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Measuring and Benchmarking Time-Varying Market Efficiency

Yali Mu[1,2,*], Stephan von Cramon-Taubadel[2], Gabriel Rosero[2], and Bernhard Brümmer[2]

[1]College of Economics and Management, Nanjing Forestry University, China

[2]University of Göttingen, Germany

*Correspondence: Yali Mu, muyali@njfu.edu.cn

Abstract: This paper develops and implements an analytical framework combining spatial space techniques with panel stochastic frontier models to assess and benchmark time-varying market efficiency, with China's pork market serving as the empirical application. We analyze spatial and temporal dynamics in adjustment speeds and compare inefficiency under a range of translog frontier specifications and market characteristics. The estimated market efficiency frontiers decline with greater geographic distances but improve with greater inter-market trade volume. Our analysis indicates that the Chinese pork market experiences significant inefficiencies (approximately 50%) in the speed of adjustment. The higher inefficiency is associated with rising diesel fuel prices. Roughly 35% of this inefficiency stems from short-term or transient shocks, and about 25% results from persistent, structural market characteristics. Overall, the study demonstrates that overlooking persistent inefficiency leads to an overestimation of the market's ability to restore or maintain efficient spatial price transmission over time.

Keywords: Time-Varying Market Efficiency, State Space Modelling, Panel Stochastic Frontier, Benchmark

1 Introduction

Efficient markets are instrumental in ensuring food security and sustainability (Goodwin, Schroeder, 1991; Headey et al., 2019; Zimmermann, Rapsomanikis, 2021), serving as critical regulators in commodity systems, absorbing supply and demand shocks and conveying essential price change signals (Pingali, 2007). Spatial market efficiency refers to the extent to which prices in geographically separated markets adjust toward their long-run equilibrium in response to shocks (Fackler, Goodwin, 2001; von Cramon-Taubadel, Goodwin, 2021). The speed with which equilibrium and thus efficiency is restored following shocks, evolves over time, influenced by factors such as the dissemination of information and infrastructure (Donaldson, 2018; Zant, 2018; Goodwin et al., 2002; Abay et al., 2023), predominantly driven by economic growth and restructuring (Abay et al., 2023). Hence, market participants are interested in understanding the extent to which individual markets adjust to shocks over time and how these markets contribute to overall price transmission (Mu, von Cramon-Taubadel, 2022). For policymakers, insights into how efficiently markets function and transmit prices are vital, especially in the context of regulatory debates, including discussions on whether speculative activity might distort price signals in spatially separated food markets, thereby exacerbating disparities in access and welfare outcomes (Fafchamps et al., 2005; Bellemare, 2015; Svanidze, Götz, 2019a; Ma et al., 2024). Identifying time-varying patterns of market efficiency is therefore critical for designing interventions that improve integration, reduce trade frictions, and strengthen the resilience of food markets across regions (von Cramon-Taubadel, Goodwin, 2021; Ma et al., 2021).

A substantial body of literature has emerged to evaluate market efficiency across spatially separated food markets, utilizing methods such as vector error correction models (VECMs) alongside Johansen cointegration and Granger causality tests (Manogna, Mishra, 2023), and panel integration techniques (Khedhiri, 2023). Market efficiency is a relative concept, the strongest and most rapid price transmission that is attainable between pairs of markets are defined as dynamic market efficiency frontiers by Mu and von Cramon-Taubadel (2022). Like Goodwin and Schroeder (1991) and Svanidze and Götz (2019a; 2019b), their empirical framework implicitly assumes that measures of market efficiency describing short-term adjustments remain constant over the sample period. However, this assumption is increasingly being questioned, as shocks disrupting equilibrium require variable adjustment times across both temporal and spatial domains, making their evaluation and evolution challenging (Ravallion, 1986). Studies have explored whether the contributions of markets to price transmission evolve over time, particularly through the application of time-varying VECM under state space formulations (Adämmer et al., 2016; Adämmer, Bohl, 2018). Thus far, the time-varying VECM approach has primarily been employed to analyse price discovery dynamics (Silverio, Szklo, 2012; Caporale et al., 2014; Vollmer et al., 2020). In this context, how market efficiency evolves in response to short-run interactions between prices of market pairs remains an open empirical question - crucial for identifying both transient and persistent inefficiencies in price transmission, yet still not well understood.

The basic benchmarking concept for market efficiency was introduced in studies by Mu and von Cramon-Taubadel (2022) and Mu et al. (2022). However, their approach is grounded on assumption that the magnitudes and speeds of market efficiency remain constant throughout the entire study period, which may not always hold in dynamic market environments. Utilizing a time-varying measures of market efficiency would relax this assumption, enabling a more nuanced examination of market efficiency dynamics and benchmarks (von Cramon-Taubadel, Goodwin, 2021). Since the pace of price transmission depends on a complex and evolving mix of logistical factors, such as trade costs influenced by technology (e.g., the introduction of refrigeration (Goodwin et al., 2002)), infrastructural developments (e.g., improvements in road and rail systems (Donaldson, 2018; Zant, 2018)) and institutional factors (e.g. variations in tariff levels or administrative costs of customs procedures). To assess the efficiency of pairs of markets, it is essential to establish a benchmark based on the observation and analysis of other market pairs across time and space - one that captures the dynamic factors influencing market efficiency "technology" and inefficiencies in price transmission over time. Such a benchmark would enable a deeper understanding of how market efficiency evolves and help identify the key drivers of inefficiency.

In this paper, we update the assessment of dynamic market efficiency using time-varying VECMs coupled with technical inefficiency effects in a panel stochastic frontier analysis (SFA) framework. Prior studies have employed cross-sectional stochastic frontier techniques to benchmark constant market efficiency measures and elucidate variations in those measures (Mu, von Cramon-Taubadel, 2022; Mu et al., 2022; Kouyaté, von Cramon-Taubadel, 2016; Svanidze, Götz, 2019a; 2019b). Utilizing cross-sectional data, Mu and von Cramon-Taubadel (2022) demonstrate a negative link between distance and market efficiency for China's pork markets, while Svanidze and Götz (2019a) identify similar patterns in Russian grain markets. Ma et al. (2024) explore the determinants (such as geographical distance between provinces and information) of the spatial price relationships in different periods of the Chinese pork market. The estimated time-varying speeds of adjustment derived from the state space model discussed above offers insights into the dynamic evolution of market efficiency. The panel stochastic frontier model includes variables that are expected to influence the time-varying speed of adjustments and associated inefficiency. In our analysis, we further examine how the time-varying market efficiency frontier is determined and how market efficiency evolves over time. To our knowledge, this is the first systematic study of the drivers that cause changes in food market efficiency over time.

Our second and principal contribution involves extending the benchmarking procedure outlined above to estimate the panel stochastic frontier that separates inefficiency into transient and persistent components while allowing for unobserved market heterogeneity (Kumbhakar et al., 2012) and accounting for time-variant inefficiency determinants (Greene, 2005a; 2005b; Badunenko, Kumbhakar, 2016). Employing panel frontier methods allows us to derive benchmarks for maximum speeds of adjustments across groups of market, offering a more comprehensive interpretation than conventional cross-sectional regressions. Moreover, the panel SFA model specification facilitates the estimation of technical change and time-varying technical inefficiency by incorporating stochastic inefficiency terms with known distributions, while simultaneously accounting for market-specific heterogeneity as well as both time-varying and time-constant inefficiency effects. The panel SFA model thus makes it possible to compare technical efficiency scores across different observations (Colombi et al., 2014).

To illustrate these contributions, we apply a time-varying econometric framework to analyze how China's provincial pork markets adjust to price shocks over time, thereby linking dynamic adjustment mechanisms to broader questions of market integration, food security, and policy design. As one of the most globally significant meats and a heavily traded agricultural commodity, pork presents a particularly relevant case for studying market efficiency. The significance of Chinese provincial markets stems from China's status as a leading pork producer and consumer worldwide. We utilize monthly wet market pork prices from 30 provinces across China over 16 years, which provide 435 market pairs with 216 monthly observations each. Over the past two decades, China has witnessed significant economic expansion and structural transformation driven by urbanization and substantial improvements in transportation and communication networks (Abay et al., 2023). These changes, along with rising incomes, have triggered structural shifts in both food demand and supply, profoundly impacting market operations (Ma et al., 2024). However, many markets, particularly those in remote or less accessible regions, continue to suffer from weak spatial integration (e.g., Dillon, Barrett, 2016; Hastings et al., 2021; Mu, von Cramon-Taubadel, 2022). Such deficiencies hinder the efficient flow of goods and information, posing challenges to market performance and ultimately affecting food security (Hadachek et al., 2023). To identify barriers of market efficiency and inform policies aimed at improving integration over time and space, we adopt a two-stage approach. In the first stage, we estimate time-varying error correction parameters for each pork market pair using state space models to examine how market efficiency has evolved over time (Adämmer et al., 2016; Adämmer, Bohl, 2018; Vollmer et al., 2020). In the second stage, we apply panel stochastic frontier techniques to benchmark market efficiency and to identify the determinants of inefficiency across market pairs relative to the estimated time-varying market efficiency frontier (e.g., Greene, 2005a; 2005b; Badunenko, Kumbhakar, 2016).

The remainer of the paper is organized as follows. Section 2 outlines the methodology and data set that we use in our analysis. Sections 3 and 4 present the results and a detailed discussion, respectively. Finally, Section 5 concludes with a summary of the findings and implications for future research.

2 Econometric Strategy

2.1 Methods

2.1.1 Measuring Time-Varying Market Efficiency

In the first stage, we employ time-varying VECMs to capture time-variant dynamic interactions between market prices. This method, as outlined by Adämmer et al. (2016) and Adämmer and Bohl (2018), allows us to estimate whether and how short-term price dynamics evolve over time. To evaluate the changing pace of adjustment across spatially separated markets, we formulate the following bivariate VECM:

$$\Delta lnp_{i,t} = \varphi_t^{ij} + \alpha_t^{ij} ec_{t-1} + \sum_{k=1}^{l} \delta_{t,k}^{ii} \Delta lnp_{i,t-k} + \sum_{k=1}^{l} \delta_{t,k}^{ij} \Delta lnp_{j,t-k} + \varepsilon_{ij,t} \tag{1a}$$

$$\Delta lnp_{j,t} = \varphi_t^{ji} + \alpha_t^{ji} ec_{t-1} + \sum_{k=1}^{l} \delta_{t,k}^{ji} \Delta lnp_{i,t-k} + \sum_{k=1}^{l} \delta_{t,k}^{jj} \Delta lnp_{j,t-k} + \varepsilon_{ji,t} \tag{1b}$$

In Equations (1a) and (1b), $i, j = \{1, 2, \ldots, 30\}$ denote provinces in China. Δ is the first difference operator. l is the lag order. Time-varying adjustment parameters α_t^{ij} and α_t^{ji} measure the speed with which deviations from the long-run equilibrium are corrected in each period t (i.e., how $lnp_{i,t}$ and $lnp_{j,t}$ respond in period t in response to any disequilibrium in the previous period $t-1$, when $ec_{t-1} \neq 0$). The parameters $\delta_{t,k}^{ii}$, $\delta_{t,k}^{jj}$, $\delta_{t,k}^{ij}$ and $\delta_{t,k}^{ji}$ in (1a) and (1b), measure the short-run dynamics of the system. The error correction term

$$ec_{t-1} = lnp_{i,t-1} - \beta_{ij,1} lnp_{j,t-1} - \beta_{ij,0} \tag{2}$$

captures the temporary deviations from the long-run equilibrium which is assumed to be time-invariant. The long-run equilibrium relationship, $lnp_{i,t-1} = \beta_{ij,0} + \beta_{ij,1} lnp_{j,t-1}$, is normalized on the higher of the two prices so that $\beta_{ij,1}$ is expected to be less than or equal to 1. Thus the adjustment parameter α_t^{ij} is expected to be negative for prices in market j in Equation (1a), and α_t^{ji} is expected to be positive for prices in market i in Equation (1b).

To estimate time-varying speed of adjustment parameters, we reformulate the outlined model (1a) and (1b) in state-space form and apply the Kalman filter. The dynamic VECM measurement Equation:

$$\Delta lnp_t = \xi_t Z_t + \varepsilon_t \tag{3}$$

with $\varepsilon_t | \psi_{t-1} \sim N(0, H_t)$

where $\Delta lnp_t = \begin{bmatrix} \Delta lnp_{i,t} \\ \Delta lnp_{j,t} \end{bmatrix}$ is the vector of price differences on the LHS of Equations (1a) and (1b), and $Z_t = \begin{bmatrix} 1 & ec_{t-1} & \Delta lnp_{j,t-1} & \Delta lnp_{i,t-1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & ec_{t-1} & \Delta lnp_{j,t-1} & \Delta lnp_{i,t-1} \end{bmatrix}$ contains the RHS variables of these Equations. ξ_t is a vector of time-varying speed of adjustment and short-run dynamic parameters, which evolves through time following a random walk:

$$\xi_t = F \xi_{t-1} + \nu_t \tag{4}$$

with $\nu_t | \psi_{t-1} \sim N(0, Q_t^*)$

where F is an identity matrix of dimension $2 * (2l + 1)$, which corresponds to the column dimension of Z_t and the row dimension of ξ_t in Equation (3) governs the transition of the state variables. ν_t is the process disturbance term which capture innovations in the adjustment dynamics. Equation (4) therefore defines the temporal evolution of the unobserved adjustment parameters that are recursively estimated using the Kalman filter (Durbin, Koopman, 2012).

To construct pairwise adjustment measures between provincial pork markets, we follow Mu and von Cramon-Taubadel (2022) and define the speed of adjustment as,

$$\alpha_{ij,t} = \alpha_t^{ji} - \alpha_t^{ij} \tag{5}$$

where α_t^{ij} and α_t^{ji} denote the adjustment speeds when market i leads and market j leads, respectively. We compute $\alpha_{ij,t}$ for each distinct pair of the 30 markets in our data by restricting $i > j$, which yields a total of 435 unique provincial market pairs. For each of these pairs, the time-vary VECM outlined above is estimated using monthly data from January 2000 to December 2017 ($n = 216$), while accounting for the expected signs of the estimated parameters. The result of our first stage generates 93,090 estimated adjustment coefficients $\alpha_{ij,t}$ from 435 bivariate time-varying VECMs.[1]

2.1.2 Benchmarking Time-Varying Market Efficiency

In the second stage, we extend the methodology proposed by Mu and von Cramon-Taubadel (2022) to a panel-data setting. Specifically, we specify a panel stochastic frontier for $\alpha_{ij,t}$ as a function of $x_{ij,t}$. The frontier serves as a benchmark, capturing the maximum achievable speed of adjustment. Any deviations from the frontier signal departures from this maximum speed of restoring market efficiency over time.

To assess time-varying market efficiency frontiers, we estimate different panel stochastic frontier models with varying assumptions regarding inefficiency, the unique heterogeneity among market pairs and structural complexity. Comparing results across these nested specifications enables us to evaluate whether accounting for persistent inefficiency and market-specific heterogeneity significantly alters the estimated efficiency dynamics.

We begin by estimating and comparing three model specifications: Pooled, True Random Effects (TRE), and Generalized True Random Effects (GTRE). The Pooled model assumes inefficiency is entirely transient and ignores the panel structure of the data, thereby failing to account for persistent inefficiency and market-specific heterogeneity. The TRE model, proposed by Greene (2005a, 2005b), introduces time-invariant unobserved heterogeneity into the panel stochastic frontier but merges persistent inefficiency with market-specific heterogeneity. In contrast, the GTRE model, developed by Kumbhakar et al. (2012) and further elaborated by Colombi et al. (2014), separates inefficiency into transient and persistent components while allowing for unobserved heterogeneity across market pairs. The GTRE model is expressed thus:

$$\alpha_{ij,T} = \alpha + \varphi x_{ij,T} + w_{ij} - h_{ij} + v_{ij,T} - u_{ij,T} \tag{6}$$

Where $\alpha_{ij,T}$ denotes the estimated speed of price adjustment at time T for market pair (i,j). The use of the time-subscript T indicates that Equation (6) is estimated using annual data. The use of annual data is necessary because some of the covariates in $x_{ij,T}$ that we use to explain variations in the speed of price adjustment are not available at the higher, monthly frequency. We aggregate the monthly series of estimated $\alpha_{ij,t}$ to the annual series $\alpha_{ij,T}$ by either extracting the June estimate ($\alpha_{ij,June}$) for each year, or by calculating the annual average estimate ($\alpha_{ij,Annual}$) for the given market pair.[2] The month of June provides a mid-year snapshot that is unaffected by seasonal extremes w_{ij} captures time-invariant heterogeneity and h_{ij} represents persistent inefficiency. $v_{ij,T}$, which follows a normal distribution $N(0, \sigma_v^2)$, accounts for random noise, and $u_{ij,T}$ with a half normal distribution $N^+(0, \sigma_u^2)$, reflects transient inefficiency. These

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1 We set the lag length to one for all market pairs, so the series of estimated parameters $\alpha_{ij,t}$ begin in the second month (t = 2) and end at the penultimate observation month ($t = 215$) for each pair. This results in a total of $214 * 435$=93,090 monthly adjustment parameters estimated across all the market pairs.

2 We acknowledge that temporally aggregating the monthly series $\alpha_{ij,t}$ to the annual series $\alpha_{ij,T}$ by either extracting the June estimates to form $\alpha_{ij,June}$, or calculating average annual estimates to obtain $\alpha_{ij,Annual}$, is a relatively coarse approach that will result in the loss of much information contained in monthly variations. However, this aggregation allows us to explore a much richer set of potential covariate of market efficiency that are only available at the annual frequency.

components are assumed to be independently distributed. By incorporating these four components, the GTRE model offers a more thorough framework than the TRE model, which fails to differentiate between heterogeneity and persistent inefficiency, or the Pooled model, which assumes that all inefficiency is temporary.

In the augmented TRE-Z and GTRE-Z models, as specified by Greene (2005a, 2005b) and Badunenko and Kumbhakar (2016), the variance of the inefficiency term is modeled as a function of explanatory variables $z_{ij,T}$, allowing us to examine how exogenous factors influence transient inefficiency:

$$\sigma^2_{u_{ij,T}} = \exp(\delta z_{ij,T}) \tag{7}$$

where $z_{ij,T}$ represents the exogenous variables and δ denotes the vector of estimated parameters. This specification links observable determinants, such as logistics infrastructure, information transparency, or market access, to the variability of inefficiency, thereby enhancing the interpretability of the model and grounding it in empirically observable heterogeneity.

2.2 Diagnostic Procedures and Assumptions

2.2.1 Diagnostic Tests for Price Series

The VECM relies on the assumptions that the differenced variables are stationary, a stable long-run cointegrating relationship exists, and residuals follow classical error properties (no autocorrelation, homoscedasticity, and normality). To verify these underlying conditions, a series of unit root, cointegration, and residual diagnostic tests were conducted prior to estimation. These tests ensure that the VECM specification is statistically consistent and the estimated adjustment parameters are reliable.

To ensure the validity of the VECM specification, we first verify its underlying statistical assumptions. The model assumes that each price series is integrated of order one, $I(1)$, and that a stable long-run cointegrating relationship exists between markets. To test these conditions, we assess the presence of unit roots in the price series using the Augmented Dickey-Fuller (ADF) test (Said, Dickey, 1984) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992). In addition, we employ the panel unit root (pCADF) test proposed by Constantini and Lupi (2013), which combines p-values from covariate ADF tests under the null hypothesis that all series are $I(1)$. To account for potential structural breaks that may affect stationarity, we apply the Zivot–Andrews (ZA) test (Zivot, Andrews, 1992), which contrasts the null hypothesis of a unit root against the alternative of a stationary process with a structural break in level and/or trend. The break date is identified as the point where the ADF test's t-statistic is most negative. After confirming the integration properties, we conduct Johansen's trace test (Johansen, 1991; 1995) to examine cointegration across all the 435 market pairs, ensuring that the long-run equilibrium relationships required for the ECM are satisfied.

We then construct panel data for the time-varying market efficiency model in Equation (6). This model is estimated twice, once with $\alpha_{ij,June}$ as the dependent variable, and once with $\alpha_{ij,Annual}$, as outlined above.

2.2.2 Distributional Assumptions of the Stochastic Frontier Model

To specify the market efficiency frontier function, we evaluate both Cobb-Douglas and translog functional forms. The Cobb-Douglas model imposes the strong assumption of constant elasticities, whereas the translog model offers greater flexibility by permitting elasticities to vary across market pairs. Since the Cobb-Douglas specification is nested within the translog, we perform Wald tests to identify the more appropriate functional form. Additionally, we normalize the variables by their sample means prior to taking logarithms, which enables the first-order coefficients of the translog function to be interpreted as partial elasticities at the sample mean.

We select the model specification that best fits the data using a nested hypothesis testing framework as outlined by Badunenko and Kumbhakar (2016). Specifically, we apply Log-likelihood ratio (LR) tests to compare the Pooled specification with the TRE model, the TRE with the GTRE model, and finally, each main model against its augmented version with inefficiency determinants (i.e., TRE-Z and GTRE-Z). First, we test for the absence of market-specific heterogeneity, with the null hypothesis assuming that there is no individual market heterogeneity ($w_{ij} = 0$). Second, we test the null hypothesis that persistent inefficiency is equal to zero ($h_{ij} = 0$). Finally, for the TRE-Z and GTRE-Z models, we test the null hypothesis that the transient inefficiency variance (as specified in Equation (7)) does not depend on specific determinants ($\delta = 0$).

A key factor that can affect time-varying market efficiency is trade cost, which encompasses multiple components such as risk costs between markets (Buccola, 1989; Mulligan, Fik, 1989). Risks associated with increased freshness losses and variations in relative prices caused by shipping delays, tend to increase with distance. While geographic distances remain constant over time, other components of trade costs such as access to market information and trade scale, have evolved over the period. For instance, the amount of market information reflected in prices can influence the speed of adjustment parameter between markets (Stephens et al., 2012). Liquid terminal markets typically possess more comprehensive sets of market information per trade than decentralized direct trade markets (Lang, Rosa, 1981). Similarly, markets with larger trading volumes are generally more efficient in transmitting prices, as low-volume markets are more susceptible to noise and distortions (Barrett, Li, 2002; Tomek, 1980). We thus hypothesize that market efficiency is a decreasing function of geographic distance, but an increasing function of trade volume. We leverage data from e-commerce platforms that track parcel exchanges, providing a proxy for commodity movement (Chang et al, 2021), using the per capita parcel number for each market pair at time t ($parcel_{ij,t}$) as an index of transaction volume. Hence, we include the geographic distance d_{ij} and the parcel variable $parcel_{ij,t}$ between markets i and j in the vector $x_{ij,t}$ in the frontier model specified in Equation (6).

The stochastic frontier model in Equation (6) is based on the assumption that the composed error term $\varepsilon_{ijT} = v_{ijT} - u_{ijT}$ consists of a two-sided noise component $v_{ijT} \sim N(0, \sigma_v^2)$ and a one-sided inefficiency term $u_{ijT} \sim N^+(0, \sigma_u^2)$, which are independently distributed across observations. In practice, however, market relationships among provinces may exhibit spatial correlation. To mitigate this, we incorporate province-pair–specific heterogeneity (w_{ij}) and persistent inefficiency (h_{ij}) in the TRE and GTRE specifications, thereby relaxing the strict homoscedasticity and *i.i.d.* assumptions typical of pooled models. Furthermore, key explanatory variables such as inter-provincial transport connectivity, fuel price variation, and logistical infrastructure are included in Equation (7) to capture spatially correlated effects that may influence market efficiency. While our specification does not model spatial dependence explicitly (e.g., via spatial stochastic frontiers), this approach substantially reduces the risk of omitted spatial correlation bias and provides a robust baseline for future extensions that incorporate explicit spatial processes.

In the TRE-Z model specified in Equation (7), the diesel fuel price index and the number of towns between markets are considered as factors influencing inefficiency of time-varying price transmission, whereas the GTRE-Z model omits time-invariant variables, assuming that they do not capture variations in transient efficiency. Fuel prices, for instance, exhibited substantial volatility during the sample period - increasing by up to 100% and subsequently declining by 30% (Mu, von Cramon-Taubadel, 2022). Since diesel prices primarily affect food prices through transportation costs, fluctuations in fuel prices can result in short-term changes linked to transient inefficiencies in price transmission (Dillon, Barrett, 2014). These mismatches reflect short-term inefficiencies, as fuel price shocks tend to transmit faster than the price signals of agricultural commodities. The number of towns between markets reflects the complexity of trade routes and the degree of market connectivity. A greater number of intermediary towns may imply more fragmented logistics and higher transaction costs, which can impede efficient price transmission (Minten, Kyle, 1999; Dillon, Barrett, 2016; Hastings et al., 2021). Conversely, well-connected regions with dense road networks and multiple trade nodes tend to facilitate more efficient information and commodity flows. Including diesel fuel price index ($fuel_{ij,t}$) and number of towns ($town_{ij,t}$) in Equation (7) can help to explain changes in the inefficiency of price transmission over time.

3 Data

We construct our dataset from multiple sources. First, we estimate the bivariate time-varying VECMs specified in Equation (1) using the natural logarithm of monthly pork prices from 30 provincial-level administrative regions in mainland China, covering the period from January 2000 to December 2017 (Ministry of Agriculture of China, 2001-2018). These provincial monthly average prices (in Yuan/kg) are derived from weekly observations at 500 wet market survey points across the country (Ministry of Agriculture of China, 2018: 208). The finalized price dataset is a panel of real pork prices for 435 market pairs across 216 months. Although data beyond December 2017 are available, we restrict our sample to this period to avoid potential structural breaks in price dynamics resulting from the African Swine Fever outbreak in late 2018 and the subsequent Covid-19 pandemic, which have notably disrupted supply and demand on Chinese pork markets (Ma et al., 2021; Ma et al., 2024). Figure 1 presents the regional price patterns, showcasing three representative pork price series.

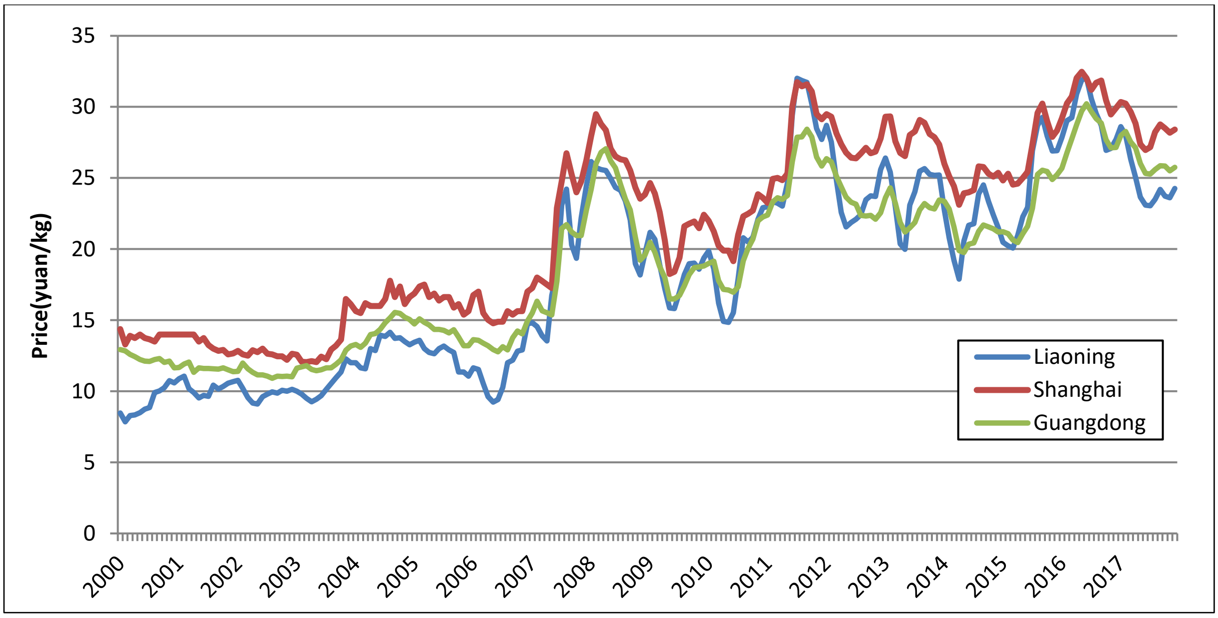

Figure 1. Three monthly pork prices series from Jan. 2000 to Dec. 2017

Source: Ministry of Agriculture of China (2001-2018)

Second, we incorporate variables into the panel stochastic frontier function for time-varying market efficiency, as outlined in Equations (6) and (7). The vectors $x_{ij,T}$ encompass distance d_{ij} and parcel volume per capita of each market pair $parcel_{ij,T}$. The traditional spatial proximity distance is quantified as the separation between the provincial capitals, measured in 1,000 km.[3] We use the per capita parcel number for each market pair($parcel_{ij,T}$) collected from the National Bureau Statistics of China as a proxy for transaction volume (NBSC, 2001-2018).[4]

[3] We use distance between provincial capitals, measured using Baidu Maps (www.map.baidu.com).

[4] In this study, a "parcel" refers to a parcel delivered through e-commerce or express logistics services, which serves as a proxy for commodity movement and transaction intensity between provinces (Chang et al., 2021). Because provinces differ substantially in population size, we use the number of parcels per capita rather than total parcel counts to control for scale effects and ensure comparability across regions. This normalization allows the variable to better reflect relative market activity and consumer engagement in trade volume than would sheer population-driven volume.

The diesel fuel price index $fuel_{ij,T}$ is province-specific and captures regional variation in transportation and production costs (EPSDATA, 2023).[5] The number of towns (township-level administrative unit below the county level in China's hierarchy) of each market pair $town_{ij,T}$, which serves as a proxy for the structural connectivity of the market network, is taken from NBSC (2001-2018). Table 1 provides a description of the variables used to estimate the frontier models in the second stage of our analysis.

Table 1. Description of variables

Variables	Definition	Mean	S.D.	Min.	Max.
Geographic distance (d_{ij})	Road distance between the capitals	1.72	0.91	0.13	4.75
Parcel per capita ($parcel_{ij,T}$)	Parcel volume per capita per year	5.19	12.12	0.03	127.92
Diesel fuel price index ($fuel_{ij,T}$)	Average index of markets i and j in each year	105.50	8.49	83.00	135.95
Number of towns ($town_{ij,T}$)	Town numbers of markets i and j in each year	1327	563	121	3399

Source: own calculations using Ministry of Agriculture of China (2001-2018)

4 Results

For each of the 30 price series individually the ADF test fails to reject the null hypothesis that the series is I(1) at the 5% level of significance, but rejects this null hypothesis for first differences of the prices. KPSS stationarity tests reject the null of stationarity for all the 30 price series, confirming the ADF test results that all price series are I(1). In addition, the *p*CADF test, the panel unit root test fails to reject the null hypothesis that all of the series are I(1). The ZA tests also confirm the ADF test results by ruling out the alternative of a stationary series with a breakpoint on a 5% significance level.[6]

The long-run relationships between the Chinese provincial pork prices that we analyse have likely changed over the 18-year sample period, for example due to improvements in transportation. However, after estimating the 435 bivariate VECMs using Johansen's (1991; 1995) maximum likelihood method and also testing for cointegration with a trend in the long-run relationship, we do not find evidence that these changes can be modelled adequately using a linear trend. Therefore, we assume that the long-run relationship between the markets is constant.

4.1 First-Step Estimates of Time-Varying Speed of Adjustment Parameter

We estimate 435 bivariate VECMs in state space form with lag-length $l = 1$ for all pairs. Figure 2 presents the distribution of the estimated time-varying speeds of price transmission ($\hat{\alpha}_{ij,June}$ and $\hat{\alpha}_{ij,Annual}$). The results depicted in Figure 2 reveal that during the sample period from 2000 to 2017, the median speed of adjustment is approximately 0.30, which suggests that for half of the 435 market pairs, at least 30% of any deviation from long-run equilibrium is corrected

[5] The index is set to 100 in a selected base period and averaged from monthly to yearly data., with subsequent values indicating percentage changes relative to that baseline. It is normalized to a mean of zero and a standard deviation of one. Consequently, higher standardized values indicate provinces with relatively higher fuel prices compared with the national average, rather than higher absolute price levels.

[6] Results of the ADF, *p*CADF, KPSS and Johansen trace test results are available on request from the authors. Detail descriptions of these test results can also be found in Mu and von Cramon-Taubadel (2022).

within one month. For the great majority of market pairs over the sample period, between 10% and 40% of any deviation is corrected within one month.

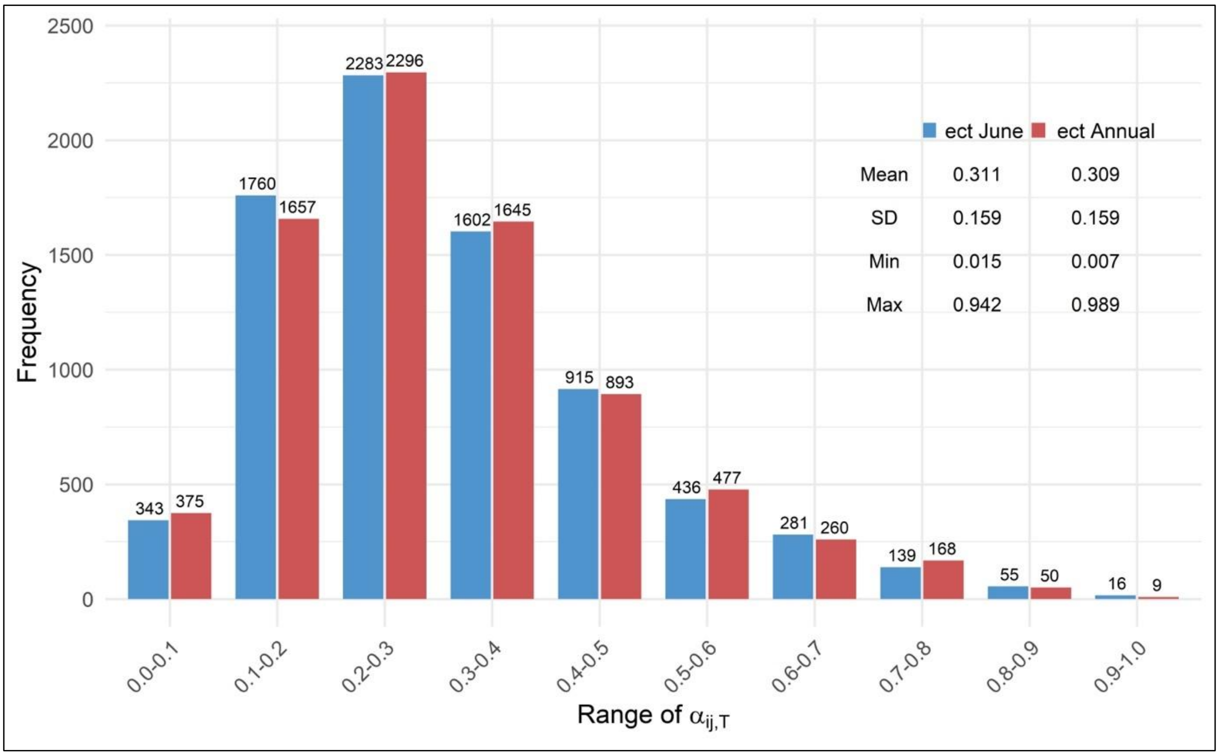

Figure 2. Distribution of the estimated time-varying speed of adjustment parameter $\hat{\alpha}_{ij,June}$ and $\hat{\alpha}_{ij,Annual}$

Source: own calculations using Ministry of Agriculture of China (2001-2018)

To illustrate the temporal dynamics of market integration, Figure 3 illustrates the evolution of $\alpha_{ij,June}$ (left panel) and of $\alpha_{ij,Annual}$ (right panel) between 2000 and 2017. Because the yearly values are averaged over 435 market pairs, the cross-sectional heterogeneity is largely smoothed, yielding a clearer view of long-term time-variance in the adjustment process. Together, these figures extend beyond the static characterization by providing a panel-based perspective on how adjustment speeds evolve across both space and time. Both the mean and median adjustment parameters exhibit a gradual downward trend over the sample period, indicating that the average speed of adjustment declines over the study period.

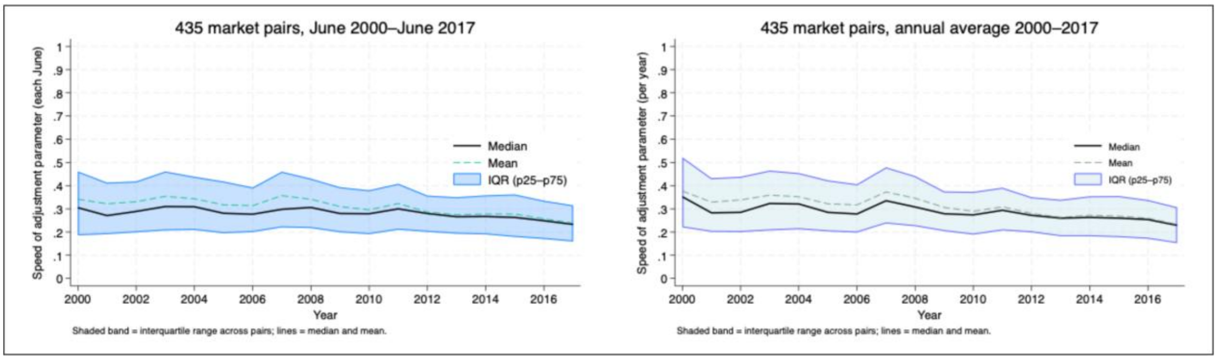

Figure 3. Temporal dynamics of the estimated time-varying speed of adjustment parameter $\hat{\alpha}_{ij,June}$ and $\hat{\alpha}_{ij,Annual}$

Source: own calculations using Ministry of Agriculture of China (2001-2018)

4.2 Second-Step Estimates of Time-Varying Speed of Restoring Market Efficiency Frontier

We conduct Wald tests to assess both Cobb-Douglas and translog functional forms for $\alpha_{ij,June}$ and $\alpha_{ij,Annual}$ model specifications. The results favor the translog specification form for $\alpha_{ij,June}$ ($\chi^2 = 116.04,\ df = 3,\ p < 0.01$), and $\alpha_{ij,Annual}$ ($\chi^2 = 154.92,\ df = 3,\ p < 0.01$). In terms of model selection, we perform several likelihood ratio (LR) tests to identify the most appropriate model for explaining technical efficiency in average pairwise price transmission between markets for $\alpha_{ij,June}$ and for $\alpha_{ij,Annual}$. We compare the pooled stochastic frontier model with the TRE specification. The LR statistics clearly reject the pooled model in favor of TRE for both cases ($LR = 2643.31,\ df = 1,\ p < 0.01$ for $\alpha_{ij,June}$; $LR = 2762.58,\ df = 1,\ p < 0.01$ for $\alpha_{ij,Annual}$), thereby indicating the presence of unobserved heterogeneity and providing support for the panel frontier structure. The LR test between the TRE and GTRE models ($LR = 7.562$, $df = 1, p < 0.01$) favors the GTRE models for $\alpha_{ij,June}$. Likewise, the comparison between the GTRE and GTRE-Z models ($LR = 11.277,\ df = 1,\ p < 0.01$) shows that adding inefficiency determinants markedly enhances the model fit, making GTRE-Z the preferred choice for $\alpha_{ij,June}$. However, we cannot reject the null hypothesis that the persistent inefficiency is equal to zero $h_i = 0$ ($LR = 2.267, df = 1, p = 0.132$) for $\alpha_{ij,Annual}$, suggesting that the GTRE do not significantly improve the model fit. Since σ_h is statistically significant at the 1% level and aligned with the $\alpha_{ij,June}$ model, the GTRE model is selected for comparability. Lastly, the TRE-Z model is the best model when compared to the TRE model for both $\alpha_{ij,June}$ ($LR = 49.678, df = 2, p < 0.01$) and $\alpha_{ij,Annual}$ ($LR = 52.34, df = 2, p < 0.01$).

Turning to the parameter estimates, the GTRE and TRE specifications are broadly consistent in sign and statistical significance for $\alpha_{ij,June}$ and $\alpha_{ij,Annual}$, albeit with some differences in magnitude. In the GTRE model for $\alpha_{ij,June}$ (Table 2), the estimated d_{ij} coefficient ranges from -0,27 to -0.31 and the coefficients on the squared distance d_{ij}^2 all equal -0.24, suggesting that greater distances correlate with lower price transmission efficiency. In contrast, the trade volume index, represented by $parcel_{ij,t}$, shows a slight positive effect of 0.03. The effect of time trend ranges from -0.02 to -0.04, indicating that the speed of market adjustment has slightly decreased over the sample period. For the $\alpha_{ij,Annual}$ GTRE specification, the estimated coefficients for d_{ij} and $parcel_{ij,t}$ are very similar to those for $\alpha_{ij,June}$, with a modest increase in the magnitude of the $parcel_{ij,t}$ coefficient. The negative sign of the coefficient on the time trend is slightly larger (-0.05), suggesting a more marked downward shift in the market efficiency frontier for $\alpha_{ij,Annual}$.

In the TRE-Z model, the coefficient estimates for the frontier Equation exhibit similar patterns (see Table 3). Notably, the distance and distance-squared coefficients remain negative (between −0.23 and -0.32 for the $\alpha_{ij,June}$ frontier and -0.23 and -0.28 for the $\alpha_{ij,Annual}$ frontier), while the $parcel_{ij,t}$ coefficient is slightly positive (0.03 and 0.05, respectively). The negative time trend coefficients (-0.04 for $\alpha_{ij,June}$ and -0.05 for $\alpha_{ij,Annual}$) closely align with those observed in the GTRE-Z model.[7]

[7] To address a reviewer's concern about potential endogeneity if parcel volumes were to respond to past market efficiency, we re-estimated both the TRE and GTRE models using lagged parcel volumes instead of contemporaneous values. The resulting frontier parameters and efficiency estimates remain highly stable across specifications, indicating that parcel volume does not systematically react to short-run inefficiency and behaves as a plausibly predetermined structural variable in our setting. In the four-component GTRE specification, the appearance of zero standard errors for some variance components reflects known identification limitations of multi-component SFA models (Colombi et al., 2014; Kumbhakar et al., 2014), rather than evidence of endogeneity. Full diagnostic tables are available from the authors upon request.

Table 2. Time-varying market efficiency frontier using translog functional form - Generalized True Random Effects

	$\alpha_{ij,June}$			$\alpha_{ij,Annual}$		
Variable	**Model 1a**	**Model 1b**	**Model 1c**	**Model 1d**	**Model 1e**	**Model 1f**
Constant	0.70	0.74	0.76	0.74	0.81	0.84
	[0.62 0.79]	[0.67 0.82]	[0.70 0.83]	[0.68 0.80]	[0.74 0.89]	[0.77 0.90]
d_{ij}	-0.31	-0.27	-0.27	-0.26	-0.25	-0.27
	[-0.39 -0.23]	[-0.33 -0.20]	[-0.34 -0.21]	[-0.34 -0.19]	[-0.34 -0.16]	[-0.33 -0.21]
$parcel_{ij,T}$		0.03	0.03		0.05	0.05
		[0.01 0.05]	[0.01 0.05]		[0.03 0.06]	[0.03 0.07]
$trend$	-0.02	-0.03	-0.04	-0.03	-0.05	-0.05
	[-0.02 -0.02]	[-0.04 -0.03]	[-0.04 -0.03]	[-0.03 -0.02]	[-0.05 -0.04]	[-0.05 -0.04]
${d_{ij}}^2$	-0.24	-0.24	-0.24	-0.22	-0.23	-0.25
	[-0.34 -0.15]	[-0.35 -0.13]	[-0.33 -0.16]	[-0.32 -0.12]	[-0.33 -0.13]	[-0.32 -0.17]
${parcel_{ij,T}}^2$		-0.01	-0.01		-0.01	-0.01
		[-0.02 -0.01]	[-0.02 -0.00]		[-0.02 -0.01]	[-0.02 -0.01]
$d_{ij} * parcel_{ij,T}$		0.03	0.03		0.03	0.03
		[0.02 0.03]	[0.02 0.03]		[0.02 0.04]	[0.02 0.04]
Constant_σ_u			-0.81			-0.84
			[-0.87 -0.76]			[-0.88 -0.79]
Z_$fuel_{ij,T}$			0.49			-0.28
			[0.12 0.87]			[-0.67 0.10]
σ_v	0.69	0.67	0.15	0.68	0.66	0.13
	[0.67 0.70]	[0.66 0.69]	[0.14 0.17]	[0.66 0.69]	[0.65 0.68]	[0.12 0.14]
σ_w	0.20	0.22	0.22	0.17	0.21	0.21
	[0.14 0.26]	[0.18 0.26]	[0.18 0.26]	[0.13 0.21]	[0.16 0.26]	[0.18 0.25]
σ_h	0.41	0.37	0.39	0.45	0.42	0.44
	[0.32 0.49]	[0.31 0.44]	[0.34 0.44]	[0.37 0.52]	[0.34 0.50]	[0.38 0.49]
λ	4.30	3.93		5.02	4.55	
	[3.84 4.76]	[3.53 4.34]		[4.48 5.57]	[4.09 5.01]	
Log Likelihood	-4574.71	-4546.82	-4541.18	-4341.07	-4300.32	-4295.86

Note: to enhance clarity, we distinguish between model specifications estimated without $parcel_{ij,T}$ (Model 1a and Model 1d in Table 2, Model 2a and Model 2d in Table 3) and those estimated with the $parcel_{ij,T}$ variable, thereby enabling a clear assessment of the robustness of our results to the inclusion of this variable. 95% confidence interval, [lower limit upper limit]. The variance ratio λ is the ratio between the variance of the transient technical efficiency and the variance of the idiosyncratic error term ($\lambda = \sigma_u/\sigma_v$).
Source: own calculations using Ministry of Agriculture of China (2001-2018)

Table 3. Time-varying market efficiency frontier using translog functional form - True Random Effects

	$\alpha_{ij,June}$			$\alpha_{ij,Annual}$		
Variable	**Model 2a**	**Model 2b**	**Model 2c**	**Model 2d**	**Model 2e**	**Model 2f**
Constant	0.39	0.47	0.47	0.39	0.51	0.51
	[0.35 0.42]	[0.41 0.52]	[0.41 0.52]	[0.36 0.43]	[0.45 0.56]	[0.46 0.56]
d_{ij}	-0.32	-0.25	-0.25	-0.28	-0.23	-0.23
	[-0.39 -0.25]	[-0.32 -0.17]	[-0.32 -0.17]	[-0.35 -0.22]	[-0.30 -0.16]	[-0.30 -0.16]
$parcel_{ij,T}$		0.03	0.03		0.05	0.05
		[0.00 0.05]	[0.00 0.05]		[0.03 0.07]	[0.03 0.07]
$trend$	-0.02	-0.03	-0.04	-0.03	-0.05	-0.05
	[-0.02 -0.02]	[-0.04 -0.03]	[-0.04 -0.03]	[-0.03 -0.02]	[-0.05 -0.04]	[-0.05 -0.04]
${d_{ij}}^2$	-0.27	-0.23	-0.23	-0.24	-0.24	-0.23
	[-0.37 -0.16]	[-0.34 -0.13]	[-0.34 -0.13]	[-0.34 -0.15]	[-0.34 -0.13]	[-0.34 -0.13]
${parcel_{ij,T}}^2$		-0.01	-0.01		-0.01	-0.01
		[-0.02 -0.01]	[-0.02 -0.01]		[-0.02 -0.01]	[-0.02 -0.01]
$d_{ij} * parcel_{ij,T}$		0.03	0.03		0.03	0.03
		[0.02 0.04]	[0.02 0.04]		[0.02 0.04]	[0.02 0.04]
Constant_σ_u	-0.83	-0.85	-0.85	-0.84	-0.86	-0.87
	[-0.88 -0.78]	[-0.91 -0.80]	[-0.91 -0.80]	[-0.89 -0.79]	[-0.91 -0.81]	[-0.92 -0.82]
$town_{ij,t}$	-0.23	-0.27	-0.27	-0.24	-0.27	-0.28
	[-0.31 -0.15]	[-0.35 -0.19]	[-0.35 -0.19]	[-0.31 -0.16]	[-0.35 -0.19]	[-0.36 -0.20]
$fuel_{ij,t}$			0.44			-0.39
			[0.07; 0.81]			[-0.78 -0.01]
σ_v	0.15	0.15	0.15	0.13	0.13	0.13
	[0.14 0.17]	[0.14 0.17]	[0.14 0.17]	[0.11 0.14]	[0.12 0.14]	[0.12 0.14]
σ_w	0.32	0.32	0.32	0.31	0.33	0.33
	[0.29 0.34]	[0.30 0.34]	[0.30 0.34]	[0.29 0.33]	[0.30 0.35]	[0.30 0.35]
Log Likelihood	-4563.04	-4528.47	-4525.76	-4325.00	-4277.28	-4275.27

Note: 95% confidence interval, [lower limit upper limit]
Source: own calculations using Ministry of Agriculture of China (2001-2018)

4.3 Technical Efficiency in the Time-Varying Speed of Restoring Market Efficiency Frontier

The inefficiency component includes two variables: the number of towns between markets $ltown_{ij,T}$) and the fuel price index ($fuel_{ij,T}$). Under the GTRE models for $\alpha_{ij,June}$ frontier shown in Table 2, the inefficiency component shows a positive relationship with $fuel_{ij,T}$ (0.49), which means that higher diesel fuel prices are associated with higher inefficiency in restoring price equilibrium. However, the inefficiency effect of the $fuel_{ij,T}$ becomes negative for $\alpha_{ij,Annual}$ frontier (-0.28). One possible reason for this difference is that yearly data mask short-term variations in diesel fuel prices, thus affecting the relationship between persistent and temporary aspects of price transmission efficiency.

Figure 4 illustrates the GTRE-Z model results, focusing on the dynamics of technical efficiency for $\alpha_{ij,June}$ (panel A) and $\alpha_{ij,Annual}$ (panel B). In both panels, the histogram of transient technical efficiency (TTE) scores displays a skewed distribution favoring higher efficiency levels, with most pair markets achieving a TTE above 0.60. The mean values, represented by the dashed blue line, reveal that the average efficiency for both $\alpha_{ij,June}$ and $\alpha_{ij,Annual}$ equals 0.65. Persistent technical efficiency scores are higher in both scenarios, with the $\alpha_{ij,June}$ data averaging 0.75, slightly surpassing the $\alpha_{ij,Annual}$ of averaging 0.73. Overall technical efficiency is considerably lower, equalling 0.49 for $\alpha_{ij,June}$ and 0.47 for $\alpha_{ij,Annual}$, indicating at least 53% of the maximum possible speed of price transmission is not reached due to technical inefficiencies. These findings highlight the critical need to address transient inefficiencies, which substantially affect overall performance, while persistent inefficiencies are less pronounced.

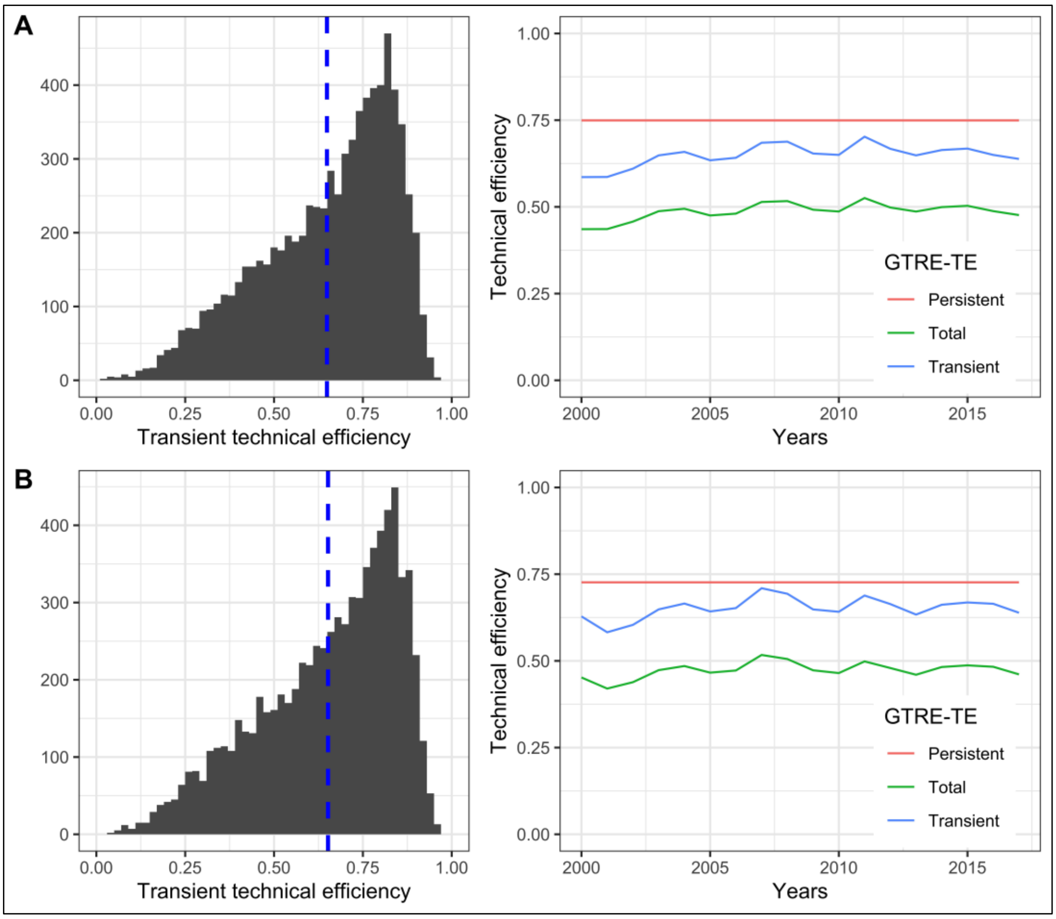

Figure 4. Distribution of transient and persistent efficiency scores with generalized true random effects

Source: own calculations using Ministry of Agriculture of China (2001-2018)

In the TRE models for the $\alpha_{ij,June}$ frontier shown in Table 3, the negative sign on $town_{ij,T}$ (-0.27) implies that having more towns is linked to lower inefficiency, which might reflect greater opportunities for intermediary trade or better infrastructure across multiple localities. By contrast, the estimated coefficient on $fuel_{ij,T}$ (0.44) is positive, indicating that inefficiency increases with rising fuel costs in the short run. For $\alpha_{ij,Annual}$, the negative coefficient on $town_{ij,T}$ is slightly larger in magnitude (-0.28), and the $fuel_{ij,T}$ switches sign to -0.39, suggesting a more nuanced relationship between persistent inefficiency, energy costs and spatial integration when aggregated over a full year.

Figure 5 illustrates the technical efficiency outcomes of the TRE-Z model for $\alpha_{ij,June}$ (Panel A) and $\alpha_{ij,Annual}$ (Panel B). The average TE (blue dashed line) for $\alpha_{ij,June}$ stands at 0.63, suggesting that, on average, units achieve 63% of their potential speed of price adjustment. In the case of $\alpha_{ij,Annual}$, the mean TE is slightly higher (0.65), indicating a small decrease in inefficiencies when we estimate with annual average speeds of price adjustment. The histograms show that most markets perform above 40% efficiency, with a concentration around 55%. There are several instances in which market efficiency approaches 100%. Over time, technical efficiency appears stable in both scenarios, with no notable upward or downward trends.

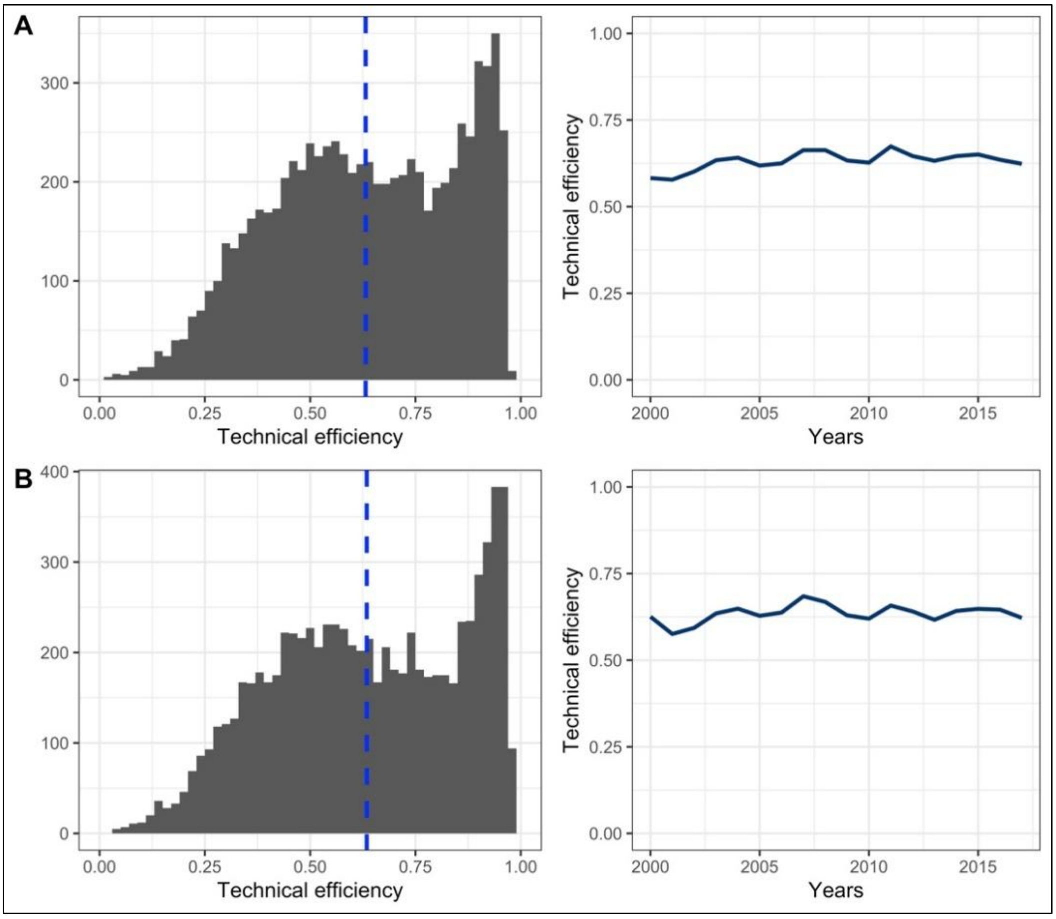

Figure 5. Distribution of technical efficiency scores in the speed of adjustment with true random effects

Source: own calculations using Ministry of Agriculture of China (2001-2018)

5 Discussion

The findings from the first-stage estimation suggest that many regional pork markets in China adjust relatively slowly to shocks, with deviations from long-run price equilibrium between market pairs often persisting over several months. However, there is notable heterogeneity in adjustment speeds across market pairs. This pattern points toward underlying structural and transient inefficiencies that shape spatial price transmission dynamics. Furthermore, our analysis demonstrates a gradual decline in market efficiency over the study period 2000 to 2017 in China, coinciding with increased concentration in pig slaughtering activities and implementation of stringent environmental regulations for pig farms (Chen et al., 2022).[8] This restructuring reduced regional dispersion of supply but increased transport distances from production to consumption centers, thereby slowing the speed of adjustment. Markets separated by long distances tend to exhibit slower speeds of market efficiency compared to those in closer proximity as shown in the second-stage results. The finding aligns with earlier findings that distance weakens spatial price transmission in agricultural markets (e.g., Mu, von Cramon-Taubadel, 2022; Serra, Goodwin, 2003). China's pork supply chain involves substantial inter-provincial flows over long distances, often exceeding 1,000 km, because major production areas in the Northeast, North, and Southwest are far from coastal and central consumption centers. These long transport distances raise logistics costs and information frictions, which in turn slow the speed of market adjustment. We also find that greater inter-market trade intensity, measured by per-capital parcel volume between two markets, increases the speed of price adjustment among China's pork markets over time, confirming the positive linkage between trade volume and market integration noted by Goodwin and Schroeder (1991) and Svanidze and Götz (2019a).

In examining the variance components in the GTRE model, the ratios λ_0, λ, and Λ shed light on the relative importance of different sources of variation.[9] The ratio of persistent inefficiency to random heterogeneity, $\lambda_0 = 1.68$, shows that the variance of long-term inefficiency is greater than the variance attributable purely to unobserved heterogeneity across markets, implying that structural inefficiency factors are significant. In addition, $\lambda = 3.93$ indicates that transient inefficiency dominates over white noise, reinforcing the idea that short-term shocks or adjustments have a substantial impact on price transmission. The ratio $\Lambda = 0.55$ indicates that, relative to transient inefficiency, persistent inefficiency constitutes a smaller yet nontrivial portion of the overall variation.

Table 4 presents descriptive statistics of the time-varying and persistent efficiency components under the TRE-Z and GTRE-Z frameworks. These results clearly indicate that neglecting persistent inefficiency can lead to overestimation of technical efficiency scores. For instance, the TRE model's time-varying technical efficiency scores (TE_TRE-Z) averages 0.63 for both $\alpha_{ij,June}$ and $\alpha_{ij,Annual}$, while the average technical efficiency scores from the GTRE-Z model (OTE_GTRE-Z) are significantly lower, at 0.49 for $\alpha_{ij,June}$ and 0.47 for $\alpha_{ij,Annual}$. The decomposition of overall technical efficiency scores into persistent (PTE_GTRE-Z) and transient (TTE_GTRE-Z) components shows that the short-term component of efficiency is approximately 0.65, whereas the persistent component ranges from 0.73 to 0.75. Multiplying these values together - OTE = PTE × TTE - yields an overall efficiency value that emphasizes the importance of both structural conditions (captured by persistent inefficiency) and time-varying shocks (captured by transient inefficiency). The difference between TE_TRE-Z (0.63) and OTE_GTRE-Z (0.49) reinforces the conclusion that failing to consider persistent inefficiency

8 Since 2010, pig-slaughtering in China has become increasingly concentrated in large-scale industrial plants, partly due to stricter environmental regulations limiting small backyard farms (Chen et al., 2022). This restructuring reduced the regional dispersion of supply but increased transport distances from production to consumption centers.

9 The variance ratios are computed using the variance coefficients from Table 2 as follows $\lambda_0 = \sigma_h/\sigma_w$ and $\Lambda = \sigma_h/\sigma_u$, where $\sigma_u = \lambda \times \sigma_v$.

results in an overestimation of the system's ability to restore or maintain efficient price transmission across space and time.

Table 4. Descriptive statistics for transient and persistent efficiency of the translog function

ECM	TE	Obs.	Mean	S.D.	Min.	Max.
$\alpha_{ij,June}$	TE_TRE-Z	7,830	0.63	0.22	0.02	0.98
	TTE_GTRE-Z	7,830	0.65	0.19	0.01	1.00
	PTE_GTRE-Z	7,830	0.75	0.11	0.32	0.90
	OTE_GTRE-Z	7,830	0.49	0.16	0.01	0.78
$\alpha_{ij,Annual}$	TE_TRE-Z	7,830	0.63	0.23	0.04	0.98
	TTE_GTRE-Z	7,830	0.65	0.19	0.05	1.00
	PTE_GTRE-Z	7,830	0.73	0.12	0.25	0.90
	OTE_GTRE-Z	7,830	0.47	0.17	0.03	0.78

Source: own calculations using Ministry of Agriculture of China (2001-2018)

By decomposing inefficiency into transient and persistent components, we identify the relative contribution of short-term shocks and long-term structural constraints to overall adjustment speeds that static models fail to capture, thereby shedding new light on the spatial pork price relationships. The results show that transient inefficiency accounts for a larger share (35%)[10], consistent with improvements in logistics and information flows. In contrast, persistent inefficiency remains a binding constraint on market performance (25%). These long-run inefficiencies stem from fixed structural characteristics, including dietary patterns, geography, and long-standing management practices, that do not change readily over time. For example, regions with cultural or religious norms that limit pork consumption may exhibit stable but systematically lower market participation, which constrains their long-term price adjustment capacity regardless of short-run improvements (Serra et al., 2006; Mu, von Cramon-Taubadel, 2022). Taken together, the decomposition highlights that while short-term responsiveness has improved, deep-rooted structural factors continue to limit the ability of certain market pairs to reach higher long-run efficiency levels.

The results also show that technical efficiency has increased over the sample period, influenced by diesel fuel price index $fuel_{ij,t}$ and town numbers of market pairs $town_{ij,t}$, with results varying by model and time frame. In the $\alpha_{ij,June}$ sample, rising diesel fuel prices are consistently linked to higher inefficiency, likely reflecting the immediate cost burden of transportation and distribution, which hinders the smooth adjustment of prices across markets. Conversely, the negative relationship between the number of towns and inefficiency may suggest that better-connected regions with more potential trade nodes facilitate more efficient price transmission.

However, the $\alpha_{ij,Annual}$ data paints a different picture. The reversal of the fuel variable's sign implies that the impact of fuel costs on inefficiency might differ from short-term dynamics, perhaps because market participants adjust to persistent high prices over time, or because seasonal variations and temporary shocks are averaged out. Similarly, the slightly stronger negative effect of the number of towns in the $\alpha_{ij,Annual}$ models reinforce the idea that denser spatial networks can support market efficiency.

[10] In the GTRE-Z models, inefficiency shares are calculated as $1 -$ efficiency. For example, the transient inefficiency share is computed as 1-0.65=0.35, based on the transient and persistent technical efficiency estimates reported in Table 4.

6 Conclusions and Suggestions for Future Research

In this paper, we provide a more nuanced assessment of Chinese pork market efficiency by employing GTRE-based panel stochastic frontier models that incorporate market-specific heterogeneity and decompose inefficiency into short-term time-varying and long-term time-invariant components. We find substantial heterogeneity in adjustment speeds and persistent inefficiencies, linked to geography, infrastructure, and trade volume. Markets with stronger road connectivity and higher parcel volume exhibit faster price adjustments to shocks, whereas prices in remote or structurally fragmented regions converge more slowly toward equilibrium. Overall, the pork market exhibits notable inefficiencies in the speed of adjustment, with short-term disruptions playing a major role and persistent structural constraints also contributing. These findings highlight that overlooking persistent inefficiency can lead to overestimation of a market's capacity to adjust to price shocks over time. In addition, distinguishing between transient and persistent technical inefficiency can help identify possible policy interventions. Short-term inefficiencies could be reduced through temporary logistic support such as fuel-cost relief, whereas persistent inefficiencies call for long-term structural solutions, such as improving transport infrastructure or strengthening inter-provincial information flows. Of course, inefficiency is not a sufficient condition for policy intervention, which should be conditional on careful cost-benefit analysis.

Beyond China's pork markets, the approach that we develop can be extended to other sectors, such as energy, agricultural, and financial markets, characterized by evolving spatial linkages and incomplete market integration (e.g., Vollmer et al., 2020; Svanidze, Götz, 2019a). However, this approach is less suitable for markets with limited price variation, insufficient time series length, or unstable cointegration relationships, where time-varying estimation or frontier benchmarking may not produce reliable results.

Several limitations of our approach warrant attention in future research. First, market efficiency may be affected by extreme events. On pork markets in China, such events include the US-China Trade War in the first half of 2018, the African Swine Fever outbreak in late 2018, and the Covid-19 pandemic in late 2019 (Ramsey et al., 2021). Including such episodes, possibly by also allowing for structural breaks in long-run equilibrium price relationships, could generate insights into market efficiency under extreme conditions (Ma et al., 2024).

Second, we present some evidence that the Chinese pork markets show time-varying and persistent inefficiency under market-specific heterogeneity. However, we cannot draw firm conclusions because our time-varying estimates of market efficiency have standard errors, which we do not account for in the inefficiency variance of the second-step SFA estimations. As suggested in Mu and von Cramon-Taubadel (2022), incorporating the standard errors of the first-step estimates of the time-varying speed of adjustment parameters into the measurement error component of the second-step estimation of the market efficiency frontier is intuitively appealing, and could be pursued in future research.

Finally, we do not explicitly account for spatial correlation in price transmission efficiency. In cases where trade between two regions (e.g., A and C) necessarily passes through an intermediate region (e.g., B), the efficiency of price transmission between A and C may be influenced by the efficiencies of both the A-B and B-C connections. For instance, transporting pork from Anhui Province to Shanghai requires passing through Jiangsu Province - specifically via the Nanjing Yangtze River Bridge - due to the geographical division created by the Yangtze River in southeastern China. As such, the efficiency of price transmission between Anhui and Shanghai is likely dependent on the transmission efficiencies between Anhui and Jiangsu, and between Jiangsu and Shanghai. Future research could address this spatial interdependence by incorporating spatial econometric or network-based frontier approaches that allow for indirect linkages and multi-node trade pathways (Fackler, Goodwin, 2001). Such extensions could provide a more comprehensive understanding of how regional interconnectivity and trade routes shape the overall dynamics of market efficiency.

Author Contributions

Yali Mu: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing – Original draft, Writing – Review & Editing, Funding acquisition. **Stephan von Cramon-Taubadel**: Conceptualization, Methodology, Writing – Review & Editing. **Gabriel Rosero**: Formal analysis, Data curation, Visualization, Writing – Review & Editing. **Bernhard Brümmer**: Methodology, Resources, Writing – Review & Editing.

AI Use

The authors did not use any AI tools for preparing the manuscript.

Competing Interests

The authors declare no competing interests.

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