to outperform the other crop types in terms of production, productivity, and growth. This is consistent with the fact that perennials are cash crops that incentivize investment. Among perennials, coffee is the most important. Rice and other crops are more likely to be food crops for the household's own consumption, and underperform compared to perennials. In contrast, in the North rice tends to overperform relative to the other crops. Farms in the North also tend to be smaller in terms of land and labor inputs and output, and experience lower growth. These differences motivate our main quantitative experiment.

3.4 Farm Dynamism

The third source of productivity differences between north and south Vietnam that we examine is differences in farm dynamism. Table 2 reports that farms in south Vietnam tend to grow faster on average than farms in north Vietnam, on average and for each crop types. Following Hsieh and Klenow (2014), we compare life cycles of farms in north and

Table 2: Crop Differences in North and South Vietnam

A. Vietnam, South

Crop Type	Mean						
	Output	Land	Labor	TFP	Wedge	TFP Growth	Obs
Rice	9.9	2.4	154.2	−0.4	−0.3	4.9	2,293
Perennials	10.6	3.9	294.6	−0.2	−0.3	10.9	1,368
Other	9.6	1.9	184.4	−0.7	−0.6	1.8	726
Total	10.1	2.8	203.0	–	–	6.2	4,387

B. Vietnam, North

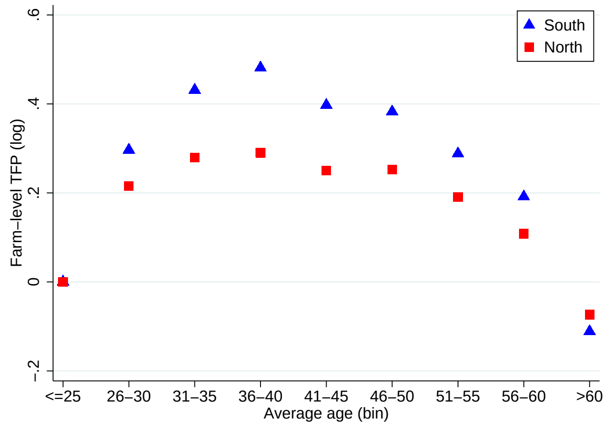
Crop Type	Mean						
	Output	Land	Labor	TFP	Wedge	TFP Growth	Obs
Rice	9.2	1.1	148.8	−0.2	−0.2	4.1	4,840
Perennials	8.7	0.7	126.7	−0.6	−0.4	−2.1	236
Other	9.0	1.2	155.4	−0.4	−0.4	−3.4	1,063
Total	9.2	1.1	149.1	–	–	2.6	6,139

Notes: Observations are at the farm-year level. Output is reported as the log of total agricultural output using real prices common across farms to sum different crops. Land is reported in acres. Labor is reported in number of effective worker days. TFP and wedges are reported in logs and constructed following the equation (1). TFP and wedges in both the South and the North are normalized by the mean in each year. TFP Growth is calculated over a two-year period as TFP Growth$_t$ $= 100 \times (\text{TFP}_{f,t} - \text{TFP}_{f,t-2})/[0.5(\text{TFP}_{f,t} + \text{TFP}_{f,t-2})]$ before TFP is normalized where t is the calendar year.

south Vietnam by constructing synthetic life cycles using a measure of farm age. We use the average age of household members weighted by their time working in crops since this measure most closely aligns with our model. We find similar life cycle profiles using the age of the head of households and the simple average age of household members (Appendix A.3). Figure 3 reports the TFP of farms in different age bins obtained from regressions of farm-level TFP on fixed effects for the age bin. We remove region-by-year variation from farm-level TFP so that the life cycle is not contaminated by time trends.

In both the North and the South, farm productivity increases rapidly until age 40 and then begins to level off before declining at much older ages. These trends are much more pronounced in the South where the initial increase in productivity is steeper. Hsieh and

Figure 3: Farm-level productivity



Notes: Farm-level TFP and age are constructed as described in the text. The figure reports the estimated of age bin fixed effects c_j^R (for $R \in \{South, North\}$) from the regression $\log \text{TFP}_{f,t} = \sum_{j \in \mathcal{A}} c_j^R 1_{age_{f,t} \in j} + \Gamma^R + \Gamma_t + \varepsilon_{f,t}$ where Γ^R and Γ_t are region and year fixed effects. The coefficient estimates are normalized such that the youngest bin has value zero.

Klenow (2014) similarly find that firms in less distorted economies experience more productivity growth over their life cycle, but do not find the decline at old ages. Prior to extensive mechanization, we expect that the decline is likely driven by declining physical abilities of older household members working in agriculture and by selection of households with older members active in agriculture.

Investment and productivity. We develop a model in the next section in which farmers invest in improving productivity to capture the productivity increase of young farmers. While we do not observe a single comprehensive measure of investment, the survey asks households about key farm investments and their participation in extension services on new technology and farming methods. First, we construct a variable $\text{Inv}_{f,t}$ that takes value one if farm f has made any cash or labor investments in irrigation or soil and water conservation. Second, we construct a variable $\text{Ext}_{f,t}$ that takes a value of one if farm f participates in extension services providing information on (a) new seeds, varieties, or breeds; (b) fertilizer use; (c) irrigation; (d) pest infestation and blight; or (e) market conditions.

Table 3 reports the relationship between investment and extension services and farm

Table 3: Investment and Farm Characteristics

A: Investment and Extension Services

	South		North	
	(1)	(2)	(3)	(4)
	$\text{Inv}_{f,t}$	$\text{Ext}_{f,t}$	$\text{Inv}_{f,t}$	$\text{Ext}_{f,t}$
$\log\ \text{TFP}_{f,t}$	0.240***	0.119***	0.253***	0.212***
	(0.0173)	(0.0180)	(0.0235)	(0.0206)
$\log \text{Wedge}_{f,t}$	-0.242***	-0.0910***	-0.225***	-0.196***
	(0.0187)	(0.0196)	(0.0236)	(0.0202)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.116	0.211	0.197	0.234
Observations	4387	4387	6139	6139

B: Farm TFP Growth

	South		North	
	(1)	(2)	(3)	(4)
	$\text{g}_{f,t}$	$\text{g}_{f,t}$	$\text{g}_{f,t}$	$\text{g}_{f,t}$
$\text{Inv}_{f,t-2}$	14.94***		-3.961*	
	(3.047)		(2.195)	
$\text{Ext}_{f,t-2}$		15.28***		8.567**
		(4.079)		(3.709)
$\log\ \text{TFP}_{f,t-2}$	-40.01***	-40.18***	-55.80***	-56.02***
	(1.429)	(1.465)	(1.745)	(1.747)
Year FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
R^2	0.263	0.262	0.320	0.320
Observations	3485	3485	4883	4883

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. $\text{Inv}_{f,t}$ takes value one if the household reports any cash or labor investment in irrigation or soil and water conservation. Farm TFP Growth is calculated over a two-year period as $g_{f,t} = 100 \times (\text{TFP}_{f,t} - \text{TFP}_{f,t-2})/[0.5(\text{TFP}_{f,t} + \text{TFP}_{f,t-2})]$ (before TFP normalization), where t is the calendar year.

characteristics, following closely König et al. (2022). Panel A reports the relationship between investment and extensions services and farm-level productivity and wedges. Panel B reports the relationship between farm-level TFP growth and previous investment and extension services. We include the farm's previous productivity to control for more productive farms growing slower in the data, which our model also replicates.

Investment and extension services are positively related to farm-level TFP and negatively related to farm-level wedges, indicating that more distorted farms are less likely to take steps to improve productivity. In the South, both investment and extension services are associated with faster growth while the relationship is weaker in the North where only extension services are associated with faster growth. These results continue to hold if we separate investment in cash and in labor and if we include the intensive margin of investment.

4 Model

We develop a model of heterogeneous farms that make cropping decisions and invest in productivity improvements. Farmers face idiosyncratic distortions, as in Restuccia and Rogerson (2008), which affects the choice of inputs relative to the first best allocation. In addition, the government imposes crop restrictions on a set of farmers. Distortions, crop restrictions, and crop-specific differences affect the allocation of resources across farms and crops, as well as the productivity distribution through farmer incentives to invest in productivity improvements.

4.1 Economic Environment

Time is discrete and indexed by $t \in \{0, 1, 2, ..., \infty\}$. The economy is populated by a mass N of households, indexed by f, half that work as farm managers and half that supply labor as farm workers. We abstract from sectoral occupational choice (structural transformation) and selection, as the impact of distortions on these channels has been well-studied and are known to amplify the productivity cost of distortions (e.g., Adamopoulos and Restuccia, 2014, 2020; Adamopoulos et al., 2022). The economy is also endowed with a mass L of land that is used in agricultural production.

Production technology. We model crops $i \in \mathcal{I}$ as a technological choice to the farmer. In this regard, we take all agricultural production to be a single final good and assume that the choice of crop directly affects farm productivity. This simplification provides tractability while preserving the core economics of the farmer's crop choice.

A farmer f that grows crop $i \in \mathcal{I}$ produces output according to the following decreasing returns to scale technology in variable inputs,

$$y^i_{f,t} = (s^i_{f,t})^{1-\gamma}(\ell^{\alpha}_{f,t} n^{1-\alpha}_{f,t})^{\gamma},$$

where $s^i_{f,t}$ is the crop-specific productivity of farmer f in period t; $\ell_{f,t}$ is the land input; and $n_{f,t}$ is the labor input. The productivity of farmer f growing crop i is equal to

$$\log s^i_{f,t} = \log z_f + \log \kappa^i + \log a_{f,t} + v_{f,t},$$

where z_f is a permanent component of farmer productivity with distribution $\Phi_z(z)$; κ^i is a crop i specific component of productivity; $a_{f,t}$ is the managerial ability of farmer f; and $v_{f,t}$ is a time varying stochastic component of farmer productivity with distribution $\Phi_v(v)$. The farmer's ability is determined through their investment decisions as we discuss below.

Investment. A farmer f can improve their managerial ability $a_{f,t}$ through investment. Farmer ability follows a ladder, such that a farmer that has successfully improved their ability h times has ability $a_{f,t} = a(h) = \lambda^h$. A farmer f that invests e_f units of the final output good improves their ability with probability $x_{f,t} = (e_f/\psi a_{f,t})^{1/\zeta}$. Rewriting this expression shows that expenditure on improving ability with success rate x_i is equal to

$$e(x_{f,t}, a_{f,t}) = \psi x_{f,t}^{\zeta} a_{f,t},$$

where $a_{f,t}$ is a scaling factor capturing that it is more costly for higher ability farmers to further improve their ability. The parameter ψ captures the level of the investment function, with the investment required to improve ability with the same probability increasing in ψ. The parameter $\zeta > 1$ captures the curvature of the investment function, which dictates how quickly increasing the success rate of improving ability increases the cost of investment.

The investment function reflects the empirical evidence showing that farmers invest to improve productivity and that younger farms experience rapid productivity improvements while the productivity of middle-aged farms experience relatively slow or flat productivity growth (Section 3). In Appendix C.7, we show a model extension that incorporates the productivity decline of older farms. This extension does not significantly alter our results.

Preferences and cropping decision. The economy is populated by a mass N of households, indexed by f, half of which are farm managers (farmers) while the remaining households are workers and supply a unit of labor to farms. With probability ξ a household survives to the next period and with probability $1 - \xi$ a household exits and is replaced by a new household. Household preferences are given by

$$U_f^o([C_t^o]) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} (\xi\beta)^t C_t^o \right] \times b_f^o,$$

where $o \in \{\mathcal{I}, W\}$ is the occupation of the household, which can either be a worker W or a manager of a crop $i \in \mathcal{I}$ farm. The value of b^o captures an idiosyncratic preference for occupation o. We normalize the preference parameters for workers such that $b_f^W = 1$. The value of b_f^i is drawn by each farm manager from a Frechet distribution, $H(b) = \exp\{-(b/\eta^i)^{-\theta}\}$, where η^i is a crop-specific preference shifter that captures a common component of the utility cost of growing a crop i. Higher values of η^i correspond to, on average, more utility from growing crop i. The common crop-specific component η^i captures the average difficulty or lost revenues from preparing plots for specific crops. For example, growing perennials involves extensive investment and seasons in which the plot does not produce output, which would be captured by lower η^i. The dispersion of preferences captures idiosyncratic factors to the farmer (e.g., slope of land, access to irrigation, soil quality) that cause farmers to prefer different crops even in the absence of market-based factors.

The idiosyncratic dispersion in the utility cost causes farmers to differ in their relative preference for growing different crops. For example, some farmers prefer to grow perennials while others prefer to grow rice, all else equal. This preference may be strong enough that some farmers choose to grow rice even if rice is less profitable than perennials. In equilibrium, this implies farmers select into crops based on both the relative market value and their relative preference for each crop, where the elasticity of selection to market forces is determined by the shape parameter θ. Modeling crop choice as a utility cost allows us to replicate the overlap in the productivity of farmers that grow different crops observed in the data (Appendix A.2). For example, there are many productive rice farmers and unproductive perennial farmers, despite perennial farmers being more productive on average.

Farmers that exit the economy are replaced by a new household that takes over management of their farm. We interpret exit as capturing both the exit of households from agriculture as well as the inter-generational transfer of the farm within families. New farmers enter the market with ability $a_{f,t} = \lambda^0$. In Appendix C.7, we extend the model to allow for entrant ability to depend on the ability of exiting farms, capturing, for example, transfers of skills from the old to the young. The extension has a negligible effect on the final results.

4.2 Market Structure

The final agricultural good is the numeraire. Following Restuccia and Rogerson (2008), we model institutional distortions in a reduced form as an idiosyncratic tax τ on farm revenues, such that farm revenues net of the tax are $(1-\tau^i_{f,t})y^i_{f,t}$. While we model the wedge as a tax on revenues, this is isomorphic to modeling wedges on factors inputs, which could capture, for example, land transaction restrictions or lack of market access to intermediate inputs. Since the relationship between land and labor and productivity is relatively similar (Table 1), we choose to model wedges parsimoniously on output. The model distortions we define directly correspond to the wedge defined in Section 3, Equation (1), as $\text{Wedge}_{f,t} = 1/(1-\tau^i_{f,t})$.

Higher values of $\tau^i_{f,t}$ imply that farmers operate smaller farms than they would in the absence of the distortion. Distortions are distributed according to

$$\log(1-\tau^i_{f,t}) = (1-\gamma)\left[\log \bar{\tau} + \log \varphi^i - \rho \log\left(s^i_{f,t}\right) + \varepsilon_{f,t}\right], \tag{2}$$

where φ^i is a crop-specific distortion that captures institutional factors affecting crop choice (e.g., market access to sell or purchase specific inputs); ρ captures the elasticity of distortions to the underlying productivity of the farm reflecting correlated distortions (e.g., land size restrictions); and $\varepsilon_{f,t}$ is a random idiosyncratic component of distortions with distribution $\Phi_\varepsilon(\varepsilon)$. Distortions are scaled by $(1-\gamma)$ to simplify algebra in the solution. We assume that the government's budget constraint is balanced by a lump-sum transfer T_t to households that is equal to the total amount collected from the idiosyncratic tax. Of particular importance for the quantitative analysis is the elasticity of distortions ρ to the farm's productivity $s^i_{f,t}$. This parameter determines the extent to which more productive farms can operate larger amounts of labor and land inputs than less productive farms, with higher values of the parameter indicating less correlation of operated inputs to farm productivity as documented in the North relative to the South (see Section 3). Higher elasticities could reflect, for example, historical differences in land rights, such as those discussed in Section 2, that prevent more productive farmers in the North from accumulating more land.

A fraction ω of farmers face government-imposed crop restrictions in which case the farmer must grow rice for their crop, such that $i = R$. This reflects a direct cropping restriction imposed by the Vietnamese government on individual farms that are quantitatively important for aggregate production (Le, 2020). These types of land-use restrictions are not captured by the standard misallocation wedges $\tau^i_{f,t}$ since they do not impact the farm's output or choice of inputs. Farmers receive the government-imposed crop restriction prior to making their crop choice, implying that some farmers facing the restriction would have still grown rice. The probability of facing the government-imposed crop restriction is unrelated to the distortions $\tau^i_{f,t}$ that farmers face implying that restricted rice farmers are otherwise identical to unrestricted rice farmers.

Timing. The timing of each period is: (i) new farmers enter; (ii) new farmers make crop choices; (iii) farmer ability and period-specific shocks (v, ε) are realized; (iv) farmers choose production inputs and realize profits; (v) farmers invest in future managerial ability; and (vi) farmers exit.

4.3 Equilibrium

We focus on the steady state equilibrium in which the distribution of farm types, allocations, and prices are constant. We drop f and t subscript and write farmer outcomes in terms of the farmer's crop choice $i \in \mathcal{I}$, permanent farmer productivity z, current ability-level h, and current shocks (v, ε).

Production problem. Farmers choose resources (n, ℓ) to maximize total profits. The farmer's production problem is

$$\pi^i_{z,h}(v, \varepsilon) = \max_{n,\ell}(1 - \tau^i_{z,h}(v, \varepsilon))s^i_{z,h}(v, \varepsilon)^{1-\gamma}(\ell^\alpha n^{1-\alpha})^\gamma - q\ell - wn.$$

Profits depend on farmer's idiosyncratic distortions $\tau^i_{z,h}(v, \varepsilon)$ and the farmer's productivity

$s^i_{z,h}(v,\varepsilon)$. Solving the farmer's production problem implies that inputs are

$$\ell^i_{z,h}(v,\varepsilon) = \left[\frac{\gamma\alpha}{q}\left(\frac{1-\alpha}{\alpha}\frac{q}{w}\right)^{\gamma(1-\alpha)}\right]^{\frac{1}{1-\gamma}} (1-\tau^i_{z,h}(v,\varepsilon))^{\frac{1}{1-\gamma}} s^i_{z,h}(v,\varepsilon),$$

$$n^i_{z,h}(v,\varepsilon) = \left[\frac{\gamma(1-\alpha)}{w}\left(\frac{\alpha}{1-\alpha}\frac{w}{q}\right)^{\gamma\alpha}\right]^{\frac{1}{1-\gamma}} (1-\tau^i_{z,h}(v,\varepsilon))^{\frac{1}{1-\gamma}} s^i_{z,h}(v,\varepsilon).$$

Given the above level of inputs, output is

$$y^i_{z,h}(v,\varepsilon) = \gamma^{\frac{\gamma}{1-\gamma}}\left(\frac{\alpha}{q}\right)^{\frac{\alpha\gamma}{1-\gamma}}\left(\frac{1-\alpha}{w}\right)^{\frac{(1-\alpha)\gamma}{1-\gamma}} (1-\tau^i_{z,h}(v,\varepsilon))^{\frac{\gamma}{1-\gamma}} s^i_{z,h}(v,\varepsilon).$$

Investment problem. Farm profits are equal to $\pi^i_{z,h}(v,\varepsilon) = (1-\gamma)(1-\tau^i_{z,h}(v,\varepsilon))y^i_{z,h}(v,\varepsilon)$. The farmer's investment problem is to choose investment e, or equivalently the success rate x, to maximize the expected value of their farm. The problem is

$$V^i_{z,h}(v,\varepsilon) = \max_x \left(\pi^i_{z,h}(v,\varepsilon) - e(x,\lambda^h)\right) + (\xi\beta)\mathbb{E}_{v',\varepsilon'}\left[xV^i_{z,h+1}(v',\varepsilon') + (1-x)V^i_{z,h}(v',\varepsilon')\right].$$

The investment decision of the farmer solves

$$x^i_{z,h} = \left[\frac{(\xi\beta)\mathbb{E}_{v',\varepsilon'}\left[V^i_{z,h+1}(v',\varepsilon') - V^i_{z,h}(v',\varepsilon')\right]}{\psi\zeta\lambda^h}\right]^{\frac{1}{\zeta-1}},$$

where the farmer's investment decision does not depend on their current state (v,ε).

Crop decision. Let $\bar{V}^i_z$ denote the expected value of a new farm with crop i, permanent productivity z, and ability-level $h = 0$ before the shock (v,ε) is realized. Farmers with the government-imposed crop restriction do not choose their crop and are forced to produce rice, $i = R$. For unrestricted farmers, the crop decision is

$$\max_{i\in\mathcal{I}} \bar{V}^i_z \times b^i.$$

The resulting share of farmers that grow crop i is equal to

$$\Omega_z^i = \begin{cases} \omega + (1-\omega)\frac{(\eta^i \bar{V}_z^i)^\theta}{\sum_{i' \in \mathcal{I}} (\eta^{i'} \bar{V}_z^{i'})^\theta} & \text{for } i = R \\ (1-\omega)\frac{(\eta^i \bar{V}_z^i)^\theta}{\sum_{i' \in \mathcal{I}} (\eta^{i'} \bar{V}_z^{i'})^\theta} & \text{for } i \neq R \end{cases}. \tag{3}$$

See Appendix B for derivation of the above expression. The fraction of (unrestricted) farmers that choose a specific crop depends on both the relative expected value of growing that crop $\bar{V}_z^i$ and the relative difficulty of growing that crop, captured by the preference parameter η^i, where θ determines the elasticity of farmers to these factors.

Farm distribution. The evolution of farmer ability depends on the success rate $x_{z,h}^i$ chosen by farmers and the survival rate ξ. The evolution of the distribution of farm abilities is described by

$$\Delta\mu_{z,h}^i = \begin{cases} \mu_{E,z}^i - (1-\xi)\mu_{z,0}^i - \xi x_{z,h}^i \mu_{z,0}^i & \text{for } h = 0, \\ -(1-\xi)\mu_{z,h}^i + \xi\left[\mu_{z,h-1}^i x_{z,h-1}^i - x_{z,h}^i \mu_{z,h}^i\right] & \text{for } h > 0, \end{cases}$$

where $\mu_{E,z}^i$ is the entry rate of farmers. In the stationary equilibrium the distribution is defined by $\Delta\mu_{z,h}^i = 0$ for all values of h and the entry rate is equal to $\mu_{E,z}^i = 1 - \xi$.

Aggregate output. Production of the agricultural good is given by

$$Y = \left[\frac{\left(\int_{v,\varepsilon} e^{\gamma\varepsilon + (1-\rho\gamma)v} d\Phi_v(v) d\Phi_\varepsilon(\varepsilon)\right) \int_z \sum_i \sum_h (\varphi^i)^\gamma (z\kappa^i\lambda^h)^{1-\rho\gamma} \mu_{z,h}^i \Omega_z^i d\Phi_z(z)}{\left(\int_{v,\varepsilon} e^{\varepsilon + v(1-\rho)} d\Phi_v(v) d\Phi_\varepsilon(\varepsilon)\right)^\gamma \left(\int_z \sum_i \sum_h \varphi^i (z\kappa^i\lambda^h)^{1-\rho} \mu_{z,h}^i \Omega_z^i d\Phi_z(z)\right)^\gamma}\right] \times N_F^{1-\gamma}(L^\alpha N_W^{1-\alpha})^\gamma, \tag{4}$$

where $N_F = 0.5N$ is the mass of farm managers and $N_W = 0.5N$ is the mass of workers. The expression in square brackets describes the average productivity of farms and the impact of misallocation on aggregate productivity. In the undistorted economy, this expression simplifies to average productivity raised to the exponent $1-\gamma$, and total output is equal to output of a farm with average productivity multiplied by the total mass of farms. Aggregate productivity depends on (i) the misallocation of factors of production (n, ℓ); (ii) the share of farms growing each crop Ω_z^i; and (iii) the distribution of farmer abilities $\mu_{z,h}^i$ through farmer investment decisions. Notably, aggregate output does not directly depend on the average level of distortions $\bar{\tau}$, which is canceled out by general equilibrium effects. The rest of the expression describes inputs of farm managers N_F, land L, and farm workers N_W to aggregate output, where aggregate output has constant returns in all three factors.

Equilibrium definition. The stationary competitive equilibrium is the set of values

$$\{C^W, q, w, T, n_{z,h}^i(v,\varepsilon), \ell_{z,h}^i(v,\varepsilon), V_{z,h}^i(v,\varepsilon), x_{z,h}^i, \mu_{z,h}^i, \Omega_z^i\}$$

for all $z \in \mathcal{Z}$, $h \in \{0, 1, 2, ..., \infty\}$, $i \in \mathcal{I}$ and values (v, ε) such that:

(i) Taking prices as given, $(n_{z,h}^i(v,\varepsilon), \ell_{z,h}^i(v,\varepsilon))$ maximize farm profits and $(V_{z,h}^i(v,\varepsilon), x_{z,h}^i)$ maximize farm value.

(ii) The lump-sum transfer T balances the government's budget.

(iii) The distributions $(\mu_{z,h}^i, \Omega_z^i)$ are consistent with farm decisions and are stationary.

(iv) The land, labor, and output markets clear.

5 Calibration

We calibrate a benchmark economy with distortions to match characteristics of south Vietnam that we observe in the data. Our main experiment in the next section adjusts distortions in the benchmark economy to match the higher measured distortions in the North.

5.1 Measurement Error

A common concern in the misallocation literature is that the estimated wedges, such as those in Section 3, reflect some degree of measurement error. For example, over-reported farm output would result in a higher measured TFP and wedge. In Appendix C.1, we employ Bils et al. (2021)'s empirical methodology to show that, at least comparatively with estimates for the manufacturing sector, there is relatively limited measurement error, around 10% at most, in our measured wedges in agriculture for both south and north Vietnam. Additionally, we expect measurement error to be similar in both the South and North such that our main experiment—which adjusts distortions in the South to match the North—should not be drastically contaminated by measurement error. Nevertheless, measurement error can impact the level and measurement of distortions and the dynamic productivity implications. As a result, we extend our model to allow explicitly for measurement error in our calibration to limit its impact on our conclusions.

We allow for measurement error on output and the composite input. Measured output is now given by $y_{f,t} = y^*_{f,t} \exp\{\iota^{out}_{f,t}\}$ and measured inputs are given by $\ell_{f,t} = \ell^*_{f,t} \exp\{\iota^{in}_{f,t}\}$ and $n_{f,t} = n^*_{f,t} \exp\{\iota^{in}_{f,t}\}$, where we use stars to indicate unobserved true values. While we interpret $\iota^{out}_{f,t}$ and $\iota^{in}_{f,t}$ as measurement error, these variables also capture any type of shock to production or inputs that farmers are unable to fully adjust to, including, for example, unexpected weather events. In this regard, the important difference between $\iota^{out}_{f,t}$ and $\iota^{in}_{f,t}$ and the random components of productivity $v_{f,t}$ and distortions $\varepsilon_{f,t}$ is that farms cannot adjust production and input decisions based on ι's. Measured farm-level TFP and Wedge are now:

$$\text{TFP}_{f,t} = \frac{y_{f,t}}{(\ell^{\alpha} n^{1-\alpha}_{f,t})^{\gamma}} = s^{1-\gamma}_{f,t} e^{\iota^{out}_{f,t} - \gamma \iota^{in}_{f,t}}, \qquad \text{and} \qquad \text{Wedge}_{f,t} = \frac{y_{f,t}}{\ell^{\alpha}_{f,t} n^{1-\alpha}_{f,t}} = \frac{e^{\iota^{out}_{f,t} - \iota^{in}_{f,t}}}{1 - \tau_{f,t}}.$$

These expressions show that measured TFP and wedges depend on both the model fundamentals, captured by $s_{f,t}$ and $\tau_{f,t}$, but also the measurement errors, $\iota^{out}_{f,t}$ and $\iota^{in}_{f,t}$. Measurement error creates an upward bias in both the standard deviation of wedges and the elasticity of wedges with respect to farm-level productivity.

The measurement errors $\iota^{out}_{f,t}$ and $\iota^{in}_{f,t}$ are drawn from normal distributions with standard deviations $\sigma_{\iota^{out}}$ and $\sigma_{\iota^{in}}$. We jointly target these parameters along with other model parameters in the calibration. We include moments on the standard deviation of farm land size and the correlation between within farm changes in output and changes in land to discipline the extent of measurement error. The correlation moment reflects intuition from Bils et al. (2021) that co-movements in producer outcomes can be used to assess the extent of measurement error, which tends to dampen this relationship. Appendix C.2 discusses the identification of measurement error and other parameters in the calibration, and shows that measurement error affects moments differently than other model parameters.

5.2 Estimated Distortions

Ignoring measurement error, the parameters related to distortions can be directly estimated by regressing measured farm-level wedges on TFP and fixed effects for the farm's crop type, following equation (2). Table 4 reports the results for south and north Vietnam.

Table 4: Estimating Distortions in the South and the North

	National	South	North
	(1) log Wedge	(2) log Wedge	(3) log Wedge
log TFP	0.907***	0.856***	0.964***
	(0.00473)	(0.00717)	(0.00491)
Perennials	-0.0989***	-0.142***	0.117***
	(0.0167)	(0.0178)	(0.0301)
Other	0.00250	-0.0350	0.0262
	(0.0142)	(0.0230)	(0.0183)
Year FE	Yes	Yes	Yes
R^2	0.907	0.905	0.917
Observations	10526	4387	6139

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. All regressions include year fixed effects.

Measurement error implies that the estimates in Table 4 are biased upwards because mismeasurement creates a positive mechanical correlation between measured TFP and wedges (see also Ayerst et al., 2024). As a result, we use the estimates in Table 4 as targets in the model calibration and jointly target other moments to discipline the extent of mismeasurement. We also target the distribution of the random component of distortions in the joint calibration.

The crop-specific distortions are not subject to the same source of mismeasurement bias, and so we set these parameters directly. We normalize the crop-specific distortion of rice to one, $\varphi^R = 1$, and set the crop-specific distortions for perennial farmers to $\varphi^P = 1.61$ and for other crop farmers to $\varphi^O = 1.12$ using the relationship $\varphi^i = \exp(-\text{Coefficient}^i/(1-\gamma))$ implied by the model. The estimated coefficients indicate that distortions disincentivize production by rice farmers (through higher τ) compared to perennial or other crop farmers.

The level of distortions, $\bar{\tau}$, does not impact misallocation since it affects all farmers equally. However, the level $\bar{\tau}$ affects profits and, consequently, the incentives for farmers to invest. We set $\bar{\tau}$ such that the average value of the wedge is equal to one and hold $\bar{\tau}$ constant in the counterfactual experiment. We find that this is a conservative assumption.

We set the government-imposed restriction $\omega = 23\%$ for south Vietnam. In the data, farmers with multiple plots may report that only some plots face restriction while crop restrictions are a binary variable in the model. To construct the data moment, we take a land-weighted average of crop-restrictions for each farmer and then average this value over all farmers in south Vietnam in the dataset. This implies, for example, a farmer in the data with one-third of their land restricted is captured in the model by three farmers with one farmer having the entirety of their crop choice restricted and the other two being unrestricted. The comparison between the North and the South remains similar with alternative constructions of this moment. For example, the share of farmers that face crop restrictions on any plot is 40.5% in the South and 61.5% in the North, whereas the share of farmers with crop restrictions on greater than 50% of the land is 34.3% in the South and 51.6% in the North.

5.3 Calibration Strategy

There are thirteen parameters common to all crops $\{L, N, \beta, \xi, \gamma, \alpha, \theta, \lambda, \psi, \zeta, \rho, \sigma_{\iota^{out}}, \sigma_{\iota^{in}}\}$, three sets of crop-specific parameters $\{\eta^i, \kappa^i, \varphi^i\}$, and three distributions $\{\Phi_z, \Phi_v, \Phi_\varepsilon\}$. We calibrate the crop-specific parameters to match the three farm types described in Section 3.

Preliminaries. A period is set to one year. The discount factor is set to $\beta = 0.96$ to match a discount rate of 4%. The total mass of households is set to $N = 2$ such that there is a unit mass of farm managers and workers. The mass of land is set to $L = 2.77$ corresponding to an average farm size of 2.77 acres in south Vietnam. The span-of-control parameter is set to $\gamma = 0.7$, implying the profit share of farm managers is 30%, which reflects the combined return to the farm manager's labor on the farm and their management expertise (see, for example, Adamopoulos et al., 2022). The land share of output is set to $\alpha = 0.5$ based on the land share from Ayerst et al. (2020). Finally, the survival rate is set to $\xi = 0.955$ to match an annual exit rate of households from cropping of 1.2% and the implied inter-generational transfer of the farm of 3.3% in the data, which is based on the minimum and average ages of the head of household of 20 and 50 years old.

The three distributions describe the distributions of the permanent farmer productivity Φ_z, the idiosyncratic component of productivity Φ_v, and the idiosyncratic component of distortions Φ_ε. The permanent farmer productivity z takes five values while the idiosyncratic component of productivity v and distortions Φ_ε take fifteen values. We parameterize all three distributions with a log-normal distribution and dispersion parameters $\{\sigma_z, \sigma_v, \sigma_\varepsilon\}$ and with node ranges between two standard deviations above and below the mean value. For computation, we restrict the maximum farmer ability to λ^{99} and note that fewer than one in ten thousand farmers are above the 25th node of the ability distribution in the stationary equilibrium. The results are not sensitive to the number of grid points used for z, v, ε, or a.

Jointly calibrated parameters. The remaining parameters are calibrated in two stages to match the moments in Table 5. The first stage exploits the fact that the preference shifters η^i can always be set such that the model exactly matches the farm share by crop in the data, regardless of the other parameter values. As a result, holding the distribution of crops fixed, the parameters $\{\lambda, \psi, \zeta, \kappa^i, \sigma_z, \sigma_v, \rho, \sigma_\varepsilon, \sigma_{\iota^{out}}, \sigma_{\iota^{in}}\}$ with κ^R normalized to one, are jointly calibrated to minimize the distance between data moments and model moments constructed from simulated data (described below). The second stage calibrates the crop-specific preferences η^i, where η^R is normalized to one, and the preference curvature θ. As in the first stage, the crop-specific preferences η^i are always set such that the crop share matches the data. The value of the shape parameter θ on the distribution of farmer preferences is chosen to minimize the magnitude of the crop-specific preferences, given by $\sum_i(\eta^i - 1)^2$. In this regard, the final moment is chosen to treat the crop-specific preference as a residual and minimize the out-of-model factors that affect crop choice.

Table 5: Calibration Moments

	Model	Data
Avg growth (%)	6.23	6.23
Std growth	75.2	75.2
Std log TFP	0.98	1.00
Std log land	1.18	1.21
Reg coefficient: growth on log TFP	−34.4	−34.4
Top 10% land share (%)	42.1	41.2
Measured elasticity	0.855	0.856
Std log Wedge	0.89	0.87
Corr($\Delta \log TFP, \Delta \log \ell$)	0.084	0.084
Relative measured TFP	(1.00 , 1.20 , 0.75)	(1.00 , 1.20 , 0.75)
Farm share by crop (%)	(49.1 , 33.1 , 17.8)	(49.1 , 33.1 , 17.8)

Notes: For Relative Measured TFP and Farm Share by Crop, we report moments first for rice farms, followed by those for perennials and then other crop farms. Farm share by crop is calculated based on (3). All other moments are calculated using a simulation of 10,000 farms. Avg Growth and Std. Growth are calculated for growth over a two-year (two-period) interval (i.e., growth is calculated from t to $t+2$). Corr($\Delta \log TFP, \Delta \log y$) measures the correlation in the within-farm two-year change in log measured TFP and change in log measured output.

Other than the farm share by crop, the model moments are calculated using simulation data generated for 10,000 farmers in the stationary equilibrium. We initialize the simulation data for the 10,000 farmers using the stationary distribution of crop types i, permanent abilities z, and ability nodes h. We then allow the productivity of the farmers to evolve as in the stationary equilibrium—accounting for farmers transitioning to higher ability and random shocks (v, ε)—and allow for exit and entry of farmers for 103 periods. We then add measurement error on output, $\iota_{f,t}^{out}$, and inputs, $\iota_{f,t}^{in}$ for each simulated observations. Finally, we drop the first 100 periods and construct model moments over the final three-period window following the same procedure in the data. For comparability, we winsorize the top and bottom 2% of the simulation data, remove exiting farms from the relevant statistics (e.g., growth), and calculate moments using only data for the first (t) and last $(t+2)$ periods such that there is a year gap in the growth and change statistics.

5.4 Calibration Moments

Our theory describes the evolution and distribution of productivities and how these relate to farm crop decisions and the institutional environment. We leverage the micro data to construct moments that describe the joint distributions of TFP and growth, crop-specific differences across farms, and distortions to discipline the model parameters. We discuss the construction of the moments and provide a qualitative discussion on their connection to parameters below. In Appendix C.2, we discuss the derived model expressions and their relation to parameters, the sensitivity of model moments to a 10% change in calibrated parameters, and report the sensitivity of calibrated parameters to changes in targeted moments (as in Andrews et al., 2017; Fujimoto et al., 2023).

Avg TFP growth. The moment reports the average growth of measured farm-level TFP. In the data, farm-level growth is calculated over a two-year period as $g_{f,t} = (TFP_{f,t} - TFP_{f,t-2})/(0.5 * (TFP_{f,t} + TFP_{f,t-2}))$, averaged over all farm-years. In the simulated data, we similarly construct the growth in TFP from t to $t+2$ and report the average value over all farms that remain active into $t+2$. The moment relates to the size λ and likelihood of improving productivity, which depends on the investment technology (λ, ψ, ζ).

Std TFP growth. The moment reports the standard deviation of $g_{f,t}$ calculated in the previous moment across all active farms in both the empirical and simulated data. While the moment depends on the size and likelihood of improving productivity, it is moment is closely related to the idiosyncratic component of productivity through σ_v and the measurement error parameters $\sigma_{\iota^{out}}$ and $\sigma_{\iota^{in}}$.

Std log TFP. The moment reports the standard deviation of measured farm-level $\mathrm{TFP}_{f,t}$ across all active farms in both the empirical and simulated data. The moment acts as a residual measure of farm-level TFP differences to discipline the dispersion in the permanent component of productivity σ_z but also relates to parameters that determine the productivity distribution, such as the investment technology (λ, ψ, ζ), the idiosyncratic component of productivity through σ_v and the measurement error parameters $\sigma_{\iota^{out}}$ and $\sigma_{\iota^{in}}$.

Std log land. The moment reports standard deviation of measured farm-level land $\ell_{f,t}$ across all active farms in both the empirical and simulated data. The moment is closely linked to parameters that cause variation in productivity, such as σ_z and σ_v, or distortions, such as σ_ε. The moment also helps disciplines measurement error on inputs $\sigma_{\iota^{in}}$ by explaining cross-sectional variation in farm size not linked with productivity or distortions.

Reg coefficient: TFP growth on log TFP. The moment measures the coefficient from regressing farm-level TFP growth on log TFP. The empirical specification is given by $g_{f,t} = \nu \log \mathrm{TFP}_{f,t-2} + \Gamma_t + \epsilon_{f,t}$ where Γ_t is a year fixed effect and ν is the reported moment. The moment is calculated similarly using the simulated data, without the time fixed effect. The moment helps discipline the investment technology (λ, ψ, ζ) nad other parameters related to the productivity distribution, such as (σ_z, σ_v). In particular, the moment helps discipline curvature of the cost function since higher curvature ζ implies investment is less elastic to incremental profitability. Correlated distortions lead to a flattening of profitability at higher ability levels implying that higher curvature ζ increases relative investment by higher ability farms. Less negative estimates of ν then correspond to higher values of ζ.

Top 10% land share. The moment is calculated as the share of land held by the 10% largest farmers (by land size) in the empirical and simulated data. A farmer's land size is closely related to both productivity and distortions. The moment helps discipline the size and likelihood of productivity improvements through investment, and is, consequently, closely related to the investment technology (λ, ψ, ζ). Intuitively, larger ability improvements (higher λ) by fewer farmers (higher costs ψ) leads to a more skewed productivity distribution and amore concentrated distribution of land.

Measured elasticity. The data moment is taken from Table 4. We construct the model moment similarly by regressing measured farm-level wedges on measured farm-level TFP where we incorporate measurement error in the construction of both variables. Despite the bias, the data moment remains useful for disciplining the elasticity of distortions ρ in the model and changes in the parameter elasticity ρ closely coincide with the measured elasticity.

Std log Wedge. The moment reports standard deviation of measured farm-level wedge across all active farms in both the empirical and simulated data. The moment helps discipline the standard deviation of the random component of wedges σ_ε that is independent of the systematic component that relates to dispersion in TFP.

Corr($\boldsymbol{\Delta} \log \mathbf{TFP}, \boldsymbol{\Delta} \log \ell$). The moment reports the correlation of within-farm changes in measured farm-level TFP and measured farm-level land. In both the empirical and simulated data, the moments are calculated over a two-year period, such that $\Delta \log \mathrm{TFP}_{f,t} =$

$\log \text{TFP}_{f,t} - \log \text{TFP}_{f,t-2}$. The moment is used to discipline the measurement error parameters $\sigma_{\iota^{out}}$ and $\sigma_{\iota^{in}}$ and builds on the intuition from Bils et al. (2021) in using within-farm changes in variables to identify measurement error. Intuitively, farms adjust land holdings with measured TFP when it captures a true change in productivity (e.g., increasing z) but not when it captures a change in measurement error (e.g., changing ι^{out}).

Relative measured TFP. The data moment is calculated by regressing farm-level TFP on crop fixed effects, $\log \text{TFP}_{f,t} = k^P \times \text{Peren.}_{f,t} + k^O \times \text{Other}_{f,t} + \Gamma_t + \epsilon_{f,t}$ where Γ_t is a year fixed effect. The empirical estimates $\exp(k^P)$ and $\exp(k^O)$ are used as targets, with rice normalized to one. The corresponding model moments are calculated as average TFP of perennial and other crop farmers normalized by the average TFP of rice farmers.

Farm share by crop. The data moment is calculated as the number of farmers that qualify as Rice, Perennial, and Other farmers based on the definition in Section 3. The model moment is calculated analytically as the share of farmers that choose to grow each crop i. For a given share of government-imposed crop restrictions ω and farm values $\bar{V}^i_{z,h}$, the crop-specific preferences η^i can be used to match directly the empirical distribution of crops using equation (3).

5.5 Parameters

Table 6 summarizes the calibrated model parameters. The ability improvement λ and the crop-specific productivity component κ need to be scaled by a factor of $1-\gamma$ to be converted into TFP values. This implies that the increase in TFP from improving ability is 11% ($\lambda^{1-\gamma} \approx 1.11$) and that perennial (other crop) farmers are 10% more (23% less) productive than rice farmers, all else equal. Relative to Adamopoulos and Restuccia (2020), we find larger differences in the crop-specific component of productivity despite smaller differences in measured TFP due to more productive farmers selecting into cash crops in Adamopoulos and Restuccia (2020). In contrast, we find substantial overlap in the productivity distribution of farm types leading us to model crop selection at the time of entry (Appendix A.2).

Table 6: Model Parameters

Parameter		Value	Parameter		Value
Discount rate	β	0.96	Survival rate	ξ	0.955
Span-of-control	γ	0.7	Land share	α	0.5
Land	L	2.77			
Crop restriction	ω	0.23	Crop-specific distortion	φ^i	(1.00 , 1.61 , 1.12)
Crop preference elasticity	θ	1.40	Preference shifter	η^i	(1.00 , 0.64 , 0.83)
Investment level	ψ	1.51	Investment curvature	ζ	1.74
Ability step size	λ	1.43	Crop-specific productivity	κ^i	(1.00 , 1.37 , 0.41)
Permanent productivity	σ_z	1.48	Random productivity	σ_v	1.79
Elasticity	ρ	0.79	Random distortion	σ_ε	0.98
Output mismeasurement	$\sigma_{\iota^{out}}$	0.25	Input mismeasurement	$\sigma_{\iota^{in}}$	0.47

In addition to productivity, the crop-specific distortions φ^i tend to incentivize farmers to grow crops other than rice, where recall that higher values of φ corresponds to lower distortions τ. The allocation of farmers across crops is offset by government-imposed crop-restrictions ω, which increase the share of rice farmers, and crop-specific preferences η^i, which imply, on average, a utility cost for non-rice crops. The estimated value of η^P is consistent with perennials requiring substantial investment by households in addition to the time that passes before the crops mature and generate income.

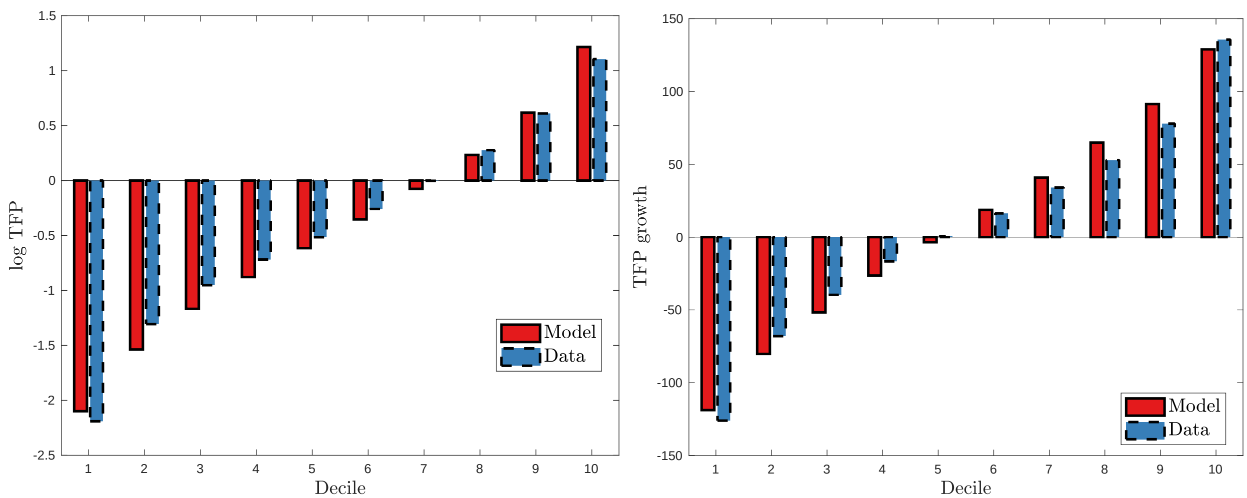
The estimated parameter elasticity is $\rho = 0.79$, which is around 0.06 lower than the measured elasticity of distortions in Table 4. The magnitude of the bias is consistent with what we find using Bils et al. (2021)'s methodology (Appendix C.1). It is worth noting that measurement error affects other parameter estimates as well, but the impact on the elasticity ρ is the most relevant to our quantitative analysis. Overall, we find a relatively small but nevertheless non-negligible role of measurement error.

The estimated curvature ζ on the ability investment is close to the quadratic value that is typically found in the manufacturing sector (e.g., Bento and Restuccia, 2017; Acemoglu et al., 2018; Ayerst, 2022). The estimated value implies that farm investment is comparatively more elastic to changes in profitability. We show that the results are robust to assuming a quadratic curvature in Section 6.5.

5.6 Other Moments and Goodness-of-Fit

Figure 4 compares the median TFP and TFP growth by percentile in the empirical and simulated data. Despite only targeting the dispersion of productivity and growth in the calibration, the simulated distribution fits the empirical distribution well.

Figure 4: Farm Productivity Distribution



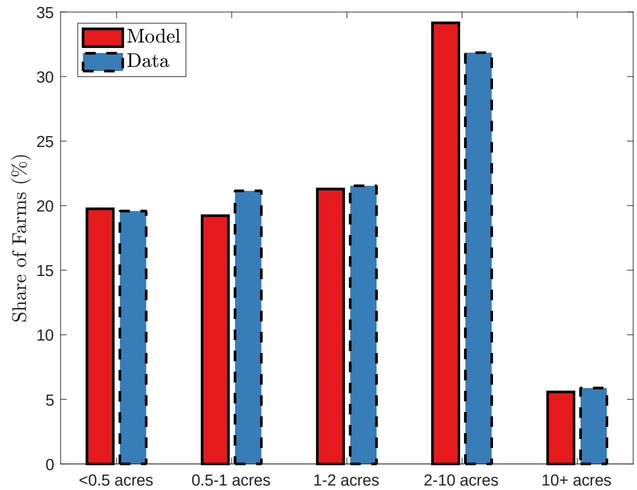
(a) TFP by decile (b) Growth by decile

Notes: Panel (a) reports log TFP for the median of each decile, i.e., the percentiles 5, 15, etc. Panel (b) similarly reports TFP growth for the median farm of each decile.

Figure 5 provides a comparison of the farm land size in the simulated model data and the data. The calibration sets the aggregate quantity L of land to match the average farm size in the model, but does not target the distribution of farms by land size. Despite this, the model almost perfectly replicates the distribution of farm land size observed in the data.

Table 7 compares other data moments with their corresponding moment constructed in the simulated data. The first set of moments validate the modeled distortions. The first row reports the fixed effects from Table 4 that are directly targeted. The second moment shows that the empirical autocorrelation of the farm-level wedge is smaller than that implied

Figure 5: Farm Land-Size Distribution



Notes: Share of farms in each farm land-size class. Land size refers to cultivated land by the farm.

by the model, supporting our choice to model ε as transitory rather than permanent to the farmer. The third moment considers a simple experiment in both the empirical and simulated data. Holding the distribution of productivities $s^i_{f,t}$ fixed, we calculate the potential gain in aggregate productivity from moving to the efficient allocation of land and labor (as in, for example Hsieh and Klenow, 2009). This moment tests the goodness of fit of the joint TFP and wedge distribution in the model and data, which determines the gains from reallocation.

The second set of moments show that the model replicates the distribution of output, land, and labor across both crops and farms. Relative output, land, and labor are calculated in the simulated data as the average of the respective outcomes for each farm type. In the data, the corresponding moments are based on the regressions reported in Appendix A.2. The moments are indirectly related to the distribution of productivities and distortions across crops and farms in the calibration. The third set of moments compares the standard deviations of measured farm output and labor inputs in the data and model. Similar to Figure 5, the moments show that the calibrated model is able to replicate the overall size distribution of farms in the data. The final set of moments shows the correlation between changes in farm-level TFP and output and labor. The calibrated model generates a similar magnitude of correlation between change in farm-level TFP and output as in the data. The model also

Table 7: Other Model Moments

	Model	Data
Crop-specific fixed effect*	(0.000 , −0.142 , −0.035)	(0.000 , −0.142 , −0.035)
Autocorrelation wedge	0.45	0.34
Gains from reallocation (%)	72.2	62.0
Relative output	(1.00 , 1.68 , 0.73)	(1.00 , 1.97 , 0.77)
Relative land	(1.00 , 1.70 , 0.92)	(1.00 , 1.96 , 0.39)
Relative labor	(1.00 , 1.70 , 0.92)	(1.00 , 1.65 , 1.07)
Std log output	1.52	1.47
Std log labor	1.18	1.07
$\text{Corr}(\Delta \log \text{TFP}, \Delta \log y)$	0.679	0.868
$\text{Corr}(\Delta \log \text{TFP}, \Delta \log n)$	0.084	−0.094

Notes: Where applicable, we first report moments for rice farms, followed by those for perennials and then other crop farms. Moments with a * indicate moments that are directly targeted in the calibration.

generates a near-zero correlation between change in farm-level TFP and employment.

6 Quantitative Analysis

The agricultural sector in north Vietnam is comparatively more distorted than south Vietnam. We also observe considerably less farm dynamism in north Vietnam and lower agricultural productivity. We assess the importance of institutional distortions in explaining these differences by imposing distortions that reflect conditions in north Vietnam on the benchmark economy, which is calibrated to match south Vietnam. Appendix C.4 reports a fully recalibrated model to the north Vietnam data.

6.1 Counterfactual Distortions

The benchmark economy has four parameters related to distortions: (1) the elasticity of distortions to farm-level productivity ρ; (2) crop-specific distortions φ^i; (3) the government-imposed crop restriction ω; and (4) the random component of distortions σ_ε. Table 8 summarizes the values estimated for the first three of these for the counterfactual experiment. Other parameters, including the random component of distortions, are held fixed at the benchmark economy values.

Table 8: Counterfactual Distortions

		Benchmark (South)	Counterfactual (North)
Elasticity	ρ	0.79	0.91
Crop-Specific Distortion	φ^i	(1.00 , 1.61 , 1.12)	(1.00 , 0.68 , 0.92)
Crop Restriction (%)	ω	23	43

Notes: Distortions are ordered for Rice, Perennial, Other crop farm types. Crop-specific distortions are implied by the coefficient estimates in Table 4 as $\varphi^i = \exp(-\text{Coefficient}^i/(1-\gamma))$.

We follow the same procedure as in the benchmark economy calibration and base the crop-specific distortions on the regression coefficients in Table 4. We adjust the elasticity of distortions ρ until the measured elasticity implied by the counterfactual economy matches the north Vietnam data. Relative to south Vietnam, distortions are more correlated with farm-level productivity, reflecting the greater difficulty productive farmers face in operating larger farm sizes, and growing perennial crops. We find a similar value of ρ when we fully recalibrate the model to the North data (Appendix C.4), suggesting that differences in ρ are not driven by differences in measurement error. We also find similar differences between the measured elasticity of distortions targeted in the calibration using only the two rice-growing delta regions (Appendix A.1), suggesting that the estimated gap in ρ is not being driven by technology or geographic differences. We set $\omega = 43\%$ to reflect the share of farmers reporting crop restriction in north Vietnam in our data. Finally, we hold the idiosyncratic component of distortions, governed by σ_ε, fixed at the benchmark economy level, but note that this parameter does not have a large impact on any of the results. Appendix C.5 reports the productivity costs relative to the undistorted economy.

6.2 Comparison with the Data

We start by examining whether the counterfactual economy moves the model moments closer to those for north Vietnam compared to the benchmark economy. Incorporating dynamics into misallocation models produces falsifiable predictions about how changes in distortions affect farm dynamics and the farm distribution. This acts as an important validation of our theory and captures an important contribution of our analysis in using farm dynamics to validate the impact of distortions more broadly. Table 9 compares the calibration moments and agricultural productivity in the benchmark and counterfactual economies as well as in the data for north Vietnam. We do not expect the counterfactual model to replicate fully the data moments for the North since other factors (e.g., average farm size) that impact the moments differ between regions. Nevertheless, Table 9 shows that the counterfactual economy is more similar to the data moments for north Vietnam than the benchmark economy.

Table 9: Comparing Counterfactual Moments with the Data for the North

	Benchmark	Counterfactual	Data
Productivity	1.00	0.59	0.42
Avg growth (%)	6.23	4.60	2.62
Std growth (%)	75.2	75.0	89.2
Std log TFP	0.98	0.90	0.84
Std log land	1.18	1.00	0.98
Reg coefficient: growth on log TFP	-34.4	-39.6	-48.2
Top 10% land share (%)	42.1	35.9	38.3
Measured elasticity	0.855	0.963	0.964
Std log wedge	0.89	0.92	0.81
Corr($\Delta \log \text{TFP}, \Delta \log \ell$)	0.084	-0.064	-0.022
Relative measured TFP	(1.00 , 1.20 , 0.75)	(1.00 , 0.99 , 0.74)	(1.00 , 0.69 , 0.80)
Farm share by crop (%)	(49.1 , 33.1 , 17.8)	(72.9 , 9.4 , 17.8)	(75.1 , 5.0 , 19.9)

Notes: Where applicable, moments are first reported for rice farms, followed by those for perennials and then other crop farms.

Our main result is the implied productivity gap between the counterfactual and benchmark economy, which is a measure of how much of the observed productivity gap can be explained by differences in the distortions between the North and South. We find that aggregate TFP in the counterfactual economy (North) is 59% of the benchmark economy (South), implying that the model accounts for almost two-thirds ($61\% \approx \log(0.59)/\log(0.42)$) of the productivity gap between the North and the South.

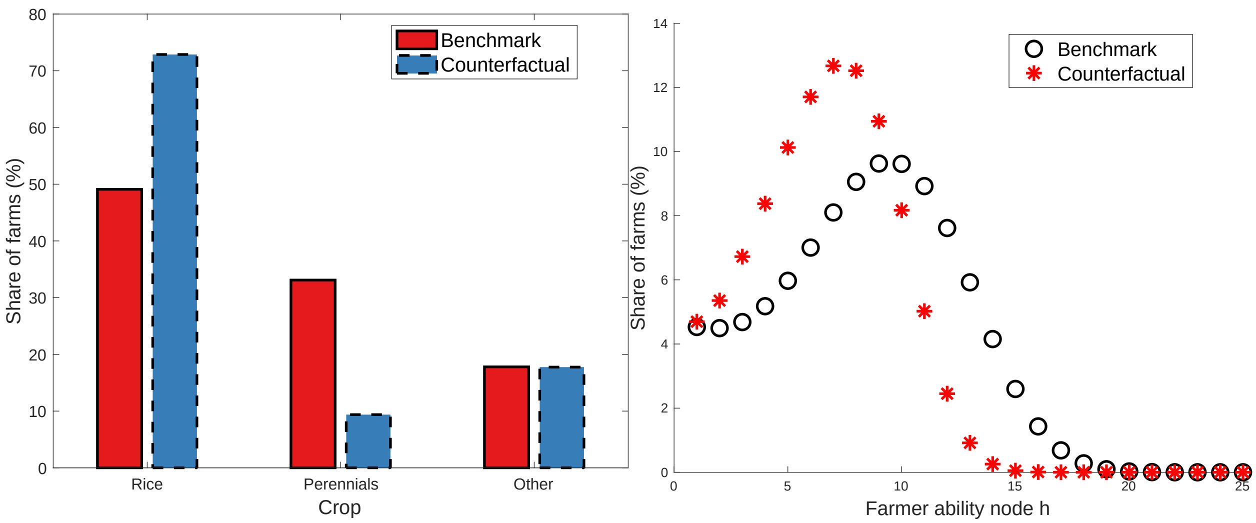
In addition, the model accounts for just under half ($(6.23 - 4.60)/(6.23 - 2.62)$) of the gap in the average productivity growth rate of farmers between the South and the North. The model also accounts almost entirely for differences in the farm share by crop in the data as well as around half of the relative measured TFP of perennial farmers. The model accounts for around half of the gap in the standard deviation of log TFP and one-third of the regression coefficient of growth on log TFP. The model over-predicts the decline in the land share of the top 10% of farmers and the impact on the correlation between the change in farm TFP and change in land. The similarity of the counterfactual economy and the north Vietnam data shows that farm-level distortions correctly predict the directions of changes in moments in the data and that changes in farm-level distortions are important for explaining variation in these outcomes.

The model does not generate an increase in the standard deviation of growth, which is relatively unchanged in the counterfactual economy. This is because the standard deviation of growth is mostly driven by the idiosyncratic dispersion in productivity σ_v (Appendix C.2), which is held fixed in the counterfactual economy. The model also does not have a large impact on the standard deviation of wedges, although the measured gap between the South and the North is relatively modest.

6.3 Drivers of the North-South Productivity Gap

Differences in measured distortions between north and south Vietnam produce a productivity loss of 41%. What channels account for this productivity loss? Following equation (4), productivity in the model depends on factor misallocation, the crop distribution, and the ability distribution. Note that the change in output is equivalent to the change in productivity in our framework since aggregate inputs are held constant. Figure 6 compares the crop and ability distributions in the benchmark and counterfactual economies. Consistent with evidence in north and south Vietnam (Ayerst et al., 2020), the figure shows that the ability distribution has more mass at higher productivity levels in the South.

Figure 6: Farm Distributions in Benchmark and Counterfactual Economies



(a) Crop Distribution (b) Ability Distribution

To better understand the three components of productivity, we design experiments to decompose the relative contributions of factor misallocation, crop choice, and farm ability. Table 10 summarizes the loss in aggregate productivity from changing channels individually from the benchmark economy to match the counterfactual economy. The sum of the losses does not equal the total gap between the benchmark and counterfactual economy because of interactions between the channels. For example, changes in the ability or crop distributions also affect the potential scope for factor misallocation through their effect on the productivity distribution. We discuss each channel and its calculation below.

Factor misallocation. We calculate the loss from factor misallocation as the change in aggregate output when distortions, $\tau^i_{f,t}$, are adjusted to match the counterfactual economy but the crop and ability distributions remain fixed at the benchmark distributions. Starting from the distribution of farm-level productivities $s^i_{f,t}$ in the benchmark economy, we recalculate the distortions $\tau^i_{f,t}$ that farmer f would receive with the counterfactual correlation ρ

Table 10: Output Loss by Channel

	Change in Output (%)	
Factor Misallocation	-19.4	
Crop Choice	-8.0	
Farm Ability	-31.6	
Sum of Channels	-59.0	
Total		-40.8

Notes: The change in output is equivalent to the change in productivity since aggregate inputs are constant.

and crop-specific distortions φ^i. We find that factor misallocation lowers agricultural output by 19.4%, accounting for just under half of the productivity gap between the counterfactual and benchmark economies.

Partitioning the interaction effects proportionately to each channel, factor misallocation accounts for around one-third ($\approx -19.4/-59.0$) of the resulting productivity loss. Factor misallocation has a negative interaction with the other two channels explaining why the sum of the losses from the individual channels is larger than the total loss in productivity. This is because factor misallocation has a smaller effect on aggregate productivity when productivity is less dispersed, as is the case in the counterfactual economy.

Crop distribution. We calculate the loss from the crop distribution as the change in aggregate output when the crop shares Ω_z^i are adjusted to match the counterfactual economy. We fix the within-crop ability distribution $\mu_{z,h}^i$ to that of the benchmark economy. However, the aggregate ability distribution, equal to $\mu_{z,h}^i \Omega_z^i \Phi_z(z)$, changes due to changes in the crop distribution. Average ability falls since perennial farmers are, on average, higher ability than rice farmers and the experiment redistributes around 25% of farmers from perennials to rice. We find that the change in the crop distribution has a relatively small contribution to the overall gap between the counterfactual and benchmark economies compared with the other channels. Nevertheless the output loss from the change in the crop distribution is a non-trivial -8.0%.

Farmer ability. We calculate the loss from farmer ability as the change in aggregate output when the ability distribution is adjusted to match the counterfactual economy. We adjust the farmer ability distribution $\mu^i_{z,h}$, conditional on crop i and permanent productivity z, to the counterfactual economy and hold the crop shares Ω^i_z fixed to that of the benchmark economy. The ability distribution in the counterfactual economy results from lower investment by farmers due to more correlated distortions, which makes higher ability levels less profitable. We find that the change in farm ability generates a loss in agricultural output of 31.6%, accounting for around three-quarters of the productivity gap between the counterfactual and benchmark economies. The effect of crop choice and farm ability together, representing the broader effects of misallocation, account for over half of the productivity loss from the sum of channels, almost double the impact of factor misallocation.

The farmer ability channel also depends on the value of the elasticity of distortions ρ. At the extreme, farmer ability investment goes to zero as the elasticity of distortions ρ goes to one, because distortions at $\rho = 1$ eliminate any profit increase that farmers receive from higher productivity. The impact of changes in ρ are asymmetric, with productivity changing more when ρ increases than when ρ decreases (see Appendix C.6). Consequently, the impact of increasing ρ from the South to the North value implies a large productivity loss despite the change in ρ being small when compared with the overall value of ρ.

6.4 Role of Individual Distortions

We also examine the role of the individual distortions, rather than channels. We measure the impact on output of individual distortions from unilaterally changing ρ, φ^i, or ω in the benchmark economy to match the North. Table 11 summarizes the results.

Table 11: Output Loss from Individual Distortions

	ρ	φ	ω	(ρ, φ, ω)
Change in Output (%)	-38.3	-7.5	-1.4	-40.8

The main driver of the gap between the benchmark and counterfactual economies is the elasticity of distortions. The elasticity of distortions has a large impact on factor misallocation by reallocating resources from high productivity to low productivity farms. The increase in elasticity also dampens the increase in profits associated with increasing farm productivity, which results in weaker incentives for farmers to invest in ability or select crops based on market factors as opposed to preferences. Our results point to a large productivity effect from seemingly small variation in the elasticity of distortions ρ between the North and the South due to the asymmetric productivity effects from changes in ρ that are magnified as ρ approaches one.

The crop-specific distortions have a more moderate effect on the productivity gap between the benchmark and counterfactual economies. Crop-specific distortions increase factor misallocation by reallocating resources across different farm types. Crop-specific distortions also affect the relative incentives for farmers to invest in improving ability since it changes the relative profitability of crops. Finally, crop-specific distortions affect the crop distribution through changing the relative market value of farm types.

Government-imposed crop restrictions have the smallest impact on productivity. Part of the reason is that crop restrictions are implemented before farmers make crop choices implying that some farmers would choose to grow rice independent of the restriction. Since around half of farmers grow rice in the benchmark economy, this reduces the impact by a comparable amount. As a back-of-the-envelope calculation, the change in productivity is approximately equal to reducing the productivity of 7% (the change in $\Delta\omega = 0.2$ times the 33.1% share of perennial farmers) of farmers by 20% (the measured productivity of perennials farmers relative to rice farmers). This calculation highlights the limited impact of crop restrictions on aggregate productivity despite the relatively large measured differences across crops.

6.5 Robustness

The results show that the interactions between distortions and farm dynamics lead to large productivity differences between north and south Vietnam. Higher distortions prevent higher ability farmers from increasing production and disincentivize investment by farmers, magnifying the overall costs of misallocation. We evaluate the robustness of our results under alternative calibrations and model extensions.

Alternative calibrations. We consider two sets of exercises related to the calibrated ability distribution to examine the robustness of our results. Table 12 reports the productivity gap generated by the model using the alternative calibration parameters.

Table 12: Robustness of Main Results to Alternative Calibrations

	Relative Counterfactual Output (%)
Baseline	59.2
Alternative calibrations:	
Fix investment-cost curvature $\zeta = 2$	58.8
Avg growth target $6.23\% - 2\%$	58.6
Avg growth target $6.23\% - 4\%$	62.4

Notes: Compares the agricultural output (productivity) effect of the counterfactual relative to the benchmark economies in the baseline and alternative calibrations of the model.

First, we consider a re-calibration of the model that fixes the ability investment curvature to be quadratic, $\zeta = 2$. The remaining parameters are re-calibrated to match the moments in Table 5. The productivity gap in the re-calibrated model implies a larger gap between the counterfactual and benchmark economies than in the baseline experiment.

Second, we consider a re-calibration of the model using alternative targets for the average growth rate in south Vietnam. Lowering the targeted growth rate results in a more compressed ability distribution relative to the benchmark calibration since the model requires that farms either grow by less or less frequently to match the moment. A concern in our baseline calibration is that part of the growth captured in the target represents economy-wide factors (e.g., technology improvements) unrelated to the ability improvements in the model. If these other factors are large, then the ability distribution may be more compact than assumed in our baseline calibration and the results overstated.

To give a sense of the quantitative importance of this factor, we re-calibrate the model using targets for average growth rates that are two and four percentage points lower than in the baseline calibration (Appendix C.2 reports the change in parameters). Table 12 shows that despite the relatively drastic changes in the targeted growth rate, the productivity gap explained by the model remains economically significant in both cases. Lowering the targeted average growth rate by two percentage points, around one third of the targeted value, has almost no impact on the relative productivity of the counterfactual economy compared to the baseline experiment. Decreasing the targeted growth rate by four percentage points lowers the productivity gap to 62.4% between the North and the South.

Model extensions. We consider two model extensions and summarize the results (see Appendix C.7 for details). First, we consider an extension of the model that replicates the hump shaped productivity life-cycle profile in Figure 3. The extended model allows for farmer ability $a_{f,t}$ to also depend on a state variable that takes values *young* or *old*. Entrants start as *young* farmers and transition to *old* farmers over time, which is the absorbing state. We recalibrate the model to match the life-cycle profile found in the data. The relative counterfactual output is around 57%, similar to the value found in the baseline experiment.

Second, we consider an extension of the model that allows for entrants to draw ability from a distribution that depends on the ability of the predecessor (the farm that the entrant replaces). Intuitively, this could be thought of as capturing the passing of knowledge between generations. We recalibrate the model and repeat the same experiment as in the baseline model. We find stronger productivity losses in this model extension due to the positive spillover of investment on the entrant productivity distribution.

7 Conclusion

We develop a model of heterogeneous production to capture two important aspects of farm dynamics in developing countries: crop choices and productivity investments. Using panel farm-level data from Vietnam, we apply this framework to study the effect of differences in institutional distortions between north and south Vietnam. Through the lens of the model, measured distortions in the North relative to the South account for 61% of the productivity gap, which represents a substantial 41% productivity loss, and around half the difference in farm dynamics, as measured by farm productivity growth. Farm ability and crop choice (dynamic misallocation) account for almost two-thirds of the productivity loss, with the remaining one-third coming through the standard channel of factor misallocation. Decomposing the sources of the productivity loss, the key institutional feature is the higher elasticity of distortions to farmer productivity in the North, which captures the weaker relationship between factor inputs and productivity in the North relative to that in the South.

While our main results on the difference between the South and North are not substantially affected by the extent of measurement error in the data, the role of measurement error is more substantial in the level effects relative to an undistorted economy. In particular, we find that the aggregate productivity effect of removing distortions in a calibrated economy that abstracts from measurement error is more than twice as large than in our calibrated model allowing for measurement error. This suggests an important role for measurement error in models with dynamic decisions that amplify the broader productivity effects from static misallocation.

Our results in the context of Vietnam agriculture provide novel quantitative evidence of the broader effects of misallocation emphasized in Restuccia and Rogerson (2017), especially when the pattern of misallocation most heavily penalizes the most productive producers, effectively lowering the return to productivity investment and growth. A promising area for future work is to examine the effects of distortions on producer dynamics in other contexts, joining recent efforts assessing the role of size-dependent policies on innovation and growth

(Aghion et al., 2021; Akcigit et al., 2022). It will also be insightful to study the dynamic consequences of misallocation in the context of reform episodes in either agriculture (Chari et al., 2021; Chen et al., 2022; Beg, 2022) or industry (Asturias et al., 2023), as well as episodes of trade reform (Pavcnik, 2002).

Finally, more work is needed in identifying the specific channels of dynamic misallocation which will facilitate a deeper understanding of the broader role of policies and reform, including the importance for productivity growth of technology adoption and diffusion, the adoption of improved managerial practices, and other productivity-enhancing investments at the producer level.

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On-line Appendix

A Data Details

A.1 Comparing the Red River and Mekong Deltas

Our baseline analysis compares the agricultural sectors in north and south Vietnam. Our theory shows how institutional differences, captured by wedges, distort farm-level decisions to lower productive investments and aggregate productivity. An advantage of our approach is that we exploit historical differences between the north and south to make within-country comparisons. Nevertheless, differences in climate and geography may still imply gaps in production capabilities across regions. In this Appendix, we show that the main empirical differences between the south and north in our analysis hold if we restrict focus only on the comparison between the two rice-growing delta regions: the Red River Delta in the north and Mekong Delta in the south, where technology and geographic differences are less likely to be a concern.

Table A.1: Red River and Mekong Delta Comparison

	Red River Delta (North)	Mekong Delta (South)
TFP growth	7.07	8.50
Std log TFP	0.75	1.02
Std log output	0.82	1.63
Std log land	0.74	1.29
Std log empployment	0.83	1.15
Measured elasticity	0.94	0.79
Std log wedge	0.73	0.85
Crop share	(88.1, 2.5 9.4)	(71.4, 15.0 , 13.6)

Table A.1 compares key moments from the two regions. The comparison shows the same patterns emphasized in our main analysis between the north and the south. Growth in the south is higher, accompanied by more dispersion in TFP, in output, and landholdings. The gap in the measured elasticity of distortions between the south and north is also larger than in the baseline analysis. Finally, while these are both primarily rice-growing regions, we find a higher share of perennial farms in the south.

A.2 Differences by Farm Type

Tables A.2 and A.3 report cross-crop differences for output, land, labor, TFP, and TFP growth by farm type. The results are consistent with the summary statistics presented in the main text. In the South, perennials farmers tend to be larger in terms of both output and inputs, more productive, and higher growth. Other crop farmers tend to be smaller, at least in terms of output, and less productive. In the North, perennial farmers perform comparatively worse than rice farmers.

Table A.2: Farm Type Comparison in South Vietnam

	(1) log Output	(2) log Land	(3) log Labor	(4) log TFP	(5) TFP Growth
Perennials	0.679*** (0.104)	0.675*** (0.0836)	0.499*** (0.0687)	0.180*** (0.0608)	6.028*** (1.723)
Other	-0.267*** (0.103)	-0.0935 (0.100)	0.0700 (0.0759)	-0.287*** (0.0609)	-2.973 (2.610)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4406	4406	4406	4387	3485

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. All regressions include year fixed effects.

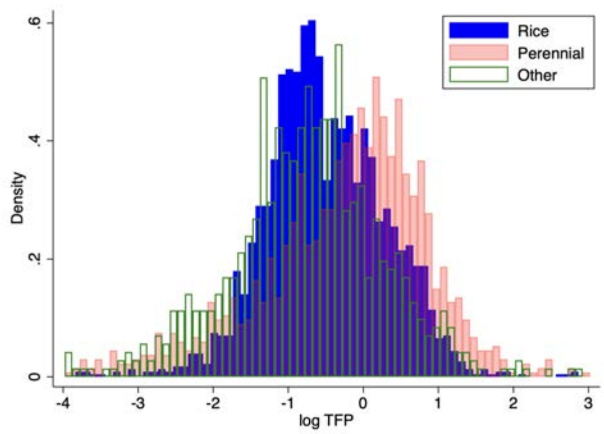
Figure A.1 reports the TFP distribution by crop for south Vietnam. The figure highlights a key empirical observation that motivates how we model selection into different crops: a substantial productivity overlap between the three farm types. That is, while perennial farmers are on average more productive than the other farm types, there is a significant mass of perennial farmers that are less productive than the typical rice or other crop farmers. In contrast, selection based on farmer ability (as in Adamopoulos and Restuccia, 2020) would imply a discrete productivity cutoff in contrast with the data.

Table A.3: Farm Type Comparison in North Vietnam

	(1) log Output	(2) log Land	(3) log Labor	(4) log TFP	(5) TFP Growth
Perennials	-0.583***	-0.478***	-0.413***	-0.376***	-5.541
	(0.148)	(0.114)	(0.109)	(0.0993)	(4.859)
Other	-0.222***	-0.108	-0.113**	-0.222***	-7.064***
	(0.0686)	(0.0772)	(0.0527)	(0.0453)	(2.427)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	6348	6348	6348	6139	5034

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. All regressions include year fixed effects.

Figure A.1: Distributions of Farm TFP by Crop



A.3 Farm Life Cycle with Different Age Definitions

Table A.4 reports the productivity life cycle of farms in North and South Vietnam using three different measures of age. The baseline measure, discussed in the main text, constructs household age as the average of household members weighted by their time spent working on household crops. The Household Head measure constructs age as the age of the member identified as the household head. The Average measure constructs age as the simple average across household members. The productivity measure is normalized in each region and year such that the regressions do not capture time trends.

We find that in all three cases the two main observations in the main text hold. First,

Table A.4: Farm Life Cycle

	(1) log TFP	(2) log TFP	(3) log TFP
Age (North)	0.0218***	0.0333***	0.0137**
	(0.00696)	(0.0117)	(0.00535)
Age (South)	0.0435***	0.0451**	0.0235***
	(0.0112)	(0.0221)	(0.00851)
Age^2 (North)	-0.000305***	-0.000374***	-0.000229***
	(0.0000740)	(0.000119)	(0.0000629)
Age^2 (South)	-0.000570***	-0.000542**	-0.000373***
	(0.000109)	(0.000219)	(0.0000921)
Age Definition	Baseline	Household Head	Average
R^2	0.0327	0.0141	0.0257
Observations	10203	9201	10520

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the household level are included in parentheses. All regressions include a region fixed effect. $\log \text{TFP}$ is normalized at the region-by-year level. Household Head measures age as the age of the household member identified as the head of household. Average measures age as the average age of all household members. Column (2) excludes households where the head of household is older than 70.

household productivity life cycles in both the North and the South display a hump-shaped pattern where households quickly increase productivity when they are young and then decline at old ages. Second, the dynamics of farms in the South are much sharper than in the North, where productivity tends to be flatter over the farm's life cycle.

A.4 Differences in Land Quality

Table A.5 compares the quality of land across Vietnamese provinces using the FAO's Global Agro-Ecological Zones data analyzed in Adamopoulos and Restuccia (2022). We follow Adamopoulos and Restuccia (2022) by measuring land quality as the average potential yield of land (across cells) within the province. We focus on two measures: an average of 27 crops and wet rice, the most prevalent crop in Vietnam. We use the rainfed, low input potential yield which most closely reflects the land quality without human intervention, see Adamopoulos and Restuccia (2022) for details and discussion.

Panel A of Table A.5 describes land quality differences between the North and South for all provinces in the country. Panel B focuses on only the twelve provinces that are included in the VARHS dataset. Panel C adjusts the mean values of land quality for the relative frequency of observations in our final dataset.

Table A.5: Comparison of Land Quality

A. All Provinces

	Mean Avg.	Sd Avg.	R9010 Avg.	Mean Rice	Sd Rice	R9010 Rice
North	88.8	0.4	3.2	1.6	0.8	6.6
South	87.3	0.3	2.0	2.1	0.5	3.2
Total	88.0	0.4	2.2	1.9	0.7	5.3

B. In Final Dataset

	Mean Avg.	Sd Avg.	R9010 Avg.	Mean Rice	Sd Rice	R9010 Rice
North	67.4	0.6	3.7	1.1	1.0	12.4
South	94.9	0.3	2.1	1.7	0.5	4.1
Total	81.2	0.5	3.5	1.4	0.9	11.3

C. In Final Dataset (observation-weighted means)

	Mean Avg.	Sd Avg.	R9010 Avg.	Mean Rice	Sd Rice	R9010 Rice
North	87.2	0.6	3.7	1.7	1.0	12.4
South	86.3	0.3	2.1	1.8	0.5	4.1
Total	86.8	0.5	3.5	1.8	0.9	11.3

Notes: Values calculated using provinces as unit of observation. "Avg." refers to statistics calculated on the average potential yield of 27 common crops. "Rice" refers to statistics calculated on the average potential yield of wet rice. "Sd" is the standard deviation of the log variable. "R9010" is the ratio between the 90th and 10th percentile observations. Panel C constructs the mean values using the relative frequency of farm-year observations in our data as weights.

Comparing Panel A and Panel C shows that after adjusting the means for the relative frequency of observations there is little difference between our final dataset and the average province in the North and South. The observed differences in land quality are not large enough to explain the productivity gap that we observe between farms in the North and

South. Taking the production function in Section 4 implies that the impact of land quality on TFP requires differences to be scaled by a factor $\alpha\gamma = 0.35$. This would further reduce the potential impact of any differences between the North and the South.

B Cropping Decision

Let $\bar{V}_z^i$ be the expected utility from consumption of choosing crop i. Then, the probability that household f chooses crop i is given by:

$$
\begin{aligned}
&= \Pr\left[\bar{V}_z^i b^i > \bar{V}_z^{i'} b^{i'} \forall i' \neq i\right], \\
&= \int_{\tilde{b}} \prod_{i' \neq i} \Pr\left[\bar{V}_z^i \tilde{b} > \bar{V}_z^{i'} b^{i'}\right] h(\tilde{b}) d\tilde{b}, \\
&= \int_{\tilde{b}} \prod_{i' \neq i} \exp\left\{-(\eta^{i'})^\theta \left(\frac{\bar{V}_z^i}{\bar{V}_z^{i'}} \tilde{b}\right)^{-\theta}\right\} \left[\theta(\eta^i)^\theta \tilde{b}^{-\theta-1} \exp\{-(\eta^i)^\theta (\tilde{b})^{-\theta}\}\right] d\tilde{b}, \\
&= \int_{\tilde{b}} \exp\left\{-\left(\sum_{i' \neq i} (\eta^{i'})^\theta \left(\frac{\bar{V}_z^i}{\bar{V}_z^{i'}}\right)^{-\theta}\right) \tilde{b}^{-\theta}\right\} \left[\theta(\eta^i)^\theta \tilde{b}^{-\theta-1} \exp\{-(\eta^i)^\theta \tilde{b}^{-\theta}\}\right] d\tilde{b}, \\
&= \int_{\tilde{b}} \exp\left\{-\left(\frac{\sum_{i' \neq i} (\bar{V}_z^{i'} \eta^{i'})^\theta}{(\bar{V}_z^i)^\theta}\right) \tilde{b}^{-\theta}\right\} \left[\theta(\eta^i)^\theta \tilde{b}^{-\theta-1} \exp\{-(\eta^i)^\theta \tilde{b}^{-\theta}\}\right] d\tilde{b}, \\
&= (\eta^i)^\theta \int_{\tilde{b}} \left[\theta \tilde{b}^{-\theta-1}\right] \exp\left\{-\left(\frac{\sum_{i' \neq i} (\bar{V}_z^{i'} \eta^{i'})^\theta}{(\bar{V}_z^i)^\theta} + \eta^i\right) \tilde{b}^{-\theta}\right\} d\tilde{b}, \\
&= (\eta^i)^\theta \frac{(\bar{V}_z^i)^\theta}{\sum_{i'} (\bar{V}_z^{i'} \eta^{i'})^\theta} \int_{\tilde{b}} \left[\theta \frac{\sum_{i'} (\bar{V}_z^{i'} \eta^{i'})^\theta}{(\bar{V}_z^i)^\theta} \tilde{b}^{-\theta-1}\right] \exp\left\{-\left(\frac{\sum_{i'} (\bar{V}_z^{i'} \eta^{i'})^\theta}{(\bar{V}_z^i)^\theta}\right) \tilde{b}^{-\theta}\right\} d\tilde{b}, \\
&= \frac{(\bar{V}_z^i \eta^i)^\theta}{\sum_{i'} (\bar{V}_z^{i'} \eta^{i'})^\theta}.
\end{aligned}
$$

C Other Quantitative Results

C.1 Measurement Error

Bils et al. (2021) develop a methodology to assess the importance of additive measurement error in misallocation models. Following Adamopoulos et al. (2022), we estimate:

$$\Delta \log y_{f,t} = \beta_1 \log Wedge_{f,t} + \beta_2 \Delta \log input_{f,t} + \beta_3 \log Wedge_{f,t} \Delta \log input_{f,t} + F_t + \upsilon_{f,t}, \tag{C.1}$$

where $input_{f,t} = \ell_{f,t}^{\alpha} n_{f,t}^{1-\alpha}$ is the Cobb-Douglas aggregate of farm inputs, F_t is a year fixed effect, and $\upsilon_{f,t}$ is an error term. Following Bils et al. (2021), the estimated value $\hat{\lambda}^{BKR} = 1 + \hat{\beta}_3/\hat{\beta}_2$ captures the ratio of dispersion in the true farm-level distortions (i.e., $\tau_{f,t}$ in the model) to the dispersion in the distortions plus dispersion in the wedge due to measurement error. Estimates of $\hat{\lambda}^{BKR}$ close to one indicate little measurement error, while values close to zero indicate that dispersion in the observed wedge is mostly due to measurement error. Without measurement error, high and low wedge farms adjust output and inputs similarly to changes in productivity and distortions, so the cross-term, β_3, is zero. With measurement error, the cross-term becomes negative as over-reporting output (under-reporting inputs) farms appear to have higher wedges but adjust inputs by less (output by more) than would be implied by the change in output (inputs).

Table C.6 reports the estimated value of $\hat{\lambda}^{BKR}$ from (C.1) and the estimated standard errors. The results indicate a relatively limited role of measurement error in both south and north Vietnam, consistent with estimates for agriculture in other contexts (Adamopoulos et al., 2022; Aragón et al., 2022).

We emphasize that while measurement error biases the estimated elasticity of distortions, from a calibrated $\rho = 0.79$ to a measured elasticity of 0.86 for south Vietnam, the quantitative impact of this bias in our results is limited by the fact that our main experiment involves assessing the aggregate productivity effects of differences in misallocation between the South

Table C.6: Estimates of Additive Measurement Error

	South	North
$\hat{\lambda}^{BKR}$	0.906	0.987
	(0.030)	(0.022)

and the North. However, it is important to note that the bias induced by measurement error has a more substantial impact on the level of misallocation measured by the reallocation gains associated with the removal of distortions, as we discuss in Appendix C.5.

C.2 Identification of Model Parameters

We expand on the discussion in Section 5 by deriving the relationship between model parameters, discussing the sensitivity of the moments to changes in model parameters, and examining the robustness of calibration results.

Model moments. We derive the relationship between the calibration moments and parameters. Most moments do not have explicit closed-form solutions and so we use this to highlight the intuition provided in the main text rather than as a proof on identification. Our quantitative analysis focuses on 11 moments.

The measured elasticity of distortions and the standard deviation of measured wedges are given by:

$$elas(Wedge, TFP) = \frac{\rho(1-\gamma)^2\sigma_s^2 + \sigma_{\iota^{out}}^2 + \gamma\sigma_{\iota^{in}}^2}{(1-\gamma)^2\sigma_s^2 + \sigma_{\iota^{out}}^2 + \gamma^2\sigma_{\iota^{in}}^2},$$

$$\sigma_{\log Wedge}^2 = (1-\rho)\sigma_s^2 + (\sigma_{\iota^{out}}^2 + \sigma_{\iota^{in}}^2) + \sigma_\varepsilon^2.$$

The above expression shows that the measured elasticity of distortions depends directly on the elasticity parameter ρ but measurement error terms can bias the estimate towards one. Similarly, the standard deviation of the wedge depends on variation of the fundamental farm productivity s and the wedges σ_ε but also on the measurement error terms.

The variance of measured TFP and land are given by:

$$\sigma^2_{\log TFP} = (1-\gamma)^2\sigma^2_s + \sigma^2_{\iota^{out}} + \gamma^2\sigma^2_{\iota^{in}} = (1-\gamma)^2[\sigma^2_a + \sigma^2_z + \sigma^2_\kappa + \sigma^2_v] + \sigma^2_{\iota^{out}} + \gamma^2\sigma^2_{\iota^{in}},$$
$$\sigma^2_{\log \ell} = (1-\rho)^2\left[\sigma^2_a + \sigma^2_z + \sigma^2_\kappa + \sigma^2_v\right] + \sigma^2_\varepsilon + \sigma^2_{\iota^{in}}.$$

The above expressions show that the variance of both TFP and land depends on the underlying drivers of productivity: the farm's fundamental productivity a, the crop-specific productivity κ, and the random component v. Additionally, both the TFP and labor variance depend on the measurement error term for inputs ι^{in}.

We use the change in log TFP to illustrate the identification of the model, rather than the growth rate calculated in the baseline model since it provides simpler expressions. The next three moments are equal to:

$$\mathbb{E}[\Delta \log TFP] = \int_z \sum_{i,h} x^i_{z,h}((1-\gamma)\log\lambda)\mu^i_{z,h}\Omega^i_z d\Phi_z(z)$$

$$\sigma^2_{\Delta \log \text{TFP}} =$$
$$(1-\gamma)^2\left(\int_z \sum_{i,h}\left((x^i_{z,h})^2 - \left(\int_z \sum_{i,h} x^i_{z,h}\right)^2\right)(\log\lambda)^2\mu^i_{z,h}\Omega^i_z + 2\sigma^2_v\right) + 2(\sigma^2_{\iota^{out}} + \gamma^2\sigma^2_{\iota^{in}})$$

$$elas(1+g, TFP) =$$
$$\frac{(1-\gamma)^2[(Cov(x,\log z) + Cov(x,\log a) + Cov(x,\log\kappa))\log\lambda - \sigma^2_v] - \sigma^2_{\iota^{out}} - \gamma^2\sigma^2_{\iota^{in}}}{\sigma^2_{\log TFP}},$$

where $1+g = TFP'/TFP$. Average TFP growth depends on the step size λ and the relative incentives to improve productivity through $x^i_{z,h}$, which itself depends on a collection of parameters. Dispersion in TFP growth depends on farm-level investment choices but also on variation in the random component of productivity v and the measurement error terms. Finally, the elasticity between growth and TFP depends on the covariance between farm investment x and endogenous farm productivity z. This term is more negative if more productive farmers invest less.

We include the correlation between the change in farm-level TFP and the change in farm land to discipline the measurement error terms. The moment is given by:

$$Corr(\Delta \log \text{TFP}, \Delta \log \ell) = \frac{(1-\rho)(1-\gamma)(\sigma^2_{\Delta \log z} + 2\sigma^2_v) - 2\gamma\sigma^2_{\iota^{in}}}{\sigma_{\Delta \log TFP}\sqrt{(\sigma^2_{\Delta \log z} + 2\sigma^2_v + 2\sigma^2_{\iota^{out}} + 2\sigma^2_{\iota^{in}})}},$$

where $\sigma^2_{\Delta \log z} = \int_z \sum_{i,h} \left[(x^i_{z,h})^2 - \left(\int_z \sum_{i,h} x^i_{z,h} \right)^2 \right] (\log \lambda)^2 \mu^i_{z,h} \Omega^i_z d\Phi_z(z)$. The above expression shows that measurement error for inputs enters the expression differently than the random component of productivity and the output measurement error term.

The relative TFP of perennials and other crops are given by:

$$\text{Rel TFP peren} = [\log \bar{z}^P - \log \bar{z}^R] + \log \kappa^P,$$
$$\text{Rel TFP other} = [\log \bar{z}^O - \log \bar{z}^R] + \log \kappa^O.$$

These expressions are directly linked with the crop-specific productivities κ^i and also through the investment decisions made by different farm types, through the average values of $\bar{z}^i$.

While the expression for land share is difficult to write in the full model, the intuition can be understood through a simpler model in which there is no misallocation, crop differences, or dispersion in the permanent or random components of farm productivity or measurement error. In this context, all farms choose a common investment rate x, then the distribution of farms across h is approximately $\delta/(x+\delta)[x(1-\delta)/(x+\delta)]^h$. Farms with production technology h have land size λ^h. The land share held by farms with productivity above some node $\bar{h}$ is then given by:

$$\text{Land Share}(\bar{h}) \approx C \sum_{n \geq \bar{n}} \frac{\delta}{x+\delta} \left(\frac{\lambda x(1-\delta)}{x+\delta} \right)^h,$$

for constant $C = (\delta - (\lambda - 1)x)/\delta$. It is straightforward to see from the above expression that the land share by the top farms becomes larger as either farms become more likely to improve productivity (i.e., higher x) or improve productivity by more (i.e., higher λ).

Sensitivity of model moments. Table C.7 summarizes the changes in moments to a 10% change in the model parameters, highlighting that the moments are highly interconnected with the set of parameters. The table also shows that no individual moment identifies an individual parameter. Nevertheless, the table shows that the chosen moments for calibration are informative about the values of parameters in the calibration. The relationship between the moments and parameters is discussed in detail in Section 5.

Table C.7: Sensitivity of Moments to Calibrated Parameters (%)

	ψ	ζ	λ	κ^P	κ^O	σ_z	σ_v	σ_ε	ρ	$\sigma_{\iota^{out}}$	$\sigma_{\iota^{in}}$
Land share	-0.2	0.3	0.1	0.3	-0.1	1.3	0.7	4.7	-10.4	0.0	1.2
Reg coeff	-0.0	-1.9	-0.7	-0.5	0.5	-9.1	6.1	0.0	8.9	1.2	2.1
Avg growth	-2.6	3.7	4.8	-0.1	0.0	-0.8	-1.5	0.7	-13.8	-0.3	-0.5
Corr($\Delta \log \text{TFP}, \Delta \log \ell$)	0.4	0.2	0.9	0.1	-0.0	0.3	54.0	-5.3	-117.9	-0.8	-49.8
Meas elas	0.0	-0.2	-0.1	-0.0	0.0	-0.7	-0.3	-0.1	8.6	0.2	1.3
Std log TFP	-0.2	1.1	0.7	0.2	-0.2	4.6	2.4	0.0	-4.7	0.5	0.9
Std log land	-0.1	0.4	0.2	0.3	-0.0	1.5	0.8	5.6	-10.4	0.0	1.3
Std log wedge	-0.2	0.8	0.5	0.0	-0.1	3.5	1.8	0.8	2.5	0.6	2.3
TFP - peren	0.3	-0.3	0.2	3.2	0.1	-0.3	-0.0	0.0	-0.8	-0.0	-0.0
TFP - other	0.3	0.1	0.2	0.2	3.5	0.2	0.2	0.1	2.3	0.0	-0.1
Std growth	-0.0	-0.0	0.1	0.0	-0.0	-0.0	4.9	-0.0	-0.1	1.1	1.8

Notes: Percent change in the moments from a 10% change in each parameter relative to the benchmark calibration value. For λ the change is calculated only on the value above one.

Sensitivity to calibration targets. As highlighted in Table C.7, the model parameters are jointly chosen to match the calibration moments. There are no parameters that are identified by individual moments. That said, some moments are more useful for identifying specific parameters. To explore this further, we show the sensitivity of the calibrated parameters to changes in the targeted moments, as suggested by Fujimoto et al. (2023) and Andrews et al. (2017). Table C.8 reports the sensitivity of the model parameters.

The table results highlight the relationship between the calibration moments and parameter values. Increasing the land share of the top 10% of farms increases the size of productivity

Table C.8: Sensitivity of Parameters to Moments (%)

	ψ	ζ	λ	κ^P	κ^O	σ_z	σ_v	σ_ε	ρ	$\sigma_{\iota^{out}}$	$\sigma_{\iota^{in}}$
Land share $\times 1.25$	59.6	-0.8	9.2	-2.6	-1.1	-4.0	1.5	17.2	-0.5	-14.1	2.5
Reg coeff $+10$	216.1	-10.3	55.9	-10.1	-4.2	17.6	-9.5	6.0	3.0	-17.4	-15.7
Avg growth -2%	140.0	-12.5	0.1	-4.7	-0.1	4.0	1.3	-0.5	-0.5	0.5	2.1
Avg growth -4%	216.1	-12.5	-14.4	-1.3	-1.3	10.7	-1.7	1.5	-0.5	27.5	-2.8
Corr($\Delta \log \text{TFP}, \Delta \log \ell$) $\times 1.5$	0.1	0.6	1.2	0.4	-1.9	0.3	-5.0	10.1	1.9	48.9	-25.9
Meas elas -0.1	-22.6	-21.3	-4.6	-13.6	12.7	-9.0	-34.6	-55.0	-19.3	116.1	-14.6
Std log land $\times 1.25$	-55.3	-34.6	-5.4	4.2	-3.6	1.8	7.8	21.3	0.8	-96.8	2.5
Std log tfp $\times 1.25$	-7.9	-7.4	2.3	0.8	-0.3	9.4	0.4	-8.3	-1.1	41.9	4.2

Notes: Percent change in the calibrated parameter from alternative calibration in which the indicated data moment is adjusted and all other moments are held at their benchmark values.

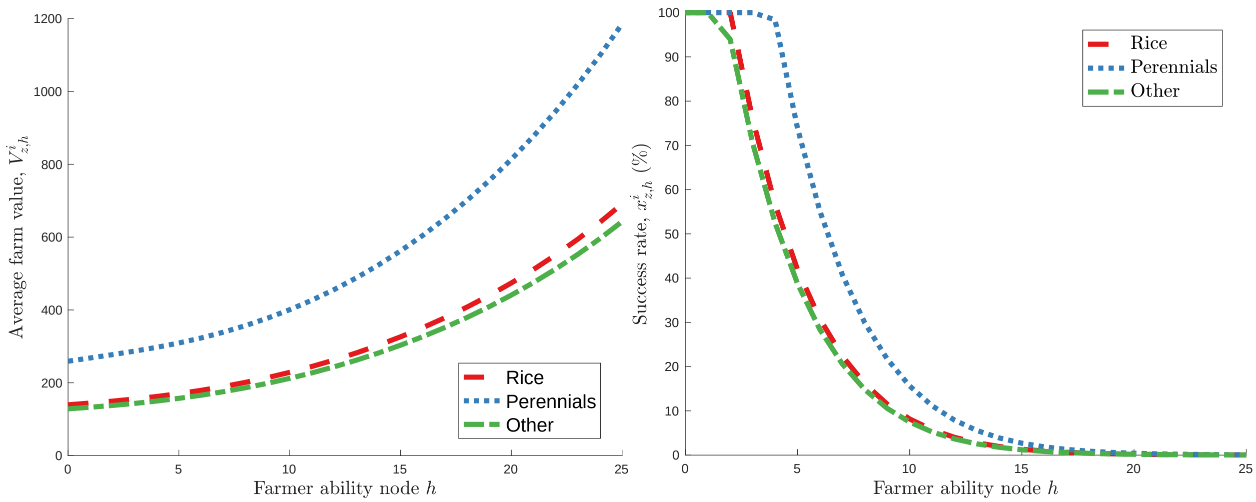
improvements λ and the cost of investment ψ such that productivity improvements become relatively more infrequent but result in a large shift of resources. Lowering the negative relationship between growth and farm TFP or lowering the growth rate results in shifts in the investment technology parameters (ψ, λ, ζ). The correlation between within-farm changes in TFP and land is mostly absorbed by changes in the measurement error terms. Lowering the measured elasticity of distortions results in a similar, albeit larger, shift in the elasticity parameter ρ as well as compensating shifts in other parameters.

C.3 Value and Policy Function

Figure C.2 plots the value and policy functions for farmers in each of the three crop types. The value functions are averaged across idiosyncratic shocks (v, ε) and plotted for a common permanent productivity $z = 1$.

The value functions of the three crops reflect differences in relative profitability stemming from differences in productivity κ^i and distortions φ^i. Despite differences in κ^i and φ^i, the value of rice and other crop farmers are similar because the two parameters have offsetting effects on profitability. The success rate x, and the corresponding investment in ability, are driven by the incremental increase in farm value that farmers receive from successfully improving ability. More productive and less distorted farmers invest more in improving ability because of the complementarity in profits between ability, other sources of productivity (i.e.,

Figure C.2: Value and Policy Function by Crop Specialization



(a) Value functions

(b) Policy functions

the permanent farmer component z or the crop-specific component κ^i), and lower distortions. However, differences in the policy functions across crops decrease at higher abilities because distortions become a limiting factor that discourage further investment.

A key feature of the policy function is that the success rate of improving ability declines as farmers become more productive. The correlation of distortions with productivity implies that the incremental increase in profitability is lower than that of investment costs as farmers improve ability. Models of firm dynamics (e.g., Klette and Kortum, 2004) typically assume that profits and investment costs grow at the same rate in order for Gibrat's law to hold in equilibrium. In contrast, we find that more productive farms tend to grow more slowly as evident by the negative relationship between TFP growth and farm productivity in Table 5.

C.4 Calibration to the North

The baseline experiment applies distortions that are set to match north Vietnam to the benchmark economy, which is calibrated to match south Vietnam. We show that the counterfactual economy moves towards the north Vietnam data moments, relative to the benchmark economy. An alternative approach is to re-calibrate the model to match the full set of moments from north Vietnam and then use this to compare with south Vietnam. We explore this approach in this section.

Calibration moments and parameters. The calibration follows the same procedure as in the baseline calibration. We adjust the total stock of land to be $L = 1.10$ to reflect the smaller average farm size in the North. The jointly calibrated parameters are selected to target the same moments as in the baseline calibration, where the values for the North are reported in Table C.9. The one difference is that we set the preference curvature θ to the value calibrated in South Vietnam and use the crop-specific preferences η^i to match the farm crop share.

Table C.9: Moments Calibrated to North Vietnam

	Model	Data
Avg growth (%)	2.62	2.62
Std growth	80.1	89.2
Std log TFP	0.85	0.84
Std log land	1.01	0.98
Reg coefficient: growth on log TFP	−49.9	−48.2
Top 10% land share (%)	36.3	38.3
Measured elasticity	0.959	0.964
Std log Wedge	0.87	0.81
Corr($\Delta \log \text{TFP}, \Delta \log \ell$)	−0.025	−0.022
Relative measured TFP	(1.00 , 0.69 , 0.80)	(1.00 , 0.69 , 0.80)
Farm share by crop (%)	(75.1 , 5.0 , 19.9)	(75.1 , 5.0 , 19.9)

Notes: Where applicable, moments are first reported for rice farms, followed by those for perennials and then other crop farms.

The parameters in the re-calibrated model are summarized in Table C.10. Overall, the parameter values in the re-calibrated model are relatively similar to those in the baseline calibration. This reflects the overall ability of the benchmark economy to match the North data moments when the North distortions were imposed. The main difference between the North and South parameters is in the ability investment function, (λ, ψ, ζ). Relative to the South, investment in the North is substantially cheaper but also has a smaller payoff.

The lower return to investment through λ explains the lower farm dynamism in the North compared with the South.

Table C.10: Parameters Calibrated to North Vietnam

Parameter		North	South
Discount rate	β	0.96	0.96
Survival rate	ξ	0.955	0.955
Land	L	1.10	2.77
Span-of-control	γ	0.7	0.7
Land share	α	0.5	0.5
Crop-specific distortion	φ^i	(1.00 , 0.68 , 0.92)	(1.00 , 1.61 , 1.12)
Crop restriction	ω	0.43	0.23
Investment level	ψ	1.20	1.51
Investment curvature	ζ	2.32	1.74
Ability step size	λ	1.25	1.43
Crop preference elasticity	θ	1.4	1.4
Preference shifter	η^i	(1.00 , 0.44 , 0.85)	(1.00 , 0.64 , 0.83)
Crop-specific productivity	κ^i	(1.00 , 0.41 , 0.49)	(1.00 , 1.37 , 0.41)
Permanent productivity	σ_z	1.22	1.48
Random productivity	σ_v	1.68	1.79
Elasticity	ρ	0.879	0.789
Random distortion	σ_ε	1.00	0.98
Output mismeasurement	$\sigma_{\iota^{out}}$	0.44	0.25
Input mismeasurement	$\sigma_{\iota^{in}}$	0.45	0.47

Notes: Where applicable, parameters are first reported for rice farms, followed by those for perennials and then other crop farms.

Aggregate productivity. The re-calibrated model generates a productivity gap between north and south Vietnam that matches closely the data. Following equation (4) for aggregate output, aggregate total factor productivity in the calibrated economy is calculated as:

$$\frac{A^{North}}{A^{South}} = \frac{Y^{North}/(L^{North})^{\alpha\gamma}}{Y^{South}/(L^{South})^{\alpha\gamma}} = 40.7\%,$$

whereas this ratio is 42% in the data. This implies that the re-calibrated model is able to account for the entirety of productivity differences between north and south Vietnam.

C.5 Undistorted Economy

The undistorted economy represents a hypothetical first-best economy that could be achieved if all institutional distortions were removed. In practice, it is unclear whether this economy is achievable since some baseline distortions may be unavoidable. With that caveat in mind, we find the undistorted economy useful as a benchmark to understand the full potential gains in productivity.

We calculate the undistorted economy by setting the parameters as in the baseline calibration and setting the government-imposed crop restrictions to $\omega = 0$, the elasticity of distortions to $\rho = 0$, the crop-specific distortions to $\varphi^i = 1$ for all crops i, and the random component of distortions $\sigma_\varepsilon = 0$. Table C.11 presents the comparison with the benchmark economy.

Table C.11: Comparison with Undistorted Economy

	Benchmark	Undistorted Economy
Productivity	1.00	3.37
Avg growth (%)	6.23	0.44
Std growth (%)	75.2	74.8
Std log TFP	0.98	0.87
Std log land	2.66	2.66
Reg coefficient: growth on log TFP	−34.4	−40.6
Top 10% land share (%)	42.1	83.6
Measured elasticity	0.855	0.228
Std log Wedge	0.89	0.47
$\text{Corr}(\Delta \log \text{TFP}, \Delta \log \ell)$	0.084	0.650
Relative measured TFP	(1.00 , 1.20 , 0.75)	(1.00 , 1.20 , 0.72)
Farm share by crop (%)	(49.1 , 33.1 , 17.8)	(48.1 , 41.8 , 10.2)

Notes: Where applicable, moments are first reported for rice farms, followed by those for perennials and then other crop farms.

The undistorted economy is over three times as productive as the benchmark economy. Table 7 shows that the gains from removing static misallocation in the benchmark economy is around 70% implying that the remaining gains are coming from improving the productivity distribution through higher investment in ability and selecting into more productive crops. Nevertheless, differences in the productivity distribution alone do not account for the remainder of the gains because of complimentarities between the channels.

Another noticeable difference between the benchmark and undistorted economy is in the average growth rate. This can be understood through two channels. First, removing correlated distortions causes investment in ability to become flat with respect to the farmer's ability because farmers are not disincentivized by larger distortions at higher abilities. All else equal, this causes higher ability farmers to invest more than in the benchmark economy. Second, removing distortions improves productivity and, consequently, the wage rate w and cost of land q, which results in lower profits for a given ability level. Lower profits disincentivize investment in ability for all farmers. The net impact is that lower ability farmers invest less in the undistorted economy while higher ability farmers invest more. This results in both more low ability farmers and more very high ability farmers in the undistorted economy. The productivity gains are then driven by these increases in the top end of the productivity distribution, which is consistent with the concentration of agricultural production in large, highly productive farms in advanced economies.

Finally, despite setting the elasticity of distortions to $\rho = 0$, the measured elasticity remains positive and larger than zero. This is also the case for the standard deviation of wedges, which only falls to around half its initial value. These results are due to the inclusion of the input and output measurement errors, which are held at their benchmark values in the undistorted economy. Measurement error tends to have a larger bias in the undistorted economy, which is also found by Ayerst et al. (2024). We emphasize that while our main results on the difference between the South and North are not substantially affected by the extent of measurement error in the data, the role of measurement error is more substantial in the level effects relative to an undistorted economy. In particular, we find that the aggregate productivity effect of removing distortions in a calibrated economy that abstracts from measurement error is more than twice as large than in our calibrated model allowing for measurement error. This suggests an important role for measurement error in models with dynamic decisions that amplify the broader productivity effects from static misallocation.

C.6 Asymmetric Effects of Elasticity of Distortions

The baseline experiment shows that increasing the elasticity of distortions ρ from 0.86 in the South to 0.96 in the North can explain a large share of the productivity gap between the two regions, despite the increase being relatively small. Mechanically, the large productivity cost from increasing ρ is driven by the disincentivizing effect of correlated distortions on investment (Farm Ability). As ρ increases farms invest less because the incremental increase in profits becomes smaller. At the extreme, when $\rho \to 1$ farms have no incentive to invest because the entirety of additional profits is absorbed by higher distortions. This leads to an increasing impact of ρ on productivity that is maximized as ρ gets closer to one.

Table C.12: Increasing and Decrease Elasticity of Distortions

	Increase $\rho = \rho + \Delta\rho$	Decrease $\rho = \rho - \Delta\rho$
Factor Misallocation	-0.16	0.13
Crop Choice	-0.02	0.02
Farm Ability	-0.27	0.21
Total	-0.42	0.39

Notes: Values report the log change in output. The elasticity of distortions is set to the South benchmark value, and the change in ρ is set equal to $\Delta\rho = 0.1$, which is the observed difference in the measured elasticity of the North and South in the data. All other parameters are set to the benchmark calibration values.

Table C.12 shows the asymmetric impact of increasing and decreasing ρ on productivity through each channel. The values are reported as log changes in productivity (rather than percent changes) for comparability. The difference in the effects is mainly driven by the farm ability channel due to the disincentivizing effect of ρ on ability investment.

C.7 Model Extensions

We consider two model extensions to capture the full farm life-cycle dynamics of productivity and the potential intergenerational transmission of ability.

C.7.1 Farm Life Cycle Dynamics

In Section 3, we show that farm productivity is hump shaped over the life cycle with the productivity of young farms increasing quickly and then deteriorating as the farm reaches older ages. Our baseline model focuses on the initial buildup of farm productivity through investments in farm ability but does not account for the decline in productivity of older farmers. We show that the main model results are relatively unchanged if we extend the model to incorporate this feature.

Model. We extend the model to allow for life cycle dynamics following a similar structure of aging as in Acemoglu et al. (2018). Farmers initially enter as young age ($j = Y$) farmers and then with probability ϕ transition to old age ($i = O$) farmers. Old age acts as an absorbing state that all farmers eventually reach (if they do not exit), albeit at different points of time. Young farmers operate as described in the main text while old farmers have ability $a_{f,t} = 1$, regardless of their previous ability h or investment. Farm ability is now given by

$$a^j_{f,t} = 1_{j=Y}\lambda^h + 1_{j=O}. \tag{C.2}$$

The age structure allows us to capture the dynamics observed in the data in a reduced form. Intuitively, the transition to old age could capture the deterioration of physical abilities of older farmers.

The model is otherwise as described in the main text. The equilibrium characterization is similar with the exceptions that the value function now accounts for the possibility of transitioning to old age and the type distribution now accounts for farms in old age.

Quantitative analysis. We consider an alternative calibration of the model to focus more on the farm productivity life cycle. The preference shifters η^i, preference curvature θ and all other parameters follow the baseline calibration procedure. We re-calibrate the jointly chosen parameters $\{\lambda, \psi, \zeta, \kappa^i, \sigma_z, \sigma_v\}$ as well as the transition probability ϕ to target a new set of moments. In addition to the baseline moments, we add two moments: (i) the average productivity of 36-40 year old farmers is 0.45 log points higher than the average productivity of 25 and younger farmers and (ii) the average productivity of 65 and older farmers is equal to average productivity of 25 and younger farmers (both from Figure **??**). We also remove the moments on the average TFP growth of farms. Table C.13 reports the parameter estimates.

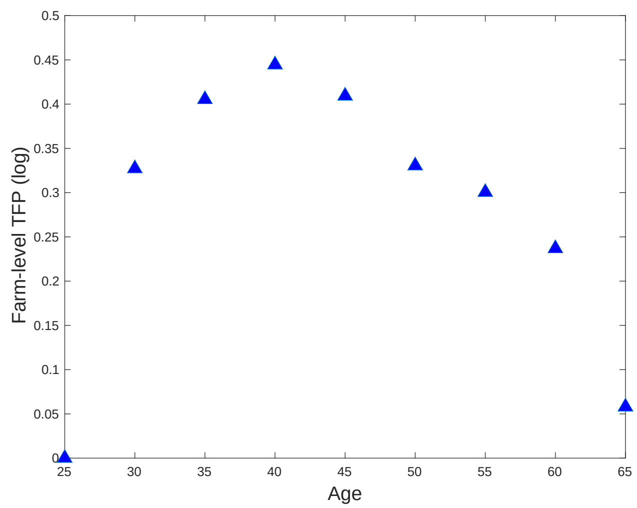
Table C.13: Parameters with Farm Life Cycle Targets

Parameter		Value
Transition to Old	ϕ	0.03
Investment Level	ψ	0.6
Investment Curvature	ζ	1.85
Ability Step Size	λ	1.45
Crop Preference Elasticity	θ	1.21
Preference Shifter	η^i	(1.00 , 0.63 , 0.83)
Crop-Specific Productivity	κ^i	(1.00 , 1.54 , 0.38)
Permanent Productivity	σ_z	1.41
Random Productivity	σ_v	1.71
Elasticity	ρ	0.91
Random distortion	σ_ε	0.94
Output mismeasurement	$\sigma_{\iota^{out}}$	0.30
Input mismeasurement	$\sigma_{\iota^{in}}$	0.49

Notes: Where applicable, parameters are first reported for rice farms, followed by those for perennials and then other crop farms.

The estimated transition to old age is around 3% indicating that farms spend an average of 33 years at young age. The main difference relative to the baseline parameters is that the estimated ability step size increases from 1.51 in the baseline to 1.68 in the extended model, which is necessary to offset some of the negative growth from aging. Figure C.3 reports the relationship between farm TFP and age. The figure highlights the same hump-shaped dynamics as in the data.

Figure C.3: Farm Productivity Life Cycle



Notes: Age bins are $\{\leq 25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, > 60\}$ and plotted according to the oldest age in the group and 65 for the oldest group. The average of farm-level log TFP is calculated using simulated data (as described in Section 5) for 100,000 farms.

The shape of farm dynamics is by construction since key features of the life-cycle productivity profile are targeted in the calibration. The purpose of the recalibration is to assess its impact on the main results. The main experiment adjusts distortions in the benchmark economy, calibrated to south Vietnam, to match distortions in north Vietnam. Table C.14 compares moments in the extended model benchmark economy, calibrated to the South, with the counterfactual economy, which adjusts distortions to match the values in the North.

The table highlights that the results in the extended model are in line with the baseline model. Aggregate productivity drops by 43%, similar to the baseline experiment (41%). We also find similar dynamics when comparing the other moments with the baseline experiment. The counterfactual economy is almost able to replicate entirely the farm crop distribution, in addition to accounting for around half of the change in the standard deviation of TFP, the regression's coefficient of growth on TFP, and the top 10% land share.

The table also shows the average growth rate in the benchmark calibration economy and

Table C.14: Comparing Counterfactual Moments with Life Cycle Targets

	Benchmark	Counterfactual	Data
Productivity	1.00	0.57	0.42
Avg growth (%)	3.56	2.43	2.62
Std growth (%)	76.7	76.2	89.2
Std log TFP	0.97	0.89	0.84
Std log land	1.18	0.97	0.98
Reg coefficient: growth on log TFP	−34.3	−40.6	−48.2
Top 10% land share (%)	42.9	35.2	38.3
Measured elasticity	0.850	0.973	0.964
Std log wedge	0.88	0.92	0.81
Corr($\Delta \log \text{TFP}, \Delta \log \ell$)	0.084	−0.088	−0.022
Relative measured TFP	(1.00 , 1.19 , 0.75)	(1.00 , 1.03 , 0.74)	(1.00 , 0.69 , 0.80)
Farm share by crop (%)	(49.1 , 33.1 , 17.8)	(71.5 , 10.5 , 18.0)	(75.1 , 5.0 , 19.9)

Notes: Where applicable, moments are first reported for rice farms, followed by those for perennials and then other crop farms.

the counterfactual economy. Unlike the main text, this is no longer a moment that is directly targeted in the calibration. As discussed in Section 6.5, the growth rate of productivity is potentially related to factors unrelated to ability investment in the model. Table C.14 provides an extreme view on the magnitude of these other factors since it attributes none of the non-life cycle growth to farmer investment. The growth rate lies within the bounds considered in the robustness exercise in Section 6.5. Overall, the evidence in Table C.14 is reassuring about the robustness of the main results.

C.7.2 Entrant Ability

In the baseline model, entrants start at the lowest ability node and then progress to higher nodes through investment. In practice, we might expect that some ability is passed on through generational learning, such that some entrants are more productive than others. We show a simple extension of the model that incorporates this feature and find that the quantitative results remain relatively unchanged.

Model. Rather than entering with ability $a = \lambda^0$, we allow entrants to draw ability $a = \lambda^h$ where $h \in \{0, 1, ..., \tilde{h}\}$ is drawn from distribution $m(h, \tilde{h})$ and $\tilde{h}$ is the ability node of the exiting farmer the entrant replaces. We include $\tilde{h}$ as the upper bound to capture the intuition that entrants are learning from the previous generation of (exiting) farmers and note that the distribution would be the same if we instead had entrants learn from active farms, since exit is random. Since our goal is to show the robustness of the baseline results, we set the distribution of entrant productivity to be uniform between 0 and $\tilde{h}$, where we expect that this would tend to overstate the persistence in ability over time.

The model is otherwise as described in the main text. The equilibrium characterization is similar with the exception that the type distribution now accounts for entry into higher nodes. Additionally, we assume that entrants draw their predecessors' permanent productivity z and preferences η^i and that entrants can only deviate from the crop choice of their predecessor by accepting ability $h = 0$, for tractability. However, quantitatively, this assumption has little impact on the results.

Quantitative analysis. Given that the model parameters are the same as in the main text, the calibration procedure is unchanged. The main difference with the baseline parameters is that the step size of ability improvements λ increases. This is necessary to match the same average growth rate since entrants now start at higher nodes where investment, and growth, would otherwise be lower (see Figure C.2).

The main experiment adjusts distortions in the benchmark economy, calibrated to south Vietnam, to match distortions in north Vietnam. Table C.15 compares moments in the extended model benchmark economy, calibrated to the South, with the counterfactual economy, adjusting distortions to match values in the North.

The results show that allowing for entrants with higher ability results in a larger productivity loss (57%) than the benchmark calibration because the transfer of ability to entrants creates a positive spillover in which investment further shifts the productivity distribution

Table C.15: Comparing Counterfactual Moments with Entrant Ability

	Benchmark	Counterfactual	Data
Productivity	1.00	0.43	0.42
Avg growth (%)	6.20	4.08	2.62
Std growth (%)	74.5	74.2	89.2
Std log TFP	0.97	0.86	0.84
Std log land	1.18	0.98	0.98
Reg coefficient: growth on log TFP	−34.8	−42.9	−48.2
Top 10% land share (%)	42.2	35.2	38.3
Measured elasticity	0.855	1.013	0.964
Std log wedge	0.89	0.92	0.81
Corr($\Delta \log \text{TFP}, \Delta \log \ell$)	0.088	−0.137	−0.022
Relative measured TFP	(1.00 , 1.20 , 0.75)	(1.00 , 0.96 , 0.75)	(1.00 , 0.69 , 0.80)
Farm share by crop (%)	(49.1 , 33.1 , 17.8)	(72.2 , 9.1 , 18.7)	(75.1 , 5.0 , 19.9)

Notes: Where applicable, moments are first reported for rice farms, followed by those for perennials and then other crop farms.

through improving entrants' productivity. Otherwise, the results are consistent with the baseline results and show the same conclusions.