Predicting The U.S. Recessions With Housing Starts In Dynamic Probit Models

Yan Cui
University of Mississippi

Follow this and additional works at: https://egrove.olemiss.edu/etd
Part of the Economics Commons

Recommended Citation
Cui, Yan, "Predicting The U.S. Recessions With Housing Starts In Dynamic Probit Models" (2015). Electronic Theses and Dissertations. 483.
https://egrove.olemiss.edu/etd/483
PREDICTING THE U.S. RECESSIONS
WITH HOUSING STARTS
IN DYNAMIC PROBIT MODELS

A Dissertation
presented in partial fulfillment of the requirements for
the degree of Doctor of Philosophy
in the Department of Economics
The University of Mississippi

by
Yan Cui
May 2015
ABSTRACT

The crash of the U.S. housing market and the 2007-2009 recession that followed have reignited discussion about forecasting recessions. Most recessions have in fact been preceded by plummets in the housing industry in the U.S. history. The present study examines the predictive power of housing starts using dynamic probit models. The yield spread between the ten-year Treasury bond and three-month Treasury bill rates, is also adopted to further demonstrate the predictive properties of the housing variable. Different model functional forms are explored in which the lag structure, especially the growth rate term for housing starts, is constructed in an innovative way to serve the comparison purpose between the current study and previous literature. Instead of the month-to-month growth, the housing variable is constructed as the monthly growth rate over time. The major objective of the present study is to emphasize the notion that it is the sustained decline in housing starts, not a temporary drop, that serves better as a recession predictor. Another proposal of this study is the adoption of the growth rate in housing starts and the interest rate combination which is found superior than the individual specification. Both in-sample and out-of-sample analyses are carried out and iterated forecasting procedure is implemented. The Adjusted-Pseudo $R^2$ measure and the Diebold-Mariano statistics, are employed to examine and compare the predictive accuracy of models.
ACKNOWLEDGEMENTS

I express my deepest appreciation to my advisor, Dr. Walter Mayer, and my committee members, Dr. William Chappell, Dr. Joshua Hendrickson and Dr. Xin Dang.

I would also like to thank the Department of Economics at the University of Mississippi. What the Doctorial program has brought me is beyond the financial aspect. I will forever be grateful for the inspiration, guidance and help I have received from the faculty and the department.

Lastly, I acknowledge the collegial support from my fellow doctoral students. You made this part of my life enjoyable and enriching.
# TABLE OF CONTENTS

**Title Page**...........................................................................................................i

**Abstract**..................................................................................................................ii

**Table of Contents**....................................................................................................iv

**List of Tables**..........................................................................................................vi

**List of Figures**.........................................................................................................vii

**Chapter I. Introduction**..........................................................................................1

**Chapter II. Literature Review**................................................................................7

  II-A. Probit Modeling Approach..................................................................................7

  II-B. Recession Prediction Using Housing Variables................................................13

**Chapter III. Model Specifications**.........................................................................21

  III-A. Forecasting Models.........................................................................................21

  III-B. Probit Models for Recession Prediction..........................................................23

  III-C. Functional Forms.............................................................................................27

**Chapter IV. Forecasting Procedure**......................................................................31

**Chapter V. Test Criteria**........................................................................................35
CHAPTER VI. VARIABLE ANALYSIS AND DATA CONSTRUCTION .......................... 37

VI-A. RECESSION INDICATOR .................................................................... 37

VI-B. HOUSING STARTS AND OTHER HOUSING VARIABLES ........................ 39

VI-C. INTEREST SPREADS ........................................................................... 42

CHAPTER VII. EMPIRICAL RESULTS .......................................................... 48

VII-A. IN-SAMPLE RESULTS ..................................................................... 48

VII-B. OUT-OF-SAMPLE RESULTS .......................................................... 61

CHAPTER VIII. CONCLUSION ................................................................. 68

BIBLIOGRAPHY........................................................................................... 70

VITA............................................................................................................ 77
## LIST OF TABLES

Table 1. Monthly Recession Reference Dates for the U.S. .................................................. 38
Table 2. Summary of Data Definitions and Sources .......................................................... 47
Table 3. Data Statistics ...................................................................................................... 47
Table 4. Functional Forms and Variable Construction ..................................................... 49
Table 5. Adjusted-Pseudo $R^2$ Measures of In-sample Fit for Interest Spread ............... 50
Table 6. Adjusted-Pseudo $R^2$ Measures of In-sample Fit for Housing Starts ............... 52
Table 7. Adjusted-Pseudo $R^2$ Measures of Dynamic In-sample Fit for Interest Spread vs. Growth Rate in Housing Starts .................................................................................. 55
Table 8. Adjusted-Pseudo $R^2$ Measures of Dynamic In-sample Fit for Growth Rate in Housing Starts and Interest Spread .................................................................................. 57
Table 9. In-sample Estimation Results for Selected Models ............................................. 58
Table 10. Adjusted-Pseudo $R^2$ Measures of Out-of-sample Fit for Selected Models ....... 63
Table 11. DM Statistics for $h=1$ ..................................................................................... 64
LIST OF FIGURES

Figure 1. Cumulative “abnormal” Contribution of Residential Investment before Recessions.  
Source: Leamer (2007) ........................................................................................................18

Figure 2. Cumulative “abnormal” Contribution of Equipment and Software before Recessions.  
Source: Leamer (2007) ........................................................................................................19

Figure 3. All-Transactions House Price Index and Recessions. Source: FRED .................41

Figure 4. Monthly Performance of Housing Starts. Source: FRED ......................42

Figure 5. Monthly Performance of the Difference Between Interest Rates on 10-year Treasury 
bond and Federal Funds Rate. Source: FRED .................................................................45

Figure 6. Probability of Recession, In-Sample Prediction ..............................................60

Figure 7. Probability of Recession One Month Ahead, Out-of-Sample Prediction ..........66
CHAPTER I

INTRODUCTION

The most recent recession back in 2007-2009 reignites discussion about whether economic downturns can be forecast in advance. Reliable forecasting of the state of the economy in the near future facilitates not only individuals when making financial plans but also the central bank or the government when conducting policies.

The economic recession we recently experienced was caused by severe problems in the housing industry. Ever since World War II, eight out of ten economic recessions in the U.S. history were preceded with plummets in the housing sector. Leamer (2007) demonstrates that residential investment plays a significant role in contributing to the weakness of GDP growth before the recessions. He points out that due to the downward inflexibility of housing prices, it is actually the volume instead of the price that matters. Kydland et al (2012) also report that residential investment leads GDP in the U.S. It is not necessarily the case for all the other five countries examined in their study. However, when residential construction activity is measured by housing starts, all the countries exhibit more conformity, that is, almost all countries show that

1
housing starts lead GDP. This present study focuses on the examination of the predictive power of housing starts to address the question policy makers and the financial market frequently ask—what is the probability that the U.S. economy goes into recession in the near future?

A housing start is defined as the beginning of excavation of the foundation for the building. From an intuitive perspective, home contractors usually do not start building a house unless they are fairly confident that it can be sold in the market. Thus, changes in housing starts can signal changes in market expectations of housing demand in the near future. Since housing is the largest component of expenditures and a long-term investment for most households, housing demand, in turn, reflects expectations about future income and employment. It is not hard to spot the link, therefore the potential forecasting relationship between housing starts and the economy. Further, housing impacts future economy through a multiplier effect. Each time a new home is started, construction employment rises. The demand for goods and services in other sectors of the economy increases as well. Particularly, it is estimated by the National Association of Home builders (NAHB) that consumer spending on goods and services related to housing counts for roughly 12-13 percent of real GDP. Combined with the residential investment contribution, the housing industry is worth 17-18 percent of the economy.

Despite the fact that housing is one of the leading contributors of output growth, and also the single sector that is held most responsible for the weakness of the economy. Housing
variables have never been treated with enough attention either in textbooks or the literature in forecasting. The exploration of recession predictors has been mainly focused on financial variables, especially interest spreads. Even among the literature that examine housing variables, housing prices seem to attract more attention than the volume. One of the objectives of the present study is to reinforce the idea that it is the volume, not the price, that accounts for the fluctuations of real production.

Hao and C.Y. Ng (2011) is the only literature I have found that specifically examines the predictive power of housing starts for recessions. Unfortunately, the study is in the context of the Canadian economy, and the housing variable is treated as one of the many variables to serve the comparison purpose between variables. It is also noted that the Canadian housing starts adopted in Hao and C.Y. Ng (2011) is the month-to-month growth rate, which is a common construction of growth rate for an examined variable in the literature. However, this present study argues that the growth rate over a period of time serves a better predictor of recessions for the U.S. economy. Empirical results and rationale are provided to support this specific construction for housing starts, and to highlight the notion that it is a sustained decline in housing starts, not a temporary change, that contributes to the weakness of the economy. The difference in the specification for the housing variable results from a different interpretation of the forecasting relationship between housing starts and the recessions.
To further demonstrate the predictive power of housing starts, the interest spread, which has stood out as the single variable that has a dominant predictive power for recessions in previous literature, is adopted in my study. The interest spread examined in this study is specifically the difference between the rates on the ten-year Treasury bond and the three-month Treasury bill. Detailed discussion of the variable is provided in a later chapter.

I would like to point out that the predictive properties of the yield curve are not questioned in my study. The intention is merely to draw more attention of housing variables to the literature as well to the public. The present study also attempts to shift focus from housing prices to real production in housing, from financial indicators to macroeconomic predictors. Further, it emphasizes the notion that it is the decline over time in housing that accounts the most for economic downturns, not temporary changes. Last but certainly not least, my study proposes to construct the recession predictor as the combination of housing starts and the interest spread, particularly the growth rate in housing starts over time. This combination exhibits dominant predictive power compared to any individual construction. Empirical results will be provided. This paragraph also serves as the summary of the main contributions of the present study.

Regarding the modeling technique, the probit model is adopted in the present analysis. The probit modeling has attracted increasing attention in the literature. Rather than predicting quantitative measures of future economic activities, it facilitates addressing a different question,
that is, is the economy going to experience a downturn in the near future? What is the probability that it occurs? Under this approach, the probability of a recession is modeled as a function of lagged values of the potential predictor. For the dynamic case, the lagged value of the binary recession indicator is also included as an explanatory variable to capture the dynamics of the recession indicator. The general finding from the previous literature is that the dynamic probit models perform better than the static counterparts. As discussed previously, since the interpretation of the forecasting relationship in this study distinguishes other literature, the difference will be explicitly reflected by the model specification, especially the construction of the housing variable. The functional forms for the interest spread will also be explored.

Both in-sample and out-of-sample performances are analyzed to test the predictive power of housing starts. Out-of-sample analysis is more realistic because it evaluates forecasting accuracy for the months or quarters beyond the estimation period. However, out-of-sample examinations suffer from sample distortion and information loss due to sample splitting. Therefore, in-sample analysis is also carried on in my study.

To compare the forecasting performance between variables and functional forms, the Adjusted-Pseudo $R^2$ statistic (Estrella, 1998) is adopted as the major measure of fit. One thing to be noted is that it is inevitable that the forecasts from two different methods are different, but what one might ask is whether the different is due to pure chance. In other words, is the
difference significant? To address this issue, I apply the Diebold-Mariano Test (DM, 1995) to access the significance of the out-of-sample forecasting difference between two forecasts with the horizon specification. As far as I know, the DM test was rarely used in previous literature in forecasting. Thus, the employment of this test counts as another feature of the present study.

Regarding the forecasting procedure, the iterated forecasting is adopted as a comparison to the direct approach. It is essentially a multi-one-period-ahead forecasting procedure. Once the first-step forecast is generated “directly”, the process is “iterated” forward for multiple periods until the forecast of the desired horizon is obtained. It facilitates the practice when information is not fully realized at the time of forecasting. In my study, it turns out that iterated forecasting works better than the direct approach in terms of producing more accurate forecasts. Detailed discussion of the difference between the two forecasting procedures will be provided.

The rest of the paper is organized as follows: CHAPTER II reviews the literature focusing on the probit modeling approach. CHAPTER III introduces the basic probit model and functional forms. It features the growth rate construction for housing starts. The forecasting procedures and test criteria are described in CHAPTER IV and V respectively. CHAPTER VI discusses the variables examined in this study in detail and the data construction for each variable. CHAPTER VI displays in-sample and out-of-sample results. Interpretations and explanations are also provided. CHAPTER VII concludes.
CHAPTER II

LITERATURE REVIEW

The literature on forecasting recessions has drawn increasing attention in recent years. They are attempted to answer the same question that is frequently addressed by policy makers as well as the public—what is the likelihood that a recession occurs in the near future? The common technique that has been developed to address this issue is probit modeling. This chapter highlights a few relevant studies on this topic, focusing on the most recent research. Many variables have potential predictive content for recessions. Most studies within this probit model framework target financial indicators, especially term spreads. Few literature include housing variables in their examination for recession prediction. All of these few studies are reviewed in my chapter. Yes, all to my best knowledge.

II-A. PROBIT MODELING APPROACH

Estrella and Mishkin (1998) focus on the examination of the predictive power of financial variables including interest rates, interest spreads, stock prices, monetary aggregates individually
and in some combinations, particularly combined with the yield curve spread. Specifically, the interest rates adopted in their study are the 3-month Treasury bill and the 10-year Treasury bond. The difference between the two rates, and the Commercial paper-Treasury spread are the two spread examined in their study. As a comparison, traditional indexes of leading indicators such as Commerce Department leading index, Stock-Watson (1989) leading index and Stock-Watson (1993) leading index are also included.

The model used for estimation and forecasting in Estrella and Mishkin (1998) is the static probit model which implies the probability of a recession is only influenced by the current or past values of the examined variable. They focus on the out-of-sample forecasting and the principal criterion they use to examine the forecasting performance of a particular variable is the Pseudo $R^2$ that they developed in an earlier paper (Estrella, 1998). It is a simple measure of fit that corresponds intuitively to the coefficient of determination in a standard linear regression where the value 0 and 1 indicate “no fit” and “perfect fit” respectively.

The empirical results of Estrella and Mishkin (1998) suggest that stock prices are useful predictors in the short run as are some well-known macroeconomic indexes. However, when the forecast horizon becomes longer, the slope of the yield curve performs consistently better, and its predictive power is confirmed by the fact that when combined with other variables, the forecasting performance of the model is undermined, which suggests there might be some over
fitting problem involved. The only exception occurs when the yield spread is combined with the stock price indexes. Therefore, they conclude that the slope of the yield curve alone or the combination of the slope and the stock price indexes is the best model that can be constructed from typical financial variables for out-of-sample recession forecasting.

To further examine the over fitting problem as mentioned in the previous paragraph, the two parsimonious models, one with the term spread and the other including both the term spread and the stock price indexes, are compared with the Commerce Department and Stock-Watson (1989) leading indexes. The reason that the Commerce Department and Stock-Watson (1989) leading indexes are used for comparison is because they are typical indicators that are susceptible to this type of over fitting issue as pointed out by Estrella and Mishkin (1998). As for the forecasting horizons in this analysis, two and four quarters are adopted. It turns out the two parsimonious models outperform the two indexes for both forecast horizons. Further, the dominance of the parsimonious models is more clear-cut for the longer horizons. These findings are encouraging because the longer horizon is more relevant in the monetary policy context. Further the parsimonious models successfully flag an early warning sign for the 1990-1991 recession while the two leading indicators completely fail. Estrella and Mishkin (1998) conclude that the addition of other variables can undermine the predictive power of a parsimonious model.

Dueker (1997) confirms the finding in Estrella and Mishkin (1998) that the slope of the
yield curve has a dominant predictive power among typical economic indicators. The set of variables examined in Dueker (1997) study include the change in the Commerce Department’s index of leading indicators, real money growth, the percentage change in the stock prices and the percentage difference in interest rates.

The most remarkable contribution of Dueker (1997) is that he explores and proposes a richer modeling approach - the dynamic probit model for forecasting. He argues that, by adding a lag of the recession indicator, the dynamic model can better capture the autocorrelation structure of time series data such as the recession indicator. Further, the plausibility of the typical assumption made on the random shock which affects the economic state can be enhanced as well. Particularly, the state of the economy is very likely to be influenced by the one in the previous period. The lack of capturing the dynamic nature of the recession indicator might lead to model misspecification. Dueker (1997) also points out that the problem of applying the conventional time-series techniques to addressing the serial correlation issue of the random shock is that the latent variable, which distinguishes the state of the economy or the recession indicator, is not observable. Therefore, he resorts to the modeling approach of adding a lagged dependent variable to resolve the serial correlation problem. As stated in his argument, the specification of the dynamic probit model is similar to adding a dependent variable to a linear regression model. The results demonstrate that the predictive power of the yield curve slope can be strengthened by the dynamic model especially for short time horizons.
Kauppi and Saikonen (2008) is one of the most influential literature on using probit models for recession forecasting. They develop a unified model framework that accommodates most probit models analyzed in the previous studies. Within the framework, new model variants are also considered which are featured by the addition of a lagged value of the recession probability function as one of the explanatory variables. The four specifications of the unified model are static probit, dynamic probit, autoregressive probit and dynamic autoregressive probit. The “dynamic” in the context refers to the recession indicator while the “autoregressive” refers to the recession probability.

Regarding the forecasting procedure, iterated forecasting is applied as a comparison to the traditional direct approach. Basically, there are two ways available to make multi-period-ahead forecasts. One is to regress the recession indicator on its past value of horizon-specific lag order and other regressors with the values known at the time of forecasting. At the end of the estimation sample, the multi-period-ahead forecast of the recession is computed “directly” from the estimated forecasting equation. The other approach is typically built on a one-step-ahead forecasting model. Once the first-step forecast is generated, the process is “iterated” forward for multiple periods until the forecast of the desired horizon is obtained. It is essentially a multi-one-period-ahead forecasting procedure. The advantage of the iterated forecasting procedure over the direct one is that: first, it serves the practical purpose since not all information is known at the time of forecasting; secondly, the information is updated along the
way before the forecast for the desired horizon is made. The iterated forecasting approach is what Kauppi and Saikonen (2008) adopt in their study, and they find the out-of-sample results in favor of their choice.

Applying different models and forecasting procedures stated above, both the in-sample and out-of-sample performance of the interest spread, the sole predictor in their study, is examined. Specifically, the interest spread is constructed as the difference between the rates on the ten-year Treasury bond (constant maturity) and the three-month Treasury bill (secondary market) based on quarterly data. Besides the Pseudo $R^2$ test criterion, the Akaike information criterion (1973, 1974), the Schwarz Bayesian information criterion (1978) and other forecast accuracy measures such as the quadratic probability score and the log probability score (see Diebold and Rudebusch, 1989) are used for comparisons among model specifications and across forecast horizons.

The results show that dynamic probit models outperform their static counterparts consistently. Among the dynamic variants, the dynamic probit works better than the autoregressive dynamic probit. In other words, the more parsimonious dynamic model is superior relative to the richer specification. Regarding the forecasting procedure, iterated forecasting is proven to yield better forecasting results than the direct approach as mentioned earlier, which can be interpreted as the multi-one-period-ahead modeling is closer to the true data-generating
process. Based on the findings that the choice of the lag order for the predicting variable has a substantial impact on forecasting accuracy, they propose that it is better to apply specific lags supported by model selection criteria rather than lags that match the forecast horizon.

II-B. RECESSION PREDICTION USING HOUSING VARIABLES

To more fully capture the risk factors such as expectations of a gloomy economic outlook from the financial market, credit or liquidity risks associated with the general economy, the negative wealth effect resulting from the bursting of asset bubbles, and signs of deteriorating economy based on macroeconomic foundations. C.Y. Ng(2012) examines a more complete set of financial indicators for recession forecasting which includes the interest spread between U.S. 10-year Treasury bonds and 3-month Treasury bills, the differential between 3-month LIBOR and 3-month Treasury bills, the changes in the equity price index (the S&P 500 equity index) and the housing price index (the S&P/Case-Shiller Home Price Index, Composite-10), and the composite index of macro leading indicators, with each one representing the corresponding risk factor stated earlier.

C.Y. Ng (2012) follows the probit model specifications and forecasting procedure as proposed in Kauppi and Saikkonen (2008). He evaluates the forecasting performance of the risk factor indicators and the models in two aspects: duration and turning points. Specifically, he
assesses the ability of the models to forecast the duration of recessions by the percentage of correct prediction of recession months, and the ability to forecast the turning points by whether the predicted peaks and troughs flag an early warning sign. Regarding the duration, C. Y. Ng (2012) show that the proposed probit models with the proposed risk factor indicators generate better forecasts than the conventional one with only yield spread or the combination of spread and equity price index included. The predictive content of the risk factors is not examined individually. As for comparison within the model specifications, the dynamic model outperforms its static counterparts. Unfortunately, dynamic models fail to signal business cycle turning points, which might be attributed to the strong “dynamic” mechanism introduced by the addition of the lagged value of the recession indicator as one of the explanatory variables. It is interesting to see that the lowering of the threshold of classifying recessions from 50% to 25% actually boosts the accuracy of the recession duration prediction.

It is noted that a housing variable, the housing price index, is used in combination with other potential variables for recession forecasting in C. Y. Ng (2012). However, as mentioned briefly in the introduction, business cycle is mainly influenced by the volume cycle of the housing sector, not the changes in housing prices. If housing prices could adjust quickly to equilibrate the demand and supply in the housing market, we would not observe any drastic volume fluctuation of housing. But the fact is, the housing prices have been rising over time in the U.S. history. It is the volume, not the price that cycles persistently, and correlates with the
fluctuations of the economy. That’s why housing starts, rather than housing prices, are chosen to be the examined predictor for recessions. Then what is the rationale for using the housing price index in C. Y. Ng (2012)? He provides no rational for the adoption of the specific housing variable unfortunately. My understanding is that prices can influence the economy via the wealth effect. Housing as an asset for individual household, when the housing bubble bursts, the overall consumption decreases as the household perceive themselves as becoming poorer. However, whether the wealth effect can be large enough to lead recessions remain doubtful. Detailed discussion about the choice of the housing variable will be provided in a later chapter.

Hao and C.Y. Ng (2011) is the only paper that I have found that examines the predictive content of housing starts within the probit model framework. Yes, I know how sad it sounds. However, what the study targets is the Canadian economy. The predictors highlighted in their study include the yield spreads between Canadian government bonds and corporate papers, the U.S. yield spread between long-term Treasury bond and short-term Treasury bill, the month-to-month growth rate of the Canadian Composite index of ten leading indicators, the Canadian M1 money supply, the month-to-month growth rate of Canadian housing starts, and the month-to-month growth rate of Canadian GDP. The six variables are those that generate the best individual in-sample results among the thirteen initial variables proposed by Hao and C.Y. Ng (2011), therefore are chosen to construct the so-called optimal three-variable combination. Particularly, the Canadian yield spread is combined with two other variables from the six
selected ones to form all possible three-variable combinations, with the lag for each of the three variables being allowed to vary. Halo and C.Y. Ng (2011) follows the four probit model specifications as proposed in Kauppi and Saikkonen (2008), and one best three-variable combination is selected for each model specification for further analysis.

Both in-sample and out-of-sample empirical results highlight the Canadian yield spread, the housing starts growth rate, the Composite index of leading indicators, and the real M1 growth rate as significant predictors for the Canadian recessions. As in C.Y. Ng (2010), Hao and C.Y. Ng (2011) evaluate the forecasting performance of the models in terms of duration and turning points and draw similar conclusions, that is, dynamic probit models outperform their static counterparts in terms of recession duration prediction, but it is not the case when it comes to forecasting the turning points. Therefore, they propose that both model categories be used as complements to access the economic outlook. In addition, Hao and C.Y. Ng (2011) find the coefficient on the lagged probability function statistically insignificant, which leads to similar estimation results between the static or dynamic model and its autoregressive counterpart.

Now let’s turn our focus to the housing variable in Hao and C.Y. Ng (2011)- housing starts. It is specified as the month-to-month growth rate of Canadian housing starts over the period from 1956M1 to 2009M6. Although the rationale for the adoption and construction of the variable are not discussed in their study, the results favor the choice of housing starts as an
effective recession predictor. However, this housing variable underperforms the Canadian yield spread in the races between different variables. The primary variable examined in my study is housing starts. How does my study differ from Hao and C.Y. Ng (2011) with respect to the employment of the variable? First of all, my target is the U.S. economic downturns, therefore the housing starts examined in my study are data from the U.S. Secondly, the construction of the growth rate in housing starts in my study distinguishes the one in Hao and C.Y. Ng (2011). Instead of the month-to-month growth rate, I find the monthly growth rate over time a better predictor of recessions. Rationale is provided to support this finding in my study. My results also indicate the superiority of housing starts over the yield spread in recession prediction. As far as I am concerned, the difference in the two aspects stated above is what contributes to the difference in the results between the two studies.

Leamer (2007) does not fall into the category of probit modeling or ever follows the main-stream of the literature. However, it is the major literature that inspired my work. His proposal is loud and clear—housing is the business cycle. Leamer (2007) mainly examines the contribution of residential investment to recessions in the U.S. by plotting the cumulative “abnormal” contributions of residential investment before each of the recessions since 1940s, against those from other sectors of the economy including equipment and software, durables, non-durables, etc.. Here are the derivation steps: first, he finds the abnormal contribution of a certain industry to GDP growth by subtracting out the normal contribution estimated by the
kernel smoother, then turns the growth rate into levels. Finally, he extracts the data around each recession and normalize by subtracting the value at the cycle peak which makes the peak value zero. To better illustrate the major point Leamer (2007) makes, I here attach a couple of graphs from his study.

Figure 1. Cumulative “abnormal” Contribution of Residential Investment before Recessions. *Source: Leamer (2007)*
Figure 1 and 2 let us visualize and compare the contribution of the housing and technology sectors, where the dot-com bubble and the housing bubble burst, before each of the U.S. recessions ever since 1940s. What the graphs illustrate is mind-blowing. As we can see clear-cut, residential investment consistently plays a major role in the weakness of the economy. Actually, eight out of the ten recessions were preceded by problems in the housing industry. Leamer (2007) also points out that the recovery in housing begins earlier than the recovery in the technology industry, which helps the economy get out of recession greatly. He also calculates the contribution to the weakness of GDP from other sectors including Durables, Non-durables, Services, Exports, etc., but finds no evidence of dominance in their contribution to economic downturns compared to the housing industry.

Figure 2. Cumulative “abnormal” Contribution of Equipment and Software before Recessions. Source: Leamer (2007)
Leamer (2007) also argues that housing is the business cycle, and it is the volume that matters, not the price. What is persistent over time is the housing cycle. Real estate prices, on the other hand, have an upward trend in the long run. Leamer (2007) attributes this downward inflexibility of housing prices mainly to human psychological factors. Simply put, we love our homes, and most of us are risk adverse. People are reluctant to sell into a weak housing market, and this stickiness of prices is what makes the housing volume more extreme than it would otherwise be.

Leamer (2007) advocates the modification of the Taylor Rule and a substitution of Taylor’s output gap with housing starts and the change in housing starts since these together can be good indicator of the business cycles as he finds.
CHAPTER III

MODEL SPECIFICATIONS

III-A. FORECASTING MODELS

Early literature focus more on forecasting “continuous variables” such as growth rate in GDP, GNP, consumption, investment and industrial production. Standard regression models are typically adopted in the analyses. For example, Bernanke (1990), Estrella and Hardouvelis (1991), and Haubrich and Dombrosky (1996). The most common issue associated with these models is that the forecasting ability of the term spread has diminished since the mid-1980s when the output growth or other macroeconomic variable are used as the dependent variable. Dotsey (1998) suggests that the spread forecasts cumulative output growth less accurately for 1985-1997 than earlier periods. Stock and Watson (2003) examine the stability of the forecasting relationship between the term spread and output growth for the U.S. and other countries. Their results show inconsistence in the forecasting performance for a large proportion of the models which are frequently used to forecast output growth. McConnell and Perez (2000), Kim and Nelson (1999), and Chauvet and Potter (2001b) find evidence of a break in 1984 which indicates

As noted by some studies, for example, Hamilton and Kim (2000) and Bordo and Habrich (2004, 2008), how the monetary policy responds to output changes impact the predictive ability of the term spread. The conduct of monetary policy is found to have shifted from being reactive to more proactive in recent periods. The changes in the monetary regime might help explain the instability that has been found in standard forecasting models. Another possibility is the change taken place in the Treasury bond market in the U.S. over the last three decades. For example, the government has been paying down federal debt using budget surpluses and suspended issuing long-term bonds since 2002 which led to a decrease in the supply of long-term debt instruments. The several rounds of quantitative easing implemented by the Federal Reserve and other monetary practices such as the operation twist also added to the uncertainty and complex of the bond market.

Another commonly applied model framework in forecasting analysis are probit models. These models are specifically used to predict recessions by linking the recession indicator and potential predictors. They have attracted much attention in the recent literature. How do they compare with models that forecast continuous dependent variables such as output growth? We
may compare these two types of models in two dimensions: accuracy and robustness. Estrella and Hardouvelis (1991) and Estrella and Mishkin (1997) note that the best binary models perform as well as the continuous models when it comes to accuracy. They also point out that the Pseudo R$^2$ measure in probit models is similar to the measure of fit in standard linear regressions. As mentioned at the beginning of the chapter, the standard forecasting models suffer from the instability problem. However, Estrella, Rodrigues, and Schich (2003) suggest that binary models which are used for recession forecasting are quite robust over time. Duarte, Venetis, and Paya (2005) use both linear and nonlinear regression models to examine the ability of the term spread to forecast output growth among the euro-zone countries. Their results show signs of instability in the linear models and mark the superiority of the nonlinear models. Given the advantage of nonlinear models in terms of robustness with respect to changes in policies and other economic conditions, the probit modeling approach is adopted in the present study to examine the predictive ability of housing starts for the U.S. recessions.

III-B. PROBIT MODELS FOR RECESSION PREDICTION

The basic model applied in the present study is the probit model where the dependent variable Y is the binary recession indicator that represents the state of the economy at time t in the following way:
\[
Y_t = \begin{cases} 
1, & \text{when the economy is in a recession at time } t \\
0, & \text{otherwise.}
\end{cases}
\]

Given the information set \( \tau_{t-1} \), \( Y_t \) follows a Bernoulli distribution:

\[
Y_t|\tau_{t-1} \sim B(p_t)
\]

If we denote \( E_{t-1}(\cdot) \) and \( P_{t-1}(\cdot) \) as the conditional expectation and probability, respectively, on the information set \( \tau_{t-1} \), the expected value for the recession indicator at time \( t \) can be specified as

\[
E_{t-1}(Y_t) = P_{t-1}(Y_t = 1) = p_t,
\]

according to the expectation property of a Bernoulli distribution.

My goal is to model \( p_t \), the probability that a recession occurs at time \( t \). The standard way to do this is to use the Cumulative Distribution Function (CDF) of the standard normal distribution \( \Phi(\cdot) \) and assume that \( p_t = \Phi(\pi_t) \) where \( \pi_t \) is specified as a linear function of the variables contained in the information set \( \tau_{t-1} \). Therefore, it boils down to finding the most fitted model specification for \( \pi_t \).
My study examines two types of probit models (1) Static Probit model; (2) Dynamic Probit model. The traditional static probit model, which is the benchmark for my study, takes the form as follows:

\[ P_{t-1}(Y_t = 1) = \Phi(\pi_t) = \Phi(\alpha + \beta X_{t-k}), \]  \hspace{1cm} (2)

where \( \pi_t \) is specified as \( \alpha + \beta X_{t-k} \) and \( k \) is the employed lag order of the examined variable. The parameters \( \alpha \) and \( \beta \) in (2) are estimated based on the standard maximum likelihood (ML) method. The estimates for the parameters are found by maximizing the following log-likelihood function

\[ \ln L(\alpha, \beta | Y) = \sum_{t=1}^{T} (Y_t \ln \Phi(\alpha + \beta X_{t-k}) + (1 - Y_t) \ln \Phi(\alpha + \beta X_{t-k})) \]  \hspace{1cm} (3)

The main drawback of (2) is that it is likely to suffer from misspecification. As we know, a recession in the current period is very likely to affect the economy in the next period. The dynamics of the recession indicator is captured by the following dynamic model:

\[ P_{t-1}(Y_t = 1) = \Phi(\pi_t) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-m}) \]  \hspace{1cm} (4)

where \( \pi_t \) is specified as \( \alpha + \beta X_{t-k} + \delta Y_{t-m} \) and \( m \) is the employed lag order of the recession
indicator. The parameters $\alpha$, $\beta$ and $\delta$ are estimated in a similar way as the static case. Under the regularity conditions including stationarity of the explanatory variables and correctness of the assumed probit specification. It can be shown that the MLE follows an asymptotic normal distribution (de Jong and Woutersen 2011).

In Kauppi and Saikkonen (2008) and some studies following in their footsteps, new model variants are also considered such as the autoregressive probit models. Those variants are featured by the inclusion of a lagged value of the recession probability function as one of the explanatory variable to allow for more dynamics of $\pi_t$. The model is then given as $P_{t-1}(Y_t = 1) = \Phi \pi t = \Phi \alpha + \beta X_t - k + \delta Y_{t-m} + \gamma \pi_{t-1}$ (5). However, no formal proof has been provided for the validity of applying the conventional large sample theory to the ML estimation for those model specifications (de Jong and Woutersen, 2011). Further, no previous study has shown such models have any competing advantage in forecasting over the conventional ones where the lagged value of the recession probability function is excluded (See Kauppi and Saikkonen, 2008 and C.Y. Ng, 2012). The basic models can always be extended somehow, but unless statistical evidence shows that it can better serve the forecasting purpose, I am not convinced to go with the flow. I will save the examination of the two richer models until the formal proof is found.
III-C. FUNCTIONAL FORMS

Two variables are examined in the present study: housing starts, the primary predictor, and the interest spread, specifically the difference between the interest rates on the ten-year Treasury bond and the three-month Treasury bill. The question is: which form should each examined variable take, the level or the growth rate form? Well, it boils down to which helps forecast recessions, doesn’t it. The best functional form for each variable has be selected before we compare across variables for the predictive power of recessions. Regarding the interest spread, it makes intuitive sense that it is the level, rather than the change, that matters. Given a change in the interest spread, the starting level that makes a difference in the change in the economy. For instance, if the spread is already above 200 basis points, a drop of 20 points would not have a big impact on the economy. But if would be a different case for a decline of the same amount from a starting level of 10 points. I carry out a comparison of the predictive power of the interest spread versus the growth rate in the spread to further illustrate the point and serve the functional form selection purpose for the interest spread.

Historically, there is not much controversy over the choice of the form of the interest spread. Only few literature adopt the growth rate in interest spread. However, things can get quite tricky when it comes to housing variables.
The present study focuses on the exploration of the functional forms for housing starts. Specifically, I will compare the forecasting performance within the housing variable between the “level” form and the “growth rate” form. Another comparison is conducted within the latter form which features the present study. What do I mean by “comparison within the ‘growth rate’ form”? Basically, there are different ways to specify the growth rate for a variable. Given monthly data, the growth rate in housing starts can be constructed typically in two ways: the month-to-month growth rate, and the monthly growth rate over a period. The month-to-month growth rate is the common specification in previous literature. For example, Stock and Watson (2003), Hao and C.Y. Ng (2011). This specific construction of the housing starts growth rate exhibit some predictive power. But generally, it underperforms the yield spread in forecasting recessions. However, I would argue the monthly growth rate over a period of time serves a better predictor of the U.S. economic downturns. Intuitively, it should be a sustained decline in housing starts that reflects more of market expectations of a coming recession, thus contains more predictive information. A temporary drop, which is implied by the month-to-month growth rate construction, can be the result of various factors, for example seasonal factors. It can not fully capture the essential element that weakens the economy. Previous studies provide no rationale for the adoption of the month-to-month growth rate in the housing variable. The results of my study not only confirms my interpretation of the forecasting relationship between housing starts and the recessions, detailed explanations are also provided for the results. Please refer to a later chapter for further discussion of the construction of the housing variable.
Let us use the dynamic probit model, which is the primary functional form examined in the present study, to illustrate the functional form comparison stated in the previous chapter. The dynamic model represented by Eq. (4) is what I call the “Level” form. Since the probit models with the lagged recession indicator specified at the first order dominates other lag choices in forecasting performance within the dynamic specifications based on my empirical results (See the Empirical Results CHAPTER for illustration), Eq. (4) can be rewritten as

$$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})$$ \hspace{1cm} (4')

where \(k\) denotes the employed lag order of the examined variable. In the present study, this functional form is applied to both the interest spread and housing starts. Also note that only results for such models are reported in the empirical results for the reason stated above.

The focus of this present study is the “Growth Rate” form, which is expressed as

$$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta \% \Delta_g X + \delta Y_{t-1})$$ \hspace{1cm} (4'')

As discussed previously, the tricky part of the functional form for housing starts boils down to the specification of this “Growth Rate” term- \(\% \Delta_g X\). There are different ways to define this term. How does my study differ from other literature? Previous studies construct this term
as $\% \Delta_g X = 100\% \times [\ln(X_g) - \ln(X_{g-1})]$, where $g$ denotes the lag order of the monthly growth, while my study defines $\% \Delta_g X = 100\% \times [\ln(X_t) - \ln(X_{t-g})]$, where $g$ denotes the length of the growth period for housing starts. To use an example to illustrate, suppose $g = 5$, what previous studies use to predict recession at time $t$ is the monthly growth rate in housing starts five months prior to that time. It is basically a temporary change in housing starts from period $t-6$ to period $t-5$. In contrast, I choose the monthly growth rate over the previous five months to predict recession at time $t$. It is essentially a change over time from period $t-5$ to period $t$. From what I can see, the difference in the construction of the housing variable between my study and other literature results from our different interpretation of the forecasting relationship between housing and the recessions. To my best knowledge, no previous literature has ever explored the growth rate over time construction for any examined variable. Does the difference in variable construction lead to different results? Absolutely. Empirical results will be presented in a later chapter.
CHAPTER IV

FORECASTING PROCEDURE

The probability that a recession occurs h-period ahead is the conditional expectation of $Y_t$ on the information set $\tau_{t-h}$:

$$E_{t-h}(Y_t) = p_{t-h}(Y_t = 1)$$  \hspace{2cm} (5)

which is the forecast equation. By the law of iterated conditional expectation and Eq.(1) and Eq.(5) can be written as

$$E_{t-h}(Y_t) = E_{t-h}(E_{t-1}(Y_t)) = E_{t-h}(p_{t-1}(Y_t = 1)) = E_{t-h}(p_t) = E_{t-h}(\Phi(\tau_t))$$ \hspace{2cm} (6)

Eq. (5) implies that, in order to forecast the h-period ahead recession indicator “directly”, all the information we use should be known at the time of forecasting. In other words, all the lag orders of the explanatory variables need to be tailored so that they do not exceed the forecast horizon. This forecasting procedure is called “direct forecasting”. Let us use the dynamic model
\( R_{-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-m}) \) as an example, Eq. (6) can be specified accordingly as:

\[
E_{t-h}(Y_t) = E_{t-h}(\Phi(\pi_t)) = E_{t-h}(\Phi(\alpha + \beta X_{t-k} + \delta Y_{t-m}))
\]  \hfill (7)

If the specification of the model is such that \( k \geq h \) and \( m \geq h \), an optimal direct forecast for \( h \)-period ahead can be made at the time of forecasting \((t - h)\). On the other hand, if we specify that \( k \leq h \) and \( m \leq h \), the only way that direct forecasting can be conducted is to set \( k = h \) and \( m = h \), which is commonly applied in practice. Now, what if \( k > h \) or \( l > h \)? Then it requires us to forecast \( X \) and \( Y \) over the periods in between \( h \) and \( k \), and \( h \) and \( l \). For example,

\[
E_{t-h}(Y_t) = E_{t-h}(\Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1}))
\]  \hfill (7’)

where \( k \geq h \) for simplicity of discussion. Notice that the lag order of the recession indicator is 1 instead of \( m \). In this case, if \( h > 1 \), the recession indicator \( Y_t \) cannot be forecast directly. For example, when \( h = 2 \), \( Y_{t-1} \) is not realized at the time of forecasting, i.e., time \( t \). Therefore, we adopt the so called “iterated” forecasting procedure proposed by Kauppi and Saikonen (2008). It is essentially a multi-one-period-ahead forecasting procedure. Once the first-step forecast is generated “directly”, the process is “iterated” forward for multiple periods until the \( h \)-period forecast is obtained.
Let us use the $h=2$ case to illustrate, then Eq. (6) can be specified as

\[
E_{t-h}(Y_t) = E_{t-2}(P_{t-1}(Y_t = 1))
= \sum_{Y_{t-1}\in\{0,1\}} P_{t-2}(Y_{t-1}) \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})
\]

(8)

where

\[
P_{t-2}(Y_{t-1}) = \Phi(\alpha + \beta X_{t-k-1} + \delta Y_{t-2})^{Y_{t-1}} \cdot [1 - \Phi(\alpha + \beta X_{t-k-1} + \delta Y_{t-2})]^{(1-Y_{t-1})}
\]

Thus, Eq. (8) is basically a function of $Y_{t-1}$ given $Y_{t-2}$ and $X$’s. There are two possible outcomes for $Y_{t-1}$, which implies that there are two paths that can lead to a recession at time $t$—recession in the previous period or no recession at that time. Suppose $Y_{t-1} = 1$, then Eq. (8) becomes

\[
E_{t-2}(P_{t-1}(Y_t = 1)) = \Phi(\alpha + \beta X_{t-k-1} + \delta Y_{t-2}) \cdot \Phi(\alpha + \beta X_{t-k} + \delta)
\]

(9)

For $h > 2$, the number of possible paths that lead to a recession at time $t$ become larger. For instance, when $h = 3$, there are four possibilities—recession in both previous periods, recession in only one period which counts for two ways and no recession in the past. When $h=4$, the number increases to eight. But the idea is the same.
In my study, both in-sample and out-of-sample analyses are carried out for forecasting. The difference is, if the prediction period is within the estimation period, it is “in-sample”. To avoid any information loss, the entire data period from 1960M1 to 2014m12 is used for our in-sample analysis. On the other hand, if the forecast period is beyond the estimation period, it is “out-of-sample”. Basically, we are using historical data to forecast into the future where data are unknown. In practice, we need to hold back a portion of the observations available from the estimation period. Usually, a recursive scheme is used such as the “iterated” forecasting procedure discussed above for generating the forecasts over the held-back period. This way, the forecasts and the actual observations can be compared for the purpose of forecast accuracy analysis.

As we can tell, out-of-sample analysis is the more realistic forecasting of the two. But out-of-sample examinations suffer from sample distortion and information loss problems due to sample splitting. Therefore, in-sample analysis is also carried on in my study and it has been shown from previous studies that in-sample analysis can sometimes produce more accurate results than the out-of-sample case.
CHAPTER V

TEST CRITERIA

The present study adopts the Adjusted-Pseudo $R^2$ statistic to examine the in-sample performance. The Adjusted-Pseudo $R^2$ was proposed by Estrella (1998) as a new measure of fit for dichotomous dependent variable models. It has various desirable properties that earlier proposals lack, and confirms with classical $R^2$ in terms of both its range and its relationship with the underlying test statistics. Specifically, the new measure is like an $R^2$ in that it is contained in the unit interval and has suitable interpretations at the endpoints of the interval. In addition, its marginal relationship with the average likelihood ratio statistic is closely in line with similar relationships between $R^2$ and the classical tests in the linear model.

The Adjusted Pseudo $R^2$ takes the form as follows

$$
\text{Adjusted Pseudo } R^2 = 1 - \left( \frac{\log(L_u) - k}{\log(L_c)} \right)^{-2\log(L_c) / T} \tag{10}
$$

where $k$ is the number of explanatory variables, $T$ is the sample size, $L_u$ is the unconstrained
maximum value of the likelihood function of the estimated model, and Lc is the maximum value under the constraint that all coefficients are zero except for the constant. The Adjusted-Pseudo $R^2$ can be interpreted in the same fashion as the conventional $R^2$.

To assess the significance of predictive superiority based on the out-of-sample analysis, this present study employs the Diebold and Mariano test (DM, 1995). Given an actual series and two competing forecasts, the DM statistic tests the hypothesis that the expected loss differential between two these forecasts is zero. Particularly, if we denote $L(e_t)$ as the loss function associated with forecast error at time t is $e_t$, then the time-t loss differential between forecast 1 and 2 is $d_{12t} = L(e_{1t}) - L(e_{2t})$. For example, if the loss function takes the quadratic form, then the loss differential becomes $d_{12t} = e_{1t}^2 - e_{2t}^2$. DM requires only that the loss differential be covariance stationary. Then the null hypothesis is simply $E(d_{12t}) = 0$ and:

$$DM_{12} = \frac{\overline{d_{12}}}{\hat{\sigma}_{d_{12}}} \rightarrow N(0,1)$$  \hspace{1cm} (11)

where $\overline{d_{12}} = \frac{1}{T} \sum_{t=1}^{T} d_{12}$ is the sample mean loss differential and $\hat{\sigma}_{d_{12}}$ is a consistent estimator of the standard deviation of $d_{12}$.

The DM statistic can be calculated by regression of the loss differential on an intercept, using heteroskedasticity and autocorrelation robust (HAC) standard errors.
CHAPTER VI

VARIABLE ANALYSIS AND DATA CONSTRUCTION

VI-A. RECESSION INDICATOR

The independent variable in my models is the binary recession indicator which takes one when recession occurs and zero when there is no recession. As a rule of thumb, recession is defined as two consecutive quarters of decline in GDP. The Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) defines the recession in a broader sense: a recession is a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales. The NBER officially announces the beginning and the ending dates of the U.S. recessions. The determination that the last contraction began in December 2007 and the last expansion began in June 2009 are the latest announcements made by them. One can infer that the time in between those two dates is the most recent recession period.

I use the NBER business cycle reference dates to construct the recession indicator data
over the period from 1960M1 to 2014 M12. Table 1 lists the monthly recession reference dates during this period. Note that the recession indicator takes the value of one if it is classified as the NBER business cycle peak while it is assigned zero if it is classified as the trough. For example, \( Y_t = 1 \) for \( t = 2007M12 \); \( Y_t = 0 \) for \( t = 2009M7 \).

Table 1. Monthly Recession Reference Dates for the U.S.

<table>
<thead>
<tr>
<th>Peak</th>
<th>Trough</th>
</tr>
</thead>
<tbody>
<tr>
<td>April 1960</td>
<td>February 1961</td>
</tr>
<tr>
<td>December 1969</td>
<td>November 1970</td>
</tr>
<tr>
<td>November 1973</td>
<td>March 1975</td>
</tr>
<tr>
<td>January 1980</td>
<td>July 1980</td>
</tr>
<tr>
<td>July 1981</td>
<td>November 1982</td>
</tr>
<tr>
<td>July 1990</td>
<td>March 1991</td>
</tr>
<tr>
<td>March 2001</td>
<td>November 2001</td>
</tr>
<tr>
<td>December 2007</td>
<td>June 2009</td>
</tr>
</tbody>
</table>

*Source: National Bureau of Economic Research*

Besides those contributions stated in the introduction, another major contribution of my study is the usage of a larger sample size compared to previous studies. The full sample in this present study covers the period from 1960M1 to 2014M12 with 660 observations in total. To my best knowledge, even the most recent studies only use data up to 2010. A larger sample size is
remarkable because it boosts the precision of results.

VI-B. HOUSING STARTS AND OTHER HOUSING VARIABLES

Housing starts is the key predictor examined in my study for its ability to forecast recessions in the U.S.. A housing start is registered at the start of the construction of a building intended primarily as a residential building. As discussed previously, home contractors usually do not start building a house unless they are confident that it can be sold upon or before its completion. So changes in housing starts signal the change in demand for homes which eventually affect economic growth. Further, not only does the housing industry contribute a large proportion of GDP, it also impacts the economy through a ripple effect. Each time a new home is started, construction employment rises and the demand for goods and services from other industries, from cement to lumber, from furniture to appliances, is also triggered. Therefore, it is not hard to imagine the significant effect housing starts has on the economy when thinking of the construction of thousands of such unit nationwide each month.

It is noted that the relevant indicator from the housing industry included in the economic indices of leading indicators are housing permits (new private housing units). For example, building permits is one of the ten components of the Conference Board Leading Economic Index for the U.S. As for literature, the few studies that examine the predictive power of individual
housing variables (For example, Estrella and Mishkin, 1998), generally adopt housing permits as a comparison to other financial variables. What is the major difference between building permits and housing starts? Building permits are based on the units that are authorized to be built whereas housing starts are based on the actual breaking of ground. In reality, lots of permits are abandoned before housing starts are registered. Also, housing starts can be obtained in certain non-permit areas. Netting these two effects along with other factors, according to the findings from U.S. Census Bureau, housing starts are roughly 2.5% less than permits in total. From my point of view, it is arguably that housing starts serves better than permits to capture real economic activities.

Further, some previous studies use housing prices to examine the predictive content of housing variables. For instance, Eric C.Y. Ng (2012) adopts the S&P/Case-Shiller Home Price Index (Composite-10) as the housing price index. Stock and Watson (2003) also use the housing price index when examining the role of asset prices in forecasting output and inflation. As pointed out by Leamer (2007), housing is the business cycle, and it is the volume that matters, not the price. The appreciation of one’s house does not contribute to GDP because the value of the house was counted when it was newly built and sold. Real estate prices do not have a direct effect on real production, thus business cycles. Further, it is the volume cycles that persist, not price cycles. Real estate prices exhibit an overall increasing trend based on historical data as illustrated by Figure 3. We can see clear-cut from the graph that housing prices stay high even in
the face of most market declines in recent decades, and do not seem to have any leading effect on economic downturns, which are indicated by the shaded areas. Leamer (2007) attributes this downward inflexibility of housing prices mainly to human psychological factors, such as our sentiment towards homes and the loss aversion assumption of human nature. People are reluctant to sell into a weak housing market, and this stickiness of the price is what makes the sales more extreme than it otherwise would be, which to some extent, adds to the predictive content of housing starts. Empirical evidence can be provided, upon request, for the weak correlation between business cycles and housing prices.

![Figure 3](image_url)  
**Figure 3.** All-Transactions House Price Index and Recessions. *Source: FRED*

All the previous discussion in this section explains the choice of housing starts in the present study. To construct the data for this primary predictor, I collected the seasonally-adjusted
monthly data of new privately owned housing units started (measured in thousands of units) from the Federal Reserve Economic Data (FRED) database. Figure 4 captures the movements of housing starts and the occurrences of recessions in the U.S. over the period from 1960M1 to 2014M12, my full data sample. As can be clearly seen, housing starts plummets significantly preceding almost each of the recessions. As discussed in the Model Specification sector, housing starts are proposed to be constructed as the growth rate over time, which features the main difference of this study from previous literature.

Figure 4. Monthly Performance of Housing Starts. Source: FRED
VI-C. INTEREST SPREADS

To demonstrate the predictive power of housing starts, the yield spread, specifically the interest spread between the ten-year Treasury bond and the three-month Treasury bill, is adopted in the present study to serve the comparison purpose.

A substantial body of literature, originated from Kessel (1965), have documented that the slope of the yield curve is a reliable predictor of future economic activities. Some studies argue that it has a dominant predictive power in comparison with other variables. For instance, Bernanke (1990), Dueker (1997), Estrella and Mishkin (1998) and Stock and Watson (2003). The basic idea is, the slope of the yield curve, i.e., the difference between interest rates on Treasury securities of different maturities, for instance, ten year minus the federal funds rate, has a negative relationship with future economic activities. The measure for which the predictive power has been found include GDP growth, growth in GDP components such as consumption, investment and industrial production, and economic recessions as dated by the National Bureau of Economic Research (NBER), with the last one being the focus of this present study. There is also evidence that interest spreads bear a negative relationship with output growth and recessions in some other countries. See Estrella and Mishkin (1997), Bernard and Gerlach (1998) and Nyberg (2010).
Although the predictive content of the term spread has been empirically documented, there is no universally agreed-on theory as to why this inverse relationship exists. That’s why the usefulness of the interest spread in forecasting output and recessions remains a “stylized fact in search for a theory” (Benati and Goodhart, 2008). A simple rule of thumb is that an inverted yield curve signals a recession. From a supply and demand perspective, short-term interest rates typically fall before or during recessions because the demand for credit weakens. Also, investors would bid up long-term rates as long-term securities become more desirable, which causes their yields to fall even more. Many studies attribute the ability of the yield spread to forecast economy to the actions by monetary authorities to stabilize output growth in the face of a recession (For example, Atta-Mensah and Tkacz, 1998). Typically, a loose monetary policy is conducted by the Fed to boost the economy, which would cause the yield curve to flatten even further. All the aforementioned expectations can translate into an inverted yield curve if the anticipated recession is large enough to offset the term premium.

I would like to use Figure 5 to illustrate. The graph depicts the movements of the interest spread, specifically the 10-year Treasury constant maturity minus the federal funds rate, and the occurrences of recessions since 1954. It can be seen that, over the last four decades, each recession was preceded by an inversion of the yield spread, which implies the predictive properties of the yield spread.
One might wonder why the interest rates on Treasury securities are used more often for economy forecasting in the literature than those on other debt instruments such as commercial paper and corporate bonds. One reason is that data for Treasury securities are available in a consistent format over time. The other reason, more importantly, the pricing of government debt securities is less subject to credit risk premium than other debt instruments. A more important question is- what maturity combination works the best among all Treasury securities? At the long end, it is obvious the ten-year security is the best choice. The thirty-year Treasury bond is known as the government debt security with the longest maturity. But it has been replaced by the ten-year Treasury bond as the most followed benchmark of the U.S. bond market. Plus, the
thirty-year bond has much less data available compared to its counterpart. At the short end, there is a wider range of choices. The federal funds rate seems like the extreme on the maturity spectrum since it is an overnight rate. However, it is closely controlled by the Federal Reserve, thus can not fully reflect the expectations of the financial market. It has been found by previous studies that the performance of the yield spread between the ten-year bond and the federal funds rate in predicting economic activities varies across time. Estrella and Mishkin (1998) suggest that the three-month Treasury bill, when combined with the ten-year Treasury bond, produces both accurate and robust predictions over long periods. Therefore, the three-month Treasury rate is adopted in the present study as the short end of the maturity combination.

All the previous discussion in this section provides rationale for the employment of the specific interest spread- the yield spread between the ten-year Treasury bond and the three-month Treasury bill rates in the present study. To construct the data, I collected the ten-year Treasury Constant Maturity Rate and the three-month Treasury Bill Secondary Market Rate from the FRED. The difference between the two rates is thus the yield spread.

Thus far, the variable analysis discussion is completed. Table 2 provides the summary of the data definitions in the present study: What follows is the layout of the data statistics represented in Table 3. Please be noted that housing starts in Table 3 are measured in thousands of units.
Table 2. Summary of Data Definitions and Sources.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
<th>Periods</th>
<th>Data sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>Recession indicator: 1 for a recession month or 0 otherwise</td>
<td>Monthly. 1960M1-2014M12</td>
<td>National Bureau of Economic Research (NBER)</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>Monthly data of new privately owned housing units started (measured in thousands of units)</td>
<td>Monthly. 1960M1-2014M12</td>
<td>Federal Reserve Bank of St. Louis Economic Data (FRED)</td>
</tr>
</tbody>
</table>

Table 3. Data Statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observation</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>660</td>
<td>.141</td>
<td>.348</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>660</td>
<td>1447.832</td>
<td>405.409</td>
<td>478</td>
<td>2494</td>
</tr>
<tr>
<td>Interest Spread</td>
<td>660</td>
<td>1.541</td>
<td>1.241</td>
<td>-2.65</td>
<td>4.42</td>
</tr>
</tbody>
</table>
CHAPTER VII

EMPIRICAL RESULTS

VII-A. IN-SAMPLE RESULTS

As discussed in the section of Functional Forms under Model Specification, we need to select the best functional form within each variable before we compare across variables. For a quick review, I use Table 4 in the following to summarize the functional forms and the construction of the examined variable in this study. Again, one feature of my study is the construction of the “growth rate” for housing starts. It is interpreted as the monthly growth rate in housing starts over the previous few months beyond the forecast period, and distinguishes the month-to-month growth rate commonly defined in other literature. Dynamic models are used here for illustration.
Table 4. Functional Forms and Variable Construction.

<table>
<thead>
<tr>
<th>Functional Form</th>
<th>Variable Construction for X</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>The “Level” Form</em>:</td>
<td></td>
</tr>
<tr>
<td>$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})$</td>
<td>Value of $X$ $k$ months prior to time $t$</td>
</tr>
<tr>
<td><em>The “Growth Rate” Form</em>:</td>
<td></td>
</tr>
<tr>
<td>$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta %\Delta_g X + \delta Y_{t-1})$</td>
<td><em>Other literature</em></td>
</tr>
<tr>
<td></td>
<td>Month-to-month growth rate in $X$ $g$ months prior to time $t$</td>
</tr>
<tr>
<td></td>
<td><em>Present study</em></td>
</tr>
<tr>
<td></td>
<td>Growth rate in $X$ over the previous $g$ months beyond time $t$</td>
</tr>
</tbody>
</table>

Table 5 report the Adjusted-Pseudo $R^2$ measures of the in-sample performance for interest spread. Comparison is conducted across three model specifications, i.e., between the static “Level” form, the dynamic “Level” form, and the dynamic “Growth rate” form. Particularly, the first row represents the results for the static “Level” probit model with the employed lag order of interest spread varying from one to twelve. The next two rows contain results for the dynamic probit model distinguished by the “Level” form and the “Growth Rate” form. Please be noted that the growth rate in the interest spread is specified as the monthly growth rate over the last few months prior to time $t$. This way, it aligns with the construction of the growth rate for housing starts, the primary variable examined in this study.
Table 5. Adjusted-Pseudo R2 Measures of In-sample Fit for Interest Spread

<table>
<thead>
<tr>
<th>The Static “Level” Form: $P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k})$</th>
<th>$k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>2</td>
</tr>
<tr>
<td>.022</td>
<td>.048</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>.197</td>
<td>.203</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Dynamic “Level” Form: $P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})$</th>
<th>$k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>2</td>
</tr>
<tr>
<td>.704</td>
<td>.712</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>.677</td>
<td>.672</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Dynamic “Growth Rate” Form: $P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta % \Delta gX + \delta Y_{t-1})$</th>
<th>$g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$1$</td>
<td>2</td>
</tr>
<tr>
<td>.650</td>
<td>.625</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>.469</td>
<td>.511</td>
</tr>
</tbody>
</table>

Comparing the static and the dynamic models, we can see that the general in-sample performance of the static model can be improved if the first lag of the recession indicator is added as one of the explanatory variables. It indicates the importance of capturing the dynamic structure of the recession indicator in forecasting. When comparing within the dynamic specification, the dynamic “Level” outperforms the dynamic “Growth Rate” across all forecast horizons, which confirms the theoretical expectation— it is the level rather than the growth rate that matters when it comes to interest spread. And it seems like the interest spread performs relatively better for short-term forecast horizons. The best in-sample fit is generated by the dynamic “Level” form with the second lag order of interest spread, thus is chosen as the best
model specification for this variable, which can be represented by Eq. (12) as follows

\[ p_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-2} + \delta Y_{t-1}) \]  

(12)

Now let us turn to the in-sample results for our primary predictor- housing starts. Table 6 displays the Adjusted-Pseudo $R^2$ results. As mentioned previously, the present study focuses on the exploration of the functional forms for housing starts. What distinguishes Table 6 from the previous table, besides the examined variable, is the comparison within the “Growth Rate” form for housing starts, which features the difference between this present study and other literature.
Table 6. Adjusted-Pseudo $R^2$ Measures of In-sample Fit for Housing Starts.

<table>
<thead>
<tr>
<th>The Static “Level” Form: $p_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k})$</th>
<th>$k$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>.088</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>-.002</td>
<td>-.002</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Dynamic “Level” Form: $p_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})$</th>
<th>$k$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>.662</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>.659</td>
<td>.658</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Dynamic “Growth Rate” Form: $p_{t-1}(Y_t = 1) = \Phi(\alpha + \beta % \Delta_g X + \delta Y_{t-1})$</th>
<th>$g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month-to-month growth rate at time t-g (other literature)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>.660</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>.660</td>
<td>.659</td>
</tr>
</tbody>
</table>

| Monthly growth rate over g periods (present study) |
|---|---|
|   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|   | .675 | .718 | .724 | .718 | .726 | .725 | .714 | .704 |
| 9 | 10 | 11 | 12 |
| .697 | .698 | .688 | .681 |

From Table 6, it is clear-cut that, the in-sample performance for each functional form is enhanced significantly once the first lag order of the recession indicator is added, just as in the previous case. I had actually explored other lag orders before reporting the results for both variables. It turned out that not that much was gained by using a longer lag of the recession
indicator. Therefore, I only report the case where the first lag order of the recession indicator is employed. In fact, the first order also dominates the out-of-sample forecasting. Recall from the earlier discussion that the use of the first lag of the recession indicator entails the iterated forecasting procedure, and the use of a longer lag enables direct forecasting. Thus, the results imply that iterated forecasting outperforms the other scheme consistently in this study.

Now back to the comparison within the dynamic “Growth Rate” form. It turns out that the monthly growth rate, the housing variable construction proposed by the present study, outperforms the month-to-month growth rate, which is commonly adopted in previous literature. Interestingly, the month-to-month growth rate construction does not improve the in-sample performance of the level form to any extent based on the results. These findings demonstrate the monthly growth rate in housing starts a more effective predictor of recessions than all the other specifications, especially the month-to-month growth rate construction. This marks one of the major contributions of the present study. Overall, the best in-sample fit for housing starts is obtained when the dynamic growth rate takes the fifth lag order, i.e.,

\[ P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta \% \Delta_5 X + \delta Y_{t-1}) \]  \hspace{1cm} (13)

Following previous discussion, it is remarkable to see that the forecasting advantage of the monthly growth rate is largely reflected when using the growth rate over a medium period,
specifically around five month. What could be the possible explanations for this finding? Can a sustained growth better pick up indicative information for recessions than a temporary change? In other words, is it a better interpretation of the forecasting relationship between housing starts and the recessions?

Here are my thoughts: when households anticipate a recession, they would expect their future income to be affected and they might get into the trouble of paying off their mortgages along the way. Let us think of the extreme case, they may lose their job due to a recession. So it’s very likely that they would choose not to purchase a house today in order to avoid the trouble later. On the other hand, even if households feel that their job is pretty secured, they would still delay their housing purchase today out of speculative motives. As we know, housing prices are expected to fall during a recession, so they would want to wait to get a good deal on the price later. Further, the mortgage rates are expected to be lowered as well because a looser monetary policy is anticipated as a reaction to a recession. People are always forward looking when making current choices as opposed to reacting at the last moment, thus housing starts would start and continue to fall in anticipation of a coming recession. All the above provide as explanations as to why a sustained decrease in housing starts can serve as a better indicator than a temporary drop which is very likely to be caused by random factors such a seasonal factor. The empirical results reinforce this notion and thus my interpretation of the forecasting relationship between housing and the recessions.
Table 7.  Adjusted-Pseudo $R^2$ Measures of Dynamic In-sample Fit for Interest Spread vs. Growth Rate in Housing Starts.

<table>
<thead>
<tr>
<th>The Dynamic “Level” Form for interest spread:</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta X_{t-k} + \delta Y_{t-1})$</td>
<td>.704</td>
<td>.712</td>
<td>.695</td>
<td>.701</td>
<td>.711</td>
<td>.701</td>
<td>.700</td>
<td>.696</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>The Dynamic “Growth Rate” Form for housing starts:</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta % \Delta_g X + \delta Y_{t-1})$</td>
<td>.677</td>
<td>.672</td>
<td>.668</td>
<td>.660</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Monthly growth rate over g periods</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Phi(\alpha + \beta % \Delta_g X + \delta Y_{t-1})$</td>
<td>.675</td>
<td>.718</td>
<td>.724</td>
<td>.718</td>
<td>.726</td>
<td>.725</td>
<td>.714</td>
<td>.704</td>
</tr>
</tbody>
</table>

The best functional form has been selected for each examined variable, i.e., the dynamic “Level” form for interest spread and the dynamic growth rate form for housing starts. For better comparison across variables and later reference, the Adjusted-Pseudo $R^2$ in-sample results for the two selected forms are reported together in Table 7, extracting from the previous two tables. When these two variables are put together, we can clearly see that the interest spread does not have a dominant predictive power over housing starts, which contradicts the findings in other literature. Then why did previous literature fail to see this? It boils down to the wrong interpretation of the forecasting relationship thus the construction of the housing starts variable. Not only did they ignore housing variables to start with, they failed to tap into the predictive potential of housing starts when examined them. If I had constructed housing starts in the form
of month-to-month growth rate as they commonly do, I would have drawn the same conclusion as in other literature. If you compare the dynamic “Level” form for interest spread with the month-to-month growth rate in housing starts, you will know what I am talking about. The finding that the interest spread does not necessarily dominate housing starts in forecasting marks another contribution of my study. As indicated previously, the best in-sample fit for each variable is emphasized in red in Table 7, and they will be used as the selected models along with another one in the following discussion for further analysis.

It is noted from Table 7 that the interest spread seems to perform better for shorter forecast horizons while the growth rate in housing starts does a relatively better job when a longer growth period is used for recession prediction. These observations intrigue me to further examine the predictive power of the combination of the two variables. Table 8 reports the Adjusted Pseudo $R^2$ in-sample results for the dynamic probit model that includes both the interest spread and the growth rate in housing starts as explanatory variables for recessions, with the lag order for each variable allowed to vary from one to eight months. The functional form listed at the top of Table 8 specifies the model design.
Table 8. Adjusted-Pseudo R² Measures of Dynamic In-sample Fit for Growth Rate in Housing Starts and Interest Spread.

<table>
<thead>
<tr>
<th>$k$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.701</td>
<td>.710</td>
<td>.692</td>
<td>.705</td>
<td>.715</td>
<td>.705</td>
<td>.703</td>
<td>.701</td>
</tr>
<tr>
<td>2</td>
<td>.729</td>
<td>.737</td>
<td>.728</td>
<td>.736</td>
<td>.743</td>
<td>.736</td>
<td>.733</td>
<td>.732</td>
</tr>
<tr>
<td>3</td>
<td>.730</td>
<td>.737</td>
<td>.729</td>
<td>.739</td>
<td>.746</td>
<td>.738</td>
<td>.737</td>
<td>.736</td>
</tr>
<tr>
<td>4</td>
<td>.729</td>
<td>.733</td>
<td>.727</td>
<td>.726</td>
<td>.730</td>
<td>.726</td>
<td>.720</td>
<td>.720</td>
</tr>
<tr>
<td>5</td>
<td>.733</td>
<td>.738</td>
<td>.723</td>
<td>.723</td>
<td>.735</td>
<td>.727</td>
<td>.725</td>
<td>.724</td>
</tr>
<tr>
<td>6</td>
<td>.731</td>
<td>.735</td>
<td>.731</td>
<td>.722</td>
<td>.730</td>
<td>.728</td>
<td>.726</td>
<td>.726</td>
</tr>
<tr>
<td>7</td>
<td>.722</td>
<td>.726</td>
<td>.711</td>
<td>.711</td>
<td>.723</td>
<td>.718</td>
<td>.720</td>
<td>.719</td>
</tr>
<tr>
<td>8</td>
<td>.716</td>
<td>.720</td>
<td>.704</td>
<td>.704</td>
<td>.715</td>
<td>.711</td>
<td>.712</td>
<td>.716</td>
</tr>
</tbody>
</table>

The results reported in Table 8 are favorable. If we compare them with previous results, we can conclude that the dynamic probit model using the combination of the interest spread and the growth rate in housing starts outperforms the conventional one where only one examined variable is included. The best in-sample fit among all combinations is obtained when the third lag of the growth rate in housing and the fifth lag of the interest spread are employed. The best model specification where both examined variables are included takes the form as

$$P_{t-1}(Y_t = 1) = \Phi(\alpha + \beta_1 \% \Delta g\text{ HOUST} + \beta_2 \text{ INTSPD}_{t-5} + \delta Y_{t-1})$$  \hspace{1cm} (14)$$

Based on the previous in-sample results, I follow up by reporting the estimation results for the three models that stand out as the best fit in Table 9. Note that the T-statistics are given in
parentheses. Further remark that the three models are selected for the subsequent out-of-sample analysis.

Table 9. In-sample Estimation Results for Selected Models.

<table>
<thead>
<tr>
<th></th>
<th>Dynamic growth rate in Housing Starts y</th>
<th>Dynamic level in Interest Spread y</th>
<th>Dynamic combination y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y(t-1)</td>
<td>3.732***</td>
<td>3.975***</td>
<td>4.033***</td>
</tr>
<tr>
<td></td>
<td>(12.74)</td>
<td>(12.24)</td>
<td>(10.92)</td>
</tr>
<tr>
<td>% Δ₃ HOUST</td>
<td></td>
<td>-5.189***</td>
<td>(-3.75)</td>
</tr>
<tr>
<td>% Δ₅ HOUST</td>
<td>-4.136***</td>
<td>-5.189***</td>
<td>(-3.75)</td>
</tr>
<tr>
<td></td>
<td>(-4.22)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTSPD(t-2)</td>
<td></td>
<td>-.534***</td>
<td>(-4.33)</td>
</tr>
<tr>
<td>INTSPD(t-5)</td>
<td></td>
<td></td>
<td>-4.64***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-3.30)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.460***</td>
<td>-1.776***</td>
<td>-2.170***</td>
</tr>
<tr>
<td></td>
<td>(-13.14)</td>
<td>(-10.86)</td>
<td>(-9.08)</td>
</tr>
<tr>
<td>Adjusted-Pseudo R²</td>
<td>.726</td>
<td>.712</td>
<td>.746</td>
</tr>
</tbody>
</table>

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

We can see from Table 9 that all coefficient estimates are highly significant and the negative signs on the coefficients are theoretically expected, that is, a shrink in the yield spread between the long-term and short-term securities does not favor the outlook of the economy. By the same token, a decline in housing units started reflects a higher expectation of a coming
To further illustrate the in-sample performance of the selected models in Table 9, I use Figure 6 to plot the predicted probabilities of recessions against the actual recessions for these models. Graphs A-C correspond to the three models respectively. The shaded areas in each graph indicate the actual recessions while the black line tracks the plots of recession forecasts based on the underlying model.

The three graphs run the entire observation sample they track the actual recessions in different patterns. We can tell from the graphs that all the three models can produce quite good in-sample fit for actual recessions. If we look at them separately, the model that uses the interest spread for forecasting seems to match with the actual values better for the recessions before the Mid-80s. The predictive ability of the interest spread diminishes for the most recent recessions. On the contrary, the model that uses the growth rate in housing starts works better in predicting the most recent recessions. The model that uses both variables as the predictor does the best job overall. All these findings reinforce the notion that the interest spread and the growth rate in housing starts can be treated as compliments when predicting recessions.
Figure 6. Probability of Recession, In-Sample Prediction

A. Housing Starts

B. Interest Spread
Now let’s turn our focus to the out-of-sample analysis of the selected models in Table 9. The iterated forecasting procedure is adopted here. Specifically, we run a rolling estimation sample from 1960M1-1984M12 to 1960M1-2013M12 with one period added each time. For each estimation sample, forecasts are made for the forecast horizons from one to eight months. For instance, if the estimation period is 1960M1-1984M12, forecasts are made for the following eight periods from 1985M1 to 1985M8. For the next round, estimation period extends to 1960M1-1985M1, and forecasts over 1985M2-1985M9 are generated accordingly. The estimation window rolls over for 349 rounds in total. Therefore, 349 forecasts are generated for
each forecast horizon.

The iterated forecasting procedure is applied to any forecast horizon beyond h=1 since the first lag order of the recession indicator is specified in the models. To use h=2 as an example, suppose we want to forecast recession at time 1985M2 based on the estimation sample 1960M1-1984M12. The value of the recession indicator for 1985M1 is unknown at the time of forecasting, i.e., Y_{t-1} is not realized. Therefore, the recession indicator at time 1985M1 has to be forecast first, then added to the estimation sample before the forecast for 1985M2 can be obtained. The whole process is essentially a two-step-one-period-ahead forecasting. As the estimation sample rolls over to 1960M1-1985M1, the forecast for 1985M3 is obtained repeating the process.
Table 10 reports the Adjusted-Pseudo $R^2$ measures of the out-of-sample results for the three selected models. In each table, different models are listed in different rows while the each column corresponds to each specific forecast horizon changing from one to eight months. It is noted that the best out-of-sample performance is obtained at $h=1$ for each model. However, the three models exhibit different patterns for the out-of-sample fit. The forecasting ability of the interest spread diminishes quite rapidly as the forecast horizon expands while the model that forecasts with the housing starts growth rate performs relatively more stable. Most remarkably, the housing starts model outperforms the interest spread model for each of the eight forecast
horizons, which demonstrates the dominance of the growth rate of housing starts over the interest spread as a forecasting tool. Lastly, when comparing across all three models, the best out-of-sample performance is obtained from the model where both variables are included, i.e., the dynamic combination.

To further compare the predictive accuracy between the selected models based on their out-of-sample forecasts. I apply the DM test for h=1 at which the best out-of-sample fit of each model is obtained. Recall that the hypothesis of the test is that the expected forecast error loss differential of two competing forecasts is zero, and particularly, the loss function for each model is set to be the squared errors in this present study. Table 11 reports the DM statistics with the \( p \)-values provided in the parentheses.

<table>
<thead>
<tr>
<th>Competing models</th>
<th>DM statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Starts vs. Interest Spread</td>
<td>-.0016</td>
</tr>
<tr>
<td></td>
<td>(0.280)</td>
</tr>
<tr>
<td>Housing Starts vs. Combination</td>
<td>.0007</td>
</tr>
<tr>
<td></td>
<td>(0.441)</td>
</tr>
<tr>
<td>Interest Spread vs. Combination</td>
<td>.0022*</td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
</tr>
</tbody>
</table>

\( P \)-values in parentheses * \( p<0.1 \), ** \( p<0.05 \), *** \( p<0.01 \)

From Table 11, we can clearly see that the loss differential between the interest spread
model and the combination model is the only one that is reported significant at the 10% level. Given the finding from previous discussion that the combination model outperforms its counterpart, we can interpret the significance as that the addition of the growth rate in housing starts does make a significant difference in the one-step ahead out-of-sample forecasting of the interest spread model. However, according to the result for the model comparison between housing starts and the one where both variables are included, we can not rationalize the addition of the interest spread by the same token. Further, Table 11 shows no significance in the forecasting difference between the two models that use individual predictors. Actually, I have also applied the DM test to forecast horizons beyond one-step ahead, but found no significant results. This finding implies that the predictive superiority is horizon specific.

The out-of-sample forecasting performance of the three selected models are further illustrated with graphs. Figure 7. A-C represent the plots of one-month ahead forecasts against actual recessions based on these models. Each graph corresponding to each examined predictor covers the forecast periods from 1985M1 to 2014M12 which include the most recent recessions including the early 1990s crisis, the dotcom crash, and subprime mortgage crisis. Focusing on each crisis, we can detect that early 1990s crisis is most accurately forecast by either the housing starts model or the combination model. The combination model produces the best out-of-sample fit for the dotcom market crash in early 2000s, and the housing starts model tracks the subprime mortgage crisis exceptionally well. Regarding the forecasting performance of the interest spread
model, the forecasts matches with the actual values most poorly compared to the other two models, especially for the early 1990s crisis and the housing bubble and credit crisis. Further, it is noted that even though the housing model works very well in predicting the most recent crisis, the combination model does a less satisfactory job. From which we can derive that the predictive power of the growth rate in housing starts seems to be deteriorated once the interest spread is included. Overall, the model with the combination of the housing starts growth rate and the interest spread has a dominant power compared to the individual models, which reinforces that proposal that both variables be used as complements for forecasting.

Figure 7. Probability of Recession One Month Ahead, Out-of-Sample Prediction

A. Housing Starts
B. Interest Spread

C. Combination of Interest Spread and Growth rate in Housing starts
CHAPTER VIII

CONCLUSION

This paper examines the predictive power of housing starts for recessions using probit models. The yield spread, specifically the difference between the rates on the ten-year Treasury bond and three-month Treasury bill, is adopted for comparison. Different model specifications and functional forms are explored and compared. Both in-sample and out-of-sample analyses are conducted. The iterated forecasting procedure and different test criteria, particularly the Adjusted-Pseudo $R^2$, are employed. The results show that the performance of the static probit models can be improved once the first lag of the recession indicator is added as one of the explanatory variables. The fact that the first order dominates other lag orders implies the iterated forecasting procedure is superior than the direct forecasting approach in this study. As for the model functional form selection for each variable, the best in-sample fit are produced when the interest spread takes on the dynamic level form while housing starts are specified as the monthly growth rate over time. The construction of the “Growth Rate” is the most remarkable feature of the present study. It distinguishes the month-to-month growth rate which is commonly adopted in other literature. This specific construction for housing starts results from a different interpretation
of the forecasting relationship between housing and recessions. One of the major objectives of the study is to propose the notion that it is a sustained decline in housing starts that reflects more of market expectations of the economic outlook, thus can better serve as a predictor of recessions. Such notion is confirmed by the empirical results. The dynamic model that uses the growth rate in housing starts for forecasting outperforms the one that predicts with the interest spread, especially over a medium period. The dominant predictive power of housing starts is mostly demonstrated in the out-of-sample performance. Further, another important finding of the study is, the most superior fit among all functional forms is generated by the dynamic probit model when housing starts and the interest spread are combined together as the recession predictor. This combination model exhibits dominant predictive power compared to any individual construction. It is particularly the case when the third lag for housing and the fifth lag for the spread are employed. This finding holds both for the in-sample and out-of-sample analyses, and the superior predictive power of the combined predictor is further illustrated by the graphical plots of the model forecasts against real values of recessions. Also, this present study finds the addition of the growth rate in housing starts to the interest spread model does improve the one-step ahead out-of-sample forecasting performance.

This present study attempts to shift focus from housing prices to real production in housing, from financial indicators to macroeconomic predictors. It emphasizes the idea that it is the decline over time in housing that counts the most for economic downturns, not temporary
changes. Last but not least, my study proposes to construct the recession predictor as the combination of housing starts and the interest spread.


VITA

CUI, YAN

EDUCATION

- University of Mississippi, Oxford, Mississippi, USA, August 2010- present
  Ph.D. in Economics, anticipated graduation May 2015

- University of Konstanz, Konstanz, Baden-Württemberg, Germany, September 2007- November 2009
  Master of Arts in International Economic Relations, November 2009

- Henan Normal University, Xinxiang, Henan, China, September 2003- July 2007
  Bachelor of Arts in Economics, July 2007

HONORS

- Dissertation Fellowship, University of Mississippi, Spring 2015
- Summer Research Fellowship, University of Mississippi, Summer 2014
- Department of Economics Graduate Assistantship, University of Mississippi, Fall 2010-present
- First Class Scholarship, Henan Normal University, 2005-2004
- First Class Scholarship, Henan Normal University, 2006-2005
- First Class Scholarship, Henan Normal University, 2007-2006 Award for The Excellent Graduate of the Province, Henan Normal University, 2007
- Award for The Top Ten Students of Henan Normal University, Henan Normal University, 2006

RESEARCH INTERESTS

Macroeconomics, Applied Econometrics, Time Series Analysis
JOB MARKET PAPER

“Forecasting the U.S. Recessions with Housing Starts in Dynamic Probit Models”.

Abstract:
The crash of the U.S. housing market and the 2007-2009 recession that followed have reignited discussion about forecasting recessions. Most recessions have in fact been preceded by plummets in the housing industry in the U.S. history. The present study examines the predictive power of housing starts using dynamic probit models. The yield spread between the ten-year Treasury bond and three-month Treasury bill rates, is also adopted to further demonstrate the predictive properties of the housing variable. Different model functional forms are explored in which the lag structure, especially the growth rate term for housing starts, is constructed in an innovative way to serve the comparison purpose between the current study and previous literature. Instead of the month-to-month growth, the housing variable is constructed as the monthly growth rate over time. The major objective of the present study is to emphasize the notion that it is the sustained decline in housing starts, not a temporary drop, that serves better as a recession predictor. Another proposal of this study is the adoption of the growth rate in housing starts and the interest rate combination which is found superior than the individual specification. Both in-sample and out-of-sample analyses are carried out and iterated forecasting procedure is implemented. The Adjusted-Pseudo $R^2$ measure and the Diebold-Mariano statistics, are employed to examine and compare the predictive accuracy of models.

PUBLICATIONS


CONFERENCES

- Southern Economic Association Conference, November 2014. “Forecasting U.S. recessions with housing starts in dynamic probit models” (oral presentation)
- Missouri Valley Economic Association Annual Conference, October 2013. “Incentives that crowd out social preferences,” (oral presentation)
WORKING PAPERS


TEACHING INTERESTS

Macroeconomics, Microeconomics, Econometrics

TEACHING EXPERIENCE

- Sole Teaching Instructor, Principles of Microeconomics, University of Mississippi, Fall 2012, Spring 2013, Fall 2013, Fall 2014
- Sole Teaching Instructor, Principles of Macroeconomics, University of Mississippi, August 2013, Spring 2014
- Teaching Assistant, Principles of Macroeconomics, University of Mississippi, Fall 2010, Spring 2011, Fall 2011, Spring 2012
- Teaching Assistant, Principles of Microeconomics, University of Mississippi, Fall 2010, Spring 2011, Fall 2012, Spring 2013
- Teaching Assistant, Principles of Labor Economics, University of Mississippi, Fall 2011, Spring 2012, Spring 2013

WORKING EXPERIENCE

- Tutor, WyzAnt Tutoring, USA, August 2012- present
- Intern, Rating Evidence GmbH, Germany April 2009- August 2009
COLLEGIAL ACTIVITIES

- Vice Chairman of the Student Union of the College of Economics and Management, Henan Normal University, Fall 2004- Fall 2005
- News Anchor of the Broadcasting Station of Henan Normal University, Henan Normal University, Fall 2004- Fall 2006

LANGUAGE PROFICIENCY

- Fluent in Chinese and English
- Basic in German

COMPUTER SKILLS

- Econometrics Software: Stata, Eviews, JMulti
- MS Office