Subprime Crisis Revisited: Effect of Payment Shock on Foreclosure Rates

Lynne Kelly
Howard University

Debby Lindsey-Taliefero
Howard University

This study investigates how payment shock from interest rate resets affects subprime mortgage foreclosure rates. Using robust econometric techniques (OLS, 2SLS, GMM), it isolates the causal effect of payment shock while accounting for house prices and borrowers' ability to pay. Our findings show a significant positive link (27%) between payment shock and foreclosure rates. It highlights economic stability's importance, showing negative correlations between foreclosure rates and ability to pay, as well as foreclosure rates and house prices. Lagged foreclosure rates show a persistent effect. The GMM model provides the most reliable estimates by addressing endogeneity, heteroscedasticity, and serial correlation.

Keywords: payment shock, interest rate reset, subprime mortgage crisis, adjustable rate mortgage, foreclosure rates

INTRODUCTION

Between 2000 and 2009, based on the National Delinquency Survey (Mortgage Bankers Association), 4.3% of all conventional loans in service were foreclosure starts. Of that, 22.8% were subprime adjustable-rate mortgages (ARMs). Even more alarmingly, 16.3% of the total foreclosure starts involved subprime ARMs that had experienced payment shock, where the monthly payment amount increased. Nearly one-quarter of all conventional loans that entered foreclosure during that decade were subprime ARMs, and over 70% of those foreclosures involved loans with payment shock. These statistics highlight how subprime ARMs, especially those with payment shock, contributed disproportionately to the foreclosure crisis.

Research on subprime ARMs provides mixed evidence for the effect of payment shock on mortgage defaults or foreclosures. Studies by Foote et al. (2009) and Ho and Pennington-Cross (2006) found no clear link between payment increases and defaults, a precursor to foreclosure. Ho and Pennington-Cross (2006) and Ambrose et al. (2005) observed a significant prepayment rise following interest rate adjustments. This suggests that borrowers facing higher payments opted to sell their homes or refinance instead of defaulting. However, it is important to note that the authors examined the effects of payment shock during periods of rising house prices, which provided borrowers with equity buffers that mitigated foreclosure risk at interest rate resets.

Studies by Ambrose et al. (2005), Ho and Pennington-Cross (2006), Cagan (2007), and Qi et al. (2021) focused on the impact of initial interest rate adjustments on defaults for hybrid ARMs or home equity lines of credit (HELOCs). Examining loans originated from 1992 to 1999 and monitored through mid-2000, Ambrose et al. (2005, p. 781) found a sharp increase in defaults coinciding with the first adjustment. Similarly, Ho and Pennington-Cross (2006, p. 22) observed a significant moderate increase in defaults during the first adjustment period for loans issued between 1998 and 2005. Cagan (2007, p. 4) found that 12 percent of subprime loans and 32 percent of teaser loans would default due to reset. Default spikes often are the precursor to upticks in potential foreclosure risk. Qi et al. (2021, p. 451) observed that the first payment shock on HELOCs positively and significantly affects default risk. Their empirical analysis showed that the monthly probability of default increases by approximately 2.3 times and the annual probability of default on a $1 million property.

Conversely, other studies have found a positive correlation between payment shock and foreclosure rates (Cagan, 2007; Edmiston & Zalneraitis, 2007). Cagan (p. 2) examined over 8 million adjustable-rate first mortgages originated between 2004 and 2006. The study carefully investigated the current equity and payment reset levels to project the number of loans likely to face the double pressure of a large reset, assuming the properties did not possess sufficient equity to enable a sale or refinance. The study projected 1.1 million foreclosures with losses of about $112 billion, spread over six years or more. Edmiston and Zalneraitis (2007, p. 125) likewise found a surge in foreclosure rates. They found that the foreclosure rates for subprime ARMs increased from 3.9 percent in the 2nd quarter of 2006 to 8 percent in the 2nd quarter of 2007. Edmiston and Zalneraitis note that increases in short-term interest rates and payment resets on these nontraditional mortgages are largely responsible for the increase in foreclosure rates of ARMs.

To further explore this complex relationship, investigate the interplay between payment shock arising from interest rate adjustments on subprime ARMs, house price fluctuations, and their combined effect on foreclosures. We employ advanced statistical methods that address the data's endogeneity, heteroscedasticity, and autocorrelation issues.

METHOD

We employed a regression model approach to investigate how payment shock influences subprime ARM foreclosure rates. Specifically, we regressed foreclosure rates on the house price appreciation rates (HPA), payment shock from interest rate resets, and factors that affect the ability to pay. Our estimation procedures included ordinary least squares (OLS), two-stage least squares (2SLS), and generalized method of moments (GMM) techniques using Statistical Analysis System (SAS) software.

The OLS technique established a baseline model that captures the relationship between the regressors and foreclosure rates. The 2SLS approach was used to address potential endogeneity issues, and the GMM method accounted for potential heteroscedasticity, serial correlation, and endogeneity in the data. To assess the model fit and the significance of the regressors, we conducted a comprehensive set of diagnostic tests, including tests for endogeneity, heteroscedasticity, serial correlation, normality, instrumental variable validity, overidentifying restrictions, collinearity, model efficiency, and statistical significance of the regressors. By employing this rigorous analytical approach, we provide a robust and comprehensive evaluation of the impact of payment shock and other variables on foreclosure rates for subprime adjustable-rate mortgages.

The quarterly data used in the analysis came from various sources, including the Mortgage Bankers Association (MBA) for foreclosure rate data, the Federal Housing Finance Agency (FHFA) for house price indices, the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS) for macroeconomic indicators, the United States Bureau of Census (USBC) for demographic information, the Federal Home Loan Mortgage Corporation (FHLMC) for mortgage market characteristics, and the Bank of England (BOE) for the 3-month London Interbank Offered Rate (LIBOR). These data sources were combined into a comprehensive dataset to rigorously examine the intricate mechanisms driving foreclosure dynamics in the subprime market.

In modeling foreclosures with house prices as a regressor, we recognize a potential endogeneity issue, which several researchers have identified in their work (Campbell et al., 2011, p. 2124; Calomiris, 2013, p. 26; Loberto, 2023, p. 399; Mian et al., 2014, p. 5). Hill et al. (2021, p. 113) present a context for the interplay between foreclosure rates and house price appreciation, termed simultaneity, feedback loop, or reciprocal endogeneity, which can explain the endogeneity between these two factors. This feedback loop best describes the dynamic relationship we aim to capture in our analysis.

The feedback loop operates as follows: As house prices decrease, more homeowners find themselves in negative equity, owing more on their mortgage than their home's value. Homeowners with negative equity are more likely to default on their mortgage payments and go into foreclosure, as they have less financial incentive to keep paying. When foreclosures increase, they add more housing supply to the market, putting further downward pressure on house prices. The declining house prices lead to more homeowners being underwater on their mortgages, feeding back into higher foreclosure rates. This creates a self-reinforcing downward spiral or "feedback loop" where falling prices lead to more foreclosures, which leads to further price declines. Conversely, the reverse causality also holds true when rising house prices reduce foreclosure risk and supply. The feedback loop between foreclosures and house prices amplifies the initial shock and makes housing cycles more volatile, as evidenced during the 2006-2012 housing bust (Federal Housing Finance Agency, 2007, p. 11).

Model Specification

We estimated a foreclosure rate model using OLS as a baseline, which does not account for foreclosure and house price endogeneity. We estimated foreclosure rates using 2SLS and GMM to control for endogeneity. The study aims to disentangle the complex, reciprocal relationship between foreclosure rates and house price fluctuations while isolating the effects of payment shock resulting from interest rate resets. The models used in this study are presented below.

Model 1: OLS Procedure

$$FR_t = \text{Ƅ}_0 + \text{Ƅ}_1 Earnpow_t + \text{Ƅ}_2 HPA_t + \text{Ƅ}_3 PMTShock_t + \text{Ƅ}_4 DFR_{t-1} + u_t \quad (1)$$

Model 2: 2SLS or GMM Procedure

First-Stage Equation: $HPA_{hat_t} = \omega_0 + \omega_1 Earnpow_t + \omega_2 PMTShock_t + \omega_3 DHPA_t + \omega_4 DFR_{t-1} + \omega_5 RCCHSI_t + v_t \quad (2)$

Second-Stage Equation: $FR_t = \text{Ƅ}_0 + \text{Ƅ}_1 Earnpow_t + \text{Ƅ}_2 HPA_{hat_t} + \text{Ƅ}_3 PMTShock_t + \text{Ƅ}_4 DFR_{t-1} + \varepsilon_t \quad (3)$

where:

FR_t =	foreclosure rates in period t
DFR_{t-1}=	lagged first difference in the foreclosure rate in period t
HPA_t =	house price appreciation rates in period t
HPA_hat_t =	estimated house price appreciation rates in period t
$DHPA_t$ =	first difference in the HPA in period t
$Earnpow_t$ =	income and employment index in period t
$PMTShock_t$ =	mortgage payment shock in period t
	1 = positive payment shock at initial rate reset for 2/28 hybrids
	0 = no payment shock at initial rate reset for 2/28 hybrids
$RCCHSI_t$=	residential construction cost and housing start index in period t
μ_t =	OLS residuals for the HPA equation at period t
v_t =	2SLS or GMM: First-stage residuals for the HPA equation in period t
ε_t =	2SLS or GMM: Second-stage residuals for the FR equation in period t

Data

Table 1 presents the variables used in the foreclosure models, their sources, and whether the authors calculated them. The table discussion focuses on the five calculated variables: the first difference in the foreclosure rates, the first difference in the house price appreciation rates, the income and employment index, the residential construction cost and housing start index, and mortgage payment shock.

To calculate the first difference in foreclosure rates, we took the difference between consecutive observations of foreclosure rates at periods t and t-1. The representation is commonly $DFR_t = FR_t - FR_{t-1}$, where FR_t and FR_{t-1} are the values of foreclosure rates in periods t and t-1, respectively. Similarly, the researchers calculated the first difference in house price appreciation rates as $DHPA_t = HPA_t - HPA_{t-1}$, where HPA_t and HPA_{t-1} are the values of house price appreciation rates in periods t and t-1, respectively. The first and lagged-first difference variables are explanatory variables that capture the temporal dependence structure of foreclosure rates and house price appreciation changes.

Principal Component Analysis (PCA) was used to derive the Income and Employment Index ($Earnpow_t$) and Residential Construction Cost and Housing Start Index ($RCCHSI_t$) to mitigate multicollinearity. The PCA for $Earnpow_t$ showed a notable relationship between employment growth ($Empg_t$) and real domestic income growth ($Rdincomeg_t$). $Empg_t$ (M = 0.60, SD = 1.68) exhibited higher variability than $Rdincomeg_t$ (M = 2.54, SD = 1.54). A positive covariance of 1.86 between $Empg_t$ and $Rdincomeg_t$ suggested their tendency to move together, supported by a correlation coefficient equal to 0.72 and a significant p-value (<.001). $Empg_t$ and $Rdincomeg_t$ exhibited high communalities, 0.830 to 0.887, respectively. The first component explained 86.11% of the total variance, with loadings of approximately 0.942 for $Empg_t$ and 0.911 for Rdincomegt, showing their significant relationship.

The PCA for $RCCHSI_t$ revealed a strong relationship between construction cost ($CCOST_t$) and housing start index (HS_t). Housing starts had higher variability (-2.94, SD = 12.95) than $CCOST_t$ (M = 3.16, SD = 4). A positive covariance of 26.691 between $CCOST_t$ and HS_t suggested they rise together, supported by a correlation coefficient equal to 0.795 and a significant p-value <.001. $CCOST_t$ and HS_t exhibited high communalities, 0.898, with one component explaining 89.80% of the total variance. Loadings of 0.947 for both $CCOST_t$ and HS_t on the extracted component reinforced their strong relationship.

The payment shock is based on 2/28 hybrid mortgages, which were primarily originated for subprime borrowers. This type of mortgage has a 2-year period with a fixed interest rate (teaser rate) followed by a 28-year period with adjustable interest rates. During the latter period, interest rates reset every six months to a rate equal to the 6-month London Interbank Offered Rate (LIBOR) plus a margin.

The payment shock is the percent change in the mortgage payment that results from the initial interest rate reset. The initial mortgage payment is based on the median US house price (USPS), measured in dollars, the initial teaser rate, and a 30-year loan term. At the initial reset date, the mortgage payment is based on the remaining loan balance, the reset rate (LIBOR plus margin), and the remaining 28-year loan term. The average margin over the sample period is 6.22%. The terms for 2/28 hybrid mortgages only allow for positive payment shock because the teaser rate represents the interest rate floor. In other words, the reset rate is set equal to the teaser rate whenever it falls below the teaser rate, and the resulting payment shock is zero. So, if there is a positive payment shock at the initial interest rate reset, we coded the variable as 1; otherwise, we coded it as 0. Fifty-eight percent of our observations typically experience a positive payment shock. For details on the 2/28 hybrid mortgage design, see Bhardwaj and Sengupta (2012).

TABLE 1
DATA USED FOR MODELING FORECLOSURE AND HOUSE PRICE APPRECIATION RATES

Variable	Description	Source
FR_t	Foreclosure Rates	MBA[a]
DFR_{t-1}	Lagged 1st Difference in the Foreclosure Rates	MBA, calculated
HPA_t	House Price Appreciation Rates	FHFA[b]
$DHPA_t$	1st Order Difference in the HPA_t	FHFA, calculated
$Earnpow_t$	Income and Employment index	BLS[c] & BEA[d], PCA calculated
$PMTShock_t$	Mortgage Payment Shock	BoE[f], USCB & HUD[g] calculated
	1 = positive payment shock at initial rate reset for 2/28 hybrids 0 = no payment shock at initial rate reset for 2/28 hybrids	
$RCCHSI_t$	Residential construction cost and housing start index	BLS & HUD, PCA calculated

[a] Mortgage Bankers Association (MBA), National Delinquency Survey. Retrieved February 6, 2024 from https://www.mba.org/news-and-research/research-and-economics/single-family-research/national-delinquency-survey
[b] US Federal Housing Finance Agency (FHFA), All-Transactions House Price Index for the United States [USSTHPI]. Retrieved February 6, 2024, from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/USSTHPI, February 6, 2024.
[c] US Bureau of Labor Statistics, Employment Levels (BLS). Retrieved February 6, 2024, from https://beta.bls.gov/dataViewer/view/timeseries/LNU02000000
[d] US Bureau of Economic Analysis (BEA), Real gross domestic product per capita. Retrieved February 6, 2024, from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/A939RX0Q048SBEA
[e] Principal Component Analysis
[f] Bank of England (BoE), 3-month London Interbank Offered Rate (LIBOR) in the United Kingdom. Retrieved February 6, 2024, from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/LIOR3MUKM
[g] US Census Bureau (USCB) and US Department of Housing and Urban Development (HUD), Median Sales Price for New Houses Sold in the United States [MSPNHSUS]. Retrieved February 6, 2024, from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/MSPNHSUS

RESULTS AND DISCUSSION

This section presents the findings of our analysis of the impact of interest rate adjustments on subprime mortgages, house price fluctuations, and their combined effect on foreclosure rates. We provide a detailed examination through five key segments: Descriptive Statistics, Model Diagnostics, Model Fit and Significance, Coefficient Interpretation and Significance, and Comparison of Models. The discussion interweaves the results to offer an inclusive interpretation and place our findings in the broader research landscape.

Descriptive Statistics

Table 2 presents descriptive statistics for several key variables related to foreclosure rates and housing market dynamics. Foreclosure rates have a mean of approximately 2.966, with a standard deviation of 1.755, suggesting moderate variability around the mean. The lagged first difference in foreclosure rates has a mean of 0.07, suggesting a relatively small average change from one period to the next. House price appreciation rates (HPA_t) demonstrate overall positive appreciation with a mean of 4.482 but substantial variability (SD = 5.7). The first difference in house price appreciation rates shows a slightly negative mean (-0.253), implying an average decrease in appreciation rates. Payment shock is experienced by 58% of our observations, showing resets are common in the dataset. These statistics provide insights into central tendencies and variations in the variables, laying the groundwork for further analysis and interpretation in the study context.

TABLE 2
DESCRIPTIVE STATISTICS FOR FORECLOSURE AND HOUSE PRICE APPRECIATION RATES

Descriptive Statistics

Variable	Mean	SD	Min	Max
$Earnpow_t$	0.068	0.859	-1.535	1.764
FR_t	2.966	1.755	1.360	6.910
DFR_t	0.070	0.552	-1.390	1.240
HPA_t	4.482	5.700	-7.151	11.937
DFR_{t-1}	0.058	0.563	-1.390	1.240
$RCCHSI_t$	0.000	1.010	-2.366	1.610
$PMTShock_t$	0.580	0.501	0.000	1.000

Note. n = 40.

Model Diagnostics

Pearson Correlation Coefficient

In Table 3, $RCCHSI_t$ and $Earnpow_t$ correlation coefficient values are r(38) = .93 (p = .001) and r(38) = .623 (p = .001), respectively. These are the key instruments in the first stage of 2SLS, and the results show they are relevant in explaining a significant portion of the HPA_t variation. $Earnpow_t$ is correlated with $RCCHSI_t$ [r(38) = .603, p = .001] and with $PMTShock_t$ [r(38) = .401, p = .01]. $DHPA_t$ is correlated with $PMTShock_t$ [r(38) = .441, p = .01] and with DFR_{t-1} [r(38) = .37, p = .05]. Here, the absolute value of the Pearson correlation coefficient among the instruments themselves or between instruments and exogenous covariates for the first-stage estimate is less than 0.8. It shows no serious problem with collinearity (Shrestha, 2020, p. 41). Please note that the observed bivariate interactions do not conclude the impact of the regressors on our system outcome variable, foreclosure rates. As a result, other rigorous tests to diagnose collinearity, including eigenvalues, condition indexes, and variance proportions, are discussed later in the article.

Collinearity

The collinearity diagnostics in Table 4 provide insights into potential multicollinearity issues in the regression models. The condition index (CIDX) measures collinearity, with higher values showing stronger collinearity. CIDX <15 usually means weak multicollinearity, 15 < CIDX < 30 is evidence of moderate multicollinearity, and CIDX > 30 shows strong multicollinearity, while an index above 100 is a sign of potential disaster in estimation (Shrestha, 2020, p. 40). The highest condition index is 4.966 for the 2SLS model, 4.756 for the GMM model, and 4.635 for the OLS model, all below the threshold of 15. These results suggest that multicollinearity is not a severe issue in the models.

A two-step approach was used to assess multicollinearity. In step (1), the Condition Indexes, we checked for CIDXs exceeding a threshold (typically 15-30, with 30 being common) [Kumar, n.d.]. High CIs imply potential multicollinearity. In Step 2, researchers examined the corresponding variance proportions if a CIDX was above 30. Any variable with a CIDX > 30 and two variance proportions exceeding 90% suggested a collinearity problem involving that variable [Kumar, n.d.]. Fortunately, all condition indices in our models fell below the critical threshold of 30. This shows that no severe multicollinearity is present that would significantly affect the estimation of the regression coefficients.

TABLE 3
PEARSON CORRELATION ANALYSIS

	First Stage: House Price Appreciation Rates										
Variables	HPA_t		$Earnpow_t$		$PMTShock_t$		DFR_{t-1}		$RCCHSI_t$		$DHPA_t$
HPA_t	-										
$Earnpow_t$	0.623	***	-								
$PMTShock_t$	0.058		0.401	**	-						
DFR_{t-1}	-0.079		0.129		0.307		-				
$RCCHSI_t$	0.930	***	0.603	***	-0.021		-0.056		-		
$DHPA_t$	0.291		-0.010		-0.441	**	-0.390	*	0.275		-

Note: *Correlation is significant at the 0.05 level (2-tailed).** Correlation is significant at the 0.01 level (2-tailed). *** Correlation is significant at the 0.001. level (2-tailed). n = 40.
Source: Authors' Computation.

TABLE 4
ARM COLLINEARITY DIAGNOSTICS

				Proportion of Variation				
Proc[a]	Dimension	Eigenvalue	CI[b]	Constant	$Earnpow_t$	HPA_t	$PMTShock_t$	DFR_{t-1}
OLS	1	2.500	1.000	0.026	0.023	0.038	0.037	0.010
	2	1.028	1.560	0.000	0.025	0.042	0.012	0.665
	3	0.990	1.589	0.060	0.285	0.004	0.013	0.082
	4	0.366	2.615	0.009	0.114	0.372	0.339	0.242
	5	0.116	4.635	0.906	0.553	0.544	0.598	0.002
2SLS	1	2.532	1.000	0.023	0.020	0.032	0.036	0.010
	2	1.028	1.569	0.000	0.023	0.034	0.012	0.666
	3	0.990	1.599	0.054	0.256	0.003	0.013	0.081
	4	0.347	2.701	0.015	0.089	0.303	0.392	0.243
	5	0.103	4.966	0.908	0.613	0.628	0.547	0.000
GMM	1	2.750	1.000	0.023	0.027	0.026	0.041	0.009
	2	0.972	1.682	0.007	0.017	0.007	0.001	0.889
	3	0.820	1.831	0.029	0.642	0.001	0.024	0.049
	4	0.336	2.862	0.052	0.014	0.172	0.817	0.044
	5	0.122	4.756	0.889	0.300	0.795	0.118	0.011

[a] Procedure.
[b] Condition Index.
Source: Authors' Computation.

Instrument Validity

To test the validity of the instruments, we used the F-statistic from the first-stage regression; HPA_t regresses on the instruments (See Table 5). The R^2 equals 0.881, and the F-statistic was statistically significant [$F(5, 34) = 50.45$, $p = .0001$]. This significant F-test shows that at least one of the first-stage regression coefficients is not equal to zero, and the regression model explains a significant portion of the variation in the HPA_t. Based on the rule of thumb for a single endogenous variable, a significant F-statistic above 10 exhibits that the instruments are not weak (Baum et al., 2003, p. 15).

Endogeneity Tests

To check for endogeneity between FR_t and HPA_t, we use the Durbin–Wu–Hausman (DWH) test, which has a chi-square distribution (χ^2). In Table 5, the initial DWH test conducted with our sample size (n=40) did not statistically reject endogeneity (χ^2 (5) = 2.29, p = 0.808). Still, the literature acknowledges the potential problem between FR_t and HPA_t. To investigate this further, we employed Monte Carlo simulations to assess the DWH test's power across different sample sizes (Chmelarova, 2007, p. 23). The simulations revealed that with a larger sample size (e.g., n=120, mimicking monthly data collection), the DWH test became statistically significant (χ^2 (5) = 26.35, p < 0.0001), suggesting endogeneity might be present. Increasing the frequency or granularity of our dataset may provide more detailed insights and allow for more precise analysis. Given this possibility and the existing literature, we also opted to use instrumental variable (IV) regression techniques, as presented in Table 5, to address potential endogeneity bias and get more reliable estimates.

Serial Correlation, Heteroscedasticity, and Normality

In Table 5, the heteroscedasticity [White's Test (13) = 12.86, p = .4583], serial correlation [Godfrey's Test = 2.3, p = .1261], and normality [Henze-Zirkler T's Test = 0.43, p = .1445] tests yield insignificant results across all models. These results suggest the residuals follow a normal distribution, and there is no evidence of serial correlation or heteroscedasticity (Young, 2017, p. 165, 225).

Specification Tests

Hansen's tests for overidentifying restrictions yielded insignificant J-statistics, $J(1) = 1.07$, p = .309 for 2SLS and $J(1) = 1.10$, p = .293 for GMM, showing that the instruments used in the model are valid, implying the overidentifying restrictions are valid (i.e., the instruments are relevant and not overly informative). Above all, the Hansen J tests' p-values are within the recommended acceptable range of $.05 \leq P(\chi^2) < .8$ but slightly above the optimal range of $.1 \leq P(\chi^2) < .25$ (Labra & Torrecillas, 2018, p. 48). The OLS model specification test is insignificant [First and Second Moment Specification statistic χ^2equals 13.63 (df = 13, p = .408), showing that the errors are homoscedastic and are independent of the regressors. According to White (1980, p. 823), the OLS model specification is valid.

Model Results

Model Fit and Significance

All three models are statistically significant (p-value < 0.001) and have high R-squared values (above 0.91), indicative of a good fit. We also conducted a likelihood ratio (LR) test to assess the overall significance of each model. The LR tests were statistically significant $\chi^2(4) = 472.28$, p = .0001 for OLS; $\chi^2(4) = 408.18$, p = .0001 for 2SLS; and $\chi^2(4) = 351.11$, p = .0001 for GMM, showing the model with the predictors provided a significantly better fit to the data than the null model with only the intercept.

Coefficient Interpretation and Significance

Notably, the $PMTShock_t$ variable, denoting mortgage payment shock, emerges as a crucial determinant across all estimation procedures. In Table 5, the unstandardized coefficients associated with $PMTShock_t$ consistently show statistical significance with p-values below the conventional threshold of 0.001 (b_{OLS} = 0.7238, 99% CI [0.2316, 1.216]; b_{2SLS} = 0.7567, 99% CI [0.2572, 1.2563]; b_{GMM} = 0.7875 [0.4146, 1.1604]). Specifically, mortgage borrowers experiencing a payment shock have foreclosure rates about 0.7875 or 27 percent [(0.7875/2.966) × 100] higher than mortgages without a payment shock, ceteris paribus.

The above finding is consistent with other positive payment shock results for defaults by Qi et al. (2021, p. 251), Ho and Pennington-Cross (2006, p. 22), and Ambrose et al. (2005, p. 324). Other researchers, Foote et al. (2008, p. 48) and Ho and Pennington-Cross (2006, p. 18), did not find a clear link between payment increases and defaults. However, these studies capture pre-crisis housing market conditions. Thus, borrowers were likely to have positive equity and more options after interest resets, such as loan repayment and refinancing. With attention to foreclosures, Cagan (2007, p. 4) and Edmiston and Zalneraitis (2007, p. 125) found a positive correlation between payment increases and higher foreclosure rates, and the latter study focused on subprime ARMs. In sum, the positive coefficient shows that payment shock significantly increases foreclosure rates, quantifying the detrimental impact of interest rate resets on mortgage performance.

The standardized coefficients for payment shock (β_{OLS} = 0.2065, 99% CI [0.0659, 0.3471]; β_{2SLS} = 0.2159, 99% CI [0.0734, 0.3584]; β_{GMM} = 0.2247, 99% CI [0.1182, 0.3312]) were used to measure effect size (Kim, 2011, p. 54). Since payment shock is binary, we can interpret the standardized coefficient as the difference in foreclosure rates in standard deviation units between borrowers who experienced a payment shock and those who did not. For example, GMM's payment shock effect size of 0.2247 suggests that for every standard deviation increase in the payment shock, foreclosure rates increase by 0.2247 standard deviations. Similarly, Ho and Pennington-Cross (2006, p. 18) found a one-standard-deviation increase in the payment shock was associated with more than a 23.6 percent increase in the probability of default. The study's effect sizes are small by Cohen's (1960, p) benchmarks, but are statistically significant. The standardized payment shock coefficient provides a direct practical estimate of the magnitude of the payment shock effect on foreclosure rates. It also shows payment shock is not the sole or dominant factor in determining foreclosure rates. Policymakers or stakeholders should consider the cumulative impact of multiple factors, including payment shock, to fully understand and address foreclosures.

Foreclosure rates show statistically significant relationships with other explanatory variables in Table 5. $Earnpow_t$, representing income and employment indices, and HPA_t, reflecting house price appreciation rates, demonstrate consistent negative coefficients across all estimation techniques. This suggests that higher levels of income, employment, and house price appreciation are associated with lower foreclosure rates, establishing the importance of economic stability in mitigating foreclosure risks. The lagged first differences in foreclosure rates (DFR_{t-1}) display positive coefficients in all models, revealing a persistent effect wherein past foreclosure rates significantly influence current foreclosure rates. These findings are consistent with other studies on mortgage foreclosures (Schloemer, 2006, p. 21), defaults (Pennington-Cross & Chromsisenghet, 2007, p. 257), and delinquencies (Beem, 2014, p. 70; Demyanyk et al. 2007, p. 1862; Zandi et al., 2007; Doms et al., 2007, p. 26) that controlled for macroeconomic and housing market conditions.

Model Comparison

In Table 5, GMM is the most efficient among the OLS, 2SLS, and GMM procedures. First, we looked at the mean absolute error (MAE), which is useful for assessing overall model performance and efficiency (Willmott & Matsuura, 2005, p. 82). For GMM, MAE is 0.382, slightly smaller than OLS (MAE = 0.385) and 2SLS (MAE = 0.389). This suggests that the GMM procedure is more efficient at producing predictions closer to the observed data on average. Second, GMM has smaller standard errors for all the model coefficients except for the lagged first difference in FR_t. The standard errors quantify the sampling variability, which is inversely related to the efficiency concept for estimates. For these reasons, the GMM approach effectively handles endogeneity and heteroscedasticity and offers the most reliable coefficients and the best overall fit. This comparison underscores the importance of selecting appropriate estimation methods in econometric analysis, particularly when examining complex financial phenomena like subprime ARM foreclosures and house price dynamics.

Our findings illuminate the critical roles of interest rate adjustments in driving foreclosure rates for subprime mortgages. They validate the hypothesis that payment shock directly impacts foreclosure rates, and these results are statistically significant across all models. The study contributes to the existing literature by highlighting the importance of using robust econometric methods to capture these intricate relationships. Our analysis provides valuable insights for policymakers and financial institutions aiming to mitigate foreclosure risks amidst fluctuating economic conditions: (1) models of credit risk should include payment shock, income, and house price variability, and refinance constraints; (2) payment smoothing should be incorporated in loan modifications and workouts; and (3) early intervention strategies should be used to stem the tide of foreclosures to promote housing market stability.

TABLE 5
ARM FORECLOSURE RATE RESULTS

	Estimation Procedure					
	OLS		2SLS		GMM	
Variables	**Statistic**	**Pr[a]**	**Statistic**	**Pr**	**Statistic**	**Pr**
Constant	3.6739	0.0001	3.5919	0.0001	3.5447	0.0001
	(0.1589)		(0.1687)		(0.1342)	
$Earnpow_t$	-0.3894	0.0054	-0.4602	0.0023	-0.4304	0.0021
	(0.1311)		(0.1398)		(0.1293)	
HPA_t	-0.2500	0.0001	-0.2351	0.0001	-0.2363	0.0001
	(0.0182)		(0.0207)		(0.0173)	
$PMTShock_t$	0.7238	0.0003	0.7567	0.0002	0.7875	0.0001
	(-0.1807)		(0.1834)		(0.1369)	
DFR_{t-1}	0.3921	0.0110	0.4089	0.0089	0.4831	0.0055
	(0.1460)		(0.1477)		(0.1633)	
R-Squared	0.9219	0.0001	0.9206	0.0001	0.9194	0.0001
Instruments			5		5	
No. of OBS	40		40		40	
Model Diagnostics	**Statistic**	**Pr**	**Statistic**	**Pr**	**Statistic**	**Pr**
Likelihood-Ratio Test	472.28	0.0001	408.18	0.0001	351.11	0.0001
Godfrey Test - Serial Correlation	0.71	0.3982	1.40	0.2375	2.34	0.1261
White’s Test - Heteroscedasticity	15.53	0.2754	14.53	0.3377	12.86	0.4583
Henze-Zirkler T Test - Normality [b]	0.25	0.3769	0.55	0.0825	0.43	0.1445
OIR and FSMS Tests[c]	13.63	0.4008	1.22	0.2703	1.10	0.2932
Mean Absolute Error	0.385	-	0.389	-	0.382	-

Note. The dependent variable is foreclosure rates.

[a] $p < .05$, R^2 is significant;$p < .05$, Wald is significant; $p > .05$, ORI shows instruments are valid; $p > .05$ Godfrey’s test shows no serial correlation; $p > .05$ White’s test signifies no heteroscedasticity; $p > .05$, Henze-Zirkler T and Shapiro-Wilk W show residuals are normally distributed.

[b] The Shapiro Wilk W test is used for OLS, and the Henze-Zirkler T test is used for 2SLS and GMM.

[c] OIR is the Overidentifying Restriction test to evaluate the instrument’s validity. 2SLS and GMM used Hansen’s J Test. OLS used the First and Second Momement Specifications (FSMS) test to evaluate homoscedasticity and correct model specification.

Source: Authors’ Computation.

CONCLUSION

This study presents robust empirical evidence on how adjustments in interest rates on subprime mortgages, fluctuations in house prices, and their combined effect impact foreclosure rates. OLS and more advanced econometric techniques, such as 2SLS and GMM, have enabled us to assess the harmful consequences of payment shock arising from interest rate resets on subprime mortgages.

Across all estimation techniques, our findings reveal that payment shock is a statistically significant factor in foreclosure rates. A payment shock, on average, leads to a 27 percent increase in foreclosure rates, highlighting the greater risk borrowers face with interest rate adjustments. This effect remains even after controlling for income/employment and house price appreciation.

The analysis also underscores the roles of economic stability and housing market conditions in managing foreclosure risks. Consistently, across all models, there is a clear correlation between lower foreclosure rates and higher income/employment levels and house price appreciation rates, emphasizing the significance of economic stability in mitigating foreclosure risks. Positive coefficients highlight the persistence effect for lagged foreclosure rates, where past foreclosures influence future occurrences.

Rigorous diagnostic tests confirmed the validity and reliability of our models, ensuring statistically significant results. In terms of efficiency and robustness, the GMM model outperformed the other two methods by effectively addressing endogeneity, heteroscedasticity, and serial correlation, resulting in the most reliable estimates.

This research underscores the critical need for robust econometric methods to decipher the complex relationship between payment shock and foreclosure rates. Our findings, which hold significant implications for policymakers and financial institutions, suggest that understanding payment shock is crucial for developing interventions to mitigate foreclosure risks, especially during economic volatility. By offering empirical evidence on the impact of these adjustments on subprime mortgage foreclosures, the study provides actionable insights for crafting policies and financial strategies that protect homeowners and promote sustainable lending practices. These insights emphasize the importance of accurate econometric analysis in addressing the challenges of subprime mortgage markets and stabilizing the housing sector.

REFERENCES

Ambrose, B.W., LaCour-Little, M., & Huszar, Z.R. (2005). A note on hybrid mortgages. *Real Estate Economics*, *33*(4), 765–782.

Bajari, P., Chu, S.C., & Park, M. (2008). *An empirical model of subprime mortgage default from 2000 to 2007* (Working Paper 14625). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w14625

Baum, C., Schaffer, M., & Stillman, S. (2003). *Instrumental variables and GMM: Estimation and testing* (Boston College Working Papers in Economics No. 545). Boston College Department of Economics. Retrieved from https://EconPapers.repec.org/RePEc:boc:bocoec:545

Cagan, C.L. (2007). *Mortgage payment reset: The issue and the impact*. Santa Ana, CA: First American CoreLogic, Inc.

Calomiris, C.W., Longhofer, S.D., & Mile, W. (2013). The foreclosure-house price nexus: A panel VAR model for US states, 1981-2009. *Real Estate Economics*, *41*(4), 709–746.

Campbell, J.Y., Giglio, S., & Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, *101*(5), 2108–2131. doi: 10.1257/aer.101.5.2108

Chmelarova, V. (2007). *The Hausman test and some alternatives, with heteroskedastic data* (Publication No. 936) [Doctoral dissertation, Louisiana State University]. LSU Digital Commons. Retrieved from https://repository.lsu.edu/gradschool_dissertations/936

Demyanyk, Y., & Hemert, O. (2011). Understanding the subprime mortgage crisis. *Review of Financial Studies*, *24*(6), 1848–1880.

Doms, M., Furlong, F., & Krainer, J. (2007). House prices and subprime mortgage delinquencies. *Federal Reserve Bank of San Francisco Economic Letter*, *14*, 1–3. Retrieved from https://www.frbsf.org/wp-content/uploads/wp07-33bk.pdf

Edmiston, K.D., & Zalneraitis, R. (2007). Rising foreclosures in the United States: A perfect storm. *Economic Review, Federal Reserve Bank of Kansas City*, *92*(4), 115–145.

Federal Housing Finance Agency. (2007). *Highlights - Part 2: Foreclosures and house prices*. Retrieved from https://www.fhfa.gov/DataTools/Downloads/Documents/HPIFocusPieces/2007Q3HPIFocusN508.pdf

Foote, C., Gerardi, K., Goette, L., & Willen, P.S. (2008). *Subprime facts: What (we think) we know about the subprime crisis and what we don't know* (Public policy discussion paper no. 08-2). Boston: Federal Reserve Bank of Boston. Retrieved from https://www.bostonfed.org/publications/public-policy-discussion-paper/2008/subprime-facts-what-we-think-we-know-about-the-subprime-crisis-and-what-we-dont.aspx
Frame, W.S. (2010). Estimating the effect of mortgage foreclosures on nearby property values: A critical review of the literature. *Economic Review*, *95*(3), 1–9.
Hill, A.D., Johnson, S.G., Greco, L.M., O'Boyle, E.H., & Walter, S.L. (2021). Endogeneity: Review and agenda for the methodology-practice divide affecting micro and macro research. *Journal of Management*, *47*(1), 105–143. https://doi.org/10.1177/014920632096
Ho, G., & Pennington-Cross, A. (2006). *The termination of subprime hybrid and fixed rate mortgages* (Working Paper 2006-042). Federal Reserve Bank of St. Louis. https://doi.org/10.20955/wp.2006.042
Kim, R.S. (2011). *Standardized regression coefficients as indices of effect sizes in meta-analysis* (Publication No. 3109) [Doctoral dissertation, Florida State University]. http://purl.flvc.org/fsu/fd/FSU_migr_etd-3109
Kumar, S. (n.d.). *Advanced diagnostics for multiple regression: A supplement to multivariate data analysis multivariate data analysis*. [Supplement materials]. Retrieved from https://www.academia.edu/24541751/Advanced_Diagnostics_for_Multiple_Regression_A_Supplement_to_Multivariate_Data_Analysis_Multivariate_Data_Analysis
Labra, R., & Torrecillas, C. (2018). Estimating dynamic panel data: A practical approach to perform long panels. *Revista Colombiana de Estadística*, *41*(1), 31–52. http://dx.doi.org/10.15446/rce.v41n1.61885
Loberto, M. (2023). Foreclosures and house prices. *Italian Economic Journal*, *9*, 397–424. https://doi.org/10.1007/s40797-021-00166-z
Mian, A., Sufi, A., & Trebbi, F. (2014). *Foreclosures, house prices, and the real economy* (Working Paper No. 6). Kreisman Working Papers Series in Housing Law and Policy. Retrieved from https://chicagounbound.uchicago.edu/cgi/viewcontent.cgi?article=1001&context=housing_law_and_policy
Pennington-Cross, A., & Chomsisengphet, S. (2007). Subprime refinancing: Equity extraction and mortgage termination. *Real Estate Economics*, *25*(2), 233–263. https://doi.org/10.1111/j.1540-6229.2007.00189.x
Qi, M., Scheule, H., & Zhang, Y. (2021). Positive payment shocks, liquidity and refinance constraints and default risk of home equity lines of credit at end of draw. *Journal of Real Estate and Finance Economics*, *62*, 423–454. https://doi.org/10.1007/s11146-020-09752-x
Schloemer, E., Li, W., Ernst, K., & Keest, K. (2006). Losing ground: Foreclosures in the subprime market and their cost to homeowners. *Center for Responsible Lending*. Durham, North Carolina. Retrieved from https://fcic-static.law.stanford.edu/cdn_media/fcic-docs/2006-1200%20Center%20For%20Responsible%20Lending%20Losing%20Ground%20Foreclosures%20in%20the%20Subprime%20Market%20and%20Their%20Cost%20to%20Homeowners.pdf
Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics*, *8*(2), 39–42. doi: 10.12691/ajams-8-2-1
White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, *48*(4), 817–838. https://doi.org/10.2307/1912934
Willmott, J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82. https://doi.org/10.3354/cr030079
Young, D.S. (2017). *Handbook of regression methods*. Taylor & Francis Group.