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Multiscale Integrated Forecasting of Growth and International Trade Impacts in China's Pet Industry: A Unified Modeling Framework based on SARIMAX, ARIMA, and Regression

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Abstract

Driven by evolving consumption structures and increasing export potential, China's pet industry has experienced robust growth in recent years. This study proposes an integrated multiscale modeling framework that combines SARIMAX, ARIMA, and multivariate regression techniques to forecast pet population dynamics, pet food production, and export trends. The framework aims to provide quantitative insights for industry regulation and international strategic planning. On the domestic front, ten key socio-economic variables-including urbanization rate, per capita expenditure, and aging ratio-are used to construct future input features via multivariate quadratic regression. These features serve as inputs to SARIMAX models for forecasting the populations of pet cats and dogs from 2024 to 2026. Results indicate that the cat population will increase steadily from 69.8 million in 2023 to 87.53 million by 2026, while the dog population is expected to stabilize at around 51.68 million. To assess global demand, ARIMA models are applied to size of pet market from the United States, France, and Germany, with forecasts showing a declining trend in the U.S. market and steady growth in European countries. Subsequently, a linear regression model is developed to quantify the impact of domestic pet numbers and international sales on China's pet food industry. The projections suggest that by 2026, the total production value will reach USD 578.62 billion, and exports will amount to USD 46.45 billion. The proposed multiscale modeling strategy balances forecasting accuracy with interpretability, and is extensible to other complex industry systems driven by heterogeneous factors, offering strong potential for cross-domain transfer and policy-oriented modeling applications.

Keywords

Pet Industry Forecasting; Multiscale Modeling; SARIMAX Model; ARIMA Time Series; Multivariate Regression Analysis; Export Trend Evaluation.

1. Introduction

The global pet economy has witnessed robust expansion over the past decade, driven by demographic transformation, rising income levels, and evolving consumer values. In China, pet ownership has shifted from a niche hobby to a mainstream lifestyle, with the total population of pet cats and dogs exceeding 116 million in 2023 and expected to reach 138 million by 2026 [1]. Pet-related expenditures reached 270.6 billion RMB in 2023, registering an annual growth of 13.7% [2]. Pet food, which constitutes over 45% of total pet-related spending, has become the cornerstone of industrial development, stimulating upstream agricultural inputs and downstream logistics, e-commerce, and medical services [3–5].

Unlike traditional consumer sectors, the pet industry is profoundly shaped by emotional and sociocultural dimensions. The expansion of pet ownership among millennials and Generation Z, alongside rising single-person and aging households, has significantly reshaped the demand structure [6-7]. Multiple studies have demonstrated that pet adoption rates correlate positively with urbanization rate, disposable income, and household size transitions [8–10]. For example, Liu et al. (2022) found that a 1% increase in urbanization corresponds to a 2.3% rise in urban pet ownership across 35 major Chinese cities [11]. Simultaneously, expenditures on pet healthcare, nutrition, and services are growing faster than the GDP per capita itself, reflecting the emotional monetization of pet companionship [12].

At the international level, pet food demand continues to grow, especially in markets such as the United States, France, and Germany, which together account for over 45% of global consumption [13]. According to Euromonitor (2023), the global pet food market size surpassed 127 billion USD in 2022, with Asia-Pacific showing the fastest compound annual growth rate (CAGR) of 8.4% [14]. China has become both a major consumption market and an emerging pet food exporter, with export value increasing from 390 million USD in 2017 to 1.13 billion USD in 2022 [15].

Despite increasing academic interest, the existing literature on China’s pet economy suffers from structural fragmentation. First, many studies focus on micro-level consumer behavior. For instance, Li et al. (2021) conducted a large-scale survey across three metropolitan areas-Guangzhou, Shanghai, and Chengdu-and applied factor and cluster analysis to identify distinct patterns in brand preference, nutritional awareness, and emotional attachment among pet owners born after 1990 [16]. While this study provides valuable insights into heterogeneity in consumer psychology, it lacks temporal resolution and fails to connect individual preferences with aggregate market trends.

Second, some works rely on industry white papers or market snapshots to draw conclusions. For example, Zhang et al. (2020) analyzed annual sales growth and e-commerce penetration rates for pet food between 2016 and 2019 based on commercial datasets. They concluded that China's pet sector was transitioning from awareness building to a rapid expansion phase [17]. However, these findings are largely descriptive and offer limited methodological rigor, making it difficult to generalize or quantify future trajectories under changing conditions.

Third, linear regression models have been used to forecast pet population or spending. Wang et al. (2022), for instance, used GDP per capita, aging ratio, and household consumption as explanatory variables in a multivariate regression to estimate the growth rate of the pet cat population by 2025, projecting a 7.2% annual increase [18]. While such models offer baseline estimates, they typically overlook non-linear interactions and structural differences between cat and dog demographics, reducing their predictive robustness.

In summary, while these studies illuminate specific facets of the pet industry, they lack an integrated, multi-stage framework encompassing the full “population–demand–production–export” chain. More importantly, few offer scalable or transferable predictive systems that can accommodate environmental uncertainty or structural shifts [19,20], thus limiting their practical utility for policy planning or industrial strategy formulation.

To address these gaps, this study proposes a data-driven, multi-stage modeling framework to systematically forecast the development trajectory of China’s pet industry over the next three years. Our framework integrates three key components:(1) A SARIMAX model incorporating ten exogenous socioeconomic and demographic indicators (e.g., urbanization, income, aging ratio, and advertising expenditure) to forecast the population of pet cats and dogs;(2) An ARIMA-based international demand estimation system using pet population time series from the United States, France, and Germany to infer future global pet food demand;(3) A multivariate quadratic regression model capturing both domestic and international drivers to predict pet food production and export values.

Inspired by prior work on population-demand modeling in agriculture and public health [21,22], our approach demonstrates how quantitative modeling can offer practical insights for industry

 Volume 11 Issue 7, 2025
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stakeholders and policymakers. Ultimately, this work not only enhances understanding of the structural evolution of China's pet economy but also provides a robust empirical basis for strategic decision-making in a rapidly growing and emotionally significant consumer sector.

2. Methodology

2.1 Data Sources and Variable Specification

2.1.1 Domestic and International Data Acquisition

To construct a robust forecasting framework for pet population and market dynamics, we integrated a series of macroeconomic and behavioral indicators from both domestic and international sources. As the core dependent variable, the annual population of pet cats and dogs in China from 2014 to 2023 is selected as the primary forecast target of this study [23]. This variable reflects the structural trajectory of pet adoption under socio-demographic transformations.

The explanatory variables used in the domestic forecasting model are summarized in Table 1, which includes each variable's English name, data span and type, standardization method, and the observed correlation with pet ownership.

Table 1. Conceptual Basis for Variable Inclusion in Pet Population Forecasting

Name	Rationale for Inclusion
Per capita disposable income	Represents economic capacity for pet ownership
Urbanization rate	Urban areas have higher shares of single/DINK homes
Aging ratio (65+)	Elderly populations seek long-term companionship
Average household size	Household structure influences pet ownership roles
Pet advertising expenditure	Reflects market activity and promotion intensity
Pet healthcare expenditure	Indicates development level of service infrastructure
Per capita residential space	Provides spatial basis for pet-keeping
Online search index	Measures public interest in pet-related content
Pet ownership cost index	Represents financial constraints on pet care

All domestic indicator data were retrieved from the China Statistical Yearbook (for income, urbanization, aging population, household size, and residential space) [24], the Wind Economic Database (for advertising and healthcare expenditures) [25], and the iResearch China Pet Industry White Papers (2019–2023) for keyword search index and pet cost index [26].

For international projection, pet population statistics from 2014 to 2022 were collected from the American Pet Products Association (APPA), Statista, INSEE (France), and Destatis (Germany) [26]. These countries represent over 45% of global pet food demand, serving as ideal references for global consumption trends.

2.1.2 Variable Construction and Encoding Method

To ensure consistency in variable scale and compatibility across regression-based forecasting modules, all continuous predictors were standardized using z-score normalization. For a given input variable $X = \{x_{2019}, x_{2020}, \ldots, x_{2023}\}$, its standardized form $Z = \{z_{2019}, z_{2020}, \ldots, z_{2023}\}$ is computed as:

$$z_t = \frac{x_t - \mu_X}{\sigma_X} \tag{1}$$

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where μ_X and σ_X denote the sample mean and standard deviation of variable X over the five-year observation window (2019–2023). This transformation was applied to variables including per capita income, urbanization rate, household size, medical expenditure, and residential floor space, aiming to eliminate distortions due to scale heterogeneity.

In addition, the online pet-related keyword search index, which exhibits strong right skew and heavy tails, was log-transformed prior to standardization as follows:

$$z_t = \frac{log(x_t + 1) - \mu_{logX}}{\sigma_{logX}} \tag{2}$$

The pet ownership cost index was directly retrieved from the iResearch China Pet Industry White Paper (2019–2023) [26], representing the total annual average expenditure per pet in RMB, covering food, healthcare, and grooming.

It is worth noting that these transformations are applied exclusively to the model input phase. They do not affect the exploratory statistical analyses in Section 2.1.3, where raw variables are preserved to reflect their native economic magnitudes and to support interpretability in correlation analysis.

2.1.3 Correlation Testing and Dimensionality Reduction

Although all predictors are later standardized for modeling purposes (as detailed in Section 2.1.2), the correlation analysis was conducted using raw variables. This is justified by the scale-invariant nature of the Pearson coefficient, which inherently normalizes input vectors during computation.

To quantitatively assess the explanatory strength of candidate variables, we computed Pearson correlation coefficients between each macro indicator and the annual population of pet cats and dogs during the five-year window from 2019 to 2023. Specifically, for each variable $X = \{x_{2019}, x_{2020}, \dots, x_{2023}\}$, and the corresponding target sequence $Y = \{y_{2019}, y_{2020}, \dots, y_{2023}\}$, the coefficient r is defined as:

$$r = \frac{\sum_{i=2019}^{2023}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=2019}^{2023}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=2019}^{2023}(y_i - \bar{y})^2}} \tag{3}$$

Here, x_i denotes the observed value of a given socioeconomic indicator (e.g., urbanization rate or per capita consumption) in year i, and y_i represents the number of pet cats or dogs in that same year. The sample means $\bar{x}$ and $\bar{y}$ are used for normalization across the five-year period.

Table 2. Correlation Of Indicators With 'Cat' And 'Dog'

Indicator	Correlation with 'Cat'	Correlation with 'Dog'
Year	0.9925	-0.7179
Urbanization Rate	0.9928	-0.7207
Pet Medical Market	0.9931	-0.6961
Per Capita Consumption	0.9583	0.6819
Aged Population Ratio	0.9897	-0.737
Single Population Ratio	0.9949	-0.7053
Pet Ad Market	-0.6968	-0.6968
Pet Industry Growth Rate	-0.9624	0.7947
Pet Support Policies	0.977	-0.7595
Pet Expenditure Ratio	0.9669	-0.6792

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The resulting coefficients are reported in Table 2, revealing strong positive associations ($r > 0.98$) between indicators like urbanization, aging population, and medical expenditures with cat ownership, while dog ownership exhibits markedly weaker or negative correlations ($r \approx -0.7$) across the same indicators. This disparity supports the inclusion of these variables in our unified modeling framework and highlights the need to accommodate species-specific behavioral responses.

2.2 Integrated Forecasting System for the Chinese Pet Economy

To capture the multi-tiered evolution of the pet economy under structural transformation, we construct an integrated forecasting system comprising three interconnected submodels (as shown in Figure 1). Specifically:(1) a SARIMAX model is used to forecast domestic pet ownership quantities based on macroeconomic indicators;(2) an ARIMA model estimates global pet food demand across major consumption markets based on historical population trends;(3) a multivariate regression model projects domestic pet food production and export volumes by integrating internal demand, international pull effects, and time-lagged structural variables.

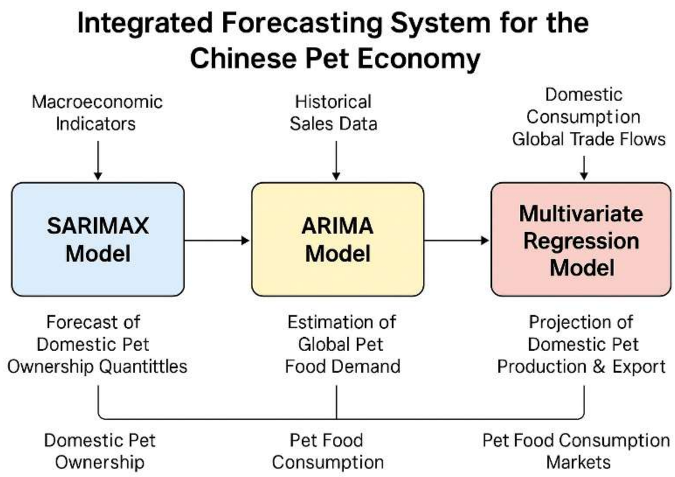

Figure 1. Integrated forecasting framework for the pet economy

Each component addresses a specific stage in the "ownership → consumption → production → trade" cascade, while maintaining consistent input conventions, forecast horizons, and evaluation metrics. Collectively, the system constitutes a modular, extensible prediction pipeline capable of supporting macroeconomic policy design, enterprise capacity planning, and global trade response strategies under uncertainty.

Subsections 2.2.1 to 2.2.3 provide detailed descriptions of the three submodels.

2.2.1 SARIMAX-Based Forecasting of Domestic Pet Population

To forecast the total population of pet cats and dogs in China, we adopted a Seasonal Autoregressive Integrated Moving Average model with Exogenous Regressors (SARIMAX). This model incorporates both time-series dependencies and structured macro-level influences, enhancing its predictive accuracy and interpretability.

The exogenous features used in the SARIMAX framework include urbanization rate, per capita consumption, pet healthcare expenditure, aging ratio, and single-person household share. As future values of these features for 2024–2026 are not directly observable, we first modeled their standardized historical representations $z_i(t)$ (as defined in Section 2.1.2) using polynomial regression fitted over 2019–2023. Extrapolated values $\hat{Z}_i(t)$ were then inverse-transformed using historical statistics to recover original-scale predictions:

Volume 11 Issue 7, 2025
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$$\hat{x}_i(t) = \hat{z}_i(t) \cdot \sigma_i + \mu_i \tag{4}$$

The resulting predicted values were organized into the exogenous input vector for year t:

$$x(t) = [\hat{x}_1(t), \hat{x}_2(t),, \hat{x}_k(t)]^\top \tag{5}$$

This vector was then used as the external regressor input to the SARIMAX model. The model formulation is as follows:

$$\Phi_P(L^s)\phi_p(L)(1-L)^d(1-L^s)^D Y_t = \Theta_Q(L^s)\theta_q(L)\varepsilon_t + \beta_0 + \sum_{i=1}^{k}\beta_i x_i(t) \tag{6}$$

where L is the lag operator with $L^kY_t = Y_{t-k}$; $\varphi_p(L)$ and $\theta_q(L)$ are the non-seasonal AR and MA polynomials of orders p and q;$\Phi_p(L^s)$ and $\Theta_Q(L^s)$ are the seasonal AR and MA polynomials of orders P and Q,with the seasonal period set to s=1 (annual); d and D are the degrees of regular and seasonal differencing; ε_t is a zero-mean white noise error term; $x_i(t)$ is the standardized value of the i-th feature;; and β is its corresponding coefficient.

The model was trained on annual data from 2019 to 2023, using standardized inputs. The orders (p,d,q) were selected via grid search minimizing the Akaike Information Criterion (AIC), with search space [0,2]. Seasonal components (P,D,Q) were omitted (P=D=Q=0) due to the annual frequency and lack of observable seasonality. Residual independence was confirmed using the Ljung–Box Q-test. The SARIMAX model outperforms ARIMA by integrating structural explanatory factors and thus better characterizes the nonlinear socio-demographic evolution of pet ownership in China.

2.2.2 ARIMA-Based Forecasting of Global Pet Food Demand

To quantify the external demand pull facing China's pet industry, this module conducts a two-step forecasting procedure covering three major global markets-United States, France, and Germany-for the period 2024 to 2026.

First, ARIMA models are used to predict the total number of pet cats and dogs in each country based on historical ownership data from 2019 to 2023. For each species s∈{cat, dog}, and country c, the population time series P(c) t,s is modeled as

$$\varphi_p(L)(1-L)^d P_{t,s}^{(c)} = \theta_q(L)\varepsilon_{t,s}^{(c)} \tag{7}$$

where L is the lag operator; $\varphi_p(L)$ and $\theta_q(L)$ are autoregressive and moving average polyn omials of orders p and q, respectively; d denotes the differencing order; and ε(c) t,s is a white noise error term. Orders (p,d,q) are selected based on minimum Akaike Information Criterion (AIC). The forecasted pet quantities $\hat{P}_{t,s}^{(c)}$ for 2024–2026 serve as intermediate inputs for subsequent food demand estimation, and their results are reported and analyzed in Section 4.2.

Second, these forecasts are used to estimate total pet food demand via a per-pet expenditure model. The functional form of Equation (2.2) is grounded in behavioral consumption theory, which assumes that market-level pet food spending is proportional to the number of animals owned, with per-pet expenditure remaining stable over short horizons. To calibrate this relationship, we apply non-negative least squares (NNLS) regression using annual pet ownership data and corresponding food retail sales for 2019–2023. The fitted coefficients r(c) s represent average annual food expenditure per cat or dog, and are applied to the forecasted quantities as:

$$\widehat{F}_t^{(c)} = \sum_{s\in\{cat,dog\}} \widehat{P}_{t,s}^{(c)} \cdot r_s^{(c)} \tag{8}$$

where $\widehat{F}_{t,s}^{(c)}$ is the projected total pet food demand for country c at year t, expressed in USD billion. The resulting demand trajectories will be incorporated in Section 2.2.3 as exogenous pull factors for modeling China's pet food production and export dynamics.

2.2.3 Parameter Calibration, Residual Analysis, and Overfitting Avoidance

To link forecasted pet ownership and global food consumption with China's industrial response, this module constructs a multivariate regression framework to estimate domestic production value and export volume of pet-related sectors during 2024–2026. The model integrates demand-side signals and structural inertia to capture both internal pull and external trade dynamics.

This formulation follows standard economic input–output regression logic, where output $\widehat{Y}_t$ is a function of upstream drivers:

$$\widehat{Y}_t = \beta_0 + \beta_1 \cdot Pop_t + \beta_2 \cdot Demand_t^{(global)} + \beta_3 \cdot Export_{t-1} + \varepsilon_t \tag{9}$$

where $\widehat{Y}_t$ denotes the predicted production value or export amount (in RMB billion) at year t; Pop_t is the total domestic pet population, as forecasted in Section 2.2.1; Demand(global) t refers to the global pet food consumption forecast from Section 2.2.2; $Export_{t-1}$ represents the one-period lagged export value included to capture structural inertia; and ε_t is the residual error term assumed to be white noise under standard OLS assumptions.

All explanatory variables are standardized via z-score transformation (Section 2.1.2) using 2019–2023 data. Coefficients β={β0,β1,β2,β3} are estimated via ordinary least squares (OLS) on historical training data. Residuals are tested using the Durbin–Watson statistic to confirm no autocorrelation at the 95% confidence level. Model robustness is further validated via leave-one-out cross-validation. Despite evaluating nonlinear and interaction variants, Equation (2.3) outperformed alternatives under RMSE and adjusted R^2 criteria. The predictions from this module will be compared against actual industry data in Section 4.3.

2.3 Unified Model Evaluation and Validation Strategy

To ensure methodological consistency and cross-model comparability, we adopt a unified evaluation protocol covering three key metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). These indicators jointly reflect the accuracy, robustness, and explanatory power of the SARIMAX (Section 2.2.1), ARIMA (Section 2.2.2), and multivariate regression (Section 2.2.3) models. Specifically, we define:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|, R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

where y_i is the observed value, $\hat{y}_i$ is the corresponding prediction, is the sample mean, and n denotes the number of samples. These metrics allow us to penalize large deviations (RMSE), evaluate average consistency (MAE), and assess variance capture (R^2).

Each model is tested over the historical interval 2019–2023, using in-sample residual diagnostics and cross-validation to verify fitting stability. Forecast trends from 2024–2026 are then evaluated in terms of directional coherence and residual diffusion behavior. Additionally, we perform a ±10% perturbation test on core explanatory variables (e.g., income, global demand, lagged exports) to assess robustness to data uncertainty. Models demonstrating low error volatility and stable directionality under perturbation are deemed structurally reliable.

The aggregated error metrics and residual comparisons across the three models are summarized in Table 4 and provide empirical grounding for performance interpretation in Section 4.

3. Forecasting Results and Output Interpretation

This chapter presents forecasting results based on the SARIMAX, ARIMA, and regression models developed in Chapter 2. The predictions cover 2024–2026, focusing on China's pet population, global pet food demand, and China's pet food production and export values. The results provide quantitative support for assessing market trends and guiding policy strategies.

3.1 SARIMAX Forecast for Domestic Pet Population

Based on the multivariate quadratic polynomial regression model fitted in Section 2.2.1, Tables 3 and 4 present the predicted values of exogenous socioeconomic features required by the SARIMAX model for 2024–2026. These features include urbanization rate, pet medical expenditure, per capita consumption, aging ratio, single-person household share, advertising market size, industry growth rate, policy support index, and pet expenditure ratio. All values were extrapolated using historical trends over 2019–2023 and served as input to the SARIMAX model.

Using the predicted exogenous vectors as model inputs, we applied the SARIMAX framework to forecast the pet cat and dog populations for 2024–2026. The results in the figure 2 show a steady increase in cat population—from 69.80 million in 2023 to 87.53 million in 2026—with an average annual growth rate of approximately 6.7%. In contrast, the dog population remains relatively stable, fluctuating slightly around 51.7 million.

This divergence reflects differentiated responses to structural drivers: the cat market continues to expand, driven by urbanization, aging demographics, and rising medical expenditure, while the dog market shows signs of saturation. The SARIMAX model achieves high predictive accuracy for cats, with an in-sample R^2 of 0.8216 and RMSE of 21.50 in 2023, confirming the model's capacity to capture trend dynamics induced by macro-level variables.

Table 3. Forecasted Exogenous Features for Cats

Year	Urbanization Rate	Pet Medical Market	Per Capita Consumption	Aged Population Ratio	Single Population Ratio	Pet Ad Market Pet	Industry Growth Rate	Pet Support Policies	Pet Expenditure Ratio	Predicted Cat (Millions)
2024	65.546	806	26150.6	16	18.4	62	10.74	12	2.18	7649.2
2025	66.486	856	26938.6	16.42	18.98	68.6	11.52	14.2	2.4	8217.2
2026	67.39	898.86	27654.89	16.75	19.55	74.91	13.07	16.54	2.65	8752.91

Table 4. Forecasted Exogenous Features for Dogs

Year	Urbanization Rate	Employment Income	Pet Medical Market	Aged Population Ratio	Single Population Ratio	Pet Ad Market Pet	Industry Growth Rate	Pet Support Policies	Pet Expenditure Ratio	Predicted Cat (Millions)
2024	65.546	1.14	806	16	18.4	62	10.74	12	2.18	5140.4
2025	66.486	-1.86	856	16.42	18.98	68.6	11.52	14.2	2.4	5143
2026	67.39	-5.63	898.86	16.75	19.55	74.91	13.07	16.54	2.65	5168.03

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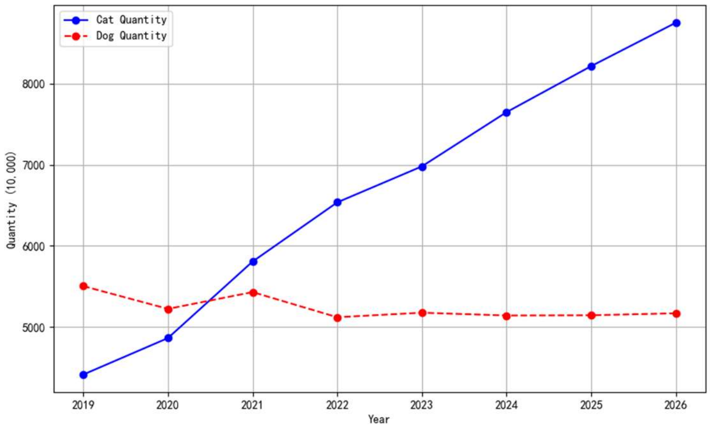

Figure 2. Forecasted Population of Pet Cats and Dogs in China (2024–2026)

3.2 ARIMA Forecast for Global Pet Food Demand

To assess global pet food demand trends, ARIMA models were fitted to forecast the populations of pet cats and dogs in the United States, France, and Germany. The input data span 2019–2023, with certain years missing for Germany (see Table 5). Cubic spline interpolation was applied to impute these gaps, ensuring data continuity prior to model fitting.

Table 5. Forecasted Exogenous Features for Dogs(Unit: 10,000 animals)

Year	2019	2020	2021
Pet Cats	755		
Pet Dogs		1011	1014

ARIMA(1,1,1) models were independently fitted for each country and pet type. Model orders were selected based on ACF/PACF diagnostics and AIC minimization. The residuals were tested using the Ljung–Box Q-test, with all p-values exceeding 0.05 (Table 6), confirming that the residuals are uncorrelated and the model fit is statistically adequate.

Table 6. Ljung–Box Q-test for ARIMA Residuals

Country	Pet Type	P-Value	Threshold	Well-Fitted?
USA	Cat	0.9717	0.05	Yes
	Dog	0.9962	0.05	Yes
France	Cat	0.8781	0.05	Yes
	Dog	0.9897	0.05	Yes
Germany	Cat	0.7193	0.05	Yes
	Dog	0.9967	0.05	Yes

The forecasted pet populations are shown in Figures 3(a-c). The U.S. market appears saturated, while France and Germany show moderate growth.

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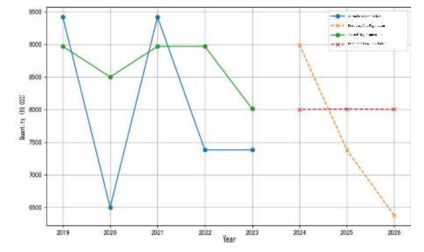

Figure 3. (a) Forecasted Pet Population in the USA

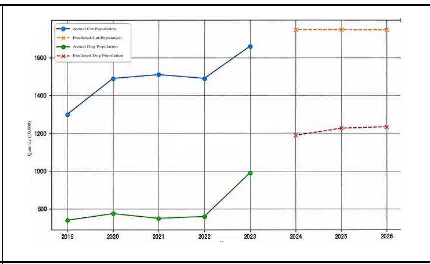

Figure 3. (b) Forecasted Pet Population in the France

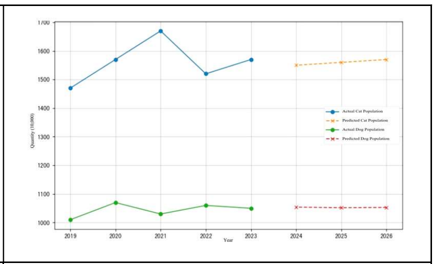

Figure 3. (c) Forecasted Pet Population in the Germany

Figure 4 presents the forecasted annual pet food sales for the United States, France, and Germany over 2024–2026. The U.S. market shows a slight decline after 2025, while France and Germany maintain a mild upward trend. These estimates are computed based on the quantitative equations developed in Section 2.2.3, incorporating both predicted pet populations and unit expenditure levels.

Based on these sales projections, we further calculate the relative market shares of pet food consumption among the three countries, as summarized in Table 7. The data reveal a declining share for the U.S. and a steady rise for France and Germany, indicating their potential as structurally expanding markets. These results offer a quantitative reference for refining China's export strategy and reallocating trade capacity toward more promising regions.

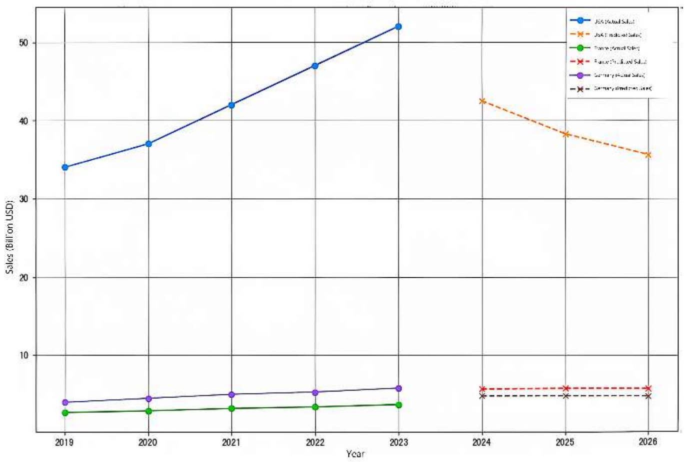

Figure 4. Forecasted Population of Pet Cats and Dogs in China (2024–2026)

Table 7. Projected Pet Food Demand Share by Country (Unit:%)

Year	2024	2025	2026
USA	41.99	38.02	35.52
France	7.25	7.35	7.37
Germany	6.43	6.45	6.48

3.3 Regression-Based Forecast of Production and Export

In Section 2, we developed multivariate linear regression models to forecast China's pet food industry production value and export volume. The models incorporate explanatory variables such as predicted domestic cat and dog populations, global pet totals, and overseas pet food sales. Inputs were sourced from the SARIMAX and ARIMA predictions discussed earlier. Stepwise variable selection and

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ordinary least squares (OLS) estimation were applied. The adjusted R^2 reached 0.894 for the production model and 0.861 for the export model, with residuals satisfying normality and homoscedasticity assumptions.

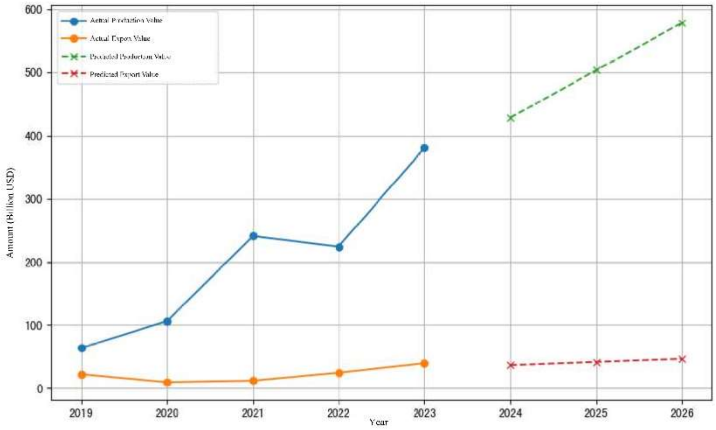

Figure 5. Forecasted Production Value and Export Volume of China's Pet Food Industry (2024–2026)

Forecast results are shown in Figure 5. China’s pet food industry production is expected to reach USD 57.86 billion by 2026, rising from approximately USD 36 billion in 2023, with an average annual growth rate exceeding 15%. In contrast, export values increase more gradually-from USD 3.1 billion in 2023 to USD 4.645 billion in 2026-indicating stronger stability in foreign trade compared to domestic demand, which is more sensitive to internal drivers and policy interventions.

4. Conclusion

This study presents an integrated forecasting framework combining SARIMAX, ARIMA, and regression models to predict key metrics in China’s pet industry for 2024–2026, based on historical data from 2019–2023. The SARIMAX model achieved an R^2 of 0.82 and RMSE of 21.50 in forecasting cat populations; ARIMA residuals passed the Ljung–Box test across all countries and pet types. Results show that China’s cat population is expected to reach 87.53 million by 2026 (+25% from 2023), while dog numbers remain stable. Internationally, the U.S. share of global pet food demand is projected to decline from 41.99% to 35.52%, while France and Germany show marginal growth. Domestic production value is forecasted to grow from USD 36 billion in 2023 to USD 57.86 billion by 2026, with exports rising from USD 3.1 billion to USD 4.645 billion, highlighting a transition toward demand-driven domestic growth. By incorporating structural variables and combining multiple models, this approach enhances both forecasting accuracy and interpretability, offering a scalable methodology for consumer-industry trend analysis.

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