On the Drivers of U.S. Breakeven Inflation

Neil Mauskar
The University of Chicago
mauskar@uchicago.edu

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Abstract

The breakeven inflation rate is an important metric of the market expectation of inflation. This paper examines the drivers, specifically economic and financial variables, that explain movements in the breakeven inflation rate over different time horizons. To do this, I evaluated a selection of potential explanatory variables using LASSO regressions and Bayesian Model Averaging. Variables that were deemed likely to explain movements in inflation were inputted in a VAR and their shocks were analyzed via a Cholesky Decomposition. The results indicate that longer term breakeven rates are more persistent and require fewer explanatory variables than short-term breakeven rates. Moreover, the results also imply that the output gap variables, prices and exchange rates variables, and financial variables are most important in examining breakeven inflation at all time horizons. The relative importance of the prices and exchange rates variables, however, decrease as the time horizon increases. On the other hand, the financial variables were more significant for longer time horizons than shorter ones. The output gap was relatively less significant for middle time horizons and was instead more significant for long- and short-term horizons.

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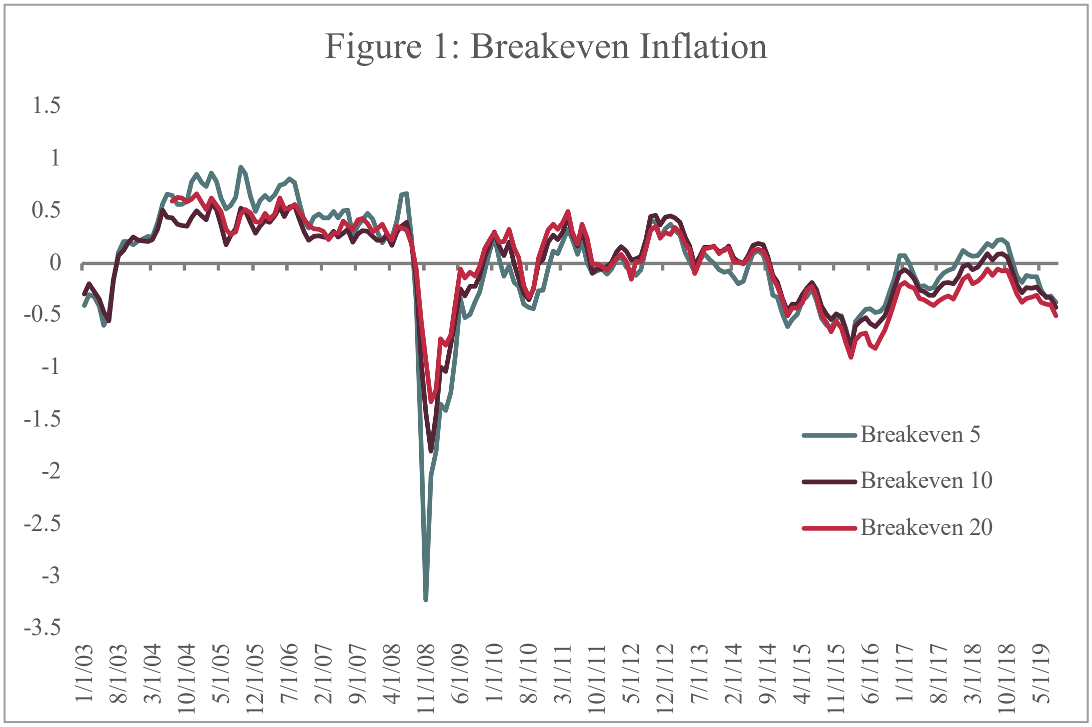
1. Introduction

The breakeven inflation rate, defined as the difference between the yield of a nominal bond and an inflation linked bond of the same maturity, calculates the market rate of expected inflation across multiple time horizons. As such, the breakeven inflation rate plays an important role in financial analysis and portfolio management. This paper examines the macroeconomic and financial determinants of U.S. breakeven inflation.

Breakeven inflation rates have played an important part in investing in the United States since Treasury Inflation Protected Securities (TIPS) were offered in 1997 by the United States Department of Treasury. It is important to note, however, that inflation protected securities have been around and rising in importance since the 1980's. True to their name, the breakeven inflation rate is the average inflation rate at which the yield of a nominal bond (such as government bonds) and inflation protected securities (such as TIPs) would be the same. Inflation protected securities are often used in portfolios for their diversification benefits.

Inflation protected securities are more profitable than their nominal counterparts when the average inflation over its time horizon is greater than the breakeven inflation. They are an important measure of the inflation expected by the market, because investors have incentive to price inflation correctly. After all, if it were priced incorrectly, there would be an arbitrage opportunity until it was priced correctly.

Due to their importance in investing, we believe that a comprehensive examination of the drivers of breakeven inflation could be useful in understanding its dynamics. Given this, the goal of this paper is to find the explanatory variables of breakeven inflation and understand how these different variables impact it. Unfortunately, despite its relevance, there has not been significant research conducted on this specific topic. In fact, I believe this is the first holistic approach in examining which variables most impact U.S. breakeven inflation. The following graph shows the development of breakeven inflation over the last few years:



Note: Graph shows the monthly breakeven inflation at the 5-year, 10-year, and 20-year time horizons. Data is collected from the St. Louis FRED.

Finding these explanatory variables, as stated in the goal of this paper earlier, is difficult. After all, in theory, there are a lot of different macroeconomic and financial variables that could impact breakeven inflation. To make examining these variables more feasible, this paper will look at 23 different variables that span across different components of the economy. These components are listed as follows: Monetary Factors, Output Gap Variables, Prices and Exchange Rates, Economic Activity Indicators, Confidence Indicators, and Financial Variables. The breakdown of variables is quite similar to Ciccareli et al. (2012), except with the addition of the output gap variables.

With these variables, we want to find a parsimonious model for multiple time horizons of breakeven inflation. By doing this, we will be able to see not only which potential explanatory variables are important in explaining fluctuations in breakeven inflation, but also how these variables change over the chosen time horizons.

To do this, we will look at monthly breakeven inflation rates at the 5-year, 10-year and 20-year time horizons from January 2003 to August 2019. From the graph displayed earlier, it would seem that the complexity decreases as the time horizon increases. That is to say, longer time horizons tend to be more persistent than shorter ones. This will be empirically proven later in the paper.

As the complexity decreases over longer time horizons, we would expect the number of explanatory variables in the model to decrease as well. However, breakeven inflation consists of two different components: the market expectation of inflation and the inflation risk premium. The inflation risk premium is the additional compensation required by investors to hold the security subject to inflation because of the additional risk that it inherently contains. As the time horizon increases, we would expect the inflation risk premium to become more important, leading to an increased emphasis on financial variables compared to shorter time horizons.

In addition, the output gap variables have an impact on liquidity risk premia as shown by Hördahl et al (2012). As mentioned before, this finding implies that there would be an increased emphasis on output gaps at the longer time horizons. We also hypothesize that output gap variables will have an impact on short-term inflation expectations, because the output gap has a profound impact on actual inflation, as shown by Mehra (2004). Because output gaps are somewhat persistent, we would expect that output gaps would impact breakeven inflation in shorter time horizons. Putting these two ideas together tells us that we would expect output gaps to have a decreased emphasis on mid-term horizon breakeven inflation rates. We also note that since we have included output gaps variables, we would expect that aggregate economic activity indicators will not have that large of an emphasis on breakeven inflation. We say this because, for the most part, these economic indicator variables are represented by the output gap variables, which better capture inflationary pressure as shown by Jahan et al (2013).

As the prices and exchange rates variables are not nearly as persistent as the output gaps, for example, we would expect that longer time horizons will be impacted less by them. Having less persistence means that investors will likely realize that the value at which prices and exchange rates are at today will have a relatively small impact on long-term inflation rates. This should be priced into the breakeven inflation rate, assuming the average investor is informed to some degree.

Finding the best model for each time horizon is quite a difficult task, since there are 2^{23} possible models for each time horizon of breakeven inflation. In order to find a parsimonious model for each of the breakeven inflation rates, we will use two techniques – Lasso Regression Analysis and Bayesian Model Averaging. Specifics about each model can be found section 3 of this paper.

Once the parsimonious model is selected, we believe that it is important to show how shocks to the selected variables impact breakeven inflation. To do this, we will run the Cholesky Decomposition on the Vector Autoregression of the selected variables. As we hope to run a VAR model, all potential explanatory variables are converted into stationary processes at the very beginning.

2. Data Description

The Variables

Potential Explanatory Variables:

The movement in breakeven inflation is complex and can be attributed to a multitude of different factors. As such, the list of potential variables that can help explain these variations is quite substantial.

This set consists of 23 potential explanatory variables that contain measures for monetary factors, output gap, prices and exchange rates, economic activity, confidence, and the financial market. These variables are broken down as follows:

1. Monetary Factors – M1 and M3
2. Output Gap – Domestic Output Gap, Participation Gap, Unemployment Gap, Temporary Workers Gap, and Involuntary Workers Gap
3. Prices and Exchange Rate – Consumer Price Index (CPI), Real Exchange Rate, Producer Price Index, Effective Federal Funds Rate, Harmonized Index of Consumer Prices (HICP), Crude Oil Price, and Raw Materials Price
4. Economic Activity Indicators – Unemployment Rate, Wage Growth, and Industrial Production
5. Confidence Indicators – Purchasing Managers Index (PMI) Composite Index, Business Confidence Index, and Consumer Confidence Index
6. Financial Variables – Treasury Yield Spread, CBOE Volatility Index, and NASDAQ Composite Index

Each of these variables is converted into a stationary process for analysis. To see the results of the Dickey Fuller unit root test for each variable please see Appendix B. For a full breakdown on the measurement and sources of all variables, please see Appendix A. It is important to note that each of these variables is significantly correlated with at least one time horizon of the breakeven inflation rate, as can be seen in Appendix C.

Measuring Breakeven Inflation:

To test the effect on breakeven inflation rates across a varying timeline, three different time horizons were used of breakeven inflation rates. The short-term measure is the 5-year breakeven inflation rate, the medium-term measure is the 10-year breakeven inflation rate, and the long-term measure is the 20-year breakeven inflation rate. These measures were all converted to stationary processes as well.

3. The Models

This paper uses a total of five different models that build upon each other. The first model is an autoregressive model to measure how persistent breakeven inflation is. The results of the autoregression tell us how many lags of breakeven inflation to include in future models. The next two models are model selection techniques to determine which potential explanatory variables are useful in explaining variations in breakeven inflation rates. These models are the LASSO regression and Bayesian Model Averaging. The reason we run both of them is because the Lasso regression, while useful, isn't as interpretable as the BMA. However, we make the assumption that the prior follows a Gaussian distribution when using BMA. In order to check that this assumption does not lead to extraneous results, we check to see if the LASSO and BMA have similar results regarding the main explanatory variables. Then, variables that are selected by the BMA are used in a Vector Autoregression to form the Impulse Response charts for analysis. This will tell us how shocks to the explanatory variables impact breakeven inflation. The specifics of the models are given in the following sections.

Autoregressive Model:

The autoregressive model is given by:

$$BEIR_{t,i} = \beta_0 + \sum_{j=1}^{n} \beta_j BEIR_{t-j,i} + \epsilon_t$$

where $BEIR_{t,i}$ is the i-year Breakeven Inflation Rate at time t and ϵ_t is the residual of the regression

After this model is run for a finite number of lags, the adjusted R^2, BIC, and AIC, will help determine the appropriate number of lags to use in future models. In addition, the AR model will help us compare the persistence of the different time horizons of breakeven inflation. This will inform us of what we should expect regarding how many variables are selected by the model for each horizon. Increased persistence should lead to fewer explanatory variables because a greater amount of the fluctuation in breakeven inflation can be attributed to past breakeven inflation data.

LASSO Regression:

The first variable selection technique used was the LASSO regression. This model is given by the following:

$$\widehat{\boldsymbol{\beta}} = \arg\min_{\beta} \left\{ \frac{1}{2N} \sum_{t=1}^{N} \left(BEIR_{t,i} - \sum_{j=1}^{23} \beta_j X_{t,j} \right)^2 + \lambda \sum_{j=1}^{23} \omega_j |\beta_j| \right\}$$

where $\widehat{\boldsymbol{\beta}}$ *is the linear lasso point estimates, N is the number of observations in the dataset,* $BEIR_{t,i}$ *is the i-year Breakeven Inflation Rate at time t,* β_j *is the coefficient of potential explanatory variable j,* $X_{t,j}$ *is the jth potential explanatory variable at time t,* ω_j *is the penalty loadings, and* $\lambda>0$ *is the lasso penalty parameter.*

This model will output a certain number of variables that it believes are useful in explaining fluctuations in breakeven inflation. While this is ultimately the goal, LASSO regressions output results that, while potentially correct, are hard to interpret, which is the ultimate goal of this paper. The LASSO is still helpful, however, because it's results should be similar to other model selection techniques if they are used properly. This allows us to confirm the validity of these other models with more interpretable results.

Bayesian Model Averaging (BMA):

Due to the inherent interpretability of the LASSO regression, we will use Bayesian Model Averaging (BMA) to evaluate the potential explanatory variables. The specific model is given by De Luca (2011).

Let's denote $\mathcal{M}_i$, with $i \in [1, I]$ where R is the number of potential models that can be run given our potential explanatory variables. Since there are 23 of these variables, $I = 2^{23}$

Essentially, the model is defined as such:

$$P\left(\mathcal{M}_i \middle| BEIR_{t,i}\right) = \frac{P(\mathcal{M}_i)P\left(BEIR_{t,i} \middle| M_i\right)}{\sum_{j=1}^{I} P(\,M_j)\{BEIR_{t,i}|M_j)}$$

where $P(\mathcal{M}_i)$ is the prior probability of the model $\mathcal{M}_i$, $P\left(BEIR_{t,i}\middle|M_i\right)$ is the marginal likelihood of achieving y in $\mathcal{M}_i$, $BEIR_{t,i}$ is the i-year Breakeven Inflation Rate at time t, and M_i represents a single model that can be run given the explanatory variables.

Then, we say that the BMA estimate of β_j is given by:

$$\widehat{\beta_J} = \sum_{i=1}^{I} \lambda_i \widehat{\beta_{J,\iota}}$$

where $\lambda_i = P\left(\mathcal{M}_i\middle|BEIR_{t,i}\right)$ and $\widehat{\beta_{J,\iota}}$ is the estimate of β_j in model $\mathcal{M}_i$.

Note: each λ_i>0 are random weights that add up to one and represent confidence in model $\mathcal{M}_i$.

For further information about this model, please see De Luca (2011), where this model is taken from.

This model is particularly helpful because it outputs the posterior inclusion probability for each variable, which allows us to interpret how significant it is in explaining breakeven inflation. We can say this because having a greater probability of being included in the model indicates that it explains some portion of breakeven inflation that the other variables do not.

It is important to note that the LASSO regression and BMA should have similar results regarding which variables were selected. If they are not similar, then it is possible that the choice of a Gaussian prior was incorrect when modeling breakeven inflation.

Vector Autoregression (VAR) and Cholesky Decomposition:

The next model run was a VAR(p) model followed by Cholesky Decomposition, where p is given by the autoregression model. The goal of this model is to see how shocks to the explanatory variables will impact breakeven inflation. The VAR model is given by:

$$Y_t = \beta_0 + \sum_{j=1}^{p} \beta_j Y_{t-j} + v_t$$

$$where\ Y_t = \begin{pmatrix} BEIR_{t.i} \\ X_1 \\ \vdots \\ X_q \end{pmatrix}, \beta_0 = \begin{pmatrix} \beta_o^{BEIR} \\ \beta_o^{X_1} \\ \vdots \\ \beta_o^{X_q} \end{pmatrix}, \beta_j\ is\ the\ correlation\ matrix, and\ v_t = \begin{pmatrix} \epsilon_t^{BEIR} \\ \epsilon_t^{X_1} \\ \vdots \\ \epsilon_t^{X_q} \end{pmatrix}.$$ *In the above, $BEIR_{t,i}$ is the i-year Breakeven Inflation Rate at time t, X_i is a variable selected by*

the BMA model, q is the number of variables selected by the BMA model, and v_t is the regression error.

After running the VAR model, a Cholesky Decomposition was run to examine the impulse responses of the resulting data. The shocks used in the Cholesky Decomposition are orthogonalized to ensure that the potential correlation of shocks does not impact the results.

4. Results:

Autoregressive Model:

The 20 lag correlogram for each time horizon shows a steady decline in the autocorrelation function (ACF). Additionally, it shows that the partial autocorrelation function is non-zero for the first two lags and is zero (or below the significance constraint) for every lag thereafter. This implies that two is the optimal number of lags for an autoregressive model. The correlogram results can be seen in Appendix H. To determine whether this interpretation of the correlogram is correct, an AR(1) model, an AR(2) model, and an AR(3) model are run and compared to each other.

The results for these autoregressive models are shown below:

Table 1: Summary Data for AR Models			
Panel A: 5 Year Break Even Inflation Rate			
	(1) Breakeven - 5	(2) Breakeven - 5	(3) Breakeven - 5
L.Breakeven5	0.920***	1.244***	1.263***
	(0.0279)	(0.0671)	(0.0719)
L2.Breakeven5		-0.351***	-0.417***
		(0.0670)	(0.112)
L3.Breakeven5			0.0518
			(0.0718)
Constant	0.000287	-0.000109	0.000308
	(0.0149)	(0.0141)	(0.0141)
Observations	199	198	197
R^2	0.847	0.866	0.866
BIC	-47.33976	-67.00198	-61.0292
Panel B: 10 Year Break Even Inflation Rate			
	(1) Breakeven - 10	(2) Breakeven - 10	(3) Breakeven - 10
L.Breakeven10	0.943***	1.381***	1.399***
	(0.0241)	(0.0635)	(0.0719)
L2.Breakeven10		-0.466***	-0.513***
		(0.0635)	(0.118)
L3.Breakeven10			0.0314
			(0.0719)
Constant	-0.000544	-0.000748	-7.80e-05
	(0.00931)	(0.00830)	(0.00833)
Observations	199	198	197
R-squared	0.886	0.911	0.911
BIC	-234.6124	-275.6629	-269.4316
Panel C: 20 Year Break Even Inflation Rate			
	(1) Breakeven - 20	(2) Breakeven - 20	(3) Breakeven - 20
L.Breakeven20	0.954***	1.309***	1.332***
	(0.0218)	(0.0699)	(0.0757)
L2.Breakeven20		-0.371***	-0.453***
		(0.0697)	(0.121)
L3.Breakeven20			0.0625
			(0.0754)
Constant	-0.00595	-0.00428	-0.00466
	(0.00881)	(0.00825)	(0.00831)
Observations	181	180	179
R-squared	0.914	0.925	0.924
BIC	-249.7777	-269.2768	-262.3009

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes. L.X represents the data one period earlier, L2.X represents the data 2 periods earlier, and L3.X represents the data 3 periods earlier.

For all three time horizons of breakeven inflation, the BIC for the AR(2) model is the lowest. This indicates that a model comprised of two lags ($BEIR_{t-1,i}$ and $BEIR_{t-2,i}$) is the best autoregressive model for breakeven inflation. Thus, for the following models, two lags of breakeven inflation will be used as potential explanatory variables.

This AR(2) model is a good metric for the persistence of each of the breakeven inflation rates. As we said earlier, we expect increased persistence to lead to fewer variables in the parsimonious models. When examining the AR(2) model, it is clear that the R^2 increases and the BIC decreases as the time horizon of the breakeven inflation increases. This implies that the number of variables should decrease as the time horizon increases because in longer time horizons, more of the variation is explained by the autoregressive components.

LASSO Regression:

The output of the LASSO regression is the variables chosen by the model and their corresponding coefficients. The results are shown below:

Table 2: Summary Data for Lasso Models

Variable Type	Variable	(1) 5 Year Breakeven Rate		(2) 10 Year Breakeven Rate		(3) 20 Year Breakeven Rate	
		Lasso	Post-Est OLS	Lasso	Post-Est OLS	Lasso	Post-Est OLS
Lagged Break Even Rate	L1.Breakeven Rate	0.742	0.731	0.918	0.892	0.867	0.859
	L2.Breakeven Rate	-0.137	-0.166	-0.204	-0.209	-0.157	-0.203
Consumer Price Index	CPI	12.611	13.763	3.125	10.041	1.890	5.437
	L1.CPI	-9.014	-10.819	-1.268	-4.828	-	-
Monetary Factors	M1	-	-	-0.001	-0.020	-	-
	M3	-	-	-	-	-	-
Output Gap	Domestic Output Gap	0.012	0.063	-	-	-	-
	Unemployment Gap	-	-	0.025	0.035	0.029	0.032
	Participation Gap	1.355	-1.874	1.012	0.874	2.273	2.841
	Temporary Workers Gap	-0.368	-1.164	-	-	-	-
	Involuntary Workers Gap	-	-	-	-	-	-
Prices and Exchange Rates	Real Exchange Rate	-0.381	-0.649	-0.485	-0.735	-0.591	-0.819
	Producer Price Index	-	-	-0.056	-0.901	-0.196	-1.111
	Effective Fed Funds Rate	-	-	-	-	-	-
	HICP	-	-	-	-	-	-
	Crude Oil Price	-	-	-	-	-	-
	Raw Materials Price	-	-	-	-	-	-
Economic Acitivity Indicators	Unemployment Rate	-	-	-	-	-	-
	Wage Growth	-	-	-	-	-	-
	Industrial Production	-	-	-	-	-	-
Confidence Indicators	PMI Composite	-	-	-	-	-	-
	Business Confidence	-	-	-	-	-	-
	Consumer Confidence	-0.003	-0.029	-	-	-	-
Financial Variables	Yield Spread	0.000	-0.037	-	-	-	-
	CBOE Volatility	-0.021	-0.023	-0.012	-0.013	-0.011	-0.011
	NASDAQ Composite	-	-	-	-	0.000	0.002
Constant	Constant	0.069	0.287	-0.033	0.011	-0.065	-0.026
Observations		194		197		176	
Lambda		0.1883		0.1323		0.0727	
Number of Variables Chosen by Lasso		11		10		9	

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes. L1.X represents the data one period earlier and L2.X represents the data 2 periods earlier. The LASSO column corresponds to the Lasso estimates of the coefficient, and the Post-Est OLS corresponds to the OLS estimates of the coefficient with the variables chosen by the LASSO.

This model shows that as the time horizon increases, the number of explanatory variables decreases. The LASSO regression selected 11 explanatory variables for the 5-year time horizon, 10 explanatory variables for 10-year time horizon, and 9 explanatory variables for the 20-year time horizon. This makes sense given the autoregression results shown earlier, where the variation in breakeven inflation is explained more in longer time horizons by lagged breakeven inflation.

For the 5-year breakeven inflation rate there was more emphasis on the output gap variables and confidence indicators as explanatory mechanisms of breakeven inflation. For both the 10-year and 20-year breakeven inflation rates, there was an increased emphasis on the prices and exchange rate variables. The 10-year breakeven inflation rate was the only time horizon for which monetary factors contributed as explanatory variables, but also had a decreased emphasis on the financial market variables relative to the 5- and 20-year time horizons. The 20-year breakeven inflation rate was the only time horizon that didn't include lagged CPI as an explanatory variable.

It is important to note that the LASSO regression did not select any of the economic activity indicators for all the breakeven inflation rates. In addition, the only variables selected across all the breakeven inflation rates were the lagged breakeven inflation rates, CPI, the Real Exchange Rate, the Participation Gap, and CBOE volatility index. To see the impact of these variables on breakeven inflation over time, refer to Appendix D, which presents their dynamic contribution in a time series chart.

Bayesian Model Averaging:

The output of this model is the posterior probability that each of the variables should be included in the model. Essentially, it corresponds to the proportion of models that contain that variable. This term is called the posterior inclusion probability (PIP) and must be in between 0 and 1 as determined by the model for each variable. The model space for each of the BMA models is 2^{25} or 33,554,432 unique models. For the purpose of this paper we will say that the variables with a significant impact on breakeven inflation are those that have a PIP greater than 0.5.

As opposed to the LASSO regression, this model helps us determine exactly how useful each variable is in explaining movements in breakeven inflation. The closer the posterior inclusion probability is to one, the more likely that the given variable is important in explaining breakeven inflation. In addition, the sum of all the posterior inclusion probabilities across the variables gives the average number of regressors in a model for a given time horizon of breakeven inflation.

The results from the BMA models are shown below:

Table 3: Summary Data for BMA Models				
Variable Type	Variable	(1) 5 Year Breakeven Rate	(2) 10 Year Breakeven Rate	(3) 20 Year Breakeven Rate
Lagged Break Even Rate	L1.Breakeven Rate	**1.00**	**1.00**	**1.00**
	L2.Breakeven Rate	**1.00**	**1.00**	**0.97**
Consumer Price Inflation	CPI	**0.91**	**0.90**	**0.75**
Monetary Factors	M1	0.13	**0.69**	0.17
	M3	0.22	0.06	0.03
Output Gap	Domestic Output Gap	**0.96**	0.27	0.15
	Unemployment Gap	**0.71**	0.33	**0.65**
	Participation Gap	**0.99**	**0.86**	**0.97**
	Temporary Workers Gap	0.27	0.20	0.34
	Involuntary Workers Gap	0.49	**0.63**	0.14
Prices and Exchange Rates	Real Exchange Rate	**0.97**	**1.00**	**1.00**
	Producer Price Index	**0.87**	**0.88**	**0.61**
	Effective Fed Funds Rate	0.04	0.08	0.11
	HICP	0.14	0.18	0.25
	Crude Oil Price	**0.77**	**0.59**	0.07
	Raw Materials Price	0.08	0.05	0.05
Economic Acitivity Indicators	Unemployment Rate	0.15	0.10	0.07
	Wage Growth	0.13	0.16	0.15
	Industrial Production	0.12	0.36	0.12
Confidence Indicators	PMI Composite	0.08	0.17	0.08
	Business Confidence	0.13	0.10	0.06
	Consumer Confidence	0.07	0.22	0.08
Financial Variables	Yield Spread	0.09	0.06	0.06
	CBOE Volatility	**1.00**	**1.00**	**1.00**
	NASDAQ Composite	0.04	0.36	**0.60**
Observations		194	194	176
Model Space		33,554,432	33,554,432	33,554,432
Average Number of Variables `		11.36	11.25	9.48
Number of Variables with High Probability		10	10	9

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes. L1.X represents the data one period earlier and L2.X represents the data 2 periods earlier. The output corresponds to the posterior inclusion probability of each variable and must be in between 0 and 1. We denote high probability variables as those with a posterior inclusion probability greater than 0.5. The high probability variables are bolded.

While the output from the BMA model may seem more complicated, it is actually quite similar to that of the LASSO results. As was true in the LASSO model, the average number of variables decreases as the time horizon of breakeven inflation increases. Moreover, many of the variables that have a high probability of being in the posterior distribution are also the ones that were chosen by the LASSO regression. The similarity of the results implies that the choice of using Gaussian priors was correct.

While the posterior inclusion probabilities of the individual variables are interesting, we are more concerned with how the high probability variables impact breakeven inflation. This will be examined further in the vector autoregression results section. However, it is important to note that CPI, Participation Gap, Real Exchange Rate, and the CBOE Volatility Index have a significant impact for all time horizons of breakeven inflation. Further analysis of these variables can be seen in Appendix G.

Regarding, the groups of variables that are included in the model, the following table contains the probability that at least one variable from each group is included in the model:

Table 4: Posterior Inclusion Probabilty for Variable Groups

Variable Type	(1) 5 Year Breakeven Rate	(2) 10 Year Breakeven Rate	(3) 20 Year Breakeven Rate
Monetary Factors	0.32	0.71	0.19
Output Gap	**1.00**	**0.98**	**0.99**
Prices and Exchange Rates	**1.00**	**1.00**	**1.00**
Economic Acitivity Indicators	0.35	0.52	0.30
Confidence Indicators	0.26	0.42	0.20
Financial Variables	**1.00**	**1.00**	**1.00**
Observations	194	194	176
Model Space	33,554,432	33,554,432	33,554,432

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. The list of variables included in each variable group can be found in Appendix A. All variables used in the BMA model have been converted to stationary processes. The output corresponds to the posterior inclusion probability that at least one variable of each group is included in the model and must be in between 0 and 1. We denote high probability variable groups as those with a posterior inclusion probability greater than 0.95. The high probability variable groups are bolded.

For the purposes of this paper, we define high probability groups of variables as those that have a posterior inclusion probability of 0.95 or higher. This means that we are 95% confident that at least one variable from this group is included in the model. From this chart, we can see that monetary factors, economic activity indicators, and confidence indicators are not significantly included in the breakeven inflation model. It is hard to examine the change in some of these other variable groups from solely the posterior inclusion probability. For example, the financial variables have a posterior inclusion probability of 1 across all the time horizons. However, this does not mean that their average effect is constant. To examine these groups properly, we will look at the average number of variables selected from each group, which is shown in the following chart:

Table 5: Avg. Number of Regressors for Variable Groups

Variable Type	(1) 5 Year Breakeven Rate	(2) 10 Year Breakeven Rate	(3) 20 Year Breakeven Rate
Monetary Factors	0.35	0.75	0.20
Output Gap	**3.42**	**2.29**	**2.25**
Prices and Exchange Rates	**3.78**	**3.68**	**2.84**
Economic Acitivity Indicators	0.40	0.62	0.34
Confidence Indicators	0.28	0.49	0.22
Financial Variables	**1.13**	**1.42**	**1.66**
Observations	194	194	176
Model Space	33,554,432	33,554,432	33,554,432

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. The list of variables included in each variable group can be found in Appendix A. All variables used in the BMA model have been converted to stationary processes. The output corresponds to the average number of variables included in the model for each group. This is calculated by adding the posterior inclusion probability for each group. The posterior inclusion probability for an individual variable is the probability that it is included in the model and must be in between 0 and 1. The bolded data refers to the groups which had a PIP greater than 0.95 of having at least one of its variables in the model.

The conclusions from this table are remarkably similar to trends that are expected from the models, which are outlined in the introduction. From Table 5, it is clear that the number of average regressors for the prices and exchange rates variables decrease as the time horizon increases. This is potentially due to the lack of persistence from these variables, which would make it less likely to impact longer term inflation expectations. Alternatively, the number of average regressors for the financial variables increases with the time horizon. As mentioned earlier, this is likely due to their impact on the inflation risk premia, which is more important for longer time horizon breakeven inflation rates. The output gap is slightly different than we expected. The data shows that the number of average regressors decreases as the time horizon increases. The trend we were expecting was a decreased importance in middle-term horizons and an increased importance in short- and long-term horizons. It is important to note, however, that this trend can be seen in the posterior inclusion probabilities from Table 4. The decrease over time is likely because only a few of the output gap variables have a significant impact on the inflation risk premia, while the persistence of the output gap variables as a whole has more of an impact on average. The dynamic contributions of all the significant variables in the BMA can be seen in Appendix E.

Impulse Responses given by Cholesky Decomposition:

The determinants of the VAR model are given by the results of the previous models. From the AR model, we saw that the two lags model breakeven inflation the best. Given this, we ran a VAR(2) model. The variables included in the VAR are those that had a posterior inclusion probability greater than 0.5 in the BMA. From the VAR, the Cholesky Decomposition was run to model the impulse responses of these variables. The results of the Cholesky Decomposition can be found in Appendix F.

In each of the time horizons, the shocks to certain variables have statistically significant implications for multiple months, implying that a dynamic model is necessary when trying to model breakeven inflation.

Across all the time horizons, the CBOE volatility index initially has a negative effect on all the time horizons of breakeven inflation. This is likely because when the volatility of the market is lower, investors are pricing in a lower risk premium and vice versa. Similarly, the real exchange rate has a negative effect on all the time horizons, implying that investors see an increase in the real exchange rate as decreasing inflationary pressure. Additionally, the participation gap initially has a negative effect followed by a positive effect in all the time periods. However, the negative effect is never statistically significant. This implies that a shock in the participation gap impacts the breakeven inflation positively after a few months. This is understandable considering an increased participation gap takes time to impact the economy. In contrast, consumer price index shocks have a negative effect on breakeven inflation. It's important to note however that its shocks only become statistically significant after a few months as well, implying that changes in CPI take time to impact an investor's perception of inflationary pressure. Shocks to the producer price index, on the other hand, are never statistically significant for all the time horizons.

The previous variables were those that were included in the VAR of all the time horizons. The crude oil price, which was included in the 5- and 10-year time horizon models, had a positive effect on both rates. Similarly, the domestic output gap had a positive effect on the 5-year time horizon as well. Unlike the participation gap however, the domestic output gap had an immediate effect on the 5-year breakeven inflation rate. All the other variables not mentioned in this section did not have a statistically significant response to their respective shock.

5. Conclusion

In this paper, I examined the drivers of breakeven inflation at multiple time horizons. To do this, I used Bayesian model selection techniques to identify explanatory variables and then examined the impact shocks to these variables have on breakeven inflation through a Cholesky decomposition. I believe that this is the first paper to conduct this type of analysis on US breakeven inflation.

The results from the BMA agreed with both the theoretical and empirical implications as outlined in the introduction. Specifically, the output gap variables were important for short- and long-term horizons. The exchange rate and prices variables decreased as the time horizon increased, while the financial variables increased with the time horizon. In addition, the aggregate economic indicator variables were not as effective in modeling inflation as the output gap variables.

The VAR showed how shocks to the significant variables impacted breakeven inflation. Many of the responses to shocks to these variables were significant for months, implying that a dynamic model is necessary in modeling breakeven inflation.

References

Andersen, Allan Sall Tang. "Inflation Risk Premia in the Term Structure of Interest Rates: Evidence from Euro Area Inflation Swaps." *SSRN Electronic Journal*, 2009. https://doi.org/10.2139/ssrn.1456831.

Ang, Andrew, and Monika Piazzesi. "A No-Arbitrage Vector Autoregression of Term Structure Dynamics with Macroeconomic and Latent Variables." *Journal of Monetary Economics* 50, no. 4 (2003): 745–87. https://doi.org/10.1016/s0304-3932(03)00032-1.

Ang, Andrew, Geert Bekaert, and Min Wei. "Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better?" *Finance and Economics Discussion Series* 2006, no. 15 (2006): 1–62. https://doi.org/10.17016/feds.2006.15.

Chernov, Mikhail, and Philippe Mueller. "The Term Structure of Inflation Expectations." *SSRN Electronic Journal*, 2008. https://doi.org/10.2139/ssrn.1101513.

Ciccarelli, Matteo, and Juan Angel García. "What Drives Euro Area Break-Even Inflation Rates?" *European Central Bank Working Paper Series*, no. 996 (2009).

D'amico, Stefania, Don H. Kim, and Min Wei. "Tips from TIPS: The Informational Content of Treasury Inflation-Protected Security Prices." *SSRN Electronic Journal*, 2014. https://doi.org/10.2139/ssrn.2422861.

García, Juan Angel, and Andrés Manzanares. "What Can Probability Forecasts Tell Us about Inflation Risks?" *European Central Bank Working Paper Series*, no. 825 (October 2007).

Güler, Mustafa Haluk, Gürsu Keleş, and Tandoğan Polat. "An Empirical Decomposition of the Liquidity Premium in Breakeven Inflation Rates." *The Quarterly Review of Economics and Finance* 63 (2017): 185–92. https://doi.org/10.1016/j.qref.2016.04.002.

Hördahl, Peter, and Oreste Tristani. "Inflation Risk Premia In The Term Structure Of Interest Rates." *Journal of the European Economic Association* 10, no. 3 (2012): 634–57. https://doi.org/10.1111/j.1542-4774.2012.01067.x.

Hördahl, Peter, and Oreste Tristani. "Inflation Risk Premia in the US and the Euro Area." *SSRN Electronic Journal*, 2010. https://doi.org/10.2139/ssrn.1716886.

Hördahl, Peter, Oreste Tristani, and David Vestin. "A Joint Econometric Model of Macroeconomic and Term Structure Dynamics." *SSRN Electronic Journal*, 2003. https://doi.org/10.2139/ssrn.424920.

Hördahl, Peter, Oreste Tristani, and David Vestin. "A Joint Econometric Model of Macroeconomic and Term Structure Dynamics." *SSRN Electronic Journal*, 2003. https://doi.org/10.2139/ssrn.424920.

Jahan, Sarwat, and Ahmed Saber Mahmud. “What Is the Output Gap?” *Finance and Development* 50, no. 3 (September 2013).

Luca, Giuseppe De, and J.r. Magnus. “Bayesian Model Averaging and Weighted Average Least Squares: Equivariance, Stability, and Numerical Issues.” *SSRN Electronic Journal*, 2011. https://doi.org/10.2139/ssrn.1894610.

Mehra, Yash P. “The Output Gap, Expected Future Inflation and Inflation Dynamics: Another Look.” *Topics in Macroeconomics* 4, no. 1 (2004). https://doi.org/10.2202/1534-5998.1194.

Söderlind, Paul. “Inflation Risk Premia and Survey Evidence on Macroeconomic Uncertainty.” *SSRN Electronic Journal*, 2010. https://doi.org/10.2139/ssrn.1147638.

Thiele, Eduardo, and Marcelo Fernandes. “The Macroeconomic Determinants of the Term Structure of Inflation Expectations in Brazi.” *Brazilian Review of Econometrics*, May 2015.

APPENDIX A: Sources and Calculations of Data

Table A1: Summary Data for Single Variable Correlation				
Variable Type	Variable	Description	Transformation	Data Source
Breakeven Inflation	5 year breakeven inflation	The breakeven inflation rate derived from the 5-Year Treasury Constant Maturity Securities and 5-Year Treasury Inflation-Indexed Constant Maturity Securities	Difference from mean	St. Louis FRED
	10 year breakeven inflation	The breakeven inflation rate derived from the 10-Year Treasury Constant Maturity Securities and 10-Year Treasury Inflation-Indexed Constant Maturity Securities	Difference from mean	St. Louis FRED
	20 year breakeven inflation	The breakeven inflation rate derived from the 20-Year Treasury Constant Maturity Securities and 20-Year Treasury Inflation-Indexed Constant Maturity Securities	Difference from mean	St. Louis FRED
Monetary Factors	M1	Measure of the money supply that is readily accessible for spending	% Change Difference from mean	St. Louis FRED
	M3	Measure of the money supply that includes M1 and other measures, such as bank deposits, savings deposits, and money market mutual funds	% Change Difference from mean	St. Louis FRED
Output Gap	Domestic Output Gap	A measure of how the real GDP differs from potential GDP	YoY Difference from mean	St. Louis FRED
	Unemployment Gap	The difference between the unemployment and NAIRU	YoY Difference from mean	St. Louis FRED
	Participation Gap	A measure of how the labor force participation rate differs from the theoretical value	YoY Difference from mean	St. Louis FRED
	Temporary Workers Gap	A measure of how the percentage of temporary workers differs from the theoretical value	YoY Difference from mean	St. Louis FRED
	Involuntary Workers Gap	A measure of how the percentage of involuntary workers differs from the theoretical value	YoY Difference from mean	St. Louis FRED
Prices and Exchange Rates	Consumer Price Index	Measure of the prices that consumers face	YoY Difference from mean	St. Louis FRED
	Real Exchange Rate	Measure of the exchange rate adjusted for nominal prices	2 Year % Change & Difference from mean	St. Louis FRED
	Producer Price Index	Measure of the prices that producers face	YoY Difference from mean	St. Louis FRED
	Effective Fed Funds Rate	The volume-weighted median of overnight federal funds transactions reported in the FR 2420 Report of Selected Money Market Rates	YoY Difference from mean	St. Louis FRED
	HICP	Similar to consumer price index but using harmonised prices	YoY Difference from mean	St. Louis FRED
	Crude Oil Price	Average price of crude oil in the US	YoY Difference from mean	World Bank
	Raw Materials Price	Average price of raw materials in the US	YoY Difference from mean	World Bank
Economic Acitivity Indicators	Unemployment Rate	A measure of employment in the US	YoY Difference from mean	St. Louis FRED
	Wage Growth	A measure of the nominal wage growth in the US	YoY Difference from mean	FRB Atlanta
	Industrial Production	A measure of real output	YoY Difference from mean	St. Louis FRED
Confidence Indicators	PMI Composite	Purchasing Mangers Index derived from monthly surveys of companies in the private sectors	Difference from mean	Quandl
	Business Confidence	A measure of business confidence regarding production, output, sales, etc. in the future	Difference from mean	OECD
	Consumer Confidence	A measure of consumer confidence/optimism in the state of the US economy	Difference from mean	OECD
Financial Variables	Yield Spread	Yield spread calclulated as the difference between the 10-Year Treasury Constant Maturity and 3-Month Treasury Constant Maturity	Difference from mean	St. Louis FRED
	CBOE Volatility	A measure of the volatilty in the financial market	Difference from mean	St. Louis FRED
	NASDAQ Composite	NASDAQ Composite Index	YoY Difference from mean	St. Louis FRED

Notes: All variables used in this paper are described in this table and sorted by their variable type. All variables are converted to stationary processes via the transformation described in the fourth column. A significant portion of the data comes from the St. Louis FRED database, but the World Bank, OECD, and Quandl were used as well. In addition, these variables have all been seasonally adjusted to remove the potential of seasonal effects in the model.

APPENDIX B: Unit Root Test Results

Table B1: Summary Data for Dickey-Fuller Test			
Variable Type	Variable	(1) Test Statistics	(2) P-Value
Consumer Price Inflation	CPI	-1.803	0.0359 **
	L1.CPI	-1.803	0.0359 **
Monetary Factors	M1	-22.656	0.0000 ***
	M3	-14.322	0.0000 ***
Output Gap	Domestic Output Gap	-1.798	0.0362 **
	Unemployment Gap	-2.018	0.0218 **
	Participation Gap	-1.571	0.0582 *
	Temporary Workers Gap	-1.574	0.0581 *
	Involuntary Workers Gap	-1.791	0.0386 **
Prices and Exchange Rates	Real Exchange Rate	-1.819	0.0350 **
	Producer Price Index	-3.639	0.0001 ***
	Effective Fed Funds Rate	-5.371	0.0000 ***
	HICP	-2.629	0.0046 ***
	Crude Oil Price	-5.395	0.0000 ***
	Raw Materials Price	-3.490	0.0003 ***
Economic Acitivity Indicators	Unemployment Rate	-4.070	0.0000 ***
	Wage Growth	-1.557	0.0603 *
	Industrial Production	-4.898	0.0000 ***
Confidence Indicators	PMI Composite	-5.331	0.0000 ***
	Business Confidence	-3.367	0.0004 ***
	Consumer Confidence	-1.510	0.0660 *
Financial Variables	Yield Spread	-2.598	0.0048 **
	CBOE Volatility	-4.679	0.0000 ***
	NASDAQ Composite	-4.217	0.0000 ***
Breakeven Inflation	Breakeven 5	-2.865	0.0023 ***
	Breakeven 10	-2.376	0.0092 ***
	Breakeven 20	-2.085	0.0192 **

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. Test statistics were calculated using the Dicky Fuller Unit Root process. The P-Value represents the probability that the variable follows a unit root process. Therefore, low p-values given by confidence above correspond to the likelihood of it being a stationary process.

Given the confidence levels of the data above, it is likely that each of the variables above are stationary processes.

APPENDIX C: Single Variable Correlation

Table C1: Summary Data for Single Variable Correlation				
Variable Type	Variable	(1) 5 Year Breakeven Rate	(2) 10 Year Breakeven Rate	(3) 20 Year Breakeven Rate
Consumer Price Inflation	CPI	0.621 ***	0.600 ***	0.614 ***
	L1.CPI	0.495 ***	0.499 ***	0.544 ***
Monetary Factors	M1	-0.315 ***	-0.246 ***	-0.189 *
	M3	-0.243 ***	-0.222 **	-0.166 *
Output Gap	Domestic Output Gap	0.497 ***	0.301 ***	0.174 *
	Unemployment Gap	-0.304 ***	-0.101	0.006
	Participation Gap	0.289 ***	0.312 ***	0.556 ***
	Temporary Workers Gap	0.158 *	0.003	-0.213 **
	Involuntary Workers Gap	-0.425 ***	-0.231 **	-0.193 **
Prices and Exchange Rates	Real Exchange Rate	-0.451 ***	-0.540 ***	-0.678 ***
	Producer Price Index	0.565 ***	0.580 ***	0.622 ***
	Effective Fed Funds Rate	0.209 **	0.024	-0.122
	HICP	0.586 ***	0.602 ***	0.642 ***
	Crude Oil Price	0.611 ***	0.609 ***	0.636 ***
	Raw Materials Price	0.336 ***	0.366 ***	0.481 ***
Economic Acitivity Indicators	Unemployment Rate	-0.389 ***	-0.352 ***	-0.191 *
	Wage Growth	0.162 *	0.058	-0.086
	Industrial Production	0.583 ***	0.585 ***	0.491 ***
Confidence Indicators	PMI Composite	0.570 ***	0.555 ***	0.394 ***
	Business Confidence	0.591 ***	0.572 ***	0.420 ***
	Consumer Confidence	0.273 ***	0.087	-0.088
Financial Variables	Yield Spread	-0.318 ***	-0.144 *	-0.099
	CBOE Volatility	-0.666 ***	-0.556 ***	-0.363 ***
	NASDAQ Composite	0.418 ***	0.461 ***	0.319 ***

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes and span from 2003 to 2019.

It is important to note that each of the variables is significant for at least one time horizon of Breakeven inflation, implying that they could potentially be selected by the model.

APPENDIX D: Dynamic Contribution of LASSO Variables

Figure D1: Lasso-OLS Coefficient Decomposition for 5 Year Breakeven Rate

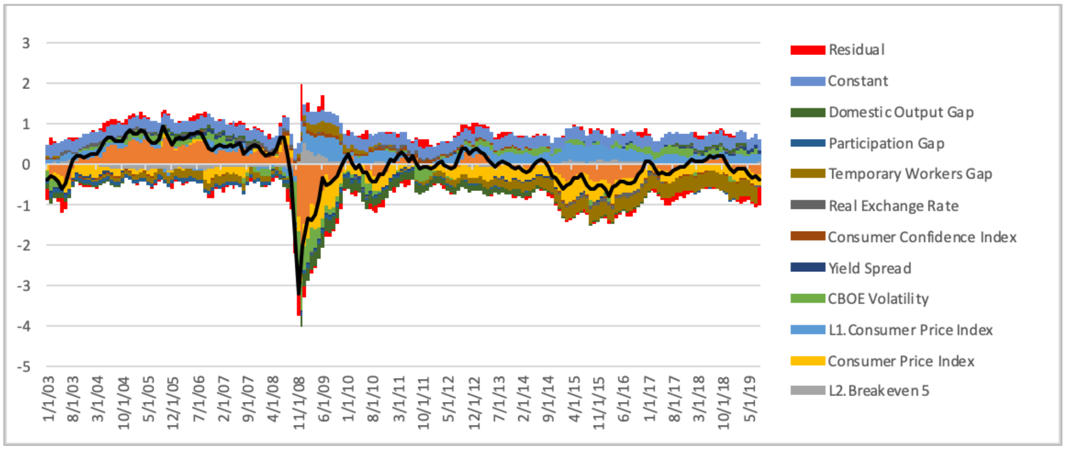


Figure D1: Lasso-OLS Coefficient Decomposition for 10 Year Breakeven Rate

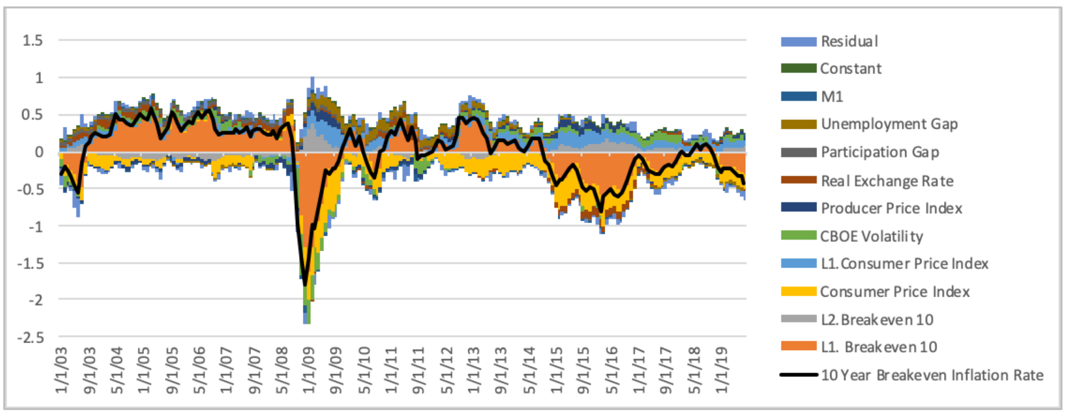
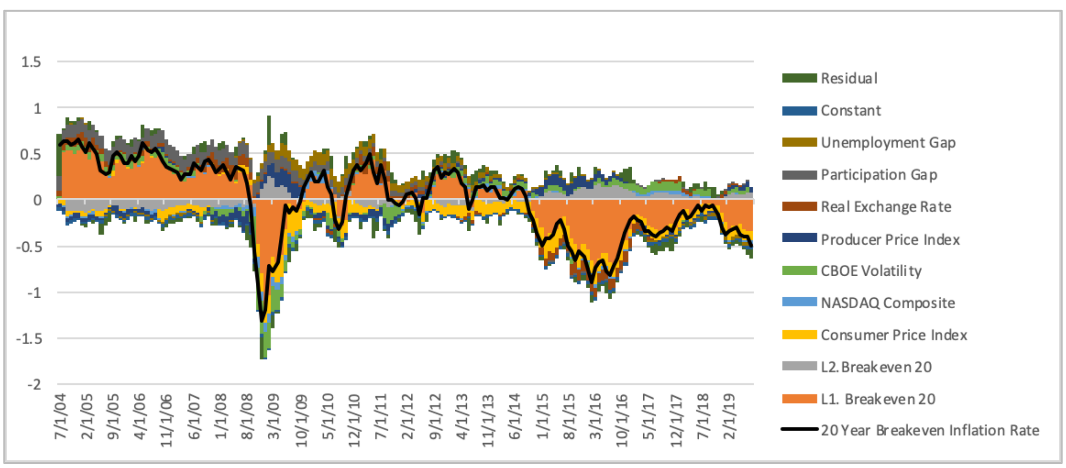


Figure D1: Lasso-OLS Coefficient Decomposition for 20 Year Breakeven Rate



Notes: This time series chart shows the dynamic contribution of each of the explanatory variables selected by the LASSO model when run in an OLS regression. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes. L1.X represents the data one period earlier and L2.X represents the data 2 periods earlier.

APPENDIX E: Dynamic Contribution of BMA Explanatory Variables

Figure E1: BMA Coefficient Decomposition for 5 Year Breakeven Rate

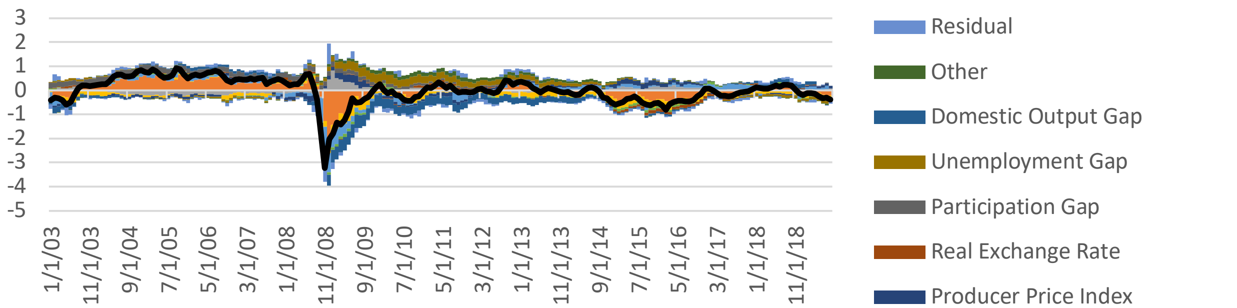


Figure E2: BMA Coefficient Decomposition for 10 Year Breakeven Rate

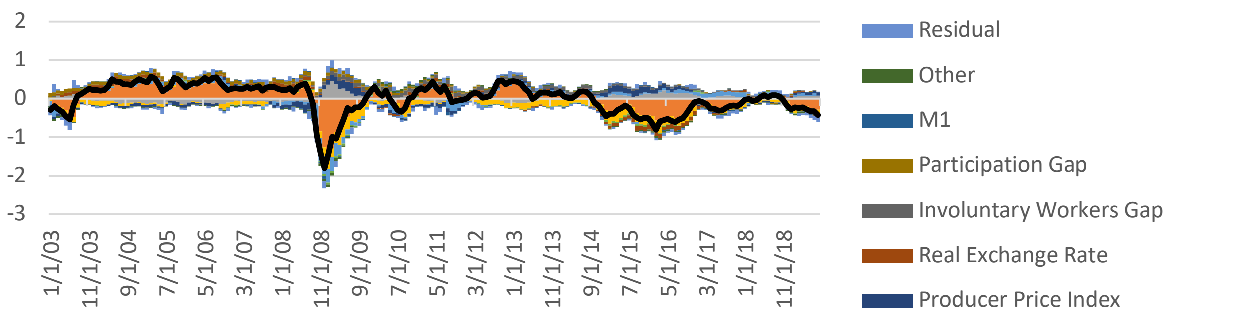
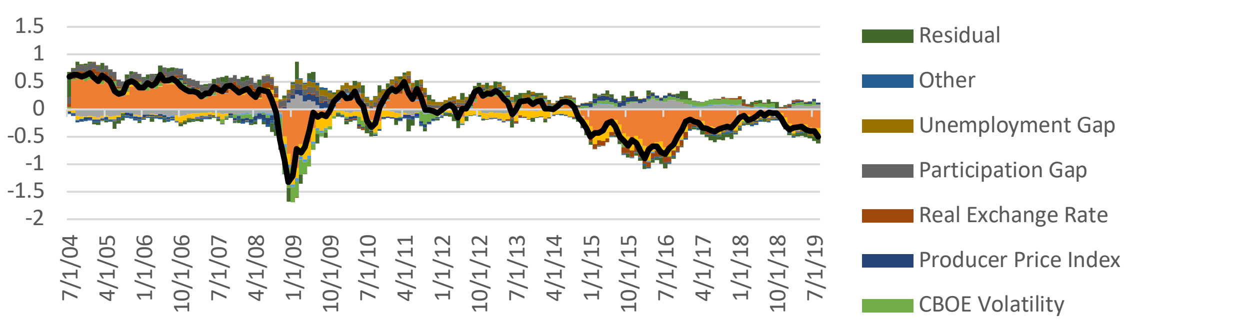


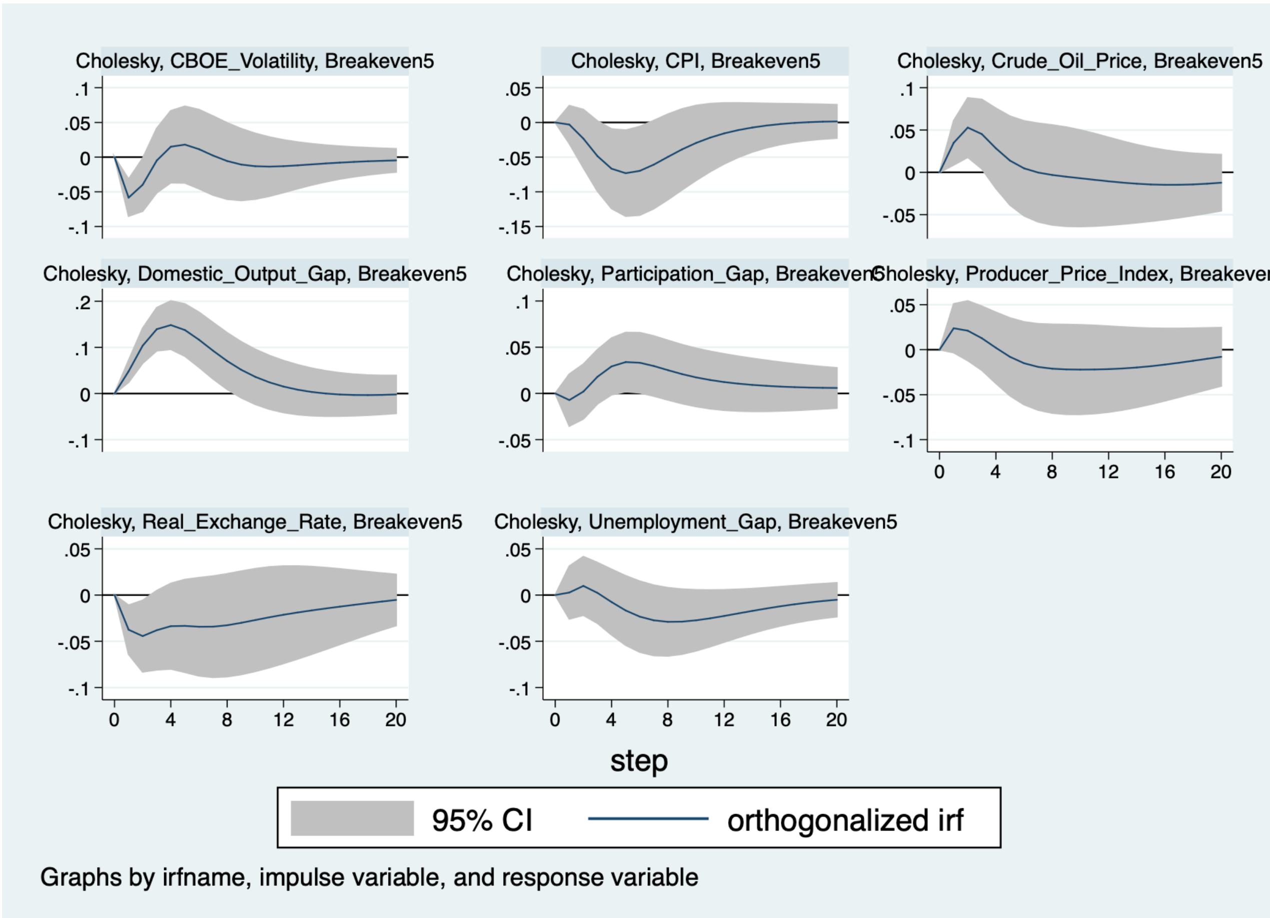
Figure E3: BMA Coefficient Decomposition for 20 Year Breakeven Rate



Notes: This time series chart shows the dynamic contribution of each of the explanatory variables selected by the LASSO model when run in an OLS regression. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes. L1.X represents the data one period earlier and L2.X represents the data 2 periods earlier.

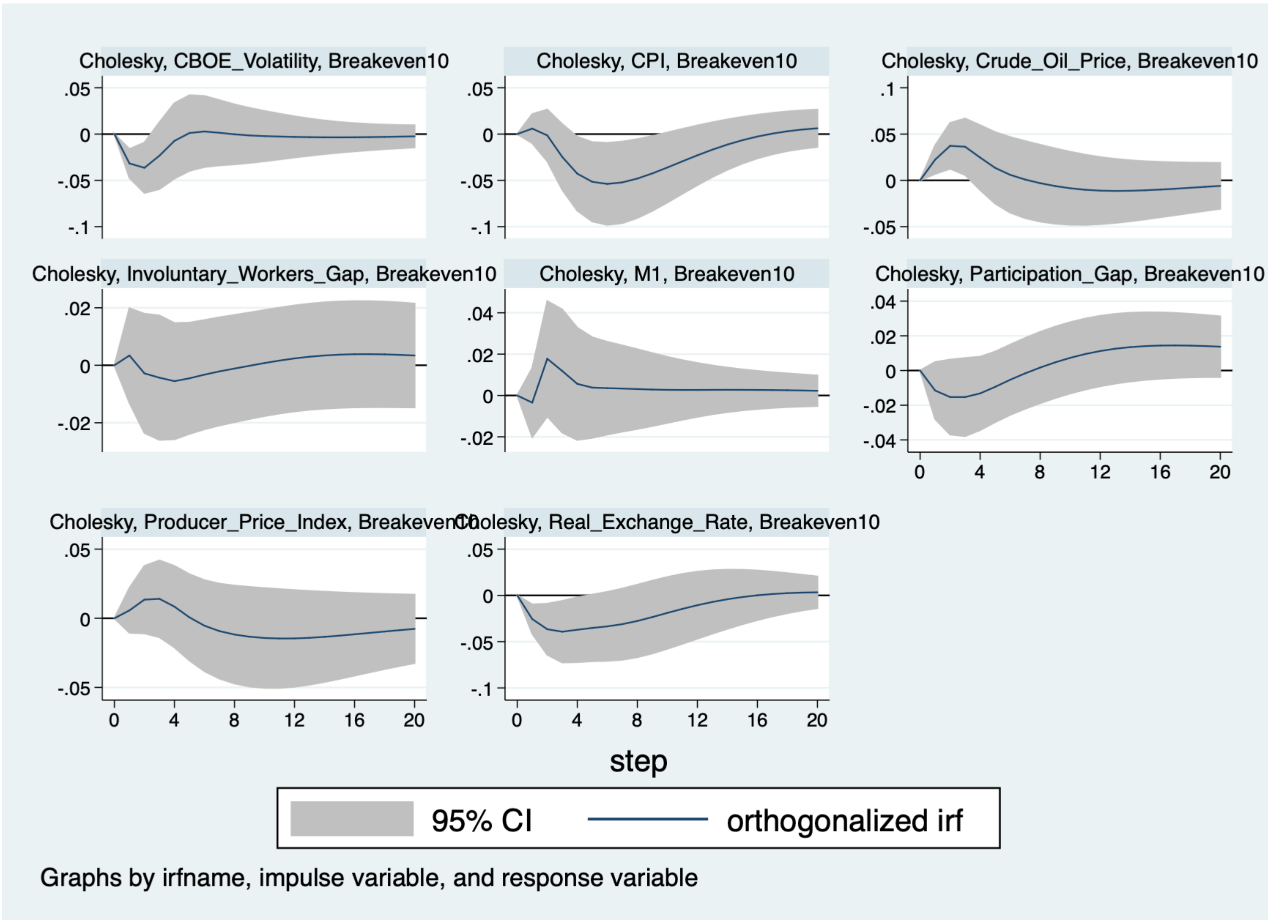
APPENDIX F: Cholesky Decomposition Data

Figure F1: Impulse Response Function of 5 Year Breakeven Inflation



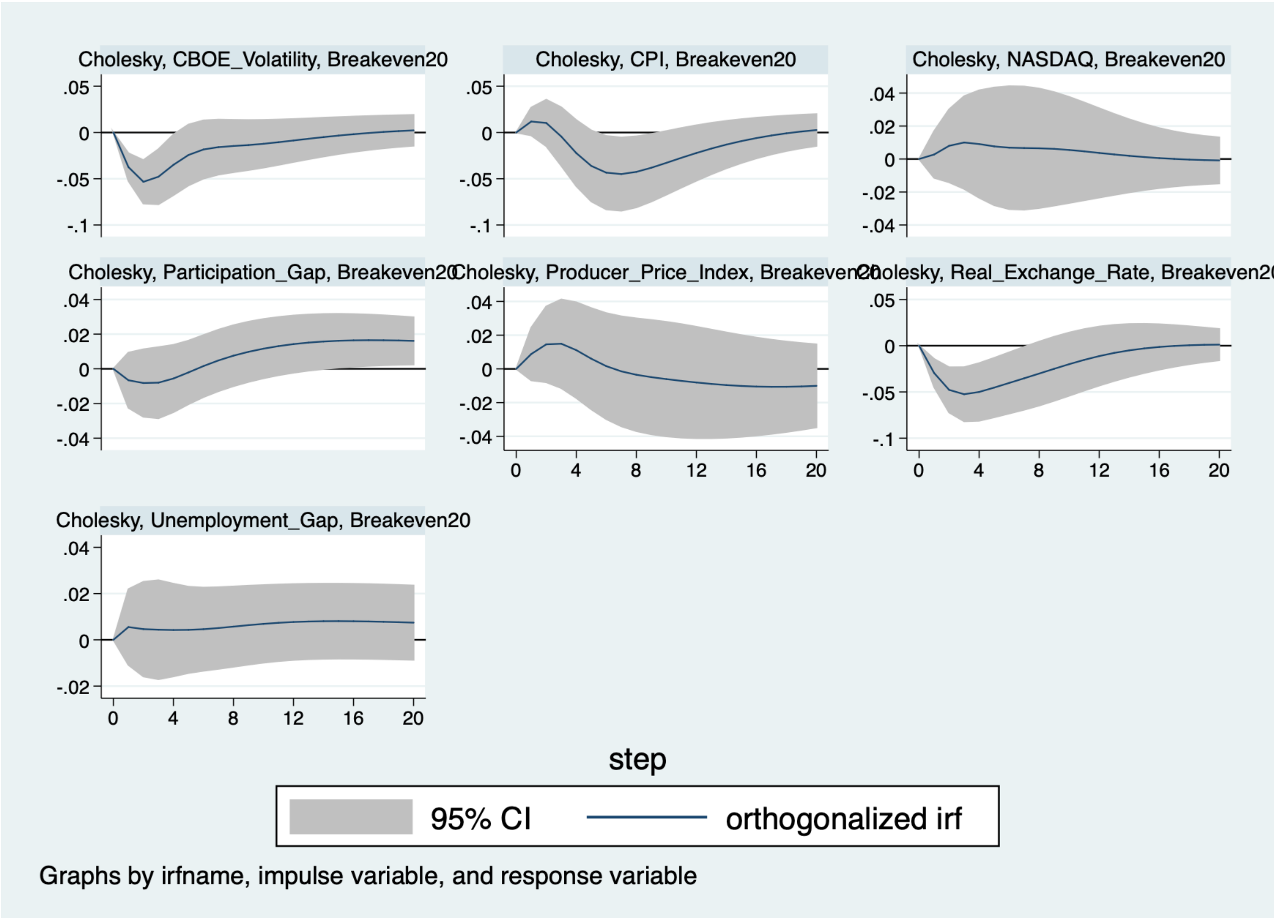
Notes: This figure shows the Impulse Response Function of the 2 period Vector Autoregression Model run on the selected variables from the BMA. The selected variables are those that had a Posterior Inclusion Probability greater than 0.5 in the BMA. The Impulse Response Function was created using the Cholesky Decomposition with orthogonalized shocks to remove the possibility of correlated shocks.

Figure F2: Impulse Response Function of 10 Year Breakeven Inflation



Notes: This figure shows the Impulse Response Function of the 2 period Vector Autoregression Model run on the selected variables from the BMA. The selected variables are those that had a Posterior Inclusion Probability greater than 0.5 in the BMA. The Impulse Response Function was created using the Cholesky Decomposition with orthogonalized shocks to remove the possibility of correlated shocks.

Figure F3: Impulse Response Function of 20 Year Breakeven Inflation



Notes: This figure shows the Impulse Response Function of the 2 period Vector Autoregression Model run on the selected variables from the BMA. The selected variables are those that had a Posterior Inclusion Probability greater than 0.5 in the BMA. The Impulse Response Function was created using the Cholesky Decomposition with orthogonalized shocks to remove the possibility of correlated shocks.

APPENDIX G: Explanatory Variables vs Breakeven

Table G1: Summary Data for AR Models			
Panel A: CBOE Volatility Index vs Breakeven Inflation			
	(1)	(2)	(3)
	Breakeven - 5	Breakeven - 10	Breakeven - 20
CBOE Volatility	-0.0433***	-0.0262***	-0.0145
	(0.00345)	(0.00278)	(0.0282)
Constant	-0.0290	-0.0175	-0.0145
	(0.0284)	(0.0229)	(0.0282)
Observations	200	200	182
R^2	0.443	0.309	0.131
Panel B: Consumer Price Index vs Breakeven Inflation			
	(1)	(2)	(3)
	Breakeven - 5	Breakeven - 10	Breakeven - 20
Consumer Price Index	25.79***	18.02***	18.51***
	(2.313)	(1.708)	(1.776)
Constant	0.428***	0.299***	0.311***
	(0.0486)	(0.0359)	(0.0381)
Observations	200	200	182
R^2	0.386	0.360	0.376
Panel C: Participation Gap vs Breakeven Inflation			
	(1)	(2)	(3)
	Breakeven - 5	Breakeven - 10	Breakeven - 20
Participation Gap	6.758***	5.275***	10.13***
	(1.596)	(1.143)	(1.132)
Constant	-0.164***	-0.128***	-0.219***
	(0.0536)	(0.0384)	(0.0352)
Observations	199	199	181
R^2	0.083	0.098	0.309
Panel D: Real Exchange Rate vs Breakeven Inflation			
	(1)	(2)	(3)
	Breakeven - 5	Breakeven - 10	Breakeven - 20
Real Exchange Rate	-3.091***	-2.677***	-3.529***
	(0.435)	(0.297)	(0.285)
Constant	-0.0682*	-0.0590**	-0.0538**
	(0.0352)	(0.0240)	(0.0226)
Observations	200	200	182
R^2	0.203	0.291	0.460

Note: *** p<0.01, ** p<0.05, * p<0.1. Data is from assorted sources but mainly from the St. Louis FRED Database. All variables in this table have been converted to stationary processes.

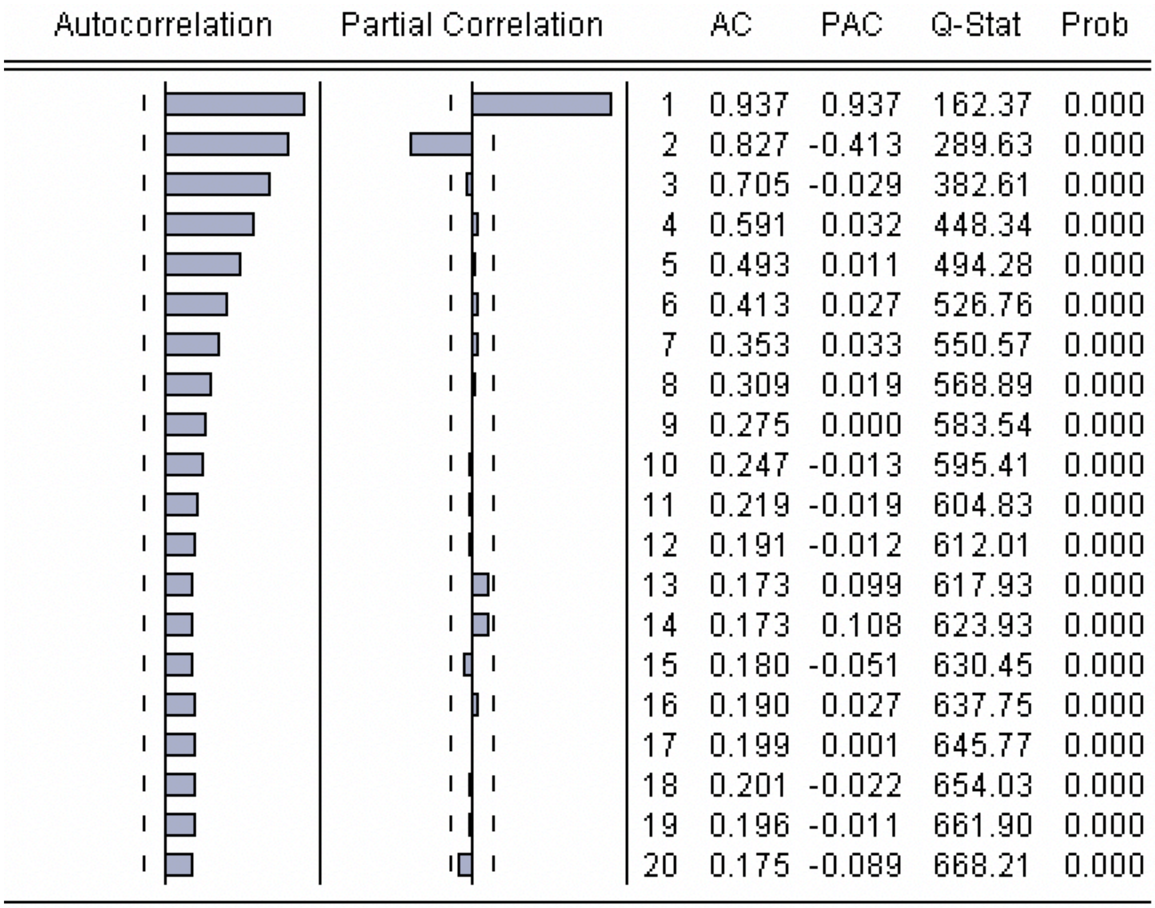
APPENDIX H: Correlogram of Breakeven Inflation Rates

Figure H1: Correlogram of 5 Year Breakeven Inflation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.915	0.915	154.83	0.000
		2	0.785	-0.318	269.48	0.000
		3	0.659	0.022	350.70	0.000
		4	0.559	0.067	409.40	0.000
		5	0.481	0.011	453.24	0.000
		6	0.417	-0.011	486.39	0.000
		7	0.356	-0.039	510.67	0.000
		8	0.316	0.116	529.87	0.000
		9	0.289	-0.005	545.99	0.000
		10	0.258	-0.067	558.98	0.000
		11	0.228	0.025	569.15	0.000
		12	0.196	-0.020	576.70	0.000
		13	0.173	0.051	582.61	0.000
		14	0.165	0.042	588.03	0.000
		15	0.169	0.043	593.76	0.000
		16	0.171	-0.020	599.69	0.000
		17	0.172	0.013	605.67	0.000
		18	0.173	0.036	611.77	0.000
		19	0.163	-0.079	617.22	0.000
		20	0.149	0.016	621.78	0.000

Note: For both bars of the ACF and PACF, the center line reflects 0 correlation and the two lines on either side of it represent the 95% confidence interval to determine that correlation is present.

Figure H2: Correlogram of 10 Year Breakeven Inflation



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.937	0.937	162.37	0.000
		2	0.827	-0.413	289.63	0.000
		3	0.705	-0.029	382.61	0.000
		4	0.591	0.032	448.34	0.000
		5	0.493	0.011	494.28	0.000
		6	0.413	0.027	526.76	0.000
		7	0.353	0.033	550.57	0.000
		8	0.309	0.019	568.89	0.000
		9	0.275	0.000	583.54	0.000
		10	0.247	-0.013	595.41	0.000
		11	0.219	-0.019	604.83	0.000
		12	0.191	-0.012	612.01	0.000
		13	0.173	0.099	617.93	0.000
		14	0.173	0.108	623.93	0.000
		15	0.180	-0.051	630.45	0.000
		16	0.190	0.027	637.75	0.000
		17	0.199	0.001	645.77	0.000
		18	0.201	-0.022	654.03	0.000
		19	0.196	-0.011	661.90	0.000
		20	0.175	-0.089	668.21	0.000

Note: For both bars of the ACF and PACF, the center line reflects 0 correlation and the two lines on either side of it represent the 95% confidence interval to determine that correlation is present.

Figure H3: Correlogram of 20 Year Breakeven Inflation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.946	0.946	165.66	0.000
		2	0.864	-0.302	304.47	0.000
		3	0.779	0.008	418.05	0.000
		4	0.696	-0.041	509.22	0.000
		5	0.619	0.005	581.70	0.000
		6	0.553	0.037	639.80	0.000
		7	0.499	0.039	687.44	0.000
		8	0.459	0.055	727.99	0.000
		9	0.427	-0.003	763.27	0.000
		10	0.400	0.010	794.42	0.000
		11	0.377	0.007	822.21	0.000
		12	0.355	-0.005	846.99	0.000
		13	0.340	0.077	869.91	0.000
		14	0.332	0.029	891.87	0.000
		15	0.329	0.045	913.59	0.000
		16	0.333	0.056	935.97	0.000
		17	0.336	-0.030	958.83	0.000
		18	0.336	0.017	981.92	0.000
		19	0.336	0.014	1005.1	0.000
		20	0.323	-0.101	1026.7	0.000

Note: For both bars of the ACF and PACF, the center line reflects 0 correlation and the two lines on either side of it represent the 95% confidence interval to determine that correlation is present.