A Forecast of Delinquency Rates on Single-Family Residential Mortgages

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Abstract

This paper suggests a model for predicting mortgage delinquency rates in the United States for the periods 2019 quarter 3, 2019 quarter 4, 2020 quarter 1, and 2020 quarter 2. The forecast is based off of the data series titled: Delinquency Rate on Single-Family Residential Mortgages, Booked in Domestic Offices, All Commercial Banks (Delinquency Rate (2019)). The data series examines the number of delinquent residential mortgage loans as a percentage of all residential mortgage loans booked in U.S. commercial banks. The Board of Governors of the Federal Reserve system qualifies a delinquent loan as one that is outstanding and no longer accruing interest or one that is past due by thirty days or more and still accruing interest. This paper finds that mortgage delinquency rates will rise in 2019 quarter 3, 2019 quarter 4, and 2020 quarter 1, and fall slightly in 2020 quarter 2.

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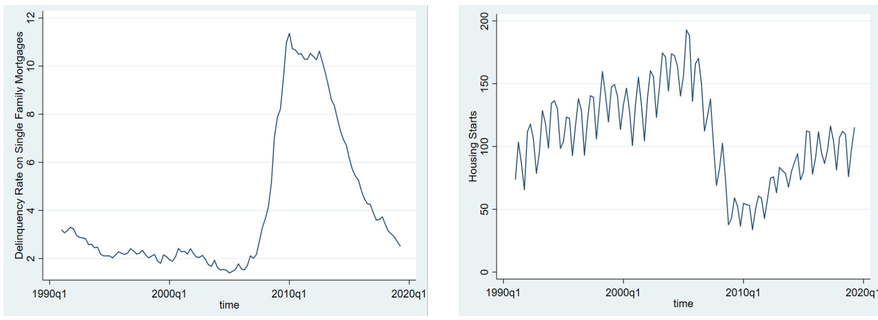
Figure 1: Time Series Plot of Delinquency Rates and Housing Starts



Delinquency Rate

Housing Starts

1 Introduction

This paper suggests a model for predicting mortgage delinquency rates in the United States for the periods 2019 quarter 3, 2019 quarter 4, 2020 quarter 1, and 2020 quarter 2. The forecast is based off of the data series titled: Delinquency Rate on Single-Family Residential Mortgages, Booked in Domestic Offices, All Commercial Banks (Delinquency Rate (2019)). This series is publicly available.

The data series examines the number of delinquent residential mortgage loans as a percentage of all residential mortgage loans booked in U.S. commercial banks. The Board of Governors of the Federal Reserve system qualifies a delinquent loan as one that is outstanding and no longer accruing interest or one that is past due by thirty days or more and still accruing interest. The paper finds that mortgage delinquency rates will rise in 2019 quarter 3, 2019 quarter 4, and 2020 quarter 1, and fall slightly in 2020 quarter 2.

The paper is organized as follows: Section 2 describes the data and characteristics of the time series. Section 3 describes the forecasting method used. Section 4 describes the model, estimates, and forecasts, and concludes the findings therein.

2 Data

The Delinquency Rate series is recorded quarterly at the end of each period, measured as a percent, and is not seasonally adjusted. A delinquency rate is a measure of outstanding loans no longer accruing interest due to late payments or lack of payment altogether. The mortgage delinquency rate is the the number of outstanding mortgage loans not accruing interest as a percentage of all outstanding mortgage loans.

The series is taken from Federal Reserve Economic Data (FRED). FRED gathers this data from a report done by the Board of Governors of the Federal Reserve System called: Charge-Off and Delinquency Rates on Loans and Leases at Commercial Banks. The Board of Governors retrieves data for this report from a publication of the Federal Financial Institutions Board of Governors called: Consolidated Reports of Condition and Income.

The Federal Financial Institutions Board of Governors is a body of multiple agencies charged with maintaining uniform principles, standards, and report forms for the examination of major financial institutions in the United States. Such responsibilities require highly accurate data accumulation and reporting.

The second data series used in this paper, the Housing Starts series, is also taken from FRED in a report called: Housing Starts: Total: New Privately Owned Housing Units Started (Housing Starts (2019)). Housing starts are a measure construction work, defined by the number of new residential construction projects started in a given period.

The Housing Starts series is recorded monthly, measured as thousands of housing units sold, and is not seasonally adjusted. It spans from month 1 of 1959 to month 9 of 2019. For the purposes of this paper, the Delinquency Rate series is aggregated into quarterly data using observations from the end of each period.

FRED collects this data from a report by the United States Census Bureau called: New Residential Construction. The Census Bureau gets data for this publication from the United States Department of Housing and Urban Development.

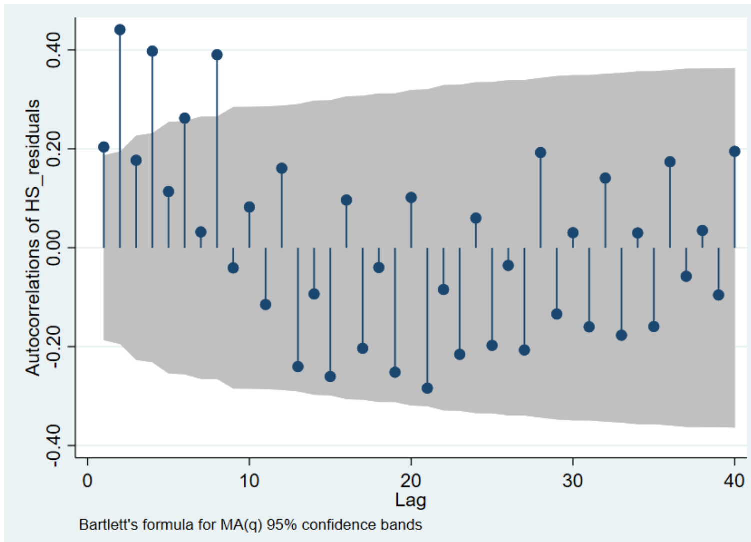
The U.S. Department of Housing and Urban Development is a cabinet of the federal government responsible for overseeing home ownership, affordable housing, and residential construction funding. It is important that accurate records of housing statistics - including housing starts - are kept and reported.

Both data series used for forecasting in this paper are made up of 114 observations spanning from 1991 quarter 1 to 2019 quarter 2. The Delinquency Rate series has a range from 1.4 (percent) to 11.36. It's median is 2.58 and its 1st and 3rd quartiles are 2.11 and 5.27 respectively. The series has a mean of 4.13 and a standard deviation of 3.02. The last observation reported (2019 quarter 2) is 2.52 percent. Heteroskedasticity is present in these data, as indicated by the significant Chi^2 statistic of 28.55 reported by the Breusch-Pagan test on the first four lags of Delinquency Rate.

The Housing Starts series has a range from 33.8 (thousand) to 192.8. It's median is 110.65 and its 1st and 3rd quartiles are 80.2 and 136.4 respectively. The series has a mean of 108.86 and a standard deviation of 36.58. The last observation used for forecasting purposes in this paper is 115.1 thousand units. These data are homoskedastic, as indicated by the insignificant Chi^2 statistic of 0.57 reported by the Breusch-Pagan test on the first four lags of Housing Starts.

In Figure 1, the Delinquency Rate series and the Housing Starts series are plotted against time. Several insights are made evident in this figure. First, there is clear seasonality present in the Housing Starts series. This finding is further supported by an auto-correlation plot of residuals for the first four lags of the Housing Starts series (see Figure 2). The points alternate in amplitude with each lag, ranging from over 0.4 to less than 0.05 in absolute value. This, combined with the undulation of points above and below zero, makes manifest somewhat of a swinging pattern in the residual points. This suggests seasonality

Figure 2: Auto-Correlation Plot of Housing Starts Residuals



in the series.

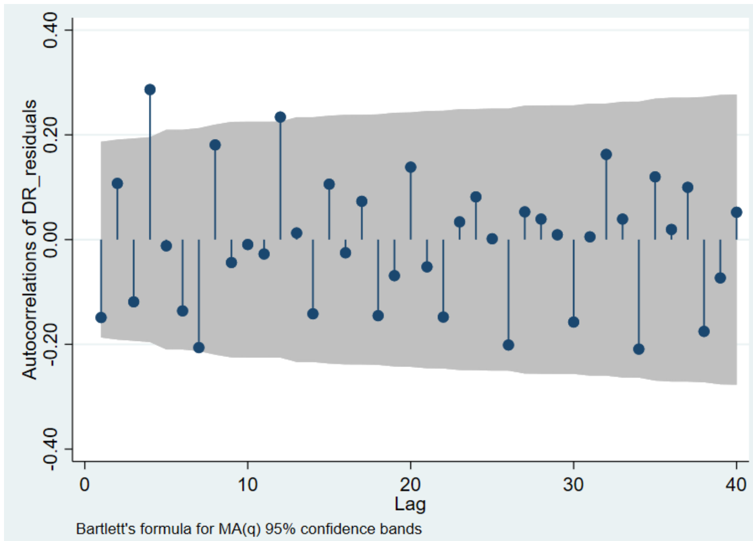
Seasonality, although not very visible in Figure 1, is also present in the Delinquency Rate series. Figure 3 shows an auto-correlation plot of residuals for the first four lags of the Delinquency Rate series. The points again alternate in amplitude and in relative position above or below zero, creating a vague pattern of undulation. This suggests seasonality in the series.

Another insight made evident in Figure 1 is the presence of a break-date - a point in the data series at which a structural change occurs. It is visibly evident that a structural change likely occurs in both data series just before the year 2010. It is very probable that this break occurs as an effect of the 2008 financial crisis. Housing starts can generally be used as an indicator for the greater economy. When an economic contraction occurs, as in 2008, new construction projects (i.e. housing starts) generally slow with the economy. This is evident in the large fall in housing starts in Figure 1.

Just as a fall in housing starts can be a product of a recession, a spike in delinquency rate can be a catalyst for one. About 2008, the Consumer Financial Protection Bureau writes, "Leading up to the crisis, some lenders originated mortgages to consumers without considering their ability to repay the loans. The decline in underwriting standards led to skyrocketing rates of mortgage delinquencies and foreclosures" (Bureau (2017)).

The credit delinquencies and mortgage foreclosures led to the collapse of the highly leveraged financial markets and disrupted the U.S. economy as a whole. It is therefore foreseeable that a structural break in these data series would occur shortly after the start of the crisis. The break is evident in the significant spike and successive fall in delinquency rates in Figure 1.

Figure 3: Auto-Correlation Plot of Delinquency Rate Residuals



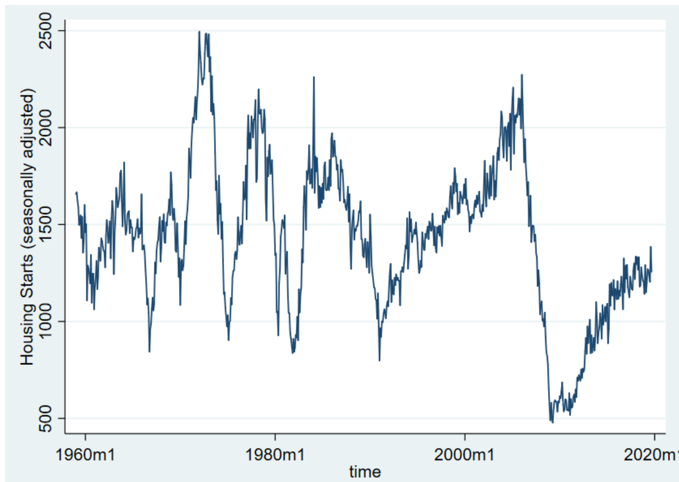
A final insight that can be drawn from Figure 1 is that both data series are back to pre-recession levels. The Delinquency Rate series has fallen back to the higher end of normal rates prior to 2008 and the Housing Starts series seems to be trending upward at the same pace as it did prior to the shock. This raises the question, will delinquency rates remain where they are or can another spike be expected?

Perhaps if the 2008 fall in housing starts is looked at as broad cyclicality rather than a shock, a rise in delinquency rates can be expected with the next cyclical fall. Figure 4 shows a time series line of the larger data set that the Housing Starts series was taken from. The larger series is seasonally adjusted and displays monthly data on housing starts from 1959 to 2019. It is visible in Figure 4 that there is cyclicality in the number of housing starts. In 2008, though, the fall appears to be greater than the previous troughs in the cycle. This could imply that 2008 was a shock, and not simply a product of the cycle.

Due to the fact that broad cyclicality is present in housing starts, it is possible that a rise in delinquency rates can be expected with the next cyclical fall (assuming that housing starts can be used as an indicator for mortgage delinquency rates). The 2008 spike in delinquency rates corresponds with the fall in housing starts. However, because the unusually large fall in housing starts was likely a shock, and because credit delinquency and the 2008 recession were specifically related, the next cyclical fall in housing starts will not likely correspond to as dramatic of a spike in delinquency rates.

The purpose of this paper is not to predict housing starts nor to estimate true causality between housing starts and delinquency rates, but to use the number of housing starts as an indicator for future delinquency rates as supported by

Figure 4: Housing Starts - Full Series, Seasonally Adjusted



Granger causality. The circular logic surrounding credit delinquency, housing starts, and the 2008 recession is not relevant to this forecast model.

3 Forecasting Method

The forecasting method used in this paper to predict the Delinquency Rate series is an auto-regressive distributed lag (ARDL) model. The ARDL model estimates delinquency rates using an auto-regression AR(2) of delinquency rates, a 1st distributed lag of housing starts, and seasonal dummies for three quarters. The coefficients are estimated using the Ordinary Least-Squares method of multiple regression. The process for selecting this method required several steps.

The first step taken was to determine the presence of seasonality. Seasonality was tested in the Delinquency Rate series by observing the auto-correlations of residuals. Figure 3 shows an auto-correlation plot of residuals for the first four lags of the Delinquency Rate series. The points alternate in amplitude with each lag, ranging roughly from 0.3 to 0.01 in absolute value. The points also regularly alternate above and below zero. These factors display a vague swinging pattern in the residual points, thus suggesting seasonality.

Seasonality was tested in the Housing Starts series by the same process. Figure 2 shows an auto-correlation plot of the residuals for the first four lags of the Housing Starts series. The points alternate in amplitude with each lag, ranging from over 0.4 to less than 0.05 in absolute value. This, combined with the undulation of points above and below zero, presents another swinging pattern in the residual points. This suggests seasonality in the series.

The next step is to determine whether homoskedastic-only or heteroskedastic-

Table 1: Akaike's Information Criterion - All

Model	n	DF	AIC
uARDL42	109	3	3.828535
uARDL22	109	4	4.163182
mARDL43	109	5	3.079552
mARDL41	109	6	4.463976
pARDL44	109	7	2.301806
pARDL21	109	4	5.836310
hARDL44	109	5	-1.28300
hARDL21	109	6	3.565187

robust standard errors were necessary for estimation. This was done by performing Breusch-Pagan tests on the AR(4) processes of each variable (Delinquency Rate and Housing Starts). The Breusch-Pagan test starts with the null hypothesis of homoskedastic errors then calculates a Chi^2 statistic on a given regression. A significant Chi^2 statistic will reject the null hypothesis and give cause to the presence of heteroskedastic errors.

The Breusch-Pagan test on Delinquency Rate returned a highly significant Chi^2 value of 28.55, concluding that heteroskedastic errors are present in the series. The test on Housing Starts returned an insignificant Chi^2 value of 0.57, concluding that homoskedastic errors are present in the series. From this, it was determined that heteroskedastic-robust standard error should be used in the forecasting model.

Next, the specific type of model to be used was determined. After some theoretical consideration, it was decided that the best way to predict successive observations of the Delinquency Rate series - in addition to looking at previous observations of itself - was to look at distributive lags of leading indicator variables. Possible leading indicators to be considered were unemployment rate, manufacturing output, building permits, and housing starts.

The leading indicator to be chosen was found by analyzing the Baysean and Akaike Information Criterion (BIC/AIC) of several different regressions. First, each leading indicator was individually regressed on delinquency rate using every combination of lags 0 through 4 for both variables (25 total regressions - see Table 2 for an example). The best two ARDL models for each leading indicator were chosen according to the lowest AIC and BIC values. Each model then had their AIC and BIC compared to one another (8 total regressions). The leading indicator associated with the lowest AIC value would be chosen. Judgement is deferred to Akaike's Information Criterion here because AIC is more of an unbiased estimate of mean-squared forecast error than BIC is, and therefore has less forecast risk.

Table 1 displays the AIC for the best models of each leading indicator. Here, uARDL refers to the model of delinquency rate and unemployment rate; mARDL refers to the model of delinquency rate and manufacturing output;

Table 2: Akaike's Information Criterion - Housing Starts

Model	n	DF	AIC	BIC
ARDL00	109	3	561.2875	572.0529
ARDL01	109	4	405.5519	419.0087
ARDL02	109	5	396.7802	412.9283
ARDL03	109	6	392.0945	410.9340
ARDL04	109	7	392.0952	413.6260
ARDL10	109	4	93.93522	107.3920
ARDL11	109	5	82.48271	98.63080
ARDL12	109	6	83.44816	102.2876
ARDL13	109	7	82.39661	103.9274
ARDL14	109	8	69.86942	94.09155
ARDL20	109	5	9.662749	25.81084
ARDL21	109	6	4.464152	23.30359*
ARDL22	109	7	6.162202	27.69298
ARDL23	109	8	7.853665	32.07580
ARDL24	109	9	3.279399	30.19288
ARDL30	109	6	9.119853	27.95929
ARDL31	109	7	4.010863	25.54165
ARDL32	109	8	5.839477	30.06161
ARDL33	109	9	7.571070	34.48455
ARDL34	109	10	3.652015	33.25684
ARDL40	109	7	5.294332	26.82512
ARDL41	109	8	0.169681*	24.39181*
ARDL42	109	9	2.042091	28.95557
ARDL43	109	10	3.926127	33.53095
ARDL44	109	11	0.090080*	32.38625

pARDL refers to the model of delinquency rate and building permits; and hARDL refers to the model of delinquency rate and housing starts. The ARDL model that includes housing starts has the lowest AIC value of -0.095. The Housing Starts series and Delinquency Rate series have a high correlation coefficient of -0.7934. Because of this evidence, the Housing Starts series is chosen to be the leading indicator for the forecast model.

After all the regressors have been selected (delinquency rates, housing starts, seasonal dummies), the degrees of the ARDL model are chosen. In order to decide how many lags of delinquency rate and housing starts are to be chosen, the AIC/BIC values are again analyzed. Table 2 displays the AIC and BIC for each combination of lags 0 through 4 of delinquency rate and housing starts. When all models are compared to each other, the best three models are chosen to be further tested. Table 2 shows that the ARDL44 model (4 lags of auto-regression and 4 lags of housing starts) has the lowest AIC value, the ARDL21 model (2 lags of auto-regression and 1 lag of housing starts) has the lowest BIC

Table 3: Augmented Dickey-Fuller (ADF) and Lag Tests

	ARDL44	ARDL41	ARDL21
p of ADF Test of Delinquency Rate	0.0468	0.0468	0.6299
p of Lag Test of Delinquency Rate Lags	0.0000	0.0000	0.0000
p of ADF Test of Housing Starts	0.5164	0.0308	0.0308
p of Lag Test of Housing Starts Lags	0.0416	0.0185	0.0201

value, and the ARDL41 model (4 lags of auto-regression and 1 lag of housing starts) has the second lowest value of both AIC and BIC.

These three models must next be tested to ensure that their lags are significant and that there is no stationarity present. The Augmented Dickey-Fuller test has the null hypothesis of no unit-root is present a given model. The presence of a unit-root would indicate that the mean of the data window is not stable; an instable mean makes forecasting inaccurate. Rejecting the hypothesis of the Dickey-Fuller test means that a unit-root is not present and the auto-regressive process is therefore stationary. The findings of the Dickey-Fuller tests run for this paper are displayed in Table 3.

Sationarity in the ARDL44 model was first tested on the four lag coefficients of delinquency rate. The test calculated a p-value (probability of a unit-root) of 0.047. This gives cause to reject the null hypothesis and assume mean stationarity for the delinquency rate series in the model. The four lag coefficients of housing starts yielded a p-value of 0.516. This suggests non-stationarity for the housing starts series.

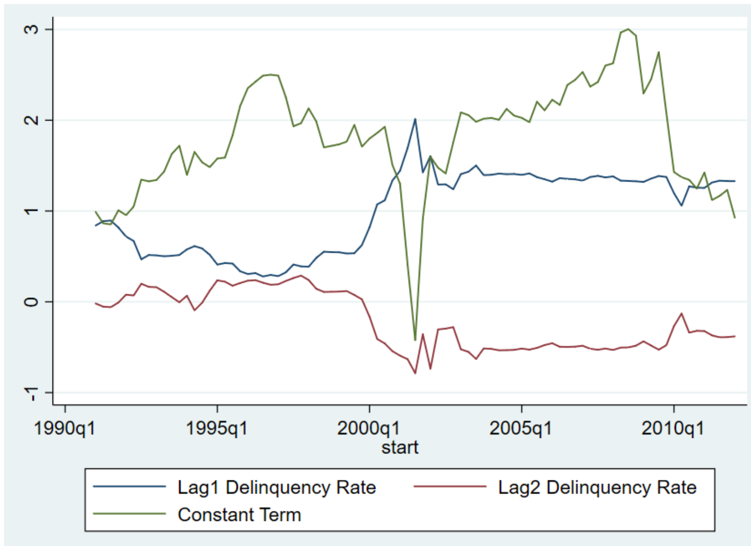
Sationarity in the ARDL41 model was tested on the four lag coefficients of delinquency rate first. The test calculated a p-value of 0.047. This again gives cause to reject the null hypothesis and assume mean stationarity for the delinquency rate series. The lag coefficient of housing starts yielded a p-value of 0.031. This suggests stationarity in the housing starts series.

Sationarity in the ARDL21 model was tested first on the two lag coefficients of delinquency rate. The test calculated a p-value of 0.629. This fails to reject the null hypothesis, and therefore non-stationarity for the delinquency rate series is assumed. The lag coefficient of housing starts yielded a p-value of 0.031. This again suggests stationarity in the housing starts series.

F-tests were also performed on each model for the lags of both variables. Each model calculated significant p-values, meaning that the lags are significant predictors of the Delinquency Rate series. The findings of the lag tests are displayed in Table 3.

The Augmented Dickey-Fuller tests indicate that the ARDL41 model (4 lags of auto-regression and 1 lag of housing starts) is the best model, even

Figure 5: Break-Date Test - Rolling Coefficients



though it did not have the lowest AIC or BIC. The ARDL44 model is also a plausible option because it has mean stationarity in its delinquency rate series. The ARDL21 may not be used because it non-stationarity is present in its delinquency rate series.

The Predictive Least-Squares (PLS) criterion is used to determine whether the ARDL44 or the ARDL41 model is best. The PLS criterion uses rolling recursive window estimations of pseudo-out-of-sample forecast errors to determine which model has the lowest mean-squared forecast error. When calculated using a window length of 30, the ARDL44 reports a PLS value of 2.341 and the ARDL41 model reports a PLS value of 1.667. This indicates that the ARDL41 model has lower mean-squared forecast error and therefore is the model that should be used.

In Section 2, it is noted that a break-date is likely present in either data series. If a break date is present, it is important that it is included in the forecasting model because if represents a structural shift in slope coefficients. In order to test for break-dates, this paper employs the Chow test. The Chow test is useful in determining the presence of a break-date for one specific period; it cannot test an entire data series to identify the most likely break-date. In order to pick a specific period to be tested for a break-date, time series plots must be visually analyzed.

Figure 5 displays the rolling window mean estimation for each window of length 30 starting in 1991 quarter 1. There is a large negative spike visible in the constant term's time series line that occurs at the same time as a positive spike in the time series line for the 1st lag of delinquency rate. This is highly suggestive of a break date that might occur between the years 2000 and 2005.

Table 4: Chow Test for Possible Break-Dates

Model	QLR	Chow Stat
2009q1	4.71	0.828144
2009q2	4.71	0.190754
2009q3	4.71	1.756347
2009q4	4.71	6.347748*
2010q1	4.71	3.432230
2010q2	4.71	1.729581
2010q3	4.71	1.375247
2010q4	4.71	1.314928

The Chow test determines whether or not there actually is a statistically significant mean shift. It tests the null hypothesis that there is no major difference in the data before and after the given period. This paper tests Chow statistics against the critical value of the Quandt-Likelihood Ratio (QLR) at the $\alpha = 0.05$ level with 3 restrictions (QLR=4.71). If the Chow statistic for a given test is greater than the QLR critical value, then the null hypothesis is rejected and a break-date is assumed.

For every quarter in the years 2000 through 2005, the null hypothesis for the Chow test on lags of delinquency rate fails to be rejected. This implies that, despite the large spike visible in Figure 5, a significant structural mean shift is not present in those years.

Figure 5 shows another shift/spike, though: just before 2010. (This second possible break-date is corroborated by the discussion of Figure 1 in Section 2.) Table 4 displays the Chow statistics of eight quarters tested for a break date against a QLR critical value of 4.71 in the years 2009 and 2010. Quarter 4 of 2009 shows a significant Chow statistic that gives cause to reject the null hypothesis and assume that there is a break date present in that period.

After considering the effects that the inclusion of a break-date in the forecasting model would have, this paper chooses not to include one. Despite the likelihood of a break-date being present, there is not enough data in the Delinquency Rate series to safely implement a coefficient shift into the forecast. A break date in 2009 quarter 4 would allow for only 73 observations to predict a coefficient in the first period and only 39 observations to predict a coefficient in the second period. Regressing such small sample sizes will likely not produce reliable coefficients. The inclusion of a break-date would only serve to compromise the forecast.

It is possible that excluding the break-date does not take away from the accuracy of the forecast. Upon analyzing the the pseudo-out-of-sample forecast errors calculated for the PLS test, it is evident that the ARDL21 model does not deteriorate toward the end of the sample. Instead of growing, the forecast errors maintain consistent size even after the suggested break-date.Therefore, despite the visual evidence of a structural shift, this paper's forecast model does

Table 5: Forecast Model

1st Lag of Delinquency Rate	1.517*** (0.134)
2nd Lag of Delinquency Rate	-0.557** (0.264
3rd Lag of Delinquency Rate	0.213 (0.106)
4th Lag of Delinquency Rate	-0.222* (0.106)
1st Lag of Housing Starts	-0.003** (0.001)
Quarter 1	-0.421*** (0.081)
Quarter 2	-0.281*** (0.065)
Quarter 3	0.013 (0.071)
Constant	0.738*** (0.224)
F-statistic	1829***
$R^2 - adjusted$	0.994
Root MSE	0.2317
Observations	110
Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$	

not include break terms.

4 Model, Estimates, and Forecast

The auto-regressive distributed lag model used for forecasting in this paper estimates delinquency rates using an auto-regression AR(4) process of delinquency rates, a 1st distributed lag of housing starts, and seasonal dummies for three quarters. This model is used to make four out-of-sample predictions for the Delinquency Rate series.

In Table 5, the estimated coefficients for each regressor are listed. The coefficients can be interpreted as follows: The current period's delinquency rate is equal to a constant 0.738, plus the delinquency rate last period multiplied by 1.52, plus the delinquency rate two periods ago multiplied by -0.56, plus the delinquency rate three periods ago multiplied by 0.21, plus the delinquency rate four periods ago multiplied by -0.22, plus the number of housing starts (in thousands) last period multiplied by -0.003. Seasonality is included by adding

Table 6: Direct Method Forecast

Period	Point Forecast	Lower-Bound CI	Upper-Bound CI
2019q3	2.634	2.165	3.104
2019q4	2.851	2.007	3.695
2020q1	2.835	1.654	4.016
2020q2	2.830	1.295	4.366

the coefficient of the current quarter to the value calculated above.

The stars next to certain coefficients represent the level of significance. It can be seen that the coefficients on the 1st and 2nd lag of delinquency rate are the greatest in significance. This suggests that the best predictor of a given period's delinquency rate is the delinquency rate of the last period. The next best predictors are the delinquency rate of two periods ago and the housing starts of one period ago.

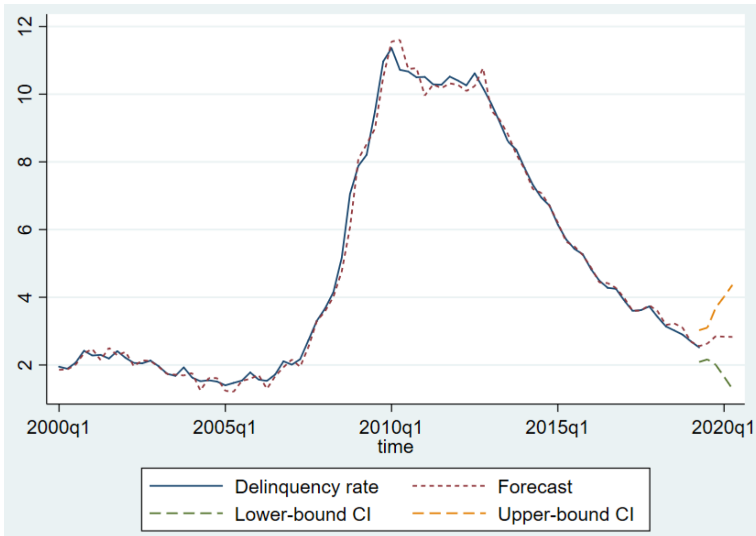
The forecasting method employed in this paper (using the above model) is the direct method. The forecasted is calculated on Stata (15.1). Due to limitations in the program used for this regression, the model used in the forecast direct method is slightly different; instead of using heteroskedastic-robust standard errors, homoskedastic-only standard errors must be used.

The forecast direct method demonstrates that the Delinquency Rate series will see an increase in rates for three consecutive quarters, then a slight fall. In Table 6, the forecast values are listed. The period directly following the completion of this paper is predicted to have a delinquency rate of 2.63. This is a 0.11 point rise from the last reported rate of 2.52. The forecast confidence interval fans out each period.

Figure 6 displays the fitted values calculated by the regression against the actual delinquency rate. The fitted values carry over to the out-of-sample period where the forecast values and confidence interval are shown.

The forecast put forth by this paper carries decent confidence. The model has a low mean-squared error and mean-squared forecast error. The regessors are almost all significant. In-sample observations of the independent variable and of the leading indicator variable series are shown to be correlated by almost 80%. Exhaustive procedures have been played out to ensure that the best predictive model has been selected. All of these factors enhance the likelihood of an accurate forecast.

Figure 6: Direct Method Forecast Plot



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