

Essays on the future of agricultural productivity and meat demand: Evidence in China and the
United States

by

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AN ABSTRACT OF A DISSERTATION

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Department of Agricultural Economics
College of Agriculture

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Abstract

Since the introduction of hybrid maize in the 1930s, U.S. corn yields have increased at the rate of 1.8 bu/acre/year. Concomitantly, corn plant populations (plants/acre) more than doubled. Thus, the increase in yields has primarily taken the form of more plants/acre, rather than more yield/plant. But this raises some important questions: What is the upper limit for plant populations, have we already reached it, and what does this imply for future corn productivity? This study investigates these questions using county-level panel data on US corn yields, plant populations, and weather variables from 1960-2023. While plant population changes have been arguably the most crucial mechanism for yield growth, this study shows we may be approaching an upper limit. U.S mean plant populations have not increased, on average, since 2015, and yield projections based on a slowdown in plant population growth suggest a major potential slowdown in yield growth.

This second article examines meat consumption behavior and its dynamics across four meat categories (pork, beef, poultry and lamb) in urban and rural China. We adopt an extended dynamic demand system that incorporates both habit formation and pre-committed effects and estimates the model using provincial level data from 30 provinces during the period 2015 to 2022. Results from the dynamic demand system show that while all four meat categories are habitual, beef is the most habitual meat in the urban and rural consumption groups, however, rural consumers display a higher degree of habit formation in their diets. Additionally, we provide evidence that factors beyond price and expenditure play a significant role in shaping both urban and rural consumer demand responses for pork and poultry. Using long-term elasticities, we

predict changes in budget shares for meat consumption over the next decade, indicating that beef and poultry are likely to take a larger portion of future meat expenditure.

This third paper uses agricultural data from 31 Chinese provinces during the 2000–2022 period to examine whether China’s Five-Year Plans (FYPs) induced or inhibited differential productivity across provinces. Productivity performance and heterogeneity are first assessed using a Malmquist productivity index. Convergence tests confirmed “catch-up” effects, where regions with lower productivity growth gradually move towards a unified steady state equilibrium state, but no clear convergence was observed nationally or regionally, except in the western provinces. Econometric analysis shows that the twelfth FYP reduced differential provincial total factor productivity (TFP), while this effect was not significantly significant in the thirteenth and fourteenth FYPs. Budgetary and financial policies appear to mitigate this divergence, whereas education policies may have induced disparities due to labor outflows and rural aging. This study has significant policy implications for the formulation and evaluation of future FYPs. Specifically, central government strategies should be closely coordinated with provincial initiatives, progress should be monitored at each stage, and plans should be continuously adjusted to ensure effective implementation. Future research could extend this analysis by incorporating survey data on the performance and evaluation of FYPs at each stage.

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Abstract

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Dedication

I would like to dedicate my work to my mom Ruilian Shen, dad Fuhua Tian, and husband Shane Li.

Chapter 1 - Is a Yield Slowdown on the Horizon? Assessing the Relationship between Yield and Plant Population in U.S Corn

1.1 Introduction

The current global population is approximately 8.2 billion and expected to grow due to continued advancements in healthcare and declining mortality rates. As a result, the global demand for food, fuel, and feed production will continue its upward trajectory, placing ever more pressure on our ability to innovate and sustainably produce more with limited resources. Increasing productivity in cereal crop production has been essential up to this point, and maize is arguably the most important cereal crop in the world (Fromme et al.,2019). The steady increase in maize production following the adoption of hybrid varieties in the 1930s has been crucial for reducing land use and keeping food costs down. Yet, in more recent years, yields for the four major global crops (maize, rice, wheat, and soybean), which provide nearly two-thirds of agricultural calories, are increasing at annual non-compounding rates of 1.6%, 1.0%, 0.9%, and 1.3%, respectively, well below the 2.4% rate needed to double global production by 2050 (Ray et al. 2013). Furthermore, with limited potential area for expanding cultivated land, as well as pressures from climate change, agricultural production is increasingly constrained. Therefore, maintaining and enhancing agricultural productivity to meet rising global demands is essential (Hemathilake and Gunathilake, 2022).

Corn grain yields have continuously increased in the U.S. since the 1930s, which can be attributed to improved agronomic practices and the widespread adoption of commercial hybrids (Ciampitti and Vyn, 2012). By 2023, US mean corn yield reached 177.3 bu/acre which is nearly nine-fold the mid-1930s average of 20 bu/acre. Several factors have contributed to this growth. Plant population, defined as the number of harvested corn plants per acre, has been an essential

aspect of this growth (Nik et al, 2011). Most cereal crops can adjust their growth by modifying tillering (the production of side shoots) based on available resources, allowing yields to remain relatively stable across a range of plant densities (Lafarge et al., 2002). Unlike other crops, corn is particularly sensitive to plant density, as modern corn hybrids lack the ability to tiller effectively and usually yield just one ear per plant regardless of density (Temeche et al., 2024). Duvick (2005) concluded that “genetic yield gain as a result of adaptation to continual increases in plant density is the most clear-cut and quantifiable change in corn hybrids over the years.” Previous winners of yield competitions have credited their success to the use of both deep tillage and high plant populations.

Figure 1.1. illustrates US mean observed corn yield and plant density from 1964 to 2023. During this period, corn yield increased from about 60 bushels per acre to 173.5 bushels per acre, while plant population increased from 14,000 to about 29,000 plants per acre. Thus, the majority of yield gains have taken the form of more plants per acre rather than more yield per plant.¹ The historical increase in plant population has been approximately linear, but since 2015 mean plant population seems to have reached a plateau, remaining essentially at the same level, on average, for seven consecutive years. This raises an important question: Does a slowdown in plant population growth imply a slowdown in yield growth? Recent evidence suggests this may be the case. From 2019 to 2023, corn yield was below trend by 3.4% (6.1 bu/acre) (Reuters, October 2023). Boussios (2025) estimated corn yield trends separately from the starting points 1988 and 2013. Through structural break tests, his study provided evidence of a slowdown in U.S corn yield growth based on the 2013 trend: it was statistically lower (1.68 bushels/year) than the 1988 trend

¹ Yield per plant increased by approximately 40% from 0.0043 to 0.006 bu/plant, whereas plants per acre increased by approximately 107%.

(2.15 bushels/year). In addition, this conclusion is supported by consecutive overestimates of corn yield by the USDA's National Agricultural Statistics Service (NASS).

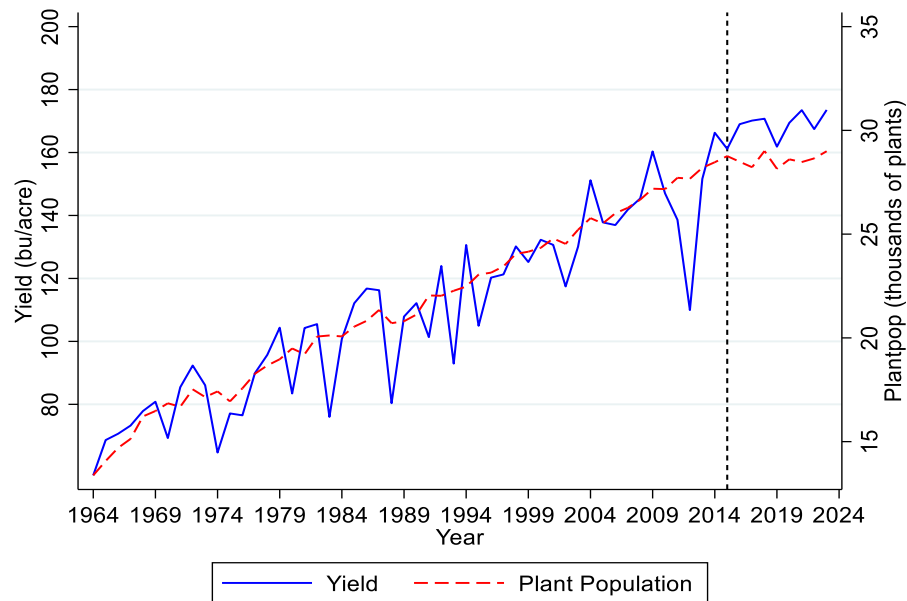


Figure 1.1. U.S maize yield (left, bu/acre) and plant population (right, plants/acre):1964-2023

Research has speculated on the reasons for stagnating plant populations, some of which include rising seed costs and less investment in traditional breeding efforts (Pecinovsky, 2011). Zhao et al. (2025) noted that the slowdown in planting density can be explained by the limited capacity to further free up or add resources, the increasing difficulty of improving modern hybrids, and the ultimate constraints of sunlight and space. These factors may restrict the potential for continued increases in planting density. More generally, there are practical limits to how many plants can be packed into a given amount of surface area, raising an important question: given that plant population has been so critical for rising corn production, what happens if it slows down? Can production continue to increase at the same rate in lieu of reduced growth in plant populations?

This leads to our research question: what is the upper limit for commercial plant populations, have we already reached it, and what does this imply for future corn productivity? While most previous work has focused on modeling corn yield in relation to plant population and identifying optimal plant densities (Farnham et al., 2001; Lashkari et al., 2011; Faria et al., 2019; Friedrich et al., 2022), there is a lack of research examining actual long-term corn production growth trends in response to plant population growth. Specifically, there is limited research on determining the critical point for plant population growth over the decades and the corresponding change in its contribution to production increases.

In this paper, we address this research gap by investigating the upper bound for plant population using a large panel dataset of 46,980 county-by-year mean yield observations spanning 773 counties across 10 states from 1964 to 2023. We first test for a temporal structural break in plant population. Both linear and nonlinear fitting functions indicate that U.S corn plant population plateaued around 2015. This finding suggests potential constraints on future corn productivity growth. To examine the effects of plant population on yield growth, we specify and estimate a yield model with plant population, weather variables, and genetically engineered (GE) adoption as the main predictors. All models indicate a statistically significant and large association between yield and plant population.

We then use this model to predict future productivity growth for the period 2024-2034. We generate predictions under two different scenarios. In one scenario, we project plant population values based on state-specific linear trends going back to 1964; this is the “business-as-usual” scenario. In the second scenario, we project plant population values based on trends starting in 2015, which coincides with the breakpoint we identify. Using these predictions, as well as values for the weather and GE adoption values, we generate predicted yield values under average weather

conditions. In addition, we compare our predictions to 10-year forecasts provided annually by the USDA. Predictions based on the recent slowdown in plant populations imply an annual yield growth trend of approximately 1.1 bu/acre, which is substantially below the historical trend of 1.8 bu/acre. Our predictions are also significantly lower than the USDA prediction of a 2 bu/acre increase per year, such that by 2034 our model predicts a national mean yield of about 189 bu/acre versus the USDA prediction of about 212 bu/acre.

This study contributes to literature in three important ways. First, we identify a breakpoint in corn plant population around 2015, after which plant population starts to level off. This suggests a potential challenge for sustaining the historical yield trend of 1.8 bu/acre. Next, a fixed effects model was developed to quantify the effect of plant population on yield growth using long-term panel data. Third, we apply this model to predict future yield growth and argue that including plant population is essential for long-term yield growth predictions.

The remainder of the paper is organized as follows. In section 2, we review related studies on yield and plant population. In section 3, we present the data and visualize trends in plant population using both linear and nonlinear models. In section 4, we introduce the yield model specification. In section 5, we examine model estimations, followed by section 6, where we predict yield trends for the next decade. Finally, in section 7, we present our concluding remarks.

1.2. Background

1.2.1 Yield and plant population definitions

It is useful to have a clear definition of crop yield and plant population before exploring their relationship. Regarding yield gain, it can be defined as the yield per unit area but also in terms of yield per plant (Wiley and Heath 1969). In the case of corn, growers typically are more concerned with the former definition. As discussed above, corn yield growth is heavily dependent

on plant populations. It is important to clarify that “plant population” differs from the closely related concept “seeding density”. Plant population is the number of plants per acre remaining at the end of the growing season, whereas the seeding density is the number of planted seeds per acre (Perry et al., 2022). These two values are connected by the germination rate, defined as the percentage of planted seeds that become yielding plants. For example, a seeding density of 20,000 seeds per acre and a germination rate of 95% would result in a plant population of 19,000 plants per acre.

1.2.2. Relationship between plant population and yield

The yield-density relationship is usually modeled as asymptotic parabolic (Wiley and Heath, 1969; Villalobos et al., 2024). For example, Holliday (1960) portrayed the relationship between crop yield and density with an approximately parabolic model in which population levels higher or lower than the optimal level result in lower yields. Similarly, Larson (2023) concluded that corn productivity generally increases with higher planting densities, but that yield gains often experience a decrease or plateau as density becomes excessive, reflecting plant competition for limited solar energy and soil resources. Previous research has confirmed this relationship, as experiments conducted in southern Minnesota found a quadratic plateau in the response of grain yield to plant density with yield maximized at $\geq 81,700$ plants per hectare (Van Roekel and Coulter, 2011). Schwalbert et al. (2018) showed corn yield has a strong quadratic relationship with plant density. Stanger and Lauer (2006) supported the quadratic relationship, identifying the yield maximizing plant populations for Bt and non-Bt corn separately. By focusing on the dependence of biomass yield on plant population, Overman et al. (2011) used an exponential model that contains two parameters. They showed no definitive peak in yield with plant population but demonstrated an asymptotic approach to maximum yield with increased plant population. Assefa

et al. (2016) found that a quadratic model of yield–density fit the data better than linear, exponential, and hyperbola models (Assefa et al., 2016).

While it is crucial to clarify the contribution of plant population to yield growth, it is important to note that this is influenced by interactions with weather and climate conditions, GE technologies, planting practices, agronomic practices, and other factors. The impact of environmental conditions makes the link between yield and plant population uncertain. The optimal planting density is not simply a genetic attribute of a hybrid variety; it is also heavily influenced by local environmental conditions and their interactions with genotype. While modern hybrids show high tolerance to abiotic and biotic stresses and allows for higher population densities (Duvick, 1997), its application in driving the yield growth strongly depends on complex interaction between genotypes and environmental factors including climate and soil conditions during the growing season. Favorable weather and climate conditions can lead to a significant increase in yield, which is why only 14% of yield gain was associated with genetic improvements (Duvick, 2005; Rizzo et al., 2022; Schwalbert et al., 2018). Additionally, improved agronomic practices such as fertilization (e.g. nitrogen), effective weed control, and tillage practices are important for plant population adjustments (Haarhoff and Swanepoel, 2018).

In summary, optimizing population is one important tool for corn production increase. Lower density can facilitate the plants with more resources per plant, but overall yield tends to be lower than when the plants are at the optimal number of plants per unit, maximizing light capture and canopy growth (Lacasa et al., 2020). Supporting this, Luo et al. (2023) utilized field experiment data from China and demonstrated maize yield could be increased by 21% on average after adopting the optimal level of planting density and the use of high-yield cultivars. This improvement was primarily attributed to the interaction between optimal planting density and

appropriate hybrids. Meanwhile, the application of advanced agronomic practices, combined with the use of better cultivars and the improvement of soil quality, significantly mitigates the impacts of climate change.

1.3. Data

Our empirical analysis utilizes 46,980 yield observations spanning 773 counties across 10 states from 1964 to 2023. This time frame was selected primarily because of data availability, as plant population data is first available in 1964. County-level yields and harvested acres were obtained from USDA-NASS annual surveys through Quick Stats for the following states: Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin.

In this paper, we focus on corn plant population as the primary variable of interest. Focusing on plant population allows us to isolate its impact on corn yield improvements from other factors that contribute to overall yield growth. Our key variable, plant population, is collected from USDA Quick Stats and provided at the state level.

While our primary goal is to examine the relationship between plant population and yields, it is important to also condition on the impact of weather and climate variables. Following Schlenker and Roberts (2009), we include variables for precipitation and temperature to account for the impact of weather and climate on corn yields, which were collected from the PRISM weather dataset. Daily minimum and maximum temperatures at the county level are used to compute daily degree days using a sinusoidal distribution with three thresholds: between 0°C and 10°C, between 10°C and 29°C, and above 29°C (Lusk et al., 2018; lee et al., 2024). More specifically, growing degree days (GDD) and harmful degree days (HDD) are defined as follows:

$$GDD = \int_{10}^{\infty} \min\{T - 10, 19\} \phi(T) dT, \text{ and}$$

$$HDD = \int_{29}^{\infty} \min\{T - 29\} \phi(T) dT,$$

where $\phi(T)$ refers to the temperature distribution. These daily variables are then aggregated over the assumed growing season of March to August.

Building on the work of Roberts et al. (2012), variables for vapor pressure deficit (VPD) are also included in the model. VPD is calculated by measuring the difference between the maximum water capacity the air could hold at saturation and its actual water amount. Specifically, VPD is defined as:

$$VPD = 0.6107 \times \left(\exp\left(\frac{17.269T_h}{237.3 + T_h}\right) - \exp\left(\frac{17.269T_l}{237.3 + T_l}\right) \right)$$

VPD impacts yield by influencing plant water loss and photosynthesis; yields increase when soil moisture is sufficient, but growth stagnates when moisture is limited. In this paper, we use two VPD variables: average VPD over the entire growing season and VPD during July and August, allowing for a more accurate assessment of the effects of VPD during critical stages of the growing season.

In addition to the foregoing variables, we include a variable that tracks the share of planted corn that is GE. In particular, we construct a variable that measures the share of planted corn that contains GE insect resistance, herbicide tolerance, or both (i.e., we do not distinguish between types of GE traits). GE traits were initially commercialized in corn in 1996, and GE adoption rates have increased steadily since then, with more than 90 percent of U.S corn produced using GE varieties by 2024 (ERS report, 2025). Research has shown that GE crop adoption has contributed to higher yields in the past two decades (Chavas et al., 2014). However, data on GE adoption rates are only available at the state level. Moreover, these data were only first reported by the USDA in

2000, four years after their introduction. To resolve this, the missing data was interpolated from 1995 to 2000 using a generalized linear model. For years prior to 1995, the GE adoption rate was zero. The diffusion rate for the interpolated GE variable is illustrated in figure 1.2.

Missing data in plant population for South Dakota, Kansas, and Missouri were addressed using linear interpolation. For instance, during periods like 1964-1969, missing values for South Dakota were interpolated based on trends observed between 1970 and 1973. Figure 1.3 illustrates the overall trend of the complete plant population data. We match yield data and the fine scale aggregated weather and climate data at the county level data with GE and plant population data at the state level to create a balanced panel data for ten states.

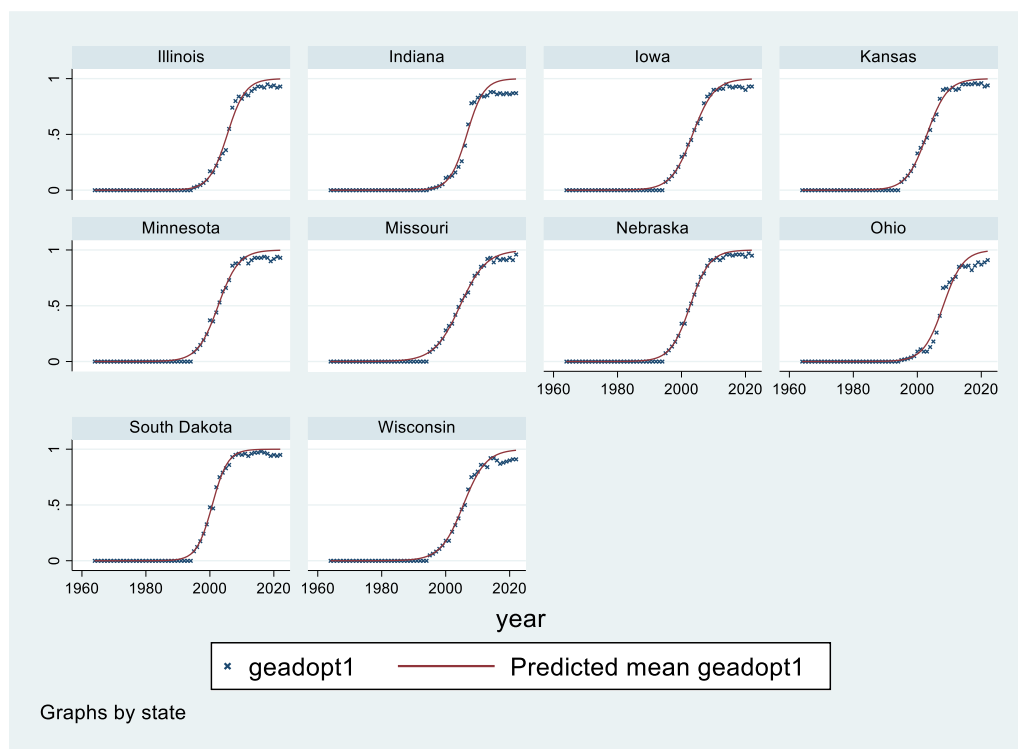


Figure 1.2. GE adoption rate between 1964 and 2023

Note: the missing data from 1995 to 2000 was interpolated using a generalized linear model. For years prior to 1994, the GE adoption rate was assumed to be zero.

Table 1.1 provides summary statistics for mean yields, harvested acres, plant population, GE adoption rates, and the weather and climate variables. The average yield across 10 states was 119.6 bushels per acre, with a minimum of 7 bushels per acre and a maximum of 246.7 bushels per acre. The average plant population per acre at harvest was 22,700 plants, ranging from a minimum of 10,700 to a maximum of 32,450 plants.

Table 1.1. Summary statistics for model variable

VARIABLES	Mean	Std Dev	Min	Max
Yield	119.6	42.37	7	246.7
Acre	71,671	57,774	100	394,700
Plant population	22.70	5.023	10.70	32.45
GE adoption rate	0.306	0.393	0	0.980
Degree-days 0°C	3,040	342.0	1,986	4,236
Degree-days 10°C	1,491	255.1	697.3	2,437
Precipitation(mm)	562.5	147.7	77.02	1,230
Vapor Pressure Deficit	1.691	0.275	0.960	3.097
Vapor Pressure Deficit JA	2.285	0.422	1.320	4.282
Degree-days 0°–10°C	1,549	98.03	1,199	1,806
Degree-days 10°–29°C	1,455	231.6	697.2	2,286
Degree days above 29°C	35.76	32.33	0.00418	259.8

Note: Total number of observations is 46980 spanning 60 years (1964-2023). GE adoption rate is defined as all corn GE variables planted.

1.3.1 Plant population and yield trends

Visualization is a useful tool for identifying plant population breakpoints. Figure 1.3. illustrates plant population trends across the ten states since 1964. In nearly all states, plant population increased until around 2015, after which this upward trend plateaued. These overall trends suggest a strong link between population and yield, though the relation between yield and plant population in Kansas exhibits a more parabolic pattern.

Yield gains also show corresponding changes following the slowdown in plant population growth, as seen in Figure 1.4.

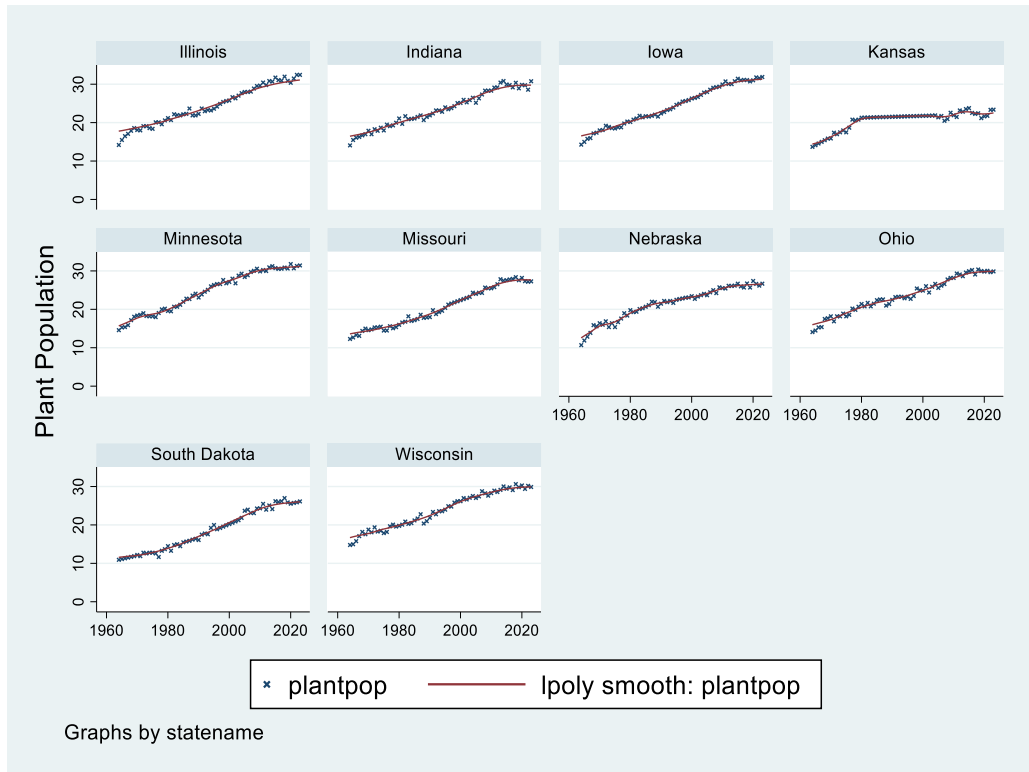


Figure 1.3. Plant population (thousands of plants/acre)

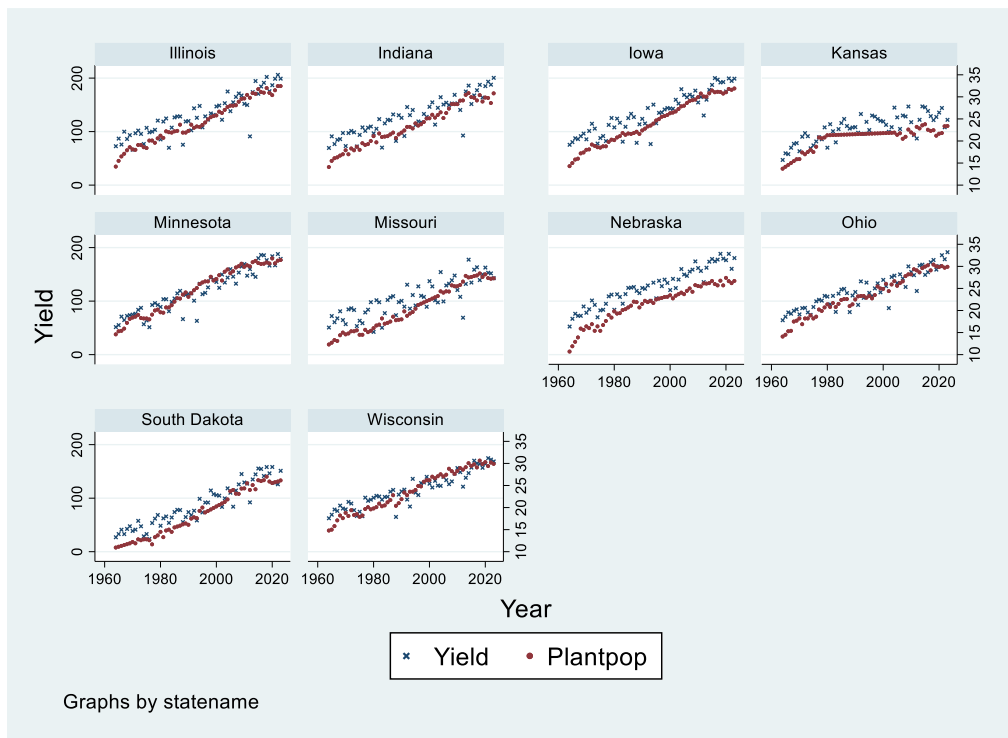


Figure 1.4. Plant population and Yield (left, thousands of plants/acre; right, bu/acre)

1.3.2. Planting population breakpoint

To determine if there is a breakpoint in plant population growth, we fit the plant population data using linear and nonlinear models. One effective method for recognizing a potential structural breakpoint is through a linear model, with plant population as the dependent variable. To begin, we fit plant population data with a linear plateau model, and the plateau value is then determined and defined according to Shafii et al. (1990):

$$y = a + b_1[\min(X, A)], \quad X = A \quad (1)$$

where a is the intercept, b_1 is the slope of the linear line up to point $X = A$

$$y = a + b_1[\min(X, A)] + b_2[-A] \quad (2)$$

Equation (2) tests for the existence of significant slope b_2 beyond point $X = A$. The fitted parameters a , b_1 , b_2 , A represent the best-fit intercept, slope, and critical A value at which the plant population transitions from one increasing trend to another trend. When x is bigger than A , plant population remains relatively constant, while when a is smaller than A , plant population is $y = a + b_1X$. Scatter plots, along with the best linear plateau fit line are presented Figure 1.5, demonstrating the presence of breakpoints around 2015 for most states.

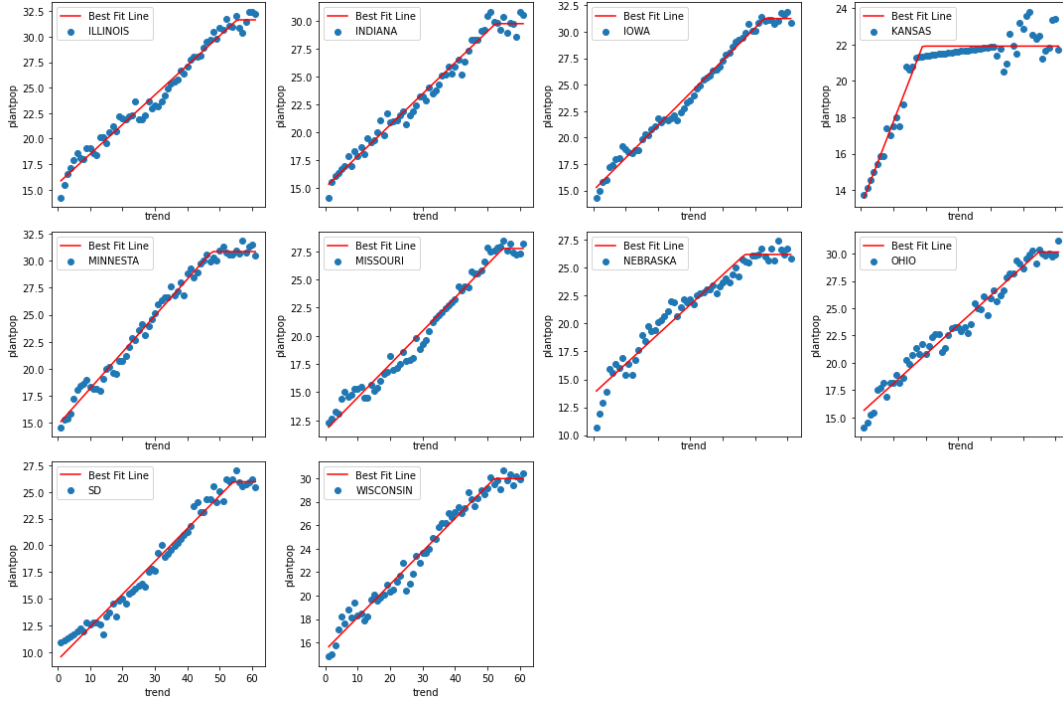


Figure 1.5. Fitted linear plateau model for plant population

Next, we explore other linear and nonlinear functions to fit the plant population data. A linear piecewise function was proposed to describe the trend of corn plant population and distinguish potential breakpoints corresponding to the optimum plant density. This function exhibited four knots in plant density trend. The linear piecewise function with four knots is defined as:

$$y = \begin{cases} ax + b & 0 < x < t^* \\ cx + d & t^* \leq x < t^{**} \\ ex + f & t^{**} < x < t^{***} \\ gx + h & t^{***} \leq x < t^{****} \end{cases} \quad \begin{matrix} (3) \\ (4) \\ (5) \\ (6) \end{matrix}$$

The x values in the model indicate where breakpoints occur. Appendix Fig A1 depicts the four knots used in the linear piecewise functions. In most of the states, the last knot marks a break in the trend around 2013 and 2015, after which the growth rate of plant population slowed down.

Alternatively, we employed several nonlinear functions including a Gompertz curve, negative exponential curve, and quadratic plateau curve to model the plant population. The negative exponential curve is defined as:

$$y = \lambda e^{-\lambda x} \quad x > 0, \quad \lambda > 0 \quad (7)$$

The negative exponential distribution is used as a survival distribution (Roussas, 2014), the parameter λ captures the rate of change in plant population for each unit increase in the trend variable x , representing either a relative increase or decrease in plant population.

The nonlinear quadratic plateau curve is given by:

$$y = \begin{cases} a + bx + cx^2, & x \leq j \\ a + bx + xj^2, & x > j \end{cases} \quad (8)$$

$$(9)$$

where, a is the intercept, b represents the linear slope of the increasing trend for corn plant population, c is the coefficient for the quadratic function curve, and j denotes the breakpoint where the plateau trend begins (Bullock and Bullock, 1994).

The Gompertz curve is expressed as:

$$y = a + (c - a) e^{-e^{b(x-d)}} \quad (10)$$

where d represents the lower asymptote, c is the upper asymptote. The parameter controls the curvature between the lower and upper asymptote. When $b < 0$, corn plant population y increases as the trend variable x increases. Conversely, when $b > 0$, y decreases as x increases, with a breakpoint occurring between these two scenarios (Winsor, 1932).

The nonlinear function stated above has something in common with linear functions in that both exhibit a breakpoint or changing curvature. Corn plant population initially increases with the

trend and then levels off after the breakpoint. However, linear functions tend to show a clearer breakpoint compared to nonlinear functions, which typically exhibit flatter curvature. The linear piecewise and plateau curves outperformed the other nonlinear models, achieving lower RMSE values of 0.71 and 0.7, except for the Gompertz function, respectively (Model fit of plant population is provided in Appendix Table A.1). Nevertheless, visualizing the data with a combined linear and nonlinear curve is insightful, as it offers a comprehensive perspective to better identify the breakpoints in plant population growth. Appendix Figure A2 shows predicted population using these four different curves.

1.4. Model

To examine the relationship between plant population and corn yields, we specify county-level mean yields as a function of plant population, weather and climate variables, and GE adoption:

$$y_{it} = \delta P_{it} + \gamma G_{it} + \mathbf{w}_{it}'\boldsymbol{\beta} + \lambda_i + \theta trend_t + \varepsilon_{it} \quad (11)$$

where y_{it} is corn yield (bushels/acre) for county i in year t ; PP_{it} is harvested plants per acre (thousands/acre) in the state associated with county i . The primary coefficient of interest is δ , which measures the relationship between plant population and corn yield. The time trend, $trend_t$, is included to capture technological trends over time (Miller et al., 2021).

The vector $\mathbf{w}_{it}$ includes weather and climate variables for county i in year t , and the term $\boldsymbol{\beta}$ is the corresponding vector of parameters. The three levels of aggregated temperature variables and precipitation variables are controlled in the model to admit the linear piecewise relation between weather, climate variables and yield growth over time. The quadratic term of precipitation is used to capture any nonlinear effects of rainfall. In addition to the temperature and precipitation

variables, mean VPD over the growing season and mean VPD during July and August are included to account for drought impacts not captured by the temperature and precipitation variables.

County fixed effects, denoted by λ_i , are included to account for unobserved time-invariant factors within a county that impact yields. For instance, soil quality is unobserved and is an important contributor to yield levels. The fixed effect model is weighted by acres to control for potential selection bias. Specifically, our dataset includes ten states, seven of which are part of the “Corn Belt”, a region known for a large proportion of U.S corn production. By weighing data according to acres, we ensure that each county’s influence on the estimated parameters is proportional to its planted acreage, helping to mitigate the distortion of underrepresentation of states with large acreage (such as those in the Corn Belt) and overrepresentation of states with relatively smaller acreage.

Following Lusk et al., (2018), standard errors are clustered at the state level to capture any potential spatial correlation of the error terms. This is particularly important because GE adoption rates and plant population data are only available at the state level, but the other variables are observed at the county-level. Thus, this clustering accounts for the fact that the county-specific values for GE adoption and plant population within a given year are identical within a state.

1.5. Results

1.5.1 Model estimation results

The estimation results are presented in Table 1.2. We divide the section into three parts. First, we discuss the impacts of the response of weather, climate and GE variables on corn yields. Next, we report and analyze the results for the five model specifications. Third, robustness checks are provided to validate the reliability and accuracy of the models employed in this study. We

provide parameter estimates for six specifications, each differing by whether a trend and/or the GE adoption variable is included.

We specify the temperature variable using two thresholds over growing degree days and then report the yield response under all possible thresholds. Almost all variable estimates are statistically significant at one percent, except for the degree days between 0°C and 10°C in models 2 and 4. The results exhibit a linear piecewise relationship between yield and temperature. Corn yields decrease dramatically with exposure to temperatures over 29°C. This is consistent with the nonlinear relation function estimated by Schlenker et al. (2009). Previous studies show adoption of GE crops has increased yield (Lusk et al., 2018). Our result in model 5 indicates an effect of 9.67 bushels per acre, while Lusk et al. (2018) report a higher effect of 18.26 bushels per acre. This difference may be due to variations in the sample or the omission of plant population as a control variable in their study.

Table 1.2. shows that both precipitation and its squared term have statistically significant effects on corn yield. Like Miao et al. (2015) and Xu et al. (2022), the negative coefficient of the squared term indicates an inverse U-shaped relationship between precipitation and yield, suggesting the presence of optimal precipitation thresholds for maximizing yields. The optimal level of precipitation can be derived from the first derivative of the yield function, defined as:

$$Precip^* = - \frac{\beta_1}{2\beta_2}$$

where β_1 and β_2 are the estimated coefficients for the precipitation, squared precipitation, respectively. Using the estimates from model 5, the optimal precipitation level to maximize the yield is 563.5mm. Beyond this threshold, additional rainfall reduces per acre yields.

In model (1), we omit the VPD, VPDJA, GE adoption and time trend variables. In the absence of these variables, the estimated coefficient for plant population indicates that every additional one thousand harvested plants result in a yield increase of 6.371 bushels per acre. In the second model, the trend is included, which leads to a decrease in the estimated effect of 3.356 bushels per acre. This suggests that the estimates from the first two models are confounded by the absence of a trend variable, which captures technological progress over time.² Next, we turn to model 3, which incorporates VPD and VPDJA to examine the effects of different weather and climate variables. The results show a strongly positive marginal relationship with VPD and a strongly negative relationship with VPDJA, which is consistent with the findings of Roberts et al. (2012) and Zhao et al. (2025). In comparison to model 2, the estimated effect for plant population in model 3 is slightly larger. In model 5, all variables are included, resulting in an estimate of 3.53 bushels per acre (for models that include a trend). This model is used to predict future yield growth trends, as it provides the best overall fit.

² An alternative possibility is that technological progress, as captured by the trend variable, may promote higher seeding rates. If true, including both variables may be problematic because of the “bad control” problem, as described in Angrist and Pischke (2009). Alternatively, inclusion of a trend also reduces the amount of identifying variation for the plant population variable, that can exacerbate measurement error. Nonetheless, for the prediction exercise we use the specification that includes both variables because, in our view, this is the more conservative approach to the influence of plant population.

Table 1.2. Regression results for effects of plant population on corn yields (bushel/acre)

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Plant Population	6.371*** (0.044)	3.356*** (0.221)	3.540*** (0.222)	3.391*** (0.226)	3.533*** (0.226)
DDays (0°–10°C)	-0.007*** (0.002)	-0.00122 (0.00179)	-0.033*** (0.002)	0.001 (0.002)	-0.027*** (0.002)
DDays (10°–29°C)	0.027*** (0.002)	0.0220*** (0.00179)	0.008*** (0.002)	0.020*** (0.002)	0.009*** (0.002)
DDays (>29°C)	-0.637*** (0.016)	-0.612*** (0.0162)	-0.482*** (0.018)	-0.607*** (0.016)	-0.444*** (0.016)
Precip (mm)	9.604*** (0.580)	11.49*** (0.568)	14.027*** (0.640)	11.387*** (0.554)	13.299*** (0.617)
Precip ² (mm ²)	-0.952*** (0.048)	-1.081*** (0.0469)	-1.220*** (0.050)	-1.070*** (0.046)	-1.180*** (0.049)
Trend		0.852*** (0.0635)	0.812*** (0.066)	0.658*** (0.062)	0.606*** (0.064)
VPD			42.623*** (2.333)		36.516*** (2.300)
VPD (July & Aug)			-26.495*** (1.045)		-27.811*** (1.054)
GE Adoption				9.378*** (0.598)	9.670*** (0.636)
Constant	-51.927*** (3.311)	-18.89*** (4.270)	22.862*** (4.842)	-17.351*** (4.305)	30.531*** (4.937)
Observations	46,980	46,980	46,980	46,980	46,980
R-squared	0.829	0.838	0.845	0.840	0.846

All models include county fixed effects. Standard errors, clustered by state, are reported in parentheses and *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

1.5.2. Robustness Checks

We conduct several robustness checks with respect to the functional form for the plant population variable. We estimate models in which we use a log representation, quadratic representation, and a squared term for the plant population variable. This last specification is the exact functional form if yield is quadratic in seeding rates, farmers maximize yields, and we observe optimal yield and seed input levels. As noted above, experimental evidence from agronomic trials indicates that per-acre maize yields are approximately quadratic in seeding rates (Assefa et al. 2016). To formalize this, we can write a quadratic yield function as

$$y_t = b(\theta_t z_t - 0.5z_t^2), \quad \theta_t > 0, b > 0 \quad (12)$$

where z_t denotes seed density (seeds per acre) at time t . Note that, with this parameterization, yield is maximized at $z_t^* = \theta_t$. Hence, θ_t , can be interpreted as what Assefa et al. (2018) term the “agronomic optimal” planting density (AOPD). Suppose we have data on yields, y_t , and planting density, z_t . Under the assumption that the AOPD is changing over time, we cannot simply regress yields on density and obtain the *causal* impact of density on yields. However, if we assume that farmers choose the AOPD, then $z_t^* = \theta_t$. After substituting for z_t , the optimal yield equation can be written as:

$$y_t^* = 0.5b z_t^{*2} + \epsilon_t = 0.5b \theta_t^2 + \epsilon_t \quad (13)$$

This shows that, insofar as we observe optimal seeding rates, they enter the model as squared values only. We elected not to use this specification for the baseline model for two reasons. First, farmers potentially take other factors such as input prices into account when choosing seeding rates, although recent evidence suggests such considerations are minimal (Perry et. al 2022). Second, the primary goal with the yield-density model is to obtain a predictive relationship

between plant population and yield, rather than a causal one. Identification of a causal relationship between plant population and yield would require exogenous variation in populations (e.g., on experimental plots). Instead, we seek to understand whether the associative relationship between population and yield has changed in recent times and, moreover, to the extent that plant population growth slows down, what this implies for future yield growth.

The alternative specifications are provided in Table A.2 of the appendix. Across all specifications the coefficients on the plant population variables are statistically significant and roughly equivalent in importance to the estimated impact in the baseline linear model. In addition, the estimated coefficients on the weather and trend variables are relatively unchanged. The estimated GE impact is as high as 15.4 bushels in model 4, although this primarily a consequence of not including a trend variable. Overall, the results are generally consistent with those presented in Table 1.3, and using alternative functional forms for the plant population variable does not significantly improve the fitness of the model.

1.6. Yield prediction for the next decade

After approaching the upper limit for plant populations, what does this imply for future yield gains? Using the estimated model, we predict yield gains for the next decade. In this section, we provide the prediction within and outside the studied data sample.

1.6.1. Within the sample prediction during 1964-2023

Our model provides yearly predictions constructed using historical weather and climate data. USDA projected yield was plotted from year 2015 to examine how accurate the USDA prediction was. As yield levels increased, so did the plant population until 2015 when it plateaued. Since then, plant population has remained relatively flat.

The predicted yield is generated by utilizing model 5 in Table 1.2. As shown in Figure 1.6, the predicted national yields align closely with actual mean yield over the observed period. The USDA prediction is higher than actual yield from 2016-2023, indicating the USDA's projected yields tend to overestimate actual yields in recent years.

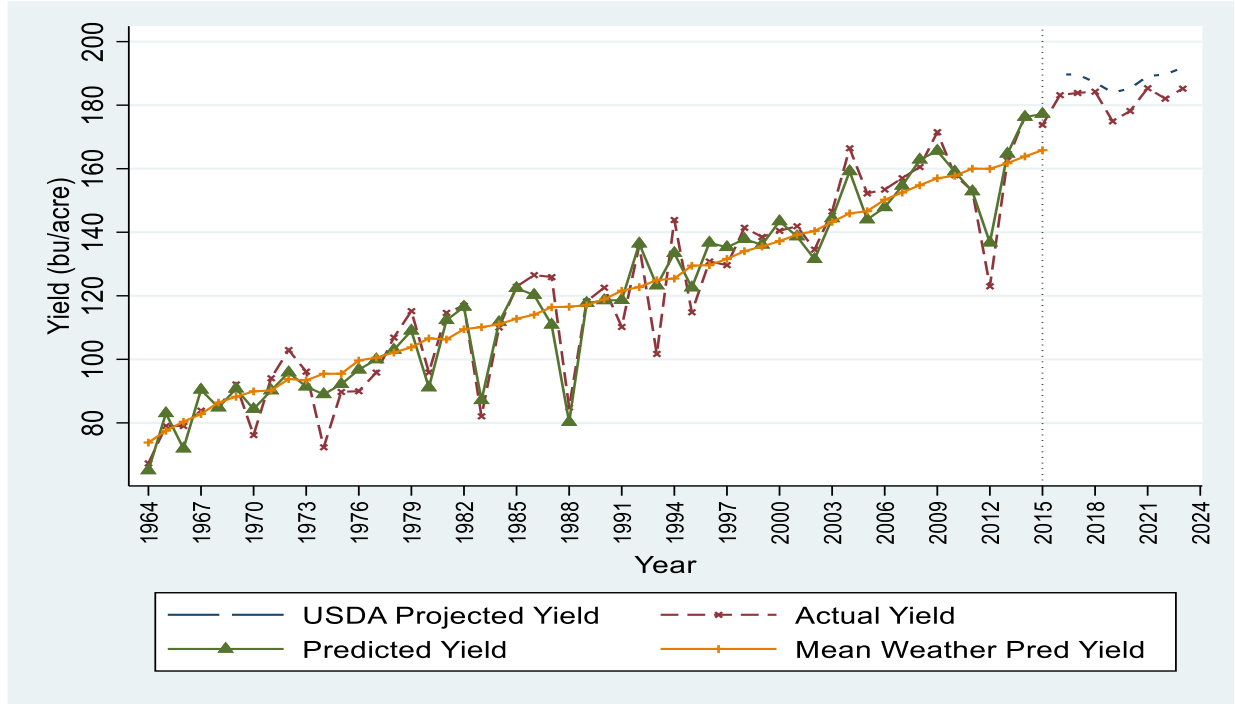


Figure 1.6. Predictions of corn yields from 1964 to 2023. Predictions were conducted during the growing season for the ten states selected in our dataset from 1964 to 2023. Our model provides yearly predictions based on average weather and climate information. USDA projected yield was plotted from year 2015.

1.6.2. Yield prediction in the next decade (2024-2034)

Using the estimated model parameters, we conduct an out-of-sample forecast for the period 2024-2034. The predicted plant population is estimated by regressing the plant population variable on state fixed effects and state-specific trends.

$$P_{st} = \eta_s + \pi_s trend_t + u_{st} \quad (14)$$

where P_{st} is observed plant population in state s in year t , π_s is the state-specific parameter on the trend, and u_{st} is the error term. The out-of-sample predicted plant population, $\hat{P}_{st}$, is obtained by using the estimated model with trend values for the years 2024-2034. We predict future plant population trends under two scenarios: one based on in-sample estimated trends from 2015 to 2024, accounting for the breakpoint observed in 2015, and another based on trends from 1964 to 2024 to assess how future projections may differ.

To obtain conservative predictions for plant population, we impose constraints that prevent any out-of-sample future downward trend, as a decline in population growth would likely be unrealistic in the future.³ This approach guarantees that future estimates either remain stable or increase over time. First, we calculate the maximum value of plant population between 2015 and 2024. If the predicted value falls below these maximum values for the years between 2025 and 2034, they are replaced with the maximum; otherwise, the original predictions are preserved. Figure A.3 in the Appendix presents the historical plant population trends and compares the two future projections.

The projection also requires predictions for the weather and GE variables. GE adoption had essentially stabilized by the end of the sample (see Figure 1.2). Thus, for the GE predictions we use the county-level average GE adoption rate from 2019 to 2023. For the weather and climate variables, the out-of-sample county-level values for temperature, precipitation, and VPD were derived from historical data for the period 2000-2023. We selected this period to account for recent long-term warming trends, which ensure more accurate estimates for the next decade. After

³ It is, of course, possible that planting rates could decrease in the future if there were drastic increases in relative seed prices or radical changes in breeding efforts.

collecting the explanatory future variables for each county, projected yields are calculated as follows:

$$\hat{y}_{it} = \delta \hat{P}_{it} + \hat{\gamma} \bar{G}_i + \bar{\mathbf{w}}_i' \boldsymbol{\beta} + \hat{\lambda}_i + \hat{\theta} trend_t \quad (15)$$

where $\hat{y}$ is the predicted yield, the coefficients matrix (here denoted as $\bar{\mathbf{w}}_i'$) corresponds to the vector of predicted weather and climate variables, δ refers to the estimated coefficient of plant population, $\hat{\gamma}$ represents the coefficient for the GE variable, and $\hat{\theta}$ denotes the coefficient for the trend variable. As described in equation 11, the county fixed effects $\hat{\lambda}_i$ are included as well. These coefficients are extracted using model 5 (table 1.2.). Two predicted yields are generated under the two scenarios discussed above, respectively. To improve accuracy, predicted yield is weighted by the acreage planted in each county.

Figure 1.6. shows that the estimates closely match the real dataset. The predictions using the average weather and climate variable align with the observed increasing trend of yield gains. However, USDA predictions tend to overestimate actual yields from 2015 to 2023. Likewise, Figure 1.7. illustrates that USDA predictions are significantly higher than our predictions over the next ten years (2025-2034). Table 1.3. presents the differences between USDA predictions and our predicted yield. The harvested acres for the next decade were predicted, allowing us to compare the average projected corn production over this period. Our predicted production is significantly lower than the USDA's estimates.

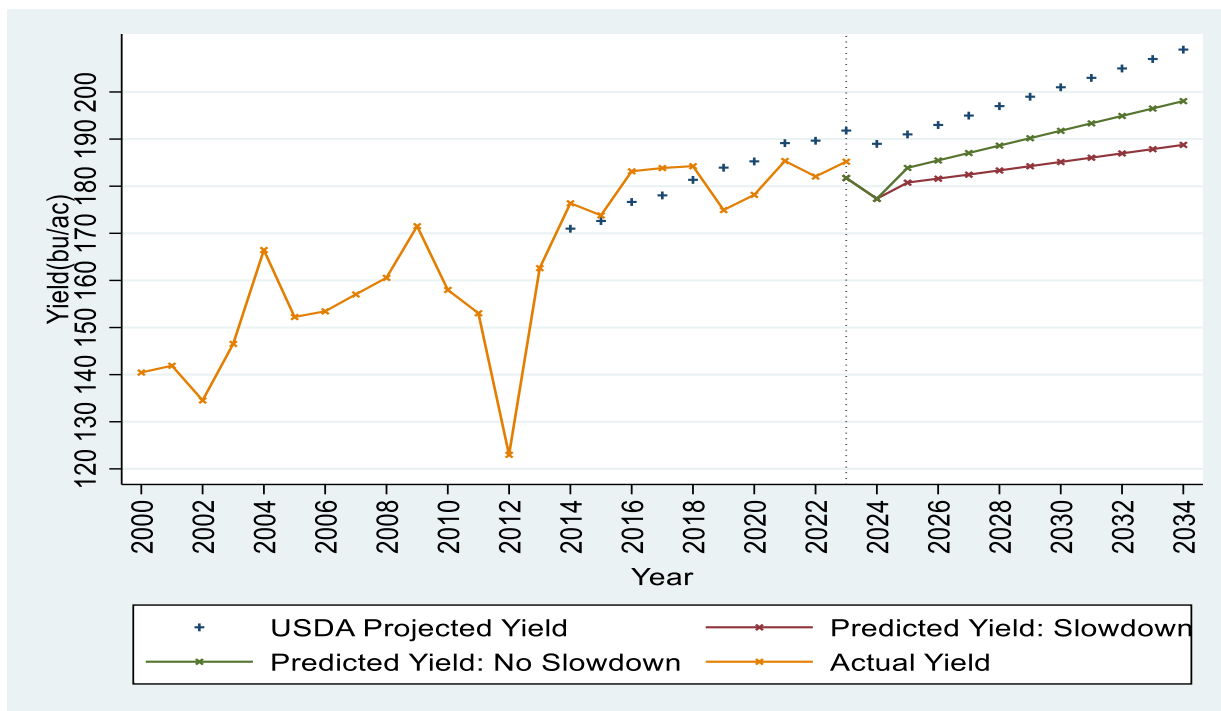


Figure 1.7. Predictions of corn yields from 2024-2034

Note: They were calculated using the historical mean weather and climate scenarios including precipitation, temperature, VPD from 2000-2023, the mean GE adopt rate (2019-2023) was estimated using generalized linear model. The predicted plant population was considered using two scenarios, 1: predicted yield: pop slowdown, predicted based on plant population trend from 2015-2024, 2: predicted yield: No slowdown, predicted based on plant population trend from 1963 to 2024. USDA projected yield was plotted from year 2015.

This clearly demonstrates the substantial impact of plant population potential yield growth. When future plant population variables are replaced with those estimated from the entire dataset, the predicted yield continues to increase. In contrast, when future plant populations are estimated from the plateaued plant populations, the predicted yield shows a slower rate of growth over the next decade. This is a significant finding for potential yield growth and predictions. The overestimation of USDA prediction can potentially be attributed to its exclusion of plant populations. Plant population is important for accurately predicting yield, and USDA predictions may want to include them for future estimates.

Table 1.3. USDA prediction, Average weather and climate prediction

Year	USDA Prediction	Averaged Predicted Production (USDA)	Predicted Yield	Averaged Predicted Production	Difference
2024	192.4	16,521,424.56	177.33	15,227,360.79	15.07(7.8%)
2025	194.4	16,783,663.97	180.77	15,606,908.10	13.63(7.01%)
2026	196.4	17,047,767.46	181.62	15,764,844.84	14.78(7.53%)
2027	198.4	17,313,733.12	182.46	15,922,700.33	15.94(8.03%)
2028	200.4	17,581,560.94	183.35	16,085,724.54	17.05(8.51%)
2029	202.4	17,851,250.91	184.25	16,250,459.39	18.15(8.97%)
2030	204.4	18,122,801.00	185.15	16,416,030.36	19.25(9.42%)
2031	206.4	18,396,215.28	186.06	16,583,332.44	20.34(9.85%)
2032	208.4	18,671,489.63	186.97	16,751,479.93	21.43(10.28%)
2033	210.4	18,948,628.21	187.87	16,919,575.96	22.53(10.71%)
2034	212.4	19,227,628.94	188.78	17,089,415.22	23.62(11.12%)

1.7. Conclusion

As the global population continues to grow, the demand for food is projected to double by the 2050s (Tilman et al., 2011). With the U.S contributing 35% of the world's corn supply and 60% of global exports (Leng, 2017), it is crucial to sustain an upward trend in corn yields in the face of a growing world population.

In this study, we use a large panel dataset and a fixed effects model to uncover a change in the U.S corn yield growth. While plant population changes have been arguably the most crucial mechanism for yield growth to the present, there are theoretical limits to how many plants can be packed into a given amount of surface area. We may be approaching that limit. U.S mean plant population has not increased statistically since 2015, and projected yields based on this population

prediction shows a yield growth slowdown. Since corn yield relies more on plant population compared to other crops such as sorghum (Assefa et al., 2016), where will future yield growth come from if it can no longer be achieved through plant population growth? Will yield growth be sustainable in future decades? Can plant population have a resurgence growth after it reaches the optimal level? To answer those questions, the underlying reasons for the plateau in corn plant population growth need to be understood, which helps achieve potential sustainable yield growth.

One possible explanation is that mean plant population has reached an optimal level, where further increases no longer result in higher yield. In addition, there is the possibility of a reduction in the marginal benefits from increasing investment in high quality seeds. Operating costs for U.S corn more than doubled, with seed costs showing the largest percentage increase, which increased 263 percent from \$27 per acre in 1996 to \$98 per acre in 2016, with a steady upward trend associated with the adoption of increasingly costly genetically engineered seeds (Saavoss et al., 2021). Although we lack data to evaluate the marginal benefits and costs of selecting different seed traits under varying climate seasons and soil conditions, it is likely that adding more traits increases seed costs. Therefore, with rising seed prices and the volatility of grain markets, reassessing corn seeding strategies may be necessary (Quinn, 2025)

In addition, variable rate seeding enables the spatial optimization of seed inputs by aligning plant populations with productivity zones within a field (Hawkins et al., 2019). This site-specific approach, which applies different sowing rates across field areas, helps optimize crop density to obtain the best agronomic and economic outcomes (Šarauskis et al., 2022). How to better utilize this precision planting technology is another important strategy for ensuring continued yield growth.

Our model analysis indicates that warming temperatures have significant negative effects on corn yield gains, but we do not consider the potential interactions between weather and plant population. Drought and excessive rainfall are the leading extreme events causing maize production losses in the U.S, accounting for 18 and 10 billion US dollars in damage, respectively, from 1989 to 2016 (Li et al., 2019). Reducing the drought sensitivity of crop yields has therefore become a key adaptation priority (Lobell et al., 2020). Using new experimental data, Lee et al. (2024) examined the effects of recently commercialized drought-tolerant (DT) traits on U.S. corn production. Their findings show that current DT hybrids may provide moderate benefits under future climate change warming scenarios. However, they do not consider the interaction of plant population with climate variables. We leave this question to future work.

Our model estimation shows that, after controlling weather, climate and GE adoption effects, plant population is associated with a 3.53 bushels per acre increase in yield for each additional thousand plants harvested per acre, but this effect varies from 3.391 to 6.371 bushels per acre depending on the level of GE adoption and technological progress. This inclusion of plant population in a yield prediction model may also benefit USDA researchers in future corn yield predictions. It may be of significant value to survey planting density decisions in the spring which could be used to obtain a more accurate yield predictions throughout the growing season. Alternatively, it may be possible to utilize satellite imagery to monitor planting rates. To have planting density in the ARMS survey as a routine measure would generate valuable data that could greatly benefit corn production research.

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Chapter 2 - Meat demand in China: A Dynamic AIDS Approach

2.1 Introduction

China initiated economic reforms and an increasing openness to world trade in 1978. Rapid, sustainable economic growth followed, which transformed the country from a low-income to middle-income market economy (Sutherland and Yao, 2011), causing significant changes in consumer food consumption patterns (Dong and Fuller, 2009). Consumers substituted from staple foods to higher levels of animal protein which normally is more expensive (Cai et al., 1998). China has become the world's largest meat consumer, with a total meat and seafood consumption of 145 million tons in 2022, compared to the U.S.'s 50.1 million tons (Wang, 2022). According to data from the National Bureau of Statistics, China's per capita meat consumption increased significantly from 25.6 kg in 2014 to 39.8 kg in 2024, an increase of 14.2 kg, or approximately 48.8%, over the ten-year period.

In China, food consumption is influenced by a blend of 'historical, medical, social, and cosmological factors' (Denton and Kaixuan, 1995). Pork is distinct among all agrifood sectors, due to the longstanding tradition of household pig raising spanning centuries (Schneider and Sharma, 2014). To answer the question why pork is so important in China, it is necessary to understand its cultural and historical significance.

Evidence on pork demand in China suggests pork consumption can be habit forming as Guariglia and Rossi (2002) described that consumers' preferences exhibit inertia, which means that when an eating habit is established, households only gradually change their consumption. Past consumption patterns are an important determinant of present consumption behaviors (Pollak, 1970; Becker and Murphy, 1988). Many economists accept that in addition to the price and income, habit formation matters when we discuss the crucial factors that impact household food

consumption behavior (Naik and Moore, 1996; Carrasco et al., 2005). When habit formation becomes particularly strong or extreme, it is referred to as addiction (Becker, 1996), as seen in cases where consumers are addicted to sweetened food or smokers to cigarettes. According to Becker and Murphy (1988), habit formation is not limited to seemingly addictive substances such as alcohol, cocaine, and cigarettes, but extends to behaviors like work, music, television, and eating. Excluding habit formation in food demand may bias the demand analysis.

As living standards have improved, meat consumption preferences in China have shifted. As per capita income has increased, the consumption of other meats like chicken, beef, and lamb has grown, while the proportion of pork consumption relative to total meat consumption has declined. Specifically, pork consumption declined from 94.1% in 2000 to 66% in 2017, while poultry accounted for 21%, beef for 8%, and lamb for 5% of meat consumption. Despite this change, pork consumption still dominates Chinese consumer's daily diets. One main objective of this paper is to evaluate potential changes in the habit formation effect on meat consumption. In addition to habit formation, extensive research has been conducted to identify pre-commitment effects that represent the component of demand that is insensitive to income and price adjustments, as studied by Piggott and Marsh (2004) and Tonsor and Marsh (2007). To more accurately estimate consumer behavior in response to price, income, pre-committed consumption, habit formation, and other demand shifters, it is essential to develop a properly specified econometric model.

This study contributes to the literature by extending Zhen et al's (2011) and Zheng et al's (2016) dynamic almost ideal demand system (AIDS) model to include both habit formation and pre-committed consumption. We estimate the demand equations using yearly, provincial data from the Chinese National Bureau of Statistics (NBS) survey for the period 2015-2022. Our results suggest that both urban and rural consumers have strong habit effects in meat consumption, with

beef consumption being the most habit-forming meat. Additionally, we provide evidence that factors beyond price and expenditure play a significant role in shaping both urban and rural consumer demand responses for pork and poultry. These improved demand modelling results provide a good understanding of Chinese meat consumers' consumption behaviors.

There have been concerns that changes in demographic structure and slowing of GDP (measured as per capita gross domestic product) growth rate might affect future meat consumption in China. China has been facing two major changes in demographic structure recently: (1) an aging population and (2) an overall population decline. There has been an increase in people aged 60 and above by 1.3% between 2022 and 2023. Given the dramatic decline in fertility and the rise in mortality, China is expected to become a fast-aging society at a rapid pace (Wang and Mason, 2007). A rapidly aging society has a significant impact on the economy and China's economic growth rate is expected to gradually slowdown in the future as it moves toward a higher level of income (Banister et al, 2012). This turning point is not unexpected, and China's birth rate has continuously declined since the implementation of the "one couple one child" policy in 1979, though it was recently replaced by the "two-child" policy in 2016 and the "three-child" policy in 2021 to mitigate the decline in birth rates. Still, the decreasing trend of population growth persists. In 2022, the population decreased by about 850,000 from 2021 which is the first time the population declined since the 1960s during the Great Famine of the Mao Zedong's era (BBC, 2023). In 2023, China's total population further dropped by 2.08 million with a record-low birth rate of 6.39 births per 1,000 people since 1949 – more than half a million people fewer than the previous year (Reuters, 2024). Meanwhile, there has been a change in GDP growth, with China's growth projected to slow to 4.4 % in 2024 by J.P Morgan (Reuters, 2024) and is predicted by the IMF to decline further to 3.4% by 2028, down from 5.2% in 2023 (VOA, 2024) The real growth

rate may be much lower because of the unpredictability and complexity of the Chinese economy. In June 2023, China's youth unemployment rate hit a record high of 21.3% (Time, 2023), which will cause income per capita to decline in the future leading to a change in food consumption. China relies significantly on the global market to satisfy its meat production and consumption (Gale and Dong, 2023). China imported a total of 9.38 million tons of meat valued at \$32.16 billion, including 2.36 million tons of beef and 5.00 million tons of pork (China Customer, 2024). Changes in future meat consumption may have a significant impact on the worldwide market. This study addresses the above concern and contributes to the literature by assessing the impacts of population decline, population aging, and falling incomes on meat consumption for China's meat consumers.

Rapid demographic aging profoundly impacts socioeconomic development and poses significant challenges for food security and agricultural sustainability (Ren et al., 2022). This study also predicts how meat demand will change for China's urban and rural residents under scenarios of continued population decline, slowing GDP growth, and an aging population. By using elasticities derived from dynamic estimation, we predict future food consumption trends. These predictions will be valuable for developing food policies tailored to different income groups, changes in demographic structures, promoting a sustainable transformation of the food system (Zhu et al., 2022).

The article is laid out as follows. First is a brief review of relevant prior research. Next, we discuss the theoretical model. Third, we summarize the data used for the empirical analysis. The article then presents empirical analysis for the results and concludes the paper with a discussion of the study's implications.

2.2. Literature Review

In the past few decades, Chinese food patterns have experienced significant changes in demand, particularly after the shift from staple foods to more higher protein foods. The rapid growth occurring in meat consumption was driven by the economic reforms and subsequent income increases among household consumers (Wang et al, 1998; Gao et al, 1996). Some researchers have captured this transition by estimating the expenditure elasticities of meat and seafood using principal component analysis, indicating the Chinese people's diets are partially replaced with fish (Shono et al., 2000). Those demand studies mostly focus on a single meat product or specific areas of China. For example, Zhu et al (2021) predicted beef consumption in the next 10 or 15 years, showing increased income can increase beef consumption, as it provides more protein and less fat compared to pork. Wang et al (2014) investigated the determinants of pork demand in urban western China and found that consumer's purchasing decision with pork are related to both economic factors and non-economic factors, such as a household characteristics.

Although these studies can shed light on Chinese food consumption, most rely on static demand models. Gao et al. (1996) adopted an empirically tractable amalgamating demand system for food commodities that combines an upper-level AIDS, and a lower level generalized linear expenditure system as a modelling framework. Ortega et al (2009) applied the linear approximate AIDS model (LA/AIDS) for the meat expenditure and demand elasticities. Zheng et al (2019) used the Quadratics AIDS model to estimate the demand elasticities with respect to income and demographic variables. However, misspecification tests show that a static model can be inappropriate, resulting in potentially inaccurate price or expenditure elasticities (Shukur, 2002). The demand for food products may be a dynamic process that results from habit formation, switching costs, and learning processes. Hence, consumers do not adjust to income and prices

change simultaneously but dynamically (Nevo, 2010; Zhou et al, 2015). After analyzing consumer behaviour in the U.S from 1948 to 1978, the dynamic AIDS framework was found to have better performance (Blanciforti et al, 1986).

Chen and Veeman (1991) conducted a study that analyzed structural changes in meat demand within Canadian consumption patterns. They examined the non-constancy of parameters in a non-linear system and found that incorporating a dynamic habit effect into the AIDS model improved the consistency between demand theory and observed data. However, the habit formation for the Chinese consumption of meat is sparse. Applying the dynamic model that includes habit formation for meat consumption could yield valuable insights into the dynamic process of meat consumption, thereby promoting more effective production and international trade policies.

In addition to income growth being a key determinant of Chinese meat consumption, researchers have examined how demographic variables influence household meat consumption. Zheng et al. (2019) employed the quadratic AIDS model to analyze how age demographics, particularly the proportion of seniors aged 65 and over and children aged 0-14 within the population, influence expenditure patterns. Their findings indicate that as per capita income rises and the population ages, there is a noticeable shift towards increased spending on foods consumed away from home, while expenditure on home-cooked meals declines. Shi et al (2015) incorporated population aging in the analysis of household meat consumption using OLS linear regression and concluded population aging had a significant negative effect on per capita meat consumption. Liao and Chern (2007) applied the conventional dynamic AIDS model and results showed that most demographic variables were significant compared to the static model. The study showed that habit

effects for all categories except eggs were significant, but their conventional dynamic model cannot exclude the possibility of negative habit formation which does not align with reality.

2.3. Model Specification

After Deaton and Muellbauer published “Almost Ideal Demand System” (AIDS), the model became one of the most popular functional forms to estimate the static demand system because of its theoretical consistency and functional flexibility. Most previous studies on food demand in China use this model. Static models typically assume that food consumption depends solely on income and prices within the same period, imposing a restrictive consumption framework. This approach can result in demand model misspecification and inaccurate elasticity estimates.

Various dynamic AIDS models have been developed to improve the accuracy of demand estimation. Two crucial problems concerning consistency with economic theory need to be addressed: 1. Derive a dynamic system from a proper expenditure function (Rathnayaka et al., 2019) and 2. Satisfy the demand theory properties and restrictions.

Blanciforti and Green (1983) extended the AIDS model to a dynamic form by incorporating habit effects, following the approach of Pollak and Wales (1969). They specified the intercept a_i in the budget share of standard AIDS model as a linear function of previous consumption levels, positing the specification below:

$$a_i = a_i^* + a_i^{**} q_{it-1} \quad (1)$$

where a_i^{**} is the estimated habit formation parameter of the i th good, a_i^* is the intercept in the linear function of a_i and q_{it-1} is lagged past consumption of i th good. This model is easy to estimate but does not satisfy the requirements for boundary restrictions. Furthermore, their specification is inconsistent with adding up (Alessie and Kapteyn, 1991).

Unlike Blanciforti and Green (1983), Ray (1984) simply added the lagged purchase item into the model and extended the static form of price index.

$$w_{it} = \alpha_i + \sum_i (r_{ij} + \theta_{ij}\mu_{t-1}) \ln p_{jt} + (\beta_i + \eta_i\mu_{t-1}) \ln \left(\frac{\mu_t}{p_t^*} \right) + u_{it} \quad (2)$$

where w_{it} is the budget share associated with the i th good in period t , p_{jt} is the price of the j th good in period t , p_t^* is the group price index, u_{it} denotes the stochastic error term and $\beta_i, \alpha_i, \theta_{ij}, \eta_i, r_{ij}$ are the parameters to be estimated. The following equation (3) is the nonlinear price index extended from the static form.

$$\ln P_t^* = a_0 + \sum_i a_i \ln P_{it} + \sum_i \delta_i e_{it-1} + \frac{1}{2} \sum_i \sum_j (\gamma_{ij} + \theta_{ij}\mu_{t-1}) \ln P_{it} \ln P_{jt} \quad (3)$$

where e_{it-1} denotes lagged purchases of item i , δ_i 's measures the lagged purchases of the individual items e_{it-1} in an additive manner, $\mu_{t-1} = \sum_i e_{it-1}$ is lagged aggregate purchase of item i .

Based on Ray's model, a flexible dynamic model of consumer demand was introduced by incorporating own past budget shares (Anderson and Blundell, 1983). However, research shows that this widely applied model proved to suffer from misspecification, specifically in terms of autocorrelation and functional misspecification (Shukur, 2002). When goods are not classified into the same category, the lagged aggregate purchases cannot be derived by summing the lagged purchases of each individual good. Ignoring this restriction in the model can lead to both theoretical and empirical misspecification. Moreover, it becomes difficult to differentiate between the changes in budget share that result from income changes or those caused by price changes.

This study builds on the model of tobacco consumption by Zheng et al. (2016) and Zhen et al. (2011) about beverage study on habit formation. The dynamic habit formation model is extended to include pre-committed demand. It is important to note that habit formation depends on past demand, meaning that previous consumption (recent and distant consumption histories) influences current decisions (Holt and Goodwin, 1997). Different from habit formation, pre-committed consumption refers to the part of demand that is insensitive to both the price and income factors (Tighe et al., 2019). Habit formation presumably changes over time while pre-committed effects remain relatively stable. Empirical research has provided evidence for both pre-commitment and habit formation effects for normal consumer goods (Holt and Goodwin, 1997; Fuhrer, 2000; Piggot et al., 2007). When integrated with a flexible parameter specification, the dynamic demand model with habit formation provides considerable versatility in including the role of a pre-committed effect within a dynamic demand analysis. To the best of the author's knowledge, this is the first study to adopt an extended model of AIDS to have both habit formation and pre-committed effects included in one model. This comprehensive model allows for a more accurate examination of meat consumption behavior in China.

We adopted this extended dynamic habit formation model for three reasons: Firstly, it adheres to defined boundaries, making it easier to meet theoretical and empirical requirements; secondly, the model can be converted between standard AIDS and dynamic AIDS. Thirdly, the model is well-suited for accurately calculating long-term elasticities. Our study design differs primarily from the previous work in that our model captures both habit formation and pre-committed effects within a single framework.

Under the assumption of utility depends not only on consumption at time t , but also on consumption at time $t-1$ (Alessie and Lusardi, 1997). Therefore, utility derived from meat

consumption can be expressed as Z_{it} , capturing the consumption in period t and earlier periods (Muellbauer and Pashardes, 1992)

$$Z_{it} = q_{it} - \phi_i q_{it-1} \quad (4)$$

We extend this utility function to include the pre-commitments that are in equation (5). Intuitively, consumer demand at time t for individual i can be understood as having both habit formation consumption and a survival level of consumption, the latter captured by the pre-committed component.

$$Z_{it} = q_{it} - \phi_i q_{it-1} + C_{it} \quad (5)$$

where $0 \leq \phi_i < 1$ measures the degree of habit formation; the higher the ϕ_i is, the higher the habit effect is. In this research, let i denote four meat commodities: pork, beef, poultry and lamb. The variable q_{it} is the per capita quantity of each commodity i at time t and q_{it-1} is the lagged term for q_{it} . C_{it} represents pre-committed information. Dynamic models using lagged quantities instead of lagged budget shares address concerns of autocorrelation and functional misspecification and therefore generally better fit to the data (Shukur, 2002).

In this study, two stage budgeting models are applied by proposing a complete demand system to replicate the consumption decision process with the assumption of weakly separable utility (Zhou et al, 2015). In the first stage, the consumer allocates income between a general meat category and all other goods. The second stage is the choices of the four meat commodities given the income from the first stage.

The second stage budget share equation is:

$$w_{it} = \alpha_i + \sum_{j=1}^4 \gamma_{ij} \ln p_{jt} + \beta_i (\ln \bar{x}_t - \ln p_t) \quad (6)$$

where p_t is the log of the group price index, and w_{it} is the conditional budget shares for the four commodities. Equation (7) is the budget share, expenditure variable $\bar{x}_t$ is endogenous as it is determined by the utility generating function Z_{it} . The nonlinear price index is given in the equation (9).

$$w_{it} = \frac{P_{it}Z_{it}}{\bar{x}_t} \quad (7)$$

$$\bar{x}_t = \sum_{i=1}^4 p_{it}Z_{it} \quad (8)$$

$$\ln p_t = \alpha_0 + \sum_{i=1}^4 \alpha_i \ln p_{it} + 0.5 * \sum_{i=1}^4 \sum_{j=1}^4 \gamma_{ij} \ln p_{it} \ln p_{jt} \quad (9)$$

where α, β, γ are parameters.

Theoretical restrictions of adding up, homogeneity, and symmetry are imposed as follows:

$$\sum_{i=1}^4 \alpha_i = 1, \sum_{i=1}^4 \beta_i = 0, \sum_{j=1}^4 \gamma_{ij} = 0, \sum_{j=1}^4 \gamma_{ij} = 0, \gamma_{ij} = \gamma_{ji} \text{ for all } i \neq j.$$

Inserting equation (5) into the budget share equation (6), and multiplying both sides by $\bar{x}_t/p_{it}$ results in the second stage quantity demand equation:

$$q_{it} = \left\{ \alpha_i + \sum_{j=1}^4 \gamma_{ij} \ln p_{jt} + \beta_i (\ln \bar{x}_t - \ln p_t) \right\} * \left(\frac{\bar{x}_t}{p_{it}} \right) - \phi_i q_{it-1} - C_{it} \quad (10)$$

The extended model can be derived in two equivalent ways. We can either extend the base dynamic model and integrate it with the pre-committed effects or build upon the base generalized AIDS (GAIDS) by adding a habit formation effect. As shown in Appendix B, both approaches lead to the same specification of the extended model. The choice of the base model primarily depends on the main research question of the study.

In addition, various factors such as demographic variables, population growth rate, and family size are added in the following linear function, as demonstrated by the previous literature (Shi and Wahl, 2015; Jin, 2021; Bittencourt et al., 2007). This approach allows us to estimate the

potential effects of declining population growth, a lower percentage of children, an increasing senior population, and smaller family size on meat consumption. To account for demographic and population growth factors, we adopt a linear function within the demand system. Specifically, the intercept a_i in equation (10) takes the following form:

$$a_i = a_{i0} + a_{i1}Growth_{it} + a_{i2}Children_{it} + a_{i3}Seniors_{it} + a_{i4}FS_{it} \quad (11)$$

where $Growth_{it}$ refers to the population growth rate for province i at year t , calculated as the difference between birth and death rate; $Children_{it}$ is the proportion of population aged 0-14, $Seniors_{it}$ is the proportion of population aged 65 and over, and FS_{it} denotes the averaged family size per household. a_{i0} through a_{i4} are parameters to be estimated.

To address income changes, we specify the first stage equation to close the demand system (Zhen et al., 2011):

$$\ln \bar{x}_t = \delta_i + \theta_i \ln(\text{income}_{it}) + \gamma_i * \ln p_t \quad (12)$$

where $\bar{x}_t$ is endogenous variable defined in equation (8), income_{it} is the average per capita income for each province in year t , $\ln p_t$ is the group price index defined in equation (9).

2.4. Data and Procedures

The empirical estimation is based on a yearly panel data of consumers' expenditures for four meats (pork, beef, poultry, and lamb) covering 30 provinces in China, from 2015 to 2022, determined by data availability. Since per capita consumption data before 2015 are generally aggregated across all meats, it is challenging to disaggregate quantities for each individual meat type. In addition, Tibet is not available in the provincial statistic yearbook. This study contributes to the literature by including the real market price data of pork, beef, lamb, and poultry which was usually missing in previous empirical studies. The price data was compiled from various issues of the China Livestock Yearbook. The widely used approach of unit values, calculated by dividing

expenditure by quantity consumed instead of using actual prices, may bias empirical analysis, since unit values are not exogenous but reflect household food quality choices within each category (Yu and Abler, 2009). Per capita consumption data were collected using the 30 provincial statistic Yearbook. Data on population growth, demographic composition, and family size come from the China Population and Employment Statistics Yearbook.

Originally, meat prices were recorded monthly. To align with per capita consumption at the yearly level, monthly data were aggregated and averaged to generate the annual averages for each province. Prior to estimation, we deflated the price data for urban and rural areas using the corresponding meat CPI for each province with 2015 as the base year, ensuring more accurate and consistent price measures.

Table 2.1 provides summary statistics of the data set used in this analysis. We can see that per capita consumption of pork is higher than that of other meat consumption. Thanks to its relatively low prices, poultry per capita consumption has increased very rapidly, and is the second largest. Demographic variables are used in this study including population growth rate, the proportion of children to the whole population (aged 0-14), the proportion of seniors to the whole population (aged sixty-five and above), and average household size. These demographic variables are used to calculate demographic variable elasticity, which allows us to predict future consumption with the relative changes in these variables. The rural resident summary data is reported in Table B.2 in Appendix

Table 2.1. Descriptive Statistics of Chinese urban resident data (2015-2022)

Variable	Definition	Mean	SD	Min	Max
Pork Price	Retail price (CNY/kg)	38.37	16.48	11	79.18
Beef Price	Retail price (CNY/kg)	76.19	20.92	51.56	163.42
Poultry Price	Retail price (CNY/kg)	21.50	6.45	12.48	48.63
Lamb Price	Retail price (CNY/kg)	71.13	14.79	38.56	114.50
Pork	Per capita consumption (kg)	20.1	8.27	1.12	45.82
Beef	Per capita consumption (kg)	2.51	1.58	0.24	10.31
Poultry	Per capita consumption (kg)	9.61	6.04	0.9	38.04
Lamb	Per capita consumption (kg)	1.98	2.66	0.15	14.79
Birth	Birth rate yearly (‰)	9.87	3.11	3.34	17.89
Death	Death rate yearly (‰)	6.53	1.03	4.26	9.09
Growth	Difference between birth and death rate (‰)	3.34	3.55	-5.75	11.4
Children	Population aged 0-14	0.14	0.03	0.08	0.2
Labor	Population aged 15-64	0.75	0.03	0.69	0.82
Seniors	Population aged over 65	0.11	0.02	0.06	0.19
Family size	Average family size (persons)	2.71	0.26	2.12	3.6
Income	Annual income per capita (CNY)	38805.65	11831.59	23767.1	84023

In China, the average annual income of urban residents is 38,805.65 CNY, which is 2.39 times higher than that of rural residents (see Table B.2 in the appendix), indicating a significant disparity between the two groups. This gap is also reflected in the per capita consumption of animal protein. This suggests that there is still potential for an increase in meat consumption in rural areas. The differences in meat consumption between urban and rural residents have evolved over time (see Table B.1 in the appendix). The gap in pork consumption between the two groups has been declining, with rural per capita consumption nearly equating urban levels by 2013. Rural residents started to surpass urban residents in per capita pork consumption after 2017. A similar trend is observed in poultry consumption. For lamb and beef, rural residents have increased poultry consumption by 64.57% over the study period, in contrast to a 21.44% increase among urban residents.

The difficulty in estimating the system of equations lies in the fact that the endogenous variable q_{it} depends on group expenditures, which include the estimated parameters $\bar{x}_t$ (Zhen et al., 2011). An instrumental variable (IV) approach is applied to address this issue. An IV variable needs to meet the following conditions: it needs to be exogenous (i.e., independent of the unobservable factors) and correlated with the endogenous variable q_{it} . Following Zheng and Henneberry (2010), $income_{it}$ is used as an identifying instrument as a function of refined total expenditure $\bar{x}_t$ and the group price index p_t . The first stage equation and demand function are estimated jointly to create a closed system which addresses the endogeneity problems in the model.

2.5. Estimation and Results

2.5.1. Habit Formation

To control for the expenditure endogeneity $\bar{x}_t$ when estimating a complete demand system in (9) and (11), a nonlinear full information maximum likelihood (FIML) estimation procedure was employed in our paper, as Zhen et al. (2001) and Zheng and Henneberry (2010) did in their work. A system of quantities equations (9) instead of budget share demand (5) was estimated for convergence purposes as in Zhen et al. (2011). Using the proc model in SAS, the model provides

Table 2.2. Selected key parameters for urban/rural consumers, 30 provinces, China, 2015-2022

Commodity	Habit Formation		Pre-committed	
	Urban	Rural	Urban	Rural
Pork	0.3242*** (0.0408)	0.3944*** (0.0350)	22.1096*** (3.9125)	22.2139*** (4.3406)
Beef	0.8589*** (0.0436)	0.9808*** (0.0246)	-1.3735 (1.6395)	1.5590 (2.3630)
Poultry	0.6355*** (0.0419)	0.8107*** (0.0389)	-12.153*** (4.1957)	-15.6599*** (4.3437)
Lamb	0.6842*** (0.0324)	0.7865*** (0.0363)	4.0944* (2.2192)	1.4212 (1.6499)

Table 2.2 reports the estimated habit formation parameters for urban and rural consumers. The results show that all habit formation parameters are statistically significant at the 1% level, indicating four meat categories have a high degree of habit formation. While pork remains an important component in consumers' diet, its dominance is gradually declining. Notably, the gap in meat consumption between the two groups is narrowing, and the difference in the habit formation parameters for pork is nearly identical (0.3242 VS 0.3944).

A comparison of the size of habit formation parameters between the two consumption groups indicates that rural consumers had a higher degree of habit formation in their diets for the four meat categories. This is particularly understandable in the case of pork, as previously discussed, owing to the continued increase of pork consumption among rural residents. For lamb and beef consumption, the results may seem counterintuitive, given that these two meats categories are more expensive, and urban residents have greater purchasing power. Nonetheless, habit formation is dynamic and can be affected by multiple factors during the formation process. First, rural meat consumers may also be producers (i.e., back yard production), hence their actual consumption includes both purchased and home-produced meat. Easy access to meat, regardless of its market price, might contribute to a high degree of habit formation. Second, rural residents

tend to buy in larger units, (i.e., one whole pig) rather than weight for a variety of reasons. For instance, they may prefer to buy a whole pig and then distribute the meat among family members and relatives or preserve it for future use. In contrast, urban consumers typically buy small quantities for immediate and fresh consumption. This difference in purchasing units indicates that consumers develop their habit formation based on the units in which they typically purchase. Third, urban consumers have greater access to food options, better nutrition awareness and higher levels of educational attainment. As a result, their meat purchasing decisions tend to be more rational, and the abundance of choices may diminish their habitual behaviour in routine meat consumption.

In rural areas, meat consumption is perceived as a symbol of good nutrition and social status. Varieties of meat food are typically offered at banquets, especially at important events like lunar Chinese New Year and weddings to boost self-esteem and earn respect from friends or relatives. Rural consumers attach greater cultural significance to meat consumption, which may potentially reinforce their habit formation.

A comparison of the magnitudes of habit formation parameters show that beef consumption is the most habit-forming meat category for each consumer group, followed by poultry, lamb, and pork. There is a slight difference in the ordering of the size of habit formation for urban consumers, where beef is followed by lamb, poultry and pork, though the difference between the two meat categories (lamb and poultry) is negligible (0.68 versus 0.64). The first explanation for this ordering of habit formation is that beef is widely accepted in each consumer group. Beef has shifted from being “rarely consumed” to “regularly consumed”, which might explain why we find a higher degree of habit formation in beef than in pork. Liu et al. (2025) identified nutritional value, health

benefits, and flavor as the three main reasons for consumers' preference for beef. Their survey conducted in North and East China found that respondents showed the highest preference for beef.

In addition, beef has been processed into convenient snacks for daily consumption, allowing consumers to meet their protein needs easily. The smaller quantities of beef snacks make it more affordable and accessible, helping to alleviate the financial burden that comes with its higher price. Nutrition and fitness experts advocate beef and chicken (particularly chicken breast) as low calorie, high protein food. These factors together contribute to the relatively high magnitude of habit formation in beef and chicken.

While high-protein beef remains popular for urban consumers, the need for nutritional variety has resulted in an approximately equivalent consumption of poultry and lamb. Urban and rural groups have relatively lower levels of pork habit formation, and this indicates consumers have experienced a substantial improvement in their living standards, which has influenced their meat consumption preference. Although pork has traditionally been considered “good meat”, it has been recently rebranded as “unhealthy red meat”. In addition, pork prices are subject to cyclical fluctuations and are highly volatile, which are often triggered by the outbreak of pandemics. Pork-related food safety issues have further eroded consumer confidence. One notable incident is the “Clenbuterol Case” at Jiyuan Shuanghui, a subsidiary of Shuanghui International Group, the leading pork processor. Despite being a trusted brand for years, the incident cast doubt on the company's reputation, with losses exceeding 12.1 billion Yuan. To regain consumer trust, Shuanghui purchased the U.S. pork giant Smithfield for \$7.1 billion in 2013. These factors may weaken habit formation associated with pork consumption.

The work by Wen et al (2024) suggests that habit formation may differ across income brackets and evolve over time. Yet, detailed income information for Chinese consumers over the

time studied is not available and hence a further investigation of heterogeneous habit formation in meat demand is not presented in this analysis. More likely, habit formation is influenced by various factors, such as geographic location (eastern, western, central, or northeastern regions), the COVID environment, and the level of educational attainment, etc. These factors are not included in the current analysis, as accounting for such heterogeneity would increase the model's complexity given the limitations of the data.

In summary, the habit formation is present for all four meat categories. Persistence for pork, which was once the most popular meat choice, has gradually declined, while beef consumption, in contrast, has increased significantly. Urban consumers, with relatively higher income and easier access to food, enjoy greater flexibility in their food choices. Their consumption patterns have become more rational and diverse. Rural consumers demonstrate a strong upward trend in overall meat consumption.

When it comes to pre-committed demand, both urban and rural consumers show significant and positive pre-commitment for pork, while displaying significant and negative pre-commitment for poultry. The finding for pork is consistent with the findings of Piggott and Marsh (2004) and Piggott et al. (2007), suggesting a stable quantity of pork is routinely purchased as part of their daily consumption, with pre-committed consumption levels being equivalent in either consumption group. Pork seems to remain in high demand in either consumption group. Traditionally, pork has been widely used as a preserved or processed food. Although modern consumers may no longer rely on preserved or processed items in their daily diets, cultural practices continue to influence the purchase behaviour for cured pork products for both consumption group.

The pre-committed result for poultry is negative, which differs with the findings of Piggot and Marsh (2004) and Piggot et al. (2007) but aligns with the results reported by Hovhannisyan and Gould (2011). One explanation for the negative C_i provided by Zheng and Henneberry (2009), is that in Chinese food consumption studies, the regularity conditions do not require C_i to be nonnegative. The absolute proportion of pre-committed poultry consumption is the second highest. The substantial pre-committed consumption in either group indicates that pork and poultry demand are more affected by nonprice and nonincome factors, while these factors possess no significant impact on beef and lamb except for lamb which is statistically significant at the 10% level in the urban consumption group. Tonsor and Marsh (2007) summarized several nonprice and nonincome factors that may potentially affect these pre-committed quantities, including food safety, generic advertising, health concerns, and differences in underlying consumption perceptions, etc. Relevant data were not collected over the same time period; hence, this study does not further examine the impact of those factors on the pre-committed demand estimates.

2.5.2. Price and expenditure elasticities

Note that the reported elasticities are derived using the estimated model parameters and averaged values for each sample point from 2015 to 2022. Estimating both short-term and long-term elasticity, particularly the latter, contributes to the literature on Chinese consumer demand analysis, where such estimates are typically neglected. Calculating long-run elasticities is challenging but critical for demand forecast and policy evaluation (Buchsbaum, 2023) as they reflect the steady state consumption patterns. Owing to unexpected price changes, false expectations, and the effects of habit formation, it usually takes time to reach a new equilibrium consumption level (Selvanathan et al., 2024). Effective decision-making in both supply and demand management thus requires consideration of both short and long run elasticities. This study

provides insights that may help improve government policies on meat consumption and production.

As shown in table 2.3, the long run group expenditure elasticities from the extended dynamic AIDS are found to be greater than unity for both urban and rural households, except for the poultry in the urban group, which has a value of 0.9. This finding is consistent with the long-term income elasticities for U.S meat demand reported by Kesavan et al (1993). As expected, the income elasticity of demand is larger in the long run than in the short run. The short run elasticities are less than unity in either consumption group which conforms with the study from Wen et al (2024).

Table 2.3. Short term and long-term Expenditure elasticities, 30 provinces, China, 2015-2022

Commodity	Longterm		Short term	
	Urban	Rural	Urban	Rural
Pork	2.3417** (0.6466)	1.8628*** (0.4554)	0.7169*** (0.0390)	0.7706*** (0.0095)
Beef	1.5721* (0.8461)	1.7580*** (0.4215)	0.4813* (0.2194)	0.7272*** (0.0741)
Poultry	0.9426* (0.3798)	1.6921*** (0.4014)	0.2886** (0.1075)	0.6999*** (0.0158)
Lamb	1.4823** (0.5042)	2.1925*** (0.9196)	0.4538*** (0.0824)	0.9069*** (0.0056)

Table 2.4. Marshallian price elasticities, urban 30 provinces, China, 2015-2022

Commodity	Pork	Beef	Poultry	Lamb
Pork	-0.6021*** (0.0256)	-0.0762** (0.0280)	0.0158 (0.0158)	-0.0549* (0.0295)
Beef	1.0050 (1.0373)	-0.4389 (0.3801)	-0.0673 (0.1671)	-0.9797 (1.0236)
Poultry	0.2737*** (0.0755)	-0.0319 (0.0515)	-0.6725*** (0.0412)	0.1427* (0.0672)
Lamb	0.0107 (0.0107)	0.3028* (0.1262)	-0.1228 (0.0778)	-0.6445* (0.1230)

Table 2.5. Marshallian price elasticities, rural 30 provinces, China, 2015-2022

Commodity	Pork	Beef	Poultry	Lamb
Pork	-0.8223*** (0.0264)	0.0034 (0.0135)	0.2311 (0.0506)	0.0341 (0.0221)
Beef	0.0775 (0.0758)	-0.7225*** (0.1299)	0.2469* (0.1234)	-0.0713 (0.1470)
Poultry	0.0557* (0.0226)	0.0069 (0.0206)	-0.7975*** (0.0174)	0.0352 (0.0231)
Lamb	0.4048 (0.5073)	-0.1805 (0.3755)	-0.1740 (0.2525)	-0.9572* (0.4975)

The Marshallian own price elasticities are negative, with relatively elastic own price responses for chicken in the long run for urban consumers and pork for rural consumers (see Table 2.4 and 2.5). Long run own price responses tend to be more elastic for rural consumers than for urban consumers, which conform with expectations. Within the rural consumption group, because meat consumption has grown substantially over the past decades as per capita income has increased, this finding is not surprising. Within the urban meat consumption group, the cross-price elasticities indicate poultry to be a substitute for pork, whereas pork is complement for beef, and lamb is a substitute for beef. In the rural consumption group, the cross-price elasticities indicate that beef and pork are both substitutes to poultry.

Hicksian elasticity estimates are presented in Appendix Table B.5 and B.6. Specifically, the price elasticity of demand for rural consumers is more elastic compared to that of urban consumers. This is possible given the relatively high income for the urban consumers whose per capita income is 2.39 times that of the rural consumers. Overall, the two sets of elasticities are generally close to each other. It is interesting to note some of the exceptions including strong substitution between pork and lamb, and between lamb and poultry, as well as complementarity between beef and poultry amongst rural meat consumption. These substitution and complementarity effects are not significant in the Marshallian elasticity. This happens because

Marshallian elasticity includes both income and substitution effects, which may offset each other, while Hicksian elasticity isolates the substitution effect by adjusting income to maintain the same utility level.

The demographic variables were included to examine the impact of population aging, slowing population growth and shrinking family size on meat demand. The findings are reported in the Appendix Table B.3 and B.4. The influence of these variables in shaping meat demand can be assessed by combining the elasticity estimates with the observed changes in these variables between 2015 and 2022. Overall, holding other factors constant, slowing population growth showed no significant effect on meat consumption among rural residents, but showed a negative impact on pork consumption in urban areas. The increasing proportion of seniors had no significant impact on meat consumption for urban consumers, whereas it had a positive effect on pork consumption and a negative effect on beef and lamb consumption among rural consumers.

2.6. Predicting budget shares changes in meat consumption in the next decade

Estimating demand elasticities allows us to better determine the patterns of meat demand changes in China. We use the estimated elasticities with the income and demographic variables to predict the influence of those factors on changed meat budget shares among urban and rural consumers in 2032. Following Zheng et al. (2019), five scenarios are considered. The first through the fifth scenarios consider the impacts of GDP growth, slowing population growth, population aging (reflected in a decreasing proportion of children in the population, and an increasing proportion for seniors), and smaller family size. Each scenario is examined separately to assess its effect on the budget shares for each consumer group. The fifth scenario looks at the combined effects of all factors occurring concurrently. The estimated budget share predictions in year 2032 are reported in tables 2.6 and 2.7. Predicted meat consumption demand in quantities resulting from

changes in the income and demographic variables in 2032 is presented in the appendix Tables B.7 and B.8.

2.6.1. Impacts of GDP growth

China's future GDP growth (measured as per capita gross domestic product) is projected by the IMF and JP morgan to be high (5.2%), medium (4.4%) and low (3.4%) over the next decade. Based on the long run income elasticities estimated, we forecast changes in per capita meat consumption and then evaluate how the budget share allocated to each meat category changes accordingly. The estimates in Tables 2.6 and 2.6 indicate that rising per capita income is predicted to diminish the budget allocations for pork while increasing allocations for beef and lamb in both consumption group, although the increases are substantially large for the urban population. With relatively higher income, consumers tend to shift from traditional meat such as pork to more expensive options like beef. There is a different effect for poultry consumption, with a slight increase amongst urban consumers and a decrease amongst rural consumers.

2.6.2. Impacts of demographics changes

Pork and poultry consumption is projected to decline in their share of total meat expenditure in response to population aging and slowing population growth for both urban and rural consumers while consumption of other meat is projected to increase. Smaller family size has a relatively larger impact on lamb consumption, followed by beef consumption, with the magnitude of the impact being greater in the urban group than in the rural group.

Table 2.6. Predicted impacts of GDP growth, demographics change, and the combined effects on the budget share of meat demand for urban consumers in 2032.

Note: GDP growth is projected under three scenarios: 5.2% (high), 4.4% (medium), and 3.4% (low)

	2022	Proportion of		Population growth	Family size	GDP growth			Combined impacts		
		seniors	children			High	Medium	Low	High	Medium	Low
Pork	0.5345	0.5039	0.5051	0.5074	0.5018	0.4069	0.4065	0.4059	0.4233	0.4238	0.4228
Beef	0.1759	0.1924	0.1931	0.1929	0.1930	0.2409	0.2412	0.2414	0.2783	0.2781	0.2786
Poultry	0.1698	0.1608	0.1597	0.1581	0.1604	0.1870	0.1872	0.1874	0.1954	0.1952	0.1956
Lamb	0.1198	0.1429	0.1421	0.1416	0.1448	0.1652	0.16517	0.16519	0.1651	0.1651	0.1651

Note: Figures indicate budget share of meat consumption in 2032

Table 2.7. Predicted impacts of GDP growth, demographics change, and the combined effects on the budget share of meat demand for rural consumers in 2032.

Note: GDP growth is projected under three scenarios: 5.2% (high), 4.4% (medium), and 3.4% (low)

	2022	Proportion of		Population growth	Family size	GDP growth			Combined impacts		
		seniors	children			High	Medium	Low	High	Medium	Low
Pork	0.5956	0.5779	0.5689	0.5642	0.6031	0.5771	0.5771	0.5771	0.5772	0.5772	0.5772
Beef	0.1213	0.1278	0.1298	0.1310	0.1262	0.1342	0.1342	0.1342	0.1593	0.1593	0.1593
Poultry	0.1753	0.1649	0.1651	0.1650	0.1565	0.1687	0.1687	0.1687	0.1717	0.1717	0.1717
Lamb	0.1079	0.1321	0.1362	0.1399	0.1143	0.1200	0.1199	0.1199	0.1372	0.1372	0.1372

Note: Figures indicate budget share of meat consumption in 2032.

2.6.3. Impacts of combined impacts

How does GDP growth and combined demographic changes affect the budget share of meat consumption? As shown in the last three columns in tables 2.6 and 2.7, rising per capita income, along with the demographic changes, is projected to lead to a significant increase in the budget share of beef consumption for urban consumers, with an increase of over 40% (30% for rural consumers), followed by a rise in poultry consumption. The quantity of poultry consumed by rural consumers remains nearly the same as before (see Appendix Table B.8). Conversely, the budget share of pork for both urban and rural consumers is expected to decline, with urban consumers reducing their pork consumption by up to 20.8%. However, the quantity of pork consumed does not change substantially in urban areas, and even shows a slight increase among rural consumers, indicating that pork continues to account for a large share of total consumption in both groups (see Tables B.7 and B.8 in the appendix). Although lamb's budget share increases in either group, its consumption quantity remains relatively stable (see Tables B.7 and B.8 in the appendix), indicating that the rise in budget share is driven primarily by price effects rather than changes in consumption levels. Lamb has good nutrients, but its special flavour and the cuisines made with lamb make it more popular in the northern and western part of China (Liu et al., 2025). This indicates that high good protein meat (beef and poultry) will represent a larger portion of meat expenditure in the future. Hence, beef and poultry consumption is expected to become essential in consumers' future diet choices.

2.7. Conclusion and Policy Implications

The extended dynamic AIDS model is applied to Chinese aggregate data to estimate meat demand and examine habit formation effects and differences in pre-committed diets in urban and rural consumption sample. In comparison, rural consumers had higher habit formation levels

compared to urban consumers, with beef consumption showing the highest degree of habit formation and pork the lowest. Furthermore, a higher-level pre-commitment for pork (compared to other meats) is indicated for both consumption groups.

With the elasticities we derive, along with the variation in the income and demographic variables, we predict the influence of those factors on changes in the budget shares of meat consumption categories in 2032. The results indicate that as per capita income increase, the population ages, population growth slows, and household size shrinks, the budget share allocated to pork declines, while the share for beef, poultry and lamb increases.

Using the predicted per capita consumption levels, the aggregate household consumption for the national population in 2032 was subsequently calculated. Over the past two decades, China's population growth rate has undergone a sustained decline, decreasing from 5.89‰ in 2005 to -0.60‰ in 2022, when the country experienced negative population growth for the first time. Using the urban and rural populations in 2022 as the baseline and assuming the same rate of population change, the projected urban and rural populations in 2032 are 915.20 million and 488.10 million, respectively. Applying the predicted per capita consumption values (as reported in Appendices B.7 and B.8), the total household consumption of pork, beef, poultry, and lamb in 2032 is estimated to be 36.37, 3.77, 15.09, and 2.88 million tons, respectively.

It is important to note that China's aggregate meat consumption can be measured using two approaches: household meat consumption and disappearance based on the assumption that total consumption equals total supply. In this study, disappearance is defined as total production plus net imports (imports minus exports), minus the change in inventories (ending inventory minus beginning inventory) (Gale and Dong, 2023). The two measures produced similar results during the 1980s, but they diverged during the 1990s as disappearance rose at a much faster pace (Gale

and Dong, 2023). Due to the unavailability of data on China meat exports and inventory changes, these components are excluded from the disappearance calculation. Consequently, meat disappearance is approximated as the sum of total domestic production and total imports. The estimated disappearance of pork is 57.17 million tons, with imports accounting for 3.08 percent of the total supply. The corresponding disappearance estimates for beef, poultry, and lamb are 9.87, 17.19, and 5.60 million tons, with import shares of 27.25, 3.40, and 6.39 percent, respectively. Assuming that the ratio between household consumption and disappearance remains unchanged (1.5960 for pork, 2.6477 for beef, 1.1483 for poultry, and 1.9639 for lamb), the projected meat disappearance in 2032 can be calculated accordingly.

Furthermore, if the proportion of imported meat to total disappearance is assumed to remain unchanged, under these assumptions, the projected import quantities in 2032 are 2.72 million tons for beef, 1.79 million tons for pork, 0.59 million tons for poultry, and 0.36 million tons for lamb. However, constrained by limited growth in key inputs, particularly land and water, along with tougher laws addressing environmental issues, an exodus of small-scale farmers, the meat production will be hard to meet the domestic consumption, therefore, the country has to rely on the large scale imports international market for satisfy the domestic food demand, especially for high value and high protein products (Sheng and Song, 2019; Gale and Dong, 2023; Ghose, 2014). As domestic production declined, China's meat imports expanded rapidly to satisfy growing consumer demand. From 2010 to 2023, the country's net meat imports grew nearly fiftyfold, with an average annual increase of 34.8% (Economic Daily, 2024). China remains the world's largest meat import despite a recent decline in import growth. In 2022 China imported 43 percent more than the second largest meat importing country, Japan (Gale and Dong, 2023). Over the past five years, net beef imports alone have risen at an average annual rate of 21.4% (Economic

Daily, 2024). If this growth rate persists, China's beef imports could reach approximately 20.64 million tons by 2032.

Given that pork is the dominant nutrient source in the Chinese diet, ensuring price stability has been a longstanding policy goal of the Chinese government. However, with declining habit formation of pork consumption, poultry emerging as a significant substitute and increasing habit effects for beef as an alternative nutrient source, navigating this transition to have meat demand, supply and trade policies become crucial. For instance, the outbreak of African Swine Fever (ASF) in August 2018 severely impacted China's hog industry, resulting in a major increase in pork prices. In response, policy efforts have centered on significant financial interventions, including billions of RMB in subsidies to large pork producers, with the aim of stabilizing prices and ensuring supply (Wang, 2022). Constrained by biological lags in hog production, restoring pork output to previous levels within a short timeframe remains challenging (Ma et al., 2021). Future policy should place greater emphasis on monitoring shifts in consumer demand to ensure that nutritional needs of consumers, especially in the context of changing demographic and income patterns. Achieving this goal involves implementing effective supportive policies, such as subsidizing domestic poultry production (Ma et al., 2021), promoting beef and related products, and diversifying beef imports from countries with a comparative advantage, such as Australia, New Zealand, Argentina, and other major beef-producing nations (Zhu et al., 2021). Additionally, understanding food consumption pattern variation of a large country like China is crucial for supporting the continued growth of international trade, particularly for export-oriented nations with substantial agricultural surplus (Halbrendt et al., 1994).

While this article does report previously unexamined habit formation and pre-committed effects in Chinese meat consumption, accounting for these factors in our demand model with seven

years of provincial-level data is challenging. Understanding the factors influencing different income brackets is essential, as it enables the government to implement targeted subsidies, price adjustment policies, and, importantly, design more effective meat trade strategies to maintain a stable domestic supply. In addition, it helps meat producers and processors optimize their product offerings and market positioning to meet the demand for healthier meat across income levels. Future work should be built upon this article by using household survey or scanner data sources to capture differences in household income over long time spans, allowing for analysis of intertemporal variations in habit formation and pre-commitment. Furthermore, there is potential to explore regional heterogeneity in these effects. The model specification is flexible and could be easily adapted to accommodate these extensions.

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Chapter 3 - Did China's Five-Year Plans Induce or Inhibit Differential Productivity across Provinces?

3.1. Introduction

For decades, China's economic narrative has been defined by remarkable growth, averaging around 9.5% per year between 1980 and 2022 (World Bank, 2024). This impressive expansion, driven by rural reforms and opening-up policies, has fundamentally reshaped its agricultural sector and positioned China as a fast-growing economy (Huang and Rozelle, 2010; Huang and Rozelle, 2018). However, this rapid growth has not been uniform, leading to a sharp increase in regional disparities (Fan et al., 2011). Do these inequalities between east and west, north and south, and urban and rural areas represent a significant challenge to China's long-term sustainable development?

One of the policies introduced by the government has been the five-year plans (FYP) to address these regional disparities and serve as the overarching framework for overall economic growth, including agricultural development. Despite their central role, it remains an open question whether these plans have successfully promoted coordinated growth or inadvertently exacerbated regional productivity gaps. This paper aims to shed light on this issue by examining the relationship between the FYPs and differential productivity across Chinese provinces.

Addressing this issue is critical because rising inequality can lead to political tensions and social instability, which can, in turn, hamper overall economic growth and hinder long-term productivity improvements (Kanbur and Lustig, 1999). Promoting balanced development is a key national goal in China, and a better understanding of how policies like the FYPs affect regional productivity is essential for designing future strategies to ensure sustainable and harmonious development across all provinces. Maintaining a balanced development requires both efficiency

and equity, but the goal should be pursued in a dynamic balance between efficiency and equity throughout development. Striking this balance involves trade-offs between efficiency and equity, with the ultimate criterion being whether it promotes economic growth, enhances productivity. During economic downturns, limiting regional disparities is crucial, prioritizing equity to prevent social tensions. In periods of faster growth, rising positive expectations ease the tension across regions, making efficiency more important to capitalize on growth opportunities.

To promote balanced regional development, *China's Agricultural Modernization Plan (2016–2020)* was implemented and targeted policies based on local conditions. Regions with favorable water and soil resources, such as the Northeast and North China, designated as “optimized development zones” are encouraged to enhance the production capacity of key agricultural products and accelerate agricultural modernization. In contrast, areas with more constrained agricultural resources and environmental conditions are designated as “moderate development zones,” where policies focus on adjustment in the agricultural structure, for example, reducing wheat cultivation while maintaining stable cotton production in the Northwest. This approach demonstrates that coordinated regional development is driven by comparative advantage and specialization, rather than a uniform economic model across all regions.

However, most previous studies on China's agricultural productivity have not focused on the role of FYPs in inducing or inhibiting these inequalities (e.g., McMillan et al., 1989; Lin, 1992; Wen, 1993; Brümmer et al., 2006; Sheng et al., 2020). Examining this link will provide valuable insights for shaping future policies to achieve more balanced development.

This paper assesses the impacts of China's FYPs by integrating the linear programming Malmquist productivity index and econometric regression analysis to examine the importance of these plans on differential productivities in two steps: Step 1: Measuring Productivity. A

Malmquist Total Factor Productivity (TFP) index is estimated to measure and analyze provincial agricultural productivity between 2001 and 2022. This is a linear programming method, that does not require specifying a functional form for the production function and can be used without price data for inputs and outputs (Lambert and Parker, 1998; Headey et al., 2010), addressing a key criticism of traditional parametric approaches (Arnade,1994). These results allow for the assessment the changes in agricultural productivity across Chinese provinces. Further, to examine if convergence occurs within each region and if provinces with lower TFP growth are experiencing catch-up effects, two convergence tests are estimated.

Step 2: Assessing the impact of FYPs. An econometric model is developed to analyze whether the FYPs have induced or inhibited differential productivity among Chinese provinces. In particular, we analyze the relationship between the FYPs and productivity, while controlling for other key determinants that may influence provincial productivity. By examining the influence of FYPs across different time periods, the study offers a unique contribution to the literature, moving beyond analyses of general reforms (Wang et al., 2019) to evaluate a central, recurring element of China's economic policy.

3.2. Brief review of China's Five-Year Plans and Agricultural Policies

3.2.1. Agricultural Five-year plan

The FYP is China's national framework for economic and social development, combining objectives and policies to correct market failures, allocate public resources effectively, and promote sustainable and coordinated growth through both market mechanisms and government intervention (Zhan,2020). Each FYP's economic policies play a crucial role in guiding high quality agricultural development by adjusting investment policies, regulating competition and governing the environment (Han et al., 2023).

Since 1949, China started to launch the FYP. Over the past seven decades, China has successively formulated and implemented fourteen FYPs, each serving as a cornerstone for advancing social and economic development. Upon completion of each FYP, prominent issues in economic and social development are identified for correction and resolution in the subsequent FYP. Furthermore, strategic considerations, such as adjustments to the socioeconomic structure, are consistently made, thereby providing guidance and recommendations for the continued advancement of the market economy system.

3.2.1.1. Planned economy (from the "first FYP" to the "fifth FYP")

Table 3.1. briefly summarizes the evolution of the fourteen FYPs, highlighting major events in each period that have significantly influenced overall economic development. The First FYP (1953-1957) was successful, promoting China's economic growth and establishing the foundation for China's industrialization (Huang,2025). However, the imbalance between industrial and agricultural development gave rise to sluggish growth of agricultural production. Following the completion of the first FYP in 1957, subsequent plans were implemented. The second FYP (1958-1962) was also known as the “Great Leap Forward”, with unrealistic quotas for both agricultural and industrial production. The industry-centered industrial policy ended in the stagnation of China’s agricultural industry and massive national famine (1959-1962). The third FYP (1966-1970) was not actually formulated due to the sudden occurrence of the Great Culture Revolution (1966-1976). During the fourth FYP (1971-1975) period, China’s economy, including agricultural production, was marred by the pursuit of unrealistic quotas and the turmoil left from Great Culture Revolution. The fifth FYP (1976-1980) is often characterized as a “New Leap Forward and Big Transition” period. While the end of the Great Cultural Revolution signified the

beginning of economic reconstruction, the pursuit of the “New Leap Forward” produced significant structural distortions in the national economy and undermined its overall development.

3.2.1.2. Transition from a planned economy system to market economy

(from the "sixth FYP" to the "ninth FYP")

The sixth FYP (1981-1985) was the first plan following the introduction of the reform and opening up policy, indicating a change in the national central task toward economic development. After implementing multiple economic reforms and policies, China’s agricultural production expanded significantly. The seventh FYP (1986-1990) was a crucial transition from a planned economy to a market-oriented economy. Building on this shift, the eighth FYP (1991-1995) further advanced the replacement of the centrally planned system and government intervention with a market mechanism (Gong, 2018). The ninth FYP (1996-2000) accelerated the pace of reforms, and this plan contributed to an average annual GDP growth of 12%.

3.2.1.3. Market Economy (from the "tenth Plan" to the "fourteenth Five-Year Plan")

The tenth FYP (2001-2005) continued a gradual shift from directive planning to market-based resource allocation, with annual GDP growing by 9.8%. In 2001, China joined the WTO, which accelerated the rapid growth of its export-oriented economy.

The eleventh FYP (2006-2010) aimed to expedite economic structural adjustments, shift the growth pattern, and promote more balanced regional development. Starting with the eleventh FYP in 2006, China replaced the term “Ji Hua” with “Gui Hua”, both of which were translated in “Plan”, a seemingly minor word change indicating a significant shift in the government’s role from a directive authority to a more regulatory and coordinative role within a market economy (BBC,

2020). Under “Ji Hua”, the government relied on detailed quantitative targets as its primary instrument of economic control. With the adoption of “Gui Hua”, the focus shifted toward strategic guidance, placing greater reliance on market mechanisms to achieve development objectives (BBC, 2020). Nonetheless, the global financial crisis that occurred in 2008 brought uncertainties to economic development. For instance, China’s agricultural trade declined sharply, with the trade surplus falling from \$15 billion at its peak in 2006 to just \$454 million in 2008. This had a negative impact on China’s overall economy, leading to a slowdown of economics growth to 12.4% over the year, which was 3.9 percent points lower than the growth rate in 2007 (NBS report, 2011)

The goal of twelfth FYP (2010-2015) was to address rising inequality and accelerate the transformation of the economic development mode. With an emphasis on long term development, the thirteenth FYP (2016-2020) prioritized coordinated and sustainable development. Towards the end of this plan, however, the sudden emergence of COVID-19 caused an unprecedented shock to the goal of sustainable development. The fourteenth FYP (2021-2025) faces numerous developmental challenges, but raising productivity to ensure stable long-term growth is certainly one of the paramount goals that the central government should give priority to (Kwong, 2025). For example, optimizing the spatial distribution of the regional economy and fostering balanced regional development is one of its main goals

Table 3.1. Five-year plans and years included

Five-year Plans	Years included	Major Events
First FYP	1953-1957	Establish a foundation for industrialization.
Second FYP	1958-1962	“Great Leap Forward”
Third FYP	1966-1970	Great Culture Revolution
Fourth FYP	1971-1975	Great Culture Revolution
Fifth FYP	1976-1980	“New Leap Forward and Big Transition”
Sixth FYP	1981-1985	Transition from a Planned Economy system to Market Economy
Seven FYP	1986-1990	
Eighth FYP	1991-1995	
Ninth FYP	1996-2000	
Tenth FYP	2001-2005	Market Economy
Eleventh FYP	2006-2010	
Twelfth FYP	2011-2015	
Thirteenth FYP	2016-2020	
Fourteenth FYP	2021-2025	

3.2.2. Agricultural Policies

Agricultural policy reform has been a major driving force in China’s agricultural sector, and those policies play a crucial role in promoting productivity growth and self-sufficiency, especially in the grain sector (Brümmer et al., 2006). In China, agricultural policies are usually developed to meet specific planning objectives, typically targeting short-term goals in particular regions or agricultural sectors. Therefore, the implementation of these policies may yield significant implications for agriculture in the short term, yet their long-term effects require further evaluation.

In the late 1950s and 1960s, forced collectivization deprived farmers of incentives to increase production, leading to a sharp decline in both agricultural production and productivity (Fan et al., 2002). Hence, the implementation of de-collectivization (a change from the commune system to the household system), price adjustments, and other reforms resulted in dramatic growth in the agriculture sector, characterized notably by the transition from the collective farming system to an individual household-based farming system (Lin, 1992). The de-collectivization and

decentralization diversified the rural economy and spurred agricultural growth (Gong, 2018). The Household Responsibility System (HRS), which restores the individual household and replaces the production team system as the unit of production and accounting in rural areas (Lin, 1987), was initially introduced in 1978. This reform was so successful that the government was encouraged to expand its implementation to other provinces, ultimately stabilizing it as the fundamental land policy in the later sixth FYP. Meanwhile, this period witnessed a “double-track system” which allowed the coexistence of planned and market factors (Garnaut et al., 2018). Since then, the market-oriented agricultural sector has established, and agricultural prices were gradually liberalized (Wang et al., 2013). However, the late 1980s experienced no significant gains because of labor outflows from the agricultural sector (Brümmer et al., 2006), rising input prices (Fan et al., 2002), declining technical efficiency, unsuccessful marketisation reforms and political uncertainties (Huang et al., 2018).

The price and market reforms for agricultural commodities, especially the abolishment of the agrarian rationing system in 1993, facilitated the transformation of China’s agriculture from a command and control system to a largely free-market system. This transition benefited farmers by facilitating the reallocation of land and labor from grain production to livestock production, which significantly improved resource allocation and increased farmers’ income (Fan et al., 2002; Lohmar et al., 2009). Moreover, the notable increase in quota prices for grains aimed at stimulating production growth and ensuring adequate food supplies contributed significantly to the growth in grain production in 1996 (Fang and Beghin, 2000). Further, farmers were encouraged to produce high value-added agricultural products that could potentially yield higher returns (Wang et al., 2013). These factors facilitated rapid productivity growth between 1990 and 1997, as examined by Fan et al. (2007), who attributed it to the increase in procurement prices.

Despite China's primary goal of achieving self-sufficiency in agricultural products, China gradually reduced tariffs and other trade barriers throughout the 1990s for agricultural products (Lohmar et al., 2009). In 2001, China's accession to the WTO led to the eventual elimination or reduction of trade distorting domestic subsidies (Fang and Beghin, 2000). The nationwide elimination of agricultural taxes on farm households in 2004 (Wang et al., 2013), along with the introduction of direct subsidies, input subsidies, price supports, and reforms in rural credit systems, were implemented to address the growing income gap between urban and rural residents (Lohmar et al., 2009). Therefore, China's agricultural policies shifted towards a comprehensive framework to solve rural welfare and income distribution issues and enhance agricultural production capacities (Zhang and Brümmer, 2011). The agricultural subsidies grew rapidly and reached 170 billion Yuan, which was eight times the government's investment in agricultural R&D (Huang and Rozelle, 2018). However, with the exception of agricultural machinery subsidies, all other subsidies were detached from individual farmers' actual production activities, resulting in a limited impact on crop output and farmer income (Huang and Rozelle, 2018). Wang et al. (2013) calculated the productivity index during the period 2000-2007 and found a decline in productivity growth.

Owing to the substantial fiscal burden and ineffective outcomes of those subsidy programs, the amount of agricultural subsidies began to decline after 2012. To optimize the fiscal support system for agriculture and improve the efficiency of agricultural subsidy policies, "three direct subsidies" (grain producers, agricultural input payments and improved seed variety subsidy) for agriculture were consolidated into agricultural support and protection subsidies (OECD, 2018). In 2004, China became a net food importer because of rising production costs (Huang and Yang, 2017), relying more on imported food to feed its 1.4 billion people. Since then, special attention

has been increasingly paid to food security. In addition, food security faces growing challenges from degraded land caused by overuse of fertilizer and chemicals, adverse climate conditions, declining agricultural labor and the constraints posed by small-scale operations on household farms (Sheng et al., 2020). In 2023, the food security guarantee law was enacted to resolve this issue in the long run. As a result, the focus of agricultural policies in recent years has shifted from an emphasis on production to a more balanced approach that integrates both production and ecological concerns. Owing to the challenges above, China's agricultural productivity growth slowed after 2009 as agricultural reform and policies progressed, suggesting the need for further institutional reforms (Sheng et al., 2019).

3.2.3. Integrate Five-Year Plans and Agricultural Policies

Because of political turmoil, ideological shifts, and natural disasters in the early decades of the last century, China's agricultural sector performed poorly. In response, the central government began rural reforms in 1978. Since the early 1980s, China has implemented a double-tier management system in rural provinces that combines collective and individual management, which has become the country's fundamental agricultural system and significantly enhanced rural productivity. Based on this agricultural system, land ownership is allocated between individuals and the collective. Individual farmers are assigned land as the basic production unit responsible for agricultural production, while the collective takes charge of public agricultural affairs, such as coordinating land transfers. This arrangement not only preserves farmers' incentives but also allows the collective to manage what is beyond the capacity of individual households. This rural agricultural system was further consolidated in subsequent FYPs. Table 3.2 summarizes the major agricultural policies under each FYP period. Different from the policies discussed earlier, agricultural strategies in the FYPs place greater emphasis on long-term stability and sustainable

development, prioritizing agriculture as the foundation of the economy, protecting the farmers' rights and interests, and promoting rural revitalization.

The most important reform of the sixth FYP (1981-1985) was the formulation and eventual predominance of Household Responsibility System (HRS) (Lin, 1997). By 1984, more than 99% of production units had adopted the HRS. During this time, national GDP grew at around 10% and the rate of poverty was reduced (Fan et al., 2002). This signified the beginning of a new chapter in China's agriculture. The seventh FYP (1986-1990) was designed to further liberalize the country's agricultural pricing and marketing system, however, reforms in procurement prices in 1985 raised production costs and brought an end to the period of rapid agricultural production growth (Fan et al., 2002).

The eighth FYP (1991-1995) continued to implement market and price reforms, and it further promoted agricultural modernization through increased investment in agriculture and advancements in science and technology. To stimulate growth in food production, the eighth FYP reformed procurement and distribution policies, encouraging major grain-production regions and farmers to accelerate agricultural production capacity. Although these market-oriented agricultural policies were successful in fostering steady growth in agricultural production, the insufficient agricultural capacity fell short of meeting the demands of the growing population. Hence, the central government decided to attain self-sufficiency in agricultural products in the subsequent ninth FYP (1996-2000).

Reforms on rural pricing and market mechanisms were continued during the ninth FYP. The removal of legal restrictions on factor market exchanges after these reforms resulted in improved resource allocation and productivity growth (Lin, 1995). The phasing out of the old centrally planned "purchase and supply" system in favor of market oriented solutions stimulated

farmers enthusiasm for production (Brümmer et al., 2006). The implementation of market oriented rural policies substantially increased the production capacity of major agricultural products, reflecting a historic shift from long-term shortages to an overall balance in agricultural supply. Nonetheless, significant challenges persisted, such as incomplete market system reforms, institutional barriers to productivity growth, inadequate technological progress, limited innovation capabilities, sluggish growth in farmers' income, and growing disparities in regional development.

To address disparities in regional development, the tenth FYP (2001–2005) called for advancing the Western Development strategy, accelerating development in central and western regions, and promoting growth in the eastern regions to create regionally distinctive economies. From this FYP onward, coordinated regional development became one of the priorities. In response to the pressing challenges in rural areas, this plan placed focus on the so-called "three rural issues" (agriculture, rural areas, and farmers), that are major concerns to the agricultural reform and modernization agenda. Policy emphasis moved towards improving the quality and efficiency of productivity development. In addition, grain procurement policies were expedited, enabling farmers to sell surplus products at protected prices and obtain financial subsidies from the central government, particularly in major intensive grain production areas. The total output of the agricultural and rural sectors saw a significant rise.

Building on the objective of coordinated regional development, the Western Development strategy was continued in the Eleventh Five-Year Plan (2006–2010). To maintain grain self-sufficiency and stabilize production, the plan prioritized enhancing agricultural productivity by strengthening the overall capacity of the sector. With the acceleration of structural adjustment in agriculture through shifts in agricultural industry structure, regional agricultural layout, and the

promotion of high quality, high value-added products, grain production yielded good harvests. Still, the challenges stated above were hindering the sustainable development of agriculture.

The twelfth FYP (2011-2015) attached significant importance to agricultural technology innovation to address those persistent problems. Meanwhile, more supportive pricing policies were implemented in the agricultural price protection system, bringing about a gradual minimum procurement price for essential grain commodities. During this period, investment in the “three rural” areas (agriculture, rural areas, and farmers) increased substantially. Agricultural production capacity improved substantially, and grain output achieved successive productive harvests. However, major challenges persisted, including rising production costs and a continuous outflow of production factors, particularly young labor in urban areas, which exacerbated the disparity between urban and rural development. Intensifying resource constraints have further undermined the sustainability of yield growth, making reliance on high input unsustainable.

Agricultural modernization has made notable progress. Yet, the need for efficiency improvement in agricultural production remains critical. Disparities in regional development were pronounced, exacerbated by inefficient spatial growth, and tightening resource restrictions. Environmental degradation has not been fundamentally reversed, and rapid aging of the population presents challenges for maintaining sustainable production growth. To promote coordinated regional development, the thirteenth FYP (2016–2020) further implemented the overall regional development strategy by advancing the Western Development strategy, the Northeast Revitalization plan, the Rise of Central China initiative, and the development of leading eastern regions, aiming to foster balanced regional growth and narrow disparities between different areas. Meanwhile, it reaffirmed its commitment to promoting agricultural modernization through improvements in technology growth and production efficiency. Also, it aimed to improve the

agricultural support and protection system, ensure a continuous rise in agricultural investment, and to establish more efficient systems for agricultural product pricing and procurement. These efforts were intended to achieve long-term development in the agricultural sector.

Under the fourteenth FYP, policies continued to promote sustainable regional development. Agricultural rural reforms extended under the fourteenth FYP, with adjustments to the agricultural structure, increased support for agricultural production, and policies designed to direct resources to rural areas. Support for agricultural investment has been further strengthened, particularly through refining the compensation mechanism for major grain-producing regions, establishing a new agricultural subsidy policy framework, and improving the minimum grain purchase policy. The implementation of these measures aims to provide policy and institutional support for the development of agriculture and rural areas. More importantly, it highlights the goal of increasing environmental quality and improving resource utilization efficiency to boost the international competitiveness of agriculture. By implementing strategies for the green development of China's agriculture, these policies can help establish a recycling system to facilitate the transition towards agricultural sustainability.

Table 3.2. Five-year plans and major policies introduced

Five-year Plans	Policy Introduced
Sixth FYP (1981-1985)	1.A “double-tier management” system in rural provinces that combines collective and individual management 2.A “double track approach” which combines both planned and market factors.
Seven FYP (1986-1990)	1.A “double track approach” which combines both planned and market factors. 2. Agricultural pricing and marketing system reforms
Eighth FYP (1991-1995)	1.Market-oriented agricultural reforms.
Ninth FYP (1996-2000)	1.Market-oriented agricultural reforms continued

Tenth FYP (2001-2005)	1. Western development strategy 2. Policies on "Three rural issues" (agriculture, rural areas, and farms). 3. Agricultural market reforms.
Eleventh FYP (2006-2010)	1. Grain self-sufficiency strategy 2. Structural adjustment in agricultural sector.
Twelfth FYP (2011-2015)	1. Regional development coordinated strategies 2. Supportive investments on "Three rural".
Thirteenth FYP (2016-2020)	1. Agricultural modernization through investments in technology. 2. Agricultural product price support and protection system
Fourteenth FYP (2021-2025)	1. Supportive investment or policies allocate resources to rural areas. 2. Green agricultural development strategy

3.3. Theoretical Framework

The Malmquist Productivity Index is employed to compute TFP (Fare et al, 1994) through either an output-oriented or input-oriented approach. TFP is a measure that uses all of inputs to the production process and is defined as the ratio of total output over total inputs (Wang et al., 2013). Let $y_t > 0$ denote the quantity of output produced during period "t" and let $x_t > 0$ signify the quantity of inputs used by the firm during period t . In this framework, $t = 0, 1$, where t_0 denotes the prior year t_0 and t_1 the current year (t).

$$\text{Productivity (t)} = \frac{y_t}{x_t} \quad (1)$$

$$\text{Productivity (t - 1)} = \frac{y_{t-1}}{x_{t-1}} \quad (2)$$

$$\text{Productivity Change} = \frac{TFP_t}{TFP_{t-1}} = \frac{\frac{y_t}{x_t}}{\frac{y_{t-1}}{x_{t-1}}} = \frac{\Delta y}{\Delta x} \quad (3)$$

Following Caves et. al (1982), the Malmquist Productivity index quantifies the radial distances of input and output vectors in the period of $t - 1$ and t associated with reference technology. D_0^{t-1} and D_0^t are the output distance function in period $t-1$ and t , respectively. Output-oriented Malmquist productivity index with respect to the technology in the period of $t - 1$ is expressed in equation (4) (Mizohuvhi, 2015).

$$OMP_0^{t-1} = \frac{D_0^{t-1}(x^{k,t}, y^{k,t})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})} \quad (4)$$

Similarly, the output orientation Malmquist productivity index relative to the reference technology in the period of t is described as:

$$OMP_0^t = \frac{D_0^t(x^{k,t}, y^{k,t})}{D_0^t(x^{k,t-1}, y^{k,t-1})} \quad (5)$$

Equation (5) expresses the change from period $t - 1$ to t when the base is the production possibility frontier at period t .

$$OPM_{t-1}^t = \sqrt{\frac{D_0^{t-1}(x^{k,t}, y^{k,t}) \times D_0^t(x^{k,t}, y^{k,t})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1}) \times D_0^t(x^{k,t-1}, y^{k,t-1})}} \quad (6)$$

The output-based Malmquist productivity (OMP) ⁴ is defined as the geometric mean of four output distance functions. Taking the geometric mean of two periods is very close to the real value

⁴ This depends on the objective function, if the objective is to maximize radial expansion of the observed output vector feasible given the input vector and the stable of technology (Headey et al, 2010), then the output-oriented Malmquist productivity should be used. In contrast, if the objective is to minimize the input quantities without changing the output quantities produced, the input-oriented Malmquist productivity is used instead. In addition, if achieving the two objectives is the goal, the graph distance function should be implemented.

which is the geometric mean of Laspeyres's index and Paasche's index. This chapter considers the current period, “ t_1 ” and previous “ t_0 ” period technologies for “ k ” DMUs (decision making units are the 31 provinces of China).

In equation (6), $(x^{k,t-1}, y^{k,t-1})$ and $(x^{k,t}, y^{k,t})$ refer to the input and output vectors in year $t - 1$ and year t respectively; D_0^{t-1} and D_0^t captures the distance functions in relation to the technology in year $t - 1$ and year t . That is: $D_0^{t-1}(x^{k,t}, y^{k,t})$ shows the technology efficiency of period t in relation to the technology in period $t - 1$; $D_0^{t-1}(x^{k,t-1}, y^{k,t-1})$ explains the technology efficiency of period $t - 1$ in regard to the technology in period $t-1$; $D_0^t(x^{k,t}, y^{k,t})$ describes the technology efficiency of period t concerning the technology in period t ; $D_0^t(x^{k,t-1}, y^{k,t-1})$ expresses the technology efficiency of period $t - 1$ in respect of the technology in period t . Equation (6) is multiplied and divided by

$$\frac{D_0^t(x^t, y^t)}{D_0^t(x^t, y^t)} \text{ and } \frac{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})}$$

$$\begin{aligned} \text{OPM}_{t-1}^t = & \sqrt{\frac{D_0^{t-1}(x^{k,t}, y^{k,t}) \times D_0^t(x^{k,t}, y^{k,t})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1}) \times D_0^t(x^{k,t-1}, y^{k,t-1})}} * \frac{D_0^t(x^t, y^t)}{D_0^t(x^t, y^t)} \\ & * \frac{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})} \end{aligned}$$

Equation (6) can be rewritten as:

$$\begin{aligned} \text{OPM}_{t-1}^t = & \left(\frac{D_0^t(x^{k,t}, y^{k,t})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})} \right) \tag{7} \\ & \times \sqrt{\frac{D_0^{t-1}(x^{k,t}, y^{k,t})}{D_0^t(x^{k,t}, y^{k,t})} \times \frac{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})}{D_0^t(x^{k,t-1}, y^{k,t-1})}} \end{aligned}$$

Equation (7) is a transformed form of equation (4) and (5). The Malmquist productivity index is decomposed into efficiency change (EC) in equation (8) and technical change (TC) in equation (9). The calculation of the Malmquist TFP index relies on deriving numerical measures of the distance function $D_0^t(x^{k,t}, y^{k,t})$ (Headey et al., 2010). Productivity change is the product of efficiency change and technical change. TC captures shifts in the frontier denoted at the current period t and previous period $t - 1$, EC represents change in efficiency over the same period (Fukuyama, 1995). The shift from C to B demonstrates a change in efficiency, while the shift from B to A illustrates a change in technology between two production possibility frontiers (see Figure 3.1).

$$\text{Efficiency Change} = \frac{D_0^t(x^{k,t}, y^{k,t})}{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})} \quad (8)$$

$$\text{Technical Change} = \sqrt{\frac{D_0^{t-1}(x^{k,t}, y^{k,t})}{D_0^t(x^{k,t}, y^{k,t})} \times \frac{D_0^{t-1}(x^{k,t-1}, y^{k,t-1})}{D_0^t(x^{k,t-1}, y^{k,t-1})}} \quad (9)$$

Technical efficiency measures the DMU's overall success utilizing its inputs (Awan et al, 2015) to maximize their output when employing the output-oriented measures, it indicates how much output quantities can be proportionally increased while keeping input quantities constant. The curve Z and Z' is upper bound of the production possibilities and point A corresponds to an inefficient firm which lies below the curve. Considering that one firm involves two output sets (q_1 and q_2) and one single input (x) (see Figure 3.2). Technical efficiency can be calculated using $TE = \frac{OA}{OB}$ by assuming CRS. In this case, the distance AB indicates technical inefficiency, illustrating the output increase can be attained without additional input (Coelli et al., 2005).

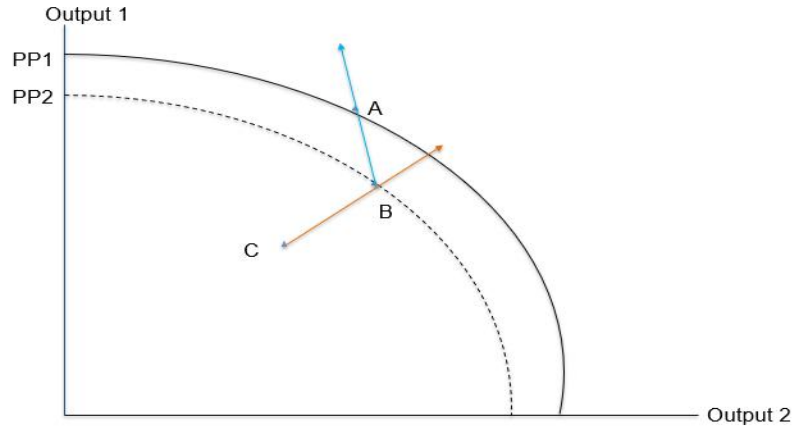


Figure 3.1. Technology change and efficiency change

Source: Author's work.

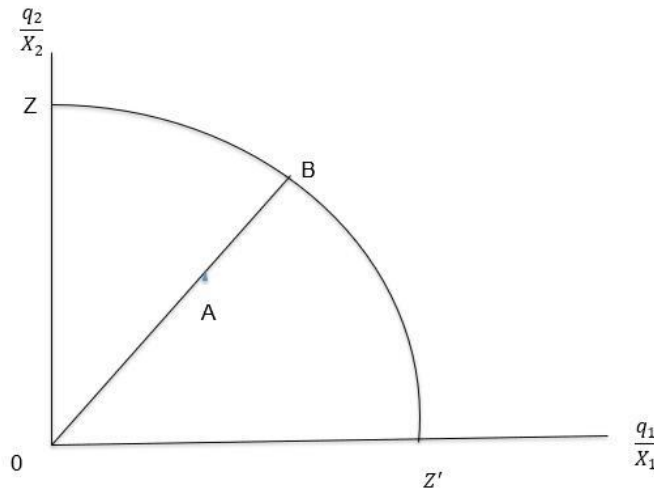


Figure 3.2. Technical efficiency from output orientation

Source: Coelli et al (2005)

To calculate the productivity of k DMUs, following Färe et al. (1994), for the output-based Malmquist index of productivity change, production technology (P) transforms the inputs vector $x^{k, t}$ into the output vectors $y^{k, t}$ over the period $t=1(2001), 2, \dots T$ (2022) for each province $k=1, 2, \dots, K$ (31) (Shaik et al, 2021). Equation (10) is the output set:

$$P(x^{k,t}) = \{y^{k,t} : x^{k,t} \text{ can produce } y^{k,t}\} \quad (10)$$

The optimal proportional change is measured by the output distance function in relation to the frontier at year $t - 1$, the output set can be expressed using the output distance function as:

$$D_0^{t-1}(x^{k,t}, y^{k,t}) = \max\{\theta : \theta y^{k,t} \in P^t(x^k)\} \quad (11)$$

The distance functions and constraints at the same period and mixed periods are expressed as:

$$\begin{aligned} D_0^t(x^{k,t-1}, y^{k,t-1})^{-1} &= \max_{\theta, z} \theta \\ \text{s.t.} \quad \theta y_j^{k,t-1} &\leq \sum_{k=1}^K z^k y_j^{k,t-1} \\ \sum_{k=1}^K z^k y_i^{k,t-1} &\leq x_i^{k,t-1} \\ z^k &\geq 0 \end{aligned} \quad (12)$$

In the equations above, θ is the decision variable, k is the number of decision-making units, j is the number of outputs, i is the number of inputs, and z^k is the intensity variables or weight constraints. The output distance function in equation (6) linked to province k 's production bundle in period t with the $t - 1$ frontier is derived by solving the linear programming model above, which can be obtained by reversing the roles of t and $t - 1$ in equation (12) (Lambert and Parker, 1998).

3.4. Data

Balanced panel data are necessary to examine and decompose productivity growth (Brümmer et al., 2006) using the linear programming Malmquist productivity index. We have panel data from 31 provinces, municipalities, and autonomous regions in China from 2000 to 2022.

The data was compiled by the China State Statistical Bureau and is available in the Chinese Statistical Yearbook.

Following Zhang and Brümmer (2011), Zhou and Zhang (2013) and Lambert and Parker (1998), variables for the production function were included. Output variables include both crops and livestock products. Inputs are categorized as follows: land (TSA, total sown areas), labor (number of farmers working in the agricultural, forestry, animal husbandry and fishery industry), machinery or capital (total power of agricultural machinery), chemical fertilizer (the yearly gross use of nitrogen, potash, compound, phosphate for each province), power or energy (rural electricity consumption) and pesticides (agricultural farmers consumed for agricultural purposes).

The variables for the study are summarized in Table 3.3. Average gross output for grain and meat products for 2000-2022 is reported. The provincial average for crop products is approximately 287,600 tons, which includes the total annual grain yield by agricultural producers encompassing summer-harvested grain, early rice, and autumn-harvested grain and covers cereals, tubers, and legumes. Meat production averages 35,300 tons, calculated as the combined slaughter-weight of various livestock and poultry after inedible parts are removed; these figures account for raw meat only and do not include processed products.

Table C.1 in the Appendix reports annual growth of output and inputs by province. Most provinces show rising crops and livestock output, though growth rates differ by province and year. Developed provinces such as Beijing, Shanghai, and Tianjin experienced an accelerated trend towards “non-agriculturalization” of land and “non-grain focus” of agriculture, resulting in a sharp decline in grain production. These provinces quickly made transition from being major production areas to major consumption centers. In contrast, undeveloped western provinces show a gradual increase in the production growth. Although the majority of these provinces have reported

increases in both crop and livestock production, Guangxi Province and Chongqing have experienced growth exclusively in crop output, while their livestock production has declined.

Table 3.3. Summary statistics

Variable	Unit	Minimum	Mean	Maximum	Standard-deviation
<i>Output sample 2000 -2022 (n=713)</i>					
Livestock	10,000 tons	3.53	250.80	866.01	197.73
Crops	10,000 tons	28.76	1852.06	7867.72	1629.13
<i>Input sample 200-2022 (n=713)</i>					
Sown Areas	10,000 hectares	88.55	5181.022	15209.41	3759.28
Labor	10,000 persons	18	894	3559	696
Machinery	10,000 Kilowatt	93.97	2829.164	13353.02	2717.864
Fertilizer	10,000 tons	2.5	169.2706	716.09	137.7461
Pesticide	10,000 tons	0.05	4.970933	17.35	4.14868
Power	10,000 kilowatts	0.34	206.0333	1949.11	317.2053

As an agricultural intensive region, the North China Plain is well known for its abundant resources. Province Henan, Shandong, and Hebei consistently rank in the top five for crop and livestock production. The major grain-production provinces are also the largest consumers of resources. For instance, Henan and Shandong provinces have the highest fertilizer consumption, while Shandong, Hubei, and Henan provinces are the top consumers of pesticides. Given environmental concerns, greater attention should be paid to meet the requirements for “green” productivity growth (less or zero growth in fertilizer and pesticide use). Province Zhejiang and Guangdong, two major provincial provinces, were facing noticeable decline in both crop and livestock production, driven by reduced sown land and a shrinking agricultural labor.

With its unique geographical and climate conditions, the Northeast region which includes Jilin, Heilongjiang, and Liaoning, is a primary base for main grain crops, accounting for 27.5% of national grain production in the fall. These three provinces have shown increases in both livestock and crop output.

3.5. Empirical Results and Discussion

This chapter uses the distance function approach discussed in theoretical framework section to examine the TFP index using multiple input- outputs for the five FYP periods from 2000 -2022, treating each of the 31 Chinese provinces in the sample as an individual decision-making unit.

3.5.1. Differential Provincial Productivity

The provincial average annual change in TFP in the 2000 – 2022 period is reported in Table C.2 in the Appendix. Clearly, it exhibited a clear differentiation in productivity performance by province. The average TFP growth rate varied from a high of 4.8 % for Jiangsu to a low of -2.4% for Hainan. Jiangsu province (4.8%) and Liaoning (3.4%) were at the forefront in the PPF expansion, while Guangdong (-2.1%) and Hainan (-2.4%) displayed the worst performance by moving away from the frontier. Declining technical progress and a lack of improvements in technical efficiency resulted in Hainan’s weak performance in TFP progress. Of the 31 provinces, 21 provinces recorded TFP growth, largely contributed by the expansion of production possibility frontier (PPF). Seven provinces experienced efficiency change rates of 1.00, underlying that they were on the best practice of frontier. Except for Sichuan and Guizhou, these provinces were leading performers in TFP growth over the studied periods.

3.5.2. Regional Differences in TFP Growth

Table C.3 in the Appendix presents results on TFP variation across the five FYPs comparing the major grain-production provinces versus non-grain production ones, as well as the eastern, central, and western regions. During the eleventh to thirteenth FYP, major grain production areas supported a TFP advantage over non-major ones, yet the latter performed better in the tenth and fourteenth FYP. This finding suggests a very promising prospect for achieving

self-sufficiency by increasing production in non major grain provinces. Regional differences are evident: the eastern coastal provinces benefit from technology and human resource advantages and place greater emphasis on non-agricultural development, while the central provinces remain the core grain-producing regions. Western provinces, constrained by unfavorable climatic conditions and technology limitations, stayed below the levels of eastern and central regions (details can be found in Figure C.1 and Table C.1 in the Appendix C).

3.5.3. Yearly and Cumulative

Figure 3.3 illustrates the average annual change in TFP between 2000-2022. The lowest TFP growth rate from 2000 to 2022 is -5.45% in 2006, which was largely owing to technical regress in the eleventh FYP, while the highest TFP growth rate was found in 2021, 10.14% in the ongoing fourteenth FYP, primarily attributed to technological progress. Technical growth exceeded TFP growth in the tenth FYP, while in the fourteenth FYP, it advanced in line with productivity growth. This indicates technological progress was a major driving force of agricultural production in China. In contrast, both the eleventh FYP and thirteenth FYP experienced a technical regression, resulting in a lower TFP growth.

It is worth noting that the average annual TFP growth maintained a high growth rate when government support and agricultural policies are more efficient (Zhou and Zhang,2013). Conversely, a low rate of agricultural TFP growth often correlates with inadequacies with agricultural policies. For example, Sheng et al. (2019) argued that the slowdown of agricultural TFP growth was associated with the incomplete implementation of marketization reforms between 1984 and 1992. Market mechanisms have played an essential role in the allocation of resources, shifting allocation away from planned distribution towards actual market conditions (BYRD, 2019). A well-developed market system is fundamental to modern agriculture. Producers are

flexible in changing the allocation of their productive assets, and this reduces the amount of inefficiency (De et al., 2004). The tenth FYP continued the transition from a planned economy to a market economy. Removal of regional market barriers between rural and urban sectors through marketization reforms, along with the opening of the domestic market to the world, has significantly contributed to China's rapid TFP growth (Sheng et al., 2019). This growth was facilitated by the improvement of marketing mechanisms and related regulations, which greatly stimulated farmer's incentives and promoted efficient use of resources (Sheng et al, 2019). In addition, agricultural modernization, particularly the industrialization of agriculture, is another significant driver of productivity growth that lowers production cost through specialized operations and large-scale agricultural production.

The substantial progress in TFP in the fourteenth FYP demonstrated a channel through which sustainable practices such as environmental preservation and encourage efficient use of resources can contribute to the TFP growth. As studied by Liu and Feng (2019), the most powerful driving factors for technological growth are the efficient use of energy resources and environmental management. These findings highlighted the importance of incorporating sustainable practices into agricultural policies, ensuring long-term viability and resilience in the face of environmental challenges.

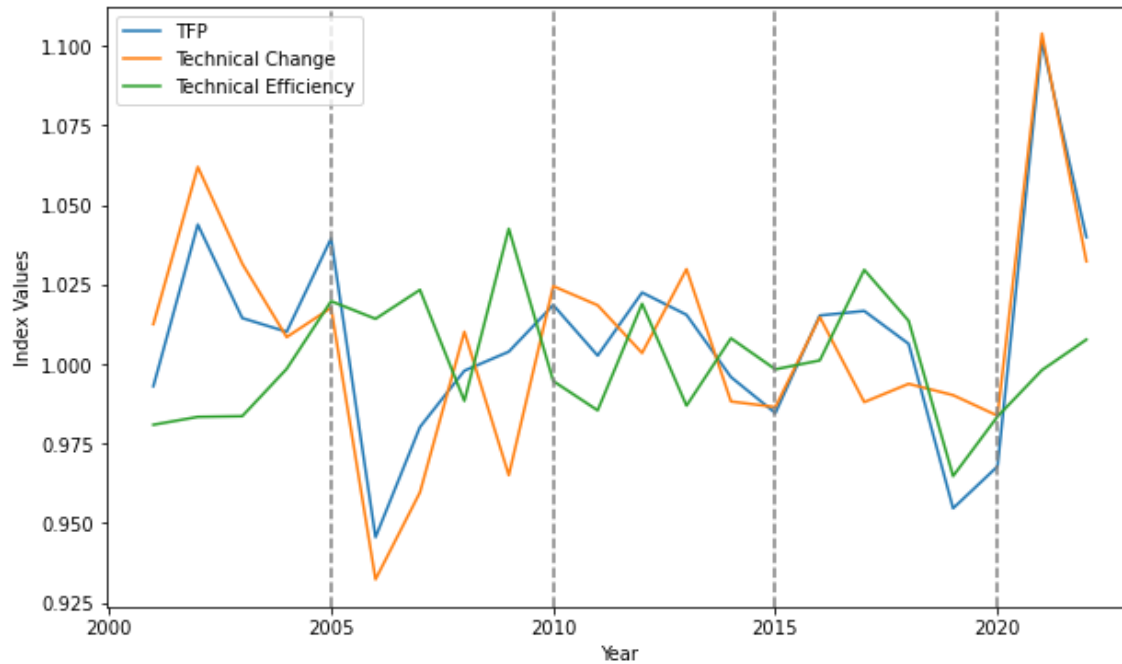


Figure 3.3. Average Annual Variation in the Malmquist TFP Measures, 2001-2022.

3.5.3. Five-Year Period

TFP variation discussion across Five-Year Periods is documented in Appendix C1.

3.5.4. Econometric Analysis of Convergence Test

Table C.9 in the Appendix reports the TFP rankings for the thirty-one provinces in the five FYP periods. In the 10th FYP, Tianjin, Beijing, Shanghai, Liaoning, and Qinghai are the top five provinces with TFP growth. In the 11th FYP period, Hebei, Heilongjiang, Jiangsu and Zhejiang entered the top five list. Qinghai ranked 23rd in the 11th FYP period but became the top 1 in 12th FYP period. The variation in TFP growth across each Five-Year Plan can be attributed to several key factors, such as differences in agricultural infrastructure, unequal allocation of resources for R&D, inconsistencies in supportive agricultural policies, and disparities in human capital.

To further examine whether convergence occurs within each region and whether provinces with lower TFP growth are experiencing catch-up effects, we conducted two convergence tests.

Convergence in TFP growth is defined as differential agricultural TFP gradually moving toward a steady-state equilibrium. This raises the question of whether there is a trade-off between overall TFP growth and convergence across provinces, as movement toward a relatively stable state may come at the cost of slower aggregate growth. This is because narrowing regional disparities may temporarily decelerate the pace of aggregate TFP growth, as policy interventions and resource allocations are often directed toward lagging regions. Yet, from China's policy perspective, such a convergence trajectory is consistent with the central government's long-term strategic objective of achieving "common prosperity." In the agricultural sector, reducing interregional development gaps not only contributes to overall social stability but also improves the efficiency of factor allocation through institutional reforms, targeted policy support, and cross-regional spillovers. This does not necessarily imply that developed regions will eventually slow their growth; rather, since their development increasingly relies on sustainable practices that facilitate structural transformation and technological progress.

To examine if the dispersion of TFP across regions is declining, this study first adopts the σ -convergence test to evaluate regional TFP convergence across regions by following Wang et al. (2019) and Gong (2020). The σ -convergence test can be calculated as follows:

$$Var(lnTFP_t) = \varphi_0 + \varphi_1 t + \varepsilon_t \quad (13)$$

Where $Var(lnTFP)_t$ denotes the variance of TFP in natural logarithms for province i at year t , and ε_t is the random error with zero mean and constant variance. Confirmation of σ -convergence occurs when the coefficient of the year trend variable is negative and significantly different from zero.

Table 3.4. provides an overview of the σ -convergence test results. Nationally, there is no evidence of convergence across all provinces. The result shows that productivity growth in western

provinces is statistically negative which is consistent with Han et al. (2023). The significant convergence effect in the western region can be attributed to the central government's launch of the Western Development Strategy(plan). This initiative aimed to address the persistent imbalance between eastern and western regions, as well as the widening economic and urban–rural disparities. Beginning with the tenth FYP, western development became the central government's priority in promoting regional balance. By implementing supportive policies and allocating significant financial resources, the government aimed to enhance the capacities of central and western regions, reduce disparities with eastern areas, and promote more equitable regional development.

Table 3.4. Estimation results of σ - convergence tests

	National	West	Central	East	Major-grain	Non major grain
Trend	-0.0004 (0.0002)	-0.002* (-0.001)	8.44E-05 (-1.784)	-0.003 (-0.002)	0.0009 (-1.757)	7.564* -2.868
Intercept	0.7368 (0.459732)	4.089* (-0.002)	-0.114 (-1.784)	6.147 (-0.003)	-1.757 (-1.399)	-0.003* (-0.001)
Results	No	Yes	No	No	No	No

Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In addition, the unconditional β -convergence test which happens if there is a “catch up” effect for the provinces lagged behind. Based on Sala-i-Martin's (1996), the unconditional β -convergence is specified in equation (14).

$$\ln(TFP_{it}) = \beta_0 + \beta_1 \ln(TFP_{i,t-1}) + U_{it} \quad (14)$$

Where $\ln(TFP_{it})$ is TFP in natural logarithms for province i at year t , $\ln(TFP_{i,t-1})$ is the lagged term for $\ln(TFP_{it})$, and U_{it} is the error term. The negative and statistically significant sign of β_1 confirms the existence of an unconditional β -convergence. The results, reported in Table 3.5, show that the coefficients at both the national and regional levels are all statistically significant and

negative, providing evidence of unconditional β -convergence. Specifically, this means provinces with lower TFP levels tend to grow faster than others. The estimated β -convergence coefficients are larger than those estimated by Wang et al. (2019), who analyzed China's agricultural sector from 2005 to 2007 using a superlative index number approach to measure multilateral TFP. However, these findings are similar to the rate of convergence estimated by Han et al. (2023) who adopted DEA analysis for the calculation of TFP. This convergence in each area can be attributed to China's proactive regional coordination policies. Since the tenth FYP, the government has emphasized balanced regional development, providing agricultural and financial support for the western regions while promoting coordinated growth in less-developed provinces through the "Rise of the Central Region" and "Leading of the Eastern Region" strategies. Policies targeting major grain-producing areas further ensured food production security. Together, these measures have facilitated harmonized development both nationally and across regions.

Table 3.5. Estimation results of unconditional β - convergence tests

	National	West	Central	East	Major-grain	Non major grain
Trend	-0.9327**** (0.0425)	-0.759*** (0.0608)	-0.8019*** (0.0747)	-1.016*** (0.0732)	-0.806*** (0.058)	-0.9427*** (0.0569)
Intercept	0.9476*** (0.043)	0.7655*** (0.0612)	0.8153*** (0.0757)	-1.016*** (0.0745)	0.8200 (0.0590)	0.9567*** (0.0575)
Results	Yes	Yes	Yes	Yes	Yes	Yes

This analysis extends beyond the β -convergence framework by including crucial determinants and, more importantly, by conditioning on the FYPs. This approach allows us to evaluate whether the FYPs contribute to provincial productivity convergence, which addresses the central research question of this study.

3.6. Factors influencing productivity change in Chinese Provincial

Agriculture

The research question is to assess the FYP induce or inhibit differential productivity across Chinese provinces. The Malmquist productivity index provided a FYP-induced provincial panel dataset. Panel regression in this section was built to understand the effects of five FYPs on provincial TFP, technical change, and efficiency change. There may not be a direct causal relation between TFP growth and the implementation of FYP. As emphasized in both our study and the broader literature, productivity growth is mainly determined by technological progress. Agricultural TFP growth in China is closely correlated with institutional reforms and policy interventions. The FYPs have contributed to productivity growth through a series of long term agricultural and rural reforms, including land policy adjustments, market-oriented agricultural policies, and “three rural” policies. Effective market reforms help stimulate the innovative potential of various market participants and promote high-quality economic development. A well-developed market system is fundamental to sustained agricultural progress, and this is precisely the channel through which China’s FYPs have influenced agricultural productivity. By contrast, the institutional reforms and policy frameworks guided by the FYPs have served as a more direct and systematic source of influence. Therefore, this study emphasizes the close association between the FYPs and agricultural productivity growth and highlights their central role in the convergence process.

$$Y_{it} = \alpha_o + \sum_{10}^{14} \beta_k FYP_k + \gamma_m X_{it} + \varepsilon_{it} \quad (15)$$

Y_{it} denotes the dependent variable provincial TFP and its decomposition technical change and efficiency change. To determine if the FYPs induced or inhibited differential productivity

across Chinese provinces, the differences between each province's value and national average for TFP, technical change, and efficiency change in each year is used as the dependent variable. The dependent variables are the absolute values of these deviations, allowing us to measure the overall variation of FYP on differential TFP growth. FYP_k refers to the implementation of FYPs ($k=10,11,12,13,14$); X_{it} represents control variables included in this model, where i refers to the province and t the year; ε_{it} is the error term. β_k and γ_m are the parameters to be estimated.

The main exogeneous variables were presented in Table 3.6, which include educational attainment level, fixed assets which is rural households' investment for agricultural production, and fiscal support from the government. The impact of education on agricultural output was found to have a positive effect on rice production in Vietnam (Nihn, 2020). However, Yong and Deng (1999) concluded there is limited evidence that formal education provides positive returns in agriculture. Fiscal investment in agricultural production, especially in support of agricultural technology and innovation in less productive regions, is a crucial step towards balanced regional development (Wang et al., 2019).

Table 3.6. Factors Influencing Agricultural Productivity Change

Variables	Description
Education	Years of schooling of the rural population (year)
Fixed Asset Invest	Rural household fixed asset investment (100 million Yuan)
Fiscal Support	Expenditure on agriculture, forestry, and water affairs by local financial governments (100 million Yuan)
Urbanization Rate	Urban population / Total population (%)
Affected Areas	Crop disaster areas/ Total crop sown areas (%)

Note: According to the Chinese education reference, the years of education level are categorized as follows: 0 years, 6 years, 9 years, 12 years and 15 years for illiterate, primary school, middle school, high school, and college or above, respectively. Fixed asset investment refers to the adoption of advanced agricultural machinery.

A random effect model was adopted to address the potential singularity problem from the inclusion of dummy variables, while first differencing was applied to the control variables to account for unit roots (Lambert and Parker, 1998). A maximum likelihood (ML) estimator is approved to be more efficient and less bias than feasible generalized least squares (FGLS) (Saha et al.,1997). Therefore, the maximum likelihood estimation (MLE) approach is applied to address heteroscedastic errors in the random effect panel data model (Chen et al., 2008).

Table 3.7 reports parameter estimates for seven models with or without control variables. Productivity growth improved with increases in technical efficiency, indicating that provinces tend to catch up with shifts in the PPF in a positive direction. The eleventh and twelfth FYP represents a critical turning point in China's reform (Chen et al., 2017) which represented the shift from a period of fast GDP growth to one that focused on a more sustainable and balanced economy. Under the eleventh and twelfth FYPs (relative to the tenth FYP), provincial TFP growth did not exhibit improvements over these two periods. However, the provincial differential TFP index was found to be negative and statistically significant for the implementation of twelfth FYP. Further decomposition shows the reduction in disparities during the twelfth FYP was largely attributed to improvements in technical efficiency. The results confirm a "catch up" effect for provincial TFP growth for provinces with lower TFP growth under the twelfth FYP.

In contrast to the significant reduction of divergence observed in earlier period, the thirteenth and fourteenth FYPs had no significant influence on provincial productivity divergence. One reason is that China's thirteenth FYP focused on quality-oriented development, primarily driven by technology innovation and green development. The ongoing fourteenth FYP outlined an accelerated economic transition towards green development through increased resource efficiency

and continuous improvement in environmental quality. Considering the regional heterogeneity in green development, provinces respond differently to the FYP (Han et al., 2023).

In the absence of any controls, the estimated twelfth FYP on differential TFP growth is -3.4%. However, when including exogenous variables, the estimate changes to -1.9%. This estimate is confounded by the absence of control variables, omitting them would bias the estimates. Education attainment is crucial for agricultural modernization. Farmers possessing higher levels of education are likely to exhibit greater capacity for adopting and acquiring new technology (Chen et al., 2008). Rural education improved technical efficiency but exacerbated provincial disparities because of the outflow of younger generation. The migration of younger generations poses challenges to the modernization of agricultural development. In addition, 60% of the population in the rural provinces are older than 45 (GAP Report, 2018). Farmers in older age groups often have lower education attainment, making it challenging for them to acquire updated agricultural skills or adopt cutting edge methods (Ren et al., 2023). The rural aging population may further complicate the effect of education in the future if migration of young people to developed provinces is not well addressed.

To increase the farmers' income and promote rural economic development, China has strengthened its budgetary and financial policies to support agriculture year by year (Gao et al., 2013). Fiscal support from the government helps to establish a strong agricultural science and technology innovation research system that has influenced agricultural productivity over several decades (Huang, 2018). Tang and Sun (2022) estimated the effect of financial support for agriculture on the urban-rural income gap using regional panel data from 2004 to 2018. The results show that urban-rural income inequality significantly declined. The negative relationship between financial support and differential productivity would tend to support this conclusion. As shown in

Table 3.7, an increase in financial support is associated with a 1.3% reduction in provincial inequality in TFP variation. Increased investments in less developed rural areas, particularly in support of agricultural technology and innovation will be crucial to help these provinces catch up with the leading provinces.

Rural household fixed assets investments, primarily the adoption of advanced agricultural machinery, have a significant effect on technical changes across provinces, but the effect is limited in boosting agricultural productivity. As expected, urbanization, measured by the proportion of the urban population to the total population, which serves as a proxy for the migration of rural labor, helps improve the technical skills of rural labor, but it does not have a significant impact on TFP growth. One primary factor explaining efficiency change is the proportion of agricultural land adversely affected by natural calamities (Lambert and Park, 1998), but it is not statistically significant in the model.

Table 3.7. Panel Data Estimation Results of TFP and its components

	Malmquist TFP		Technical Change		Efficiency Change		
FYP_11	-0.015** (0.007)	0.002 (0.009)	0.009 (0.005)	0.014* (0.007)	-0.008 (0.006)	0.006 (0.006)	
FYP_12	-0.034*** (0.007)	-0.019** (0.009)	-0.011* (0.006)	-0.007 (0.007)	-0.026*** (0.006)	-0.013** (0.006)	
FYP_13	-0.011 (0.007)	0.002 (0.009)	0.001 (0.006)	0.005 (0.007)	-0.009 (0.006)	-0.0002 (0.006)	
FYP_14	-0.011 (0.010)	0.009 (0.011)	0.003 (0.008)	0.009 (0.009)	-0.020* (0.004)	-0.008 (0.007)	
△Education		0.009*** (0.003)		-0.001 (0.003)		0.013*** (0.003)	
△Fixed Asset		0.003 (0.003)		0.006**** (0.002)		0.001 (0.002)	
△Fiscal Support		-0.013** (0.005)		-0.011*** (0.004)		-0.006 (0.004)	
△Urbanization		-0.015 (0.016)		0.012 (0.012)		-0.030* (0.014)	
△Affected Area							-0.0003 (0.003)
Constant	0.065*** (0.005)	0.050*** (0.007)	0.041*** (0.004)	0.035*** (0.006)	0.047*** (0.004)	0.036*** (0.005)	0.035*** (0.003)
Observations	660	475	660	475	660	475	600
Log-likelihood	699.661	631.12	939.20	945.26	1029.12	896.57	932.90

3.7. Conclusion

This study estimates the Malmquist productivity index for 31 provinces in China from 2000 to 2022 to assess changes in multi-factor agricultural productivity. Comparing the five FYP periods, TFP growth was more pronounced during the tenth FYP, followed by a slowdown in the next three FYPs, and then rebounded in the fourteenth FYP. Nonetheless, the results showed a substantial differentiation in productivity performance by province. The σ Convergence test showed significant year to year variation across central and eastern China, as well as between major grain-production and non major grain production areas with the exception of the western province. The unconditional β convergence tests found evidence of “catch up” effects at both the national and regional levels.

To assesses whether FYP induced or inhibited differential productivity across provinces a MLE-based panel method is conducted. The results show that the twelfth FYP inhabited the differences of provincial TFP, which may have played a significant role in the convergence of provincial TFP growth. However, in the following thirteenth and fourteenth FYP periods, this effect was not statistically significant. With an emphasis on sustainable green development, China is currently undergoing an economic transition from quantity-driven growth to quality-oriented growth. As expected, this process takes an extended period of adjustment for different provinces to achieve balanced development.

In addition, the factors effecting provincial difference in agricultural productivity is estimated. The results show that financial support significantly reduced disparities across provinces, primarily by increasing investments that promoted technical change in undeveloped provinces. Rural education, however, widened these disparities, primarily because of the outflow of agricultural labor.

The formulation and evaluation process of the FYPs is not fully transparent, and assessing the implementation of such a complex plan is highly challenging (BBC, 2020). The findings contribute to the literature with a focus on the impact of China's FYP on the reduction of differential agricultural productivity, which is rarely explored in earlier studies. This study offers significant policy implications for future FYP development and assessment: central government policies should be harmonized across provinces, and tailored strategies should be formulated to address the unique strengths and challenges of each province. More importantly, successful implementation of agricultural policies requires an effective evaluation mechanism to guide the implementation of the FYPs throughout their duration. Since the achievement of each FYP depends on implementation at various stages. The evaluation system is monitored at each stage, with policies modified in response to the outcomes observed during evaluation.

China's rise into the world's second largest economy and its elimination of extreme poverty has been achieved through an array of short- and long-term plans, mostly notably the FYPs, which sheds light on our evaluation of quantifiable and comprehensive goalposts in each FYP(SCMP, 2025). For example, the Fourteenth FYP's agricultural development priorities aim to strengthen overall agricultural production capacity. A key quantitative target to is to raise the comprehensive mechanization rate of crop cultivation and harvesting to 75%. Since the five-year plan spans multiple years, provinces are likely to achieve this target at different rates. Assessing the pace and extent of progress across provinces, as well as its impact on provincial productivity, requires coordinated surveys at the provincial level. Including such data in NBS surveys would support future FYPs evaluations. More comprehensive goals, such as optimizing agricultural production layouts and developing agricultural product with a comparative advantage, should be tailored to local conditions with feasible targets. Progress should be evaluated at each stage of

implementation, and goals should be continuously adjusted in response to emerging challenges. At the closed stage of each plan, a comprehensive review and recommendation should be conducted. Incorporating such information into NBS annual surveys would undoubtedly support the successful implementation of the FYPs.

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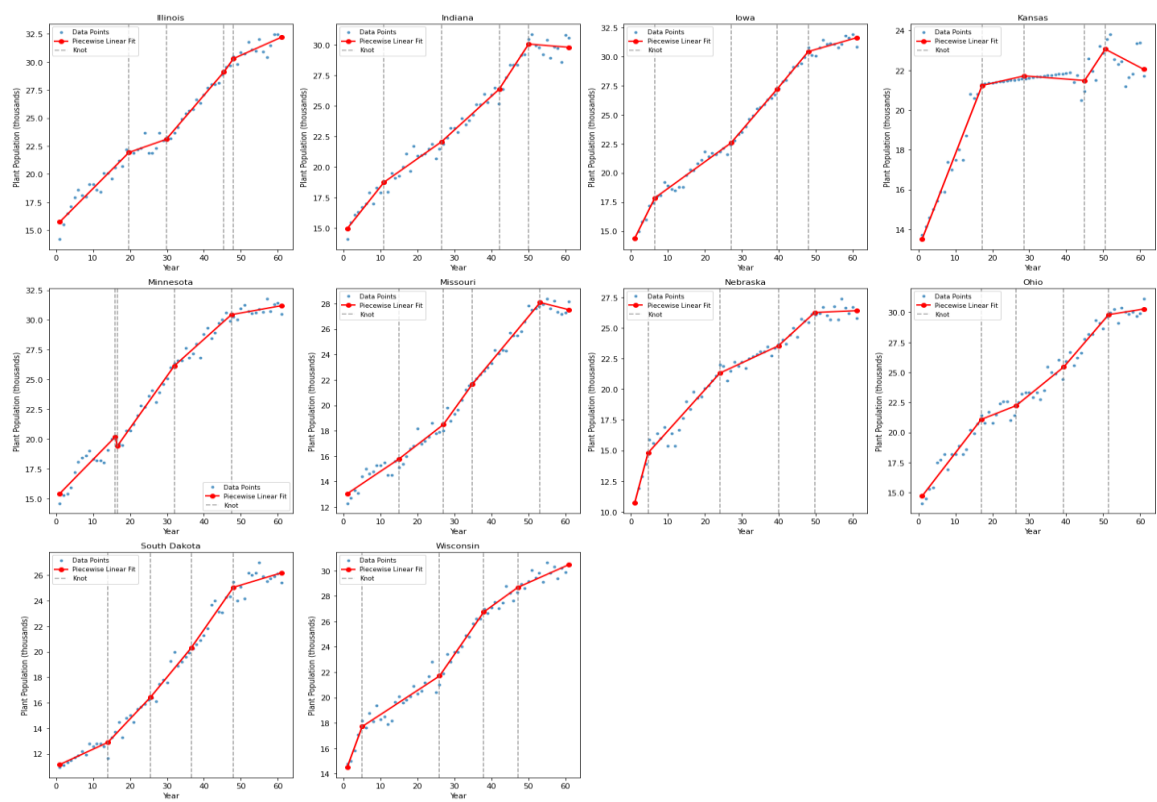
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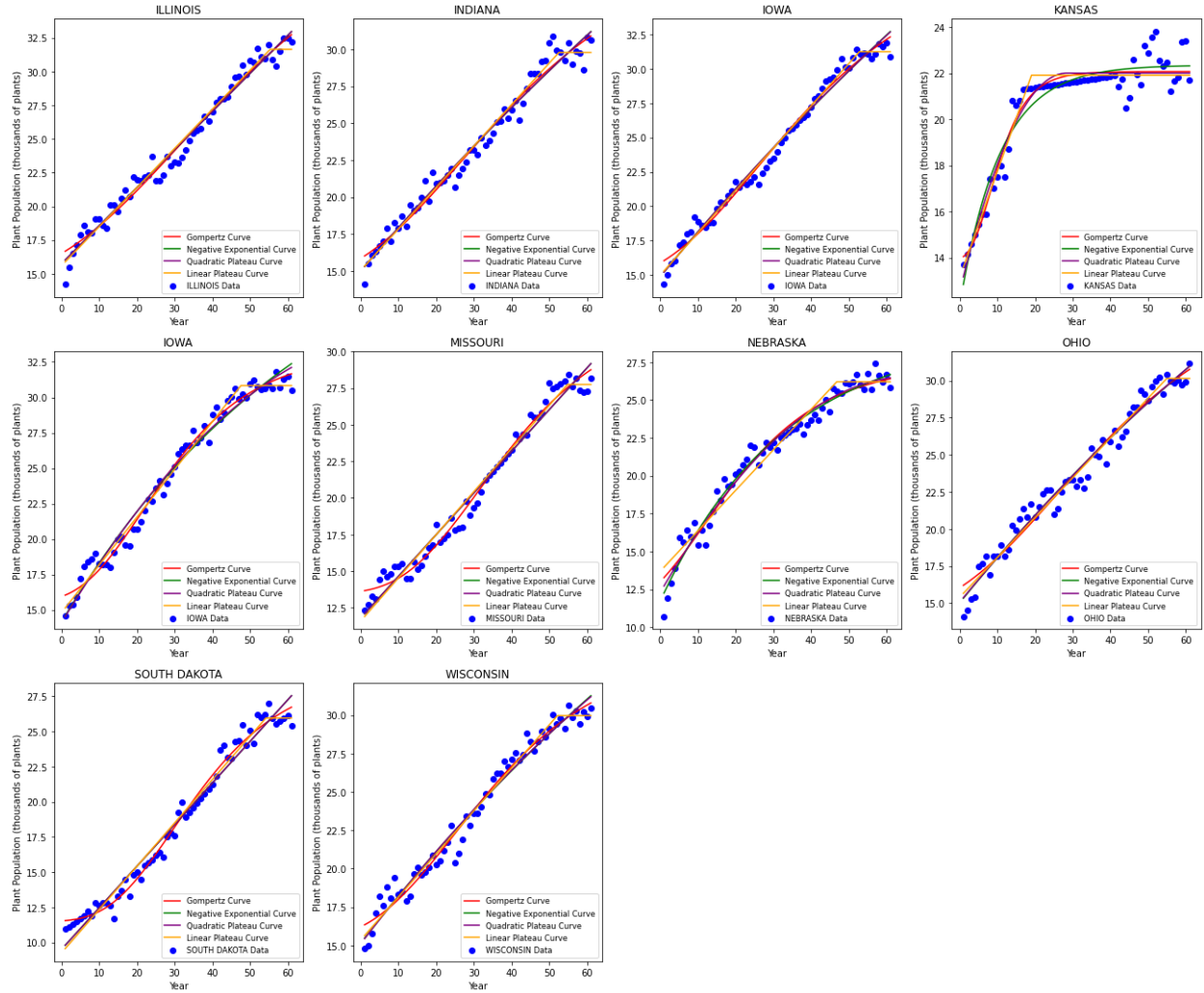
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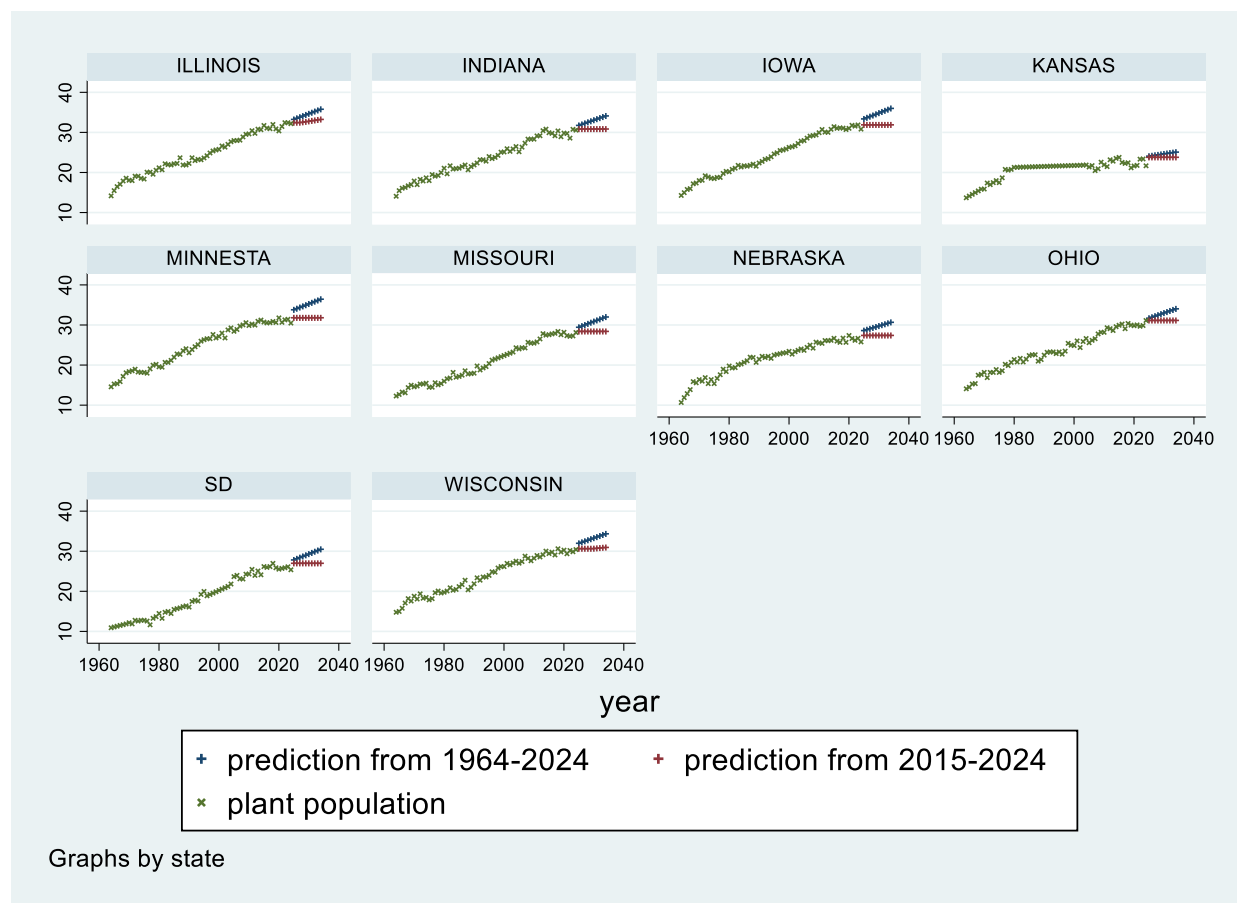
Appendix A: Corn Yield and Plant Population



Appendix Figure A. 1. Linear piecewise with four knots



Appendix Figure A. 2. Fitted linear and nonlinear model for plant population



Appendix Figure A. 3. Plant population and its predictions based on data from 1964-2015 and 2015-2024

Appendix Table A. 1. Model fit of plant population comparison

Model	Average RMSE
Linear Plateau	0.71
Linear Piecewise (one knot)	0.70
Linear Piecewise (two knots)	0.60
Linear Piecewise (three knots)	0.56
Linear Piecewise (four knots)	0.52
Negative Exponential	0.74
Quadratic Plateau	0.74
Gompertz Function	0.70

Appendix Table A. 2. Robustness check

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
plant population		0.240 (0.342)			4.542*** (0.402)
plant population2		0.072*** (0.007)	0.077*** (0.004)	0.066*** (0.005)	0.015 (0.010)
Trend	1.134*** (0.059)	0.810*** (0.065)	0.820*** (0.060)		
DDays(0°–10°C)	-0.034*** (0.002)	-0.027*** (0.003)	-0.026*** (0.003)	-0.026*** (0.002)	-0.026*** (0.002)
DDays(10°–29°C)	0.010*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.012*** (0.002)	0.012*** (0.002)
DDays(>29°C)	-0.493*** (0.017)	-0.449*** (0.017)	-0.446*** (0.018)	-0.410*** (0.016)	-0.411*** (0.016)
Precip(mm)	14.565*** (0.665)	13.642*** (0.620)	13.627*** (0.626)	11.621*** (0.586)	11.606*** (0.581)
Precip(mm2)	-1.259*** (0.052)	-1.197*** (0.049)	-1.197*** (0.049)	-1.075*** (0.047)	-1.075*** (0.047)
VPD	41.969*** (2.474)	38.311*** (2.291)	37.925*** (2.443)	31.537*** (2.128)	31.511*** (2.126)
VPD(Jul & Aug)	-25.563*** (1.065)	-27.512*** (1.071)	-27.567*** (1.046)	-30.401*** (1.110)	-30.366*** (1.112)
Ln(plant pop)	50.216*** (4.341)			47.957*** (4.041)	
GE adoption rate				15.422*** (1.358)	15.469*** (1.378)
Constant	-66.583*** (12.069)	59.421*** (5.556)	62.115*** (3.990)	-45.701*** (10.261)	27.927*** (5.303)
R-squared	0.839	0.847	0.847	0.843	0.843

Appendix B: Meat Demand in China

Appendix Equation B. 1. How to drive the habit formation model integrated with pre-committed effects.

The extended model can be derived in two equivalent ways. One approach is to extend the base dynamic model by incorporating pre-commitment effects. Alternatively, we can begin with the generalized Almost Ideal Demand System (GAIDS) framework and integrate habit formation into the model structure.

The base model is pre-committed, and we integrate it with dynamic habit information Generalized AIDS, no dynamic formation.

$$W_{it} = \frac{C_{it}P_{it}}{M_t} + \frac{M_t^*}{M_t} \times \left[a_i + \sum_{j=1}^n \gamma_{ij} \times \ln(P_{it}) + \beta_i \ln\left(\frac{M^*}{P}\right) \right] \quad (B1)$$

where $M_t = \sum_{i=1}^n P_{it}Z_{it}$,

$Z_{it} = q_{it} - \phi_i q_{it-1} + C_{it}$,

$$M_t^* = M_t - \sum_{i=1}^n C_{it} \times P_{it} = \sum_{i=1}^n P_{it}Z_{it} - \sum_{i=1}^n C_{it} \times P_{it}$$

where M_t^* refers to supernumerary expenditure, M_t demotes the total expenditure, and dynamic habit formation is included in the utility-generating function.

The quantity demand estimating equation is described in equation (2).

$$q_{it} = \left\{ \frac{C_{it}P_{it}}{M_t} + \frac{M_t^*}{M_t} \times \left[a_i + \sum_{j=1}^n \gamma_{ij} \times \ln(P_{it}) + \beta_i \ln\left(\frac{M^*}{P}\right) \right] \right\} * \left(\frac{M_t}{P_{it}} \right) - \phi_i q_{it-1} - C_{it} \quad (B2)$$

Multiply (B2) by P_{it} , we have

$$P_{it} \times q_{it} = W_{it} * M_t + \phi_i q_{it-1} \times P_{it} - C_{it}P_{it} \quad (B3)$$

Here we plug in $M_t = \sum_{i=1}^n P_{it} Z_{it}$, $Z_{it} = q_{it} - \phi_i q_{it-1} + C_{it}$

Move $C_{it} P_{it}$ to the left, we can obtain

$$P_{it}(q_{it} - \phi_i q_{it-1} + C_{it}) = W_{it} \sum_{i=1}^n P_{it}(q_{it} - \phi_i q_{it-1} + C_{it}) \quad (B4)$$

$$W_{it} = \frac{P_{it}(q_{it} - \phi_i q_{it-1} + C_{it})}{\sum_{i=1}^n P_{it}(q_{it} - \phi_i q_{it-1} + C_{it})} \quad (B5)$$

Alternatively, we can start with dynamic models.

$$w_{it} = \alpha_i + \sum_{j=1}^4 \gamma_{ij} \ln p_{jmt} + \beta_i (\ln \bar{x}_{mt} - \ln p_{mt}) \quad (B6)$$

where $Z_{it} = q_{it} - \phi_i q_{it-1} + C_{it}$, $X_t = \sum_{i=1}^n P_{it} Z_{it}$

Now we integrate both habit formation and pre-committed into one model.

$$q_{it} = \left\{ \alpha_i + \sum_{j=1}^4 \gamma_{ij} \ln p_{jt} + \beta_i (\ln \bar{x}_t - \ln p_t) \right\} * \left(\frac{\bar{x}_t}{p_{it}} \right) - \phi_i q_{it-1} - C_{it} \quad (B7)$$

Multiply (B7) by P_{it} , we have

$$P_{it} \times q_{it} = W_{it} * X_t + \phi_i q_{it-1} \times P_{it} - C_{it} P_{it} \quad (B8)$$

$$P_{it}(q_{it} - \phi_i q_{it-1} + C_{it}) = W_{it} X_t \quad (B9)$$

Next, plug $X_t = \sum_{i=1}^n P_{it} Z_{it}$

$$W_{it} = \frac{P_{it}(q_{it} - \phi_i q_{it-1} + C_{it})}{\sum_{i=1}^n P_{it} Z_{it}} = \frac{P_{it}(q_{it} - \phi_i q_{it-1} + C_{it})}{\sum_{i=1}^n P_{it}(q_{it} - \phi_i q_{it-1} + C_{it})} \quad (B10)$$

Clearly, the two approaches come to the same budget share.

Appendix Equation B. 2. The price elasticity of long run derivation

Long run price elasticity is the accumulative percentage change of quantity after several periods.

$$\begin{aligned}
 \eta_{ij} &= \frac{d \ln q_{it}}{d \ln p_{jt}} = \frac{d(\ln w_{it} * \frac{\bar{X}_{it}}{P_{it}})}{d \ln p_{jt}} + \frac{d(\ln \phi_{it-1})}{d \ln p_{jt}} - \frac{d C_{it}}{d \ln p_{jt}} \\
 &= \frac{d \ln w_{it}}{d \ln p_{jt}} + \frac{d \ln \bar{X}_t}{d \ln p_{jt}} - \frac{d \ln P_{it}}{d \ln p_{jt}} \\
 &= -\delta_{ij} + \frac{d \ln w_{it}}{d \ln p_{jt}}
 \end{aligned}$$

where, $\bar{X}_t$ is a single variable, hence $\frac{d \ln \bar{X}_t}{d \ln p_{jt}} = 0$

First, let's calculate

$$\begin{aligned}
 \frac{d \ln w_{it}}{d \ln p_{jt}} &= \frac{dw_{it}}{w_{it} d \ln p_{jt}} = \frac{1}{w_{it}} \frac{dw_{it}}{d \ln p_{jt}} \\
 &= \frac{d(\sum_j^n \gamma_{ij} \ln p_{jt})}{d \ln p_{jt}} + \beta_i \frac{d \ln(X_t) - d \ln P_t}{d \ln p_{jt}} \\
 &= \gamma_{ij} - \beta_i \frac{d \ln P_t}{d \ln p_{jt}}
 \end{aligned}$$

Next, let's calculate

$$\frac{d \ln P_t}{d \ln p_{jt}} = a_j + \sum_k^n \gamma_{kj} \ln p_k$$

$$\text{Hence, } \eta_{ij} = -\delta_{ij} + \frac{1}{w_{it}} (\gamma_{ij} - \beta_i (a_j + \sum_k^n \gamma_{kj} \ln p_k))$$

where $it = j, \delta_{ij} = 0, \text{ otherwise, } \delta_{ij} = 1$

Appendix Table B.1. Per capita consumption comparison between urban and rural residents

year	Pork-U	Pork-R	Bf- Lm-U	Bf-Lm-R	Poul-U	Poul-R
1990	18.46	10.54	3.28	0.8	3.42	1.25
1995	17.24	10.58	2.44	0.71	3.97	1.83
2000	16.73	13.28	3.33	1.13	5.44	2.81
2005	20.15	15.62	3.71	1.47	8.97	3.67
2010	20.73	14.4	3.78	1.43	0.21	4.17
2011	20.63	14.42	3.95	1.9	10.59	4.54
2012	21.23	14.4	3.73	1.96	10.75	4.49
2013	20.4	19.1	3.3	1.5	8.1	6.2
2014	20.8	19.2	3.4	1.5	9.1	6.7
2015	20.74	19.45	3.87	1.75	9.45	7.11
2016	20.43	18.68	4.31	2.02	10.17	7.91
2017	20.62	19.49	4.22	1.98	9.74	7.87
2018	22.74	22.96	4.19	2.16	9.83	7.99
2019	20.31	20.23	4.32	2.20	11.42	10.01
2020	19.04	17.11	4.47	2.29	12.99	12.43
2021	25.10	25.40	4.80	2.70	12.30	12.40
2022	26.04	28.13	4.70	2.88	11.90	11.43

Note: "Pork-U" represents per capita pork consumption for urban residents, while "Pork-R" refers to that of rural residents. "Bf-Lm-U" denotes the combined per capita consumption of beef and lamb for urban residents, and "Bf-Lm-R" indicates that of rural residents. "Poul-U" refers to per capita poultry consumption for urban residents, and "Poul-R" refers to that of rural residents.

Appendix Table B.2. Descriptive statistics of Chinese rural resident data (2015-2022)

Variable	Definition	Mean	SD	Min	Max
Pork Price	Retail price (CNY/kg)	31.38	8.74	18.47	56.60
Beef Price	Retail price (CNY/kg)	73.95	15.65	51.05	162.42
Poultry Price	Retail price (CNY/kg)	20.92	5.47	12.98	35.79
Lamb Price	Retail price (CNY/kg)	69.72	14.62	38.02	116.10
Pork	Per capita consumption (kg)	20.42	9.30	1.12	46.26
Beef	Per capita consumption (kg)	1.57	1.66	0.155	10.31
Poultry	Per capita consumption (kg)	9.15	6.74	1.4	38.04
Lamb	Per capita consumption (kg)	1.77	3.05	0.1	17.14
Birth	Birth rate yearly (‰)	9.87	3.11	3.34	17.89
Death	Death rate yearly (‰)	6.53	1.03	4.26	9.09
Growth	Difference between birth and death rate (‰)	3.34	3.55	-5.75	11.4
Children	Population aged 0-14	0.18	0.05	0.05	0.28
Labor	Population aged 15-64	0.67	0.05	0.57	0.82
Seniors	Population aged over 65	0.15	0.04	0.06	0.27
Family size	Average family size (persons)	3.09	0.45	1.96	3.99
Income	Annual income per capita (CNY)	16312.25	6266.96	6936	40122.36

Appendix Table B.3. Demographic variables elasticities, urban 30 provinces, China, 2015-2022

Commodity	Growth	Children	Seniors	Family-size
Pork	-0.0086 (0.0014)	-0.0307 (0.1717)	-0.0147 (0.2412)	0.0964*** (0.0151)
Beef	0.0038 (0.0008)	-0.1136 (0.0815)	0.0220 (0.1027)	-0.0396*** (0.00642)
Poultry	0.0021* (0.0009)	0.0146 (0.0770)	0.0578 (0.0951)	0.0008 (0.0105)
Lamb	0.0029* (0.0010)	0.1295 (0.1398)	-0.0679 (0.7098)	-0.0616** (0.0226)

Appendix Table B.4. Demographic variables elasticities, rural 30 provinces, China, 2015-2022

Commodity	Growth	Children	Seniors	Family-size
Pork	-0.0086 (0.0014)	-0.0307 (0.1717)	-0.0147 (0.2412)	0.0964*** (0.0151)
Beef	0.0038 (0.0008)	-0.1136 (0.0815)	0.0220 (0.1027)	-0.0396*** (0.00642)
Poultry	0.0021* (0.0009)	0.0146 (0.0770)	0.0578 (0.0951)	0.0008 (0.0105)
Lamb	0.0029* (0.0010)	0.1295 (0.1398)	-0.0679 (0.7098)	-0.0616** (0.0226)

Appendix Table B. 5. Hicksian price elasticities, urban 30 provinces, China, 2015-2022

Commodity	Pork	Beef	Poultry	Lamb
Pork	-0.0668 (0.0685)	-0.1114*** (0.0244)	-0.1141*** (0.0281)	0.058 (0.0509)
Beef	1.3644 (1.1523)	-0.4719 (0.3726)	-0.1889 (0.1815)	-0.8739 (1.0284)
Poultry	0.4891*** (0.0668)	-0.0517 (0.0664)	-0.7454*** (0.0472)	0.2061** (0.0623)
Lamb	0.3495** (0.1160)	0.2718* (0.1522)	-0.2375** (0.0783)	-0.5448*** (0.1107)

Appendix Table B.6. Hicksian price elasticities, rural 30 provinces, China, 2015-2022

Commodity	Pork	Beef	Poultry	Lamb
Pork	0.086 (0.1605)	0.1210 (0.1624)	-0.2332*** (0.0541)	0.0889 (0.0583)
Beef	0.9347 (0.2638)	-0.6116** (0.2121)	-0.1912* (0.1123)	-0.0196 (0.1608)
Poultry	0.8808*** (0.1538)	0.1138 (0.1593)	-1.2193*** (0.0782)	0.0849 (0.0564)
Lamb	1.4738* (0.8659)	-0.0422 (0.3449)	-0.7205* (0.4139)	-0.8927* (0.4817)

Appendix Table B.7. Predicted impacts of GDP growth, demographics change, and the combined effects on the budget share of meat demand for urban consumers in 2032.

Note: GDP growth is projected under three scenarios: 5.2% (high), 4.4% (medium), and 3.4% (low)

	2022	Proportion of		Population growth	Family size	GDP growth			Combined impacts		
		Seniors	Children			High	Medium	Low	High	Medium	Low
Pork	24.98	24.96	25.02	24.89	24.79	25.37	25.30	25.22	25.37	25.30	25.22
Beef	2.97	2.97	2.98	2.96	2.98	3.00	3.00	2.99	3.00	2.99	2.99
Poultry	10.64	10.70	10.63	10.41	10.64	10.71	10.70	10.68	10.71	10.69	10.68
Lamb	2.04	2.03	2.02	2.00	2.06	2.06	2.06	2.06	2.07	2.06	2.05

Note: Figures indicate predicted meat consumption demanded resulting from variation in demographic variables and GDP growth.

Appendix Table B.8. Predicted impacts of GDP growth, demographics change, and the combined effects on the budget share of meat demand for rural consumers in 2032.

Note: GDP growth is projected under three scenarios: 5.2% (high), 4.4% (medium), and 3.4% (low)

	2022	Proportion of		Population growth	Family size	GDP growth			Combined impacts		
		Seniors	Children			High	Medium	Low	High	Medium	Low
Pork	26.56	28.17	26.81	26.26	30.14	26.89	26.83	26.76	26.94	26.88	26.81
Beef	2.07	2.05	2.07	2.08	2.07	2.10	2.09	2.09	2.10	2.09	2.09
Poultry	10.72	10.61	10.70	10.54	10.72	10.84	10.82	10.79	10.84	10.82	10.79
Lamb	2.02	1.89	2.00	2.05	2.02	2.05	2.04	2.03	2.02	2.03	2.04

Note: Figures indicate predicted meat consumption demanded resulting from variation in demographic variables and GDP growth.

Appendix C: China's Five-Year Plan

Appendix Table C. 1. Annual Growth Rate in Input and Output by Province, 2000-2022

Province	Crops	Livestock	TSA	Labor	Capital	Fertilizer	Pesticide	Energy
Beijing	-7.941	-3.247	-4.478	-1.674	-5.109	-4.244	-3.651	3.214
Tianjin	1.051	3.514	-0.763	-0.942	-1.904	-0.026	-2.386	4.443
Hebei	0.959	1.947	-0.465	-1.289	1.115	0.045	-1.238	5.023
Shanxii	4.114	2.935	-0.456	-0.073	1.056	0.827	1.597	5.245
Inner Mongolia	3.347	5.496	1.836	0.397	5.895	5.374	5.367	7.643
Liaoning	3.312	4.087	0.851	0.181	3.411	0.821	1.358	3.092
Jilin	1.550	4.628	1.474	0.027	6.875	3.412	4.237	4.514
Heilongjiang	3.524	5.541	2.304	-1.093	7.025	3.233	4.052	5.774
Shanghai	-1.790	-2.325	-2.853	-5.828	-1.351	-4.676	-6.116	14.572
Jiangsu	0.055	1.013	-0.234	-7.277	2.724	-0.971	-1.501	6.159
Zhejiang	-0.466	-2.867	-2.451	-7.159	-0.474	-1.287	-2.628	6.384
Anhui	2.228	2.616	-0.006	-2.695	4.061	0.519	0.400	9.249
Fujian	3.686	-2.270	-2.232	-2.006	1.854	-1.286	-0.851	6.920
Jiangxi	3.245	1.400	0.085	-1.740	7.019	0.114	-0.182	8.196
Shandong	2.125	1.766	-0.067	-1.844	2.535	-0.666	-0.903	4.119
Henan	1.543	2.492	0.520	-2.035	3.022	1.662	0.272	6.658
Hubei	3.114	1.054	0.370	-2.468	5.888	0.273	-0.851	6.404
Hunan	1.615	0.444	0.355	-1.042	5.245	0.810	0.667	11.550
Guangdong	-1.710	-1.309	-0.534	-0.565	1.784	0.845	-0.088	3.278
Guangxi	2.672	-0.382	0.075	-0.357	4.525	2.131	1.962	10.062
Hainan	3.152	-1.200	-1.160	1.603	5.431	2.026	3.280	20.723
Chongqing	1.629	0.358	-0.105	-4.544	4.587	0.987	-0.591	5.464
Sichuan	1.146	0.287	0.289	-2.606	5.053	-0.148	-1.624	6.002
Guizhou	3.193	0.155	0.633	-1.380	7.462	0.346	0.034	13.196
Yunan	4.492	1.351	0.976	-0.241	3.978	2.358	2.820	8.029
Tibet	3.170	0.585	0.906	0.152	8.379	1.292	0.415	19.654

Shanxi	2.260	0.878	-0.328	-1.871	4.171	1.946	0.734	4.776
Gansu	4.239	2.686	0.382	0.065	4.354	0.880	7.180	7.087
Qinghai	3.347	1.438	0.320	36.231	3.178	-1.507	-1.896	10.045
NingXia	3.480	1.926	0.783	-1.532	2.910	2.121	1.712	8.740
Xinjiang	4.367	4.277	3.165	2.210	6.045	5.365	2.388	11.403

Appendix Table C. 2. Average Annual Changes of Malmquist TFP Index, Chinese Province Data, 2001-2022

Province	Malmquist Index	Technical Change	Efficiency Change
Beijing	0.983	1.009	0.974
Tianjin	1.032	1.013	1.017
Hebei	1.020	1.018	1.005
Shanxii	1.021	1.005	1.020
Inner Mongolia	1.002	1.002	1.000
Liaoning	1.034	1.029	1.005
Jilin	1.005	1.005	1.000
Heilongjiang	1.029	1.029	1.000
Shanghai	1.002	0.980	1.014
Jiangsu	1.048	1.048	1.003
Zhejiang	0.999	1.024	0.979
Anhui	1.018	1.018	1.002
Fujian	1.032	1.023	1.010
Jiangxi	1.001	1.001	1.001
Shandong	1.016	1.019	0.999
Henan	1.014	1.019	0.997
Hubei	1.017	1.012	1.004
Hunan	0.985	0.994	0.990
Guangdong	0.979	0.996	0.985
Guangxi	0.995	0.992	1.004
Hainan	0.976	0.984	0.992
Chongqing	1.003	1.003	1.000
Sichuan	0.989	0.989	1.000
Guizhou	0.996	0.995	1.000
Yunan	0.996	0.986	1.011
Tibet	0.984	0.984	1.000
Shanxi	1.002	1.000	1.003
Gansu	1.014	1.010	1.005
Qinghai	1.030	1.017	1.012
Ningxia	1.008	1.008	1.000
Xinjiang	1.007	1.006	1.002

Appendix Table C. 3. Averaged China's Agricultural TFP in each Five-Year Plan

	FYP 10	FYP 11	FYP 12	FYP 13	FYP 14
Intensity provinces of grain production					
TFP	1.010	1.009	1.010	1.008	1.008
Technical change	1.026	1.009	1.026	1.009	1.009
Technical efficiency	0.984	1.001	0.984	1.001	1.000
Non intensity provinces of grain production					
TFP	1.020	1.007	1.007	1.007	1.008
Technical change	1.026	1.006	1.007	1.006	1.007
Technical efficiency	0.993	1.001	1.001	1.001	1.002
Eastern provinces					
TFP	1.022	1.010	1.010	1.009	1.011
Technical change	1.034	1.010	1.010	1.009	1.011
Technical efficiency	0.987	1.000	1.000	1.000	1.001
Middle provinces					
TFP	1.015	1.016	1.016	1.014	1.014
Technical change	1.032	1.014	1.014	1.013	1.014
Technical efficiency	0.982	1.002	1.002	1.001	1.000
Western provinces					
TFP	1.012	1.007	1.010	1.007	1.007
Technical change	1.021	1.006	1.010	1.007	1.007
Technical efficiency	0.991	1.001	1.000	1.001	1.001

Appendix Table C. 4. Averaged Annual Change of Malmquist TFP index, Chinese Province Data, 10th FYP (2001-2005)

Province	Malmquist Index	Technical Change	Efficiency Change	Location
Beijing	1.07	1.07	1.00	East
Tianjin	1.07	1.04	1.03	East
Hebei	1.03	1.05	0.98	East
Shanxi	1.08	1.03	1.05	East
Inner Mongolia	1.03	1.03	1.00	West
Liaoning	1.07	1.05	1.02	East
Jilin	1.03	1.03	1.00	Middle
Heilongjiang	1.00	1.00	1.00	West
Shanghai	1.11	0.98	1.08	East
Jiangsu	1.00	1.06	0.94	East
Zhejiang	0.98	1.06	0.93	East
Anhui	1.01	1.06	0.96	Middle
Fujian	1.01	1.03	0.98	East
Jiangxi	0.97	1.01	0.96	Middle
Shandong	1.04	1.05	0.98	East
Henan	1.03	1.05	0.98	Middle
Hubei	1.01	1.03	0.98	Middle
Hunan	1.00	1.02	0.98	Middle
Guangdong	1.01	1.01	1.00	East
Guangxi	0.97	1.02	0.96	West
Hainan	1.03	1.03	1.00	East
Chongqing	1.03	1.03	1.00	West
Sichuan	1.01	1.01	1.00	West
Guizhou	0.97	0.97	1.00	West
Yunan	1.04	1.02	1.02	West
Tibet	1.09	1.09	1.00	West
Shaanxi	1.01	0.99	1.02	West
Gansu	1.00	1.02	0.98	West
Qinghai	1.06	1.05	1.02	West
Ningxia	1.03	1.03	1.00	West
Xinjiang	1.07	1.04	1.03	West

Appendix Table C. 5. Averaged Annual Change of Malmquist TFP index, Chinese Provincial Data, Eleventh FYP (2006-2010)

Province	Malmquist Index	Technical Change	Efficiency Change	Location
Beijing	0.97	0.97	1.00	East
Tianjin	0.96	0.96	1.00	East
Hebei	1.01	0.98	1.03	East
Shanxi	1.00	0.98	1.02	East
Inner Mongolia	0.97	0.97	1.00	West
Liaoning	1.00	1.00	1.00	East
Jilin	0.97	0.97	1.00	Middle
Heilongjiang	1.07	1.07	1.00	West
Shanghai	1.00	1.00	1.00	East
Jiangsu	1.03	1.00	1.04	East
Zhejiang	1.01	1.00	1.01	East
Anhui	1.02	0.99	1.03	Middle
Fujian	1.00	0.98	1.02	East
Jiangxi	1.02	0.97	1.05	Middle
Shandong	1.00	0.99	1.02	East
Henan	1.00	0.99	1.02	Middle
Hubei	1.02	0.97	1.04	Middle
Hunan	0.97	0.98	1.00	Middle
Guangdong	0.96	0.96	1.00	East
Guangxi	1.04	0.98	1.07	West
Hainan	0.96	0.96	1.00	East
Chongqing	0.98	0.98	1.00	West
Sichuan	0.96	0.96	1.00	West
Guizhou	0.93	0.93	1.00	West
Yunan	0.95	0.96	0.99	West
Tibet	0.96	0.96	1.00	West
Shaanxi	0.99	0.96	1.03	West
Gansu	0.99	0.99	1.00	West
Qinghai	0.98	0.99	0.99	West
Ningxia	0.97	0.97	1.00	West
Xinjiang	0.96	0.94	1.02	West

Appendix Table C. 6. Averaged Annual Change of Malmquist TFP index, Chinese Provincial Data, Twelfth FYP (2006-2010)

Province	Malmquist Index	Technical Change	Efficiency Change	Location
Beijing	1.03	1.03	1.00	East
Tianjin	1.02	1.01	1.00	East
Hebei	1.02	1.03	0.99	East
Shanxi	1.02	1.02	1.00	East
Inner Mongolia	0.99	0.99	1.00	West
Liaoning	1.02	1.02	1.00	East
Jilin	1.03	1.03	1.00	Middle
Heilongjiang	1.03	1.03	1.00	West
Shanghai	0.94	0.94	1.00	East
Jiangsu	1.03	1.02	1.00	East
Zhejiang	1.00	1.03	0.97	East
Anhui	1.02	1.01	1.01	Middle
Fujian	1.01	1.01	1.00	East
Jiangxi	1.02	1.01	1.01	Middle
Shandong	1.01	1.01	1.00	East
Henan	1.02	1.02	1.00	Middle
Hubei	1.01	1.00	1.01	Middle
Hunan	0.99	1.00	0.99	Middle
Guangdong	0.96	1.01	0.96	East
Guangxi	0.97	0.97	1.00	West
Hainan	0.97	0.97	1.00	East
Chongqing	1.01	1.01	1.00	West
Sichuan	0.99	0.99	1.00	West
Guizhou	1.01	1.01	1.00	West
Yunan	0.98	0.97	1.01	West
Tibet	0.98	0.98	1.00	West
Shaanxi	1.00	1.01	0.99	West
Gansu	1.02	1.01	1.00	West
Qinghai	1.03	1.00	1.04	West
Ningxia	1.00	1.00	1.00	West
Xinjiang	1.00	1.01	0.99	West

Appendix Table C. 7. Averaged Annual Changes of Malmquist TFP Index, Chinese Provincial Data, Thirteenth FYP (2016-2020)

Province	Malmquist Index	Technical Change	Efficiency Change	Location
Beijing	0.82	0.92	0.90	East
Tianjin	1.00	1.00	1.00	East
Hebei	1.03	1.00	1.03	East
Shanxi	1.04	0.97	1.08	East
Inner Mongolia	1.03	1.03	1.00	West
Liaoning	1.03	1.03	1.00	East
Jilin	0.97	0.97	1.00	Middle
Heilongjiang	0.99	0.99	1.00	West
Shanghai	0.96	0.98	0.98	East
Jiangsu	1.09	1.06	1.03	East
Zhejiang	0.98	0.99	0.99	East
Anhui	1.01	1.00	1.01	Middle
Fujian	1.06	1.02	1.04	East
Jiangxi	0.99	0.99	1.00	Middle
Shandong	1.02	1.02	1.01	East
Henan	1.00	1.00	1.00	Middle
Hubei	0.96	1.01	0.95	Middle
Hunan	0.92	0.95	0.97	Middle
Guangdong	0.99	0.98	1.01	East
Guangxi	0.94	0.95	0.99	West
Hainan	0.92	0.94	0.97	East
Chongqing	0.97	0.97	1.00	West
Sichuan	0.98	0.98	1.00	West
Guizhou	1.03	1.03	1.00	West
Yunan	0.98	0.96	1.02	West
Tibet	0.95	0.95	1.00	West
Shaanxi	1.01	1.04	0.97	West
Gansu	1.03	1.00	1.02	West
Qinghai	1.02	1.02	1.00	West
Ningxia	1.03	1.03	1.00	West
Xinjiang	0.98	1.01	0.97	West

Appendix Table C. 8. Averaged Annual Changes of Malmquist TFP index

Province	Malmquist Index	Technical Change	Efficiency Change	Location
Beijing	1.00	1.04	0.96	East
Tianjin	1.04	1.04	1.00	East
Hebei	1.03	1.04	0.99	East
Shanxi	0.99	1.00	1.00	East
Inner Mongolia	0.99	0.99	1.00	West
Liaoning	1.10	1.10	1.00	East
Jilin	1.09	1.09	1.00	Middle
Heilongjiang	1.10	1.10	1.00	West
Shanghai	1.03	1.00	1.03	East
Jiangsu	1.16	1.16	1.00	East
Zhejiang	1.08	1.05	1.03	East
Anhui	1.02	1.04	0.98	Middle
Fujian	1.15	1.15	1.00	East
Jiangxi	1.06	1.07	0.99	Middle
Shandong	1.02	1.04	0.98	East
Henan	1.03	1.05	0.98	Middle
Hubei	1.22	1.10	1.10	Middle
Hunan	1.11	1.07	1.03	Middle
Guangdong	1.01	1.12	0.91	East
Guangxi	1.17	1.14	1.02	West
Hainan	1.10	1.12	0.98	East
Chongqing	1.11	1.11	1.00	West
Sichuan	1.06	1.06	1.00	West
Guizhou	1.07	1.07	1.00	West
Yunan	1.10	1.10	1.00	West
Tibet	1.08	1.08	1.00	West
Shaanxi	1.07	1.01	1.06	West
Gansu	1.05	1.04	1.02	West
Qinghai	1.08	1.08	1.00	West
Qinghai	1.00	1.00	1.00	West
Xinjiang	1.08	1.05	1.02	West

Appendix Table C. 9. Changes of TFP Rankings in each FYP for all 31 Provinces

Province	FYP 10th	FYP 11th	FYP 12th	FYP 13th	FYP 14th
Beijing	2	25	2	31	29
Tianjin	1	31	12	14	21
Hebei	13	2	6	9	23
Shanxi	8	14	11	3	30
Inner Mongolia	15	21	23	5	31
Liaoning	4	18	13	6	9
Jilin	12	12	4	24	11
Heilongjiang	22	4	3	16	8
Shanghai	3	1	31	26	22
Jiangsu	24	3	5	1	3
Zhejiang	29	5	22	20	14
Anhui	14	7	7	12	25
Fujian	18	10	17	2	4
Jiangxi	31	9	10	18	19
Shandong	11	11	16	10	26
Henan	10	17	8	15	24
Hubei	25	8	14	25	1
Hunan	20	19	24	29	6
Guangdong	26	6	30	17	27
Guangxi	30	24	29	28	2
Hainan	16	28	28	30	10
Chongqing	19	13	18	23	5
Sichuan	23	26	25	21	18
Guizhou	28	28	15	7	16
Yunan	7	27	27	22	7
Tibet	17	22	26	27	12
Shaanxi	27	20	20	13	17
Gansu	21	16	9	8	20
Qinghai	5	23	1	11	15
Ningxia	9	30	19	4	28
Xinjiang	6	15	21	19	13

Note: within each Five-year Plan, each province is ranked according to its TFP growth rate, from highest to lowest.

Appendix C.1. TFP Variation Across Five-Year Periods

Examining provincial TFP within each FYP allows to show differential productivity gains. Table C.4 in the Appendix reports the TFP growth and the decomposition over the tenth FYP. Despite declining in agricultural production inputs, Shanghai achieved the highest TFP growth rate of 10.8%, primarily attributed to an enhancement in technical efficiency. There is wide variation in the magnitude of TFP growth rate across the five FYP periods. In the Eleventh FYP, Shanghai's TFP annual growth stagnated primarily because of the absence of technological progress (see Table C.5 in the Appendix). In the twelfth FYP, technical regress slowed its TFP growth, and this deficit performance persisted throughout the thirteenth FYP (see Table C.6 and C.7 in the Appendix). It was not until the fourteenth FYP that Shanghai's TFP growth began to bounce back (see Table C.8 in the Appendix). During the tenth FYP, the top five performing provinces are all located in the eastern region, proximity to coastal areas and have favorable conditions for agricultural production.

When it comes to the eleventh FYP, TFP growth stagnated because of increasing production costs, rendering the grain production unprofitable. One priority objective in this period was to increase the farmer's income, consequently agricultural taxes were abolished in 2006, and this policy significantly eased the burden on farmers. Further, the government introduced a set of direct subsidy policies for farmers, but these subsidies were mainly designed to support major grain-production areas. Owing to increased production costs and rising off-farm wages, these policies had minimal impact on the overall rural residents' income and failed to provide strong production incentives (Gale, 2013). Therefore, productivity growth was notably poor, with an average yearly rate of -1.08%, largely owing to the technical regress at -2.17% (details are reported in Table C.5 in the Appendix). In response to the challenges in the eleventh FYP, the twelfth FYP raised the minimum procurement prices to establish a price floor under market prices. The steady

rise in domestic prices ignited farmers' enthusiasm for production, resulting in improvement in the average TFP of 1.5%, though it remained below the tenth FYP's growth. The decline of TFP growth in the thirteenth FYP, largely due to the result of technical regress. The highest FYP growth in TFP across all periods was 21.8 % in the fourteenth FYP which is aided by improvements in the technology growth of 10 % and technology efficiency of 10% (details are provided in Table C.8 in the Appendix).