

PROJECT REPORT






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WHAT MOVES THE HOUSING MARKET?

GROUP 11

CLEVERT BOATENG
CRUZE SHIRLEY
ALEJANDRO RODRIGUEZ BUSTAMANTE
VENKATA SAI PRASAD KANCHARANA

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INTRODUCTION



Introduction

Housing is a powerful engine of the U.S. economy. Its pass-through and ripple effects in the socio-economic aspects of life such as construction, employment, banking, health outcomes, education, social equity, household balance sheets, etc. cannot be over-stated.

Hence, our project asks a simple but consequential question: what macroeconomic factors push U.S. new single-family home sales above or below their normal path? Going deeper, we investigate how unexpected deviations from trend in interest rate, housing supply, prices, labor market tightness, and consumer sentiment relate to departures of housing sales from their long-run path. Our analysis focuses on cyclical movements rather than long-term growth.

In our view, pinpointing the macro drivers of these short-run fluctuations sharpens our understanding of how monetary policy and economic conditions transmit to real activity, while offering practical insights for policymakers, builders, and financial institutions navigating periods of tightening or easing financial conditions.

Our analysis is motivated by a large empirical literature on housing demand and sales that highlights the importance of financing costs, house prices, labor market conditions, and expectations or sentiment such as those captured by consumer confidence and housing expectations surveys. Prior studies, such as Poterba (1984, 1987) and later work by Iacoviello and Minetti (2003) consistently show that mortgage rates and policy rates affect housing affordability, while house prices and income or employment conditions shape demand. More recent work including Case, Shiller, and Thompson (2012) and Kuchler, Piazzesi, and Stroebel (2022) emphasizes the role of expectations and confidence in amplifying housing cycles.

This project contributes by explicitly focusing on short-run deviations from trend using a long monthly U.S. dataset spanning 1991–2024. By removing long-run trends and modeling dynamics with ARIMAX, the analysis isolates cyclical movements in housing sales and identifies the macroeconomic shocks behind short-run booms and slowdowns.



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DATA OVERVIEW



Data Description

Our analysis uses national-level U.S. macroeconomic time series data, consisting of 408 monthly observations from January 1991 to December 2024, covering key variables relevant to housing sales including:

Houses_Sold is the dependent variable and measures the annualized monthly rate of new single-family home sales in the United States, expressed in thousands of units; higher values indicate stronger housing market activity (U.S. Census Bureau).

Source: US Census Bureau

[https://www.census.gov/econ/currentdata/dbsearch?programCode=RESSALES&startYear=1991&endYear=2024&categories\[\]=ASOLD&dataType=TOTAL&geoLevel=US&adjusted=1¬Adjusted=0&errorData=0#table-results](https://www.census.gov/econ/currentdata/dbsearch?programCode=RESSALES&startYear=1991&endYear=2024&categories[]=ASOLD&dataType=TOTAL&geoLevel=US&adjusted=1¬Adjusted=0&errorData=0#table-results)

CCI (Consumer Confidence Index) captures household sentiment about current and future economic conditions, with values above 100 indicating above-average confidence and values below 100 reflecting pessimism (FRED).

Source: FRED

<https://fred.stlouisfed.org/series/USACSCICP02STSAM>

Fund_Rate (Federal Funds Effective Rate) represents the overnight interbank lending rate targeted by the Federal Reserve and serves as a key indicator of monetary policy stance, with higher rates signaling tighter policy and lower rates more accommodative conditions (FRED).

Source: FRED

<https://fred.stlouisfed.org/series/fedfunds>

HPI (Housing Price Index) measures changes in U.S. single-family home prices using repeat-sales data, with higher values indicating rising prices; the index is normalized to 100 in 1991 (FHFA).

Source: FHFA

<https://www.fhfa.gov/data/hpi>

Unemployment (Unemployment Rate) is the U.S. unemployment rate, expressed as a percentage of the labor force, where higher values reflect weaker labor market conditions (FRED).

Source: FRED

<https://fred.stlouisfed.org/series/UNRATE/>

Houses_Built (Housing Units Completed) captures monthly completions of new privately owned housing units, measured in thousands, and proxies housing supply and construction activity (FRED).

Source: FRED

<https://fred.stlouisfed.org/series/computsa>

Mortgage_Monthly (30-Year Mortgage Rate) is the average monthly 30-year fixed mortgage rate, expressed as a percent per annum, with higher rates typically reducing housing affordability and demand (FRED).

Source: FRED

<https://fred.stlouisfed.org/series/MORTGAGE30US/>

Exploratory Data Description

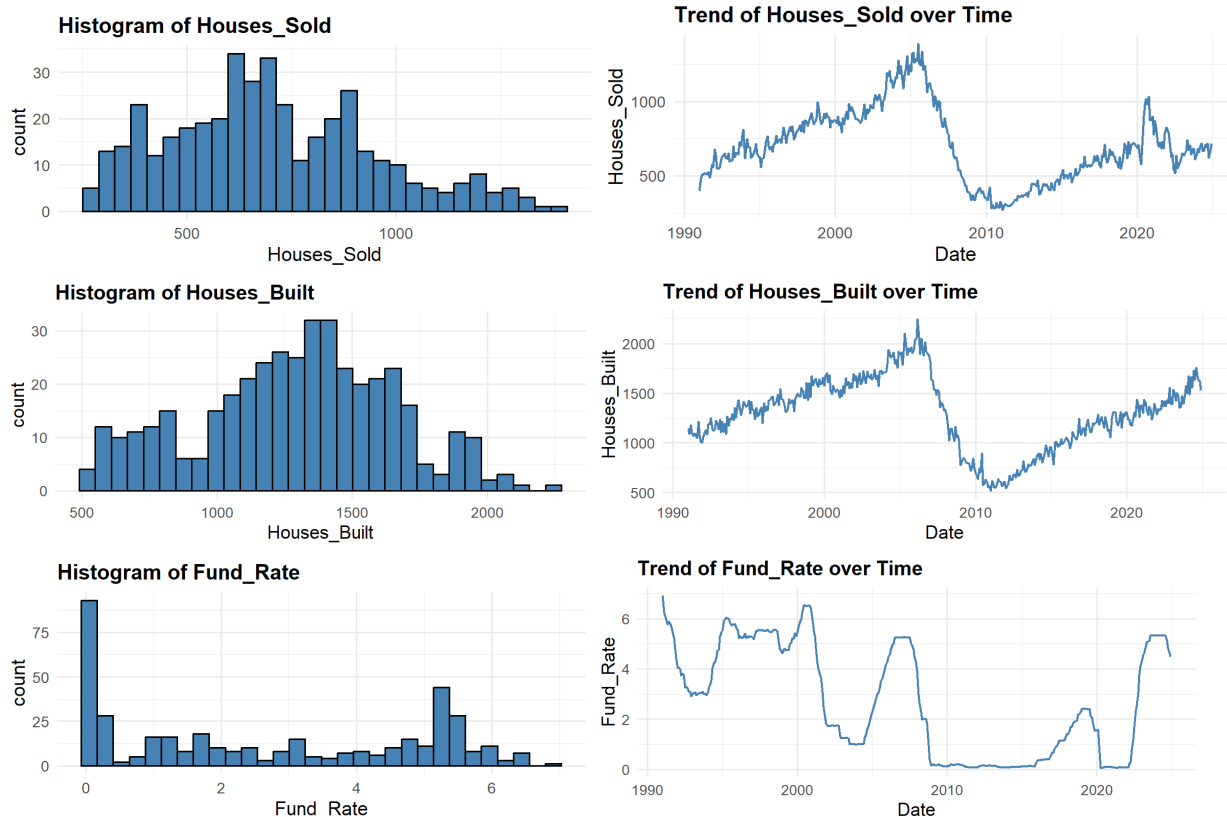
Table 1 presents summary statistics for all variables, offering a first look at their scale, central tendency, and variability before analyzing time-series dynamics.

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Houses Sold	270.0	525.5	677.5	703.0	871.0	1389.0
Houses Built	520	1070	1316	1291	1540	2245
Fund Rate	0.050	0.190	2.305	2.687	5.145	6.910
HPI	100.0	133.5	191.8	203.6	232.1	433.1
Mortgage Monthly	2.684	4.195	6.090	5.877	7.144	9.637
Unemployment	3.400	4.400	5.400	5.718	6.700	14.800
CCI	53.80	80.96	94.36	91.80	102.38	120.51

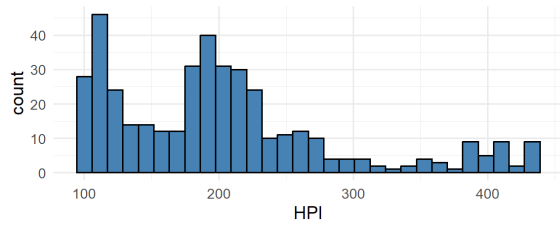
Table 1

Source: FRED, US Census Bureau, Project Works

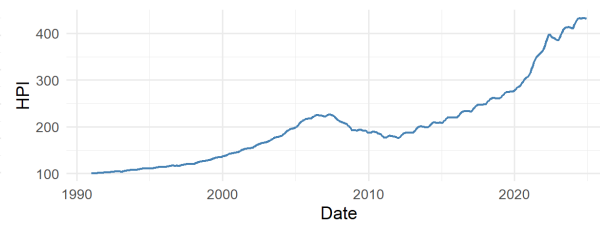
Housing-market variables (Houses Sold and Houses Built) display substantial variation, capturing significant booms and busts from 1991 to 2024. Monetary indicators such as the Federal Funds Rate and 30-year Mortgage Rate also fluctuate widely, reflecting multiple interest-rate cycles over the period. Consumer-related measures, including unemployment and CCI, cover broad ranges, underscoring shifts in the macroeconomic environment. Detailed distributional patterns and temporal dynamics are examined in the visual analysis that follows.



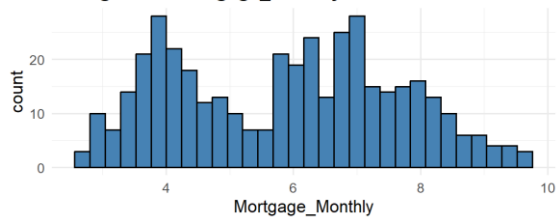
Histogram of HPI



Trend of HPI over Time



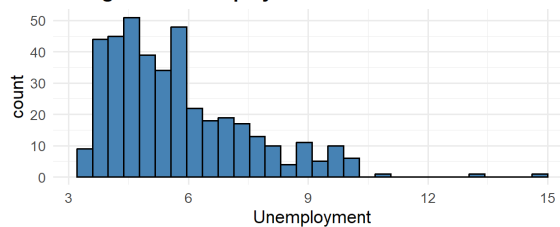
Histogram of Mortgage_Monthly



Trend of Mortgage_Monthly over Time



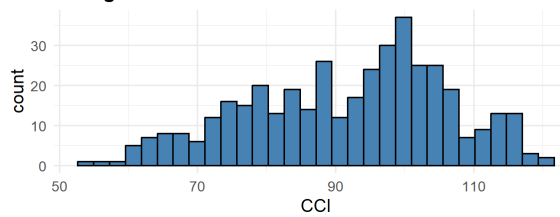
Histogram of Unemployment



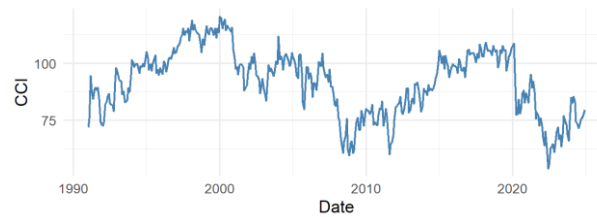
Trend of Unemployment over Time



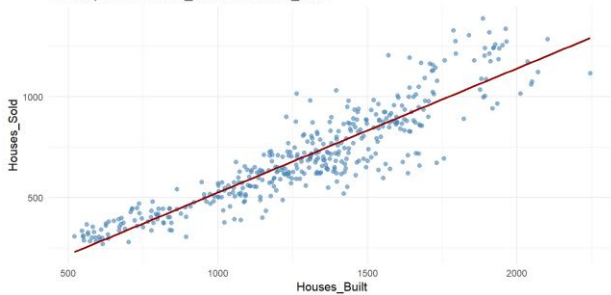
Histogram of CCI



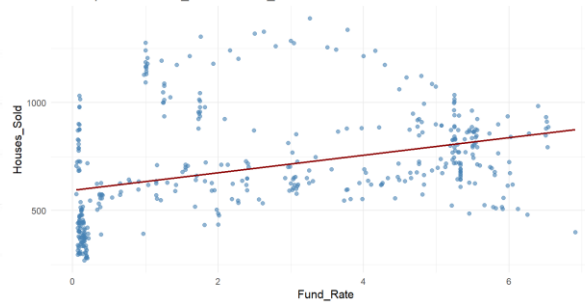
Trend of CCI over Time



Scatterplot of Houses_Sold vs Houses_Built



Scatterplot of Houses_Sold vs Fund_Rate





Source: Projects Data Computation Software

From the above visualisations, dependent variable, *Houses_Sold*, is positively skewed, with most values clustered mid-range and occasional surges creating a long right tail. The time series shows clear long-run patterns: steady growth in the 1990s, acceleration during the early 2000s housing boom, a sharp drop after the 2007–2008 financial crisis, gradual recovery through the 2010s, and a spike in the early 2020s likely due to COVID-19–driven low interest rates and surging demand. *Houses_Built* follows a similar long-term trend, closely tracking sales, though construction did not jump during COVID-19 due to labor, materials, and timing constraints.

The Federal Funds Rate reflects policy cycles rather than a trend, staying around 3–5% in the 1990s and early 2000s, dropping near zero post-crisis, and rising sharply to ~5% in 2022–2024 amid post-pandemic inflation. The scatterplot shows a slight positive association with sales, likely reflecting broader economic cycles. The Housing Price Index (HPI) rises almost monotonically, except during 2007–2011, making scatterplots versus sales hard to interpret because shared trends dominate.

The 30-year mortgage rate is bimodal, with high rates in the early 1990s, low rates in the 2010s, and a sharp rise after 2021. Scatterplots suggest a weakly positive relationship with sales, though non-linearities are apparent. Unemployment is highly skewed, typically 3–6% but spiking to nearly 10% after the financial crisis and 15% during COVID-19, showing a clear negative association with sales. Consumer Confidence (CCI) is negatively skewed, with major drops in 2001, the Great Recession, early 2020, and 2021–2022. Scatterplots indicate a strong positive link with sales, consistent with the idea that confident consumers are more likely to purchase homes.

MODEL AND RESULTS



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Model & Results

Based on our analysis, the time-varying behavior of the series and the limitations of a simple OLS in levels suggest that housing-market data are best treated as time series rather than cross-sectional. Accordingly, we first remove deterministic trends from all variables, working with detrended series that fluctuate around a constant mean.

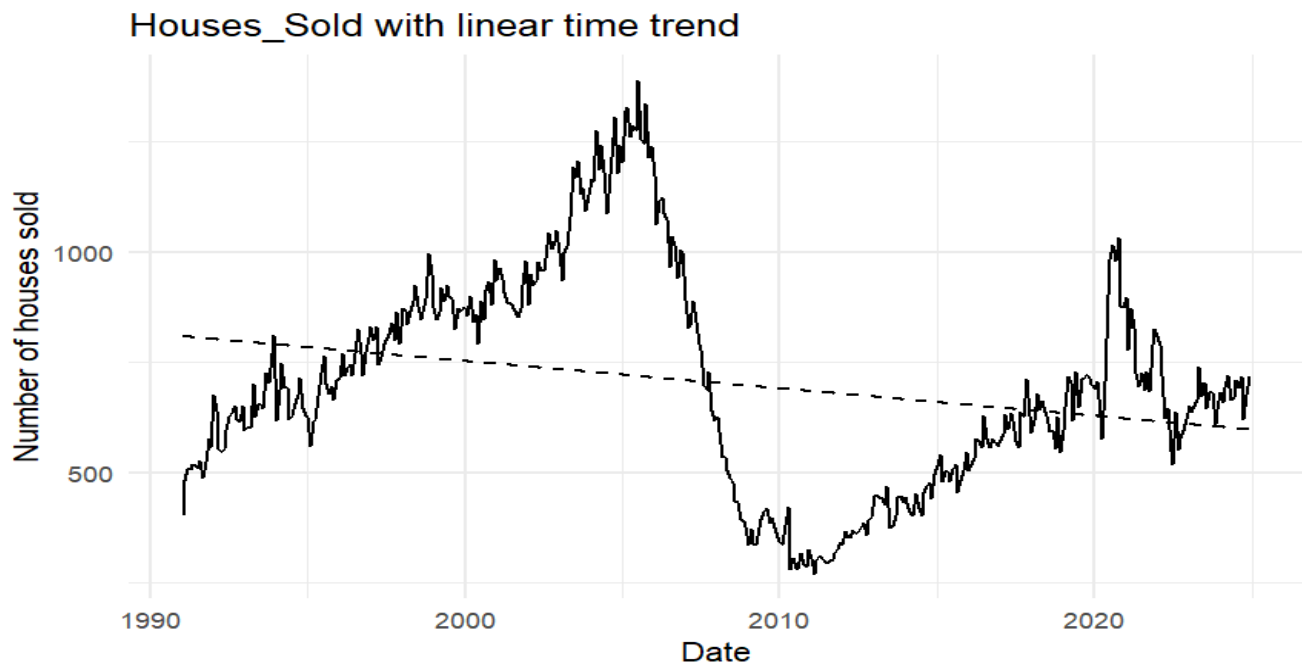


Figure 1

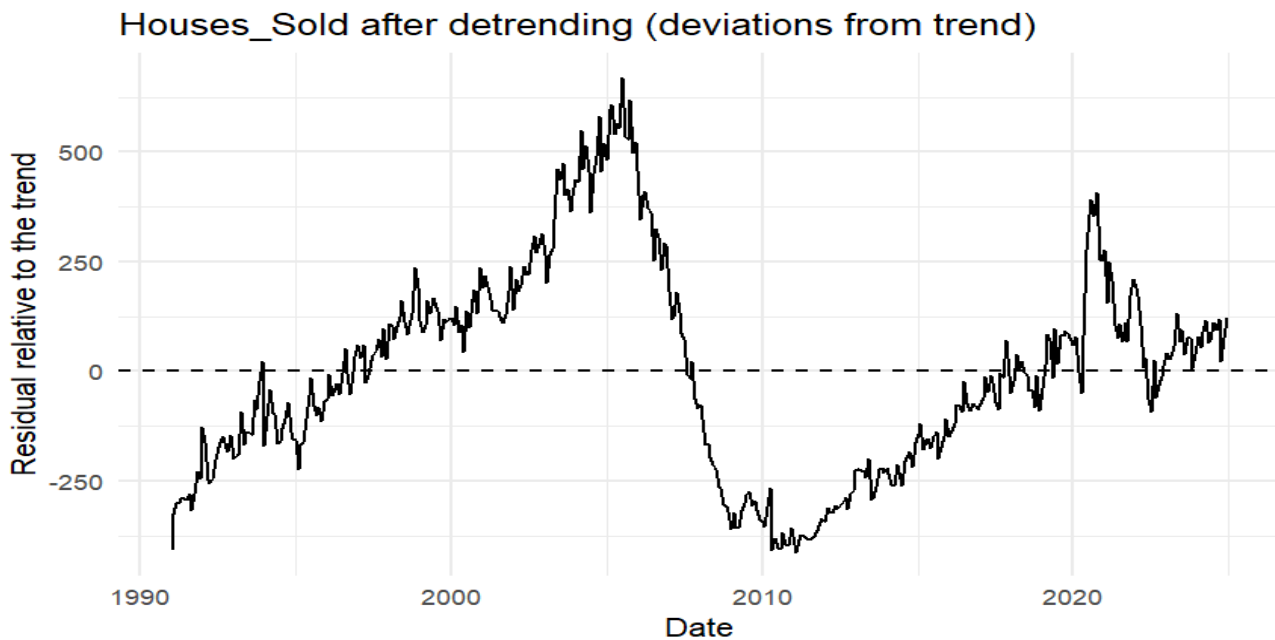


Figure 2

To highlight deterministic trends, Figure 1 plots existing home sales alongside a fitted linear time trend. While the series clearly exhibits boom–bust cycles, it also shows a mild downward drift over the full sample, particularly when comparing the early 1990s with the post-2010 period.

Figure 2 presents the detrended series, obtained as the residuals from regressing housing sales on the time index. The boom–bust dynamics remain, but the series now oscillates around zero, with positive values indicating above–trend months and negative values indicating below–trend months.

These figures motivate our decision to work with detrended data; removing the deterministic linear trend from each variable reduces the risk of spurious correlations driven by common trends and allows us to focus on short run fluctuations around the long run path of the housing market.

As a first step, we estimate a static linear regression using detrended variables. The dependent variable is detrended housing sales, and the regressors are the detrended macroeconomic variables:

$$\begin{aligned} \text{Houses_Sold}_t^{(dt)} &= \beta_0 + \beta_1 \text{Fund_Rate}_t^{(dt)} + \beta_2 \text{Houses_Built}_t^{(dt)} + \beta_3 \text{HPI}_t^{(dt)} + \beta_4 \text{Mortgage_Monthly}_t^{(dt)} \\ &+ \beta_5 \text{Unemployment}_t^{(dt)} + \beta_6 \text{CCI}_t^{(dt)} + u_t \end{aligned}$$

where the superscript (dt) denotes that each variable has been detrended. The error term u_t captures the remaining unexplained deviations of housing sales from their trend.

In addition to the baseline detrended OLS model, we estimate two extended specifications incorporating a COVID-19 dummy and either a quadratic or interaction term. The dependent variable remains detrended housing sales $\text{Houses_Sold}_t^{(dt)}$, and all regressors are detrended macroeconomic variables. The first extension allows for a non-linear effect of house prices by including a quadratic term in the detrended HPI and a COVID dummy (1 from March 2020 onward, 0 before) Covid_t to capture the pandemic's structural impact.

The specification can be written as:

$$\begin{aligned} \text{Houses_Sold}_t^{(dt)} &= \beta_0 + \beta_1 \text{Fund_Rate}_t^{(dt)} + \beta_2 \text{Houses_Built}_t^{(dt)} + \beta_3 \text{HPI}_t^{(dt)} + \beta_4 \text{HPI}_t^{(dt)2} \\ &+ \beta_5 \text{Mortgage_Monthly}_t^{(dt)} + \beta_6 \text{Unemployment}_t^{(dt)} + \beta_7 \text{CCI}_t^{(dt)} + \beta_8 \text{Covid}_t + u_t \end{aligned}$$

This model delivers an adjusted R^2 of approximately 0.905, which is essentially the same as the baseline linear specification.

Secondly, we consider a specification with an interaction between mortgage payments and consumer confidence, again including the COVID dummy. The interaction term $\text{Mortgage_Monthly}_t^{(dt)} \times \text{CCI}_t^{(dt)}$ allows the effect of confidence on housing sales to depend on financing conditions, when mortgage payments are unexpectedly high, changes in sentiment may influence sales differently than when financing costs are low. The model is:

$$\begin{aligned} \text{Houses_Sold}_t^{(dt)} &= \beta_0 + \beta_1 \text{Fund_Rate}_t^{(dt)} + \beta_2 \text{Houses_Built}_t^{(dt)} + \beta_3 \text{HPI}_t^{(dt)} + \beta_4 \text{Mortgage_Monthly}_t^{(dt)} \\ &+ \beta_5 \left(\text{Mortgage_Monthly}_t^{(dt)} \times \text{CCI}_t^{(dt)} \right) + \beta_6 \text{Unemployment}_t^{(dt)} + \beta_7 \text{CCI}_t^{(dt)} + \beta_8 \text{Covid}_t \\ &+ u_t \end{aligned}$$

The adjusted R^2 of this interaction model is about 0.905 as well, very close to the baseline specification.

Overall, all three detrended OLS models produce similar adjusted R^2 values (~0.905), and adding quadratic or interaction terms does not meaningfully improve fit. To maintain parsimony and interpretability, we retain the baseline detrended OLS specification.

Variable	Estimate ($\hat{\beta}$)	Std. Error	t-value	p-value
<i>Intercept</i>	0.00	3.63	0.00	1.00
<i>Fund_Rate_t^(dt)</i>	-6.30	4.05	-1.55	0.12
<i>Houses_Built_t^(dt)</i>	0.66	0.02	33.1	< 0.001
<i>HPI_t^(dt)</i>	0.89	0.25	3.54	< 0.001
<i>Mortgage_Monthly_t^(dt)</i>	-65.8	7.10	-9.27	< 0.001
<i>Unemployment_t^(dt)</i>	12.6	3.58	3.51	< 0.001
<i>CCI_t^(dt)</i>	2.31	0.49	4.74	< 0.001

Table 2

$$R^2 = 0.9069, \text{ Adjusted } R^2 = 0.9055, F\text{-statistic} = 651.2, p\text{-value} < 2.2 \times 10^{-16}$$

The table shows the baseline detrended OLS results, with an R^2 of about 0.90, indicating that macroeconomic factors explain most short-run deviations in housing sales. The F-test is highly significant ($p < 0.01$), confirming the joint relevance of the regressors.

For each regressor X_j in the baseline detrended OLS model we test the usual null and alternative hypotheses:

$$H_0: \beta_j = 0 \quad (\text{no partial effect of } X_j \text{ on detrended housing sales}),$$

$$H_1: \beta_j \neq 0 \quad (\text{non-zero partial effect}).$$

The test statistic is:

$$t_j = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)},$$

which under H_0 approximately follows a t distribution with 400 degrees of freedom. At the 5% significance level we reject H_0 when $|t_j| > 1.96$ (equivalently, when the p-value is below 0.05).

Table X reports the estimated coefficients, standard errors and t-statistics. At the 5% level we reject the null $H_0: \beta_j = 0$ for *Houses_Built_t^(dt)*, *HPI_t^(dt)*, *Mortgage_Monthly_t^(dt)*, *Unemployment_t^(dt)*, and *CCI_t^(dt)* as their t-values are large in absolute value and the corresponding p-values are well below 0.05. By contrast, the t-statistic for *Fund_Rate_t^(dt)* is about -1.55 with a p-value of 0.12, so we fail to reject H_0 .

Under standard OLS assumptions, the detrended regression coefficients can be interpreted as follows:

Fund_Rate_t^(dt): Not statistically significant, suggesting short-run deviations in the policy rate do not meaningfully affect housing sales once other factors are controlled.

Houses_Built_t^(dt): A one-unit above-trend increase in construction is associated with a 0.66-unit rise in detrended sales, indicating that stronger construction coincides with stronger sales.

HPI_t^(dt): A one-unit above-trend increase in house prices corresponds to a 0.89-unit increase in sales, showing that short-run price booms align with above-trend sales.

Mortgage_Monthly_t^(dt): A one-unit increase in above-trend mortgage payments reduces sales by about 65.8 units, highlighting the strong negative impact of unexpected financing costs.

Unemployment_t^(dt): A one-unit increase above trend is associated with a 12.6-unit rise in sales conditional on other variables, reflecting conditional correlations rather than a direct causal effect.

CCI_t^(dt): A one-unit increase in consumer confidence above trend raises sales by 2.31 units, consistent with more optimistic households buying more homes.

Next, we assess the statistical adequacy of the model by examining the residual diagnostic plots in Figure 3

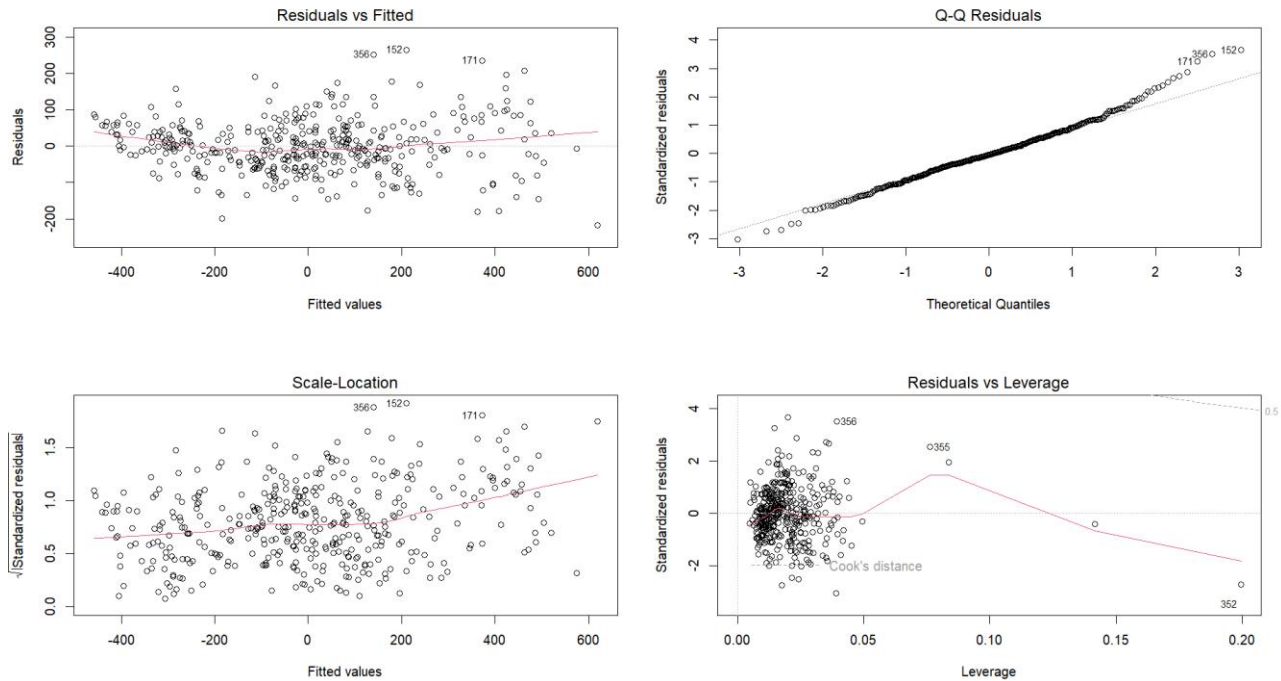


Figure 3

Figure 3 shows standard diagnostic plots for the detrended OLS regression. Residuals vs. fitted and scale–location plots indicate mild non-linearity and heteroskedasticity, with greater dispersion at higher fitted values. The Q–Q plot shows roughly normal residuals with slightly heavy tails, and the residuals vs. leverage plot reveals a few high-leverage points that are not strongly influential. Overall, the model provides a reasonable first approximation, but these issues motivate a closer look at the residuals' time-series properties

ACF of residuals from detrended OLS model

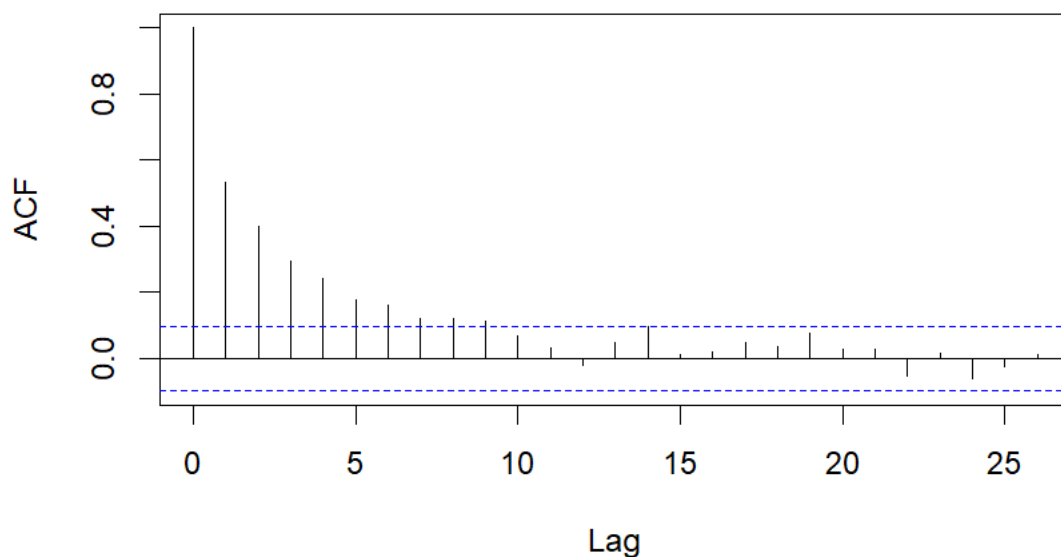


Figure 4

Figure 4 displays the autocorrelation function (ACF) of the detrended OLS residuals. Early lags show large positive autocorrelations that decay slowly, with several values exceeding the confidence bands, indicating that the residuals are not white noise. This persistent serial correlation suggests that the detrended OLS model fails to capture dynamic patterns, motivating the use of a dynamic time-series specification.

PACF of residuals from detrended OLS model

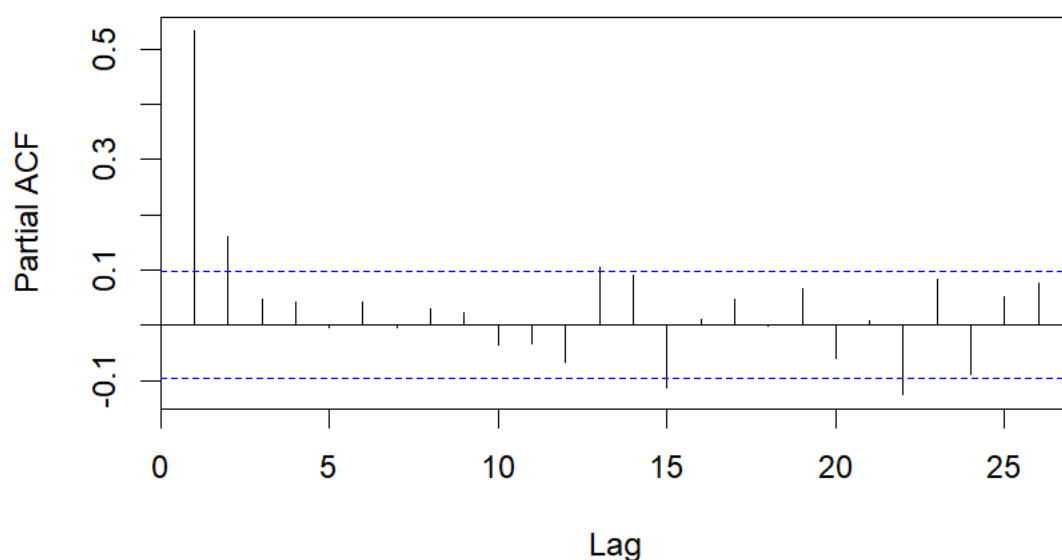


Figure 5

The PACF of the residuals (Figure X) shows a large spike at lag 1, with remaining lags small and mostly within the confidence bands. This indicates that each month's residual is strongly influenced by the previous month, while additional lags contribute little once lag 1 is accounted for. Combined with the ACF, this points to a low-order autoregressive structure, roughly AR(1), rather than white-noise residuals.

We also performed a Ljung–Box test on the residuals of the detrended OLS model, using 12 lags (one year of monthly data). The test statistic is:

$$Q(12) = 268.68, \quad df = 12, \quad p\text{-value} < 2.2 \times 10^{-16}$$

The Ljung–Box test (lag 12) strongly rejects the null of no autocorrelation, confirming that detrended OLS residuals exhibit significant serial correlation. This indicates that a static OLS model is inadequate, motivating a dynamic ARIMAX specification with explicit autoregressive terms.

ACF of residuals from ARIMAX(1,0,0)

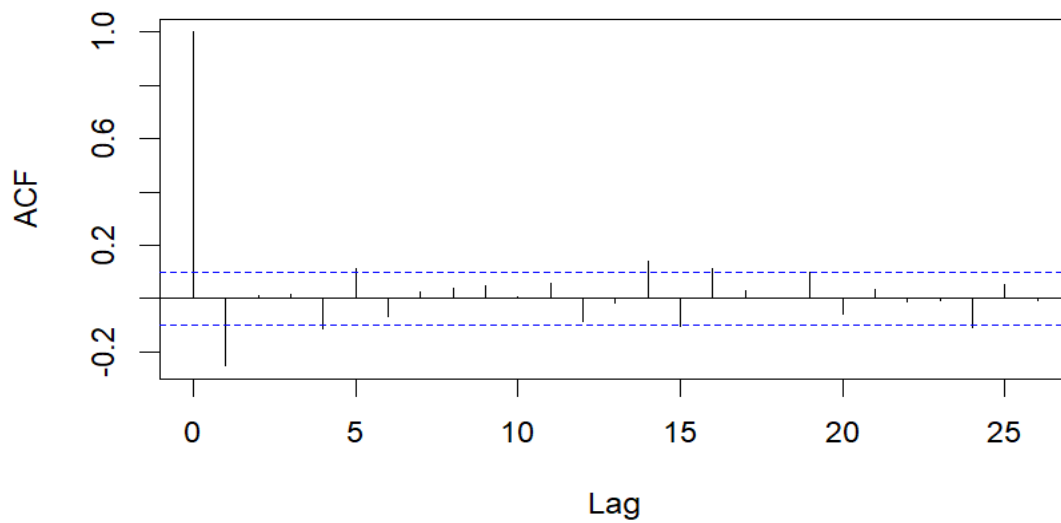


Figure 6

PACF of residuals from ARIMAX(1,0,0)

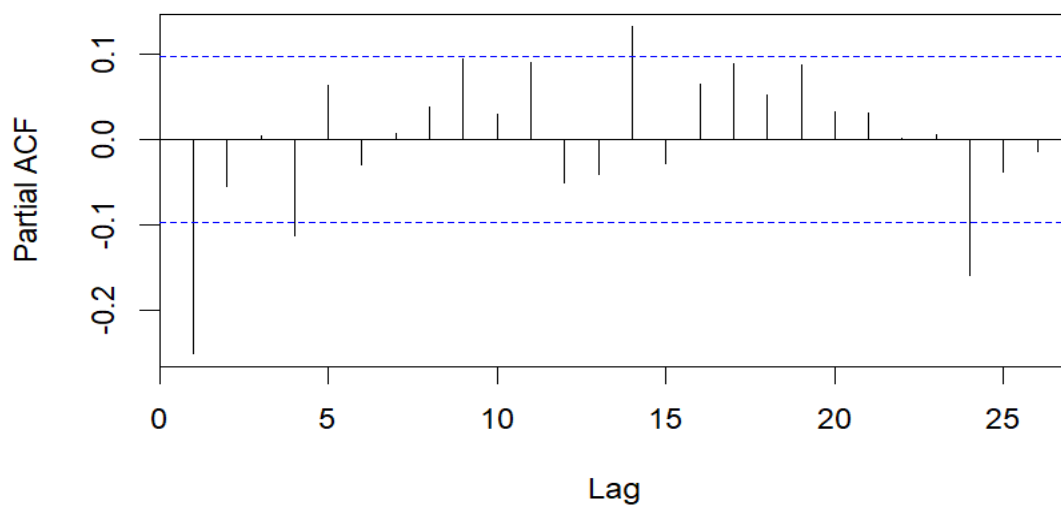


Figure 7

Figures 6 and 7 show the ACF and PACF of ARIMAX (1,0,0) residuals. Compared to detrended OLS, autocorrelations are much smaller, though a few early lags in the ACF still exceed the 95% confidence bands. The PACF shows a strong lag-1 spike and a few isolated medium-lag spikes, with most others within the bands. Overall, the AR (1) term captures most persistence, but some residual dependence remains.

This is confirmed by the Ljung–Box test on the ARIMAX (1,0,0) residuals using 12 lags. The test statistic is:

$$Q(12) = 44.98, \quad df = 12, \quad p\text{-value} < 1.0 \times 10^{-5}$$

Since the p-value is far below 0.05, we reject the null of no autocorrelation up to lag 12. This confirms that, although the AR (1) term reduces persistence, the residuals still exhibit significant serial correlation, so we move to an ARIMAX (2,0,0) specification.

ACF of residuals from ARIMAX(2,0,0)

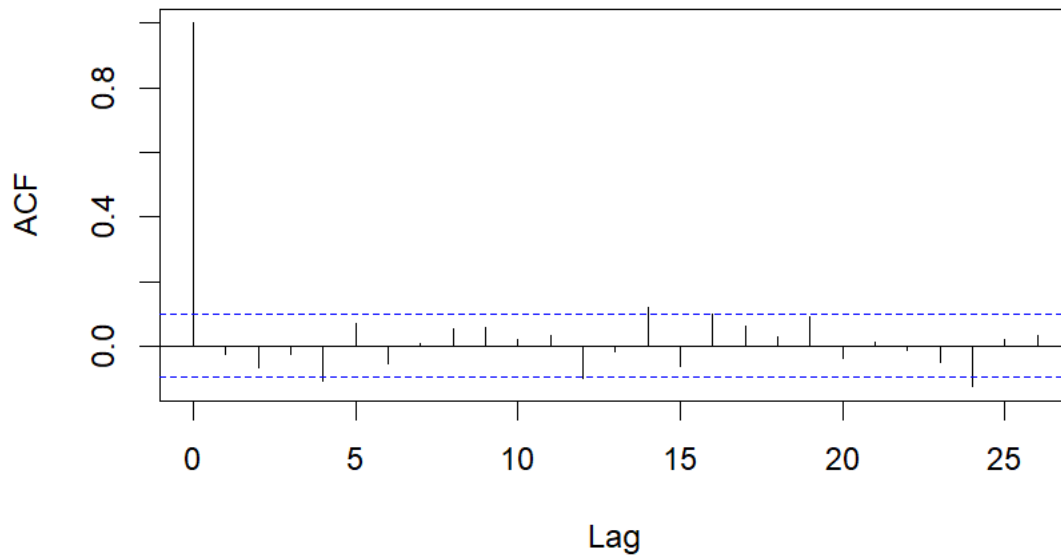


Figure 8

PACF of residuals from ARIMAX(2,0,0)

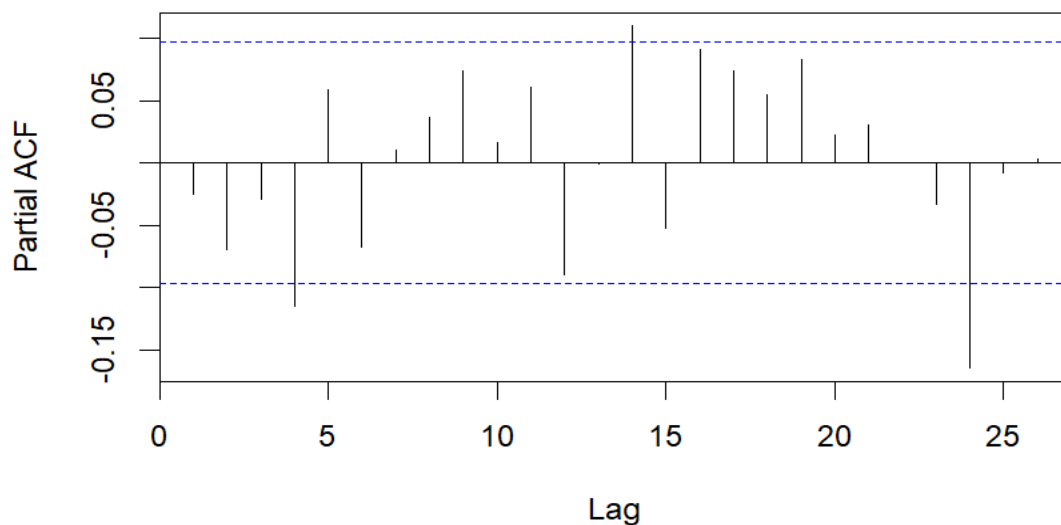


Figure 9

Overall, the ARIMAX (2,0,0) model performs well: residual ACF–PACF plots show only a trivial lag-0 spike, with all other autocorrelations small and within the 95% confidence bounds, displaying no clear pattern.

This visual evidence is confirmed by the Ljung–Box test, which yields:

$$Q(12) = 17.93, \quad df = 12, \quad p\text{-value } 0.12 > 0.05$$

The Ljung–Box test no longer rejects the null of uncorrelated residuals up to lag 12, indicating that the AR (2) term absorbs the remaining serial correlation from the ARIMAX (1,0,0) model. With a lower AIC (4329.4 vs. 4354.1), the ARIMAX (2,0,0) provides a better fit despite

increased complexity. We therefore adopt this model as our preferred dynamic specification and use it to analyze the short-run effects of macroeconomic variables on detrended housing sales.

$$\begin{aligned} \text{Houses_Sold}_t^{(dt)} &= \alpha + \phi_1 \text{Houses_Sold}_{t-1}^{(dt)} + \phi_2 \text{Houses_Sold}_{t-2}^{(dt)} + \beta_1 \text{Fund_Rate}_t^{(dt)} + \beta_2 \text{Houses_Built}_t^{(dt)} \\ &+ \beta_3 \text{HPI}_t^{(dt)} + \beta_4 \text{Mortgage_Monthly}_t^{(dt)} + \beta_5 \text{Unemployment}_t^{(dt)} + \beta_6 \text{CCI}_t^{(dt)} + u_t \end{aligned}$$

Variable	Estimate	Std. Error	t-value	p-value
<i>ar1</i>	0.723	0.048	15.04	< 0.001
<i>ar2</i>	0.254	0.048	5.26	< 0.001
<i>Intercept</i>	-10.128	90.495	-0.11	0.911
<i>Fund_Rate</i> _t ^(dt)	-9.963	11.585	-0.86	0.390
<i>Houses_Built</i> _t ^(dt)	0.083	0.032	2.60	0.00943
<i>HPI</i> _t ^(dt)	1.228	1.081	1.14	0.256
<i>Mortgage_Monthly</i> _t ^(dt)	-39.724	11.057	-3.59	0.000327
<i>Unemployment</i> _t ^(dt)	-9.927	4.282	-2.32	0.0204
<i>CCI</i> _t ^(dt)	0.693	0.543	1.28	0.202

Table 3

Table X shows the ARIMAX (2,0,0) estimates. Both AR (1) and AR (2) terms are positive and highly significant, indicating strong two-month persistence in detrended housing sales. Among macro regressors, only *Houses_Built*_t^(dt) (small positive effect), *Mortgage_Monthly*_t^(dt) ~ (-40), and *Unemployment*_t^(dt) ~ (-10) remain significant at 5%, showing that higher-than-trend construction modestly boosts sales, while unexpected increases in financing costs or unemployment sharply reduce them. The coefficients on *Fund_Rate*_t^(dt), *HPI*_t^(dt), and *CCI*_t^(dt) are no longer significant, suggesting their marginal short-run impact is limited once AR dynamics are accounted for.

CONCLUSION



Conclusion

This project examined which macroeconomic factors drive short-run deviations in U.S. new single-family home sales from 1991 to 2024. Using detrended monthly data and dynamic ARIMAX modelling, we isolated cyclical movements in housing activity and identified the variables most strongly associated with above- or below-trend sales. The preferred ARIMAX (2,0,0) specification effectively captured serial correlation that persisted in static OLS models and provided a robust framework for interpreting short-run dynamics.

Our analysis shows that housing completions, mortgage payment deviations, and unemployment are the key short-run predictors. Months with above-trend construction activity tend to coincide with modestly higher sales, while unexpected increases in mortgage payments and unemployment are associated with substantial declines. Variables such as the Federal Funds rate, house prices, and consumer confidence, though significant in some static regressions, lose predictive power once dynamic persistence is accounted for, highlighting the dominant role of financing costs, labor markets, and supply conditions in driving short-term fluctuations.

These findings have practical implications. Policymakers seeking to stabilize housing demand should be aware of the sensitivity of sales to unexpected changes in mortgage costs. While housing supply provides useful information on current market conditions, it reacts more slowly to shocks and cannot fully offset rapid swings in demand. The results, while not strictly causal, benefit from detrending and dynamic modelling that mitigate spurious correlations and capture short-run propagation of shocks.

Limitations include reliance on national aggregates, linear detrending, potential endogeneity of some regressors, and monthly data frequency. Future work could explore regional-level heterogeneity, alternative detrending methods, distributed-lag or seasonal effects, and causal identification strategies such as instrumental variables or natural experiments to strengthen inference. Overall, this study highlights the central role of financing, labor markets, and construction activity in shaping short-run housing market dynamics, while providing a framework for more granular or causal analyses in future research.



CITATIONS

The citations we used here are in APA 7th edition, which uses in-text author–date format (e.g., Case, Shiller, & Thompson, 2012) and an alphabetical references list. Article titles are in sentence case, journal titles and volumes are italicized, and URLs are listed without a period.

Case, K. E., Shiller, R. J., & Thompson, A. (2012). What have they been thinking? Home buyer behavior in hot and cold markets. *Brookings Papers on Economic Activity*, 2012(2), 265–298. <https://doi.org/10.1353/eca.2012.0015>

Federal Housing Finance Agency (FHFA). (n.d.). *House Price Index (HPI)*. Retrieved December 12, 2025, from <https://www.fhfa.gov/data/hpi>

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