POLITECNICO DI MILANO

SCHOOL OF ARCHITECTURE URBAN PLANNING CONSTRUCTION ENGINEERING

MASTER OF SCIENCE IN MANAGEMENT OF BUILT ENVIRONMENT

Economic Curriculum

Machine Learning-Based Prediction of Shanghai Housing Price Trends and Analysis of Influencing Factors

Author: Fan Chen

Student ID:221459

Supervisor: Marzia Morena

Co-Supervisor: Tommaso Truppi

Mats Wilhelmsson

Academic Year 2024/2025

Master of science thesis

Title:	Machine Learning-Based Prediction of Shanghai Housing Price Trends and Analysis of Influencing Factors
Author:	Fan Chen
Department:	Architecture, Built Environment and Construction Engineering
Supervisor:	Marzia Morena, Tommaso Truppi, Mats Wilhelmsson
Keywords:	Housing Prices, XGBoost, SHAP, Shanghai, Machine Learning, Real Estate, Price Momentum, Macroeconomics, Financial Market, Policy Impact, Sentiment

Abstract

This thesis develops a machine learning-based forecasting model to predict monthly housing price growth in Shanghai, with the aim of capturing short-term market dynamics through a combination of macroeconomic, financial, policy, and sentiment-based indicators. The model is built using the XGBoost algorithm and is interpreted using SHAP values to ensure transparency in feature attribution.

By reformulating the prediction target as monthly price growth and aligning it with percentage-based input features, the study improves model coherence and performance. The results show that recent price momentum plays a key role in shaping expectations, while liquidity conditions—particularly money supply (M2)—emerge as strong macro-financial predictors. In contrast, other variables such as CPI and policy scores show more limited and variable impact, while consumer sentiment proxies demonstrate moderate influence, with their contribution varying depending on broader market conditions. The inclusion of financial market indicators further confirms the influence of investor sentiment and capital reallocation in short-term housing price movements.

Beyond its technical contribution, the study offers a structured and explainable framework for urban housing market forecasting. It demonstrates the value of integrating data-driven models with economic reasoning and provides insights relevant to policymakers, analysts, and stakeholders seeking to understand and anticipate price changes in complex real estate environments.

Tesi di Laurea Magistrale

Titolo:	Previsione dei trend dei prezzi delle abitazioni a Shanghai basata su tecniche di Machine Learning e analisi dei fattori influenti
Autore:	Fan Chen
Dipartimento:	Architettura, Ingegneria delle Costruzioni e Ambiente Costruito
Supervisori:	Marzia Morena, Tommaso Truppi, Mats Wilhelmsson
Parole chiave:	Prezzi delle abitazioni, XGBoost, SHAP, Shanghai, Apprendimento automatico, Mercato immobiliare, Slancio dei prezzi, Macroeconomia, Mercato finanziario, Impatto delle politiche, Sentimento

Sommario

Questa tesi sviluppa un modello di previsione basato su tecniche di machine learning per stimare la crescita mensile dei prezzi delle abitazioni a Shanghai, con l'obiettivo di catturare le dinamiche di mercato a breve termine attraverso una combinazione di indicatori macroeconomici, finanziari, politici e legati al sentimento dei consumatori.
Il modello è costruito utilizzando l'algoritmo XGBoost ed è interpretato tramite i valori SHAP per garantire trasparenza nell'attribuzione delle caratteristiche.

Riformulando l'obiettivo di previsione come crescita mensile dei prezzi e allineandolo a variabili di input espresse in percentuale, lo studio migliora la coerenza e le prestazioni del modello. I risultati mostrano che lo slancio recente dei prezzi ha un ruolo centrale nel formare le aspettative, mentre le condizioni di liquidità — in particolare l'offerta di moneta (M2) — emergono come forti predittori macro-finanziari. Al contrario, variabili come l'indice dei prezzi al consumo (CPI) e i punteggi di politica mostrano un impatto più limitato e variabile, mentre i proxy del sentimento dei consumatori hanno un'influenza moderata, che varia in funzione delle condizioni di mercato generali. L'inclusione di indicatori di mercato finanziario conferma ulteriormente l'influenza del sentimento degli investitori e della riallocazione del capitale nei movimenti a breve termine dei prezzi delle abitazioni.

Oltre al contributo tecnico, lo studio offre un quadro strutturato e interpretabile per la previsione del mercato immobiliare urbano. Dimostra il valore dell'integrazione tra modelli basati sui dati e il ragionamento economico, fornendo spunti utili per decisori politici, analisti e stakeholder interessati a comprendere e anticipare i cambiamenti dei prezzi in ambienti immobiliari complessi.

Acknowledgment

Starting from late 2023, I began thinking about my thesis topic and reaching out to potential supervisors. In the summer of 2024, I received the exciting news that I had been accepted for an exchange semester at KTH, passed the final exam of my master’s coursework, returned to China for the summer break, and began learning about the background and technical knowledge relevant to my research. In mid-October, I returned to Milan to resume academic work: reading literature, writing the review, collecting data, planning the model, and finalizing the exchange arrangements with KTH.

In January, I arrived in Stockholm and met with my KTH supervisor for the first time. Together, we revised some earlier content, and in mid-February I completed my first seminar and shared updates with my professors at Politecnico di Milano. In the following months, I expanded data collection, processed datasets, began modeling, and continued regular discussions with my KTH supervisor. In early May, I held my second seminar and continued refining the work based on feedback. By the end of May, this thesis finally took shape.

First and foremost, I would like to thank my family. I am deeply grateful to my mother for her unconditional support, and to the rest of my family for taking such good care of themselves and understanding my academic priorities. Their well-being gave me peace of mind and allowed me to focus fully on my studies.

I also want to sincerely thank my supervisors at Politecnico di Milano—Professor Morena and Professor Truppi—who guided me from the initial topic selection to the final stages of this thesis. Even when I left Milan to continue my research at KTH, their support and encouragement remained constant.

I am equally thankful to Professor Wilhelmsson at KTH, who warmly welcomed me as a visiting student from another institution. His consistent feedback and professionalism ensured that I remained on track. I truly enjoyed working with all my supervisors. Although I had to prepare extensively before each meeting, our discussions were always enjoyable. Their smiles helped ease my anxiety, and their feedback kept me moving forward.

Finally, I would like to thank my long-distance partner. Maintaining a relationship across countries is never easy, and I truly appreciate his continued effort and care that helped us stay connected.

As I near graduation, I feel proud of the choices I have made and the efforts I’ve put in. I am thankful to both Politecnico di Milano and KTH for providing me with the opportunity to grow, explore, and complete this thesis.

Goodbye, for now. As I turn back and wave, I can almost see myself standing in front of the main building for the first time. Farewell—until we meet again in a better future.

Fan Chen
Stockholm,June 2025

Contents

1. Introduction 10

1.1. Research Background 10

1.2. Housing Market Context in China and Shanghai 11

1.2.1. Housing System Reform and Marketization in China 11

1.2.2. Structural Features of Shanghai's Housing Market 11

1.2.3. Policy Cycles and Regulation Patterns (1999–2024) 13

1.2.4. Current Market Trends and Challenges 14

1.3. Research Objectives 15

1.4. Research Question 15

1.5. Scope of the Study 16

1.6. Structure of the Thesis 16

1.7. Summary 17

2. Literature Review 18

2.1. Existing Housing Price Prediction Models 18

2.1.1. Traditional Statistical Models 18

2.1.2. Machine Learning-Based Models 18

2.2. Factors Influencing Housing Prices 20

2.2.1. Economic Factors 20

2.2.2. Financial Market Factors 20

2.2.3. Policy Factors 21

2.2.4. Non-Economic Factors 21

2.3. Research Gap & Contribution 22

2.3.1. Identified Research Gaps 22

2.3.2. Contribution 22

2.4. Summary 22

3. Theoretical Framework 24

3.1. Demand-Side Determinants in Urban Economic Theory 24

3.2. Monetary Policy Transmission and Housing Markets 24

3.3. Financial Market Theories: Capital Flow and Stock-Housing Linkages 25

3.4. Market Efficiency Hypothesis 26
3.5. Behavioral Economics and Public Sentiment 26
3.6. Summary 27
4. Methodology 28
4.1. Data Collection and Preprocessing 28
4.1.1. Data Sources 28
4.1.2. Data Preprocessing 36
4.2. Model Selection and Implementation 44
4.2.1. Machine Learning Model: XGBoost 45
4.2.2. SHAP Analysis for Model Interpretability 45
4.3. Comparison with Traditional Methods 45
4.4. Summary 46
5. Results and Analysis 47
5.1. Model Setup and Evaluation Metrics 47
5.2. Visual Validation of Predicted Trends 48
5.3. Benchmark Comparison: Linear Regression Model 50
5.4. SHAP-based Feature Importance Analysis 51
5.5. Model Evolution and Comparison 54
5.6. Summary 56
6. Discussion 57
6.1. Momentum-Based Price Dynamics 57
6.2. Assumptions Underlying the Predictive Framework 57
6.3. Interpreting the Role of Macro-Financial Variables 58
6.4. Behavioral Sentiment and Predictive Relevance 58
6.5. Implications for Policy and Practice 59
6.6. Limitations 59
6.7. Future Research Directions 60
7. Conclusion 61
References 62
Appendix A. Original Data (2000–2024) 68
A1. Shanghai Quarterly GDP Data 68

A2. Shanghai Consumer Price Index (CPI) Monthly Data 68
A3. China Broad Money Supply (M2) Growth Rate Monthly Data 71
A4. Shanghai Loan Prime Rate (LPR) and Benchmark Interest Rates 73
Appendix B. Processed Intermediate Data 74
B1. Interpolated and Adjusted Monthly Prices 74
B2. GDP Estimation Based on CPI 78
B3. Monthly Indicators: LPR, M2, SSE & Policy Scores 85
B4. Consumer Confidence Index (CCI) Monthly Data 93
Appendix C. Final Input Data 97
C1. Monthly Feature Matrix for Model Input...97

List of Tables

Table 1. Annual Average Sales Price of Residential Commercial Housing in Shanghai (2000–2024), in Yuan per Square Meter....28

Table 2. 1994-1999 Shanghai Real Estate Policy....30

Table 3. 2000-2004 Shanghai Real Estate Policy....31

Table 4. 2005-2009 Shanghai Real Estate Policy....32

Table 5. 2010-2015 Shanghai Real Estate Policy....33

Table 6. 2016-2021 Shanghai Real Estate Policy....34

Table 7. 2022-2024 Shanghai Real Estate Policy....34

Table 8. Summary of Variables Used in the Final Prediction Model....44

Table 9. Summary of Model Version Evolution and Performance Comparison....54

List of Figures

Figure 1. Annual Average Sales Price of Residential Commercial Housing in Shanghai (2000–2024), in Yuan per Square Meter 12

Figure 2. Timeline of Major Housing Policy Shifts in China (1998–2024) 13

Figure 3. Final Adjusted Monthly Housing Prices (2000–2024) 38

Figure 4. Predicted vs. Actual Monthly Housing Prices in Shanghai (2021–2024) using Final XGBoost Model 49

Figure 5. Predicted vs. Actual Monthly Housing Prices in Shanghai (2021–2024) using Linear Regression Model 50

Figure 6. SHAP-Based Feature Importance for V5 Model 52

1. Introduction

Shanghai’s real estate market has emerged as a focal point of academic and policy attention due to its strategic economic role and high volatility. Understanding the dynamics of housing price fluctuations is crucial for ensuring economic stability, guiding investment behavior, and formulating effective housing policies.

In response to the limitations of traditional forecasting models,this study proposes a machine learning–based framework to predict housing prices and analyze their key determinants.

This chapter introduces the research context, presents an overview of China’s and Shanghai’s housing systems, and outlines the study’s objectives along with its research questions. It also defines the scope of the analysis, outlining its temporal, spatial, and thematic boundaries.

1.1. Research Background

Shanghai, as a global economic and financial hub, plays a pivotal role both domestically and internationally. Its strategic position in China’s economic development and its status as a pilot zone for reform make its housing market a focal point for policymakers, investors, and researchers alike. The city’s real estate sector has become increasingly complex due to rapid urbanization, high population density, capital inflows, and regulatory shifts.

In recent years, housing markets worldwide have exhibited heightened volatility in response to macroeconomic shifts, financial cycles, and sociopolitical uncertainties. Shanghai’s housing market is no exception. Understanding and predicting housing price trends has become a pressing concern for stakeholders seeking to navigate policy interventions, manage investment risk, and ensure housing affordability. However, traditional forecasting models—such as linear regressions or autoregressive methods—often rely on fixed assumptions and fail to capture the nonlinear, multi-factorial dynamics of real-world housing markets.

To address these limitations, there is growing interest in applying machine learning techniques to real estate forecasting. These approaches are well-suited to accommodate complex relationships among a diverse array of variables, including economic indicators, financial sentiment, and policy changes. This study builds on this methodological evolution by developing a predictive framework that integrates structured economic data with policy scores and sentiment metrics, aiming to produce more robust short-term forecasts.

Specifically, this research focuses on monthly housing price dynamics in Shanghai, incorporating macroeconomic indicators, stock market variables, public sentiment indices, and a manually coded policy measure. By combining data-driven modeling with contextual economic understanding, the study aims to not only enhance forecasting accuracy but also provide actionable insights into the short-run drivers of housing market fluctuations. These findings are intended to inform both academic discourse and real-world decision-making in urban economics and real estate policy.

1.2. Housing Market Context in China and Shanghai

1.2.1. Housing System Reform and Marketization in China

China's housing market has undergone dramatic transformation since the late 20th century. Before 1998, urban housing was primarily allocated through a welfare-based system, where work units (danwei) provided accommodation as a public good. This changed fundamentally with the issuance of the 1998 State Council notice, which officially ended the welfare housing distribution system and marked the beginning of full marketization. Since then, the commercial housing market has expanded rapidly, driven by urbanization, rising incomes, and increasing investment demand.

A unique feature of China's housing system is the state ownership of land. Urban land cannot be privately owned; instead, it is leased from the government through long-term land-use rights, typically 70 years for residential use. These land sales are a major source of local government revenue, a model often referred to as "land finance." As a result, local authorities have strong fiscal incentives to maintain land values and housing demand.

While the legal framework for post-70-year renewal remains under development, in practice, residential property owners retain full rights to their homes, and automatic renewal without significant financial burden is expected under current regulatory guidance.

1.2.2. Structural Features of Shanghai's Housing Market

Shanghai, as China's largest city by population and a global financial hub, plays a special role in the national housing landscape. Its housing market is characterized by high demand from internal migration, limited land supply, and a high degree of regulatory oversight. The city is often used as a testing ground for pilot housing reforms, including early implementation of home purchase restrictions, credit tightening policies, and public rental programs.

Over the past two decades, the city's housing prices have risen dramatically, from an average of approximately 3,300 yuan per square meter in 2000 to over 47,000 yuan per square meter by 2024 (Shanghai Municipal Statistics Bureau, 2025).

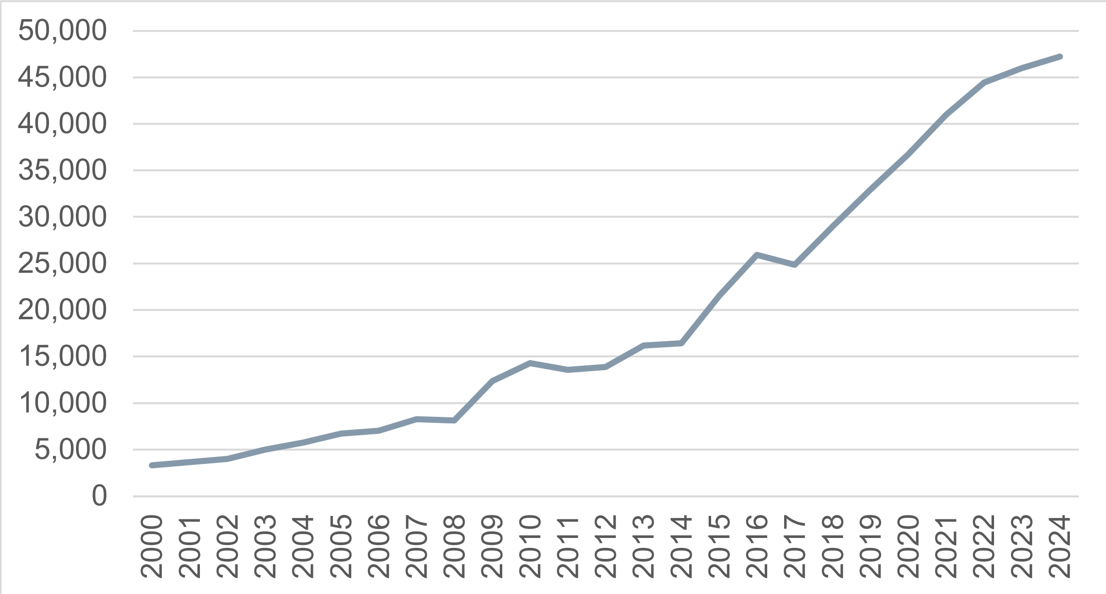

Figure 1. Annual Average Sales Price of Residential Commercial Housing in Shanghai (2000–2024), in Yuan per Square Meter

Source: Author's own visualization based on data from the National Bureau of Statistics of China (2000–2023) and Shanghai Municipal Statistics Bureau (2024).

This growth reflects Shanghai's rapid urban development, strong economic expansion, and a permanent resident population that reached approximately 24.80 million by the end of 2024 (Shanghai Municipal Statistics Bureau, 2025). The city's GDP consistently ranks among the highest in China, further reinforcing its strategic significance.

Housing in Shanghai is not just a consumption good but also serves as a primary investment vehicle for many households. Due to limited access to diversified financial markets, real estate remains the dominant asset class for urban Chinese families, especially in high-tier cities. This dual role of housing intensifies price volatility and amplifies policy sensitivity.

Beyond economic utility, housing in China is deeply embedded in social norms and life milestones. For many urban households, homeownership is considered a prerequisite for marriage and family formation. Moreover, access to public education is geographically determined, creating intense demand for "school district housing" (xuequfang), where prices often significantly exceed market averages. In China, access to public primary and secondary education is often based on a household's registered address, which must fall within the school's designated catchment area. As a result, housing located within top-ranked school zones commands a significant price premium, making xuequfang one of the most sought-after and expensive segments of the urban property market.

1.2.3. Policy Cycles and Regulation Patterns (1999–2024)

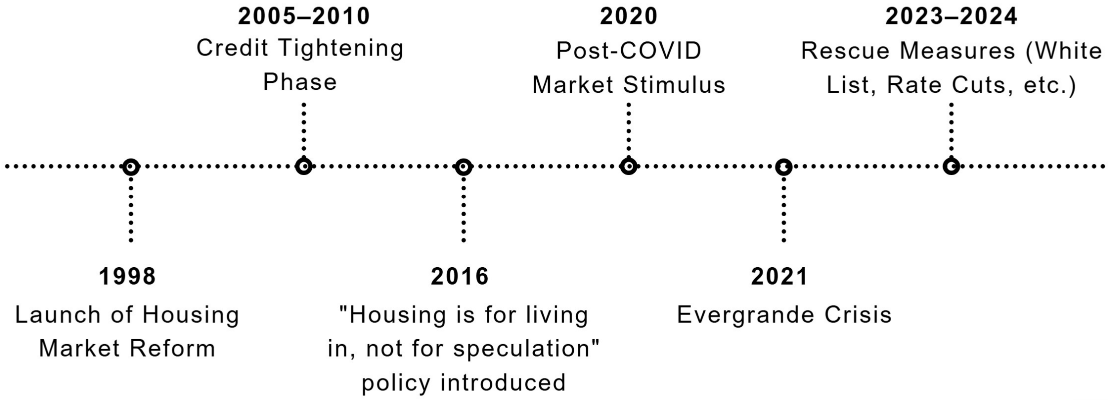

Figure 2. Timeline of Major Housing Policy Shifts in China (1998–2024)

As summarized in Figure 2, China's housing policy has evolved through alternating cycles of expansion and restriction, deeply shaping the dynamics of the real estate market. Following the 1998 reform that privatized urban housing, speculative investment surged throughout the 2000s, prompting gradual regulatory responses. By the mid-2000s, policymakers introduced credit tightening and tax adjustments to mitigate overheating risks.

Between 2010 and 2015, nationwide purchase restrictions and lending curbs were widely implemented, particularly targeting non-local buyers and owners of multiple properties. These measures aimed to curb speculative demand and slow rapid price growth. A major policy shift occurred in 2016 with the introduction of the principle that "housing is for living in, not for speculation," reflecting a longer-term orientation focused on market stabilization and financial risk control (Xinhua News Agency, 2016).

In response to economic uncertainty after 2020—including the COVID-19 pandemic—policy direction again shifted toward easing, with lower interest rates, relaxed eligibility requirements, and reduced down payment thresholds designed to support the housing market. Despite these measures, investor confidence weakened further in the wake of high-profile developer defaults, most notably the Evergrande crisis in 2021. The collapse of Evergrande, driven by over-leveraging, presale dependency, and cross-sector overexpansion, triggered widespread financial distress across the sector, exposing structural vulnerabilities in China’s housing finance system (BBC News, 2024; YIP Institute, 2024). Its downfall marked a turning point in regulatory enforcement and expectations, making housing market stabilization a national priority.

These evolving policy patterns and their macroeconomic context set the stage for this study’s investigation. A detailed classification of Shanghai’s local housing policy phases, which forms the basis for the construction of a policy score variable in the prediction model, is presented in Chapter 4.

1.2.4. Current Market Trends and Challenges

In recent years, Shanghai’s housing market has entered a period of correction. While prices rose steadily for two decades, data since 2022 show signs of stagnation and decline in certain segments. Credit conditions have loosened in recent years, as reflected in the steady decline of the Loan Prime Rate (LPR) for both short- and long-term lending (Bank of China, 2025). However, consumer sentiment remains cautious due to persistent economic uncertainty and weak income expectations (Wright et al., 2024).

The central government has shifted its focus toward stabilizing the housing market and restoring expectations through a series of supportive policy measures, including white-list financing, urban renovation programs, and interest rate reductions. These actions have shown early signs of effectiveness, as noted in official reports of improved transaction volumes and renewed consumer interest (State Council 2024).A series of pro-housing policies—including the white-list financing mechanism, renovation subsidies, and mortgage interest rate reductions—have been rolled out to stabilize both supply and sentiment, with early indicators showing “positive changes in the market” (State Council 2024).

Structural issues in China’s housing finance system further magnify risk transmission. Under the pre-sale model, buyers begin paying mortgages before their homes are delivered, while banks disburse funds to developers based on minimal project progress. In distressed cases, local governments and state-owned banks have absorbed developer losses to avoid widespread social unrest, effectively converting private debt into public cost. Economists note that such monetary responses—especially when funded by credit expansion—can function as implicit taxation through inflation and currency depreciation.

These evolving conditions reflect the dual challenges of sustaining economic stability while addressing deeply rooted inefficiencies in the real estate financing system. As the market transitions toward a more regulated and risk-conscious model, understanding the short-term dynamics of housing prices has become both more complex and more critical—particularly in cities like Shanghai that act as bellwethers for national housing trends.

1.3. Research Objectives

This study aims to predict housing price trends in Shanghai by applying advanced machine learning techniques. Specifically, the objectives are:

- To develop a predictive model based on the XGBoost algorithm, capable of capturing nonlinear relationships among economic, financial, policy, and sentiment-related factors.
- To identify and quantify the relative importance of different influencing factors through model interpretation techniques, providing insights into the dynamics of Shanghai's real estate market.
- To evaluate the model's predictive performance using appropriate statistical metrics and validate its applicability in a volatile market environment.
- To offer evidence-based recommendations for policymakers, investors, and stakeholders based on the model's findings.

Through these objectives, the study seeks to enhance the understanding of housing price movements in Shanghai and contribute to the broader application of machine learning approaches in real estate market analysis.

1.4. Research Question

This study addresses the following primary research question:

How can XGBoost be effectively utilized to predict housing prices in Shanghai by integrating macroeconomic indicators and lagged price variables, and how can SHAP analysis provide insights into the relative importance of these features?

Sub-questions:

- What are the key economic indicators influencing housing price predictions in Shanghai, and how significant are their contributions according to SHAP analysis?
- How accurately does the XGBoost model capture housing price dynamics in

Shanghai based on macroeconomic indicators and lagged price variables?

- What policy implications can be derived from the model's findings, particularly in relation to economic fluctuations and market volatility?

1.5. Scope of the Study

This study focuses on forecasting housing price trends in Shanghai by leveraging macroeconomic, financial, and policy-related indicators at a monthly frequency from 2000 to 2024.

The period from 2000 to 2024 was selected to balance both theoretical significance and data availability. While the nationwide housing marketization reform was initiated in 1998, consistent and high-quality monthly data on housing prices, macroeconomic indicators, and financial variables only become reliably available from 2000 onwards. The early 2000s also mark the beginning of Shanghai's rapid housing price growth and intensified policy interventions, making it a more empirically viable starting point for modeling. The end point of 2024 captures the latest available data, including post-pandemic recovery and the structural policy shifts following the 2021 developer crisis. This time range thus reflects both long-term structural transformation and short-term volatility in the housing sector.

Micro-level factors such as neighborhood quality, building age, or household-level income are not included due to the macro-oriented research scope.

The results should be interpreted as associative rather than strictly causal. Although the SHAP-based interpretation provides insights into variable importance, it does not establish causal inference. In addition, future housing market behavior may be influenced by unforeseeable policy shifts or socio-economic shocks that lie beyond the model's predictive range.

Thus, this thesis emphasizes trend interpretation and comparative variable contribution rather than precise value prediction or policy simulation.

While the analysis focuses exclusively on Shanghai, the methodological framework and feature set could be adapted to other large Chinese cities with similar data availability. However, differences in local policy implementation and market maturity may limit direct generalizability.

1.6. Structure of the Thesis

This thesis is structured into seven chapters. Chapter 1 introduces the research background, situating Shanghai's housing market within China's broader economic and policy landscape, clearly defines the research objectives, and specifies the research questions guiding this study. Chapter 2 reviews relevant literature on housing price forecasting and influencing factors, highlighting existing gaps that this study aims to fill. Chapter 3 establishes the theoretical framework, integrating economic theories and financial market dynamics, monetary policy effects, and behavioral factors to justify the predictive variables selected. Chapter 4 describes the methodology, detailing data collection and preprocessing procedures, the rationale and implementation of the XGBoost model, interpretability through SHAP analysis, and a comparative assessment with traditional regression models. Chapter 5 presents the empirical results, encompassing model performance evaluation, benchmark comparisons, and comprehensive SHAP-based feature importance analyses, along with adjusted predictions incorporating error-correction procedures. Chapter 6 discusses the empirical findings in relation to the theoretical framework, addresses implications for policymaking and real estate practice, acknowledges methodological limitations and provides recommendations for future research such as incorporating real-time sentiment data or extending prediction horizons. Finally, Chapter 7 concludes the thesis by synthesizing the main findings, reflecting on the study's methodological contributions, and briefly reiterating its significance for housing market analysis, policymaking, and investment strategy.

1.7. Summary

This chapter introduced the background and motivation for this study, highlighting the complexity of Shanghai's housing market and the limitations of traditional forecasting approaches. It clarified the research objectives and formulated precise research questions. The scope of the study was explicitly defined, specifying the temporal, spatial, and methodological boundaries within which the analysis is conducted. The next chapter reviews relevant literature on housing price prediction models and influencing factors, identifying current gaps in knowledge and methodological limitations that this study seeks to address.

2. Literature Review

This chapter sets the foundation for the theoretical and methodological development of this study by reviewing prior research on housing price forecasting. It outlines key modeling approaches that have been used in the literature, with a particular focus on the evolution from traditional statistical models to machine learning techniques. In addition, it introduces the main categories of factors commonly associated with housing price dynamics. Through this review, the chapter prepares the ground for identifying knowledge gaps and motivating the construction of a robust theoretical framework in the following chapter.

2.1. Existing Housing Price Prediction Models

2.1.1. Traditional Statistical Models

Traditional statistical models have long been used for housing price prediction due to their interpretability and theoretical foundation. Linear regression remains a widely applied method, as demonstrated in a study on the Indian real estate market, which found it effective for modeling housing prices based on property characteristics (Verma et al., 2023). However, its assumption of linear relationships limits its ability to capture complex market dynamics.

Time-series models, such as GARCH, have also been applied to forecast housing price volatility. A study in Malaysia found that GARCH models effectively captured price fluctuations, yet they rely on historical trends and struggle to incorporate external economic factors (Suleiman et al., 2023).

Another approach, Support Vector Regression (SVR) with bagging integration, has been proposed to enhance predictive accuracy. A study applying SVR with the Whale Optimization Algorithm (WOA) in China showed improved forecasting performance over traditional time-series models, though at the cost of increased computational complexity (Wang et al., 2021).

While traditional models provide a solid theoretical basis, their limitations in handling nonlinear interactions and external influences have led to a growing preference for machine learning approaches.

2.1.2. Machine Learning-Based Models

Machine learning models have increasingly become prominent in housing price prediction, offering the ability to capture nonlinear relationships and handle complex datasets effectively. Among these, XGBoost has been widely recognized for its predictive accuracy and computational efficiency. Multiple studies have demonstrated that XGBoost outperforms traditional models such as linear regression and support vector regression, particularly after hyperparameter tuning (Sharma et al., 2024; Weng, 2022).

To further optimize XGBoost, researchers have implemented techniques such as Bayesian optimization, which systematically searches for the optimal combination of hyperparameters to enhance model performance in housing price prediction (Weng, 2022). Additionally, SHAP (SHapley Additive exPlanations) analysis has been widely applied to quantify the contribution of each feature to the model’s predictions, allowing for a deeper understanding of how specific variables influence housing prices. For instance, SHAP has been employed to assess the impact of key property attributes such as floor area, building age, and proximity to public transport, effectively illustrating how SHAP can highlight the relative importance of different predictors (Teoh et al., 2023).

Recent comparative studies have further validated these advantages. Saraswathi et al. (2024) evaluated a series of regression-based models—including linear regression, Lasso, and Ridge—and compared them with XGBoost. The results showed that XGBoost consistently outperformed the traditional models in terms of predictive accuracy under the same dataset structure, reinforcing the value of machine learning models in capturing complex, nonlinear price dynamics.

Beyond housing price prediction, XGBoost has also been effectively applied in various other domains. For instance, it has been employed to predict groundwater levels in Malaysia using climatic variables such as rainfall, temperature, and evaporation (Osman et al., 2021). Similarly, it has been used to assess the compressive strength of ultra-high performance concrete, highlighting its utility in predicting construction material properties (Ahmed et al., 2021). In the medical domain, XGBoost has been utilized for breast cancer classification by combining it with deep learning feature extraction, effectively improving prediction accuracy (Liu et al., 2023).

In addition to XGBoost, other advanced models such as multi-modal deep learning approaches have been explored to integrate structured data with textual and visual information, significantly enhancing predictive accuracy compared to single-source models (Hasan et al., 2024). Furthermore, ensemble methods such as Random Forest and hybrid models have demonstrated robustness in predictive modeling by mitigating overfitting and improving generalizability (Zhou et al., 2023).

In summary, the integration of advanced machine learning techniques, including XGBoost and SHAP analysis, has markedly improved housing price prediction by capturing complex patterns and enhancing interpretability. The combination of model optimization, feature selection, and explainability tools not only increases predictive accuracy but also extends the applicability of these models to other predictive tasks, further validating their robustness and adaptability.

2.2. Factors Influencing Housing Prices

2.2.1. Economic Factors

Macroeconomic conditions significantly influence housing prices, with key factors including GDP, inflation, money supply, and population growth. Research analyzing OECD countries suggests that GDP growth has a stronger correlation with rising house prices than inflation, as economic expansion increases housing demand and investment activity (Lewandowska et al., 2023). Similarly, studies on Turkey's housing market confirm that macroeconomic indicators such as employment rates and credit supply directly impact price fluctuations (Akça, 2023).

Monetary policy also plays a crucial role. Empirical research using a VAR model shows that an increase in M2 money supply has a unidirectional positive effect on housing prices in China, fueling speculative investment and potential market overheating (Huang, 2023). Another study highlights the importance of rent dynamics and population changes, demonstrating that shifts in household income and urbanization patterns significantly affect real estate price trends (Yang et al., 2022).

These studies collectively illustrate that macroeconomic indicators interact in complex ways to shape housing market trends, requiring comprehensive models to capture these relationships effectively.

2.2.2. Financial Market Factors

Stock markets play a crucial role in influencing housing prices, with their impact observed through wealth effects, portfolio adjustments, and investor sentiment. A study on seven European countries found a unidirectional causality from stock prices to house prices, indicating that rising equity markets often lead to increased housing demand as investors shift capital toward real estate (Irandoust, 2021).

Similarly, research on the UK real estate market demonstrated that regional house prices and stock prices exhibit significant correlations, though the strength of this relationship varies depending on market conditions (Bissoondeeal, 2021). The study suggests that stock market fluctuations influence investor confidence in the housing sector, particularly during economic downturns.

Another study examined the spillover effects between stock market sentiment and real estate prices in the US. It found that pessimistic stock market sentiment tends to drive real estate investment, as investors seek safer assets during financial uncertainty, whereas optimism in stock markets can divert capital away from housing (Zheng & Osmer, 2021).

These studies highlight the complex interplay between stock market performance, investor behavior, and housing price movements, emphasizing the need for integrated predictive models that incorporate financial market variables.

2.2.3. Policy Factors

Government policies significantly influence housing price dynamics through monetary policy, macroprudential regulations, and land policies. Interest rate adjustments and liquidity conditions impact mortgage affordability and investment activity (Chen & Lin, 2022). Macroprudential measures, such as loan-to-value (LTV) ratios and debt-to-income (DTI) limits, have been shown to curb speculative demand and stabilize prices (LinLin et al., 2024). Land supply regulations play a critical role, with studies indicating they exert the strongest long-term influence on housing prices (Hu, 2022). Additionally, fiscal policies such as property taxes and subsidies affect affordability but have mixed effects on price stabilization (Tunc & Gunes, 2023).

While most studies rely on binary indicators or event-time dummies to model policy effects, they often fall short in capturing the directional intensity and cumulative nature of multiple policies over time. To address this, the current study develops a structured scoring system to reflect the monthly impact of policy interventions in Shanghai. Although such semi-subjective scoring is uncommon in mainstream economic modeling, it finds support in related fields. For example, Brkanić (2023) used structured user-informed weighting to quantify apartment quality based on spatial features. Similarly, the OECD (2022) endorses the use of subjective measures—such as perceived affordability and satisfaction—as valid proxies for housing policy assessment. These precedents support the use of structured, interpretable scoring methods when objective metrics are insufficient or unavailable.

2.2.4. Non-Economic Factors

Beyond economic and financial drivers, non-economic factors such as public sentiment, environmental conditions, and urban amenities significantly influence housing prices. A study integrating property characteristics, amenities, traffic data, and emotional sentiment analysis found that positive emotions, convenience, and accessibility contribute to higher real estate values, while negative sentiments associated with traffic congestion and lack of amenities decrease demand (Zhao et al., 2022).

Social media has also become a crucial factor shaping real estate market sentiment. AI-driven sentiment analysis of social media posts and online discussions indicates that public opinions on housing affordability, government policies, and investment opportunities correlate with short-term market movements (Qian et al., 2022). These studies highlight the growing importance of sentiment-driven influences in shaping real estate price trends beyond traditional market fundamentals.

2.3. Research Gap & Contribution

2.3.1. Identified Research Gaps

Despite extensive research on housing price prediction, several key gaps remain. Most studies rely on a single data source, such as macroeconomic indicators, financial market data, or policy changes, failing to provide a comprehensive understanding of housing price dynamics. There is a lack of research that integrates economic indicators, financial markets, policy interventions, and market sentiment into a unified framework to better capture the complex interactions influencing housing prices.

Although machine learning models have improved predictive accuracy, many studies lack a focus on explainability. Existing research has not fully utilized techniques like SHAP analysis to systematically quantify and compare the independent contributions of stock market fluctuations, policy regulations, and market sentiment to housing price changes. Understanding these influences in a structured manner remains a key research gap.

2.3.2. Contribution

To address these gaps, this study integrates multiple data sources—including macroeconomic indicators, financial market trends, policy measures, and sentiment analysis—into a unified machine learning framework for housing price prediction. By leveraging advanced techniques such as SHAP analysis, the research aims to provide an interpretable model that quantifies the independent effects of different influencing factors. This approach enhances both the predictive accuracy and explanatory power of housing price models, contributing to a more comprehensive understanding of real estate market dynamics.

2.4. Summary

This chapter reviewed existing models used in housing price prediction and categorized the major factors influencing housing market dynamics. It also identified several research gaps, particularly the lack of integrated, interpretable models that combine macroeconomic, financial, policy, and sentiment indicators. The next chapter builds on these insights by developing a comprehensive theoretical framework that links these variables to established economic and behavioral theories, guiding the design of the empirical model.

3. Theoretical Framework

This chapter outlines the theoretical foundations that guide the selection of predictive features in this study. It draws from five key perspectives: demand-side housing theory, monetary policy transmission mechanisms, financial market behavior, the efficient market hypothesis, and behavioral economics. Together, these perspectives allow the model to capture structural, institutional, informational, and psychological determinants of housing price dynamics. Each theoretical lens provides a rationale for incorporating specific variables and helps frame the interpretation of model outputs in relation to real-world mechanisms.

3.1. Demand-Side Determinants in Urban Economic Theory

Urban housing prices are primarily shaped by demand-side dynamics such as income growth, demographic shifts, and the cost of borrowing. The theoretical foundation for this understanding is drawn from the classic four-quadrant model developed by DiPasquale and Wheaton (1996), which integrates both the user and asset markets in determining housing prices. While their model also includes supply-side considerations, this study deliberately focuses on demand-side mechanisms to better capture the macroeconomic and financial forces most relevant to price fluctuations.

Two key variables are derived from this framework:

- **Gross Domestic Product (GDP)** represents macro-level purchasing power and is widely used as a proxy for housing demand. Higher GDP growth generally indicates increased income and population inflows, both of which create upward pressure on housing prices.

- **Loan Prime Rate (LPR)** is included in this section as a proxy for household borrowing cost. While LPR is determined by monetary policy, its direct effect on mortgage affordability makes it relevant to demand-side analysis. A lower LPR increases household purchasing power by reducing the cost of home financing, thereby encouraging housing consumption.

By focusing on GDP and LPR as demand-side indicators, the model captures both the structural capacity and financial feasibility of housing purchases.

3.2. Monetary Policy Transmission and Housing Markets

Monetary policy, implemented through interest rate adjustments, money supply regulation, and inflation control, significantly impacts housing markets. Goodhart and Hofmann (2008) emphasize that housing prices are particularly sensitive to credit availability and monetary aggregates, especially in economies where real estate serves as both a consumption good and an investment vehicle.

In the context of Shanghai's real estate market, this study examines the following three indicators:

- **Loan Prime Rate (LPR)** is also examined as a monetary policy instrument. Its adjustments reflect the central government's intent to manage macroeconomic conditions through credit availability. From this angle, LPR serves as a policy signal that indirectly shapes housing market dynamics by altering the broader liquidity environment and influencing investor expectations.
- **Money Supply (M2)** represents the level of liquidity in the financial system. An increase in M2 may drive speculative investment in real estate, contributing to price growth.
- **Consumer Price Index (CPI)** indicates changes in the general price level. Higher CPI is expected to reduce real purchasing power but may increase construction costs, leading to complex effects on housing prices.

Together, these variables capture the direct and indirect effects of monetary policy on housing market behavior.

3.3. Financial Market Theories: Capital Flow and Stock-Housing Linkages

Financial markets influence housing markets through shifts in investor sentiment and capital allocation strategies. Caballero and Krishnamurthy (2008) articulate this mechanism through the concept of "flight to quality," in which investors reallocate capital from volatile financial assets such as equities into more stable assets such as real estate during periods of heightened market uncertainty. This behavioral shift may lead to increased housing demand and price appreciation, independent of fundamental conditions.

To explore these dynamics, this study includes two key stock market indicators:

- **SSE Composite Index** reflects the overall performance of the Shanghai stock market. A rising index is expected to signal investor confidence and liquidity, which may either divert investment from real estate or, conversely, reflect broader economic optimism that boosts both markets.
- **Real Estate Industry Index (000006)** tracks the performance of property-related stocks and offers insights into sector-specific investor expectations. A strong performance is expected to indicate optimism in the real estate sector

and positively influence property prices.

By including both general and sector-specific indices, the model assesses whether fluctuations in stock market performance are associated with corresponding shifts in housing demand and prices.

3.4. Market Efficiency Hypothesis

The Efficient Market Hypothesis (EMH), developed by Fama (1970), asserts that asset prices fully and instantly reflect all available information. Under this assumption, financial markets—including housing markets—are expected to incorporate macroeconomic conditions, policy signals, and investor expectations without systematic delay or bias. This implies that any attempt to consistently forecast future price movements using publicly known variables should be unsuccessful, as such information is already embedded in current prices.

However, the dynamics of housing markets often differ from those of more liquid asset classes like stocks or bonds. Real estate markets are characterized by higher transaction costs, lower trading frequency, and greater informational asymmetries. These characteristics may result in slower adjustment to new information, creating potential predictability in price trends. Empirical studies such as Case and Shiller (1989) have demonstrated that housing prices exhibit momentum and are not fully efficient, with past prices significantly influencing future values.

In the context of this study, the inclusion of lagged macroeconomic and financial variables—such as interest rates, monetary supply, and policy scores—provides a framework to empirically examine whether the Shanghai housing market fully conforms to the assumptions of market efficiency. If these factors exhibit predictive power in the subsequent analysis, it may suggest that the market is not perfectly efficient and that certain information is incorporated into housing prices with a temporal lag.

3.5. Behavioral Economics and Public Sentiment

Traditional economic models often assume rational decision-making, but behavioral economics highlights the role of emotions, sentiment, and psychological biases in shaping market behavior. Shiller (2003) emphasizes that speculative behavior, anchored expectations, and shifts in consumer confidence can lead to housing market volatility, especially when detached from underlying fundamentals.

This study incorporates the Consumer Confidence Index (CCI) as a key indicator of public sentiment. Higher CCI values indicate optimism about future economic conditions, which may increase housing demand as consumers feel more secure in making long-term investments. Conversely, a declining CCI reflects uncertainty or pessimism, which may suppress housing activity even when macroeconomic fundamentals remain strong.

By including sentiment indicators, the model accounts for the less tangible but powerful influence of psychological factors in shaping housing market trends.

3.6. Summary

This chapter has provided the theoretical rationale for selecting each predictive feature included in the model. Rather than assuming full market efficiency, the study incorporates lagged macroeconomic and financial variables to account for potential frictions in information absorption and price adjustment. This is grounded in the insight that real estate markets, unlike liquid asset markets, often display inertia and delayed responses to external signals.

Each variable—whether representing structural demand, monetary policy, capital flow, or public sentiment—was selected with a theoretical expectation of its directional effect on housing prices. These expectations serve not only to justify variable inclusion but also to guide the interpretation of empirical results. In Chapter 5, the SHAP analysis builds on this framework to quantify each factor’s relative contribution and assess whether observed relationships align with theoretical assumptions.

4. Methodology

This chapter outlines the full methodological framework used in this study, including data collection, preprocessing, feature engineering, model design, and interpretability approach. Given the complexity of macro-financial environments and the time-dependent nature of real estate dynamics, the approach integrates a wide range of economic indicators, policy measures, and sentiment variables. After assembling and aligning multi-source data, predictive features are engineered to reflect market behavior. The XGBoost algorithm is selected as the core modeling technique due to its robustness and ability to handle non-linear interactions, while SHAP (SHapley Additive exPlanations) is introduced as the interpretability method to be applied in the analysis phase.

4.1. Data Collection and Preprocessing

4.1.1. Data Sources

This study integrates multi-source datasets to enhance the robustness of housing price predictions. The data span from 2000 to 2024 and include Shanghai's commercial housing sales prices, macroeconomic indicators, stock market data, policy-related information, and public sentiment. These datasets are sourced from authoritative institutions, covering multiple economic dimensions to support a comprehensive analysis of housing price trends.

- **Commercial housing sales price**

Shanghai's commercial housing sales price data from 2000 to 2023 are obtained from the National Bureau of Statistics (NBS), while the 2024 figure is sourced from the Shanghai Municipal Bureau of Statistics. All data are available on an annual basis. This dataset reflects the overall price level of Shanghai's real estate market and serves as a fundamental variable for analyzing housing price trends.

Table 1. Annual Average Sales Price of Residential Commercial Housing in Shanghai (2000–2024), in Yuan per Square Meter

Year	Sales price	Year	Sales price	Year	Sales price
2000	3,326	**2009**	12,364	**2018**	28,981
2001	3,658	**2010**	14,290	**2019**	32,926
2002	4,007	**2011**	13,566	**2020**	36,741
2003	4,989	**2012**	13,870	**2021**	40,974
2004	5,761	**2013**	16,192	**2022**	44,430
2005	6,698	**2014**	16,415	**2023**	45,997

2006	7,039	**2015**	21,501	**2024**	47,223
2007	8,253	**2016**	25,910		
2008	8,115	**2017**	24,866		

Source: Author's compilation based on data from the National Bureau of Statistics of China (2000–2023) and Shanghai Municipal Statistics Bureau (2024).

- **Macroeconomic indicators**

The macroeconomic indicators considered in this study include Shanghai's Gross Domestic Product (GDP), the Consumer Price Index (CPI), China's Broad Money (M2) Year-on-Year Growth Rate, and the Loan Prime Rate (LPR). The first three indicators are all sourced from the National Bureau of Statistics (NBS). Shanghai's GDP data are available on an annual basis from 2000 to 2004, while from 2005 to 2024, they are reported as quarterly cumulative values, providing a more detailed depiction of Shanghai's economic growth. A detailed table of quarterly cumulative GDP values for Shanghai from 2000 to 2024 is provided in Appendix A1.

The Consumer Price Index (CPI) captures fluctuations in Shanghai's price levels. From 2000 to 2024, this dataset is available monthly, using the year-on-year comparison method (previous year's same month = 100) to measure inflation trends. Detailed monthly CPI values are provided in Appendix A2.This dataset allows for the analysis of inflationary trends and the integration of price-level effects into the housing price prediction model.

China's Broad Money (M2) Year-on-Year Growth Rate is an indicator of market liquidity. Reported monthly, this dataset reflects changes in monetary supply trends, which play a crucial role in determining market liquidity and financing costs in the real estate sector. A full summary of monthly M2 growth rates from 2000 to 2024 is provided in Appendix A3.

The Loan Prime Rate (LPR) has served as the benchmark for bank lending rates since August 2019. It is determined through quotations from 18 representative banks, including the Bank of China, and is published on the 20th of each month (or the following business day if it falls on a holiday). This dataset is available via the Bank of China's official website.

Before 2019, China's lending rates were primarily based on the benchmark interest rates published by the People's Bank of China (PBOC). Among these, the 5-year benchmark lending rate was a key reference point. The benchmark rates were adjusted on a discretionary basis by the PBOC and made publicly available on its official website. A detailed list of benchmark lending rate changes and 5-year Loan Prime Rate (LPR) from 2000 to 2024 is presented in Appendix A4.

- **Stock market**

This study selects the Shanghai Stock Exchange Composite Index (SSEC) and the Real Estate Industry Index (000006) as representative stock market indicators. Monthly growth rates for both indices are used to reflect overall stock market performance trends.

The Shanghai Stock Exchange Composite Index (SSEC) reflects the overall stock price movements of companies listed on the Shanghai Stock Exchange and serves as a key benchmark for measuring the performance of China’s stock market. The data are sourced from Investing.com.

The Real Estate Industry Index (000006) tracks the stock performance of China's real estate sector, covering listed companies engaged in real estate development and related industries. It provides insights into overall market conditions within the real estate industry. The data are sourced from Sohu Securities.

- **Policy measures**

China’s housing policy has undergone significant transformations since the late 1990s, shaping the real estate market’s trajectory. Shanghai, as a key metropolitan area, has experienced distinct policy phases that have influenced housing prices and market dynamics. This study categorizes Shanghai’s housing policies from 2000 onward into five key stages: marketization reform and housing system transformation (2000-2005), alternating periods of regulation and stimulus (2006-2009), full implementation of purchase restrictions and tightening (2010-2015), the “Housing is for Living, Not for Speculation” era with long-term regulatory mechanisms (2016-2021), and post-pandemic market adjustment (2022-present).

Table 2. 1994-1999 Shanghai Real Estate Policy

Policy Content	Date	Expected impact
Individuals from other provinces and cities who purchase commercial housing in this city with a construction area of 70 square meters or more can apply for a blue-stamp household registration for themselves, their spouse, and their immediate family members.	1994-02-01	Stimulate

Change the distribution method of housing benefits in kind to a monetary wage distribution method based mainly on distribution according to work	1994-07-18	Stimulate
Purchase of commercial housing can enjoy personal income tax base (i.e. personal income tax payable) deduction	1998-06-01	Stimulate
In the second half of 1998, the distribution of housing in kind was stopped and the monetization of housing was gradually implemented.	1998-07-03	Stimulate
The state stipulates that the transaction tax is 1.5% of the total house price, but individuals only need to pay 0.75%, and the other half is subsidized by the Shanghai Finance Department.	1999-07-01	Stimulate

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

During the marketization reform period (2000-2005), the real estate market in Shanghai was primarily driven by policy support, including land supply adjustments, mortgage accessibility, and tax incentives. The government encouraged homeownership through financial liberalization while gradually introducing minor regulatory measures, such as restrictions on excessive speculation. However, these policies were not intended to suppress price growth but rather to prevent overheating.

Table 3. 2000-2004 Shanghai Real Estate Policy

Policy Content	Date	Expected impact
Stop accepting applications for blue-stamp household registration in this city	2002-04-01	Suppress
The deed tax is adjusted from 0.75% of the total house price to 1.5%	2002-09-01	Suppress
The policy of deducting the personal income tax base (i.e. the amount of personal income tax payable) of buyers of commercial housing has ended	2003-05-31	Suppress
The real estate industry has a high degree of correlation and strong driving force, and has become a pillar industry of the national economy.	2003-08-12	Stimulate

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

The 2005-2009 phase marked alternating cycles of market tightening and stimulus. Initially, the government introduced measures to curb speculative investments, such as higher transaction taxes, stricter land use policies, and increased oversight of housing supply. However, the 2008 global financial crisis prompted a policy shift toward market stimulation. Measures such as reduced down payment requirements, tax relief on housing transactions, and looser mortgage lending policies were introduced to revive demand, stabilizing the market after the initial economic downturn.

Table 4. 2005-2009 Shanghai Real Estate Policy

Policy Content	Date	Expected impact
For individuals who resell their homes within two years after purchase, business tax will be levied on the full amount of the sales income;	2005-06-01	Suppress
If a house is resold within 5 years of purchase, business tax will be levied on the full amount of the sale proceeds;	2006-06-01	Suppress
Individual income tax is levied on income from the transfer of personal housing.	2006-08-01	Suppress
Land value-added tax is levied on second-hand housing transactions that are not ordinary housing in this city. The sale of a house where an individual has lived for 5 years or more is exempt from land value-added tax; if the individual has lived in the house for less than 3 years, land value-added tax is levied at 0.5% of the transfer income; if the individual has lived in the house for more than 3 years but less than 5 years, the land value-added tax is halved.	2007-07-15	Suppress
Shanghai individuals will not be subject to business tax if they transfer ordinary housing purchased more than 2 years ago	2008-11-01	Stimulate
Individuals do not pay personal income tax for income from the transfer of a house that they have used for more than two years and is the only house used for their family's living.		
The housing registration fee for individuals purchasing ordinary housing and the housing transaction (transfer) fee for individuals buying and selling existing ordinary housing are waived.		
For the purchase of ordinary housing for self-use, the minimum down payment ratio of housing provident fund loans is adjusted to 20%;		

The lower limit of commercial personal housing loan interest rates will be expanded to 0.7 times the loan base rate.		

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

From 2010 to 2015, Shanghai's housing market entered a period of comprehensive purchase restrictions and tightening financial policies. The first formal purchase restriction (April 2010) limited non-local residents from buying properties without meeting specific social security or tax requirements. Subsequently, lending policies became increasingly restrictive, with higher down payment ratios for second-home buyers and elevated mortgage rates to deter speculative activities. These measures collectively contributed to a controlled slowdown in price appreciation and a shift toward a more regulated market environment.

Table 5. 2010-2015 Shanghai Real Estate Policy

Policy Content	Date	Expected impact
For families purchasing their first self-occupied housing with a floor area of more than 90 square meters, the down payment ratio of the loan shall not be less than 30%	2010-04-17	Suppress
Residents of Shanghai and other provinces and cities can only New Purchase One commercial housing unit (including second-hand housing stock)	2010-10-07	Suppress
Households with local household registration Purchase restrictions 2 sets, social security or personal tax for non-local resident families for more than 1 year Purchase restrictions 1 set	2011-02-01	Suppress
At the implementation level, restrictions are imposed on non-local singles from buying houses	2012-06-27	Suppress
The purchase restriction requirement for non-Shanghai households has been raised from "1 year of social insurance" to "2 years of social insurance"	2013-11-08	Suppress

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

The 2016-2021 phase introduced the "Housing is for Living, Not for Speculation" policy framework, marking a transition toward long-term market stabilization rather than short-term cyclical interventions. The regulatory focus shifted to rental market expansion, optimized land supply mechanisms, and financial risk prevention. Under continued restrictions on speculative investments, housing prices remained stable, reflecting the long-term regulatory framework's effectiveness in mitigating excessive market fluctuations.

Table 6. 2016-2021 Shanghai Real Estate Policy

Policy Content	Date	Expected impact
The purchase restriction requirement for non-Shanghai households has been raised from "2 years of social insurance" to "5 years of social insurance".	2016-03-24	Suppress
The down payment ratio for a resident household purchasing its first home shall not be less than 35%.	2016-11-29	Suppress
The VAT exemption period for second-hand housing is increased from 2 years to 5 years	2021-01-22	Suppress

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

Since 2022, the market has entered a post-pandemic adjustment phase, characterized by a gradual relaxation of purchase restrictions and financial policies. In response to declining transaction volumes and weakened buyer confidence, authorities lowered down payment requirements, reduced mortgage rates, and eased restrictions on non-local buyers. However, market recovery remains uncertain, with ongoing policy adjustments aimed at striking a balance between economic stability and housing affordability.

Table 7. 2022-2024 Shanghai Real Estate Policy

<table>
<tr><th>Policy Content</th><th>Date</th><th>Expected impact</th></tr>
<tr><td>The lower limit of the first mortgage interest rate is adjusted to no less than LPR minus 10 basis points (previously LPR + 35 BP)</td><td rowspan="2">2023-12-15</td><td rowspan="2">Stimulate</td></tr>
<tr><td>The minimum down payment ratio for the first home is adjusted to no less than 30% (previously 35%)</td></tr>
<tr><td>Non-local residents who have paid social security/individual tax for 5 years are limited to purchasing one house outside the outer ring road (previously, non-local singles were not eligible to purchase a house)</td><td>2024-01-31</td><td>Stimulate</td></tr>
</table>

The social security limit for non-local residents is reduced from 5 years to 3 years	2024-05-28	Stimulate
Expand the scope of housing purchase for single people who are not registered in the city, and allow them to purchase second-hand houses within the outer ring road		
The lower limit of the first mortgage interest rate is adjusted to no less than LPR minus 45 basis points		
The minimum down payment ratio for the first home is adjusted to no less than 20% (previously 30%)		
The social security and personal tax requirements for non-local residents who purchase properties outside the outer ring road are reduced from 3 years to 1 year	2024-10-01	Stimulate
For non-local residents who have been paying social security and personal income tax for 3 years, the home purchase qualification is adjusted from 1 house every 3 years to 2 houses every 3 years.		
The minimum down payment ratio for the first home is adjusted to no less than 15% (previously 20%)		
The VAT exemption period for second-hand housing is adjusted from 5 years to 2 years		

Source: Author's summary based on official policy documents from multiple government and data websites (see full references for details).

The housing policy data summarized in this section were compiled and categorized based on official announcements and regulatory reports from institutions such as the Shanghai Housing Bureau, the Shanghai Municipal Government, the State Council of China, and the People's Bank of China. Additional context was derived from reputable media platforms including Sina Finance, Sohu News, and Xinhua Finance.

The compiled dataset includes policy enactment dates, descriptions, and expected market impacts, and serves as a key input for the machine learning model developed in this study. While not every policy is individually cited, all major sources are listed in the References section.

- **Public Sentiment**

The Consumer Confidence Index (CCI) data used in this study is sourced from the CEI

Data platform (ceidata.cei.cn), which provides nationwide monthly consumer confidence data for China. The CCI reflects consumer sentiment regarding the current economic situation and future expectations.

The baseline value of CCI is set at 100:

- CCI > 100: Indicates optimistic consumer sentiment.
- CCI < 100: Suggests pessimistic consumer sentiment.

Since consumer sentiment can directly impact housing market trends, the CCI is incorporated as an explanatory variable in this study.

4.1.2. Data Preprocessing

To ensure consistency between housing price records and macroeconomic indicators, all data used in this study is standardized to a monthly frequency. Since some original datasets—such as annual housing prices or cumulative GDP—do not align with this granularity, a series of temporal transformations is applied. These transformations are designed to retain realistic economic dynamics while minimizing artificial distortions during interpolation.

- **Conversion of Annual Housing Prices to Monthly Prices**

The transformation of annual housing prices into monthly values involved three sequential steps: smoothing outliers, interpolation using PCHIP, and mean-preserving scaling.

Step 1: Smoothing of abnormal fluctuations

To mitigate the effect of outlier years that exhibited sharp and potentially artificial jumps in average prices, selected structurally volatile years (2014, 2015, 2016, 2018, and 2020) were smoothed. The price for each such year was replaced with the mean of its adjacent years. This helped avoid introducing distortion into the interpolated curve, which can otherwise result from abrupt changes in the original data.

Step 2: Interpolation using PCHIP

Interpolation was performed between each pair of consecutive years, dividing the interval into twelve equal parts to simulate monthly resolution. Instead of interpolating based on actual calendar dates, years were treated as sequential numeric indices (e.g., 2010 = 0, 2011 = 1, etc.), allowing monthly points to be generated uniformly within each year.

The interpolation method adopted was the Piecewise Cubic Hermite Interpolating

Polynomial (PCHIP). PCHIP is a shape-preserving interpolation technique that differs from standard cubic spline interpolation. Unlike splines, which may produce unwanted oscillations between data points, PCHIP ensures that the interpolated curve maintains the monotonicity and general shape of the data. This makes it especially suitable for economic and financial data where artificial peaks or dips can mislead interpretation.

To allow for interpolation of the final observed year (2024), a synthetic data point for 2025 was extrapolated based on the growth rate from 2023 to 2024. This extrapolated point was used strictly for technical completeness—so that monthly prices for 2024 could be generated—and was excluded from subsequent modeling and analysis.

Step 3: Mean-preserving adjustment

Since the interpolation step alone does not guarantee that the average of the twelve monthly values within a given year will match the original annual average, a scaling adjustment was applied. For each year y, a scaling factor s_y was calculated as:

$$s_y = \frac{P_y^{\text{annual}}}{\bar{P}_y^{interp}}$$

where P_y^{annual} is the original average price in year y, and $\bar{P}_y^{interp}$ is the mean of the twelve interpolated monthly values for that year. Then, each monthly interpolated price was multiplied by this factor:

$$P_{y,m}^{\text{adjusted}} = P_{y,m}^{\text{interp}} \cdot s_y$$

This adjustment ensures that the transformed monthly prices remain consistent with the original annual data, preserving the integrity of the source dataset while enabling monthly-level analysis.

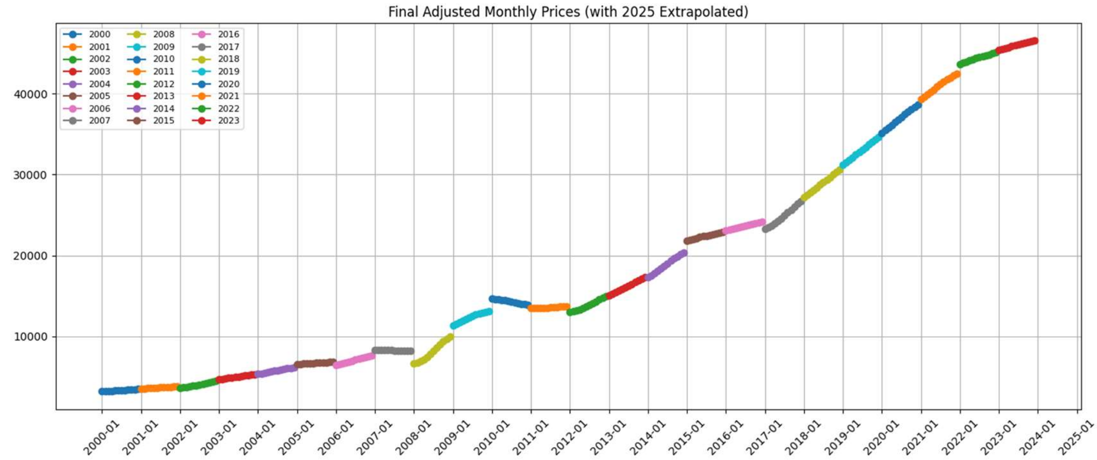

Figure 3. Final Adjusted Monthly Housing Prices (2000–2024)

Source: Author's own visualization based on official housing price data.

This figure displays the interpolated and adjusted monthly housing prices after applying outlier smoothing, PCHIP interpolation, and mean-preserving adjustment. Each segment is color-coded by calendar year. The extrapolated 2025 data point was used solely for interpolation purposes and is excluded from model training.The visualization confirms the continuity and stability of the adjusted time series, providing a structurally sound basis for subsequent predictive modeling.

This approach strikes a balance between structural fidelity and computational simplicity. It was favored over real-date-based interpolation because the annual data represent averaged figures rather than point observations. Moreover, this method provides clearer control over the number and structure of the interpolated points, which is desirable in the context of machine learning feature construction.

The full table of interpolated and adjusted monthly housing prices is provided in Appendix B1.

- **Computation of CPI Growth Rate**

To standardize the representation of consumer prices in the model, this study does not use raw CPI index values. Instead, it calculates the year-over-year (YoY) growth rate for each month to reflect inflation dynamics more intuitively. This transformation allows the model to learn from relative price changes, rather than being influenced by large but consistent absolute index levels.

The CPI growth rate is calculated as:

$$CPI\_YoY_{m,t} = \frac{CPI_{m,t} - 100}{100}$$

where:

- $CPI_{m,t}$ is the CPI index for month m in year t, where the index is based on the previous year's same month (100100100 represents no change).

This transformation ensures that the model captures inflation trends rather than absolute price levels while maintaining consistency with the original CPI data format.

- **GDP Data Processing**

To integrate GDP data into the analysis, it is necessary to convert available records into a structured format suitable for machine learning. The dataset consists of annual GDP values for 2000-2004 and cumulative quarterly GDP values from 2005 onward. The following steps outline the preprocessing methodology applied to transform these data points into monthly values.

Step 1: Conversion of Cumulative Quarterly GDP to Independent Quarterly GDP (2005-2024)

Since GDP from 2005 onward is reported as cumulative values, independent quarterly GDP figures are derived using the following calculation:

$$GDP_{Q_i} = Accumulated\ GDP_{Q_i} - Accumulated\ GDP_{Q_{i-1}}$$

where:

- GDP_{Q_i}represents the independent GDP value for quarter i.
- $Accumulated\ GDP_{Q_i}$ is the cumulative GDP reported at the end of quarter i.
- $Accumulated\ GDP_{Q_{i-1}}$ is the cumulative GDP reported at the end of the previous quarter.

For Q1 of each year, the accumulated GDP is taken directly as its independent quarterly value.

Step 2: Estimation of Quarterly GDP for 2000-2004

Since quarterly GDP data is not available for 2000-2004, an estimation is performed using the average quarterly proportions from 2005-2010:

$$GDP_{Q_i} = GDP_{Year} \times Ratio_{Q_i}$$

where:

- GDP_{Year} represents the total GDP of the year.
- $Ratio_{Q_i}$ is the average proportion of GDP allocated to quarter i, calculated as:

$$Ratio_{Q_i} = \frac{\sum_{y=2005}^{2010} GDP_{Q_i,y}}{\sum_{y=20}^{2010} \quad GDP_{Year,y}}$$

where the numerator represents the sum of all GDP values in quarter i over the years 2005-2010, and the denominator represents the total GDP across those years.

Step 3: Monthly GDP Distribution Using CPI Proportions

With quarterly GDP values established, a further transformation is required to obtain monthly GDP values. The monthly GDP is allocated within each quarter based on the Consumer Price Index (CPI) proportions. The logic behind this approach is that inflation trends influence economic activity distribution, allowing for a more refined allocation of GDP across months.

For each quarter, the sum of CPI values across the three constituent months is calculated to determine the relative weight of each month. The corresponding monthly GDP is then derived as follows:

$$GDP_m = GDP_Q \times \frac{CPI_m}{\sum_{i=1}^{3} CPI_i}$$

where:

- GDP_Q is the estimated GDP for a given quarter.
- CPI_m is the Consumer Price Index for a specific month.
- $\sum_{i=1}^{3} CPI_i$ is the sum of CPI values within the quarter.

Step 4: Calculation of GDP Growth Rate

Once monthly GDP values are obtained, it is essential to compute the GDP growth rate to reflect economic trends more effectively. The GDP growth rate is calculated as the percentage change in GDP compared to the previous month:

$$GDPGrowth_m = \frac{GDP_m - GDP_{m-1}}{GDP_{m-1}}$$

where:

- $GDPGrowth_m$ represents the GDP growth rate for month mmm.
- GDP_m is the GDP value for the current month.

- GDP_{m-1} is the GDP value for the previous month.

By converting absolute GDP values into monthly growth rates, this transformation ensures consistency in economic trend analysis and facilitates comparisons with other macroeconomic indicators. Additionally, expressing GDP in relative terms mitigates heteroscedasticity issues, making the data more suitable for machine learning applications. Detailed GDP estimation and monthly growth rates from 2000 to 2024 are provided in Appendix B1.

- **Loan Prime Rate (LPR) Processing**

LPR (Loan Prime Rate) is a critical macroeconomic indicator reflecting borrowing costs. Since the dataset contains monthly LPR values, the month-over-month (MoM) growth rate was calculated using:

$$LPRGrowth_m = \frac{LPR_m - LPR_{m-1}}{LPR_{m-1}}$$

This ensures that changes in LPR over time are captured rather than using absolute values, which may introduce scale differences.

- **Money Supply (M2) Growth Rate Processing**

M2 money supply represents broad liquidity in the economy. The original dataset provides M2 growth rates in percentage form, which were converted into decimal format for consistency:

$$M2Growth_m = \frac{M2_{grow}}{100}$$

This transformation maintains numerical consistency across all macroeconomic variables.

- **Policy Data Processing**

To incorporate policy impacts into the machine learning model, this study quantifies the effects of Shanghai's real estate policies using a scoring system. Instead of categorizing policies into specific types such as purchase restrictions, loans, or taxes, this method directly assigns a numerical score based on the policy's impact direction and intensity.

Step 1: Determine Policy Impact Direction Policies are classified as either stimulative or suppressive based on their expected effect on the housing market:

- Stimulative policies encourage housing transactions or reduce financial burdens for buyers.
- Suppressive policies impose restrictions, increase costs, or limit access to housing purchases.

Step 2: Assign Policy Intensity Scores Each policy is assigned a score based on its intensity:

- Strong policies (e.g., major changes in mortgage interest rates, down payment ratios, or significant tax adjustments) are assigned ±2.
- Moderate policies (e.g., adjustments to purchase restrictions, minor tax modifications) are assigned ±1.
- Minor policies (e.g., small administrative changes or minor procedural adjustments) are assigned ±0.5.

For example:

- An increase in the required down payment ratio from 30% to 35% is a strong suppressive policy (-2).
- Reducing the social security requirement for home purchases from five years to three years is a moderate stimulative policy (+1).
- A minor tax exemption adjustment might be categorized as a minor stimulative policy (+0.5).

Step 3: Monthly Policy Score Calculation For each month, the total policy score is calculated as the sum of all policies implemented in that month. If no new policies were introduced, the score remains 0. The policy score is not cumulative across months, ensuring that the dataset reflects only the impact of newly enacted policies.

The complete dataset of monthly LPR changes, M2 supply growth, stock market indices, and corresponding policy scores is provided in Appendix B3.

- **Public Sentiment Data Processing**

Instead of using absolute values, this study employs the Year-on-Year (YoY) growth rate of the CCI to capture long-term consumer sentiment trends while mitigating potential scale differences. The formula is:

$$CCI\_YoY_m = \frac{CCI_m - CCI_{m-12}}{CCI_{m-12}}$$

where:

- CCI_m represents the consumer confidence index in month mmm.
- CCI_{m-12} represents the index value from the same month in the previous year.

This approach helps eliminate seasonal variations and ensures a more meaningful comparison of consumer sentiment over time. For reference, detailed monthly CCI values and computed YoY growth rates are available in Appendix B4.

The full monthly feature matrix constructed from all processed variables and used as input for model training is provided in Appendix C1.

4.1.3 Feature Engineering

To enhance the model's ability to capture temporal dynamics and macroeconomic influences on housing price changes, a series of engineered features were constructed based on both domain knowledge and empirical validation.

The core prediction target in this study is the next month's price growth rate, denoted as next_month_growth, which represents the percentage change in average sales price from one month to the next.

To support this task, a key explanatory feature named prev_month_growth was introduced. It represents the most recently observed price momentum—i.e., the percentage change from the previous month. Although both variables are derived from the same housing price series, they refer to distinct time steps and contain no information leakage. This design allows the model to capture autocorrelation and trend persistence in housing price dynamics.

In addition to momentum features, a set of macro-financial indicators was included. Based on both theory and data behavior, some of these variables were lagged by one month to reflect behavioral delays in market response. These include several variables with a one-month lag, such as:

- Policy_Score_lag1 — to capture delayed effects of government interventions;
- LPR_lag1 — the Loan Prime Rate, reflecting changes in financing costs;
- M2_lag1 — broad money supply growth, as a proxy for liquidity conditions;
- CCI_lag1 — the Consumer Confidence Index, capturing sentiment-driven demand.

Other indicators, such as Shanghai's monthly economic growth, CPI growth, and stock market performance (SSE Index and Real Estate Index), were retained in their original monthly form, assuming more immediate effects on buyer behavior and affordability.

All feature selections were guided by iterative model testing and further validated through SHAP-based interpretation. The final feature set was optimized to strike a balance between predictive performance and interpretability, while minimizing redundancy or overfitting.

Table 8 summarizes the final set of model variables.

Table 8. Summary of Variables Used in the Final Prediction Model

Variable	Description	Type	Lagged?
next_month_growth	Target: price % change from current month	Target	No
prev_month_growth	Price % change from previous month	Feature	No
CPI_YoY	Shanghai CPI, year-over-year change	Feature	No
LPR_MoM_lag1	Monthly change in Loan Prime Rate	Feature	Yes
M2_YoY_lag1	Broad money supply growth (M2)	Feature	Yes
SSE_Index_MoM	Shanghai Stock Exchange Index growth	Feature	No
RE_Index_MoM	Real Estate Sector Index growth	Feature	No
Policy_Score_lag1	Monthly policy score	Feature	Yes
CCI_YoY_lag1	Consumer Confidence Index, YoY change	Feature	Yes

This table lists all variables used in model training, including the target variable and input features. Lagged variables indicate a one-month delay introduced to capture temporal causality.

4.2. Model Selection and Implementation

The primary objective of this study was to construct an accurate and interpretable model for predicting prices in Shanghai. After reviewing various modeling approaches—including traditional statistical models and machine learning algorithms—XGBoost (eXtreme Gradient Boosting) was selected as the core method due to its robustness, high predictive performance, and compatibility with SHAP-based interpretability tools.

4.2.1. Machine Learning Model: XGBoost

XGBoost, a gradient boosting framework based on decision trees, offers high flexibility in modeling complex patterns and is robust against multicollinearity and overfitting. Its ability to scale effectively with high-dimensional input and capture complex interactions makes it particularly suited for macroeconomic forecasting problems.

To align the prediction target with the scale and behavior of input variables, this study framed the task as a growth rate forecasting problem, rather than predicting absolute price levels. Specifically, the model learns to forecast the next month's price growth rate, which is then used to reconstruct the actual price trajectory. This transformation avoids scale mismatch and improves numerical stability, particularly when using economic indicators expressed as percentage changes.

Rather than adopting a rolling-window or random cross-validation strategy, a fixed time-based split was used: training on data from January 2014 to December 2020 and testing on data from January 2021 to December 2024. This reflects the practical requirement of forecasting future periods using past data while preserving the chronological structure needed for lagged feature modeling.

4.2.2. SHAP Analysis for Model Interpretability

While XGBoost is often categorized as a black-box model, its compatibility with SHAP (SHapley Additive exPlanations) enables clear, consistent interpretation of feature contributions. SHAP assigns an additive importance score to each feature for every prediction, offering both global insight into which variables matter most, and local explanations for individual predictions.

This interpretability framework was used throughout model development to guide feature selection and validate that the model's learned patterns aligned with economic logic. For example, variables with persistently low SHAP contributions were considered for removal in later versions, helping reduce noise and improve transparency.

4.3. Comparison with Traditional Methods

Traditional econometric models such as ARIMA, VAR, and multiple linear regression have been widely used in housing market research. However, these models require assumptions (e.g., linearity, stationarity, homoscedasticity) that are often violated in real-world macro-financial data.

A benchmark linear regression model was also constructed for comparison. While interpretable, it performed significantly worse than XGBoost in both RMSE and MAE, and showed high sensitivity to input volatility. The inability of linear models to capture interaction effects and threshold dynamics limits their predictive power in this context.

4.4. Summary

This chapter detailed the methodological underpinnings of the study, starting from multi-source data integration to granular monthly preprocessing. Special emphasis was placed on transforming diverse datasets—including annual housing prices, cumulative GDP, monetary indicators, and policy measures—into a consistent and analytically meaningful monthly format. Feature engineering leveraged both domain knowledge and empirical validation, introducing autoregressive signals, lagged macroeconomic variables, and policy sentiment into the modeling pipeline.

XGBoost was selected as the primary model due to its proven performance and interpretability when paired with SHAP analysis. A fixed time-based training/testing split was applied to reflect real-world forecasting conditions and avoid data leakage. The chapter also established a benchmark comparison with linear regression, reinforcing the necessity of nonlinear, ensemble-based models for capturing complex market interactions.

Together, these methodological components lay the foundation for the results presented in the next chapter, where model performance, interpretability, and feature importance are systematically evaluated and discussed.

5. Results and Analysis

This chapter presents the empirical analysis and evaluation of the forecasting models developed in this study. The section begins by outlining the modeling setup and performance metrics, followed by a detailed assessment of the final XGBoost model's predictive accuracy. A linear regression model is used as a benchmark for comparison, and SHAP analysis is employed to interpret feature contributions. The chapter also reviews the iterative development of model versions and concludes with a summary of key findings, with explicit reference to the theoretical expectations outlined in Chapter 3.

5.1. Model Setup and Evaluation Metrics

Given the presence of time-lagged economic signals and potential non-linear dependencies in the housing market, this study employed the XGBoost algorithm as the primary forecasting model.

The model was trained to predict the next-month price growth rate (defined as the percentage change in housing price compared to the previous month). This formulation allowed the target variable to align with the scale of macroeconomic indicators (typically expressed as growth rates or percentages), improving numerical stability and consistency across the feature set.

The modeling process followed these main steps:

- **Data Split**: Data from January 2000 to December 2020 was used as the training set, while data from January 2021 to December 2024 was reserved as the test set. This time-based split respects the chronological nature of the data and avoids future leakage.

- **Feature Set**: The final model included temporal variables (month), autoregressive indicators (previous month's growth), and selected macroeconomic and policy features, including:

    - Shanghai Growth MoM, Shanghai CPI Growth YOY, M2_lag1, LPR_lag1, Policy Score_lag1, CCI_lag1, SSE Index Growth, and SSE Real Estate Index Growth.

- **Model Parameters:** The XGBoost model was configured with the following hyperparameters based on grid search and manual tuning:

    - n_estimators = 500,

- learning_rate = 0.03,
- max_depth = 3,
- subsample = 0.9,
- colsample_bytree = 0.8,
- random_state = 42.

These settings represent a trade-off between model complexity and generalization, aiming to reduce overfitting while capturing relevant patterns.

To evaluate model performance, two common regression metrics were used:

- **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

  - RMSE penalizes large errors more heavily and reflects the overall prediction accuracy.

- **Mean Absolute Error (MAE):**

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

  - MAE provides a more interpretable measure of the average deviation between predicted and actual values.

Both metrics are reported on the reconstructed price level, which was derived from predicted growth rates by recursively applying the predicted growth to the lagged price.

This setup provides a comprehensive framework for evaluating both accuracy and interpretability, laying the foundation for subsequent analysis and model comparison.

5.2. Visual Validation of Predicted Trends

The final model (Version 5), developed through iterative enhancement and rigorous feature selection, achieved strong performance in forecasting Shanghai's monthly housing prices from 2021 to 2024.

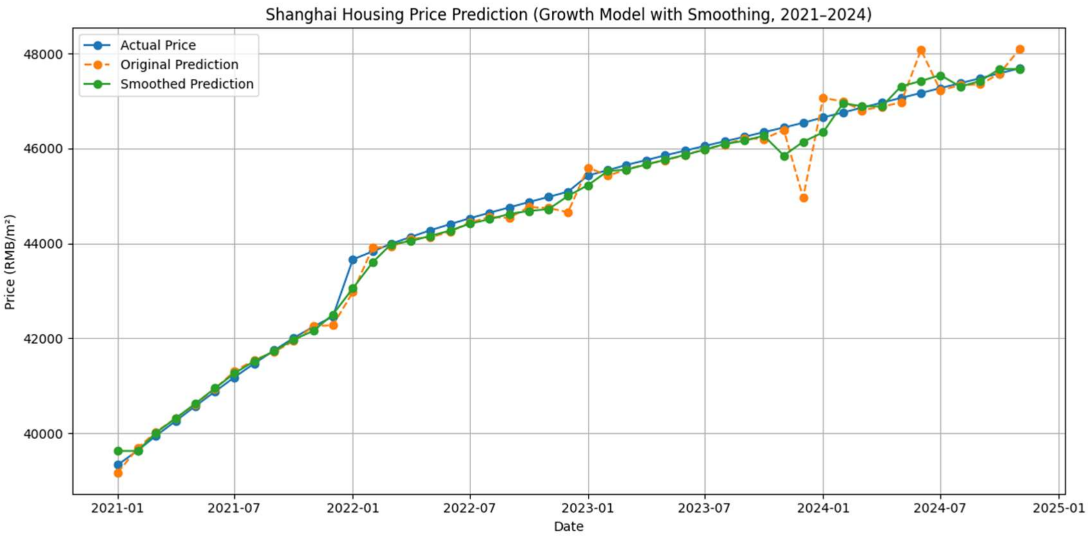

Figure 4. Predicted vs. Actual Monthly Housing Prices in Shanghai (2021–2024) using Final XGBoost Model

As shown in Figure 4, the model's predicted price series (orange) closely follows the actual housing price trend (blue) throughout the test period. After applying a three-month centered rolling average (green), the prediction series becomes even smoother, effectively reducing noise while preserving key turning points in early 2022 and mid-2024.

Quantitatively, the model reached:

- Root Mean Squared Error (RMSE): 320.06
- Mean Absolute Error (MAE): 176.82

These results represent a substantial improvement over previous versions (e.g., RMSE = 18222.69 in the baseline), with an error reduction exceeding 98%. This level of accuracy affirms the model's ability to capture both macro-level market signals and short-term dynamics.

Importantly, the model was trained to predict next-month growth rates and then reconstruct absolute prices by chaining the predicted growth to previous prices. This design ensures consistency with the percentage-based input variables and stabilizes the learning process.

The final model thus provides a reliable and interpretable tool for understanding housing market trends and serves as a foundation for further analysis, including benchmark comparisons and feature importance interpretation in the following sections.

5.3. Benchmark Comparison: Linear Regression Model

To benchmark the performance of the XGBoost model, a multiple linear regression (OLS) model was trained using the same set of input features as the final model (month, prev_month_growth, and lagged macroeconomic indicators including Policy Score, LPR, M2, CCI, etc.). The linear regression model was set up to predict the next-month price growth rate, consistent with the XGBoost target definition. Predictions were subsequently scaled back to actual price levels using the lag-1 price as a reference.

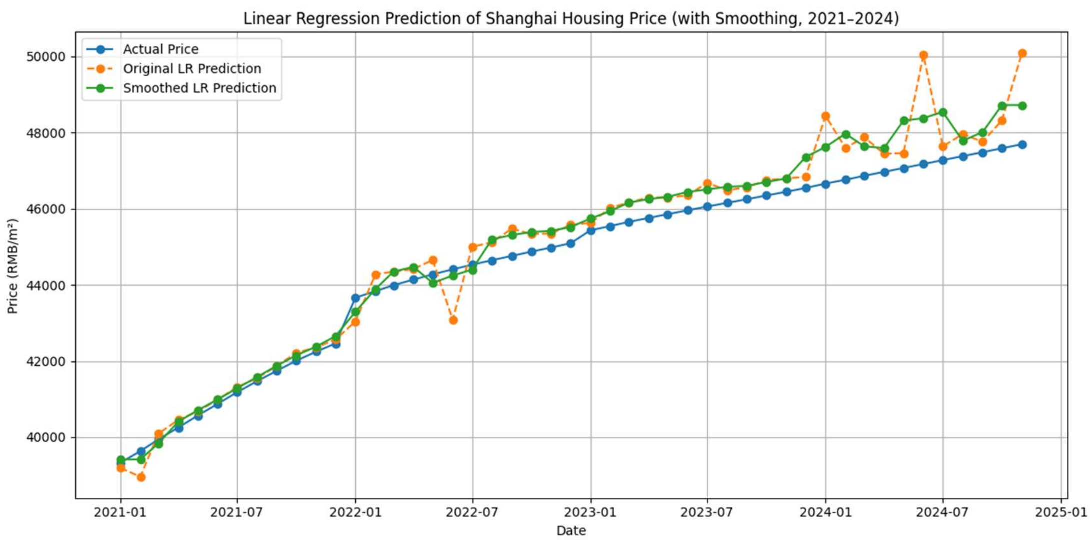

Figure 5. Predicted vs. Actual Monthly Housing Prices in Shanghai (2021–2024) using Linear Regression Model

Figure 5 presents the prediction results from the linear regression model, compared against actual housing prices from 2021 to 2024. While the smoothed curve offers a more stable trajectory, the original prediction line displays significant volatility, particularly in the later stages (e.g., mid to late 2024). The model tends to overreact to small fluctuations in feature values, leading to sharp, often unrealistic price movements.

The benchmark linear regression model yielded a Root Mean Squared Error (RMSE) of 761.82 and a Mean Absolute Error (MAE) of 533.38.

Despite sharing the same features, the linear model performs significantly worse than

XGBoost, particularly in terms of RMSE, which is more sensitive to large errors. This highlights several key limitations of linear regression in this context:

- **Lack of non-linear modeling capacity:** Real estate markets often exhibit threshold effects, interaction terms, and diminishing returns that cannot be captured by a linear formulation.
- **No robustness to feature scale or multicollinearity:** Variables such as lagged growth rates and macro indicators may interact in complex ways, which tree-based models like XGBoost can inherently manage.
- **Higher volatility in outputs:** The linear model exhibits sharp jumps and dips, especially in periods of macroeconomic change, resulting in poor temporal stability.

In contrast, the XGBoost model effectively captures both local trends and macroeconomic influences through non-linear interactions and decision-tree ensembles, resulting in significantly improved predictive accuracy and smoother price trajectories. The performance gap between the models further validates the assumption made in the theoretical framework that housing price movements are shaped by nonlinear, lagged, and interacting mechanisms.

5.4. SHAP-based Feature Importance Analysis

To enhance the interpretability of the final XGBoost model, SHAP (SHapley Additive exPlanations) values were used to quantify the contribution of each input feature to the model’s predictions. SHAP offers a unified framework grounded in cooperative game theory to fairly attribute prediction outcomes to individual features, making it particularly well-suited for interpreting complex models like XGBoost.

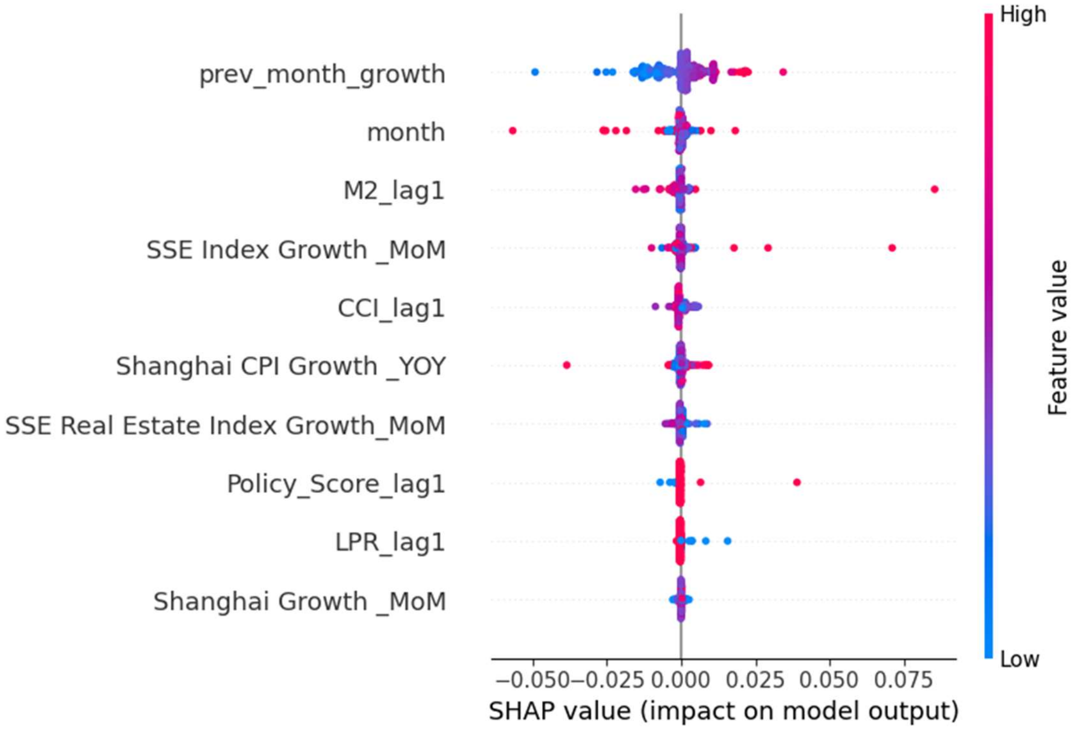

Figure 6. SHAP-Based Feature Importance for V5 Model

Figure 6 presents the SHAP summary plot of the final model. Each dot represents a single data point, with color indicating the feature value (red = high, blue = low), and position on the x-axis indicating the SHAP value (i.e., the impact on the model's predicted output).

Key insights from the SHAP analysis include:

- prev_month_growth stands out as the most influential variable, confirming the predictive value of short-term price momentum in housing markets. High values of previous growth tend to push the prediction upward,consistent with the hypothesis of market inertia and deviation from full efficiency (as discussed under the EMH framework).
- month captures seasonality effects. Specific months (e.g., early spring or end-year months) may systematically associate with stronger or weaker housing activity in Shanghai.

Among the macroeconomic indicators:

- M2_lag1 (lagged money supply growth) exhibits substantial influence, validating the role of liquidity conditions in stimulating housing demand—an effect consistent with monetary transmission mechanisms.
- SSE Index Growth and SSE Real Estate Index Growth both exhibit meaningful contributions, indicating that stock market dynamics, especially in the real estate sector, have spillover effects on housing prices. This aligns with financial market theories emphasizing capital flow and substitution effects between asset classes.
- CCI_lag1 (lagged consumer confidence) also demonstrates predictive power, linking household sentiment to market behavior, in accordance with behavioral economics theory.
- Shanghai CPI Growth_YOY ranks modestly in contribution. While its average effect is limited, some data points show positive influence, possibly reflecting inflation's indirect impact through construction costs or household purchasing decisions.
- Policy_Score_lag1 and LPR_lag1 show modest average impact but notable asymmetric SHAP distributions. This indicates that while they may not influence prices consistently, they do affect forecasts during critical regulatory shifts or interest rate adjustments—supporting their theorized role as policy signaling instruments.
- Shanghai Growth MoM contributes the least among all variables, with SHAP values tightly concentrated near zero. While urban economic theory suggests that rising GDP reflects stronger housing demand, the empirical result indicates that short-term GDP growth has limited explanatory power for monthly housing price fluctuations. This discrepancy may stem from the fact that GDP data is more reflective of long-term structural trends, whereas housing price changes at the monthly level are more sensitive to financial, policy, and sentiment-driven shocks.

These findings are largely—but not entirely—consistent with the theoretical expectations outlined in Chapter 3. The model confirms the predictive relevance of monetary conditions, investor sentiment, and behavioral factors, while revealing that certain macro fundamentals, such as short-term GDP growth, play a surprisingly limited role in short-run predictions. This divergence underscores the importance of aligning theoretical assumptions with the temporal scale of forecasting. The SHAP-based interpretation validates the model's structure and enhances transparency by illustrating how each factor contributes to the final output.

5.5. Model Evolution and Comparison

To assess how different modeling strategies and feature designs impact predictive performance, a total of five model versions were developed through a step-by-step process. Each version introduced distinct improvements in data representation, feature engineering, or model configuration. Table 9 summarizes these model iterations alongside their Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics.

Table 9. Summary of Model Version Evolution and Performance Comparison

Model Version	Key Changes	RMSE	MAE
V1 (Baseline)	Initial macro and market indicators only	18,222.69	15,751.78
V2	Added time variables (month/quarter), price lags (lag1, lag2)	7,589.45	7,194.67
V3	Added rolling price averages (lag3_avg, lag6_avg) and price momentum (prev_month_growth)	7,182.95	6,800.05
V4	Adopted Grid Search best parameters	6,703.00	6,255.95
V5 (Final)	Switched target to next-month growth, refined macro lag selection (Policy, LPR, M2, CCI), removed redundant lags	320.06	176.82

Key Observations:

- From V1 to V4, the model used the raw housing price level (in RMB/m²) as the prediction target. While this approach is intuitive, it created a significant scale mismatch between the target variable (typically 40,000–50,000 RMB/m²) and the input features (mostly expressed in small percentage growth terms, such as macroeconomic indicators). This discrepancy limited the model's ability to learn effective patterns and contributed to high prediction errors.
- V2 and V3 introduced major improvements in feature engineering by incorporating time-aware and autoregressive variables. Temporal variables like month and quarter were added to capture seasonal patterns, while lagged housing prices (lag1_price, lag2_price) and rolling averages (lag3_avg, lag6_avg) helped the model recognize short-term memory and local trends.

The addition of prev_month_growth (price momentum) further enhanced the model's ability to detect trend shifts. These changes led to a more than 50% reduction in RMSE compared to the baseline, demonstrating the strong predictive value of temporal structure and recent price history.

- While the focus of early models (V1–V3) was primarily on feature expansion, it's important to note that manual parameter tuning (e.g., adjusting n_estimators, learning_rate, max_depth) was also applied during this phase. Though not systematic, these parameter settings contributed to performance improvements alongside feature engineering.

- V4 implemented Grid Search hyperparameter tuning with time-series-aware cross-validation. This brute-force optimization method systematically explored combinations of model parameters—such as number of estimators (n_estimators) and learning rate (learning_rate)—to identify the most stable and high-performing configuration, resulting in improved model robustness.

- V5 (Final) introduced a critical refinement by switching the prediction target from absolute price to next-month growth rate, aligning the target with the percentage-based scale of macroeconomic indicators. This normalization significantly improved the model's learning behavior and interpretability. Moreover, all lagged price level features—such as lag1_price, lag2_price, lag3_avg, and lag6_avg—were removed entirely to reduce redundancy and potential noise. Instead, only prev_month_growth was retained to preserve recent price momentum. Key macroeconomic variables (Policy Score, LPR, M2, CCI) were lagged by one month to account for delayed effects, while other inputs remained in their original form. This streamlined feature set was selected based on SHAP importance scores and empirical validation.

The iterative improvement of features—from macroeconomic indicators to sentiment, policy, and momentum variables—mirrors the theoretical evolution from fundamentals to expectations and regulation effects, as outlined in Chapter 3. This modeling process highlights that performance gains came not just from tuning algorithms, but more importantly from thoughtful target selection, feature design, and domain knowledge integration. The final model (V5) achieved over 98% reduction in RMSE compared to the baseline, while maintaining interpretability through SHAP-based feature analysis. It offers a strong and explainable tool for understanding Shanghai's housing market dynamics.

5.6. Summary

This chapter evaluated the performance, interpretability, and developmental progression of the forecasting models. The final XGBoost model achieved a substantial error reduction compared to early versions and significantly outperformed the linear regression baseline, affirming the value of tree-based algorithms for capturing complex housing market dynamics.

Key insights included the benefits of reframing the prediction target as next-month growth rate and the critical role of carefully selected lagged macroeconomic features. SHAP-based interpretation further validated the contribution of short-term momentum and market-sensitive variables while highlighting the limited influence of broader growth indicators. The results were largely consistent with the theoretical expectations presented in Chapter 3, confirming the relevance of behavioral, financial, and policy-based determinants in explaining housing price fluctuations.

Overall, the findings demonstrate that both algorithmic improvements and domain-informed feature design are essential for enhancing predictive power and ensuring model transparency in the context of housing price forecasting.

6. Discussion

This chapter contextualizes the results of the final XGBoost model, linking the observed variable importance and prediction dynamics to the theoretical framework established in Chapter 3. In addition to discussing the roles of price momentum, macro-financial variables, and sentiment factors, it also examines the methodological assumptions underlying the predictive framework and evaluates the model's practical limitations and implications.

6.1. Momentum-Based Price Dynamics

The final model predicts monthly housing price growth rather than absolute price levels. In this context, the only price-related feature retained is prev_month_growth, representing recent market momentum. Its consistently high SHAP value indicates that short-term trend continuation plays a key role in shaping buyer expectations and investment decisions in Shanghai's housing market.

Rather than reflecting autoregressive price inertia based on historical levels, the influence of prev_month_growth reveals behavioral anchoring effects. Market participants appear to extrapolate recent gains or losses when forming future price expectations. This finding is aligned with real-world market psychology and reinforces the value of incorporating trend signals in forecasting models.

6.2. Assumptions Underlying the Predictive Framework

While this study does not formulate formal statistical hypotheses in the traditional empirical sense—such as null versus alternative hypotheses tested through significance levels—it does establish theoretical expectations for each predictive variable based on established economic, financial, and behavioral frameworks (as outlined in Chapter 3). These expectations inform both variable selection and result interpretation, but they are not subjected to direct hypothesis testing.

In addition, the predictive framework operates under several methodological assumptions that are critical for interpreting the model's outcomes and applying them to policy or investment contexts.

First, the model assumes that the relationships among macroeconomic indicators, policy variables, and housing prices observed in historical data are sufficiently stable to support machine learning–based forecasting. In other words, it presumes a degree of structural continuity over time, allowing patterns from the past to inform predictions of future dynamics.

Second, the use of SHAP values to interpret model outputs is based on the assumption that these values reliably approximate the relative importance of input variables. SHAP enhances transparency by offering localized explanations for model predictions, but it does not imply causality. Interpretations derived from SHAP should be understood as reflecting associations rather than definitive mechanistic pathways.

Third, the model implicitly assumes the absence of major structural breaks—such as abrupt policy regime changes, significant shifts in data quality, or large-scale macroeconomic shocks—that would compromise the relevance of historical relationships. If such discontinuities were to occur, the predictive accuracy and generalizability of the model could be undermined.

Together, these assumptions clarify the scope and limitations of the modeling framework. They emphasize the probabilistic and associative nature of the study's conclusions and should be taken into account when translating the findings into real-world decision-making.

6.3. Interpreting the Role of Macro-Financial Variables

Among the macro-financial indicators, lagged money supply (M2_lag1) emerged as one of the most important features, supporting the view that liquidity conditions drive investment behavior and housing affordability. SHAP results suggest that higher money supply growth is generally associated with positive price momentum, likely due to enhanced borrowing capacity and speculative activity.

The SSE Composite Index and the Real Estate Industry Index, both included in growth form, demonstrated meaningful contributions as well. These indicators appear to capture investor sentiment and capital reallocation across asset classes. When equity markets underperform or volatility rises, capital may shift to real estate, supporting the "flight to quality" mechanism described by Caballero and Krishnamurthy (2008). Conversely, periods of strong stock performance may draw investment away from property.

Meanwhile, Policy_Score_lag1, LPR_lag1, and CCI_lag1 contributed moderately, indicating that monetary policy stance, public sentiment, and regulatory conditions do affect short-term price expectations, though not always with dominant predictive power.

6.4. Behavioral Sentiment and Predictive Relevance

The lagged Consumer Confidence Index (CCI) variable showed non-negligible predictive importance. While CCI is a coarse, monthly proxy, its contribution supports behavioral economics theory suggesting that public optimism or pessimism materially shapes housing investment behavior. CCI likely captures responses to macro news, job prospects, and general financial confidence—all of which influence real estate decisions.

However, the SHAP distribution also shows that CCI effects vary by context. In some periods, sentiment has stronger predictive relevance, particularly during or after external shocks. More nuanced, real-time sentiment measures may enhance this component in future work.

6.5. Implications for Policy and Practice

The results suggest that short-term housing price trends are most strongly driven by recent market momentum and liquidity conditions, rather than fundamental macro indicators or direct policy interventions. For policymakers, this underscores the importance of pre-emptive and well-timed action if attempting to influence price cycles. Slow-moving tools may be outpaced by behavioral and financial responses.

For investors and developers, the findings highlight the continued usefulness of monitoring market sentiment, monetary trends, and asset substitution signals. Trend-following and liquidity-sensitive strategies may offer competitive advantages in short-horizon forecasting and risk mitigation.

6.6. Limitations

Despite the model's strong predictive accuracy, several limitations warrant discussion. First, the representation of policy variables is simplified. In this study, policy effects were manually scored based on qualitative interpretation, which, while practical, may oversimplify the complexity of real-world interventions. This approach may fail to reflect variations in policy intensity, timing, or the interaction effects between multiple regulatory tools.

Second, the model uses the monthly growth rate of the Consumer Confidence Index (CCI) as a sentiment indicator, which offers only a coarse and delayed approximation of public psychology. While it captures general economic optimism or pessimism, it may not adequately reflect rapid shifts in expectations driven by real-time news, social media reactions, or sudden external events.

Third, the model does not incorporate supply-side indicators. As a demand-driven framework, it omits important variables such as land supply, construction pipeline data, and developer sentiment, all of which may significantly influence housing prices, particularly in urban contexts like Shanghai where supply constraints are structurally important.

Finally, the model is optimized for short-term, one-month-ahead forecasting. While this horizon is useful for tracking near-term fluctuations, it limits the model's applicability to long-range strategic planning or evaluation of gradual structural reforms that require longer timeframes to manifest.

6.7. Future Research Directions

Building on the findings and limitations of this study, several directions for future research can be proposed to enhance both the predictive performance and the explanatory power of housing price models.

Firstly, the manual scoring of policy variables could be replaced or supplemented by automated techniques. Natural Language Processing (NLP) methods—such as topic modeling, sentiment analysis, or regulatory tone detection—could be applied to government announcements, media reports, or legal documents to dynamically quantify policy intensity and uncertainty.

Secondly, sentiment indicators could be refined using real-time data sources. Instead of relying solely on aggregated indices such as the Consumer Confidence Index (CCI), researchers may integrate alternative indicators derived from online search trends, social media platforms, or financial news feeds. These sources may offer more granular and timely reflections of public expectations.

Thirdly, incorporating supply-side information—such as land release statistics, project approval data, or developer financing conditions—would provide a more balanced and complete understanding of market drivers. These variables are especially relevant in supply-constrained urban contexts like Shanghai.

Fourthly, future work could explore multi-step or rolling forecast strategies to extend the predictive horizon. Such designs may uncover lagged or cumulative effects of macroeconomic and policy variables, and would allow researchers to evaluate longer-term market dynamics, including potential regime shifts or sustained policy interventions.

Lastly, future research could experiment with alternative model architectures, including recurrent or attention-based neural networks (e.g., LSTM or transformer models), to capture sequential dependencies and improve the interpretability of dynamic feature interactions over time. Such architectures may be particularly effective in modeling the evolving nature of housing markets.

These future directions offer multiple avenues for enhancing the robustness, generalizability, and explanatory capacity of machine learning models applied to real estate forecasting.

7. Conclusion

This study developed a machine learning-based forecasting model to predict monthly housing price growth in Shanghai by integrating macroeconomic, financial, policy, and sentiment-based variables. Grounded in urban economic theory and implemented using XGBoost with SHAP interpretability, the research aimed to enhance both predictive accuracy and model transparency in short-term real estate forecasting.

Sub-question 1: What are the key economic indicators influencing housing price predictions in Shanghai, and how significant are their contributions according to SHAP analysis?
The SHAP analysis identified several important predictors. Among them, recent market momentum (prev_month_growth) exhibited the highest contribution, followed by macro-financial variables such as lagged M2 growth, the SSE Composite Index, and the Real Estate Industry Index. These results align with theories linking liquidity conditions and investor sentiment to short-run market dynamics. Policy variables and behavioral sentiment (e.g., CCI_lag1) also showed moderate influence, particularly during periods of macroeconomic uncertainty.

Sub-question 2: How accurately does the XGBoost model capture housing price dynamics in Shanghai based on macroeconomic indicators and lagged price variables?
The final XGBoost model, using a feature set that includes temporal indicators, lagged price momentum, and macro-policy variables, achieved a strong predictive performance, with RMSE and MAE values indicating high accuracy in short-term forecasting. The model effectively captures the non-linear interactions between key drivers and provides interpretable output through SHAP values, though it is optimized for one-month-ahead forecasting and does not model long-term structural shifts.

Sub-question 3: What policy implications can be derived from the model's findings, particularly in relation to economic fluctuations and market volatility?
The findings highlight that short-term housing price movements respond primarily to recent market momentum and liquidity conditions, emphasizing the necessity of timely, forward-looking policy interventions sensitive to market sentiment and financial trends.

In conclusion, this research demonstrates that machine learning techniques, when thoughtfully combined with economic logic and interpretability tools, can generate meaningful insights into housing market behavior. The model contributes both a methodological framework and a policy-relevant analytical tool for understanding short-term real estate fluctuations in complex urban environments like Shanghai.

References

Akça, T 2023, 'House price dynamics and relations with the macroeconomic indicators in Turkey', International Journal of Housing Markets and Analysis, vol. 16, no. 4, pp. 812–827, viewed 13 February 2025, https://doi.org/10.1108/IJHMA-04-2022-0059.

Bank of China 2025, Loan Prime Rate (LPR) history, Bank of China, viewed 13 March 2025, https://www.bankofchina.com/fimarkets/lilv/fd32/201310/t20131031_2591219.html.

BBC News 2024, *Evergrande: Why should I care if China property giant collapses?*, viewed 18 October 2024, https://www.bbc.com/news/business-68123983.

Bissoondeeal, RK 2021, 'The links between regional house prices and share prices in the UK', Regional Studies, vol. 55, no. 2, pp. 256–268, viewed 13 February 2025, https://doi.org/10.1080/00343404.2020.1795108.

Brkanić, I 2023, 'Housing quality assessment model based on the spatial characteristics of an apartment', *Buildings*, vol. 13, no. 9, p. 2181, viewed 3 February 2025, https://doi.org/10.3390/buildings13092181

Caballero, RJ & Krishnamurthy, A 2008, 'Collective risk management in a flight to quality episode', The Journal of Finance, vol. 63, no. 5, pp. 2195–2230, viewed 14 February 2025, https://doi.org/10.1111/j.1540-6261.2008.01394.x.

Case, KE & Shiller, RJ 1989, 'The efficiency of the market for single-family homes', The American Economic Review, vol. 79, no. 1, pp. 125–137, viewed 1 June 2025, http://www.jstor.org/stable/1804778.

CEIC Data 2025, *China Consumer Confidence Index (CCI), national monthly data (2000–2024)*, viewed 11 February 2025, https://www.ceidata.cei.cn/.

Chen, SS & Lin, TY 2022, 'Revisiting the link between house prices and monetary policy', The B.E. Journal of Macroeconomics, vol. 22, no. 2, pp. 481–515, viewed 14 February 2025, https://doi.org/10.1515/bejm-2021-0099.

China Tax Bureau 2005, Notice on resale tax for home transactions, viewed 10 March 2025, https://shanghai.chinatax.gov.cn/zcfw/zcfgk/qs/200506/t289326.html.

DiPasquale, D 1995, Urban economics and real estate markets, Prentice Hall, Englewood Cliffs, NJ, viewed 10 February 2025, http://archive.org/details/urbaneconomicsre0000dipa.

Fama, EF 1970, 'Efficient capital markets: a review of theory and empirical work', The

Journal of Finance, vol. 25, no. 2, pp. 383–417, viewed 1 June 2025, https://doi.org/10.2307/2325486.

Goodhart, C & Hofmann, B 2008, 'House prices, money, credit, and the macroeconomy', Oxford Review of Economic Policy, vol. 24, no. 1, pp. 180–205, viewed 14 February 2025, https://doi.org/10.1093/oxrep/grn009.

Hasan, MH, Jahan, MA, Ali, ME, Li, Y-F & Sellis, T 2024, A multi-modal deep learning based approach for house price prediction, arXiv, viewed 13 February 2025, https://arxiv.org/abs/2409.05335.

Hu, Z 2022, 'Six types of government policies and housing prices in China', Economic Modelling, vol. 108, article no. 105764, viewed 4 February 2025, https://doi.org/10.1016/j.econmod.2022.105764.

Huang, Y 2023, 'An empirical study on the interconnections between money supply and housing price', *Highlights in Business, Economics and Management*, vol. 14, pp. 1–6, viewed 04 February 2025, https://doi.org/10.54097/hbem.v14i.8927.

Ibrahem Ahmed Osman, A et al. 2021, 'Extreme gradient boosting (Xgboost) model to predict the groundwater levels in Selangor Malaysia', *Ain Shams Engineering Journal*, vol. 12, no. 2, pp. 1545–1556, viewed 1 February 2024, https://doi.org/10.1016/j.asej.2020.11.011.

Irandoust, M 2021, 'The causality between house prices and stock prices: evidence from seven European countries', *International Journal of Housing Markets and Analysis*, vol. 14, no. 1, pp. 137–156, viewed 20 January 2025, https://doi.org/10.1108/IJHMA-02-2020-0013.

Investing.com 2025, *Shanghai Composite Index (SSEC), historical monthly data (2000–2024)*, viewed 9 February 2025, https://cn.investing.com/indices/shanghai-composite-historical-data.

Lewandowska, G, Taracha, M & Maciuk, K 2023, 'Socio-economic factors associated with house prices: Evidence based on key macroeconomic aggregates globally', *Budownictwo i Architektura*, vol. 22, no. 3, pp. 45–58, viewed 23 January 2025, https://doi.org/10.35784/bud-arch.3635.

Liew, XY, Hameed, N & Clos, J 2021, 'An investigation of XGBoost-based algorithm for breast cancer classification', *Machine Learning with Applications*, vol. 6, article no. 100154, viewed 28 January 2025, https://doi.org/10.1016/j.mlwa.2021.100154.

LinLin, S, Yawen, Z & Xiaojun, X 2024, 'The effects of macroprudential policies on house prices: evidence from non-ordinary house purchasing policy using China real transaction data', *Economic Analysis and Policy*, vol. 84, pp. 2086–2101, viewed 24 January 2025, https://doi.org/10.1016/j.eap.2024.10.057.

National Bureau of Statistics of China 2024, *Annual sales prices of commercial housing in Shanghai (2000–2023)*, viewed 4 February 2025, https://data.stats.gov.cn/easyquery.htm?cn=E0105&zb=A03&reg=310000.

National Bureau of Statistics of China 2024, *Gross Regional Product of Shanghai (2000–2004), annual data*, viewed 4 February 2025, https://data.stats.gov.cn/easyquery.htm?cn=E0103&zb=A0201&reg=310000&sj=2024.

National Bureau of Statistics of China 2025, *Broad money (M2) YoY growth rate, monthly data (2000–2024)*, viewed 3 June 2025, https://data.stats.gov.cn/easyquery.htm?cn=A01&zb=A0D01&sj=202505.

National Bureau of Statistics of China 2025, *Gross Regional Product of Shanghai (2005–2024), quarterly cumulative data*, viewed 2 April 2025, https://data.stats.gov.cn/easyquery.htm?cn=E0102&zb=A0101&reg=310000&sj=2025A.

National Bureau of Statistics of China 2025, *National Consumer Price Index (CPI), monthly YoY change (2000–2024)*, viewed 3 June 2025, https://data.stats.gov.cn/easyquery.htm?cn=A01&zb=A010101&sj=202505.

Nguyen, N-H et al. 2022, 'Efficient estimating compressive strength of ultra-high performance concrete using XGBoost model', *Journal of Building Engineering*, vol. 52, article no. 104302, viewed 7 February 2025, https://doi.org/10.1016/j.jobe.2022.104302.

OECD 2022, *Subjective measures on housing (HC1.4)*, OECD Affordable Housing Database, viewed 3 June 2025, https://www.oecd.org/social/HC1-4-Subjective-Measures-on-Housing.pdf

People's Bank of China 2015, *Benchmark lending rates of financial institutions in China (1991–2019)*, viewed 9 February 2025, https://www.pbc.gov.cn/zhengcehuobisi/125207/125213/125440/125838/125888/2968985/index.html.

Qian, C et al. 2022, 'Understanding public opinions on social media for financial sentiment analysis using AI-based techniques', *Information Processing & Management*, vol. 59, no. 6, article no. 103098, viewed 23 December 2024, https://doi.org/10.1016/j.ipm.2022.103098.

ReformData.org 1998, Termination of welfare housing distribution, viewed 12 March 2025, http://www.reformdata.org/1998/0703/5532.shtml.

Saraswathi, P et al. 2024, 'House price prediction with advanced machine learning techniques', *AIP Conference Proceedings*, vol. 3214, no. 1, article no. 020054, viewed 23 November 2024, https://doi.org/10.1063/5.0239036.

Shanghai Housing Bureau 2021, Policy guidelines for urban housing reform, viewed 18 March 2025, https://fgj.sh.gov.cn/zdgk/20210121/6b2011f79ed948969916d6852e2e7453.html.

Shanghai Housing Bureau 2023, News release on policy changes, viewed 17 March 2025, https://zjw.sh.gov.cn/xwfb/20231215/2f374d7d37bb4538811f57c10b24fe60.html.

Shanghai Housing Bureau 2024a, Official policy communication: 2024 measures, viewed 14 March 2025, https://fgj.sh.gov.cn/qtgw/20240130/027c0c9b1087481c8863b15ad85ef862.html.

Shanghai Housing Bureau 2024b, Policy Q&A on the 2024 housing adjustment, viewed 18 March 2025, https://fgj.sh.gov.cn/zcjd/20240527/80e4d1af209843bdbfa4b0ccc24bf4db.html.

Shanghai Municipal Bureau of Statistics 2025, *2024 Shanghai real estate market overview*, viewed 4 June 2025, https://tjj.sh.gov.cn/tjfx/20250224/bd3a7d138b11452a847b4e306490fb47.html.

Shanghai Municipal Government 2016, Notice on home purchase regulations for talent households, viewed 17 March 2025, https://www.shanghai.gov.cn/nw39664/20200821/0001-39664_47491.html.

Shanghai Municipal Government 2024, Policy bulletin on household registration and housing purchases, viewed 20 March 2025, https://www.shanghai.gov.cn/nw12344/20240527/e489e9cb4bde42759ce5c4f6697e979f.html.

Shanghai Municipal Housing and Urban-Rural Development Bureau 2024, Recent housing policy announcements, viewed 16 March 2025, https://fgj.sh.gov.cn/qtgw/20240929/e66e5975328e411ca736811e67bee559.html.

Shanghai Public Security Bureau 2002, Policy on blue-stamp household registration applications, viewed 19 March 2025, https://gaj.sh.gov.cn/shga/wzXxfbGj/detail?pa=f29e49897a33ad73.

Sharma, H, Harsora, H & Ogunleye, B 2024, 'An optimal house price prediction algorithm: XGBoost', *Analytics*, vol. 3, no. 1, pp. 30–45, viewed 8 February 2025, https://doi.org/10.3390/analytics3010003.

Shiller, RJ 2003, 'From efficient markets theory to behavioral finance', *Journal of Economic Perspectives*, vol. 17, no. 1, pp. 83–104, viewed 2 January 2025, https://doi.org/10.1257/089533003321164967.

Sina Finance 2008, History of Shanghai real estate transaction tax reforms, viewed 19 March 2025, https://m.cj.sina.cn/page/aHR0cDovL2ZpbmFuY2Uuc2luYS5jb20uY24vY2hpbmEvaGdqai8yMDA4MTAyMS8wMDMwNTQxMDI1OS5zaHRtbA?from=redirect.

Sohu News 2008, Policy update on administrative fee reduction and housing transaction taxation, viewed 13 March 2025, https://news.sohu.com/20081023/n260190763.shtml.

Sohu Securities 2025, *Real Estate Sector Index (000006), historical data*, viewed 9 February 2025, https://q.stock.sohu.com/zs/000006/lshq.shtml.

State Council of China 2003, Notice on promoting the sustainable and healthy development of the real estate market, viewed 15 March 2025, https://www.gov.cn/gongbao/content/2003/content_62364.htm.

State Council of China 2016, Central policy briefing on real estate, viewed 11 March 2025, https://www.gov.cn/xinwen/2016-11/29/content_5139219.htm.

State Council of China 2024, China unveils new measures to stabilize housing market, Xinhua News Agency, viewed 13 March 2025, https://english.www.gov.cn/news/202410/17/content_WS67111067c6d0868f4e8ebfd0.html.

Teoh, EZ et al. 2023, 'Explainable housing price prediction with determinant analysis', International Journal of Housing Markets and Analysis, vol. 16, no. 5, pp. 1021–1045, viewed 20 January 2025, https://doi.org/10.1108/IJHMA-02-2022-0025.

Tunc, C & Gunes, A 2023, 'Monetary policy and house prices in emerging markets', International Journal of Housing Markets and Analysis, vol. 16, no. 5, pp. 873–891, viewed 21 November 2024, https://doi.org/10.1108/IJHMA-03-2022-0041.

Weng, W 2022, 'Research on the house price forecast based on machine learning algorithm', BCP Business & Management, vol. 32, pp. 134–147, viewed 6 December 2024, https://doi.org/10.54691/bcpbm.v32i.2881.

Wright, L, Boullenois, C, Jordan, CA, Tian, E & Quinn, R 2024, No quick fixes: China's long-term consumption growth, Rhodium Group, viewed 2 June 2025, https://rhg.com/research/no-quick-fixes-chinas-long-term-consumption-growth.

Xinhua Finance 2013, Reform directions of the housing system, viewed 11 March 2025, http://jjckb.xinhuanet.com/2013-11/08/content_475399.htm.

Xinhua News Agency 2016, *Central Economic Work Conference clarifies housing development direction: "Housing is for living in, not for speculation"*, The State Council of the People's Republic of China, 16 December, viewed 14 March 2025, https://www.gov.cn/zhengce/2016-12/16/content_5149066.htm.

Yang, C-H, Lee, B & Lin, Y-D 2022, 'Effect of money supply, population, and rent on real estate: a clustering analysis in Taiwan', Mathematics, vol. 10, no. 7, article no. 1155, viewed 25 October 2024, https://doi.org/10.3390/math10071155.

YIP Institute 2024, *Economic implications of Evergrande collapse*, viewed 16 January 2025, https://yipinstitute.org/articles/evergrande-crisis.

Zhao, Y, Ravi, R, Shi, S, Wang, Z, Lam, EY & Zhao, J 2022, 'PATE: property, amenities, traffic and emotions coming together for real estate price prediction', Proceedings of the 2022 IEEE 9th International Conference on Data Science and Advanced Analytics (DSAA), IEEE, Shenzhen, China, pp. 1–10, viewed 8 November 2024, https://doi.org/10.1109/DSAA54385.2022.10032416.

Zheng, Y & Osmer, E 2021, 'Housing price dynamics: the impact of stock market sentiment and the spillover effect', The Quarterly Review of Economics and Finance, vol. 80, pp. 854–867, viewed 16 November 2024, https://doi.org/10.1016/j.qref.2019.02.006.

Zhou, J et al. 2023, 'Effective house price prediction using machine learning', in C Iwendi, Z Boulouard & N Kryvinska (eds.), Proceedings of ICACTCE'23—The International Conference on Advances in Communication Technology and Computer Engineering, Springer Nature Switzerland, pp. 425–436, 28 October 2024, https://doi.org/10.1007/978-3-031-37164-6_32.

Appendix A. Original Data (2000–2024)

A1. Shanghai Quarterly GDP Data

Shanghai Gross Domestic Product (GDP) Quarterly Cumulative Value (Billion Yuan)				
Quarter / Year	Q1	Q2	Q3	Q4
2000	/	/	/	4,812.20
2001	/	/	/	5,257.70
2002	/	/	/	5,795.00
2003	/	/	/	6,804.00
2004	/	/	/	8,101.60
2005	1,801.60	3,930.64	6,111.68	9,143.95
2006	2,296.72	4,781.93	7,359.18	10,296.97
2007	2,630.50	5,561.91	8,590.97	12,001.16
2008	3,040.76	6,530.73	9,929.52	13,698.15
2009	3,150.47	6,612.00	10,214.82	14,900.93
2010	3,810.63	7,980.16	12,109.52	16,872.42
2011	4,327.63	9,164.10	13,725.64	19,195.69
2012	4,593.85	9,552.24	14,374.23	20,101.33
2013	4,937.50	10,168.52	15,474.13	21,602.10
2014	5,313.07	10,952.64	16,607.08	23,560.94
2015	5,815.79	11,887.00	17,866.24	24,964.99
2016	6,225.39	12,956.99	19,529.67	27,466.15
2017	6,922.84	13,908.57	21,617.52	30,133.86
2018	8,104.28	17,101.98	25,604.72	36,011.82
2019	8,360.04	17,659.78	27,328.90	37,987.55
2020	7,903.48	17,428.05	27,385.22	38,963.30
2021	9,529.00	20,171.00	31,028.00	43,653.00
2022	10,097.00	19,514.00	31,227.00	44,809.00
2023	10,615.00	21,549.00	33,269.00	47,219.00
2024	11,098.00	22,346.00	34,389.00	53,927.00

A2. Shanghai Consumer Price Index (CPI) Monthly Data

2000-2024 Shanghai Consumer Price Index (CPI) (Same Month of Previous Year = 100)						
Month / Year	**01**	**02**	**03**	**04**	**05**	**06**
2000	106.3	106.8	105.6	103.5	103.2	102.5
	07	**08**	**09**	**10**	**11**	**12**
	102.3	103.1	98.7	98.4	99.7	99.9

2001	**01**	**02**	**03**	**04**	**05**	**06**
	100.2	97.8	99.2	100.2	100.2	100.2
	07	**08**	**09**	**10**	**11**	**12**
	101.5	100.3	98.1	100.0	101.1	101.4
2002	**01**	**02**	**03**	**04**	**05**	**06**
	101.0	102.9	101.1	99.6	100.4	100.9
	07	**08**	**09**	**10**	**11**	**12**
	100.2	100.7	101.7	99.8	98.5	99.2
2003	**01**	**02**	**03**	**04**	**05**	**06**
	98.9	98.6	99.6	100.3	100.2	100.1
	07	**08**	**09**	**10**	**11**	**12**
	99.5	100.1	100.2	100.9	101.3	101.4
2004	**01**	**02**	**03**	**04**	**05**	**06**
	101.9	100.1	101.6	102.3	102.4	102.9
	07	**08**	**09**	**10**	**11**	**12**
	103.6	103.2	102.4	102.0	101.9	101.6
2005	**01**	**02**	**03**	**04**	**05**	**06**
	99.9	102.9	101.6	101.2	100.5	100.0
	07	**08**	**09**	**10**	**11**	**12**
	100.2	101.3	101.4	101.1	100.8	100.5
2006	**01**	**02**	**03**	**04**	**05**	**06**
	102.1	100.8	100.6	100.8	101.5	101.8
	07	**08**	**09**	**10**	**11**	**12**
	101.8	101.2	101.0	100.9	100.9	101.3
2007	**01**	**02**	**03**	**04**	**05**	**06**
	100.9	101.3	102.2	102.0	101.8	102.7
	07	**08**	**09**	**10**	**11**	**12**
	102.7	103.9	104.5	105.1	105.2	105.4
2008	**01**	**02**	**03**	**04**	**05**	**06**
	105.9	107.5	107.2	107.9	107.1	107.1
	07	**08**	**09**	**10**	**11**	**12**
	107.1	105.5	104.8	104.1	103.6	102.1
2009	**01**	**02**	**03**	**04**	**05**	**06**
	101.7	99.8	99.6	98.6	98.8	98.5
	07	**08**	**09**	**10**	**11**	**12**
	98.1	99.4	99.5	99.7	100.2	101.2
2010	**01**	**02**	**03**	**04**	**05**	**06**
	101.1	101.3	102.1	102.6	103.2	103.2
	07	**08**	**09**	**10**	**11**	**12**
	103.9	103.2	103.8	104.1	104.3	104.5
2011	**01**	**02**	**03**	**04**	**05**	**06**
	104.3	104.7	104.7	105.1	105.3	105.9

	07	**08**	**09**	**10**	**11**	**12**
	105.6	105.8	105.7	105.6	104.9	104.5
2012	**01**	**02**	**03**	**04**	**05**	**06**
	104.9	103.9	103.8	103.6	103.0	102.4
	07	**08**	**09**	**10**	**11**	**12**
	102.1	102.2	102.0	102.0	102.0	102.2
2013	**01**	**02**	**03**	**04**	**05**	**06**
	102.1	102.6	102.2	102.2	102.1	102.5
	07	**08**	**09**	**10**	**11**	**12**
	102.0	102.1	102.5	102.6	102.4	102.4
2014	**01**	**02**	**03**	**04**	**05**	**06**
	103.0	102.7	102.5	102.3	102.9	102.6
	07	**08**	**09**	**10**	**11**	**12**
	103.0	102.6	102.7	102.4	102.6	102.6
2015	**01**	**02**	**03**	**04**	**05**	**06**
	101.8	102.6	102.5	102.6	102.3	102.4
	07	**08**	**09**	**10**	**11**	**12**
	102.6	102.8	102.2	102.4	102.4	102.3
2016	**01**	**02**	**03**	**04**	**05**	**06**
	102.5	102.8	103.5	103.4	103.0	103.2
	07	**08**	**09**	**10**	**11**	**12**
	103.4	103.0	103.6	103.5	103.7	103.3
2017	**01**	**02**	**03**	**04**	**05**	**06**
	103.6	101.6	101.4	101.6	101.8	101.5
	07	**08**	**09**	**10**	**11**	**12**
	101.1	101.7	101.7	101.5	101.2	101.5
2018	**01**	**02**	**03**	**04**	**05**	**06**
	101.1	102.6	101.6	101.4	101.4	101.2
	07	**08**	**09**	**10**	**11**	**012**
	101.3	101.8	101.5	102.2	101.9	101.2
2019	**01**	**02**	**03**	**04**	**05**	**06**
	101.1	101.7	102.2	102.4	102.6	102.7
	07	**08**	**09**	**10**	**11**	**12**
	102.8	102.3	102.2	102.6	103.2	103.8
2020	**01**	**02**	**03**	**04**	**05**	**06**
	104.3	103.0	102.8	102.5	102.0	101.7
	07	**08**	**09**	**10**	**11**	**12**
	101.6	101.4	101.3	100.3	99.9	100.1
2021	**01**	**02**	**03**	**04**	**05**	**06**
	99.8	100.3	100.7	100.9	101.2	101.2
	07	**08**	**09**	**10**	**11**	**12**
	101.3	101.3	101.1	102.2	102.5	101.8

2022	**01**	**02**	**03**	**04**	**05**	**06**
	101.6	101.5	102.2	104.3	104.6	102.9
	07	**08**	**09**	**10**	**11**	**12**
	102.9	102.4	102.6	101.8	101.6	102.1
2023	**01**	**02**	**03**	**04**	**05**	**06**
	102.6	101.3	100.9	98.9	98.6	100.1
	07	**08**	**09**	**10**	**11**	**12**
	100.4	100.7	100.8	100.4	99.8	99.7
2024	**01**	**02**	**03**	**04**	**05**	**06**
	98.9	100.8	99.7	100.0	100.0	100.2
	07	**08**	**09**	**10**	**11**	**12**
	100.3	100.3	99.9	100.0	100.2	100.1

A3. China Broad Money Supply (M2) Growth Rate Monthly Data

China Broad Money (M2) Supply Year-on-Year Growth (%)						
Month / Year	**01**	**02**	**03**	**04**	**05**	**06**
2000	14.9	12.8	13.0	13.7	12.7	13.7
	07	**08**	**09**	**10**	**11**	**12**
	13.4	13.3	13.4	12.3	12.4	12.3
2001	**01**	**02**	**03**	**04**	**05**	**06**
	13.5	12.0	13.2	12.8	12.1	14.3
	07	**08**	**09**	**10**	**11**	**12**
	13.5	13.6	16.4	12.9	17.6	14.4
2002	**01**	**02**	**03**	**04**	**05**	**06**
	13.1	13.0	14.4	14.1	14.0	14.7
	07	**08**	**09**	**10**	**11**	**12**
	14.4	15.5	16.5	17.0	16.6	16.8
2003	**01**	**02**	**03**	**04**	**05**	**06**
	19.3	18.1	18.5	19.2	20.2	20.8
	07	**08**	**09**	**10**	**11**	**12**
	20.7	21.6	20.7	21.0	20.4	19.6
2004	**01**	**02**	**03**	**04**	**05**	**06**
	18.1	19.4	19.1	19.1	17.5	16.2
	07	**08**	**09**	**10**	**11**	**12**
	15.3	13.6	13.9	13.5	14.0	14.6
2005	**01**	**02**	**03**	**04**	**05**	**06**
	14.1	13.9	14.0	14.1	14.7	15.7
	07	**08**	**09**	**10**	**11**	**12**
	16.3	17.3	17.9	18.0	18.3	17.6
2006	**01**	**02**	**03**	**04**	**05**	**06**
	19.2	18.8	18.8	18.9	19.1	18.4

	07	**08**	**09**	**10**	**11**	**12**
	18.4	17.9	16.8	17.1	16.8	16.9
2007	**01**	**02**	**03**	**04**	**05**	**06**
	15.8	17.8	17.3	17.1	16.7	17.1
	07	**08**	**09**	**10**	**11**	**12**
	18.5	18.1	18.5	18.5	18.5	16.7
2008	**01**	**02**	**03**	**04**	**05**	**06**
	18.9	17.4	16.2	16.9	18.1	17.4
	07	**08**	**09**	**10**	**11**	**12**
	16.4	16.0	15.3	15.0	14.8	17.8
2009	**01**	**02**	**03**	**04**	**05**	**06**
	18.8	20.5	25.5	26.0	25.7	28.5
	07	**08**	**09**	**10**	**11**	**12**
	28.4	28.5	29.3	29.4	29.7	27.7
2010	**01**	**02**	**03**	**04**	**05**	**06**
	26.0	25.5	22.5	21.5	21.0	18.5
	07	**08**	**09**	**10**	**11**	**12**
	17.6	19.2	19.0	19.3	19.5	19.7
2011	**01**	**02**	**03**	**04**	**05**	**06**
	17.2	15.7	16.6	15.3	15.1	15.9
	07	**08**	**09**	**10**	**11**	**12**
	14.7	13.6	13.0	12.9	12.7	13.6
2012	**01**	**02**	**03**	**04**	**05**	**06**
	12.4	13.0	13.4	12.8	13.2	13.6
	07	**08**	**09**	**10**	**11**	**12**
	13.9	13.5	14.8	14.1	13.9	13.8
2013	**01**	**02**	**03**	**04**	**05**	**06**
	15.9	15.2	15.7	16.1	15.8	14.0
	07	**08**	**09**	**10**	**11**	**12**
	14.5	14.7	14.2	14.3	14.2	13.6
2014	**01**	**02**	**03**	**04**	**05**	**06**
	13.2	13.3	12.1	13.2	13.4	14.7
	07	**08**	**09**	**10**	**11**	**12**
	13.5	12.8	12.9	12.6	12.3	12.2
2015	**01**	**02**	**03**	**04**	**05**	**06**
	10.8	12.5	11.6	10.1	10.8	11.8
	07	**08**	**09**	**10**	**11**	**12**
	13.3	13.3	13.1	13.5	13.7	13.3
2016	**01**	**02**	**03**	**04**	**05**	**06**
	14.0	13.3	13.4	12.8	11.8	11.8
	07	**08**	**09**	**10**	**11**	**12**
	10.2	11.4	11.5	11.6	11.4	11.3

2017	**01**	**02**	**03**	**04**	**05**	**06**
	11.3	11.1	10.6	10.5	9.6	9.4
	07	**08**	**09**	**10**	**11**	**12**
	9.2	8.9	9.2	8.8	9.1	8.2
2018	**01**	**02**	**03**	**04**	**05**	**06**
	8.6	8.8	8.2	8.3	8.3	8.0
	07	**08**	**09**	**10**	**11**	**12**
	8.5	8.2	8.3	8.0	8.0	8.1
2019	**01**	**02**	**03**	**04**	**05**	**06**
	8.4	8.0	8.6	8.5	8.5	8.5
	07	**08**	**09**	**10**	**11**	**12**
	8.1	8.2	8.4	8.4	8.2	8.7
2020	**01**	**02**	**03**	**04**	**05**	**06**
	8.4	8.8	10.1	11.1	11.1	11.1
	07	**08**	**09**	**10**	**11**	**12**
	10.7	10.4	10.9	10.5	10.7	10.1
2021	**01**	**02**	**03**	**04**	**05**	**06**
	9.4	10.1	9.4	8.1	8.3	8.6
	07	**08**	**09**	**10**	**11**	**12**
	8.3	8.2	8.3	8.7	8.5	9.0
2022	**01**	**02**	**03**	**04**	**05**	**06**
	9.8	9.2	9.7	10.5	11.1	11.4
	07	**08**	**09**	**10**	**11**	**12**
	12.0	12.2	12.1	11.8	12.4	11.8
2023	**01**	**02**	**03**	**04**	**05**	**06**
	12.6	12.9	12.7	12.4	11.6	11.3
	07	**08**	**09**	**10**	**11**	**12**
	10.7	10.6	10.3	10.3	10.0	9.7
2024	**01**	**02**	**03**	**04**	**05**	**06**
	8.7	8.7	8.3	7.2	7.0	6.2
	07	**08**	**09**	**10**	**11**	**12**
	6.3	6.3	6.8	7.5	7.1	7.3

A4. Shanghai Loan Prime Rate (LPR) and Benchmark Interest Rates

2000-2024Loan Prime Rate (LPR) (%)					
Date	**5Y LPR**	**Date**	**5Y LPR**	**Date**	**5Y LPR**
10/06/1999	6.21	20/11/2019	4.80	20/07/2022	4.45
21/02/2002	5.76	20/12/2019	4.80	22/08/2022	4.30
29/10/2004	6.12	20/01/2020	4.80	20/09/2022	4.30
28/04/2006	6.39	20/02/2020	4.75	20/10/2022	4.30
19/08/2006	6.84	20/03/2020	4.75	21/11/2022	4.30
18/03/2007	7.11	20/04/2020	4.65	20/12/2022	4.30

19/05/2007	7.20	20/05/2020	4.65	20/01/2023	4.30
21/07/2007	7.38	22/06/2020	4.65	20/02/2023	4.30
22/08/2007	7.56	20/07/2020	4.65	20/03/2023	4.30
15/09/2007	7.83	20/08/2020	4.65	20/04/2023	4.30
21/12/2007	7.83	21/09/2020	4.65	22/05/2023	4.30
16/09/2008	7.74	20/10/2020	4.65	20/06/2023	4.20
09/10/2008	7.47	20/11/2020	4.65	20/07/2023	4.20
30/10/2008	7.20	21/12/2020	4.65	21/08/2023	4.20
27/11/2008	6.12	20/01/2021	4.65	20/09/2023	4.20
23/12/2008	5.94	22/02/2021	4.65	20/10/2023	4.20
20/10/2010	6.14	22/03/2021	4.65	20/11/2023	4.20
26/12/2010	6.40	20/04/2021	4.65	20/12/2023	4.20
09/02/2011	6.60	20/05/2021	4.65	22/01/2024	4.20
06/04/2011	6.80	21/06/2021	4.65	20/02/2024	3.95
07/07/2011	7.05	20/07/2021	4.65	20/03/2024	3.95
08/06/2012	6.80	20/08/2021	4.65	22/04/2024	3.95
06/07/2012	6.55	22/09/2021	4.65	20/05/2024	3.95
22/11/2014	6.15	20/10/2021	4.65	20/06/2024	3.95
01/03/2015	5.90	22/11/2021	4.65	22/07/2024	3.85
11/05/2015	5.65	20/12/2021	4.65	20/08/2024	3.85
28/06/2015	5.40	20/01/2022	4.60	20/09/2024	3.85
26/08/2015	5.15	21/02/2022	4.60	21/10/2024	3.60
24/10/2015	4.90	21/03/2022	4.60	20/11/2024	3.60
20/08/2019	4.85	20/04/2022	4.60	20/12/2024	3.60
20/09/2019	4.85	20/05/2022	4.45		
21/10/2019	4.85	20/06/2022	4.45		

Appendix B. Processed Intermediate Data

B1. Interpolated and Adjusted Monthly Prices

Monthly Housing Prices (Interpolated and Adjusted)					
Date	**Interpolated Price**	**Adjusted Price**	**Date**	**Interpolated Price**	**Adjusted Price**
2000-01	3,326	3,182	2012-07	14,789	13,884
2000-02	3,353	3,208	2012-08	15,022	14,103
2000-03	3,380	3,234	2012-09	15,263	14,329
2000-04	3,407	3,260	2012-10	15,506	14,557
2000-05	3,435	3,286	2012-11	15,746	14,783
2000-06	3,462	3,312	2012-12	15,976	14,999
2000-07	3,490	3,339	2013-01	16,192	15,100

2000-08	3,518	3,365	2013-02	16,398	15,293
2000-09	3,545	3,392	2013-03	16,605	15,485
2000-10	3,573	3,418	2013-04	16,813	15,679
2000-11	3,602	3,445	2013-05	17,023	15,875
2000-12	3,630	3,472	2013-06	17,235	16,073
2001-01	3,658	3,518	2013-07	17,450	16,273
2001-02	3,685	3,544	2013-08	17,669	16,478
2001-03	3,711	3,569	2013-09	17,893	16,686
2001-04	3,736	3,593	2013-10	18,122	16,900
2001-05	3,761	3,617	2013-11	18,356	17,119
2001-06	3,785	3,641	2013-12	18,598	17,344
2001-07	3,811	3,665	2014-01	18,847	17,273
2001-08	3,837	3,690	2014-02	19,117	17,520
2001-09	3,865	3,718	2014-03	19,416	17,795
2001-10	3,896	3,747	2014-04	19,738	18,090
2001-11	3,929	3,779	2014-05	20,075	18,398
2001-12	3,966	3,815	2014-06	20,418	18,713
2002-01	4,007	3,626	2014-07	20,761	19,027
2002-02	4,057	3,671	2014-08	21,096	19,334
2002-03	4,119	3,728	2014-09	21,415	19,626
2002-04	4,192	3,794	2014-10	21,710	19,897
2002-05	4,274	3,867	2014-11	21,974	20,139
2002-06	4,362	3,947	2014-12	22,199	20,345
2002-07	4,454	4,031	2015-01	22,378	21,776
2002-08	4,549	4,117	2015-02	22,524	21,917
2002-09	4,644	4,203	2015-03	22,655	22,044
2002-10	4,738	4,287	2015-04	22,773	22,160
2002-11	4,828	4,369	2015-05	22,881	22,265
2002-12	4,912	4,445	2015-06	22,981	22,362
2003-01	4,989	4,657	2015-07	23,075	22,453
2003-02	5,059	4,723	2015-08	23,164	22,540
2003-03	5,127	4,786	2015-09	23,252	22,625
2003-04	5,192	4,846	2015-10	23,339	22,710
2003-05	5,255	4,905	2015-11	23,429	22,798
2003-06	5,316	4,963	2015-12	23,522	22,889
2003-07	5,377	5,020	2016-01	23,622	23,117
2003-08	5,438	5,077	2016-02	23,722	23,215
2003-09	5,499	5,134	2016-03	23,814	23,305
2003-10	5,562	5,192	2016-04	23,902	23,392
2003-11	5,626	5,252	2016-05	23,988	23,476
2003-12	5,692	5,314	2016-06	24,074	23,559
2004-01	5,761	5,337	2016-07	24,162	23,646

2004-02	5,836	5,406	2016-08	24,255	23,736
2004-03	5,917	5,481	2016-09	24,354	23,834
2004-04	6,003	5,561	2016-10	24,463	23,940
2004-05	6,092	5,644	2016-11	24,583	24,057
2004-06	6,183	5,727	2016-12	24,716	24,188
2004-07	6,273	5,811	2017-01	24,866	23,300
2004-08	6,360	5,892	2017-02	25,053	23,475
2004-09	6,444	5,969	2017-03	25,291	23,699
2004-10	6,521	6,041	2017-04	25,574	23,964
2004-11	6,590	6,105	2017-05	25,894	24,264
2004-12	6,650	6,160	2017-06	26,243	24,591
2005-01	6,698	6,548	2017-07	26,615	24,939
2005-02	6,736	6,585	2017-08	27,001	25,301
2005-03	6,769	6,617	2017-09	27,395	25,670
2005-04	6,797	6,644	2017-10	27,789	26,039
2005-05	6,821	6,668	2017-11	28,175	26,401
2005-06	6,843	6,690	2017-12	28,547	26,749
2005-07	6,864	6,711	2018-01	28,896	27,160
2005-08	6,886	6,732	2018-02	29,232	27,475
2005-09	6,909	6,754	2018-03	29,568	27,791
2005-10	6,934	6,779	2018-04	29,904	28,107
2005-11	6,964	6,808	2018-05	30,240	28,422
2005-12	6,998	6,841	2018-06	30,575	28,738
2006-01	7,039	6,486	2018-07	30,911	29,054
2006-02	7,100	6,542	2018-08	31,247	29,370
2006-03	7,191	6,625	2018-09	31,583	29,685
2006-04	7,304	6,729	2018-10	31,919	30,001
2006-05	7,433	6,848	2018-11	32,255	30,317
2006-06	7,571	6,976	2018-12	32,590	30,632
2006-07	7,713	7,106	2019-01	32,926	31,179
2006-08	7,850	7,233	2019-02	33,262	31,497
2006-09	7,978	7,351	2019-03	33,597	31,815
2006-10	8,088	7,453	2019-04	33,932	32,132
2006-11	8,175	7,533	2019-05	34,268	32,450
2006-12	8,233	7,585	2019-06	34,603	32,767
2007-01	8,253	8,317	2019-07	34,938	33,085
2007-02	8,250	8,314	2019-08	35,274	33,402
2007-03	8,243	8,306	2019-09	35,609	33,720
2007-04	8,231	8,295	2019-10	35,944	34,037
2007-05	8,217	8,281	2019-11	36,279	34,355
2007-06	8,201	8,264	2019-12	36,615	34,672
2007-07	8,184	8,247	2020-01	36,950	35,170

2007-08	8,167	8,230	2020-02	37,287	35,491
2007-09	8,151	8,214	2020-03	37,628	35,816
2007-10	8,137	8,199	2020-04	37,970	36,142
2007-11	8,125	8,188	2020-05	38,314	36,469
2007-12	8,118	8,180	2020-06	38,658	36,796
2008-01	8,115	6,690	2020-07	39,000	37,122
2008-02	8,182	6,745	2020-08	39,341	37,446
2008-03	8,368	6,899	2020-09	39,678	37,767
2008-04	8,655	7,135	2020-10	40,011	38,084
2008-05	9,020	7,437	2020-11	40,339	38,396
2008-06	9,445	7,787	2020-12	40,660	38,702
2008-07	9,908	8,169	2021-01	40,974	39,329
2008-08	10,390	8,566	2021-02	41,289	39,632
2008-09	10,870	8,961	2021-03	41,610	39,940
2008-10	11,327	9,339	2021-04	41,936	40,253
2008-11	11,742	9,681	2021-05	42,261	40,565
2008-12	12,095	9,971	2021-06	42,583	40,874
2009-01	12,364	11,352	2021-07	42,897	41,176
2009-02	12,587	11,557	2021-08	43,201	41,467
2009-03	12,813	11,765	2021-09	43,490	41,744
2009-04	13,038	11,971	2021-10	43,761	42,005
2009-05	13,256	12,171	2021-11	44,011	42,244
2009-06	13,464	12,362	2021-12	44,235	42,459
2009-07	13,658	12,540	2022-01	44,430	43,661
2009-08	13,834	12,702	2022-02	44,603	43,831
2009-09	13,987	12,842	2022-03	44,764	43,989
2009-10	14,113	12,958	2022-04	44,914	44,136
2009-11	14,209	13,046	2022-05	45,054	44,274
2009-12	14,269	13,101	2022-06	45,186	44,404
2010-01	14,290	14,630	2022-07	45,311	44,527
2010-02	14,276	14,615	2022-08	45,431	44,644
2010-03	14,236	14,575	2022-09	45,547	44,758
2010-04	14,177	14,514	2022-10	45,660	44,869
2010-05	14,102	14,438	2022-11	45,772	44,979
2010-06	14,018	14,351	2022-12	45,884	45,089
2010-07	13,928	14,259	2023-01	45,997	45,431
2010-08	13,838	14,167	2023-02	46,110	45,542
2010-09	13,754	14,081	2023-03	46,218	45,650
2010-10	13,679	14,004	2023-04	46,324	45,754
2010-11	13,620	13,943	2023-05	46,427	45,855
2010-12	13,580	13,903	2023-06	46,527	45,955
2011-01	13,566	13,472	2023-07	46,627	46,053

2011-02	13,569	13,474	2023-08	46,725	46,150
2011-03	13,576	13,482	2023-09	46,823	46,247
2011-04	13,588	13,494	2023-10	46,921	46,344
2011-05	13,605	13,511	2023-11	47,020	46,442
2011-06	13,626	13,531	2023-12	47,121	46,541
2011-07	13,651	13,556	2024-01	47,223	46,656
2011-08	13,679	13,584	2024-02	47,327	46,758
2011-09	13,712	13,616	2024-03	47,430	46,861
2011-10	13,747	13,651	2024-04	47,535	46,964
2011-11	13,785	13,690	2024-05	47,639	47,067
2011-12	13,826	13,730	2024-06	47,743	47,170
2012-01	13,870	13,022	2024-07	47,848	47,273
2012-02	13,938	13,085	2024-08	47,953	47,377
2012-03	14,047	13,188	2024-09	48,058	47,481
2012-04	14,192	13,324	2024-10	48,164	47,585
2012-05	14,368	13,489	2024-11	48,270	47,690
2012-06	14,569	13,678	2024-12	48,376	47,794

B2. GDP Estimation Based on CPI

2000-2024 GDP Estimation Process Based on CPI Distribution						
Year-Month	**CPI**	**Quarte-rly CPI**	**CPI Proportion**	**Quarterly GDP**	**Monthly GDP**	**GDP Growth (MoM)**
1999-10	105.8	316.6	/	1,240.55	/	/
1999-11	105.3		/		/	/
1999-12	105.5		0.3332		413.39	/
2000-01	106.3	318.7	0.3335	1,046.78	349.14	-0.1554
2000-02	106.8		0.3351		350.79	0.0047
2000-03	105.6		0.3313		346.85	-0.0112
2000-04	103.5	309.2	0.3347	1,167.91	390.94	0.1271
2000-05	103.2		0.3338		389.81	-0.0029
2000-06	102.5		0.3315		387.16	-0.0068
2000-07	102.3	304.1	0.3364	1,183.65	398.18	0.0285
2000-08	103.1		0.3390		401.30	0.0078
2000-09	98.7		0.3246		384.17	-0.0427
2000-10	98.4	298.0	0.3302	1,413.87	466.86	0.2152
2000-11	99.7		0.3346		473.03	0.0132
2000-12	99.9		0.3352		473.98	0.0020
2001-01	100.2	297.2	0.3371	1,143.68	385.59	-0.1865
2001-02	97.8		0.3291		376.35	-0.0240

2001-03	99.2		0.3338		381.74	0.0143
2001-04	100.2	300.6	0.3333	1,276.03	425.34	0.1142
2001-05	100.2		0.3333		425.34	0.0000
2001-06	100.2		0.3333		425.34	0.0000
2001-07	101.5	299.9	0.3384	1,293.23	437.69	0.0290
2001-08	100.3		0.3344		432.51	-0.0118
2001-09	98.1		0.3271		423.03	-0.0219
2001-10	100.0	302.5	0.3306	1,544.76	510.66	0.2072
2001-11	101.1		0.3342		516.28	0.0110
2001-12	101.4		0.3352		517.81	0.0030
2002-01	101.0	305.0	0.3311	1,260.56	417.43	-0.1939
2002-02	102.9		0.3374		425.28	0.0188
2002-03	101.1		0.3315		417.85	-0.0175
2002-04	99.6	300.9	0.3310	1,406.43	465.54	0.1141
2002-05	100.4		0.3337		469.28	0.0080
2002-06	100.9		0.3353		471.61	0.0050
2002-07	100.2	302.6	0.3311	1,425.39	471.99	0.0008
2002-08	100.7		0.3328		474.34	0.0050
2002-09	101.7		0.3361		479.05	0.0099
2002-10	99.8	297.5	0.3355	1,702.62	571.17	0.1923
2002-11	98.5		0.3311		563.73	-0.0130
2002-12	99.2		0.3334		567.73	0.0071
2003-01	98.9	297.1	0.3329	1,480.04	492.68	-0.1322
2003-02	98.6		0.3319		491.19	-0.0030
2003-03	99.6		0.3352		496.17	0.0101
2003-04	100.3	300.6	0.3337	1,651.31	550.99	0.1105
2003-05	100.2		0.3333		550.44	-0.0010
2003-06	100.1		0.3330		549.89	-0.0010
2003-07	99.5	299.8	0.3319	1,673.57	555.44	0.0101
2003-08	100.1		0.3339		558.79	0.0060
2003-09	100.2		0.3342		559.35	0.0010
2003-10	100.9	303.6	0.3323	1,999.08	664.38	0.1878
2003-11	101.3		0.3337		667.02	0.0040
2003-12	101.4		0.3340		667.68	0.0010
2004-01	101.9	303.6	0.3356	1,762.31	591.50	-0.1141
2004-02	100.1		0.3297		581.05	-0.0177
2004-03	101.6		0.3347		589.76	0.0150
2004-04	102.3	307.6	0.3326	1,966.23	653.92	0.1088
2004-05	102.4		0.3329		654.56	0.0010
2004-06	102.9		0.3345		657.75	0.0049
2004-07	103.6	309.2	0.3351	1,992.74	667.68	0.0151
2004-08	103.2		0.3338		665.11	-0.0039

2004-09	102.4		0.3312		659.95	-0.0078
2004-10	102.0		0.3339		794.74	0.2042
2004-11	101.9	305.5	0.3336	2,380.32	793.96	-0.0010
2004-12	101.6		0.3326		791.62	-0.0029
2005-01	99.9		0.3282		591.26	-0.2531
2005-02	102.9	304.4	0.3380	1,801.60	609.02	0.0300
2005-03	101.6		0.3338		601.32	-0.0126
2005-04	101.2		0.3354		714.15	0.1876
2005-05	100.5	301.7	0.3331	2,129.04	709.21	-0.0069
2005-06	100.0		0.3315		705.68	-0.0050
2005-07	100.2		0.3308		721.49	0.0224
2005-08	101.3	302.9	0.3344	2,181.04	729.41	0.0110
2005-09	101.4		0.3348		730.13	0.0010
2005-10	101.1		0.3343		1,013.76	0.3885
2005-11	100.8	302.4	0.3333	3,032.27	1,010.76	-0.0030
2005-12	100.5		0.3323		1,007.75	-0.0030
2006-01	102.1		0.3364		772.64	-0.2333
2006-02	100.8	303.5	0.3321	2,296.72	762.80	-0.0127
2006-03	100.6		0.3315		761.29	-0.0020
2006-04	100.8		0.3315		823.77	0.0821
2006-05	101.5	304.1	0.3338	2,485.21	829.49	0.0069
2006-06	101.8		0.3348		831.94	0.0030
2006-07	101.8		0.3349		863.04	0.0374
2006-08	101.2	304.0	0.3329	2,577.25	857.95	-0.0059
2006-09	101.0		0.3322		856.26	-0.0020
2006-10	100.9		0.3329		977.97	0.1421
2006-11	100.9	303.1	0.3329	2,937.79	977.97	0.0000
2006-12	101.3		0.3342		981.85	0.0040
2007-01	100.9		0.3315		871.94	-0.1119
2007-02	101.3	304.4	0.3328	2,630.50	875.39	0.0040
2007-03	102.2		0.3357		883.17	0.0089
2007-04	102.0		0.3328		975.54	0.1046
2007-05	101.8	306.5	0.3321	2,931.41	973.63	-0.0020
2007-06	102.7		0.3351		982.24	0.0088
2007-07	102.7		0.3301		999.95	0.0180
2007-08	103.9	311.1	0.3340	3,029.06	1,011.63	0.0117
2007-09	104.5		0.3359		1,017.48	0.0058
2007-10	105.1		0.3329		1,135.29	0.1158
2007-11	105.2	315.7	0.3332	3,410.19	1,136.37	0.0010
2007-12	105.4		0.3339		1,138.53	0.0019
2008-01	105.9	320.6	0.3303	3,040.76	1,004.42	-0.1178
2008-02	107.5		0.3353		1,019.59	0.0151

2008-03	107.2		0.3344		1,016.75	-0.0028
2008-04	107.9		0.3350		1,169.10	0.1498
2008-05	107.1	322.1	0.3325	3,489.97	1,160.43	-0.0074
2008-06	107.1		0.3325		1,160.43	0.0000
2008-07	107.1		0.3374		1,146.85	-0.0117
2008-08	105.5	317.4	0.3324	3,398.79	1,129.72	-0.0149
2008-09	104.8		0.3302		1,122.22	-0.0066
2008-10	104.1		0.3360		1,266.35	0.1284
2008-11	103.6	309.8	0.3344	3,768.63	1,260.26	-0.0048
2008-12	102.1		0.3296		1,242.02	-0.0145
2009-01	101.7		0.3378		1,064.11	-0.1432
2009-02	99.8	301.1	0.3315	3,150.47	1,044.23	-0.0187
2009-03	99.6		0.3308		1,042.13	-0.0020
2009-04	98.6		0.3332		1,153.45	0.1068
2009-05	98.8	295.9	0.3339	3,461.53	1,155.79	0.0020
2009-06	98.5		0.3329		1,152.28	-0.0030
2009-07	98.1		0.3303		1,190.02	0.0328
2009-08	99.4	297.0	0.3347	3,602.82	1,205.79	0.0133
2009-09	99.5		0.3350		1,207.01	0.0010
2009-10	99.7		0.3311		1,551.66	0.2855
2009-11	100.2	301.1	0.3328	4,686.11	1,559.44	0.0050
2009-12	101.2		0.3361		1,575.01	0.0100
2010-01	101.1		0.3320		1,265.20	-0.1967
2010-02	101.3	304.5	0.3327	3,810.63	1,267.71	0.0020
2010-03	102.1		0.3353		1,277.72	0.0079
2010-04	102.6		0.3320		1,384.45	0.0835
2010-05	103.2	309.0	0.3340	4,169.53	1,392.54	0.0058
2010-06	103.2		0.3340		1,392.54	0.0000
2010-07	103.9		0.3342		1,380.00	-0.0090
2010-08	103.2	310.9	0.3319	4,129.36	1,370.70	-0.0067
2010-09	103.8		0.3339		1,378.67	0.0058
2010-10	104.1		0.3327		1,584.59	0.1494
2010-11	104.3	312.9	0.3333	4,762.90	1,587.63	0.0019
2010-12	104.5		0.3340		1,590.68	0.0019
2011-01	104.3		0.3325		1,438.86	-0.0954
2011-02	104.7	313.7	0.3338	4,327.63	1,444.38	0.0038
2011-03	104.7		0.3338		1,444.38	0.0000
2011-04	105.1		0.3323		1,607.06	0.1126
2011-05	105.3	316.3	0.3329	4,836.47	1,610.12	0.0019
2011-06	105.9		0.3348		1,619.29	0.0057
2011-07	105.6	317.1	0.3330	4,561.54	1,519.07	-0.0619
2011-08	105.8		0.3336		1,521.95	0.0019

2011-09	105.7		0.3333		1,520.51	-0.0009
2011-10	105.6	315.0	0.3352	5,470.05	1,833.77	0.2060
2011-11	104.9		0.3330		1,821.61	-0.0066
2011-12	104.5		0.3317		1,814.67	-0.0038
2012-01	104.9	312.6	0.3356	4,593.85	1,541.57	-0.1505
2012-02	103.9		0.3324		1,526.87	-0.0095
2012-03	103.8		0.3321		1,525.41	-0.0010
2012-04	103.6	309.0	0.3353	4,958.39	1,662.42	0.0898
2012-05	103.0		0.3333		1,652.80	-0.0058
2012-06	102.4		0.3314		1,643.17	-0.0058
2012-07	102.1	306.3	0.3333	4,821.99	1,607.33	-0.0218
2012-08	102.2		0.3337		1,608.90	0.0010
2012-09	102.0		0.3330		1,605.76	-0.0020
2012-10	102.0	306.2	0.3331	5,727.10	1,907.79	0.1881
2012-11	102.0		0.3331		1,907.79	0.0000
2012-12	102.2		0.3338		1,911.53	0.0020
2013-01	102.1	306.9	0.3327	4,937.50	1,642.62	-0.1407
2013-02	102.6		0.3343		1,650.66	0.0049
2013-03	102.2		0.3330		1,644.22	-0.0039
2013-04	102.2	306.8	0.3331	5,231.02	1,742.54	0.0598
2013-05	102.1		0.3328		1,740.83	-0.0010
2013-06	102.5		0.3341		1,747.65	0.0039
2013-07	102.0	306.6	0.3327	5,305.61	1,765.08	0.0100
2013-08	102.1		0.3330		1,766.81	0.0010
2013-09	102.5		0.3343		1,773.73	0.0039
2013-10	102.6	307.4	0.3338	6,127.97	2,045.31	0.1531
2013-11	102.4		0.3331		2,041.33	-0.0019
2013-12	102.4		0.3331		2,041.33	0.0000
2014-01	103.0	308.2	0.3342	5,313.07	1,775.62	-0.1302
2014-02	102.7		0.3332		1,770.45	-0.0029
2014-03	102.5		0.3326		1,767.00	-0.0019
2014-04	102.3	307.8	0.3324	5,639.57	1,874.36	0.0608
2014-05	102.9		0.3343		1,885.35	0.0059
2014-06	102.6		0.3333		1,879.86	-0.0029
2014-07	103.0	308.3	0.3341	5,654.44	1,889.09	0.0049
2014-08	102.6		0.3328		1,881.76	-0.0039
2014-09	102.7		0.3331		1,883.59	0.0010
2014-10	102.4	307.6	0.3329	6,953.86	2,314.94	0.2290
2014-11	102.6		0.3336		2,319.46	0.0020
2014-12	102.6		0.3336		2,319.46	0.0000
2015-01	101.8	306.9	0.3317	5,815.79	1,929.12	-0.1683
2015-02	102.6		0.3343		1,944.28	0.0079

2015-03	102.5		0.3340		1,942.39	-0.0010
2015-04	102.6		0.3339		2,027.03	0.0436
2015-05	102.3	307.3	0.3329	6,071.21	2,021.10	-0.0029
2015-06	102.4		0.3332		2,023.08	0.0010
2015-07	102.6		0.3336		1,994.38	-0.0142
2015-08	102.8	307.6	0.3342	5,979.24	1,998.26	0.0019
2015-09	102.2		0.3322		1,986.60	-0.0058
2015-10	102.4		0.3334		2,367.02	0.1915
2015-11	102.4	307.1	0.3334	7,098.75	2,367.02	0.0000
2015-12	102.3		0.3331		2,364.71	-0.0010
2016-01	102.5		0.3319		2,066.39	-0.1262
2016-02	102.8	308.8	0.3329	6,225.39	2,072.44	0.0029
2016-03	103.5		0.3352		2,086.55	0.0068
2016-04	103.4		0.3340		2,248.22	0.0775
2016-05	103.0	309.6	0.3327	6,731.60	2,239.52	-0.0039
2016-06	103.2		0.3333		2,243.87	0.0019
2016-07	103.4		0.3335		2,192.31	-0.0230
2016-08	103.0	310.0	0.3323	6,572.68	2,183.83	-0.0039
2016-09	103.6		0.3342		2,196.55	0.0058
2016-10	103.5		0.3333		2,645.49	0.2044
2016-11	103.7	310.5	0.3340	7,936.48	2,650.61	0.0019
2016-12	103.3		0.3327		2,640.38	-0.0039
2017-01	103.6		0.3379		2,339.22	-0.1141
2017-02	101.6	306.6	0.3314	6,922.84	2,294.07	-0.0193
2017-03	101.4		0.3307		2,289.55	-0.0020
2017-04	101.6		0.3332		2,327.81	0.0167
2017-05	101.8	304.9	0.3339	6,985.73	2,332.40	0.0020
2017-06	101.5		0.3329		2,325.52	-0.0029
2017-07	101.1		0.3320		2,559.52	0.1006
2017-08	101.7	304.5	0.3340	7,708.95	2,574.71	0.0059
2017-09	101.7		0.3340		2,574.71	0.0000
2017-10	101.5		0.3337		2,841.58	0.1036
2017-11	101.2	304.2	0.3327	8,516.34	2,833.18	-0.0030
2017-12	101.5		0.3337		2,841.58	0.0030
2018-01	101.1		0.3311		2,683.73	-0.0556
2018-02	102.6	305.3	0.3361	8,104.28	2,723.55	0.0148
2018-03	101.6		0.3328		2,697.00	-0.0097
2018-04	101.4		0.3336		3,001.21	0.1128
2018-05	101.4	304.0	0.3336	8,997.70	3,001.21	0.0000
2018-06	101.2		0.3329		2,995.29	-0.0020
2018-07	101.3	304.6	0.3326	8,502.74	2,827.73	-0.0559
2018-08	101.8		0.3342		2,841.69	0.0049

2018-09	101.5		0.3332		2,833.32	-0.0029
2018-10	102.2		0.3348		3,483.80	0.2296
2018-11	101.9	305.3	0.3338	10,407.10	3,473.58	-0.0029
2018-12	101.2		0.3315		3,449.72	-0.0069
2019-01	101.1		0.3315		2,771.15	-0.1967
2019-02	101.7	305.0	0.3334	8,360.04	2,787.59	0.0059
2019-03	102.2		0.3351		2,801.30	0.0049
2019-04	102.4		0.3328		3,094.88	0.1048
2019-05	102.6	307.7	0.3334	9,299.74	3,100.92	0.0020
2019-06	102.7		0.3338		3,103.94	0.0010
2019-07	102.8		0.3345		3,234.58	0.0421
2019-08	102.3	307.3	0.3329	9,669.12	3,218.84	-0.0049
2019-09	102.2		0.3326		3,215.70	-0.0010
2019-10	102.6		0.3314		3,532.23	0.0984
2019-11	103.2	309.6	0.3333	10,658.65	3,552.88	0.0058
2019-12	103.8		0.3353		3,573.54	0.0058
2020-01	104.3		0.3363		2,658.28	-0.2561
2020-02	103.0	310.1	0.3322	7,903.48	2,625.15	-0.0125
2020-03	102.8		0.3315		2,620.05	-0.0019
2020-04	102.5		0.3347		3,188.34	0.2169
2020-05	102.0	306.2	0.3331	9,524.57	3,172.78	-0.0049
2020-06	101.7		0.3321		3,163.45	-0.0029
2020-07	101.6		0.3339		3,324.51	0.0509
2020-08	101.4	304.3	0.3332	9,957.17	3,317.97	-0.0020
2020-09	101.3		0.3329		3,314.69	-0.0010
2020-10	100.3		0.3340		3,867.07	0.1666
2020-11	99.9	300.3	0.3327	11,578.08	3,851.65	-0.0040
2020-12	100.1		0.3333		3,859.36	0.0020
2021-01	99.8		0.3318		3,161.55	-0.1808
2021-02	100.3	300.8	0.3334	9,529.00	3,177.39	0.0050
2021-03	100.7		0.3348		3,190.06	0.0040
2021-04	100.9		0.3327		3,540.32	0.1098
2021-05	101.2	303.3	0.3337	10,642.00	3,550.84	0.0030
2021-06	101.2		0.3337		3,550.84	0.0000
2021-07	101.3		0.3336		3,621.38	0.0199
2021-08	101.3	303.7	0.3336	10,857.00	3,621.38	0.0000
2021-09	101.1		0.3329		3,614.23	-0.0020
2021-10	102.2		0.3334		4,209.71	0.1648
2021-11	102.5	306.5	0.3344	12,625.00	4,222.06	0.0029
2021-12	101.8		0.3321		4,193.23	-0.0068
2022-01	101.6	305.3	0.3328	10,097.00	3,360.15	-0.1987
2022-02	101.5		0.3325		3,356.85	-0.0010

2022-03	102.2		0.3348		3,380.00	0.0069
2022-04	104.3		0.3345		3,150.07	-0.0680
2022-05	104.6	311.8	0.3355	9,417.00	3,159.13	0.0029
2022-06	102.9		0.3300		3,107.79	-0.0163
2022-07	102.9		0.3342		3,914.48	0.2596
2022-08	102.4	307.9	0.3326	11,713.00	3,895.46	-0.0049
2022-09	102.6		0.3332		3,903.07	0.0020
2022-10	101.8		0.3332		4,525.85	0.1596
2022-11	101.6	305.5	0.3326	13,582.00	4,516.96	-0.0020
2022-12	102.1		0.3342		4,539.19	0.0049
2023-01	102.6		0.3366		3,573.16	-0.2128
2023-02	101.3	304.8	0.3323	10,615.00	3,527.89	-0.0127
2023-03	100.9		0.3310		3,513.96	-0.0039
2023-04	98.9		0.3323		3,633.64	0.0341
2023-05	98.6	297.6	0.3313	10,934.00	3,622.62	-0.0030
2023-06	100.1		0.3364		3,677.73	0.0152
2023-07	100.4		0.3326		3,897.61	0.0598
2023-08	100.7	301.9	0.3336	11,720.00	3,909.25	0.0030
2023-09	100.8		0.3339		3,913.14	0.0010
2023-10	100.4		0.3348		4,670.16	0.1935
2023-11	99.8	299.9	0.3328	13,950.00	4,642.25	-0.0060
2023-12	99.7		0.3324		4,637.60	-0.0010
2024-01	98.9		0.3303		3,665.97	-0.2095
2024-02	100.8	299.4	0.3367	11,098.00	3,736.40	0.0192
2024-03	99.7		0.3330		3,695.63	-0.0109
2024-04	100.0		0.3331		3,746.84	0.0139
2024-05	100.0	300.2	0.3331	11,248.00	3,746.84	0.0000
2024-06	100.2		0.3338		3,754.33	0.0020
2024-07	100.3		0.3338		4,019.68	0.0707
2024-08	100.3	300.5	0.3338	12,043.00	4,019.68	0.0000
2024-09	99.9		0.3324		4,003.65	-0.0040
2024-10	100.0		0.3330		6,506.16	0.6251
2024-11	100.2	300.3	0.3337	19,538.00	6,519.17	0.0020
2024-12	100.1		0.3333		6,512.67	-0.0010

B3. Monthly Indicators: LPR, M2, SSE & Policy Scores

2000-2024 LPR,M2 Supply,Stock Market and Policy Indicators						
Year-Month	**LPR**	**LPR Growth Rate(MoM)**	**China M2 Supply Growth(YoY)**	**SSE Index**	**SSE Real Estate Index**	**Policy Score**
2000-01	6.21	0.0000	0.149	0.1232	-0.0664	0
2000-02	6.21	0.0000	0.128	0.1170	-0.0181	0

2000-03	6.21	0.0000	0.13	0.0499	-0.0092	0
2000-04	6.21	0.0000	0.137	0.0201	0.2610	0
2000-05	6.21	0.0000	0.127	0.0317	-0.0468	0
2000-06	6.21	0.0000	0.137	0.0177	0.0311	0
2000-07	6.21	0.0000	0.134	0.0495	-0.1014	0
2000-08	6.21	0.0000	0.133	-0.0012	0.0667	0
2000-09	6.21	0.0000	0.134	-0.0549	0.0064	0
2000-10	6.21	0.0000	0.123	0.0268	-0.0433	0
2000-11	6.21	0.0000	0.124	0.0557	0.0238	0
2000-12	6.21	0.0000	0.123	0.0014	0.0027	0
2001-01	6.21	0.0000	0.135	-0.0038	-0.0415	0
2001-02	6.21	0.0000	0.12	-0.0515	-0.0409	0
2001-03	6.21	0.0000	0.132	0.0784	-0.0853	0
2001-04	6.21	0.0000	0.128	0.0030	-0.0487	0
2001-05	6.21	0.0000	0.121	0.0449	-0.0692	0
2001-06	6.21	0.0000	0.143	0.0017	0.0992	0
2001-07	6.21	0.0000	0.135	-0.1342	-0.0032	0
2001-08	6.21	0.0000	0.136	-0.0449	-0.0826	0
2001-09	6.21	0.0000	0.164	-0.0378	0.0395	0
2001-10	6.21	0.0000	0.129	-0.0429	-0.0380	0
2001-11	6.21	0.0000	0.176	0.0348	-0.0108	0
2001-12	6.21	0.0000	0.144	-0.0584	0.0258	0
2002-01	6.21	0.0000	0.131	-0.0938	-0.0905	0
2002-02	5.76	-0.0725	0.13	0.0221	0.2625	0
2002-03	5.76	0.0000	0.144	0.0519	-0.1496	0
2002-04	5.76	0.0000	0.141	0.0398	-0.0048	-2
2002-05	5.76	0.0000	0.14	-0.0912	0.0092	0
2002-06	5.76	0.0000	0.147	0.1432	-0.0504	0
2002-07	5.76	0.0000	0.144	-0.0468	0.0385	0
2002-08	5.76	0.0000	0.155	0.0091	-0.1094	0
2002-09	5.76	0.0000	0.165	-0.0510	0.0187	-1
2002-10	5.76	0.0000	0.17	-0.0469	0.0912	0
2002-11	5.76	0.0000	0.166	-0.0486	-0.0126	0
2002-12	5.76	0.0000	0.168	-0.0534	0.0132	0
2003-01	5.76	0.0000	0.193	0.1047	0.0803	0
2003-02	5.76	0.0000	0.181	0.0081	0.0211	0
2003-03	5.76	0.0000	0.185	-0.0009	-0.0565	0
2003-04	5.76	0.0000	0.192	0.0072	0.0700	0
2003-05	5.76	0.0000	0.202	0.0360	0.0844	-1
2003-06	5.76	0.0000	0.208	-0.0572	-0.1125	0
2003-07	5.76	0.0000	0.207	-0.0062	-0.0574	0
2003-08	5.76	0.0000	0.216	-0.0371	0.0008	1

2003-09	5.76	0.0000	0.207	-0.0386	-0.0301	0
2003-10	5.76	0.0000	0.21	-0.0138	-0.0225	0
2003-11	5.76	0.0000	0.204	0.0363	0.0905	0
2003-12	5.76	0.0000	0.196	0.0714	-0.0527	0
2004-01	5.76	0.0000	0.181	0.0626	-0.0692	0
2004-02	5.76	0.0000	0.194	0.0530	0.0680	0
2004-03	5.76	0.0000	0.191	0.0397	-0.0239	0
2004-04	5.76	0.0000	0.191	-0.0838	-0.0317	0
2004-05	5.76	0.0000	0.175	-0.0249	0.0224	0
2004-06	5.76	0.0000	0.162	-0.1007	0.0588	0
2004-07	5.76	0.0000	0.153	-0.0093	0.0101	0
2004-08	5.76	0.0000	0.136	-0.0318	-0.0541	0
2004-09	5.76	0.0000	0.139	0.0407	0.0245	0
2004-10	6.12	0.0625	0.135	-0.0545	-0.0375	0
2004-11	6.12	0.0000	0.14	0.0153	-0.0126	0
2004-12	6.12	0.0000	0.146	-0.0554	-0.0489	0
2005-01	6.12	0.0000	0.141	-0.0590	0.1122	0
2005-02	6.12	0.0000	0.139	0.0958	-0.0174	0
2005-03	6.12	0.0000	0.14	-0.0955	0.0049	0
2005-04	6.12	0.0000	0.141	-0.0187	0.0279	0
2005-05	6.12	0.0000	0.147	-0.0849	-0.0650	0
2005-06	6.12	0.0000	0.157	0.0190	-0.0260	-2
2005-07	6.12	0.0000	0.163	0.0019	0.0362	0
2005-08	6.12	0.0000	0.173	0.0737	-0.0700	0
2005-09	6.12	0.0000	0.179	-0.0062	-0.0310	0
2005-10	6.12	0.0000	0.18	-0.0543	0.0952	0
2005-11	6.12	0.0000	0.183	0.0059	0.0642	0
2005-12	6.12	0.0000	0.176	0.0562	0.0757	0
2006-01	6.12	0.0000	0.192	0.0835	-0.0498	0
2006-02	6.12	0.0000	0.188	0.0326	0.0585	0
2006-03	6.12	0.0000	0.188	-0.0006	-0.0299	0
2006-04	6.39	0.0441	0.189	0.1093	0.0063	0
2006-05	6.39	0.0000	0.191	0.1396	-0.0412	0
2006-06	6.39	0.0000	0.184	0.0188	-0.0047	-2
2006-07	6.39	0.0000	0.184	-0.0356	-0.0532	0
2006-08	6.39	0.0000	0.179	0.0285	-0.0382	-2
2006-09	6.39	0.0000	0.168	0.0565	-0.0315	0
2006-10	6.39	0.0000	0.171	0.0488	-0.0420	0
2006-11	6.39	0.0000	0.168	0.1422	-0.1165	0
2006-12	6.39	0.0000	0.169	0.2745	0.1495	0
2007-01	6.39	0.0000	0.158	0.0414	-0.0015	0
2007-02	6.39	0.0000	0.178	0.0340	0.0323	0

2007-03	7.11	0.1127	0.173	0.1051	0.0255	0
2007-04	7.11	0.0000	0.171	0.2064	-0.0390	0
2007-05	7.20	0.0127	0.167	0.0699	-0.0093	0
2007-06	7.20	0.0000	0.171	-0.0703	0.0317	0
2007-07	7.38	0.0250	0.185	0.1702	0.0100	-1
2007-08	7.56	0.0244	0.181	0.1673	0.0015	0
2007-09	7.83	0.0357	0.185	0.0639	0.0192	0
2007-10	7.83	0.0000	0.185	0.0725	0.0026	0
2007-11	7.83	0.0000	0.185	-0.1819	0.0219	0
2007-12	7.83	0.0000	0.167	0.0800	0.0080	0
2008-01	7.83	0.0000	0.189	-0.1669	-0.1144	0
2008-02	7.83	0.0000	0.174	-0.0080	0.2294	0
2008-03	7.83	0.0000	0.162	-0.2014	0.0206	0
2008-04	7.83	0.0000	0.169	0.0635	-0.0216	0
2008-05	7.83	0.0000	0.181	-0.0703	0.1213	0
2008-06	7.83	0.0000	0.174	-0.2031	0.0187	0
2008-07	7.83	0.0000	0.164	0.0145	-0.0061	0
2008-08	7.83	0.0000	0.16	-0.1363	-0.0147	0
2008-09	7.83	0.0000	0.153	-0.0432	-0.0167	0
2008-10	7.20	-0.0805	0.15	-0.2463	0.0409	0
2008-11	6.12	-0.1500	0.148	0.0824	0.0117	5
2008-12	5.94	-0.0294	0.178	-0.0269	-0.2064	0
2009-01	5.94	0.0000	0.188	0.0933	0.0492	0
2009-02	5.94	0.0000	0.205	0.0463	0.0220	0
2009-03	5.94	0.0000	0.255	0.1394	0.1016	0
2009-04	5.94	0.0000	0.26	0.0440	-0.0162	0
2009-05	5.94	0.0000	0.257	0.0627	-0.1166	0
2009-06	5.94	0.0000	0.285	0.1240	-0.1713	0
2009-07	5.94	0.0000	0.284	0.1530	-0.0479	0
2009-08	5.94	0.0000	0.285	-0.2181	-0.0479	0
2009-09	5.94	0.0000	0.293	0.0419	0.2754	0
2009-10	5.94	0.0000	0.294	0.0779	0.1559	0
2009-11	5.94	0.0000	0.297	0.0666	0.0294	0
2009-12	5.94	0.0000	0.277	0.0256	-0.1000	0
2010-01	5.94	0.0000	0.26	-0.0878	0.3845	0
2010-02	5.94	0.0000	0.255	0.0210	0.2113	0
2010-03	5.94	0.0000	0.225	0.0187	0.0358	0
2010-04	5.94	0.0000	0.215	-0.0767	0.0433	-1
2010-05	5.94	0.0000	0.21	-0.0970	-0.0208	0
2010-06	5.94	0.0000	0.185	-0.0748	0.1151	0
2010-07	5.94	0.0000	0.176	0.0997	-0.0218	0
2010-08	5.94	0.0000	0.192	0.0005	-0.0075	0

2010-09	5.94	0.0000	0.19	0.0064	0.0275	0
2010-10	6.14	0.0337	0.193	0.1217	0.0546	-0.5
2010-11	6.14	0.0000	0.195	-0.0533	-0.0717	0
2010-12	6.40	0.0423	0.197	-0.0043	-0.0368	0
2011-01	6.40	0.0000	0.172	-0.0062	-0.0477	0
2011-02	6.60	0.0312	0.157	0.0410	-0.0046	-1
2011-03	6.60	0.0000	0.166	0.0079	-0.0772	0
2011-04	6.80	0.0303	0.153	-0.0057	0.1098	0
2011-05	6.80	0.0000	0.151	-0.0577	0.0902	0
2011-06	6.80	0.0000	0.159	0.0068	0.0057	0
2011-07	7.05	0.0368	0.147	-0.0218	-0.1563	0
2011-08	7.05	0.0000	0.136	-0.0497	0.0894	0
2011-09	7.05	0.0000	0.13	-0.0811	0.0144	0
2011-10	7.05	0.0000	0.129	0.0462	-0.1055	0
2011-11	7.05	0.0000	0.127	-0.0546	0.0152	0
2011-12	7.05	0.0000	0.136	-0.0574	-0.0208	0
2012-01	7.05	0.0000	0.124	0.0424	0.2423	0
2012-02	7.05	0.0000	0.13	0.0593	0.0049	0
2012-03	7.05	0.0000	0.134	-0.0682	0.0184	0
2012-04	7.05	0.0000	0.128	0.0590	0.0375	0
2012-05	7.05	0.0000	0.132	-0.0101	-0.0805	0
2012-06	6.80	-0.0355	0.136	-0.0619	-0.0598	-1
2012-07	6.55	-0.0368	0.139	-0.0547	-0.0337	0
2012-08	6.55	0.0000	0.135	-0.0267	0.0280	0
2012-09	6.55	0.0000	0.148	0.0189	0.1173	0
2012-10	6.55	0.0000	0.141	-0.0083	-0.0405	0
2012-11	6.55	0.0000	0.139	-0.0429	0.0915	0
2012-12	6.55	0.0000	0.138	0.1460	0.0416	0
2013-01	6.55	0.0000	0.159	0.0513	-0.0086	0
2013-02	6.55	0.0000	0.152	-0.0083	-0.1036	0
2013-03	6.55	0.0000	0.157	-0.0545	0.0435	0
2013-04	6.55	0.0000	0.161	-0.0262	-0.1094	0
2013-05	6.55	0.0000	0.158	0.0563	-0.0203	0
2013-06	6.55	0.0000	0.14	-0.1397	-0.0671	0
2013-07	6.55	0.0000	0.145	0.0074	0.0861	0
2013-08	6.55	0.0000	0.147	0.0525	-0.0728	0
2013-09	6.55	0.0000	0.142	0.0364	0.0062	0
2013-10	6.55	0.0000	0.143	-0.0152	0.0482	0
2013-11	6.55	0.0000	0.142	0.0368	-0.0032	-1
2013-12	6.55	0.0000	0.136	-0.0471	0.0310	0
2014-01	6.55	0.0000	0.132	-0.0392	0.0059	0
2014-02	6.55	0.0000	0.133	0.0114	-0.0848	0

2014-03	6.55	0.0000	0.121	-0.0112	0.0777	0
2014-04	6.55	0.0000	0.132	-0.0034	-0.0304	0
2014-05	6.55	0.0000	0.134	0.0063	-0.0468	0
2014-06	6.55	0.0000	0.147	0.0045	0.1662	0
2014-07	6.55	0.0000	0.135	0.0748	-0.0527	0
2014-08	6.55	0.0000	0.128	0.0071	-0.1045	0
2014-09	6.55	0.0000	0.129	0.0662	-0.1563	0
2014-10	6.55	0.0000	0.126	0.0238	0.0328	0
2014-11	6.15	-0.0611	0.123	0.1085	0.0393	0
2014-12	6.15	0.0000	0.122	0.2057	-0.1186	0
2015-01	6.15	0.0000	0.108	-0.0075	-0.0677	0
2015-02	6.15	0.0000	0.125	0.0311	0.0260	0
2015-03	6.15	0.0000	0.116	0.1322	0.0921	0
2015-04	6.15	0.0000	0.101	0.1851	0.0327	0
2015-05	5.65	-0.0813	0.108	0.0383	-0.2618	0
2015-06	5.40	-0.0442	0.118	-0.0725	0.0774	0
2015-07	5.40	0.0000	0.133	-0.1434	0.1800	0
2015-08	5.15	-0.0463	0.133	-0.1249	0.0859	0
2015-09	5.15	0.0000	0.131	-0.0478	0.0869	0
2015-10	4.90	-0.0485	0.135	0.1080	0.3292	0
2015-11	4.90	0.0000	0.137	0.0186	0.0688	0
2015-12	4.90	0.0000	0.133	0.0272	0.1981	0
2016-01	4.90	0.0000	0.14	-0.2265	-0.0990	0
2016-02	4.90	0.0000	0.133	-0.0181	0.2637	0
2016-03	4.90	0.0000	0.134	0.1175	-0.1915	-1
2016-04	4.90	0.0000	0.128	-0.0218	-0.0931	0
2016-05	4.90	0.0000	0.118	-0.0074	-0.1713	0
2016-06	4.90	0.0000	0.118	0.0045	0.1224	0
2016-07	4.90	0.0000	0.102	0.0170	-0.2173	0
2016-08	4.90	0.0000	0.114	0.0356	-0.1669	0
2016-09	4.90	0.0000	0.115	-0.0262	-0.2158	0
2016-10	4.90	0.0000	0.116	0.0319	-0.0747	0
2016-11	4.90	0.0000	0.114	0.0482	-0.0226	-2
2016-12	4.90	0.0000	0.113	-0.0450	-0.0138	0
2017-01	4.90	0.0000	0.113	0.0179	0.0409	0
2017-02	4.90	0.0000	0.111	0.0261	-0.2161	0
2017-03	4.90	0.0000	0.106	-0.0059	0.0624	0
2017-04	4.90	0.0000	0.105	-0.0211	-0.0858	0
2017-05	4.90	0.0000	0.096	-0.0119	0.1579	0
2017-06	4.90	0.0000	0.094	0.0241	0.3208	0
2017-07	4.90	0.0000	0.092	0.0252	-0.1054	0
2017-08	4.90	0.0000	0.089	0.0268	0.3368	0

2017-09	4.90	0.0000	0.092	-0.0035	0.2792	0
2017-10	4.90	0.0000	0.088	0.0133	0.1654	0
2017-11	4.90	0.0000	0.091	-0.0224	0.1115	0
2017-12	4.90	0.0000	0.082	-0.0030	0.0352	0
2018-01	4.90	0.0000	0.086	0.0525	0.0838	0
2018-02	4.90	0.0000	0.088	-0.0636	0.4021	0
2018-03	4.90	0.0000	0.082	-0.0278	0.0193	0
2018-04	4.90	0.0000	0.083	-0.0273	0.0041	0
2018-05	4.90	0.0000	0.083	0.0043	0.1678	0
2018-06	4.90	0.0000	0.08	-0.0801	0.1261	0
2018-07	4.90	0.0000	0.085	0.0102	-0.0270	0
2018-08	4.90	0.0000	0.082	-0.0525	0.0388	0
2018-09	4.90	0.0000	0.083	0.0353	-0.0164	0
2018-10	4.90	0.0000	0.08	-0.0775	0.0942	0
2018-11	4.90	0.0000	0.08	-0.0056	0.0622	0
2018-12	4.90	0.0000	0.081	-0.0364	0.0944	0
2019-01	4.90	0.0000	0.084	0.0364	0.0557	0
2019-02	4.90	0.0000	0.08	0.1379	0.0764	0
2019-03	4.90	0.0000	0.086	0.0509	-0.0776	0
2019-04	4.90	0.0000	0.085	-0.0040	0.0767	0
2019-05	4.90	0.0000	0.085	-0.0584	0.1388	0
2019-06	4.90	0.0000	0.085	0.0277	-0.0209	0
2019-07	4.90	0.0000	0.081	-0.0156	0.0083	0
2019-08	4.85	-0.0102	0.082	-0.0158	-0.0883	0
2019-09	4.85	0.0000	0.084	0.0066	-0.0817	0
2019-10	4.85	0.0000	0.084	0.0082	-0.1546	0
2019-11	4.80	-0.0103	0.082	-0.0195	0.1015	0
2019-12	4.80	0.0000	0.087	0.0620	0.0304	0
2020-01	4.80	0.0000	0.084	-0.0241	-0.0610	0
2020-02	4.75	-0.0104	0.088	-0.0323	-0.0188	0
2020-03	4.75	0.0000	0.101	-0.0451	-0.0732	0
2020-04	4.65	-0.0211	0.111	0.0399	0.0306	0
2020-05	4.65	0.0000	0.111	-0.0027	-0.0481	0
2020-06	4.65	0.0000	0.111	0.0464	-0.0325	0
2020-07	4.65	0.0000	0.107	0.1090	-0.1080	0
2020-08	4.65	0.0000	0.104	0.0259	-0.0343	0
2020-09	4.65	0.0000	0.109	-0.0523	-0.1407	0
2020-10	4.65	0.0000	0.105	0.0020	0.0357	0
2020-11	4.65	0.0000	0.107	0.0519	0.1025	0
2020-12	4.65	0.0000	0.101	0.0240	0.1279	0
2021-01	4.65	0.0000	0.094	0.0029	-0.0662	-2
2021-02	4.65	0.0000	0.101	0.0075	0.0169	0

2021-03	4.65	0.0000	0.094	-0.0191	-0.0705	0
2021-04	4.65	0.0000	0.081	0.0014	-0.0357	0
2021-05	4.65	0.0000	0.083	0.0489	-0.0531	0
2021-06	4.65	0.0000	0.086	-0.0067	-0.0421	0
2021-07	4.65	0.0000	0.083	-0.0540	-0.0965	0
2021-08	4.65	0.0000	0.082	0.0431	0.0362	0
2021-09	4.65	0.0000	0.083	0.0068	-0.0249	0
2021-10	4.65	0.0000	0.087	-0.0058	-0.0402	0
2021-11	4.65	0.0000	0.085	0.0047	0.0102	0
2021-12	4.65	0.0000	0.09	0.0213	0.0837	0
2022-01	4.60	-0.0108	0.098	-0.0765	-0.0653	0
2022-02	4.60	0.0000	0.092	0.0300	-0.0943	0
2022-03	4.60	0.0000	0.097	-0.0607	-0.0541	0
2022-04	4.60	0.0000	0.105	-0.0631	-0.0374	0
2022-05	4.45	-0.0326	0.111	0.0457	-0.0017	0
2022-06	4.45	0.0000	0.114	0.0666	3.6545	0
2022-07	4.45	0.0000	0.12	-0.0428	0.1657	0
2022-08	4.30	-0.0337	0.122	-0.0157	-0.1173	0
2022-09	4.30	0.0000	0.121	-0.0555	0.0325	0
2022-10	4.30	0.0000	0.118	-0.0433	0.0956	0
2022-11	4.30	0.0000	0.124	0.0891	0.0383	0
2022-12	4.30	0.0000	0.118	-0.0197	-0.1380	0
2023-01	4.30	0.0000	0.126	0.0539	-0.0499	0
2023-02	4.30	0.0000	0.129	0.0074	0.0329	0
2023-03	4.30	0.0000	0.127	-0.0021	-0.0400	0
2023-04	4.30	0.0000	0.124	0.0154	-0.0501	0
2023-05	4.30	0.0000	0.116	-0.0357	-0.0472	0
2023-06	4.20	-0.0233	0.113	-0.0008	-0.0443	0
2023-07	4.20	0.0000	0.107	0.0278	-0.0050	0
2023-08	4.20	0.0000	0.106	-0.0520	0.0432	0
2023-09	4.20	0.0000	0.103	-0.0030	0.0222	0
2023-10	4.20	0.0000	0.103	-0.0295	0.0623	0
2023-11	4.20	0.0000	0.1	0.0036	-0.0761	0
2023-12	4.20	0.0000	0.097	-0.0181	0.0239	3
2024-01	4.20	0.0000	0.087	-0.0627	0.0606	1
2024-02	3.95	-0.0595	0.087	0.0813	0.1009	0
2024-03	3.95	0.0000	0.083	0.0086	0.0161	0
2024-04	3.95	0.0000	0.072	0.0209	-0.0916	0
2024-05	3.95	0.0000	0.07	-0.0058	-0.0404	5
2024-06	3.95	0.0000	0.062	-0.0387	0.0274	0
2024-07	3.85	-0.0253	0.063	-0.0097	0.0468	0
2024-08	3.85	0.0000	0.063	-0.0328	0.0381	0

2024-09	3.85	0.0000	0.068	0.1739	0.0271	0
2024-10	3.60	-0.0649	0.075	-0.0170	-0.0541	3
2024-11	3.60	0.0000	0.071	0.0142	0.1562	0
2024-12	3.60	0.0000	0.073	0.0076	0.0379	0

B4. Consumer Confidence Index (CCI) Monthly Data

2000-2024 CCI Values and Year-on-Year Growth Rates in China					
Year-Month	**CCI**	**CCI Growth Rate(YoY)**	**Year-Month**	**CCI**	**CCI Growth Rate(YoY)**
1999-01	105.9	/	2012-01	103.9	0.0400
1999-02	106.2		2012-02	105	0.0542
1999-03	105.7		2012-03	100	-0.0706
1999-04	105.8		2012-04	103	-0.0338
1999-05	106.6		2012-05	104.2	-0.0151
1999-06	107.6		2012-06	99.26	-0.0818
1999-07	106.5		2012-07	98.19	-0.0702
1999-08	108.3		2012-08	99.41	-0.0532
1999-09	108.4		2012-09	100.84	-0.0248
1999-10	108.3		2012-10	106.06	0.0553
1999-11	108.6		2012-11	105.1	0.0835
1999-12	109.9		2012-12	103.7	0.0318
2000-01	109.7	0.0359	2013-01	104.5	0.0058
2000-02	110	0.0358	2013-02	108.2	0.0305
2000-03	110.4	0.0445	2013-03	102.6	0.0260
2000-04	110.6	0.0454	2013-04	103.7	0.0068
2000-05	111.1	0.0422	2013-05	99	-0.0499
2000-06	111.2	0.0335	2013-06	97	-0.0228
2000-07	111.4	0.0460	2013-07	97.2	-0.0101
2000-08	111.8	0.0323	2013-08	97.8	-0.0162
2000-09	112.4	0.0369	2013-09	99.8	-0.0103
2000-10	112.5	0.0388	2013-10	102.9	-0.0298
2000-11	112.7	0.0378	2013-11	98.9	-0.0590
2000-12	112.9	0.0273	2013-12	102.3	-0.0135
2001-01	113.2	0.0319	2014-01	101.1	-0.0325
2001-02	112.9	0.0264	2014-02	103.1	-0.0471
2001-03	113.2	0.0254	2014-03	107.9	0.0517
2001-04	113.8	0.0289	2014-04	104.8	0.0106
2001-05	113.4	0.0207	2014-05	102.3	0.0333
2001-06	113.6	0.0216	2014-06	104.7	0.0794
2001-07	114.5	0.0278	2014-07	104.4	0.0741
2001-08	113.8	0.0179	2014-08	103.8	0.0613

2001-09	113.5	0.0098	2014-09	105.4	0.0561
2001-10	113.4	0.0080	2014-10	103.4	0.0049
2001-11	113.1	0.0035	2014-11	105.5	0.0667
2001-12	113.3	0.0035	2014-12	105.8	0.0342
2002-01	113.1	-0.0009	2015-01	105.7	0.0455
2002-02	113.3	0.0035	2015-02	109.8	0.0650
2002-03	113.4	0.0018	2015-03	107.1	-0.0074
2002-04	113.3	-0.0044	2015-04	107.6	0.0267
2002-05	113.3	-0.0009	2015-05	109.9	0.0743
2002-06	113.5	-0.0009	2015-06	105.54	0.0080
2002-07	113.5	-0.0087	2015-07	104.48	0.0008
2002-08	113.4	-0.0035	2015-08	104	0.0019
2002-09	113.5	0.0000	2015-09	105.6	0.0019
2002-10	113.6	0.0018	2015-10	103.8	0.0039
2002-11	113.9	0.0071	2015-11	104.1	-0.0133
2002-12	113.8	0.0044	2015-12	103.7	-0.0198
2003-01	114	0.0080	2016-01	104	-0.0161
2003-02	114.1	0.0071	2016-02	104.4	-0.0492
2003-03	113.9	0.0044	2016-03	100	-0.0663
2003-04	103.5	-0.0865	2016-04	101	-0.0613
2003-05	100	-0.1174	2016-05	99.8	-0.0919
2003-06	103.4	-0.0890	2016-06	102.9	-0.0250
2003-07	106.4	-0.0626	2016-07	106.8	0.0222
2003-08	108.2	-0.0459	2016-08	105.6	0.0154
2003-09	108.6	-0.0432	2016-09	104.6	-0.0095
2003-10	109.9	-0.0326	2016-10	107.2	0.0328
2003-11	110.3	-0.0316	2016-11	108.6	0.0432
2003-12	111.2	-0.0228	2016-12	108.4	0.0453
2004-01	111.3	-0.0237	2017-01	109.2	0.0500
2004-02	111.1	-0.0263	2017-02	112.6	0.0785
2004-03	111.3	-0.0228	2017-03	111	0.1100
2004-04	110.8	0.0705	2017-04	113.4	0.1228
2004-05	108	0.0800	2017-05	112	0.1222
2004-06	105.1	0.0164	2017-06	113.3	0.1011
2004-07	106.3	-0.0009	2017-07	114.6	0.0730
2004-08	105.9	-0.0213	2017-08	114.7	0.0862
2004-09	106.5	-0.0193	2017-09	118.6	0.1338
2004-10	107.1	-0.0255	2017-10	123.9	0.1558
2004-11	108.2	-0.0190	2017-11	121.3	0.1169
2004-12	108.7	-0.0225	2017-12	122.6	0.1310
2005-01	109.1	-0.0198	2018-01	122.3	0.1200
2005-02	109.6	-0.0135	2018-02	124	0.1012

2005-03	110.1	-0.0108	2018-03	122.3	0.1018
2005-04	110.5	-0.0027	2018-04	122.9	0.0838
2005-05	110	0.0185	2018-05	122.9	0.0973
2005-06	110.4	0.0504	2018-06	118.2	0.0432
2005-07	110.1	0.0357	2018-07	119.7	0.0445
2005-08	110.3	0.0415	2018-08	118.6	0.0340
2005-09	110	0.0329	2018-09	118.5	-0.0008
2005-10	109.3	0.0205	2018-10	119.1	-0.0387
2005-11	109.2	0.0092	2018-11	122.1	0.0066
2005-12	110	0.0120	2018-12	123	0.0033
2006-01	110.3	0.0110	2019-01	123.7	0.0114
2006-02	109.2	-0.0036	2019-02	126	0.0161
2006-03	109.9	-0.0018	2019-03	124.1	0.0147
2006-04	109.4	-0.0100	2019-04	125.3	0.0195
2006-05	109.4	-0.0055	2019-05	123.4	0.0041
2006-06	109.8	-0.0054	2019-06	125.9	0.0651
2006-07	109.7	-0.0036	2019-07	124.4	0.0393
2006-08	110.2	-0.0009	2019-08	122.4	0.0320
2006-09	111.7	0.0155	2019-09	124.1	0.0473
2006-10	111.6	0.0210	2019-10	124.3	0.0437
2006-11	112	0.0256	2019-11	124.6	0.0205
2006-12	113.1	0.0282	2019-12	126.6	0.0293
2007-01	112.4	0.0190	2020-01	126.4	0.0218
2007-02	111.8	0.0238	2020-02	118.9	-0.0563
2007-03	111	0.0100	2020-03	122.2	-0.0153
2007-04	112.3	0.0265	2020-04	116.4	-0.0710
2007-05	112.8	0.0311	2020-05	115.8	-0.0616
2007-06	113.7	0.0355	2020-06	112.6	-0.1056
2007-07	112.9	0.0292	2020-07	117.2	-0.0579
2007-08	113.5	0.0299	2020-08	116.4	-0.0490
2007-09	113.1	0.0125	2020-09	120.5	-0.0290
2007-10	112.6	0.0090	2020-10	121.7	-0.0209
2007-11	112	0.0000	2020-11	124	-0.0048
2007-12	113.1	0.0000	2020-12	122.1	-0.0355
2008-01	111.6	-0.0071	2021-01	122.8	-0.0285
2008-02	110	-0.0161	2021-02	127	0.0681
2008-03	110.3	-0.0063	2021-03	122.2	0.0000
2008-04	109.7	-0.0232	2021-04	121.5	0.0438
2008-05	110	-0.0248	2021-05	121.8	0.0518
2008-06	109.8	-0.0343	2021-06	122.8	0.0906
2008-07	110.2	-0.0239	2021-07	117.8	0.0051
2008-08	109.3	-0.0370	2021-08	117.5	0.0095

2008-09	108.9	-0.0371	2021-09	121.2	0.0058
2008-10	107.9	-0.0417	2021-10	120.2	-0.0123
2008-11	105.2	-0.0607	2021-11	119.5	-0.0363
2008-12	101.8	-0.0999	2021-12	119.8	-0.0188
2009-01	101.3	-0.0923	2022-01	121.5	-0.0106
2009-02	101	-0.0818	2022-02	120.5	-0.0512
2009-03	100.3	-0.0907	2022-03	113.2	-0.0736
2009-04	100.5	-0.0839	2022-04	86.7	-0.2864
2009-05	101.2	-0.0800	2022-05	86.8	-0.2874
2009-06	101	-0.0801	2022-06	88.9	-0.2761
2009-07	102.1	-0.0735	2022-07	87.9	-0.2538
2009-08	102.7	-0.0604	2022-08	87	-0.2596
2009-09	102.8	-0.0560	2022-09	87.2	-0.2805
2009-10	103.2	-0.0436	2022-10	86.8	-0.2779
2009-11	103.3	-0.0181	2022-11	85.5	-0.2845
2009-12	103.9	0.0206	2022-12	88.3	-0.2629
2010-01	104.7	0.0336	2023-01	91.2	-0.2494
2010-02	104.2	0.0317	2023-02	94.7	-0.2141
2010-03	107.9	0.0758	2023-03	94.9	-0.1617
2010-04	106.6	0.0607	2023-04	87.1	0.0046
2010-05	108	0.0672	2023-05	88.2	0.0161
2010-06	108.5	0.0743	2023-06	86.4	-0.0281
2010-07	107.8	0.0558	2023-07	86.4	-0.0171
2010-08	107.3	0.0448	2023-08	86.5	-0.0057
2010-09	104.1	0.0126	2023-09	87.2	0.0000
2010-10	103.8	0.0058	2023-10	87.9	0.0127
2010-11	102.9	-0.0039	2023-11	87	0.0175
2010-12	100.4	-0.0337	2023-12	87.6	-0.0079
2011-01	99.9	-0.0458	2024-01	88.9	-0.0252
2011-02	99.6	-0.0441	2024-02	89.1	-0.0591
2011-03	107.6	-0.0028	2024-03	89.4	-0.0580
2011-04	106.6	0.0000	2024-04	88.2	0.0126
2011-05	105.8	-0.0204	2024-05	86.4	-0.0204
2011-06	108.1	-0.0037	2024-06	86.2	-0.0023
2011-07	105.6	-0.0204	2024-07	86	-0.0046
2011-08	105	-0.0214	2024-08	85.8	-0.0081
2011-09	103.4	-0.0067	2024-09	85.7	-0.0172
2011-10	100.5	-0.0318	2024-10	86.9	-0.0114
2011-11	97	-0.0573	2024-11	86.2	-0.0092
2011-12	100.5	0.0010	2024-12	86.4	-0.0137

Appendix C. Final Input Data

C1. Monthly Feature Matrix for Model Input

The following variables were used in the predictive model.

Y represents the target variable (housing price), and X1–X8 are the input features.

- X1: Shanghai Growth_MoM
- X2: Shanghai CPI Growth_YOY
- X3: China LPR Growth_MoM
- X4: China M2 Growth_YoY
- X5: SSE Index Growth_MoM
- X6: SSE Real Estate Index Growth_MoM
- X7: Policy Score
- X8: China CCI Growth_YoY

Year-Month	Y	X1	X2	X3	X4	X5	X6	X7	X8
2000-01	3,182	-0.155	0.063	0.000	0.149	0.123	-0.066	0.0	0.036
2000-02	3,208	0.005	0.068	0.000	0.128	0.117	-0.018	0.0	0.036
2000-03	3,234	-0.011	0.056	0.000	0.130	0.050	-0.009	0.0	0.044
2000-04	3,260	0.127	0.035	0.000	0.137	0.020	0.261	0.0	0.045
2000-05	3,286	-0.003	0.032	0.000	0.127	0.032	-0.047	0.0	0.042
2000-06	3,312	-0.007	0.025	0.000	0.137	0.018	0.031	0.0	0.033
2000-07	3,339	0.028	0.023	0.000	0.134	0.050	-0.101	0.0	0.046
2000-08	3,365	0.008	0.031	0.000	0.133	-0.001	0.067	0.0	0.032
2000-09	3,392	-0.043	-0.013	0.000	0.134	-0.055	0.006	0.0	0.037
2000-10	3,418	0.215	-0.016	0.000	0.123	0.027	-0.043	0.0	0.039
2000-11	3,445	0.013	-0.003	0.000	0.124	0.056	0.024	0.0	0.038
2000-12	3,472	0.002	-0.001	0.000	0.123	0.001	0.003	0.0	0.027
2001-01	3,518	-0.186	0.002	0.000	0.135	-0.004	-0.042	0.0	0.032
2001-02	3,544	-0.024	-0.022	0.000	0.120	-0.052	-0.041	0.0	0.026
2001-03	3,569	0.014	-0.008	0.000	0.132	0.078	-0.085	0.0	0.025
2001-04	3,593	0.114	0.002	0.000	0.128	0.003	-0.049	0.0	0.029
2001-05	3,617	0.000	0.002	0.000	0.121	0.045	-0.069	0.0	0.021
2001-06	3,641	0.000	0.002	0.000	0.143	0.002	0.099	0.0	0.022
2001-07	3,665	0.029	0.015	0.000	0.135	-0.134	-0.003	0.0	0.028
2001-08	3,690	-0.012	0.003	0.000	0.136	-0.045	-0.083	0.0	0.018
2001-09	3,718	-0.022	-0.019	0.000	0.164	-0.038	0.040	0.0	0.010
2001-10	3,747	0.207	0.000	0.000	0.129	-0.043	-0.038	0.0	0.008
2001-11	3,779	0.011	0.011	0.000	0.176	0.035	-0.011	0.0	0.004
2001-12	3,815	0.003	0.014	0.000	0.144	-0.058	0.026	0.0	0.004

2002-01	3,626	-0.194	0.010	0.000	0.131	-0.094	-0.091	0.0	-0.001
2002-02	3,671	0.019	0.029	-0.072	0.130	0.022	0.263	0.0	0.004
2002-03	3,728	-0.017	0.011	0.000	0.144	0.052	-0.150	0.0	0.002
2002-04	3,794	0.114	-0.004	0.000	0.141	0.040	-0.005	-2.0	-0.004
2002-05	3,867	0.008	0.004	0.000	0.140	-0.091	0.009	0.0	-0.001
2002-06	3,947	0.005	0.009	0.000	0.147	0.143	-0.050	0.0	-0.001
2002-07	4,031	0.001	0.002	0.000	0.144	-0.047	0.039	0.0	-0.009
2002-08	4,117	0.005	0.007	0.000	0.155	0.009	-0.109	0.0	-0.004
2002-09	4,203	0.010	0.017	0.000	0.165	-0.051	0.019	-1.0	0.000
2002-10	4,287	0.192	-0.002	0.000	0.170	-0.047	0.091	0.0	0.002
2002-11	4,369	-0.013	-0.015	0.000	0.166	-0.049	-0.013	0.0	0.007
2002-12	4,445	0.007	-0.008	0.000	0.168	-0.053	0.013	0.0	0.004
2003-01	4,657	-0.132	-0.011	0.000	0.193	0.105	0.080	0.0	0.008
2003-02	4,723	-0.003	-0.014	0.000	0.181	0.008	0.021	0.0	0.007
2003-03	4,786	0.010	-0.004	0.000	0.185	-0.001	-0.057	0.0	0.004
2003-04	4,846	0.110	0.003	0.000	0.192	0.007	0.070	0.0	-0.086
2003-05	4,905	-0.001	0.002	0.000	0.202	0.036	0.084	-1.0	-0.117
2003-06	4,963	-0.001	0.001	0.000	0.208	-0.057	-0.113	0.0	-0.089
2003-07	5,020	0.010	-0.005	0.000	0.207	-0.006	-0.057	0.0	-0.063
2003-08	5,077	0.006	0.001	0.000	0.216	-0.037	0.001	1.0	-0.046
2003-09	5,134	0.001	0.002	0.000	0.207	-0.039	-0.030	0.0	-0.043
2003-10	5,192	0.188	0.009	0.000	0.210	-0.014	-0.023	0.0	-0.033
2003-11	5,252	0.004	0.013	0.000	0.204	0.036	0.091	0.0	-0.032
2003-12	5,314	0.001	0.014	0.000	0.196	0.071	-0.053	0.0	-0.023
2004-01	5,337	-0.114	0.019	0.000	0.181	0.063	-0.069	0.0	-0.024
2004-02	5,406	-0.018	0.001	0.000	0.194	0.053	0.068	0.0	-0.026
2004-03	5,481	0.015	0.016	0.000	0.191	0.040	-0.024	0.0	-0.023
2004-04	5,561	0.109	0.023	0.000	0.191	-0.084	-0.032	0.0	0.071
2004-05	5,644	0.001	0.024	0.000	0.175	-0.025	0.022	0.0	0.080
2004-06	5,727	0.005	0.029	0.000	0.162	-0.101	0.059	0.0	0.016
2004-07	5,811	0.015	0.036	0.000	0.153	-0.009	0.010	0.0	-0.001
2004-08	5,892	-0.004	0.032	0.000	0.136	-0.032	-0.054	0.0	-0.021
2004-09	5,969	-0.008	0.024	0.000	0.139	0.041	0.025	0.0	-0.019
2004-10	6,041	0.204	0.020	0.063	0.135	-0.055	-0.038	0.0	-0.025
2004-11	6,105	-0.001	0.019	0.000	0.140	0.015	-0.013	0.0	-0.019
2004-12	6,160	-0.003	0.016	0.000	0.146	-0.055	-0.049	0.0	-0.022
2005-01	6,548	-0.253	-0.001	0.000	0.141	-0.059	0.112	0.0	-0.020
2005-02	6,585	0.030	0.029	0.000	0.139	0.096	-0.017	0.0	-0.014
2005-03	6,617	-0.013	0.016	0.000	0.140	-0.096	0.005	0.0	-0.011
2005-04	6,644	0.188	0.012	0.000	0.141	-0.019	0.028	0.0	-0.003
2005-05	6,668	-0.007	0.005	0.000	0.147	-0.085	-0.065	0.0	0.019
2005-06	6,690	-0.005	0.000	0.000	0.157	0.019	-0.026	-2.0	0.050

2005-07	6,711	0.022	0.002	0.000	0.163	0.002	0.036	0.0	0.036
2005-08	6,732	0.011	0.013	0.000	0.173	0.074	-0.070	0.0	0.042
2005-09	6,754	0.001	0.014	0.000	0.179	-0.006	-0.031	0.0	0.033
2005-10	6,779	0.388	0.011	0.000	0.180	-0.054	0.095	0.0	0.021
2005-11	6,808	-0.003	0.008	0.000	0.183	0.006	0.064	0.0	0.009
2005-12	6,841	-0.003	0.005	0.000	0.176	0.056	0.076	0.0	0.012
2006-01	6,486	-0.233	0.021	0.000	0.192	0.084	-0.050	0.0	0.011
2006-02	6,542	-0.013	0.008	0.000	0.188	0.033	0.059	0.0	-0.004
2006-03	6,625	-0.002	0.006	0.000	0.188	-0.001	-0.030	0.0	-0.002
2006-04	6,729	0.082	0.008	0.044	0.189	0.109	0.006	0.0	-0.010
2006-05	6,848	0.007	0.015	0.000	0.191	0.140	-0.041	0.0	-0.005
2006-06	6,976	0.003	0.018	0.000	0.184	0.019	-0.005	-2.0	-0.005
2006-07	7,106	0.037	0.018	0.000	0.184	-0.036	-0.053	0.0	-0.004
2006-08	7,233	-0.006	0.012	0.000	0.179	0.029	-0.038	-2.0	-0.001
2006-09	7,351	-0.002	0.010	0.000	0.168	0.057	-0.032	0.0	0.015
2006-10	7,453	0.142	0.009	0.000	0.171	0.049	-0.042	0.0	0.021
2006-11	7,533	0.000	0.009	0.000	0.168	0.142	-0.117	0.0	0.026
2006-12	7,585	0.004	0.013	0.000	0.169	0.275	0.150	0.0	0.028
2007-01	8,317	-0.112	0.009	0.000	0.158	0.041	-0.002	0.0	0.019
2007-02	8,314	0.004	0.013	0.000	0.178	0.034	0.032	0.0	0.024
2007-03	8,306	0.009	0.022	0.113	0.173	0.105	0.026	0.0	0.010
2007-04	8,295	0.105	0.020	0.000	0.171	0.206	-0.039	0.0	0.027
2007-05	8,281	-0.002	0.018	0.013	0.167	0.070	-0.009	0.0	0.031
2007-06	8,264	0.009	0.027	0.000	0.171	-0.070	0.032	0.0	0.036
2007-07	8,247	0.018	0.027	0.025	0.185	0.170	0.010	-1.0	0.029
2007-08	8,230	0.012	0.039	0.024	0.181	0.167	0.002	0.0	0.030
2007-09	8,214	0.006	0.045	0.036	0.185	0.064	0.019	0.0	0.013
2007-10	8,199	0.116	0.051	0.000	0.185	0.073	0.003	0.0	0.009
2007-11	8,188	0.001	0.052	0.000	0.185	-0.182	0.022	0.0	0.000
2007-12	8,180	0.002	0.054	0.000	0.167	0.080	0.008	0.0	0.000
2008-01	6,690	-0.118	0.059	0.000	0.189	-0.167	-0.114	0.0	-0.007
2008-02	6,745	0.015	0.075	0.000	0.174	-0.008	0.229	0.0	-0.016
2008-03	6,899	-0.003	0.072	0.000	0.162	-0.201	0.021	0.0	-0.006
2008-04	7,135	0.150	0.079	0.000	0.169	0.064	-0.022	0.0	-0.023
2008-05	7,437	-0.007	0.071	0.000	0.181	-0.070	0.121	0.0	-0.025
2008-06	7,787	0.000	0.071	0.000	0.174	-0.203	0.019	0.0	-0.034
2008-07	8,169	-0.012	0.071	0.000	0.164	0.015	-0.006	0.0	-0.024
2008-08	8,566	-0.015	0.055	0.000	0.160	-0.136	-0.015	0.0	-0.037
2008-09	8,961	-0.007	0.048	0.000	0.153	-0.043	-0.017	0.0	-0.037
2008-10	9,339	0.128	0.041	-0.080	0.150	-0.246	0.041	0.0	-0.042
2008-11	9,681	-0.005	0.036	-0.150	0.148	0.082	0.012	5.0	-0.061
2008-12	9,971	-0.014	0.021	-0.029	0.178	-0.027	-0.206	0.0	-0.100

2009-01	11,352	-0.143	0.017	0.000	0.188	0.093	0.049	0.0	-0.092
2009-02	11,557	-0.019	-0.002	0.000	0.205	0.046	0.022	0.0	-0.082
2009-03	11,765	-0.002	-0.004	0.000	0.255	0.139	0.102	0.0	-0.091
2009-04	11,971	0.107	-0.014	0.000	0.260	0.044	-0.016	0.0	-0.084
2009-05	12,171	0.002	-0.012	0.000	0.257	0.063	-0.117	0.0	-0.080
2009-06	12,362	-0.003	-0.015	0.000	0.285	0.124	-0.171	0.0	-0.080
2009-07	12,540	0.033	-0.019	0.000	0.284	0.153	-0.048	0.0	-0.074
2009-08	12,702	0.013	-0.006	0.000	0.285	-0.218	-0.048	0.0	-0.060
2009-09	12,842	0.001	-0.005	0.000	0.293	0.042	0.275	0.0	-0.056
2009-10	12,958	0.286	-0.003	0.000	0.294	0.078	0.156	0.0	-0.044
2009-11	13,046	0.005	0.002	0.000	0.297	0.067	0.029	0.0	-0.018
2009-12	13,101	0.010	0.012	0.000	0.277	0.026	-0.100	0.0	0.021
2010-01	14,630	-0.197	0.011	0.000	0.260	-0.088	0.385	0.0	0.034
2010-02	14,615	0.002	0.013	0.000	0.255	0.021	0.211	0.0	0.032
2010-03	14,575	0.008	0.021	0.000	0.225	0.019	0.036	0.0	0.076
2010-04	14,514	0.084	0.026	0.000	0.215	-0.077	0.043	-1.0	0.061
2010-05	14,438	0.006	0.032	0.000	0.210	-0.097	-0.021	0.0	0.067
2010-06	14,351	0.000	0.032	0.000	0.185	-0.075	0.115	0.0	0.074
2010-07	14,259	-0.009	0.039	0.000	0.176	0.100	-0.022	0.0	0.056
2010-08	14,167	-0.007	0.032	0.000	0.192	0.001	-0.008	0.0	0.045
2010-09	14,081	0.006	0.038	0.000	0.190	0.006	0.028	0.0	0.013
2010-10	14,004	0.149	0.041	0.034	0.193	0.122	0.055	-0.5	0.006
2010-11	13,943	0.002	0.043	0.000	0.195	-0.053	-0.072	0.0	-0.004
2010-12	13,903	0.002	0.045	0.042	0.197	-0.004	-0.037	0.0	-0.034
2011-01	13,472	-0.095	0.043	0.000	0.172	-0.006	-0.048	0.0	-0.046
2011-02	13,474	0.004	0.047	0.031	0.157	0.041	-0.005	-1.0	-0.044
2011-03	13,482	0.000	0.047	0.000	0.166	0.008	-0.077	0.0	-0.003
2011-04	13,494	0.113	0.051	0.030	0.153	-0.006	0.110	0.0	0.000
2011-05	13,511	0.002	0.053	0.000	0.151	-0.058	0.090	0.0	-0.020
2011-06	13,531	0.006	0.059	0.000	0.159	0.007	0.006	0.0	-0.004
2011-07	13,556	-0.062	0.056	0.037	0.147	-0.022	-0.156	0.0	-0.020
2011-08	13,584	0.002	0.058	0.000	0.136	-0.050	0.089	0.0	-0.021
2011-09	13,616	-0.001	0.057	0.000	0.130	-0.081	0.014	0.0	-0.007
2011-10	13,651	0.206	0.056	0.000	0.129	0.046	-0.106	0.0	-0.032
2011-11	13,690	-0.007	0.049	0.000	0.127	-0.055	0.015	0.0	-0.057
2011-12	13,730	-0.004	0.045	0.000	0.136	-0.057	-0.021	0.0	0.001
2012-01	13,022	-0.150	0.049	0.000	0.124	0.042	0.242	0.0	0.040
2012-02	13,085	-0.010	0.039	0.000	0.130	0.059	0.005	0.0	0.054
2012-03	13,188	-0.001	0.038	0.000	0.134	-0.068	0.018	0.0	-0.071
2012-04	13,324	0.090	0.036	0.000	0.128	0.059	0.038	0.0	-0.034
2012-05	13,489	-0.006	0.030	0.000	0.132	-0.010	-0.081	0.0	-0.015
2012-06	13,678	-0.006	0.024	-0.035	0.136	-0.062	-0.060	-1.0	-0.082

2012-07	13,884	-0.022	0.021	-0.037	0.139	-0.055	-0.034	0.0	-0.070
2012-08	14,103	0.001	0.022	0.000	0.135	-0.027	0.028	0.0	-0.053
2012-09	14,329	-0.002	0.020	0.000	0.148	0.019	0.117	0.0	-0.025
2012-10	14,557	0.188	0.020	0.000	0.141	-0.008	-0.041	0.0	0.055
2012-11	14,783	0.000	0.020	0.000	0.139	-0.043	0.092	0.0	0.084
2012-12	14,999	0.002	0.022	0.000	0.138	0.146	0.042	0.0	0.032
2013-01	15,100	-0.141	0.021	0.000	0.159	0.051	-0.009	0.0	0.006
2013-02	15,293	0.005	0.026	0.000	0.152	-0.008	-0.104	0.0	0.030
2013-03	15,485	-0.004	0.022	0.000	0.157	-0.055	0.044	0.0	0.026
2013-04	15,679	0.060	0.022	0.000	0.161	-0.026	-0.109	0.0	0.007
2013-05	15,875	-0.001	0.021	0.000	0.158	0.056	-0.020	0.0	-0.050
2013-06	16,073	0.004	0.025	0.000	0.140	-0.140	-0.067	0.0	-0.023
2013-07	16,273	0.010	0.020	0.000	0.145	0.007	0.086	0.0	-0.010
2013-08	16,478	0.001	0.021	0.000	0.147	0.053	-0.073	0.0	-0.016
2013-09	16,686	0.004	0.025	0.000	0.142	0.036	0.006	0.0	-0.010
2013-10	16,900	0.153	0.026	0.000	0.143	-0.015	0.048	0.0	-0.030
2013-11	17,119	-0.002	0.024	0.000	0.142	0.037	-0.003	-1.0	-0.059
2013-12	17,344	0.000	0.024	0.000	0.136	-0.047	0.031	0.0	-0.014
2014-01	17,273	-0.130	0.030	0.000	0.132	-0.039	0.006	0.0	-0.033
2014-02	17,520	-0.003	0.027	0.000	0.133	0.011	-0.085	0.0	-0.047
2014-03	17,795	-0.002	0.025	0.000	0.121	-0.011	0.078	0.0	0.052
2014-04	18,090	0.061	0.023	0.000	0.132	-0.003	-0.030	0.0	0.011
2014-05	18,398	0.006	0.029	0.000	0.134	0.006	-0.047	0.0	0.033
2014-06	18,713	-0.003	0.026	0.000	0.147	0.005	0.166	0.0	0.079
2014-07	19,027	0.005	0.030	0.000	0.135	0.075	-0.053	0.0	0.074
2014-08	19,334	-0.004	0.026	0.000	0.128	0.007	-0.105	0.0	0.061
2014-09	19,626	0.001	0.027	0.000	0.129	0.066	-0.156	0.0	0.056
2014-10	19,897	0.229	0.024	0.000	0.126	0.024	0.033	0.0	0.005
2014-11	20,139	0.002	0.026	-0.061	0.123	0.109	0.039	0.0	0.067
2014-12	20,345	0.000	0.026	0.000	0.122	0.206	-0.119	0.0	0.034
2015-01	21,776	-0.168	0.018	0.000	0.108	-0.008	-0.068	0.0	0.045
2015-02	21,917	0.008	0.026	0.000	0.125	0.031	0.026	0.0	0.065
2015-03	22,044	-0.001	0.025	0.000	0.116	0.132	0.092	0.0	-0.007
2015-04	22,160	0.044	0.026	0.000	0.101	0.185	0.033	0.0	0.027
2015-05	22,265	-0.003	0.023	-0.081	0.108	0.038	-0.262	0.0	0.074
2015-06	22,362	0.001	0.024	-0.044	0.118	-0.073	0.077	0.0	0.008
2015-07	22,453	-0.014	0.026	0.000	0.133	-0.143	0.180	0.0	0.001
2015-08	22,540	0.002	0.028	-0.046	0.133	-0.125	0.086	0.0	0.002
2015-09	22,625	-0.006	0.022	0.000	0.131	-0.048	0.087	0.0	0.002
2015-10	22,710	0.191	0.024	-0.049	0.135	0.108	0.329	0.0	0.004
2015-11	22,798	0.000	0.024	0.000	0.137	0.019	0.069	0.0	-0.013
2015-12	22,889	-0.001	0.023	0.000	0.133	0.027	0.198	0.0	-0.020

2016-01	23,117	-0.126	0.025	0.000	0.140	-0.227	-0.099	0.0	-0.016
2016-02	23,215	0.003	0.028	0.000	0.133	-0.018	0.264	0.0	-0.049
2016-03	23,305	0.007	0.035	0.000	0.134	0.118	-0.192	-1.0	-0.066
2016-04	23,392	0.077	0.034	0.000	0.128	-0.022	-0.093	0.0	-0.061
2016-05	23,476	-0.004	0.030	0.000	0.118	-0.007	-0.171	0.0	-0.092
2016-06	23,559	0.002	0.032	0.000	0.118	0.005	0.122	0.0	-0.025
2016-07	23,646	-0.023	0.034	0.000	0.102	0.017	-0.217	0.0	0.022
2016-08	23,736	-0.004	0.030	0.000	0.114	0.036	-0.167	0.0	0.015
2016-09	23,834	0.006	0.036	0.000	0.115	-0.026	-0.216	0.0	-0.009
2016-10	23,940	0.204	0.035	0.000	0.116	0.032	-0.075	0.0	0.033
2016-11	24,057	0.002	0.037	0.000	0.114	0.048	-0.023	-2.0	0.043
2016-12	24,188	-0.004	0.033	0.000	0.113	-0.045	-0.014	0.0	0.045
2017-01	23,300	-0.114	0.036	0.000	0.113	0.018	0.041	0.0	0.050
2017-02	23,475	-0.019	0.016	0.000	0.111	0.026	-0.216	0.0	0.079
2017-03	23,699	-0.002	0.014	0.000	0.106	-0.006	0.062	0.0	0.110
2017-04	23,964	0.017	0.016	0.000	0.105	-0.021	-0.086	0.0	0.123
2017-05	24,264	0.002	0.018	0.000	0.096	-0.012	0.158	0.0	0.122
2017-06	24,591	-0.003	0.015	0.000	0.094	0.024	0.321	0.0	0.101
2017-07	24,939	0.101	0.011	0.000	0.092	0.025	-0.105	0.0	0.073
2017-08	25,301	0.006	0.017	0.000	0.089	0.027	0.337	0.0	0.086
2017-09	25,670	0.000	0.017	0.000	0.092	-0.004	0.279	0.0	0.134
2017-10	26,039	0.104	0.015	0.000	0.088	0.013	0.165	0.0	0.156
2017-11	26,401	-0.003	0.012	0.000	0.091	-0.022	0.112	0.0	0.117
2017-12	26,749	0.003	0.015	0.000	0.082	-0.003	0.035	0.0	0.131
2018-01	27,160	-0.056	0.011	0.000	0.086	0.053	0.084	0.0	0.120
2018-02	27,475	0.015	0.026	0.000	0.088	-0.064	0.402	0.0	0.101
2018-03	27,791	-0.010	0.016	0.000	0.082	-0.028	0.019	0.0	0.102
2018-04	28,107	0.113	0.014	0.000	0.083	-0.027	0.004	0.0	0.084
2018-05	28,422	0.000	0.014	0.000	0.083	0.004	0.168	0.0	0.097
2018-06	28,738	-0.002	0.012	0.000	0.080	-0.080	0.126	0.0	0.043
2018-07	29,054	-0.056	0.013	0.000	0.085	0.010	-0.027	0.0	0.045
2018-08	29,370	0.005	0.018	0.000	0.082	-0.053	0.039	0.0	0.034
2018-09	29,685	-0.003	0.015	0.000	0.083	0.035	-0.016	0.0	-0.001
2018-10	30,001	0.230	0.022	0.000	0.080	-0.078	0.094	0.0	-0.039
2018-11	30,317	-0.003	0.019	0.000	0.080	-0.006	0.062	0.0	0.007
2018-12	30,632	-0.007	0.012	0.000	0.081	-0.036	0.094	0.0	0.003
2019-01	31,179	-0.197	0.011	0.000	0.084	0.036	0.056	0.0	0.011
2019-02	31,497	0.006	0.017	0.000	0.080	0.138	0.076	0.0	0.016
2019-03	31,815	0.005	0.022	0.000	0.086	0.051	-0.078	0.0	0.015
2019-04	32,132	0.105	0.024	0.000	0.085	-0.004	0.077	0.0	0.020
2019-05	32,450	0.002	0.026	0.000	0.085	-0.058	0.139	0.0	0.004
2019-06	32,767	0.001	0.027	0.000	0.085	0.028	-0.021	0.0	0.065

2019-07	33,085	0.042	0.028	0.000	0.081	-0.016	0.008	0.0	0.039
2019-08	33,402	-0.005	0.023	-0.010	0.082	-0.016	-0.088	0.0	0.032
2019-09	33,720	-0.001	0.022	0.000	0.084	0.007	-0.082	0.0	0.047
2019-10	34,037	0.098	0.026	0.000	0.084	0.008	-0.155	0.0	0.044
2019-11	34,355	0.006	0.032	-0.010	0.082	-0.020	0.102	0.0	0.020
2019-12	34,672	0.006	0.038	0.000	0.087	0.062	0.030	0.0	0.029
2020-01	35,170	-0.256	0.043	0.000	0.084	-0.024	-0.061	0.0	0.022
2020-02	35,491	-0.012	0.030	-0.010	0.088	-0.032	-0.019	0.0	-0.056
2020-03	35,816	-0.002	0.028	0.000	0.101	-0.045	-0.073	0.0	-0.015
2020-04	36,142	0.217	0.025	-0.021	0.111	0.040	0.031	0.0	-0.071
2020-05	36,469	-0.005	0.020	0.000	0.111	-0.003	-0.048	0.0	-0.062
2020-06	36,796	-0.003	0.017	0.000	0.111	0.046	-0.033	0.0	-0.106
2020-07	37,122	0.051	0.016	0.000	0.107	0.109	-0.108	0.0	-0.058
2020-08	37,446	-0.002	0.014	0.000	0.104	0.026	-0.034	0.0	-0.049
2020-09	37,767	-0.001	0.013	0.000	0.109	-0.052	-0.141	0.0	-0.029
2020-10	38,084	0.167	0.003	0.000	0.105	0.002	0.036	0.0	-0.021
2020-11	38,396	-0.004	-0.001	0.000	0.107	0.052	0.103	0.0	-0.005
2020-12	38,702	0.002	0.001	0.000	0.101	0.024	0.128	0.0	-0.036
2021-01	39,329	-0.181	-0.002	0.000	0.094	0.003	-0.066	-2.0	-0.028
2021-02	39,632	0.005	0.003	0.000	0.101	0.008	0.017	0.0	0.068
2021-03	39,940	0.004	0.007	0.000	0.094	-0.019	-0.071	0.0	0.000
2021-04	40,253	0.110	0.009	0.000	0.081	0.001	-0.036	0.0	0.044
2021-05	40,565	0.003	0.012	0.000	0.083	0.049	-0.053	0.0	0.052
2021-06	40,874	0.000	0.012	0.000	0.086	-0.007	-0.042	0.0	0.091
2021-07	41,176	0.020	0.013	0.000	0.083	-0.054	-0.097	0.0	0.005
2021-08	41,467	0.000	0.013	0.000	0.082	0.043	0.036	0.0	0.009
2021-09	41,744	-0.002	0.011	0.000	0.083	0.007	-0.025	0.0	0.006
2021-10	42,005	0.165	0.022	0.000	0.087	-0.006	-0.040	0.0	-0.012
2021-11	42,244	0.003	0.025	0.000	0.085	0.005	0.010	0.0	-0.036
2021-12	42,459	-0.007	0.018	0.000	0.090	0.021	0.084	0.0	-0.019
2022-01	43,661	-0.199	0.016	-0.011	0.098	-0.077	-0.065	0.0	-0.011
2022-02	43,831	-0.001	0.015	0.000	0.092	0.030	-0.094	0.0	-0.051
2022-03	43,989	0.007	0.022	0.000	0.097	-0.061	-0.054	0.0	-0.074
2022-04	44,136	-0.068	0.043	0.000	0.105	-0.063	-0.037	0.0	-0.286
2022-05	44,274	0.003	0.046	-0.033	0.111	0.046	-0.002	0.0	-0.287
2022-06	44,404	-0.016	0.029	0.000	0.114	0.067	3.655	0.0	-0.276
2022-07	44,527	0.260	0.029	0.000	0.120	-0.043	0.166	0.0	-0.254
2022-08	44,644	-0.005	0.024	-0.034	0.122	-0.016	-0.117	0.0	-0.260
2022-09	44,758	0.002	0.026	0.000	0.121	-0.056	0.033	0.0	-0.281
2022-10	44,869	0.160	0.018	0.000	0.118	-0.043	0.096	0.0	-0.278
2022-11	44,979	-0.002	0.016	0.000	0.124	0.089	0.038	0.0	-0.285
2022-12	45,089	0.005	0.021	0.000	0.118	-0.020	-0.138	0.0	-0.263

2023-01	45,431	-0.213	0.026	0.000	0.126	0.054	-0.050	0.0	-0.249
2023-02	45,542	-0.013	0.013	0.000	0.129	0.007	0.033	0.0	-0.214
2023-03	45,650	-0.004	0.009	0.000	0.127	-0.002	-0.040	0.0	-0.162
2023-04	45,754	0.034	-0.011	0.000	0.124	0.015	-0.050	0.0	0.005
2023-05	45,855	-0.003	-0.014	0.000	0.116	-0.036	-0.047	0.0	0.016
2023-06	45,955	0.015	0.001	-0.023	0.113	-0.001	-0.044	0.0	-0.028
2023-07	46,053	0.060	0.004	0.000	0.107	0.028	-0.005	0.0	-0.017
2023-08	46,150	0.003	0.007	0.000	0.106	-0.052	0.043	0.0	-0.006
2023-09	46,247	0.001	0.008	0.000	0.103	-0.003	0.022	0.0	0.000
2023-10	46,344	0.193	0.004	0.000	0.103	-0.030	0.062	0.0	0.013
2023-11	46,442	-0.006	-0.002	0.000	0.100	0.004	-0.076	0.0	0.018
2023-12	46,541	-0.001	-0.003	0.000	0.097	-0.018	0.024	3.0	-0.008
2024-01	46,656	-0.210	-0.011	0.000	0.087	-0.063	0.061	1.0	-0.025
2024-02	46,758	0.019	0.008	-0.060	0.087	0.081	0.101	0.0	-0.059
2024-03	46,861	-0.011	-0.003	0.000	0.083	0.009	0.016	0.0	-0.058
2024-04	46,964	0.014	0.000	0.000	0.072	0.021	-0.092	0.0	0.013
2024-05	47,067	0.000	0.000	0.000	0.070	-0.006	-0.040	5.0	-0.020
2024-06	47,170	0.002	0.002	0.000	0.062	-0.039	0.027	0.0	-0.002
2024-07	47,273	0.071	0.003	-0.025	0.063	-0.010	0.047	0.0	-0.005
2024-08	47,377	0.000	0.003	0.000	0.063	-0.033	0.038	0.0	-0.008
2024-09	47,481	-0.004	-0.001	0.000	0.068	0.174	0.027	0.0	-0.017
2024-10	47,585	0.625	0.000	-0.065	0.075	-0.017	-0.054	3.0	-0.011
2024-11	47,690	0.002	0.002	0.000	0.071	0.014	0.156	0.0	-0.009
2024-12	47,794	-0.001	0.001	0.000	0.073	0.008	0.038	0.0	-0.014