Essays on Interest Rates and the Housing Market

Dissertation

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By

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Abstract

In the first essay of this dissertation, "Monetary Policy and the Housing Cycle," I investigate the role of monetary policy in a housing boom that precipitated the U.S. financial crisis of 2007. I find expansionary policy between 2002 and 2005 accounts for about 50% of the peak deviation of real residential investment from its long-run trend, which occurred in the second quarter of 2005. To determine if monetary policy was a contributor to the housing boom I estimate a large dynamic stochastic general equilibrium model (DSGE) to fit the economy in several different time periods. I mathematically isolate a series of changes in the Fed Funds rate that are statistically unrelated to changes in the macroeconomy and classify these deviations as a measure of monetary policy. The magnitude of the monetary policy series is relatively small during the housing boom but explains half of the 2005 peak in residential investment because of inertia in the Fed Funds rate.

My second essay follows up on a paper I wrote with Donald Haurin that was published in the Journal of Housing Economics in December 2009. The 2009 paper look at the usefulness of a housing-specific consumer sentiment index as a proxy for housing demand. The index is derived from the Survey of Consumers question: "do you think it is a good time or a bad time to buy a house?" We showed the consumer sentiment series is more predictive of turning points in the housing market than the
more commonly used Housing Market Index. A detailed examination of the sentiment data reveals that interest rates play a significant role in determining consumer sentiment. In "Predicting Reversals in New House Construction" I investigate 20 economic, financial, and sentiment time series for evidence of usefulness in predicting turning points in the housing market and find several that rival the one identified in Croce and Haurin at predicting reversals. However, all of the best-performing indicators are too early to signal a housing market peak in the period before the crisis of 2007 and individual indicators performed very differently at different turning points.
This work is dedicated to my parents, Carlo Maria Croce and Frances Kay Huebner.

Their guidance and support have been critical throughout my graduate studies.
Acknowledgments

I benefited greatly from the help of many people during my time at Ohio State—too many to name here—but several people stand out as having been critical to my development as an economist.

My primary advisor Bill Dupor was amazing. He spent countless hours helping me develop and refine my job market paper and preparing me for job interviews and presentations. Bill aggressively lobbied his connections in the field, resulting in dozens of interviews at the national meetings of the American Economic Association. His help preparing me for those interviews was a major part of why I had fourteen second-round interviews and campus visits and why I received several attractive job offers. In addition, Bill’s imperturbable personality helped keep the stresses of the job market manageable.

Donald Haurin, our department chair and a member of my dissertation committee, offered me the opportunity to collaborate with him on a housing-related topic and gave me my first lessons in how to do academic research. When a paper was published based on this work, Don listed me as a co-author even though I had been his research assistant on the project. This early exposure to housing markets went on to influence all my research at Ohio State and the credibility I gained from having worked with Don provided me with several job opportunities I would not have had without it.
Aubhik Khan—a member of my committee—and Julia Thomas were very generous with their time and helped me refine my job market paper and presentations beyond what I would have been able to achieve without their help. They invited me to participate in their student workshop despite the fact that my work falls outside their primary areas of interest. Aubhik’s numerical methods course was a source for powerful computational tools that will serve me well in my next endeavor and I regret not having had the time to pursue Aubhik and Julia’s approach to macroeconomics more aggressively.

Paul Evans, a member of my dissertation committee, taught the single most influential course of my graduate career. It was his second-year macroeconomics field course and it surveyed several different strands of the most important macroeconomics literature. What made the course so impactful were the 50+ unbelievably insightful essay questions Professor Evans gave us to prepare for the macroeconomics field exam. Preparing answers to these questions illuminated subtle relationships between the papers that I would have missed entirely. The broad view of the field Professor Evans provided us with helped me to know where to look for tools once I started having research questions of my own.

Belton Fleisher was invaluable as our department placement officer and I enjoyed working for him as a graduate assistant. Stopping by his office to talk about his trips to Italy, to ask for advice on topics from classroom management to producing perfect espresso, or to complain about the tedium of life as a graduate student were among the highlights of my free time at Ohio State.

Pok-Sang Lam provided my first (and only) taste of finance from within the department. He was generous with his time and guided me in independent study.
Hajime Miyazaki was a devoted and attentive DGS. In my six years at Ohio State I have seen the competitiveness of our Ph.D. program improve each year as a result of Hajime’s efforts. He encouraged me to pursue coursework outside the department that had a meaningful effect on my ability to do research.

My colleagues in the economics Ph.D. classes of 2010-2012 played an important role in my success at Ohio State.

Lastly, I would like to acknowledge three professors from Penn State who had a significant impact on my decision to pursue graduate study: Russell Chuderewicz, Mark Roberts, and Jim Tybout. Without them, I would not have received the guidance I needed in order to successfully prepare for and apply to graduate programs.
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Fields of Study

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# Table of Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>ii</td>
</tr>
<tr>
<td>Dedication</td>
<td>iv</td>
</tr>
<tr>
<td>Acknowledgments</td>
<td>v</td>
</tr>
<tr>
<td>Vita</td>
<td>viii</td>
</tr>
<tr>
<td>List of Tables</td>
<td>xi</td>
</tr>
<tr>
<td>List of Figures</td>
<td>xii</td>
</tr>
<tr>
<td>1. Monetary Policy and the Housing Cycle</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Related Literature</td>
<td>6</td>
</tr>
<tr>
<td>1.3 Regression Estimates</td>
<td>15</td>
</tr>
<tr>
<td>1.3.1 Rolling Regressions</td>
<td>15</td>
</tr>
<tr>
<td>1.3.2 Vector Autoregressions</td>
<td>19</td>
</tr>
<tr>
<td>1.4 A Theoretical Macroeconomic Model with Residential Investment</td>
<td>22</td>
</tr>
<tr>
<td>1.4.1 Final Goods Producers</td>
<td>24</td>
</tr>
<tr>
<td>1.4.2 Intermediate Goods Producers</td>
<td>24</td>
</tr>
<tr>
<td>1.4.3 Households</td>
<td>27</td>
</tr>
<tr>
<td>1.4.4 Loan Market Clearing, the Resource Constraint, and Equilibrium</td>
<td>33</td>
</tr>
<tr>
<td>1.4.5 Functional Form Assumptions</td>
<td>33</td>
</tr>
<tr>
<td>1.4.6 Monetary Policy in the Model</td>
<td>34</td>
</tr>
<tr>
<td>1.5 Parameterization and Estimation of the Model</td>
<td>35</td>
</tr>
<tr>
<td>1.5.1 Calibration</td>
<td>35</td>
</tr>
<tr>
<td>1.5.2 Estimation</td>
<td>38</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>1.5.3 Estimation Results</td>
<td>39</td>
</tr>
<tr>
<td>1.6 Quantifying the Impact of Monetary Policy During the Housing Boom</td>
<td>43</td>
</tr>
<tr>
<td>1.7 Conclusion</td>
<td>48</td>
</tr>
<tr>
<td>2. Predicting Reversals in New House Construction</td>
<td>50</td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>50</td>
</tr>
<tr>
<td>2.2 Related Literature</td>
<td>53</td>
</tr>
<tr>
<td>2.3 Data Descriptions</td>
<td>61</td>
</tr>
<tr>
<td>2.4 Sequential Probability Recursion Methodology</td>
<td>72</td>
</tr>
<tr>
<td>2.5 SPR Results</td>
<td>77</td>
</tr>
<tr>
<td>2.6 Conclusion</td>
<td>90</td>
</tr>
<tr>
<td>Bibliography</td>
<td>92</td>
</tr>
</tbody>
</table>
## List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 Parameters in the DSGE Model</td>
<td>26</td>
</tr>
<tr>
<td>1.2 Parameters Fixed in Estimation</td>
<td>36</td>
</tr>
<tr>
<td>1.3 Estimation of DSGE Model Parameters</td>
<td>40</td>
</tr>
<tr>
<td>2.1 Quadratic Probability Scores for the Leading Indicators</td>
<td>80</td>
</tr>
</tbody>
</table>
## List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>10</td>
</tr>
<tr>
<td>1.2</td>
<td>18</td>
</tr>
<tr>
<td>1.3</td>
<td>20</td>
</tr>
<tr>
<td>1.4</td>
<td>41</td>
</tr>
<tr>
<td>1.5</td>
<td>45</td>
</tr>
<tr>
<td>1.6</td>
<td>46</td>
</tr>
<tr>
<td>2.1</td>
<td>62</td>
</tr>
<tr>
<td>2.2</td>
<td>64</td>
</tr>
<tr>
<td>2.3</td>
<td>68</td>
</tr>
<tr>
<td>2.4</td>
<td>69</td>
</tr>
<tr>
<td>2.5</td>
<td>75</td>
</tr>
<tr>
<td>2.6</td>
<td>81</td>
</tr>
<tr>
<td>2.7</td>
<td>83</td>
</tr>
<tr>
<td>2.8</td>
<td>85</td>
</tr>
<tr>
<td>2.9</td>
<td>86</td>
</tr>
</tbody>
</table>
Chapter 1: MONETARY POLICY AND THE HOUSING CYCLE

1.1 Introduction

In this paper I investigate the role of monetary policy in a housing boom that precipitated the U.S. financial crisis of 2007. I find that expansionary monetary policy between 2002 and 2005 contributed about 70% to the peak in real residential investment relative to its long run trend and extended the boom by five quarters. This finding differs substantially from other research on the housing boom because the other models fail to capture the explosive response of housing in the most recent period, when interest rates were very low. The model I develop and estimate in this paper shows why residential investment responded explosively to expansionary monetary policy during the housing boom: expansionary policy was withdrawn too slowly. I find high sensitivity to monetary policy was not limited to the housing sector, ruling out many housing-specific explanations of the boom.

This is not the whole story. Residential investment began increasing almost monotonically in 1991 and-unlike every other recession since the Great Depression-did not
fall during the recession of 2001. Using the theoretical model developed and estimated in this paper I show that policymakers are likely victims of their own success. Responsive monetary policy during the tenure of Alan Greenspan stabilized residential investment during the 2001 recession. If policy had not been so successful in this respect, subprime mortgages would not be clogging the balance sheets of U.S. banks today. From the perspective of the model in this paper, the Federal Reserve moved too slowly to withdraw expansionary policy in the recent period. The result was a sizable contribution to the housing boom.

A debate on the source of the boom began when John Taylor (2007) presented a paper attributing the housing boom to expansionary monetary policy. Taylor observed that policy was less responsive to inflation and output between 2002 and 2006 than it had been in the past, compared policy to the notoriously expansionary 1970s, and showed that a higher policy rate produced lower housing starts in a stylized econometric model. Ben Bernanke (2010) responded to the criticism by showing econometric evidence of a change in the relationship between the macroeconomy and house price after 2001, suggesting that the proliferation of mortgage-backed securities and lower underwriting standards led to the increase in house prices. However, both of the studies above are highly stylized and Taylor himself calls for analysis using a model with microeconomic foundations like the one in this paper.

1 For these reasons I will refer to the period from 1990 through 2009 as “the housing boom period.”

2 This is based on an argument in Khandani, Lo, and Merton (2009) showing the coincidence of rising house prices, low interest rates, and cheap refinancing can generate large systemic risk.

3 Bernanke had two other central points. First, that the Fed was responding to forecasts of future inflation which were lower than current inflation, and second, other countries with similarly expansionary policy did not experience a housing boom of the same magnitude as the U.S.
Several other studies examining the housing boom with different methodological approaches will be discussed in section 2. In general, these models find that monetary policy contributed modestly to the increase in residential investment, especially late in the boom. No study of which I am aware suggests a monetary policy contribution of the magnitude I find here.

Aside from this paper, the two studies that employ micro-founded macroeconomic models attribute the vast majority of the housing boom to demand shocks rather than monetary policy. However, there is some cause for skepticism toward these results as they follow from Bayesian estimations that are particularly susceptible to misspecification. Because the functional form of demand shocks in these papers is specified ad-hoc to achieve identification and because these shocks turn out to be so important, the issue of misspecification is especially acute. Using a different estimation methodology and data from different time periods, this paper shows that policy may have played a much larger role than the other theoretical papers allow for. The size of the response to policy is very sensitive to the time period studied, perhaps because the level of the interest rate has an impact on investment apart from its stance relative to inflation and output. A more robust approach is to study several time periods and examine how the structural parameters in the economy change.

The analysis begins in section 3.1 with rolling estimates of the Fed’s response to inflation and output. The regressions capture the dynamic nature of policy across business cycles as it shifts between inflation-fighting and demand-stimulation. Additionally, the estimates capture the smoothness with which the Fed implements policy and thus how long an expansionary policy action will remain in the economy. Higher

4The papers I refer to here are Iacoviello and Neri (2010) and Edge, Kiley, and Laforte (2008). I discuss both in section 2.
smoothness implies that the Fed is less responsive to the economy in the current period and instead gears policy more toward what happened in the past. The results of the rolling estimates in section 3.1 show monetary policy during the housing boom was very unresponsive to the economy, acted with a high degree of inertia, and allowed expansionary actions to persist in the economy for an extended period. Did the economy behave differently under the less responsive policy? I address this question with a large statistical model in section 3.2.

The statistical model of the macroeconomy in section 3.2 is substantially larger than those of Taylor or of Bernanke in the sense that it includes more data series and a longer time horizon. I break the data into several overlapping subperiods in a vector version of the rolling regressions used to portray monetary policy in section 3.1. I find the economy responded very differently to monetary policy in different time periods. The differing responses illustrate why it is inadequate to evaluate the housing boom with a purely empirical model, as in Bernanke, an issue that will be discussed more in section 2.\(^5\) It also highlights how analysis focusing on a single time period can be misleading.

The responses of all the macroeconomic variables studied were exceptionally strong in the housing boom period, 1990-2009. The responses of consumption, capital investment, and residential investment to changes in monetary policy were more than twice as strong as the next strongest period, which was during the 1960s and 1970s. Is the housing boom related to the unusually strong economic responses to monetary policy? If so, then the generality of the large responses indicates the housing boom

\(^5\)Lucas (1976) argues that it is naive to predict the effects of a change in economic policy entirely on the basis of historical empirical relationships, especially when using aggregated data. Lucas suggests modeling the “deep parameters” governing agent behavior and drawing conclusions from a micro-founded model.
was not caused by a housing-specific shock, as was found in other studies. To answer this question I write and estimate a micro-founded macroeconomic model in sections 4 and 5.

Motivated to understand why the economy responded differently to policy in different time periods and whether the cause of these differences played a role in the housing boom, I write a macroeconomic model in the spirit of Christiano, Eichenbaum, and Evans (JPE 2005, henceforth CEE) in section 4 and estimate it in section 5. Examining how the estimates differ across time periods in relation to the size of the responses may help us understand what changed in the macroeconomy. The model includes a housing production sector, housing consumption by agents, and several frictions that enhance its empirical relevance by creating the highly inertial, hump-shaped macroeconomic responses to policy seen in the data. I estimate the model by fitting it to the empirical responses of macroeconomic variables to monetary policy.

The model attributes the very large responses to policy during the 1990-2009 period to inertia in the monetary policy rule. The Federal Reserve over-emphasized smooth implementation of policy during the housing boom. Having established that changes in monetary policy explain why the economy reacted differently to policy during the boom, the last step in the analysis is to quantify policy during the housing boom and consider whether such policy produces a large expansion in residential investment in the estimated model.

I identify monetary policy in section 6 by statistically relating the Federal Funds rate to the rest of the macroeconomy between 1960 and 2009 and attributing statistical model errors for the Funds rate to monetary policy. This is a more conservative approach than is generally taken in the literature because it compares policy during
the period of interest to “average” policy. Next, I feed the monetary policy from the housing boom period through the estimated theoretical model and collect the model-implied economic responses. This process quantifies the aggregate impact of monetary policy on residential investment after 1990.

The results in section 6 will show monetary policy likely extended the housing boom by five quarters and contributed 70% to the peak value of residential investment relative to its long-run trend. The results also suggest policy was successful in countering the impact of the business cycle on residential investment during the recession of 2001. The success of policy in this regard may well have contributed to a public perception of safety in the housing market and thus to unsustainable developments in mortgage finance thereafter.

1.2 Related Literature

A debate about the source of the housing boom began at the Federal Reserve Bank of Kansas City Economic Policy Symposium at Jackson Hole, Wyoming, in August 2007. John Taylor presented a paper that models housing starts as a function of several lags of the Federal Funds rate, simulates the model with a higher Federal Funds rate, and shows the counterfactual model produces a substantially smaller boom in

6 The more common strategy is to use errors from the statistical model during the period being evaluated. However, if monetary policy was consistently more expansionary during the period of interest, the usual approach will understate the accommodative stance. An example of this approach is Edge, Kiley, and Laforte (2008). Another approach taken in the literature is to estimate the policymaker’s response function during a period chosen to represent “good” policy, and then compare the interest rate implied by that model to the actual rate set by the monetary authority. Ang, Boivin, Dong, and Loo-Kung (2009) find the interest rate in 2003-2004 was about 2% lower than it would have been if policymakers behaved as they did in 2000. Both papers are discussed in section 2.

7 I opt for a conservative approach when taking policy to the model as well and only collect the first 24 quarters of model responses. The response of residential investment to policy has not completely subsided at the end of year 6.
housing starts circa 2005. Federal Reserve Chairman Ben Bernanke responded in a January 2010 presentation to the American Economic Association. Bernanke uses a vector autoregression to produce out of sample forecasts of house prices based on several other macroeconomic variables. He shows that actual house prices lie well above the 99% confidence interval from the dynamic forecast, suggesting the relationship between house prices and the macroeconomy changed substantially in the boom period. Thus policy is not to blame for the housing boom and subprime lending is the likely culprit.

Alan Greenspan’s (2009) critique of Taylor’s analysis applies equally well to Bernanke: “His statistical analysis carries empirical relationships of earlier decades into the most recent period where they no longer apply.”

One reason to think statistical relationships between housing and the macroeconomy may have changed in the boom period: interest rates were very low by historical standards. Himmelberg, Mayer, and Sinai (2005, henceforth HMS) shows sensitivity of house prices to macroeconomic fundamentals increases as interest rates fall.

The theoretical model in HMS also predicts the semi-elasticity of house prices with respect to real rates is over 20. If true, this implies a reduction of mortgage rates by two percent would explain most of the boom in house prices. Glaeser, Gottlieb, and

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8Bernanke estimates a vector autoregression model that includes real GDP, inflation, unemployment, residential investment, house prices, and the Federal Funds rate 1977-2001, then feeds post-2001 values for all variables except house prices through the model to produce a dynamic house price forecast.

9Bernanke’s paper is based on a paper by Dokko et al (2009). The Dokko paper makes three arguments that the housing boom was not caused by poor monetary policy: (i) policy was properly responding to expected future inflation, which was lower than current inflation, (ii) other countries with similar policy did not have a boom of the same magnitude, and (iii) the vector autoregression suggesting a change in the relationship between house price and the macroeconomy.

10The semi-elasticity of house price with respect to interest rates is the expected percentage increase in house prices when interest rates fall by 1%.
Gyourko (2010, henceforth GGG) study the behavior of the HMS model after adding realistic features to the agent’s optimization problem.\textsuperscript{11} They find the new features reduce the theoretical semi-elasticity to around 8%, still a substantial number, and do not affect the prediction that lower rates increase residential investment sensitivity. Thus the analyses in HMS and in GGG suggest empirical relationships of past periods would have changed in the recent period because interest rates were at historic lows. A potential solution to this Lucas (1976) critique is to study the economy with a micro-founded model. This approach would permit counterfactual experiments as in Taylor while keeping sight of changes optimality for individual agents.\textsuperscript{12} Taylor himself recognizes this and called for a study like the one in this paper at his 2007 presentation. At least two papers have taken a Bayesian approach to estimating micro-founded models of the housing boom: Iacoviello and Neri (2010) and Edge, Kiley, and Laforte (2008, henceforth EKL).

Iacoviello and Neri write a multi-sector model with housing, non-durable goods, and nominal frictions – as in this paper – but model the housing sector in more detail à la Davis and Heathcote (2005). Iacoviello and Neri focus on spillovers from housing markets to consumption but, because they use a full information estimation, their model captures the dynamics of the boom. The estimates in Iacoviello and Neri suggest policy shocks played a larger role during the housing boom period (1989-2006) than in a prior period (1965-1982) but they attribute most of the housing boom to "housing preference shocks." This result highlights a critical difference between the

\textsuperscript{11}GGG add (i) mean reversion in the interest rate, (ii) the possibility of wanting to move in the future, and (iii) credit constraints to the model.

\textsuperscript{12}The Lucas Critique points out that the behavior of agents likely evolves with the economic state of the world. Lucas suggests using a theoretical model that includes the "deep parameters" governing agent behavior.
estimation approach in Iacoviello and Neri and the partial information approach I use in this paper: interpreting Bayesian shocks. The full information approach in Iacoviello and Neri necessitates postulating forms for each stochastic process. If the functional form is not correct then the model is misspecified.

As noted by Tovar (2009), some Bayesian shocks in the literature are difficult to interpret. For example, markup shocks may capture changes in taxes or the degree of competition. Similarly, investment-specific shocks may capture unmodeled financial market dynamics. There is, then, cause for concern about the interpretation of demand shocks.

I plot the real annualized yield on three month treasuries in Figure 1. The horizontal axis in the figure is plotted at the mean of the data. Notice that the real interest rate is below average between 1975 and 1981, mostly above average from 1982-2002, then below average again after 2002. Interestingly, this is similar (inversely) to the pattern of the demand shocks plotted in Figure 7 of Iacoviello and Neri. Perhaps some portion of the demand shock is capturing nonlinear aspects of the response of housing to interest rates, the existence of which is suggested by HMS and by GGG. If this is the case, then the demand shocks may not be orthogonal to policy and certainly are not orthogonal to the observable interest rate. Kocherlakota (2007) shows that incorrectly assuming two fluctuations are independent can lead to substantial model misspecification. He suggests only modeling shocks for which we have some a priori information in order to avoid this problem. Because there is no auxiliary information about most of the shocks in Iacoviello and Neri and in EKL, I instead opt to minimize the distance between the theoretical model impulse responses and those of the data.
Notes: The figure above is produced using St. Louis Fed F.R.E.D. database series TB3MS for the three month treasury rate and CPIAUCSL for the consumer price index. The real rate is computed as: \( \text{real} = \text{nominal} - 400 \ast \Delta \log(CPI) \). Compare with Figure 7 in Iacoioello and Neri (2010).

EKL estimates a model similar to the one in this paper for the period 1984:Q4-2007:Q2. They find that the dynamics of residential investment are almost entirely the result of "intertemporal IS curve shocks." 13 The finding suggests that either (i) the monetary policy shocks found in EKL are exceptionally small or (ii) the model finds a negligible relationship between interest rates and housing investment. If (ii)

13The four findings in EKL are: (i) almost all the dynamics of residential investment were the result of "intertemporal IS curve shocks" and almost none were the result of policy shocks, (ii) the most important shock to explain forecast error variance in residential investment was the shock to the residential investment Euler equation (Tobin’s Q), (iii) accommodative policy during the 2001-2005 period was crucial to support employment, and (iv) deviations from the estimated policy rule were small and accounted for almost no increase in residential investment.
is the cause, myriad papers conflict with this finding.\footnote{Examples include Taylor (2007), Hamilton (2008), Cardelli, Igan, and Rebucci (2008), and Eickmeier and Hofmann (2010).} If (i) is the issue, there is still difficulty interpreting the shocks identified in the paper because the financial market in EKL is not modeled in detail. The estimated shocks could be picking up demand or supply factors that are not, in fact, orthogonal to monetary policy. Further, these shocks are a possible source of misspecification. Because sources of the fluctuations in residential investment during the housing boom are of particular interest in this paper, I take the more conservative approach of using a limited information estimation that does not necessitate specifying a form for residential investment model errors.

A purely empirical Bayesian study of the housing boom by Jarociński and Smets (2008) includes a demand shock similar to the one in EKL. Robert King (2008) points out in a discussion of Jarociński and Smets that the response of residential investment to the housing demand shock defies intuition, which suggests a hump-shaped response should arise out of time-to-build. Instead the response of residential investment peaks immediately, suggesting the shock captures some other phenomenon. Interestingly, this observation applies to Iacoviello and Neri and to EKL as well.

Eickmeier and Hofmann (2010) investigate the housing boom using a factor-augmented vector autoregression. Their goal is to examine whether monetary policy transmission through private sector balance sheets, risk spreads, and asset markets can explain the (i) high house price inflation, (ii) high private debt growth, and (iii) low risk spreads observed in the data. They find that policy has a large, persistent impact on house prices and private sector debt and a large, short-lived effect on spreads. Eickmeier and Hofmann conclude that policy contributed a third of the house price appreciation seen in the late stage of the housing boom. They do not investigate the
contribution of policy during the 1990s nor do they examine the impact of policy on residential investment.

The three stylized facts in Eickmeier and Hofmann are similar to the motivations in Khandani, Lo, and Merton (2009, henceforth KLM). KLM builds a theoretical model to investigate whether the coincidence of (i) low rates, (ii) rising house prices, and (iii) cheap refinancing can lead to a synchronization of refinancing and an increase in systemic risk. They calibrate and simulate their model both with and without the risk-enhancing mechanism and find that such a mechanism would have amplified the financial market impact of falling house prices. In Section 6 I will show that monetary policy likely prevented a contraction in the housing market during the recession of 2001. Considering this in the light of KLM suggests that the success of monetary policy during the recession of 2001 was a factor in increasing the systemic risk posed by mortgages.

Also related to Eickmeier and Hofmann is a paper by Mian and Sufi (2009) in which cross-sectional data is used to show the expansion of mortgage credit to subprime zip codes is correlated with the rate of subprime securitization and that large increases in household debt were largely made up of home equity. This explicitly supports the hypothesis in KLM.

A second strand of literature relevant for the current study deals with methodologies for quantifying the stance of monetary policy, as I do in Section 3 of this paper. While most of the literature focuses on providing unbiased estimates of policy over a long horizon, my focus in this paper recommends a simpler estimation methodology that requires less data. A model with minimal data requirements is appealing because monetary policy does not simultaneously fight inflation and unemployment – it has to
choose. When the level of inflation is more of a concern to policymakers than the level of unemployment, policy will be contractionary. When the level of unemployment is more of a concern than the level of inflation, policy will be expansionary. Estimating the policy rule over rolling short horizons captures the stance of the policy during short periods of time, permitting us to infer the evolution of the Federal Reserve’s primary concern. I use rolling constrained nonlinear least squares to estimate the stance of monetary policy with respect to inflation, GDP growth, and past policy.¹⁵ I am not aware of any other studies using this econometric methodology.

Molodtsova, Nikolsko-Rzhevskyy, and Papell (2008, henceforth MNP) use nonlinear least squares to estimate both forward-looking and backward-looking Taylor rules. They find that the results are nearly identical. This finding is supported by Taylor (1999) who argues forecasts of the future are based on current and lagged data so inflation forecast rules are no more forward-looking than rules explicitly based on current and lagged data. Boivin (2005) notes that forward-looking Taylor rule estimation is susceptible to endogeneity bias, a problem I avoid by using the backward-looking specification in Section 3. Given the result in MNP, this choice should not have a qualitative impact on my results.

Mehra and Minton (2007) use a similar specification to the one in Section 3 of this paper but include an autoregressive error term. They find the autoregressive coefficient is statistically significant, suggesting the specification in this paper produces biased estimates. However, because the nature of the serial correlation is largely systematic throughout the sample period, it cannot be responsible for the low-frequency

¹⁵I estimate a policy rule in which the Federal Reserve targets a rate of GDP growth because estimates of the output gap have been revised considerably over the years and because the true output gap is unobservable.
oscillation in the policy parameters I observe in Section 3. Properties of the con-
strained least squares estimator include substantially smaller mean squared errors
and larger bias than an ordinary least squares estimator.\textsuperscript{16}

Despite the potential for bias in the coefficient estimates, the results produced
by the methodology are strongly supported by other studies. For example, Boivin
finds that the Fed’s response to inflation was strong before 1973, weak in the second
half of the 1970s, and gradually regained strength in the early 1980s, exactly as I
find here. My rolling regression results differ from Boivin in the 1990s where he
finds a minor reduction in the response to inflation and I find a very large one, with
the response to inflation falling to near zero between 1992 and 1994 then gradually
increasing. However, a study by Ang, Boivin, Dong, and Loo-Kung (2009, henceforth
ABDL) supports the latter result, finding policy was exceptionally unresponsive to
the economy during the mid-1990s.

I find that the policy response to inflation falls below unity as data for the re-
cession of 2001 enters the estimation horizon and that the response to output begins
to increase. The response to inflation was near zero between 2000 and 2004 then
increases as data for the Fed tightening of late 2004 enters the estimation horizon.
Telling a similar story, the response to output is over one between 2000 and 2005, but
falls quickly once the tightening of late 2004 enters the estimation horizon. The re-
results in ABDL are supportive of results in Section 3 showing policy was unresponsive
to inflation in the recent period.

In the next section I will address the stance of monetary policy during the housing
boom.

\textsuperscript{16}See Liew (1976) for a Monte Carlo study of CLS.
1.3 Regression Estimates

In this section I quantify the response of monetary policy to inflation and economic growth by estimating a rolling Taylor rule. The estimates produce a dynamic view of monetary policy, capturing the evolution of policymakers’ priorities with respect to output growth and stable prices. I find the coefficient on inflation was well below unity during the post-2001 period singled out by Taylor and that the smoothing parameter was over 0.89 during the period 1999:Q2-2004:Q1.

Following the rolling regressions, I estimate the response of the economy to monetary policy using a large vector autoregression model (VAR). I estimate the VAR over several overlapping 20-year periods to illustrate that the response of the economy to monetary policy differs substantially among the periods. In particular, the response of all the macroeconomic variables examined was largest in the period between 1990 and 2010.

1.3.1 Rolling Regressions

The goal of the rolling regressions in this section is to capture the dynamics of policymakers’ response to inflation and output growth. Using constrained non-linear least squares, I estimate (1) for every five year interval occurring between 1954:Q3 and 2009:Q4. The parameter $\rho$ measures inertia in the Federal Funds rate. Inertia captures the Federal Reserve’s desire to implement policy slowly to avoid shocking the economy. The parameters $\beta_\pi$ and $\beta_y$ capture the amount the Fed would raise the interest rate in response to a 1% increase in inflation or output, respectively, in the absence of a smoothing motive. The variable $r_t$ is the average effective Federal Funds rate in the first month of quarter $t$, while $\pi_{t-1}$ and $\Delta y_{t-1}$ are the growth rates of the
Consumer Price Index and real GDP over the four quarters ending in quarter $t - 1$.

$$ r_t = (1 - \rho) \cdot [\beta_0 + \beta_\pi \cdot \pi_{t-1} + \beta_y \cdot \Delta y_{t-1}] + \rho \cdot r_{t-1} + \varepsilon_t \quad (1.1) $$

The responses to economic variables are constrained to lie on the interval $\beta_i \in [0, 3]$ where $i \in \pi, y$ and the inertia parameter is constrained to lie on the unit interval. I constrain $\beta_0 = 0$.\textsuperscript{18} The backward-looking specification of the model in (1) helps avoid endogeneity.\textsuperscript{19} Constraining the nonlinear least squares estimator substantially reduces the standard error of the coefficient estimates and produces precise estimates with relatively small amounts of data.

The regression errors are positively serially correlated, suggesting the regression estimates may express a positive bias. A second potential source of bias is restriction on $\beta_0$. It is possible that constraining the estimation amplifies these biases relative

\textsuperscript{17}It is more common to see this equation written with the output gap in place of the change in real GDP. However, because knowledge of potential output is dubious, I have opted here to model central bank policy with respect to targeting a particular level of output growth. Equation (1) can be derived from a standard Taylor rule as follows:

$$ r_t = (1 - \rho) \cdot [(r^* + \pi_{t-1} + \gamma_\pi \cdot (\pi_{t-1} - \pi^*) + \beta_y \cdot (\Delta y_{t-1} - \Delta y^*)] + \rho \cdot r_{t-1} $$

$$ = (1 - \rho) \cdot [(r^* + -\gamma_\pi \cdot \pi^* - \beta_y \cdot \Delta y^*) + (1 + \gamma_\pi) \cdot \pi_{t-1} + \beta_y \cdot \Delta y_{t-1}] + \rho \cdot r_{t-1} $$

$$ = (1 - \rho) \cdot [\beta_0 + \beta_\pi \cdot \pi_{t-1} + \beta_y \cdot \Delta y_{t-1}] + \rho \cdot r_{t-1} $$

where $\beta_0 = (r^* + -\gamma_\pi \cdot \pi^* - \beta_y \cdot \Delta y^*)$, $\beta_\pi = 1 + \gamma_\pi$, and where asterisks indicate the policymaker’s long-run target level of a variable.

\textsuperscript{18}The constant term in a Taylor rule, as shown in footnote 17, includes the Fed’s long-run real target interest rate and transformations of the target rates of inflation and output growth and is difficult to identify econometrically with a small data sample. Other papers (including Clarida, Gali, Gilchrist (2000)) make the identifying assumption that the Fed’s target real interest rate is equal to the average observed during the estimation period. Assuming the average over a 5-year period (the length of the data in each of my rolling regressions) is equal to the Fed’s target is not as reasonable as making the assumption over the longer horizons estimated in these other papers. Further, given the illustrated volatility in the monetary policy rule, it is not clear that the long-run real interest rate target should be constant.

\textsuperscript{19}Recall from Section 2 of this paper that Molodtsova, Nikolsko-Rzhevskyy, and Papell find a backward-looking model estimated with nonlinear least squares achieves very similar results to a forward-looking specification, so the cost involved in making this choice is likely low.
to ordinary least squares. However, because all the sources of bias are systematic, they are not the source of the low-frequency fluctuations we observe in the rolling regression results.

The rolling regression estimates are plotted in Figure 2 and show the Federal Reserve was unresponsive to inflation during the period between 2001 and 2005, as suggested by Taylor. The estimates of $\beta_\pi$ are below unity for every regression between 1997:Q4 and 2005:Q2. Over this same time period, the estimates of $\rho$ are between 0.76 and 0.89. High values of $\rho$ alone are enough to characterize policy as unresponsive, as they indicate that policy responds very slowly to the economy. This is consistent with an aggressive response by the Federal Reserve to a deflation threat during the period. It could also be interpreted as evidence the Federal Reserve kept short-term interest rates too low for too long.

It is interesting to note the point estimates for $\rho$ were elevated throughout the period after 1990 and that the increase coincides closely with the appointment of Alan Greenspan as Chairman of the Federal Reserve Board of Governors in 1987:Q3. The value of $\beta_\pi$ fluctuated a great deal under Greenspan in the 1990s, with a strong response to inflation in the second half of the 1990s but a very weak response in the first half. Note that the higher values of $\rho$ during the period mute the corresponding response to inflation even when estimates for $\beta_\pi$ are high. Comparing policy during the period 1980-1990 to policy after 1990, the primary differences are: (i) policy after 1990 is characterized by consistently higher values of $\rho$ and (ii) $\beta_\pi$ during the period

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20 See Liew (1976) for a Monte Carlo study of CLS.


22 See remarks by Chairman Alan Greenspan before the Economic Club of New York, December 19 2002.
Notes: Panel (a) plots the policy responses to inflation and to output prior to accounting for the Federal Reserve’s desire to smooth the policy rate. Panel (b) plots estimates of the smoothing parameter. I estimate the equation via constrained least squares over rolling 5-year intervals. I implement the algorithm using a nonlinear search to find the parameter values that minimize the sum of squared errors. I constrain the search to values of $\beta_{\pi}$ and $\beta_y$ between zero and three and values of $\rho$ to the unit interval. $\beta_0$ is set to zero in every period. Each estimate is plotted in the middle of the period over which it was estimated. For example, the points plotted for 2002:Q3 are estimated over the period 2000:Q1-2004:Q4. The 80% confidence interval is included in each plot.

1980-1990 is consistently above unity, while after 1990 it takes values both above and below one.
The rolling regression results confirm Taylor’s comparison of the period after 2001 to the late 1970s. Both periods are characterized by low values of $\beta_\pi$ and high values of $\rho$. However, low values of $\beta_\pi$ persist much longer in the late 1970s and high values of $\rho$ persist much longer after 1990. They also suggest there may have been a substantial change in policy sometime around 1990, with a move toward more inertia and larger fluctuations in $\beta_\pi$ and $\beta_y$.

Do the macroeconomic responses to monetary policy vary in response to changes in $\beta_\pi$, $\beta_y$, and $\rho$? In Section 3.2, I answer this question using several overlapping VARs, the vector equivalent of rolling regressions.

### 1.3.2 Vector Autoregressions

I use vector autoregression and the recursiveness assumption to estimate the impact of a monetary policy shock on residential investment and other macroeconomic variables during the periods 1960-1979, 1970-1989, 1980-2000, and 1990-2009. I use two lags of each of the following variables: real GDP, real consumption, the consumer price index, real nonresidential fixed investment, real residential fixed investment, the real wage rate, the Fed Funds rate, the growth rate of real M2, real corporate profits, and the real price of oil. Figure 2 plots the impulse responses of output, consumption, inflation, investment, and the Funds rate to a recursively-identified negative 1% Federal Funds shock in each of the periods examined. The responses of each variable are very different across periods.

It is interesting to notice that the relative magnitude of the responses to policy across time periods is the same for all the economic variables.\(^\text{23}\) In each case the

\(^{23}\)For the purposes of this paper, “the response of monetary policy” refers to parameters $\rho$, $\beta_\pi$, and $\beta_y$. The terms “policy actions” and “policy shocks” refer to recursively-identified VAR shocks to the Federal Funds rate.
Figure 1.3: Impulse Responses to a -1% Fed Funds Shock

Notes: Nonresidential and residential fixed investment, the average wage rate, the M2 measure of money supply, corporate profits and oil price are deflated with the consumer price index. All series except for Fed Funds and the growth rate of M2 are logged. All data are from the Federal Reserve Bank of St. Louis FRED database. The Schwartz criterion selected either one or two lags in each case. I chose two lags to maintain consistency across the estimates.

The smallest response is from 1980-1999, followed by 1970-1989, 1960-1979, and finally by 1990-2009. The response of the Federal Funds rate to a policy action in the model estimated 1990-2009 also has a peculiar shape—it increases after the initial impact and implies the monetary authority implemented policy in a super-persistent manner during this final period. There is considerable evidence of overshooting in the Funds
rate during the 1960-1979 and 1990-2009 periods, implying monetary policy over-
shot the policymaker’s desired economic outcome and later corrected in the opposite
direction, adding to macroeconomic volatility. This is in contrast to the 1980-1999
period where there is no evidence of overshooting. These results are consistent with
Boivin and Giannoni (2006), who find that the impulse responses of a smaller set of
macroeconomic variables between 1980 and 2002 were statistically not different from
zero and attribute the difference to better monetary policy.

Examining the responses of inflation to a Federal Funds shock raises an interesting
question. Despite the persistence of the Funds rate following a shock in the 1990-
2009 period, the estimated inflation response never rises reliably above zero. The
second- and third-most persistent Fed Funds shocks produced larger, more sustained
inflations. This result suggests inflation did not respond in the usual way to monetary
shocks during the recent period. Perhaps this is evidence of the deflationary forces
cited by Greenspan as his rationale for low rates during the housing boom.

The fact that VAR impulse responses differ so substantially across periods echoes
the Lucas critique – that as economic circumstances change, so does the optimizing
behavior of economic agents. The takeaway from Lucas is that a theoretical economic
model built on economic first principles and then estimated to fit the data will produce
more robust results to counterfactual experiments than a purely empirical analysis
as in Taylor. In Section 4 I develop such a model by building upon the work of
Christiano, Eichenbaum, and Evans (2005). The model will provide a framework
for studying the questions raised by the VAR: why is the response of residential
investment so large and why does inflation respond so timidly to policy shocks in the
1990-2009 period?
1.4 A Theoretical Macroeconomic Model with Residential Investment

In this section I extend the model of Christiano, Eichenbaum, and Evans (2005, henceforth CEE) to include residential investment and housing consumption. The model in CEE is an appropriate starting point because it reproduces the shape and magnitude of empirical impulse responses from vector autoregressions. Matching the timing of the responses is particularly important because (i) we want to fit the model to the data to make inferences regarding economic parameters and (ii) without matching the timing of the empirical responses, we cannot accurately attribute the portion of residential investment due to policy in a given quarter. The model generates realistic, hump-shaped macroeconomic responses to policy shocks.

The primary frictions in the model are sticky prices and wages, habit formation, partial capacity utilization, and investment adjustment costs.

Wage and price frictions help generate highly persistent responses of macroeconomic variables to monetary policy. I include them with an inertial version of the Calvo (1983) mechanism. Sticky prices follow from including a perfectly competitive final goods firm that combines the outputs of a continuum of monopolistically competitive intermediate goods firms. Only a fixed fraction of intermediate goods producers are permitted to reset prices optimally and the others instead index to prior-period inflation. Similarly, the household is a monopoly supplier of differentiated labor which it sells to intermediate goods producers. A fixed fraction of households are able to adjust wages optimally, while the rest index to past inflation.
Households consume only one type of good. They form habits with regard to the level of consumption, helping to generate the hump-shaped responses we see in the VARs from Section 3.

Households invest in both capital and housing. The investment process transforms consumption goods into the respective investment goods. The relationship between investment and the stock of investment goods is governed by investment adjustment costs that help generate the slow, inertial investment responses to policy observed in the data. Households then rent capital and a portion of the housing stock to intermediate goods firms to use as inputs in the production process. Partial capacity utilization helps mute the response of marginal cost and inflation to the monetary policy shock.

When the monetary policy authority changes the interest rate, the rental rate for capital and housing used in the production of intermediate goods changes. Changes in rental rates change the shadow price of capital and housing, causing households to re-optimize their holdings of each through investment.

In what follows, pay particular attention to the inclusion of buildings in the utility and production functions and the optimality conditions governing housing investment. Other than monetary policy only these aspects of the model differ materially from CEE. I provide a full exposition for completeness.

24 The consumption good aggregates consumption of nondurable goods and services.
1.4.1 Final Goods Producers

The final consumption good, \( Y_t \), is produced by a perfectly competitive firm. The firm combines a continuum of intermediate goods, indexed by \( j \in [0, 1] \), into the final good using the technology

\[
Y_t = \left[ \int_0^1 Y_{jt}^{\lambda_f} dj \right]^{\lambda_f} \tag{1.2}
\]

where \( 1 \leq \lambda_f < \infty \) and \( Y_{jt} \) is time \( t \) input of intermediate good \( j \). If \( P_t \) is the price of the final good at time \( t \) and \( P_{jt} \) is the price of intermediate good \( j \) at time \( t \) then profit maximization yields the Euler equation:

\[
\left( \frac{P_t}{P_{jt}} \right)^{\frac{\lambda_f}{1-\lambda_f}} = \frac{Y_{jt}}{Y_t}. \tag{1.3}
\]

Dividing each side of (3) by \( Y_t \) and plugging into (4) we arrive at a relationship between the price of intermediate and final goods:

\[
P_t = \left[ \int_0^1 P_{jt}^{\frac{1}{1-\lambda_f}} dj \right]^{1-\lambda_f}. \tag{1.4}
\]

1.4.2 Intermediate Goods Producers

Each intermediate good producer \( j \in (0, 1) \) is a monopolistic competitor who uses the following technology:

\[
Y_{jt} = \begin{cases} 
B''_{jt}^{\alpha_b} k_{jt}^{\alpha_k} L_{jt}^{1-\alpha_b-\alpha_k} - \phi & \text{if } B''_{jt}^{\alpha_b} k_{jt}^{\alpha_k} L_{jt}^{1-\alpha_b-\alpha_k} \geq \phi \\
0 & \text{otherwise}
\end{cases} \tag{1.5}
\]

where \( 0 < \alpha_i < 1 \) for \( i \in \{b, k\} \). The variables \( B''_{jt}, k_{jt}, \) and \( L_{jt} \) are the quantities of real estate, capital services, and aggregate labor used by intermediate firm \( j \) in production at time \( t \), respectively.\(^{25}\) The parameter \( \phi \) is the fixed cost of production.

\(^{25}\)Real estate is included in the production function in order to identify a Tobin’s \( Q \) price for houses. This price will drive housing investment and consumption decisions.
Intermediate goods producers rent all three factors of production from households in perfectly competitive factor markets and their profits are distributed to households as a dividend at the end of each time period.

Let $R^b_t, R^k_t$, and $W_t$ denote the nominal rental rates for real estate, capital, and labor respectively. As in CEE I assume that workers must be paid in advance of production with borrowed funds. CEE found this mechanism reduces the model’s reliance on sticky prices to propagate monetary policy shocks and brings the value of $\xi_p$ into the range suggested by microeconomic data. The entire wage bill, $W_t L_{jt}$, is borrowed from the financial intermediary at the beginning of the period and repayment occurs at the end of the period at the gross interest rate, $R_t$, which we will equate with the Fed Funds rate. It follows that each intermediate firm faces real marginal costs

$$s_t = (\frac{1}{\alpha_b})^{\alpha_b}(\frac{1}{\alpha_k})^{\alpha_k}(\frac{1}{1-\alpha_b - \alpha_k})^{1-\alpha_b - \alpha_k} (R^b_t)^{\alpha_b} (R^k_t)^{\alpha_k} (w_t R_t)^{1-\alpha_b - \alpha_k}$$

where lower case letters indicate the variable has been deflated by the price level $P_t$.

I employ an inertial version of Calvo (1983) pricing where intermediate goods firms that are not permitted to reoptimize their prices instead index them to past inflation. This setup produces more persistence in inflation and thus helps the model respond more slowly and persistently to monetary policy shocks than models without this feature. Specifically, firms that are unable to reoptimize price instead set

$$P_{jt} = \pi_{t-1} P_{j,t-1}$$

where $\pi_{t-1} = \frac{P_{t-1}}{P_{t-2}}$.  

25
Table 1.1: Parameters in the DSGE Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( b )</td>
<td>Habit</td>
<td>( \beta )</td>
<td>Discount factor</td>
</tr>
<tr>
<td>( \delta^k )</td>
<td>Capital Depreciation</td>
<td>( \delta^b )</td>
<td>Structure Depreciation</td>
</tr>
<tr>
<td>( \alpha_k )</td>
<td>Capital share in production</td>
<td>( \alpha_b )</td>
<td>Structures share in production</td>
</tr>
<tr>
<td>( \mu )</td>
<td>Steady-state money supply growth</td>
<td>( 1/\sigma_q )</td>
<td>Interest semi-elasticity of money demand</td>
</tr>
<tr>
<td>( \psi_0 )</td>
<td>Relative weight of leisure in utility</td>
<td>( \rho )</td>
<td>Interest rate smoothing</td>
</tr>
<tr>
<td>( \lambda_f )</td>
<td>Price markup</td>
<td>( \lambda_w )</td>
<td>Wage markup</td>
</tr>
<tr>
<td>( 1/\chi^k )</td>
<td>Elasticity of capital investment to ( p_k )</td>
<td>( 1/\chi^b )</td>
<td>Elasticity of structure investment to ( p_b )</td>
</tr>
<tr>
<td>( \beta_\pi )</td>
<td>Interest rate response to inflation</td>
<td>( \beta_y )</td>
<td>Interest rate response to output</td>
</tr>
</tbody>
</table>

Firms that can reoptimize price at time \( t \) all choose the same price, \( \tilde{P}_t \), as per the well-known result.\(^{26}\) The firm chooses \( \tilde{P}_t \) to maximize

\[
E_{t-1} \sum_{l=0}^{\infty} (\beta \xi_p)^l v_{t+l}[\tilde{P}_t X_{t+l} - s_{t+l} P_{t+l}] Y_{j,t+l} \tag{1.8}
\]

subject to (4), (7), and

\[
X_{t+l} = \begin{cases} 
\pi_t \times \pi_{t+1} \times \cdots \times \pi_{t+l-1} & \text{for } l \geq 1 \\
1 & \text{for } l = 0
\end{cases} \tag{1.9}
\]

The first order condition is then

\[
E_{t-1} \sum_{l=0}^{\infty} (\beta \xi_p)^l v_{t+l} Y_{j,t+l}[\tilde{P}_t X_{t+l} - \lambda_f P_{t+l} s_{t+l}] = 0 \tag{1.10}
\]

\(^{26}\)See Woodford (1996).
where \( \nu_t \) is the marginal value of a dollar to households, which firms treat as exogenous. Equation (11) linearizes

\[
\hat{p}_t = E_{t-1}[\hat{s}_t + \sum_{l=1}^{\infty} (\beta \xi_p)^l (\hat{s}_{t+l} - \hat{s}_{t+l-1}) + \sum_{l=1}^{\infty} (\beta \xi_p)^l (\hat{\pi}_{t+l} - \hat{\pi}_{t+l-1})]
\] (1.11)

where \( \hat{p}_t = \hat{P}_t / P_t \) and hats signify the percent deviation from steady state. Following the literature, one can solve (11) to obtain the inertial inflation equation:

\[
E_{t-1} \hat{\pi}_t = \frac{1}{1 + \beta} \hat{\pi}_{t-1} + \frac{\beta}{1 + \beta} E_{t-1} \hat{\pi}_{t+1} + \frac{(1 - \beta \xi_p)(1 - \xi_p)}{(1 - \beta) \xi_p} E_{t-1} \hat{s}_t.
\] (1.12)

The various frictions included on the production side of the economy contribute substantially to the model’s ability to reproduce the impulse responses from the VAR in Section 3.

**1.4.3 Households**

A continuum of households indexed by \( j \in (0, 1) \) make consumption, capital and real estate investment, wage and labor supply, and capacity utilization decisions in each period. Each household \( j \) is a supplier of differentiated labor \( l_{j,t} \) in period \( t \) at wage rate \( W_{j,t} \). Individual households are chosen randomly to re-optimize their wages similar to the mechanism by which intermediate goods producers set price. A household not selected to re-optimize instead indexes its wage to inflation in the prior period. I assume households are homogeneous with respect to consumption and investment and heterogeneous with respect to wage rates and hours worked.

The \( j^{th} \) household maximizes its utility function

\[
E_{t-1} \sum_{l=0}^{\infty} \beta^{l-t} [u(c_{t+l} - b \cdot c_{t-l}) + u(B'_{t+l}) - z(l_{j,t+l}) + v(q_{t+l})]
\] (1.13)
where $b$ measures the degree of habit formation in the utility function and where $c_t, B'_t,$ and $q_t$ denote time $t$ non-housing consumption, housing consumption, and real cash balances respectively.

The household’s assets evolve according to

$$M_{t+1} = R_t[\mu_t M_t - P_t q_t] + Q_t + W_{j,t} + R_t^B B'_t + R_t^k u_t \bar{k}_t + D_t - P_t[i_t^b + i_t^k + c_t + a(u_t)\bar{k}_t]$$

(1.14)

where $M_t$ is the household’s money stock at the beginning of period $t$ and $\mu_t$ is the growth rate of money. The money stock is separated out into its components – bank deposits and cash balances. The first bracketed quantity on the right hand side of (14) is the amount the household deposits at the bank. This quantity earns the gross nominal interest rate $R_t$. Variable $Q_t$ is the nominal value of cash held at the beginning of period $t$. The next three terms are the household’s wage income, real estate rental income, and capital rental income, respectively. The term $D_t$ is a dividend received by the household from the profits of intermediate goods producers. The last bracketed term on the right hand side is the nominal value of all expenditures in period $t$. These include investment, both in new real estate and capital capital, consumption, and replacement of depreciated capital and real estate.

The household’s first order condition with respect to consumption is

$$u_{c,t}^c = \psi_t$$

(1.15)

where $\psi_t$ is the marginal value of a unit of consumption to the household. The first order condition for $M_{t+1}$ is given by

$$\psi_t = \beta E_t \psi_{t+1} \frac{R_{t+1}}{\pi_{t+1}}$$

(1.16)
where \( \pi_t = P_t/P_{t-1} \). This familiar equation implies agents are just indifferent between using a dollar to consume today or depositing it and receiving interest rate \( R_t \).

**The Household Wage Decision**

Each household is assumed to be a monopoly supplier of differentiated labor \( l_{jt} \) which is sold to a representative competitive firm where it is transformed into aggregate labor, \( L_t \) for input into the production process. The aggregation is accomplished with technology such that

\[
L_t = \left[ \int_0^1 l_{jt}^{1/\lambda_w} dj \right]^{\lambda_w}.
\]

The demand curve for each differentiated labor input is given by:

\[
l_{jt} = \left( \frac{W_t}{W_{jt}} \right)^{\lambda_w/\lambda_w - 1} L_t, \quad 1 \leq \lambda_w < \infty
\]

where \( W_t \) is the aggregate wage rate and relates to individual household wages via

\[
W_t = \left[ \int_0^1 (W_{jt})^{1-\lambda_w} dj \right]^{1-\lambda_w}.
\]

Individual households take the aggregate wage rate and labor supply as given and set their differentiated wage rates in the same way intermediate goods firms set prices. The constant probability that a particular household will be selected to reoptimize is \( 1 - \xi_w \); and households not selected to reoptimize their wage rate instead index it to past inflation. Households that do reoptimize choose \( \tilde{W}_t \) to satisfy the first order condition:

\[
E_{t-1} \sum_{l=0}^{\infty} (\xi_w \beta)^l I_{j,t+l} \psi_{t+l} \left[ \frac{\tilde{W}_t X_{tt}}{P_{t+l}} - \lambda_w \frac{z_{h,t+l}}{\psi_{t+l}} \right] = 0
\]

where \( X_{t,t} \) is defined in (9), \( \psi_{t+l} \) is the household's shadow value of consumption in period \( t + l \), and where \( z_{h,t+l} \) is the disutility of labor.
Household Real Balances

The household first order condition for money holding, $M_t$, is

$$v'(q_t) + \psi_t = \psi_t R_t$$ (1.21)

where (21) holds for each possible realization of the current period money growth rate because the decision to hold cash is made after the money growth rate is known. The equation tells us that the marginal utility of holding a dollar of cash must equal the marginal utility of depositing the dollar and earning interest on it.

Investment

The household stocks of real estate and capital evolve according to:

$$B_{t+1} = (1 - \delta^b)B_t + F^b(i_t^b, i_{t-1}^b)$$ (1.22)

and

$$\bar{k}_{t+1} = (1 - \delta^k)\bar{k}_t + F^k(i_t^k, i_{t-1}^k)$$ (1.23)

where $B_t$ is the stock of buildings in the economy. The buildings are disaggregated into homes, $B'_t$, and factories, $B''_t$. The relationship between buildings and factories is given by $B_t = B'_t + B''_t$ and buildings can be converted from residential to industrial use costlessly. The parameters $\delta^b$ and $\delta^k$ are the depreciation rates of buildings and capital, respectively. The functions $F_b(\cdot)$ and $F_k(\cdot)$ summarize the technology with which current and past investment are transformed into installed capital and structures in the following period. I allow for partial capital capacity utilization to dampen changes in the marginal cost of production by reducing fluctuations in the rental rate which in turn reduce the decline in labor productivity that would otherwise
follow a monetary policy shock. Capital services are related to the stock of capital by the level of utilization, $u_t$, in the equation
\[ K_t = u_t \bar{k}_t. \] (1.24)

No buildings sit empty because households inhabit structures not used in the industrial process.

The first order conditions for $\bar{k}_{t+1}$, $i^k_t$, and $i^b_t$ imply:
\[ E_{t-1}\psi_t = \beta E_{t-1}\psi_{t+1}\left[\frac{u_{t+1}\bar{r}^k_{t+1} - a(u_{t+1}) + P_{k,t+1}(1 - \delta^k)}{P_{k,t}}\right], \] (1.25)
\[ E_{t-1}\psi_t = E_{t-1}\{\psi_t P_{k,t} F^k_{1,t} + \beta[\psi_{t+1} P_{k,t+1} F^k_{2,t+1}]\}, \] (1.26)
and
\[ E_{t-1}\psi_t = E_{t-1}\{\psi_t P_{b,t} F^b_{1,t} + \beta[\psi_{t+1} P_{b,t+1} F^b_{2,t+1}]\}. \] (1.27)

The functions $F^k_{l,t}$ and $F^b_{l,t}$ are the partial derivatives of the adjustment cost function with respect to their $l^{th}$ arguments.

Two Euler equations emerge from the household’s first order conditions for houses and factories. Optimal occupation of houses implies:
\[ E_{t-1}P_{b,t}\psi_t = E_{t-1}\{\frac{1}{B'_t} + \beta\psi_{t+1}[-\delta^b + (1 - \delta^b)P_{b,t+1}]\}. \] (1.28)

The left hand side of (27) gives the value of a unit of housing in terms of marginal utility. This value is equated with the sum of a utility dividend plus the continuation value of the housing unit in terms of future marginal utility. Optimal utilization of houses as factories implies:
\[ E_{t-1}P_{b,t}\psi_t = E_{t-1}\{\beta\psi_{t+1}[\bar{r}^b_{t+1} - \delta^b + (1 - \delta^b)P_{b,t+1}]\}. \] (1.29)

\[ ^{27}\]To see this, note from Section 4.5 (below) that housing utility takes a log form.
Note that the difference between the two kernels is that the utility dividend in (28) is replaced in (29) by rental income from leasing the property. The relationship between (28) and (29) identifies optimal housing occupancy in relation to the rental rate. It is given by:

\[ E_{t-1} \frac{1}{B_t'} = E_{t-1} \beta \psi_{t+1} r_{t+1} B_t'. \] (1.30)

Equation (30) captures the inverse relationship between the quantity of buildings households want to occupy and the rental rate for structures. The left hand side of (30) gives the expected marginal benefit of a single unit of housing. The right hand side of (30) is the expected discounted value, in terms of the marginal benefit of consumption, of the rental income a unit of structures generates. In equilibrium, the marginal benefit of occupying a structure must be exactly equal to the marginal benefit of the consumption one could purchase with forgone rental income.

**Capacity Utilization**

The Euler equation by which households decide on capacity utilization is:

\[ \psi_t[r_t^k - a'(u_t)] = 0. \] (1.31)

The expression equates the marginal benefit of raising capacity utilization with its cost in terms of depreciation. Linearizing the expression gives

\[ \hat{r}_t^k - \sigma_a \hat{u}_t = 0 \] (1.32)

where \( \sigma_a \) denotes \( a''/a' \), the ratio of the second derivative to the first derivative of \( a \) evaluated at the steady state. This mechanism helps mute the response of marginal cost and inflation to a monetary policy shock.
1.4.4 Loan Market Clearing, the Resource Constraint, and Equilibrium

Financial intermediaries receive $M_t - Q_t$ as deposits from households and a transfer $(\mu_t - 1)M_t$ from the monetary authority. Financial intermediaries lend all this money to intermediate goods firms, which in turn use it to pay for labor $L_t$. Thus loan market clearing requires

$$W_tL_t = \mu_t M_t - Q_t. \quad (1.33)$$

In the model, increases in the money supply are absorbed by households because money demand from firms does not respond contemporaneously to policy shocks. The only way to induce households to increase money holdings is to reduce the interest rate. This is the channel through which the money supply interacts with the interest rate.

1.4.5 Functional Form Assumptions

The functions characterizing utility are given by:

$$u(\cdot) = \log(\cdot)$$
$$z(\cdot) = \psi_0(\cdot)^2$$
$$v(\cdot) = \psi_q(\cdot)^{1-\sigma_q} \frac{1}{1-\sigma_q}. \quad (1.34)$$

The investment adjustment cost equations are given by:

$$F(i^j_t, i^j_{t-1}) = (1 - S^j(\frac{i^j_t}{i^j_{t-1}}))i^j_t \quad (1.35)$$

where $j \in b, k$ and where each function $S$ satisfies: $S(1) = S'(1) = 0$ and $\chi \equiv S''(1) > 0$. The assumptions $S(\cdot)$ ensure that $F_1 = 1$ and $F_2 = 0$ so that the steady state shadow price of buildings and capital, $\bar{P}_B$ and $\bar{P}_k$, are both equal to 1. While the
steady state of the model does not depend on the value of adjustment cost parameters \(\chi^b\) or \(\chi^k\), the dynamics do. Once the model is log-linearized, no other details about \(S(\cdot)\) are required. I estimate values of the adjustment cost parameters in the next section.

Capacity utilization function \(a(u_t)\) is also restricted such that \(u = 1\) in the steady state. By (32) this implies \(a' = r^k\). Further, I assume that \(a(1)=0\). Under this pair of assumptions the steady state of the model is independent of \(\sigma_a\) while the dynamics are not.

1.4.6 Monetary Policy in the Model

Monetary policy in the model is implemented through the interest rate. In response to an increase in inflation or output the policy authority raises the interest rate to combat inflationary pressure. In response to decreasing inflation or output the authority lowers the interest rate. The monetary authority has an interest-rate smoothing objective as well, as it wants to implement policy in a gradual manner to avoid adverse shocks to the economy. The monetary authority arrives at an interest rate target using a policy rule of the form:

\[
\hat{r}_t = (1 - \rho) \cdot (\beta_\pi \hat{\pi}_{t-1} + \beta_y \hat{y}_{t-1}) + \rho \cdot \hat{r}_{t-1}
\]  

(1.36)

where \(r_t\) is the interest rate set by the monetary authority in period \(t\), \(\pi_{t-1}\) and \(y_{t-1}\) are inflation and output in period \(t-1\), and where hats indicate deviation from steady state. The parameters \((1 - \rho)\beta_\pi\) and \((1 - \rho)\beta_y\) are the monetary authority’s responses
to inflation and output respectively. Parameter $\rho$ captures the smoothing motive of the policymaker.

### 1.5 Parameterization and Estimation of the Model

After linearizing the DSGE model laid out in Section 4, I take it to the data in four steps. First, I compute steady state ratios of several important macroeconomic variables to GDP from the Bureau of Economic Analysis (BEA) Fixed Asset Tables and National Income and Product Accounts. Second, I use these ratios to back out depreciation rates for capital and structures implied by a no-growth steady state. Third, I select plausible values for parameters that cannot be easily identified from the data in this study. Fourth, I estimate the remaining parameters over several different time periods to study how they evolve over time in relation to the macroeconomy and housing investment.

#### 1.5.1 Calibration

The data-driven portion of the calibration involves defining ratios in the model to fit closely with ratios in the data available from the BEA. Using annual estimates from the BEA’s Fixed Asset Tables and the National Income and Product Accounts, I compute the following ratios, find the average between 1960 and 2009, and assign them to their counterpart in the DSGE model: (i) consumption of nondurable goods and services to GDP, $\frac{C}{Y} = 0.7282$, (ii) the stock of residential structures to GDP, $\frac{B'}{Y} = 1.1212$, (iii) the stock of nonresidential structures to GDP, $\frac{B''}{Y} = 1.2565$, (iv) the stock of non-structure capital (including consumer durable goods) to GDP, $\frac{K}{Y} = 0.8464$, (v) investment in structures to GDP, $\frac{I_b}{Y} = 0.0817$, and (vi) investment in non-structure capital to GDP, $\frac{I_k}{Y} = 0.1992$. 

35
Table 1.2: Parameters Fixed in Estimation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
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<tr>
<td>$\beta$</td>
<td>Discount factor</td>
<td>0.99</td>
</tr>
<tr>
<td>$\delta^k$</td>
<td>Capital Depreciation</td>
<td>0.0588</td>
</tr>
<tr>
<td>$\delta^b$</td>
<td>Structure Depreciation</td>
<td>0.0085</td>
</tr>
<tr>
<td>$\alpha_k$</td>
<td>Capital share in production</td>
<td>0.23</td>
</tr>
<tr>
<td>$\alpha_b$</td>
<td>Structures share in production</td>
<td>0.09</td>
</tr>
<tr>
<td>$\bar{\mu}$</td>
<td>Steady-state money supply growth</td>
<td>1.017</td>
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<tr>
<td>$\sigma_q$</td>
<td>Interest semi-elasticity of money demand</td>
<td>9.966</td>
</tr>
<tr>
<td>$\psi_0$</td>
<td>Relative weight of leisure in utility</td>
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</tr>
<tr>
<td>$\lambda_f$</td>
<td>Firm pricing power</td>
<td>1.2</td>
</tr>
<tr>
<td>$\lambda_w$</td>
<td>Household labor market power</td>
<td>1.05</td>
</tr>
<tr>
<td>$\beta_\pi$</td>
<td>Interest rate response to inflation</td>
<td>1.5</td>
</tr>
<tr>
<td>$\beta_y$</td>
<td>Interest rate response to output</td>
<td>0.5</td>
</tr>
</tbody>
</table>

I assume that investment exactly replaces depreciated assets. This assumption, data on the steady state stock of structures and capital, and data on steady-state investment in capital and structures, allow me to compute the depreciation rate of buildings, $\delta^b = 0.0086$, and of non-building capital, $\delta^k = 0.0589$. The depreciation rates imply buildings depreciate at an annual rate of 3.5% and that non-building capital depreciates at an annual rate of about 24%. Note that if factories and capital were aggregated, they would depreciate at 13%, slightly higher than the 10% number used in CEE. The difference owes to the inclusion of consumer durables in the capital stock.

I choose a discount rate of $\beta = 0.99$, implying a steady-state nominal interest rate of approximately 4%. Given the steady state ratios, depreciation rates, and discount rate, I compute the contribution of structures, $\alpha^b = 0.23$, and of capital, $\alpha^k = 0.09$, to the Cobb-Douglas production process.
I calibrate several parameters to match CEE. I set both the steady state labor supply and the marginal disutility of labor to one. I also set the steady state money growth rate $\bar{\mu} = 1.017$, implying a steady state growth rate of the money supply of 1.7%, and the inverse of the interest rate semi-elasticity of money holding $\psi_q = 9.966$. Last, I set monopolistically-competitive intermediate goods firm markups over marginal cost to $\lambda_f = 1.05$ and household wage markups over the expected marginal rate of substitution between consumption and leisure to $\lambda_w = 1.20$.

There are a number of papers that focus on the importance of $\beta_\pi$, the monetary policy authority’s response to inflation for stable prices.\(^{28}\) From a modeling standpoint, $\beta_\pi$ is crucial because standard DSGE models do not have unique solutions for $\beta_\pi \leq 1$. These other papers generally find substantial differences in the policy-smoothing parameter $\rho$ between high- and low-inflation periods but do not highlight its practical importance. In this paper I focus on $\rho$. To understand why $\rho$ is of crucial importance, consider the policy rule in equation (36). When the inflation response parameter is large – $\beta_\pi = 2$ for example – if $\rho$ is very high, the policy response to inflation will still be small because $\beta_\pi$ is pre-multiplied by $(1 - \rho)$. In an economy where real variables respond to the interest rate, we should focus on $\rho$.

I parameterize monetary policy by setting $\beta_\pi = 1.5$ and $\beta_y = 0.5$ and estimate the persistence parameter $\rho$. The main reason for doing so is because $\beta_\pi$ and $\beta_y$ fluctuate to an extent that causes the model solution algorithm to become unstable. This makes proper impulse response function matching impossible. There does not seem to be a high cost to this simplifying assumption as changes in $\rho$ are sufficient to change the interest rate in the model. When the true values of $\beta_\pi < 1.5$ or $\beta_y < 0.5$,\(^{28}\) Examples include Clarida, Gali, Gertler (2000) and Boivin and Giannoni (2006).

\(^{28}\) Examples include Clarida, Gali, Gertler (2000) and Boivin and Giannoni (2006).
the estimates of $\rho$ will be biased upward. When the estimation produces a high value for $\rho$, policy in the model is less responsive to both inflation and output during the estimation period. I interpret higher parameter estimates for $\rho$ as a general reduction in the responsiveness of policy, rather than of one specific to interest rate inertia.

1.5.2 Estimation

Remaining are the habit parameter $b$, the sticky wage and price parameters $\xi_w$ and $\xi_p$, the parameter governing the response of the rental rate to interest rate shocks $\sigma_a$, the investment adjustment cost parameters $\chi^b$ and $\chi^k$, and the monetary policy parameter $\rho$. I estimate the value of $\gamma$ where:

$$\gamma = \{\rho, \chi^b, \chi^k, \xi_w, \xi_p, b, \sigma_a\}$$  

by minimizing a function of the squared distance between the model responses of output, consumption, inflation, the two types of investment, wages, and the interest rate to a monetary policy shock. Letting $\Psi(\gamma)$ denote the mapping from $\gamma$ to the model impulse responses and $\hat{\Psi}$ denote the corresponding empirical estimates from the VAR in Section 3.2, my estimator of $\gamma$ is the solution to

$$J = \min_\gamma (\hat{\Psi} - \Psi(\gamma))' V^{-1}(\hat{\Psi} - \Psi(\gamma))$$  

where $V$ is a diagonal matrix made up of bootstrapped variance estimates from the empirical impulse response functions.

Given a set of values for the vector $\gamma$, I solve the model using the methodology in Christiano (2000). The important feature in the Christiano approach is that it allows me to limit the information available to the household to match the identification assumptions in our VARs from Section 3. Note from equations 8, 10-13, 20, and
25-30 that households optimize based on information up through the prior period and are unaware of monetary policy shocks on impact. This implies only a subset of the macroeconomic variables in the model should respond to policy immediately. This is an information filtering problem accommodated by the solution methodology in Christiano.

1.5.3 Estimation Results

Several interesting observations emerge from the estimation results. First, the smallest private-sector responses to policy occur in the period where \( \rho \) is smallest and thus where policy is most responsive to the private sector. Similarly, the responses are largest in the period where policy is least-responsive to the private sector. These observations support Taylor. Second, the estimated price elasticities of residential and capital investment, \( 1/\chi^b \) and \( 1/\chi^k \), are smallest during the periods where monetary policy was least responsive to the macroeconomy and largest during periods where monetary policy was most responsive to the macroeconomy. These findings explain why Bernanke found the relationship between the macroeconomy and the housing market changed during the boom. Third, prices were most rigid during the 1980-1999 period and least rigid prior to 1980, while wages were most rigid in the most recent period. Fourth, the estimates are generally quite unstable across time.

Observation one – the magnitude of \( \rho \) is positively correlated with the magnitude of private sector responses to policy – suggests unresponsive policy may be related to larger macroeconomic responses. Examining this, I consider a counterfactual experiment: would a reduction in \( \rho \) in the 1990-2009 period reduce the magnitude of
<table>
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<tr>
<th>Parameter</th>
<th>60Q1-79Q4</th>
<th>70Q1-89Q4</th>
<th>80Q1-99Q4</th>
<th>90Q1-09Q4</th>
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<tr>
<td>ρ</td>
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<td>0.8060</td>
<td>0.6221</td>
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<tr>
<td></td>
<td>(0.0096)</td>
<td>(0.0055)</td>
<td>(0.0170)</td>
<td>(0.0003)</td>
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<tr>
<td>χ^b</td>
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<tr>
<td>χ^k</td>
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<td></td>
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<td>ξ_p</td>
<td>0.2802</td>
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<td>(0.0297)</td>
<td>(0.0421)</td>
<td>(0.0059)</td>
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<td>ξ_w</td>
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<td></td>
<td>(0.0236)</td>
<td>(0.0126)</td>
<td>(0.0424)</td>
<td>(0.0031)</td>
</tr>
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<td>b</td>
<td>0.6968</td>
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<td>(0.0262)</td>
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<td>σ_a</td>
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<td>(0.0477)</td>
<td>(0.4592)</td>
<td>(0.0055)</td>
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</table>

Notes: Standard errors are computed using the delta method. For more information, see Newey and McFadden (1994).

private sector responses to policy? I replace the value of ρ in the model estimated 1990-2009 with the value estimated in the smallest-response period, 1980-1999. The results are plotted in Figure 4. The counterfactual produces much smaller responses to monetary policy. This result suggests unresponsive monetary policy caused the large responses to policy during the housing boom. In Section 6 below I will examine whether the large responses to policy, coupled with policy observed during the period,
explain the housing boom. It is interesting to note that the responses in the counterfactual experiment are actually smaller than those in some of the prior periods. The explanation for this is that the economy is more rigid in the 1980-1999 period, mostly the result of much smaller investment elasticities.

Figure 1.4: VAR, Model Estimate, and Counterfactual for 1990-2009

Notes: The black, crossed line is the fitted model from 1990-2009. The VAR to which it was fitted is plotted in a solid red line along with its 80% confidence interval. The blue, dashed line is generated by the model estimated 1990-2009 where the parameter $\rho$ has been replaced with its value from the period 1980-2000.

Observation two – the negative relationship between $\rho$ and investment elasticities – means that investment in the model estimated between 1990 and 2009 is relatively
unresponsive to changes in the interest rate. The large impulse responses of investment during the period are the result of very inertial policy. Without highly inertial policy the responses would have been small, as shown in the counterfactual above. This result explains Bernanke’s finding that the relationship between the macroeconomy and house prices changed during the housing boom. House prices rose faster relative to residential investment during the boom because the price elasticity of residential investment was very low. As noted by Poterba (1984), this is consistent with an increase in demand caused by a reduction in the interest rate and with it, the user cost of housing. The intuition is that low interest rates increase demand for housing, bringing about equilibrium in a region of the supply curve that is nearly vertical. The theoretical model in Poterba also suggests that residential investment should be particularly sensitive to changes in the interest rate when rates are already low. Thus Bernanke’s finding of a change in the macroeconomy does not refute the culpability of policy – in fact, it supports it.

Observation three – prices were most rigid during the 1980-1999 period and least rigid prior to 1980, while wages were most rigid in the most recent period – supports a role for responsive policy in price stability. It is interesting to note that the period with the lowest responsiveness, 1990-2009, was not the period with the least price rigidity. This may be a residual effect of very responsive policy in the prior period. Perhaps responsive policy between 1980 and 1990 reduced inflation expectations, leading to less inflation even after the responsiveness of policy eroded.

Observation four – that the parameter estimates are quite unstable across time – suggests that the parameters being estimated are not, in fact, structural. This is an unfavorable result with respect to the usefulness of estimating a model like the
one in Section 5 in order to avoid a Lucas critique. Instead, the result suggests a
better approach is to estimate theoretical models over several shorter time periods
and observe the evolution of the parameters, as I do in this paper. It also suggests
one should be suspicious of conclusions based on such models estimated over one long
time period. The results of such a model are not representative of any particular
moment in time on the interval.

1.6 Quantifying the Impact of Monetary Policy During the
Housing Boom

In this section I quantify monetary policy during the housing boom by comparing
it to the average response of the Federal Funds rate to the macroeconomy between
1960 and 2010. I find a long series of expansionary statistical policy errors during the
housing boom. I use the theoretical model estimated for 1990-2009 to measure the
predicted impact of the statistical model errors on residential investment by creating
24 quarters of impulse responses for each statistical Federal Funds error between
1990:Q1 and 2009:Q4. Next, I aggregate the impulse responses to arrive at the portion
of residential investment in each quarter due to the deviation of monetary policy from
the “average”. The results suggest that policy contributed 70% to the peak in real
residential investment and extended the boom by five quarters.

I quantify “average” monetary policy by estimating the VAR model from Section
3.2 on the entire data set 1960-2009. Using the recursiveness assumption, I identify
the portion of the errors in the equation for the Funds rate that is orthogonal to other
variables in the VAR and attribute them to monetary policy, plotting them in Figure
5. Several features of the estimated policy series stand out. First, a large degree
of variation in the magnitude of policy is apparent in the figure. The magnitude of
the policy adjustments was fairly small in the early 1960s, grew substantially during the 1970s, peaked in the early 1980s, and then settled down after 1986. The figure includes a moving average standard deviation for the policy series to captures the evolution of policy volatility. Second, there are a series of large negative actions in the late 1970s, coinciding with the Great Inflation frequently attributed to expansionary monetary policy. Third, there are sixteen expansionary policy actions during the twenty quarters between 2001:Q2 and 2006:Q2. How much of the housing boom was due to this expansionary policy? To answer this question I feed the monetary policy identified in this section into the theoretical model estimated for the housing boom period.

I feed each monetary policy shock occurring during the period 1990-2009 through the theoretical model estimated on this same period. The model produces 24 quarters of impulse responses for each statistical model error. I then align the impulse responses and aggregate them. The first VAR impulse I consider is 1990:Q3, as I used two lags for the VAR and the housing boom data sample began in 1990:Q1. The contribution of monetary policy to residential investment in 1990:Q3 is the immediate response of residential investment to the shock policy in 1990:Q3. In 1990:Q4, the contribution of monetary policy to residential investment is the second period response to policy from 1990:Q3 plus the first period response to policy in 1990:Q4. I continue the aggregation until I have contributions to residential investment in each quarter during the housing boom period. Note that I assume policy has no impact on the economy after 24 quarters.

Figure 1.5: Monetary Policy Implied by the 1960-2009 VAR

Notes: The VAR includes two lags each of: real GDP, real consumption, the consumer price index, real nonresidential fixed investment, real residential fixed investment, the real wage rate, the Federal Funds rate, the growth rate of real M2, real corporate profits, and the real price of oil. Real nonresidential and residential investment, the real growth of M2 and the real price of oil are all computed by deflating by the consumer price index for all consumers all items. All data is from the Federal Reserve Bank of St. Louis F.R.E.D. database. The standard deviations in the figure are the centered 3-year moving average standard deviation of the policy series.

I apply a similar procedure to the Federal Funds rate to obtain policy contributions to the level of the Federal Funds rate. Last, I subtract the policy contributions from the observed levels of the Federal Funds rate and residential investment, arriving at model-based estimates of the series in the absence of policy. In Figure 6 I plot the Federal Funds rate, residential investment, and my estimates of how the series would have looked in the absence of policy.\textsuperscript{30}

\textsuperscript{30}By absence of policy, I mean if policy had adhered strictly to its long-run relationship with the macroeconomy as captured by the VAR in this section.
Figure 1.6: The Contribution of Monetary Policy to the Housing Boom

Notes: Starting in 1990 I compute the contribution of monetary policy to the Federal Funds rate and to residential investment using the policy identified in Figure 5 and the model estimated for 1990-2009. I subtract these policy contributions from the observed values of the Federal Funds rate and residential investment to produces counterfactual series for each starting in 1990. Panel (a) plots the Federal Funds rate in a plain, blue line. The counterfactual path of the Federal Funds rate is plotted in a red, crossed line starting in 1990. In panel (b) I plot detrended real residential fixed investment in a plain blue line. Real residential investment is computed as nominal investment deflated by the consumer price index for all urban consumers, all items. I then regress 100 \cdot \log(\text{real residential investment}) on a constant and a time trend. The errors from the regression are the detrended series. The counterfactual path of real residential investment is plotted in a red, crossed line starting in 1990.

First, observe the path of the counterfactual Federal Funds rate after 2001 in panel (a) of Figure 6. It is qualitatively similar to Figure 1 in Taylor, confirming his assertion that policy was expansionary by historical standards. The figure suggests
the Funds rate was much lower than usual relative to the macroeconomy throughout
the period of fastest housing investment. The Federal Funds rate was also very low
by historical standards in the early 1990s.

Examining panel (b) of Figure 6 it is clear that both periods of expansionary
policy had substantial impacts on residential investment. During the first expan-
sionary period, which lasted from 1991:Q2 through 1994:Q4, residential investment
was about 29.25% higher relative to trend than it would have been in the absence of
policy. During the second expansionary period, 2001:Q2-2007:Q3, policy contributed
a maximum of 26.67% of trend to residential investment in 2006:Q3. This second
expansionary period extended the boom in residential investment by five quarters
and increased it by 70%, from 21.7% above trend to 36.85% above.

Panel (b) also suggests policy largely counteracted any business cycle fluctuations
in real residential investment between 1990 and 2007. The recession of 2001 is the
only recession on record during which residential investment does not fall. The coun-
terfactual illustrates this point and has more normal business cycle properties around
the 2001 recession. Policy was responsible for a sharp increase in housing investment
in 1991 and then largely insulated the housing market from the business cycle un-
til the crash in 2007. Conjecturing further, these results suggest that, had policy
not been so successful at smoothing the housing cycle between 1991 and 2005, hous-
ing market risk may have been harder to underestimate during the period when the
bubble inflated. In this regard, policymakers are likely victims of their own success.
1.7 Conclusion

In this paper I have shown: (i) that monetary policy during the housing boom was unresponsive to the macroeconomy, (ii) that the unresponsive stance of policy made the economy particularly sensitive to monetary policy impulses, and (iii) that such impulses after 1990 increased the magnitude of the housing boom by 70%.

The results in this paper differ from others in the literature because I estimate the model over several short periods. The rolling regression results and changes observed in the VAR impulse responses across periods confirm that economic parameters are time-varying. Thus it is crucial to isolate the period of interest as specifically as possible.

The parameter estimates show the elasticity of residential investment falls considerably between the third and fourth period, suggesting a substantial increase in the sensitivity of house prices relative to the macroeconomy during the boom. These findings reconcile the findings presented by Bernanke with those presented by Taylor. Recall from Section 2 that Bernanke used a VAR estimated 1977-2001 to produce a dynamic forecast of house prices after 2001 and found actual prices were above the confidence interval from the forecasts. The estimates of my DSGE model during the 1990-2009 period suggest Bernanke found this because low rates increased the demand for houses such that equilibrium occurred in a price-inelastic portion of the residential investment supply curve. The higher volatility of house prices relative to the macroeconomy follow naturally from this lower elasticity.

According to the model, monetary policy prevented residential investment from contracting during the recession of 2001. Had investment contracted, the relationship between house prices and investment suggests there would not have been the
substantial increase in systemic risk noted by Khandani, Lo, and Merton. The results further show that policy was a net contributor to residential investment in most quarters after 1990 and the aggregate stance of policy was expansionary.
Chapter 2: PREDICTING REVERSALS IN NEW HOUSE CONSTRUCTION

2.1 Introduction

In this paper I examine the usefulness of several sentiment, asset return, and macroeconomic/monetary factors for predicting turning points in the housing market. It is a follow up to my 2009 paper “Predicting Turning Points in the Housing Market,” written jointly with Donald Haurin. In the 2009 paper we find that a housing-related consumer sentiment index can be used to produce reliable and timely signals of upcoming turning points in the housing market. In this paper I take up the natural follow-up question: are there other series that might provide even better, more timely signals of upcoming reversals. In order to answer this question I first compile a list of time series that have been successfully used to predict business cycles in the macroeconomics literature. To this list I add monetary and macroeconomic time series that make sense in light of findings in my job market paper, “Monetary Policy and the Housing Cycle” (2010) and the sentiment index studied in my 2009 paper.
In section 2 of this study I review a sampling of academic work related to this study. This work falls into two distinct categories. First, there is an econometrics literature that addresses methods for predicting turning points. Based on the results in these prior studies, I adopt a sequential probability recursion (SPR) for the analysis in this paper. It allows me to estimate a probability that there has been a turning point in a leading indicator for the housing market rather than providing a binary signal and model the statistical distribution of upturn and downturn regimes in economic time series as independent of one another. The SPR is a more concise special case of the Markov chain estimation introduced by Hamilton (1989) and allows me to model the statistical distribution of upturn and downturn economies separately without resorting to rolling Markov chain simulation.

The second literature I review in section 2 is a small subsample of the studies examining the usefulness of various economic and financial time series as leading indicators for macroeconomic output. They include data series falling into three categories: sentiment, asset returns, and macroeconomic/monetary policy factors. To this list, I add series suggested by my own prior work on the housing market. Several interest rates and interest rate spreads have proven useful for predicting the future direction of output. I examine findings from my prior work that may inform the current study.

In section 3 of this paper I describe the housing market data and each potential leading indicator I use in this paper in detail. My proxies for the housing market are new permits issued and housing starts. This choice is ambitious, as both are themselves leading indicators for house sales.
In section 4 of this paper I detail the econometric methodology that I will use to transform economic and financial time series into probabilities of a turning point in the housing market. The methodology has three parts. First, I separate each leading indicator series into portions that correspond to upturns and downturns in the housing market. I accomplish this using the maximum distance criterion from discriminant analysis. Next, I build a model of the statistical distribution of each leading indicator series in upturns and downturns. Last, I compare the most recent observation in each leading indicator series to the statistical models of each regime and infer the likelihood that it was drawn from an upturn or downturn. In practice, I do this iteratively by starting in the first period of the third full housing market cycle, as I use the first two cycles to calibrate the model, and draw inference as to which regime each leading indicator was drawn from. Then I step forward one period and draw inference again. As the number of iterations increases, the number of observations and prior estimates informing the statistical models of each type of regime also increase, presumably improving the performance of the model. The methodology is pseudo out of sample in that none of the leading indicator or housing cycle data occurring after the prediction period is used to calibrate the statistical model.\footnote{One of the leading indicator series is not, in fact, ex-ante in this regard: Shocks. This will be discussed in detail in section 3.} However, the data I am using here is not real time and several of the sentiment and macroeconomic data series are subject to revision.

In section 5 of this paper I compute a quadratic loss function for each potential leading indicator series as in Diebold and Rudebusch (1989) and examine the performance of each indicator both by the loss function metric and by qualitatively examining the turning point predictions. I find that the loss function does not fully
reflect the qualitative usefulness of each leading indicator but that it still captures useful information in a concise way. The results suggest that several of the leading indicators I study here provide timely early warning of reversals in the housing market. The five best leading indicators based on the loss function metric are the mortgage interest rate, the consumer sentiment series, the default premium, the term premium, and the difference between the federal funds rate and the interest rate that would be set by a Taylor (1993) rule monetary policy.

Section 6 concludes.

2.2 Related Literature

The present study draws on findings in two distinct literatures from econometrics and macroeconomics. The first of these is the literature on business cycle forecasting, which has been a topic of interest since Burns and Mitchell (1946). I will focus on two aspects of forecasting: (i) the econometric methodologies used to extract predictive information and (ii) leading indicator series with predictive content. The second literature I will discuss here has to do with the impact of monetary policy and interest rates on the housing market, a much newer topic.

The study of business cycles began with Burns and Mitchell, which provides an impressive documentation of the business cycle properties of over 1000 economic time series. Their primary goal is to begin addressing the question: How do economic time series behave during the periods of time occupied by business cycles? They provide a detailed exposition of their proposed methods of measuring cyclical behavior and offer a wholesale application of these methods.
Burns and Mitchell break individual economic series into subsamples of a single cycle, peak-trough-peak, by looking for "wave-like" movements in the data and comparing them to similar patterns in "general business activity." Then they study the properties of these individual cycles by looking at several different sets of statistics. The first group of measures captures time and duration. For each time series, lower and upper turning points, troughs and peaks, are identified ad hoc and the distribution of the distance in time between reversals is cataloged. In addition to these durations, reference cycles are determined by the points around which the individual series turning points seem to be distributed. These reference cycles then become Burns and Mitchell’s measure of general business activity. Leads and lags are the distance in time between reference turning points and specific series turning points.

The second group of measures relates to movements of specific variables within each cycle. Each variable is expressed as a percent of its mean over the cycle, which eliminates any inter-cycle trends that might have been present in the data but faithfully preserves intra-cycle trends. The methodology results in a specific cycle pattern for each series. The third group of measures Burns and Mitchell compute is for the amplitudes of specific cycles relative to the reference cycle.

Koopmans (1947) strongly criticizes Burns and Mitchell in "Measurement without Theory" by arguing that they "deliberately spurn" the toolkit of the theoretical economist by ignoring the behavior of individual economic agents. While Koopmans is clearly right that Burns and Mitchell abstract from economic theory entirely, he could not have known that their work would set the foundation for later research that unites the study of business cycles with proper economic and statistical theory.
An important example applying rigorous theory to the topic of business cycles is Neftci (1982). Neftci was motivated by his observation that Burns and Mitchell’s economic cycles seem to exhibit very different behavior during expansions and contractions and by the fact that the profession had not yet brought statistical precision to bear on the issue. His primary contribution is the modeling of upturn and downturn regimes with different density functions. Taking this approach, one can observe innovations in a series and compare them to the distribution of innovations during past downturns and upturns in order to make some probabilistic inference with regard to the regime from which the innovation was drawn. Neftci also provides a simple statistical approach for making this inference.

Neftci’s approach modifies Bayes’ rule to condition each period’s estimated prior probability on the posterior probability estimated one period earlier and the name for the approach, sequential probability recursion (SPR), stems from this iterative conditioning. Neftci illustrates the usefulness of his approach for forecasting future turning points in economic activity using an index of leading indicators for the U.S. between 1970 and 1979. The intuition for his illustration is as follows: if turning points in a leading indicator series occur prior to turning points in some economic series of interest, then using an SPR to identify the probability that the leading series has already switched regime effectively estimates the probability of forthcoming regime change in the economic time series of interest.

Neftci’s methodology is used in several other studies. An example is Diebold and Rudebusch (1989), which examines the usefulness of the composite index of leading indicators for predicting business cycle turning points as identified by the National Bureau of Economic Research. Using Neftci’s SPR, Diebold and Rudebusch produce
rolling real-time turning point probability forecasts and develop scoring rules that allow for the rigorous and systematic evaluation of leading indicator forecasts. They find that the index of leading indicators can in fact be used to predict forthcoming expansions and contractions in business activity. Later in this paper I will use their scoring metrics to compare the usefulness of 20 leading indicators for predicting turning points in the housing market.

A relative weakness in the Neftci approach is the need for the researcher to use her own judgment to partition the data set into upturn and downturn regimes. Hamilton (1989) develops an econometric methodology for dealing with discrete shifts in regime without partitioning the data and estimating two different density functions. He assumes the existence of a latent state variable that determines the parameterization of the density function from which the data series is drawn. This effectively implements a Markov switching regression that can be estimated via maximum likelihood. Post-estimation, one can implement the nonlinear filter provided by Hamilton to uncover optimal estimates of the probability that the economy was in a particular state at dates in the past. The Hamilton methodology is particularly attractive because it formalizes inferences with regard to prior states by which the different regimes are calibrated. However, it turns out that Neftci is a special case of Hamilton in which the following two assumptions are made: (i) only the most recent turning point affects the density function for current observations, and (ii) there is known to be a possibility of at most one turning point observed during a given interval of time. These two assumptions are particularly appropriate in the context of this paper and I will discuss them further in section 4.
Stock and Watson (1993) takes an entirely different approach to estimating the probability that the economy will be in a recession at a particular date in the future. Rather than trying to forecast turning points, their model focuses on forecasting a binary time series that takes value 1 if the economy is in a recession. They start by producing quantitative definitions of recession and non-recession periods and then compute the probability that the economy will be in recession via stochastic simulation of an economic forecasting model. Stock and Watson produces very effective leading indicators for the macroeconomy but they miss the sharp downturn in economic activity circa 1990. Their approach aggregates many leading indicator series, thus obscuring the marginal contributions of each one and making it inappropriate for my objective in this paper.

The study in this paper is a follow-up on Croce and Haurin (2009), which conducts a horse race between several sentiment-related leading indicators for the housing market. Of particular interest to the authors is whether an index of housing-specific consumer sentiment is valuable as a leading indicator for housing market reversals. The consumer sentiment data is from the University of Michigan/Reuters Survey of Consumers, which asks approximately 500 households a month if they think it is a good time to buy a house. Responses are transformed into an index of consumer housing sentiment called GTTB for "Good Time to Buy".

Croce and Haurin compares the usefulness of GTTB against that of an index of home builder sentiment called the Housing Market Index (HMI), which is produced by the National Association of Homebuilders and Wells Fargo. The HMI is a composite of three sub-indices measuring single-family home sales, builders’ forecasts of single-family home sales over the next six months, and potential buyer traffic. They
also examine the performance of the HMI sub-indices as leading indicators. They compute turning point forecasts using Neftci’s SPR and then compare them using the metrics developed by Diebold and Rudebusch. Croce and Haurin find that the consumer sentiment data produces substantially better forecasts of upcoming peaks in the housing market than HMI or its components. However, they do not find any evidence that the series they study help predict housing market bottoms.

In the present paper I want to explore the possibility that there are other strong leading indicators for the housing market. The macroeconomics forecasting literature is a natural place to search for such series. The predictive content of countless economic data and asset price series have been examined for evidence of predictive content. Stock and Watson (1990) provides a nice summary of then-current findings on the subject. They conclude that some asset prices have statistically significant predictive power for output some of the time. However, this content may be difficult or impossible to exploit because which series has predictive power changes from decade to decade.

Stock and Watson (1990) demonstrates that in-sample significance tests like Granger causality provide little or no information about whether a series might be a reliable leading indicator. This is because predictive relationships in the data are very unstable and a variable that was predictive during one business cycle may not be during another. This finding is very useful for the present study, which will dispose of the Granger causality tests in Croce and Haurin. The predictive economic data and asset price series cataloged in Stock and Watson include: the commercial paper interest
rate, the term spread, the default spread, stock prices, and dividend yields. The commercial paper interest rate is the yield to maturity on short-term low-risk corporate debt.

Sims (1980) shows that including rates in a vector autoregression with output and inflation eliminated the marginal predictive content of money for real output.

Bernanke (1990) catalogues the relative predictive power of several interest rates, finding that the Federal Funds rate performs well as a predictive indicator for several macroeconomic variables.

The term spread measures the difference in yields between treasury bonds of long duration and those with short duration. According to theories of the term structure of interest rates, the term spread should contain information about market participant expectations about future short-term interest rates. If future rates are expected to be lower than current rates, then market participants expect monetary policy to become more accommodative, signaling a recession in the near future. This idea was formalized in work by several researchers in the late 1980s, including Stock and Watson (1989).

Default spreads are the difference in yield to maturity on low credit quality and high-quality bonds of the same duration. Default spreads may be predictive of future economic activity because they capture information about how much compensation market participants require in order to take risk and have been studied by several economists, including Stock and Watson (1989) and Friedman and Kuttner (1992). Bernanke shows that the spread between yields on short term corporate debt and Treasury debt is also a particularly good predictive variable, theorizing that its predictive power is due to how well it captures monetary policy. Bernanke and Blinder
(1990) find that the 10 year U.S. government bond rate has the highest marginal significance among several potential leading indicators for housing starts. Their study did not include the mortgage interest rate, however, and it is plausible that the 10 year bond rate did very well in their study because of its similarity to mortgage rates. Because of this possibility, I will consider both the 10 year government bond rate and the 30 year fixed rate conforming mortgage rate as potential leading indicators in this paper.

Stock prices and dividend yields could reasonably be expected to have some forecasting power because they should, in theory, contain information about firms' future earnings. Intuitively, when market participants expect the economy to suffer a recession, the expected future earnings of firms falls, reducing their stock price in advance of the onset of recession. However, stock returns were shown not to have predictive power for economic output by Fama (1980) and earnings yield was shown not to be predictive by Campbell (1999).

In "Monetary Policy and the Housing Cycle," (2010) I show that Federal Reserve policy played a role in a housing boom that precipitated the global financial crisis of 2008. The methodology in the paper identifies a series of monetary policy shocks—innovations in the federal funds rate that deviate from the long-run relationship between the funds rate and the macroeconomy—and compares policy during the housing boom to a Taylor rule. Because results in my 2010 paper suggest monetary policy has a substantial influence on the housing market, I will consider both the policy shocks and deviations from a Taylor rule as potential leading indicators for housing reversals.
2.3 Data Descriptions

In this paper I characterize the housing market using two time series: permits issued for new construction (Permits), and starts of new single-family house construction (Starts).\textsuperscript{32} I chose these variables because they are both strong leading indicators for the housing market in general and because the Permits and Starts are available for a substantially longer time period than are house price data.\textsuperscript{33} Figure 1 plots Permits and Starts in panels (a) and (b), respectively. The cyclical peaks and troughs I identify for each series are included in the plots, with peaks being marked by downward-facing red triangles and with troughs indicated by green upward-facing triangles.\textsuperscript{34} While my turning point identifications generally adhere to the business cycle, note that I do not identify a housing market cycle around the recession of 2001 because the fluctuations in housing series were extremely minor around this recession relative to those observed during every other recession on record. Another interesting feature of the housing market data is that housing starts generally reach cyclical peaks and troughs in the same period as, or prior to, those of Permits. This is counterintuitive because the home building process involves getting a permit to build prior to starting construction and it suggests that not all permits issued are acted upon by builders.

\textsuperscript{32}Data on Permits and Starts is available from the U.S. Census Bureau.

\textsuperscript{33}National house price data becomes available starting in 1975. Some versions of the data start in 1971. Starts and Permits data series begin in 1959 and 1960, respectively.

\textsuperscript{34}Note that I identify fewer peaks and troughs in the housing market here than in the 2009 paper. The prior study was written with a view that it is imperative there be a large number of cycles on which to test the model. Here, I am more concerned with the accuracy of the turning points and I base my peaks and troughs on the business cycle, as in Burns and Mitchell.
Notes: Panel (a) of Figure 1 plots the natural log of annualized, seasonally adjusted permit issuance data from the U.S. Census Bureau. I identify turning points in the series by looking for local maxima and minima in the vicinity of recession dates identified by the National Bureau of Economic Research. Peaks are indicated in the figure using red, downward-facing triangles. Troughs are indicated by green, upward-facing triangles. Panel (b) of Figure 1 plots the natural log of annualized, seasonally adjusted housing start data from the U.S. Census Bureau. I identify turning points in the series exactly as I did for permits. As for permits, peaks in the housing start series are indicated in the figure using red, downward-facing triangles and troughs are indicated by green, upward-facing triangles.

The potential leading indicator series I will consider in this paper fit into three categories: (i) sentiment, (ii) asset returns, and (iii) macro/monetary policy. In the sentiment category I include a consumer sentiment index shown in Croce and
Haurin to predict future downturns in the housing market. Also in the sentiment category I include several interest rate spreads that have been used in the academic and forecasting literature: the term spread (Term), the default spread (Def), and the short spread (Short). I consider these measures of sentiment because they should, in theory, capture the compensation that market participants demand in return for facing different types of risk and their perception of the magnitude of those risks. In the asset return category I include S&P returns, the federal funds rate, the commercial paper rate, the 10 year U.S. Treasury rate, and the mortgage interest rate. The macro/monetary policy variables I examine are the output gap, monetary policy shocks identified in a large vector autoregression model and deviations from a Taylor rule monetary policy.

The consumer housing sentiment index is from the University of Michigan Survey of Consumers. The survey is conducted monthly with a sample size of about 500 households. Question 23 of the survey asks respondents "Do you think that now is a good time or a bad time to buy a house?" Possible responses include "it is a good time to buy a house," "it is a bad time to buy a house," "uncertain," and "don’t know." I derive a housing-specific index of consumer sentiment based on these responses: GTTB (for "good time to buy") is computed as GTTB= ( # of "good" - # of "bad" +100)/2. The index can take values between 0 and 100 with higher values indicating improving housing sentiment. I plot GTTB in panel (a) of Figure 2 below. It is interesting to note that GTTB peaks well in advance of recessions and that it generally reaches a trough sometime during a recession, leading the overall business cycle, and leading it by longer at peaks than at troughs.
Figure 2.2: Sentiment Data

Notes: Panel (a) of Figure 2 plots the Good Time To Buy index. The index is computed using data from the University of Michigan Survey of Consumers question #23, which asks respondents “Do you think that now is a good time or a bad time to buy a house.” The index can take values between zero and 100 and higher values indicate a larger number of respondents think it is a good time to buy or fewer think it is a bad time to buy. A value of 50 indicates equality in the percentage of respondents thinking it is a good time to buy and those thinking it is a bad time to buy. Panel (b) of Figure 2 plots the term premium: the difference in yield between a 10 year U.S. Treasury bond and a 3-month Treasury bill. According to theories of the term structure of interest rates, higher term premia indicate market expectations of higher short-term interest rates in the future. Panel (c) of Figure 2 plots the default premium: the difference in yield on low-quality long-duration corporate bonds from high-quality corporate bonds of the same duration. This metric captures the extra compensation market participants require in order to take on additional risk. Because the credit quality of both types of bonds used to compute this series is fixed, the series captures changes in the price of risk at the long end of the yield curve. Panel (d) of Figure 2 plots the short premium: the difference in yield between 3-month commercial paper, which is not risk free, and 3-month treasury bonds, which are riskless. This risk premium captures a market price for risk at the short end of the yield curve.
Term is the premium (in terms of yield to maturity) on U.S. government securities with ten years to maturity relative to those with 3 months to maturity.\textsuperscript{35} Based on theories of the term structure of interest rates, Term should capture market participants’ expectations for the future path of short-term nominal interest rates. Intuitively, if short rates are expected to fall in the future, this suggests the Federal Reserve is expected to lower interest rates. This expectation is consistent with an upcoming recession. Similarly, if the term premium increases it may indicate that market participants expect increasing rates from the Federal Reserve in response to an upturn in business activity. I plot the term premium in panel (b) of Figure 2. Note that it generally peaks shortly after the end of recessions, then gradually declines until the beginning of the subsequent recession.

The default premium (Def) is the premium on BAA rated thirty year corporate debt over AAA debt.\textsuperscript{36} Def captures how much extra return market participants require in order to accept the higher default probability inherent in an investment in BAA-rated bonds relative to AAA-rated bonds. This premium rises during recessions—sometimes beginning its rise before the onset of recession. Def peaks very near the end of recessions. The intuition for using Def as a leading indicator is that risk tolerance has a direct impact on the availability of credit to borrowers with productive uses for capital. Higher risk-aversion in credit markets signals tighter credit conditions for businesses and a higher likelihood that productive projects will not get funded.

The short premium (Short) is similar to Def, but is computed at the short end of the yield curve. Specifically, Short is the difference in yield to maturity on commercial

\textsuperscript{35}I compute Term using series GS10 and TB3MS from the Federal Reserve Bank of St. Louis FRED database; Term = GS10-TB3MS

\textsuperscript{36}These series are available from the Federal Reserve Bank of St. Louis FRED database.
paper and 3-month U.S. government securities.\textsuperscript{37} I plot Short in panel (d) of Figure 2.

The second group of leading indicators I will consider is comprised of asset returns. The first of these is monthly returns on the S&P 500 index and appears in panel (a) of Figure 3, below.\textsuperscript{38} Theoretically, equity prices are the present value of expected future firm earnings. Higher stock prices-positive S&P returns-portend expectations of higher future corporate profits. They should capture aspects of the market’s expectation for future economic activity. The figure makes it apparent that S&P volatility increases in advance of recessions, but no other pattern in returns relative to recessions is readily visible.

The federal funds rate (Fedfunds) is a market interest rate charged by banks to lend to one another overnight and is plotted in panel (b) of Figure 3.\textsuperscript{39} Since the mid-1980s the Federal Reserve has implemented monetary policy by explicitly targeting a level for the federal funds rate so it should be among the most direct sources of information about the stance of monetary policy. I will consider two other interest rates as potential leading indicators for the housing market: the 10 year U.S. Treasury bond rate (GS10) and the monthly average interest rate on conforming 30-year fixed

\textsuperscript{37}I compute Short using FRED series TB3MS, CPF3M, and CP3M. CP3M is the 3-month commercial paper yield to maturity and CPF3M is the 3-month financial firm commercial paper yield to maturity. CP3M is available only until 1997 and CPF3M is only available after 1996. Thus I create a commercial paper rate by splicing the two series together in January 1997. Then Short = CP-TB3MS.

\textsuperscript{38}The S&P 500 index is a value-weighted index of equity prices for the 500 largest public companies in the U.S. The data was obtained from the FRED database.

\textsuperscript{39}Fedfunds is the monthly average effective federal funds rate during the month and is obtained from the FRED database.
rate mortgages (Mortg).\textsuperscript{40} Bernanke and Blinder (1990) find that the 10-year bond rate also performs well as a leading indicator for housing starts so I will consider it here as well. Because houses are usually purchased using a mortgage, one might reasonably expect Mortg to have the highest marginal significance in our forecasting exercise. Fedfunds, GS10, and Mortg are plotted in panels (b),(c), and (d) of Figure 3.

The final group of potential leading indicators is designed to capture information about the macroeconomy and monetary policy that may not be apparent merely by looking at interest rates or asset prices. The macro/monetary factors I will consider are (i) the output gap (Gap), (ii) monetary policy deviations from a Taylor rule (RelativePolicy), and (iii) monetary policy shocks identified using a vector autoregression (Shocks).

The output gap is a measure of the difference between current real GDP and the maximum sustainable non-inflationary level of output. If GDP is below potential, then the output gap is negative and one can say that the economy is not fully utilizing its resources. I plot it in panel (a) of Figure 4. It captures the level of unutilized resources in the economy. Because the output gap is a good measure of the relative health of the macroeconomy, it is worth considering as a leading indicator for the housing market.\textsuperscript{41} Notice from the plot that the output gap peaks in advance of the onset of recessions, much like the housing market series but it seems to reach a trough concurrent with or after the end of recessions.

\textsuperscript{40}Both GS10 and Mortg are available from the FRED database. Conforming mortgages are loans to prime borrowers that are written using a house as collateral and that are guaranteed by one of the government-sponsored mortgage finance enterprises.

\textsuperscript{41}I compute the output gap as Gap= (real GDP-real Potential GDP)/real potential GDP. Real GDP and real potential GDP are both available from the FRED database.
Monetary policy deviations from the Taylor rule measure the distance between the monetary policy rule suggested by Taylor (1993) and the actual federal funds rate. The Taylor rule is generally expressed as:

\[ r_t = \pi_t + \beta \cdot (\pi_t^* - \pi_t) + \beta_x \cdot x_t \]  

(2.1)
Figure 2.4: Macro/Monetary Series

Notes: Panel (a) of figure 4 plots the output gap, which is the difference between actual GDP and an estimate of potential GDP from the Congressional Budget Office. When the output gap is negative, it indicates that output is below potential. Panel (b) plots the difference between the actual effective federal funds rate and the rate suggested by computation of a Taylor (1993) rule. Panel (c) plots deviations of the federal funds rate from its long-run relationship with the macroeconomy as computed by a large vector autoregression model.

where $r_t$ is the current level of the federal funds rate, $r^*$ is the desired real long run federal funds rate, $\pi_t$ is inflation during the current quarter, $\pi^*$ is the target level for the inflation rate, and $x_t$ is the output gap in the current quarter. The sum of the first two terms on the right hand side of (1) is the nominal short term interest
rate the Federal Reserve would like to achieve via monetary policy over the long run. The term being multiplied by \( \beta_\pi \) is the distance between the current inflation rate and the inflation target the monetary policy authority would like to achieve in the long run. If \( \beta_\pi > 0 \), then inflation in excess of the inflation target would cause the current monetary policy interest rate, \( r_t \), to increase. The last term on the right hand side of (1) captures policy responses to realizations of output below potential. When real GDP is less than real potential GDP, then \( x_t < 0 \) and, if \( \beta_x > 0 \), it follows that the interest rate will fall, stimulating economic growth. To compute the Taylor rule level for the federal funds rate, I assume \( r^* = 2\% \) and that \( \pi^* = 2\% \). I set \( \beta_\pi = \beta_x = 0.5 \), values John Taylor (1993) suggests reflect good policy. I compute inflation using the annualized quarterly rate of change in the personal consumption expenditures chain-weighted price index for all goods. I subtract the resulting series from the actual federal funds rate to arrive at a measure of the relative tightness or looseness of monetary policy compared to the Taylor rule (RelativePolicy). I plot RelativePolicy in panel (b) of figure 4; notice from the figure that relative to the Taylor rule, the federal funds rate was continually too low between 2002 and 2006. There was a similar period of Funds rates that were lower than a Taylor rule would have suggested between 1972 and 1981. The relationship with recessions is less clear for RelativePolicy than for most of the other potential leading indicators I consider here.

In "Monetary Policy and the Housing Cycle," (2010, henceforth MPHC) I show that Federal Reserve policy played a role in a housing boom that precipitated the global financial crisis of 2008. The methodology in the 2010 paper identifies a series of monetary policy shocks, which are changes in the federal funds rate beyond what
we would expect given changes in other economic variables and their long run relationship with the funds rate. Because MPHC suggests these shocks had a powerful effect on housing investment I consider them here as potential leading indicators. I compute the long-run relationship between the macroeconomy and the federal funds rate by estimating a large vector autoregression model that includes two lags each of: real GDP, real personal consumption expenditures, the consumer price index, real nonresidential investment, real residential investment, real wages, the federal funds rate, real corporate profits, and real oil prices. The residuals from the seventh regression equation—the equation for the federal funds rate—capture changes in monetary policy that are orthogonal to all the other macroeconomic variables included in the regression. I interpret these residuals as policy shocks and will examine their usefulness as a potential leading indicator for the housing market in section 5. These policy shocks are plotted in panel (c) of figure 4. There is not a clear relationship between Shocks and the recessions plotted in the figure. Because I estimate the relationship between the federal funds rate and the rest of the economy ex-post, forecasts based on these shocks are not truly ex-ante. However, if the policy shocks perform well, it will be possible to institute a rolling VAR estimation to achieve results more representative of a real-time forecast.

In addition to considering the levels of the potential leading indicators for predicting turning points, I also consider the usefulness of the first differences of each series (except for S&P returns and Shocks). To see why it makes sense to consider differences as leading indicators, imagine two series, A and B, that display roughly the same business cycle properties but where A consistently reaches turning points before B. In this case, observing the level of A is uninformative with regard to whether B is
in an upturn or a downturn. Instead, observing whether A is increasing or decreasing gives us this information. When A is moving a different direction than B, this signals a turning point will arrive shortly for series B.

2.4 Sequential Probability Recursion Methodology

In this section I describe the sequential probability recursion (SPR) I will use to compute the probability that we are in an upturn or downturn regime in each leading indicator series in section 5 of this paper. If a series is a good leading indicator, an estimator that can approximate the probability that the leading indicator series has switched from one regime to another will be useful because it signals an upcoming change in homebuilding activity. Exactly such an estimator is developed in Neftci (1982). Given a leading indicator series, Neftci’s methodology estimates a probability that it was drawn from either an upturn or downturn regime. It accomplishes this by comparing the newest realization to the first and second moments of the historical realizations during past upturn and downturn phases. This comparison yields a relative probability that the observation was drawn from an upturn or a downturn. The Neftci methodology is a modification of pure Bayesian estimation because each estimate incorporates an extra layer of information by including the probability estimate from the previous period.

The Neftci methodology is a special case of the better-known Markov Chain framework proposed by Hamilton (1989). In order to go from Hamilton to Neftci, one needs to assume that (i) the type of turning point that occurred most recently determines the density function against which current observations are compared and (ii) there
is at most one turning point observed during a given interval of time. These assumptions are quite natural given the goals of this paper. Consider a builder trying to determine the near-term direction of the housing market. She is reasonably certain that there was a peak in late 2005 or early 2006. Thus, she is now concerned with estimating the probability that the leading indicators for the housing market have begun to signal expansion. In order to estimate the probability that we are in an expansion phase of the leading indicator, the builder compares recent observations of the leading series to statistical moments of innovations during past upturns (assumption (1)) in order to arrive at the probability that the innovations are drawn from the same data generating process as prior expansions. This implicitly assumes that the leading series will not reach both a trough and the subsequent peak during the period over which the builder is looking (assumption (2)).

As is noted by Croce and Haurin, the Neftci methodology allows for the same asymmetry between expansions and contractions that a Markov chain would allow but the methodologies differ in how they estimate the distributional parameters. Hamilton estimates the mean and variance of each regime simultaneously via maximum likelihood by including a latent state variable. I impose more structure than this by assuming that one can correctly infer the state in periods prior to the most recent turning point in the housing market series. This allows me to estimate the distributional parameters of each regime directly. The observability assumption is reasonable because turning points are only unobservable in real time because whether today constitutes a peak or trough for a housing series is conditional on that series’ unobserved future values. With the benefit of hindsight however, this critical conditioning information is available.
The first step in implementing an SPR is to judge the distance by which the leading series leads the coincident series at each turning point. I do this using the maximum distance criterion (MDC) from discriminant analysis. MDC involves linking the leading series to the housing series so as to maximize the difference in the average slope between downturn and upturn regimes in the leading series. I accomplish this by taking the historical cycle of the housing series (X) as given:

\[
\{P_i, T_i, P_{i+1}\}
\]

where \(P_i\) and \(T_i\) indicate the dates of the \(i\)th peak and trough, respectively. I assume a similar cycle in the leading series (Y), which leads by \(\tau_{P_i}\) months at the \(i\)th peak and by \(\tau_{T_i}\) at the \(i\)th trough. The distance is defined as the difference between the mean value of \(\Delta Y_t\) in an expansion and a contraction. This procedure can be expressed as:

\[
\max_{n_2 \leq \tau_{P_i}, \tau_{P_{i+1}} \leq n_1} \left[ m_u(T_i - \tau_{T_i} + 1, P_{i+1} - \tau_{P_{i+1}}) - m_d(P_i - \tau_{P_i} + 1, T_i - \tau_{T_i}) \right] \quad (2.2)
\]

where \(m_u\) and \(m_d\) are the mean of \(\Delta Y_t\) for the upturn and downturn regimes, respectively, and the two values in the parenthesis are the left and right endpoints of the interval over which the means are taken. I implement this procedure iteratively by fixing an arbitrary value of two months for the lead time at peak 1, \(\tau_{P_1}\), and then find optimal values for \(\tau_{T_1}\) and \(\tau_{P_2}\). Next, I compute an optimal value for \(\tau_{P_1}\), then roll forward again and compute \(\tau_{T_1}\) and \(\tau_{P_2}\). This back-and-forth is continued until convergence is achieved, at which point I continue forward with the optimization. The results of the separation exercise are expressed in two sets, \(D_i\) and \(U_i\), for the \(i\)th cycle. These are given by:

\[
D_i = \{Y_t|t = P_i - \tau_{P_i} + 1, ..., T_i - \tau_{T_i}\} \quad (2.3)
\]

\[
U_i = \{Y_t|t = T_i - \tau_{T_i} + 1, ..., P_{i+1} - \tau_{P_{i+1}}\}. \quad (2.4)
\]
I illustrate the maximum distance criterion in Figure 5 and interested readers should see Croce and Haurin for more discussion of the approach.

Figure 2.5: The Maximum Distance Criterion

Notes: Figure 5 illustrates the maximum distance criterion. The criterion seeks values of $\tau_{P_1}$, $\tau_{T_1}$, and $\tau_{P_2}$ that maximize the difference between the slopes of lines A and B. In practice, this is accomplished by guessing a value for $\tau_{P_1}$, finding the maximizing values of $\tau_{T_1}$ and $\tau_{P_2}$, and recalculating the optimal $\tau_{P_1}$. I iterate this first set of optimal $\tau$s to convergence, and then proceed forward.

Next, I calculate the posterior probability that $Y_t$ belongs to a downturn regime using Bayes’ Rule:

$$P(Y_t \in D|Y_t) = \frac{P(Y_t \in D) \cdot f(Y_t|Y_t \in D)}{\sum_{j=U,D} P(Y_t \in j) \cdot f(Y_t|Y_t \in j)}. \quad (2.5)$$

Here, $P(Y_t \in D)$ is the prior probability that $Y_t$ comes from a downturn regime ($D$), and $f(Y_t|Y_t \in D)$ and $f(Y_t|Y_t \in U)$ are the densities of $Y$ during downturns and upturns ($U$), respectively. I calculate the specific densities as the normal probability
of drawing \( Y_t \) given that \( Y_t \in D \) based on the previously observed distribution of innovations in upturn and downturn regimes. I calculate \( P(Y_t \in U | Y_t) \) similarly.

A simple Bayesian classification can now be implemented by comparing \( P(Y_t \in D | Y_t) \) and \( P(Y_t \in U | Y_t) \). If \( P(Y_t \in D | Y_t) > P(Y_t \in U | Y_t) \), it is an indication of a downturn regime and when received during an upturn regime, it signals an imminent peak in the housing market series of interest. A similar argument can be made by reversing the inequality. In this way I could generate a binary signal. However, Neftci takes this one step further.

In order to implement Neftci’s sequential recursion, I include the probability estimated in the prior period as part of the information set in the probability estimate for the current period. Doing so allows me to compute an explicit probability of being in a particular regime rather than just a binary signal. The modification occurs in the prior probabilities, which will now be a function of the posterior probability estimated in the previous period:

\[
P(Y_t \in D) = P_{t-1} + (1 - P_{t-1})\Gamma^u_t \quad (2.6)
\]
\[
P(Y_t \in U) = (1 - P_{t-1})(1 - \Gamma^u_t) \quad (2.7)
\]

where \( \Gamma^u_t \) denotes the probability of a peak occurring between \((t-1)\) and \(t\) conditional on a peak not having occurred previously, and \( P_{t-1} \) is the posterior probability estimated in the prior period. To predict a trough, we exchange \( f(Y_t | Y_t \in U) \) for \( f(Y_t | Y_t \in D) \) and replace \( \Gamma^u_t \) with \( \Gamma^d_t \). I model the unconditional probability of a turning point as independent of regime duration and thus impose \( \Gamma^u_t = \tau_u \) and \( \Gamma^d_t = \tau_d \), each calculated as the reciprocal of the average regime duration in the sample prior to the prediction date.
I follow Croce and Haurin in assuming that if a peak has just occurred, the probability of being in an upturn regime is zero, and that if a trough has just occurred the probability of being in a downturn regime is zero. I also limit predicted probabilities to a maximum of 0.95.

Using the methodology described above, I compute the sequential probabilities of turning points in Permits and Starts using each of the leading indicators and several of their first-differences, one at a time. In the next section of this paper I score each of the leading indicators using a single metric and examine qualitative properties of each of the time series of estimates.

2.5 SPR Results

In this section I examine the results of applying the SPR methodology developed in the previous section to the problem of predicting turning points in the housing market. I find that GTTB, the stance of monetary policy relative to a Taylor rule, and several interest rates and spreads have strong predictive power for housing permits and starts. I illustrate this first by computing a single goodness of fit metric for each series of probability estimates and then by exploring the qualitative properties of each sequence of recursions.

In order to provide a single metric of the goodness-of-fit for each leading indicator series, I compare the probabilities they generate in SPRs to those of an ideal leading indicator. As in Croce and Haurin, I score the leading indicators using a quadratic probability score (QPS) by assuming that an ideal leading indicator would produce SPR probability estimates of 100% in the 24 months prior to a turning point and of
0% when it is more than 24 months before a turn.\textsuperscript{42} I compute a loss function as the average squared difference between this ideal and the probabilities produced by the sequential recursions. In other words, I assume that the period loss function is equal to $(1 - P(Y_t \in D|Y_t))^2$ in the 24 months before a peak, $(1 - P(Y_t \in U|Y_t))^2$ in the 24 months before a trough, $P(Y_t \in D|Y_t)$ in an upturn more than 24 months prior to a peak, and $P(Y_t \in U|Y_t)$ in a downturn more than 24 months prior to a trough.

I evaluate each series by computing the loss function starting in the third full cycle, thus allowing the model two cycles of history with which to be calibrated. I stop computing the loss function at the peak identified in 2006 because I have not identified any turning points occurring after this date. Note that the QPS penalizes a leading indicator heavily if it predicts regime changes too early. This is appealing when trying to gauge the usefulness of turning point predictions but is not in line with the true nature of $P(Y_t \in U|Y_t)$ and $P(Y_t \in D|Y_t)$, which are just the probability that the most recent draw from the leading indicator series came from a particular regime. Because of this, it is important to examine the qualitative features of the SPR estimates individually to confirm that the recursions producing the lowest QPS values do, in fact, provide early indication of upcoming turning points in homebuilding activity. A sensitivity analysis shows that the ordering of leading indicators from best to worst by QPS is somewhat sensitive to the horizon for which we set the ideal probability to 1, here 24 months.\textsuperscript{43} In what follows, I will limit the discussion to

\textsuperscript{42}I choose an optimal lead time of 24 months based on the fact that home building is an industry characterized by very long lead times. A builder who wants to undertake a new construction venture has to seek funding, apply for and receive permits to build, and then undertake the process of building houses. This process can take well over a year.

\textsuperscript{43}I conducted a sensitivity analysis by computing QPS scores for horizons $h$ of between 6 and 24 months. The ordering of the best scores changed mildly across these specifications. For this reason it is important to examine the qualitative features of the SPR estimates in addition to looking at their QPS scores.
predicting turning points in Permits because the results are very similar to those for Starts.


A discussion of the qualitative features of each set of probability forecasts is now appropriate. I start this discussion by plotting the probability estimates based on levels of the sentiment variables. Note that the estimates do not begin until the third housing cycle observed in my data. The reason for this is that I am estimating a recursive model and I allow the model two full cycles with which to be calibrated. The intuition for this is that, observing a new data series with regime switching, I would need to observe multiple cycles of the data in order to get a sense of its upturn and downturn behavior.

Panel (a) in Figure 6 plots the SPR estimates of the likelihood of a turning point in Permits based on GTTB. At first glance, GTTB appears to do quite poorly, in line with its QPS (19th out of 20). The reason for this is that GTTB predicts the most recent peak in the housing market ten years too early. It turns out that this is not unusual among our leading indicators—most of them flashed a false peak signal during the housing boom well before the peak. However, GTTB seems to do a very good job predicting all other turning points. It correctly predicts both turning points in the 1970s in a timely manner—neither much too early nor too late. It predicts both
Table 2.1: Quadratic Probability Scores for the Leading Indicators

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Notes: The quadratic probability score is computed as the sum of the squared distance between the SPR probability estimates and an ideal probability that takes a value of 1 for the six months prior to a peak or trough and zero in all other periods divided by the total number of observations considered in the computation. Note that computation of the QPS stops with the last identified turning point, which was the peak of 2006. This is because it is not yet clear when the subsequent housing market bottom occurred.

turning points in the 1980s and the one in 1990 with similar accuracy. It seems, then, that the very poor QPS score for this leading indicator is due exclusively to the large miss at the most recent peak. Also of note is that GTTB begins flashing a trough warning very quickly after the housing market peaks. Given what we know now, it appears to have been much too early calling the yet unidentified trough.
Panel (b) of Figure 6 plots the SPR results from the term spread, which had a QPS that was 6th of the 17 leading indicators scored. Interestingly, although Term flashed a long false alarm prior to the peak of 2006, it later retracted the false alarm and then correctly predicted the peak. Like GTTB, Term began warning of a trough in the housing market very quickly after the peak of 2006, a warning that appears to
have come much too early. Term was also much too early to predict the trough of 1990, but appears to have performed well in the 1970s and early 1980s.

Panel (c) of Figure 6 plots the SPR for the Def, the difference in return between BAA and AAA bonds. In contrast to GTTB and Term, Def did not flash a mid-1990s false peak alarm. Instead, Def began increasing after 2000 and the probability of a peak in Permits reached 50% in 2003.

Panel (d) of Figure 6 plots the SPR results for Permits using the short premium—the difference between commercial paper rates and treasury bill rates. Note that the time series of data for Short is substantially shorter than for the other three variables in Figure 6 and I do not begin estimating probabilities until well into the 1980s. That said, Short does not appear to perform well qualitatively. It completely misses the housing market peak in 2006 and predicts the trough of 1990 much too early.

In Figure 7 I plot the asset return levels SPRs. Panel (a) shows the pseudo-real time probability estimate of a turning point in Permits based on prior observation S&P 500 returns. Qualitatively S&P returns appear to do better than did Short, because for turning points prior to 1990 stock returns did well and Short had zero successes. Instead, the QPS scores suggest that Short is the better leading indicator. Quantitatively this finding stems from the fact that stock returns predicted the trough of 1990 and peak of 2006 far too early.

In panel (b) of Figure 7 I plot the turning point probabilities based on the level of the federal funds rate, which is 16th best of the 20 leading indicators I study here, according to QPS. Fedfunds arguably helps predict the trough and peak of the 1970s, but produces a very noisy warning for the 1980s trough. The mid-1980s signal
for a peak was timely, but then Fedfunds predicts the trough of 1990 too early and completely misses the peak of 2006.

Panel (c) of Figure 7 shows the turning point probability estimates for the 10-year government bond rate, GS10. It is apparent from the figure that the GS10 SPR performs well during the 1980s, but that performance deteriorates progressively after 1980 with each of the next three turning point predictions coming progressively more
early. GS10 also predicts a housing market bottom almost immediately after the peak in 2006, a prediction which appears to have been too early. The poor performance later in the observation period leads to a poor QPS score, where GS10 is 15th of the 20 indicators studied.

Panel (d) of Figure 7 shows the probabilities of a turning point in permits computed using Mortg. The SPR offers a well-timed warning of the trough of 1990 but does not offer any warning whatsoever of the peak of 2006. This is surprising given that Mortg had the second-best QPS score of any variable studied here. The primary reason for this is that the prediction of no turning point produces a lower QPS score than a very early prediction, of which all the best leading indicators had at least one.

In panel (a) of Figure 8, I plot the SPR for Permits computed using the level of the output gap. Gap was 18th out of our 20 leading indicators, yet in the SPR plot, it made several well-timed calls. It was a bit late to predict the trough of the mid-1970s but predicts the peak of the late 1970s in a timely manner. Further, it produced a decent, albeit somewhat noisy prediction of a trough in the early 1980s. The trough call for 1990 was early, but the call for a peak during the housing boom came less early than it did with most of the other variables I consider here. For these reasons I argue that the high QPS score understates the usefulness of the output gap in predicting turning points.

Panel (b) of Figure 8 shows the RelativePolicy SPR, which was 7th best among the leading indicators studied here according to the QPS metric. This success is evident in the plot, as peak and trough predictions occur in a timely manner up until the trough of 1990, for which there is an initial false alarm prior to the correct trough
Notes: Figure 8 plots the sequential probability estimates produced when the macroeconomic series are used in the SPR model.

indication. Warning of the peak of 2006 arrives early, but not as early as for most of the other leading indicators.

Panel (c) of Figure 8 plots the SPR for monetary policy shocks identified by the large vector autoregression. The model correctly predicts the trough of the early 1970s and the subsequent peak. However, model performance erodes significantly
after 1980, conceivably because of a high level of heteroskedasticity in the Shocks series and the high volatility in Shocks around 1980.

Figure 2.9: Sentiment Differences SPR

![Diagram showing sentiment differences SPR for different series: (a) Δ GTTB, (b) Δ Term, (c) Δ Def, and (d) Δ Short.](image)

Notes: Figure 9 plots the sequential probability estimates generated by first differences of the sentiment series.

In Figure 9, I plot SPRs based on the differenced sentiment series. Several are among the best performing indicators. The SPR for the first difference of GTTB is in panel A and scored third-best by the QPS metric. Notice that it makes timely calls
for both scored turning points in the 1970s and the first turn in the 1980s but that it is too early to predict the peak of the late 1980s and the trough of the early 1990s. Further, indication of the housing market peak in 2006 comes far too late. Note that differenced GTTB began signaling a housing market trough almost immediately after the peak and given what we know now, this is probably too early.

Panel (b) of Figure 9 shows the probabilities estimated via the differenced term premium. The plot confirms the poor rating given by the QPS metric, which ranks differenced Term as 14th of the 20 leading indicators considered here.

Panel (c) of Figure 9 plots the differenced default premium SPR, which was fifth best by the QPS metric. Notice that it provided timely warnings for both scored turning points during the 1970s and for the trough of the 1980s. However, it was very early in predicting the peak of the 1980s and the trough of 1990. The strong QPS score results from a much more timely–less early–prediction for the peak of 2006.

Panel (d) of Figure 9 shows the SPR turning point estimates for the differenced short premium, which ranked 9th of the 20 leading indicators studied here. The reason for this strong showing, given the poor qualitative performance, stems from the fact that most of the leading indicators were very early to predict the peak of 2006. Relative to being several years early to predict a turning point, predicting no turning point at all produces a lower QPS.

Figure 10 shows the differenced interest rate SPRs. Panel (a) illustrates that the differenced federal funds rate SPR performs well during the 1970s and 1980s but that it is much too early in predicting the housing market trough of 1990 and completely misses the housing market peak of 2006. This performance yields a QPS score that is 11th out of 20.
Notes: Figure 10 plots the sequential probability estimates generated using the first difference of asset return series. I do not include the S&P 500 differences, as they were already stationary.

In panel (b) of Figure 10, I plot the SPR for the differenced 10 year government bond yield, which scored 13th of the 20 leading indicators studied by the QPS metric. The relatively poor QPS showing is strictly the result of being much too early predicting the peak of 2006, as all other turning points were predicted in a timely manner and not too early. Panel (c) of Figure 10 plots the SPR of the indicator with
the best QPS score—the differenced mortgage rate. Note that, because of the shorter data set for mortgage rates, there are only two scored turning points, a fact that may have led to a stronger score than might otherwise have been computed. There were false alarms for both of the scored turning points for the first difference of the mortgage interest rate. However, the short false alarms prior to the peak of 2006 had
a negligible impact on the QPS score of this indicator relative to an alternative of being very early to predict the peak, as we saw in panel (b).

In Figure 11, I plot the differenced macro variable SPRs, both of which were excellent leading indicators for the housing market. In panel (a) I plot the SPR based on the first-difference of the output gap, which produced the 12th best QPS score but qualitatively looks like it is among the best leading indicators in this study. I say that because the first difference of Gap produced well-timed turning point predictions for all scored points except the peak of 2006, which was predicted to arrive too early. Note that the change in the output gap predicted a trough in the housing market quickly after the 2006 peak, a prediction that also appears to be incorrect.

Lastly, in panel (b) of Figure 11, I plot the turning point predictions based on the change in the stance of monetary policy relative to a Taylor rule, which scored 8th among the 20 indicators considered in this study. Qualitatively, the first difference of relative policy is the best leading indicator in this study. It produces timely predictions of every turning point and while it is early to signal the peak of 2006, it does not reach a maximum probability until 2004, much later than for the other good leading indicators available since 1960.

### 2.6 Conclusion

In this paper I have documented that several sentiment, asset return, and macroeconomic/monetary time series are useful if trying to predict reversals in the housing market. This research also shows that different leading indicators performed better at different historical turning points. This finding mirrors Stock and Watson (1990), which finds that no single time series produces a consistently reliable leading indicator.
for output. They address the problem by producing a hybrid leading indicator series that performs better than any of the individual indicators. Given my findings with regard to the heterogeneous performance of individual leading indicators across time, an approach similar to Stock and Watson’s seems fertile ground for future research on predicting turning points in the housing market.

In the context of my work on the impact of monetary policy on the housing market, it is interesting to notice the very strong performance of RelativePolicy. The first difference of this series was qualitatively the best leading indicator in this study. Further, other interest rates and sentiment series performed well. Among these were the mortgage interest rate and the consumer sentiment index GTTB.
Bibliography


