ESSAYS ON MACROECONOMIC FORECASTING AND THE BUSINESS CYCLE

A Dissertation

Presented to

The Faculty of the Department of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Teodora A. Stoica

May, 2012

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AND THE BUSINESS CYCLE

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Abstract

This dissertation consists of two essays on forecasting real GDP growth and predicting recessions in the United States. In the first essay, we create a new indicator of economic activity based on a business cycle pattern, able to better forecast real output changes. The second essay utilizes the same indicator with the purpose of improving recession forecast.

The accurate prediction of economic activity is valuable for the business community, policymakers, and the general public because better forecasts of GDP growth have the potential to improve economic conditions. In the first essay, we create a new indicator based on the correlation of residential and non-residential marginal product of capital (MPK) estimates and use it to improve forecasts of output growth. The correlation of residential and non-residential MPK is highly negative during recessions, while in expansions the same correlation is positive. For six out of seven expansions, the correlation of the two series becomes zero between one and three quarters before the subsequent recession. This cyclical behavior allows the use of a measure based on the correlation of the MPKs to create a better forecast of GDP growth. To this end, we compare the out-of-sample predictability of the model including the indicator against a benchmark model, and strongly reject the hypothesis of no out-of-sample predictability from the newly created indicator to GDP growth. We also provide evidence in favor of highly improved in-sample fit when the new indicator is included, and conclude that it Granger-causes GDP growth. The improvement in GDP growth forecasts is greater when an oil price measure is included in the models.

The second paper employs a probit model for the US to describe the probability of an economic recession during the next five quarters, using the new indicator based on the

correlation of residential and non-residential marginal product of capital. We find that in every one to three quarters prior to a recession, the correlation of the two series is not significantly different from zero, with the exception of the Great Recession. We show that models including the new measure improve both in-sample fit and out-of-sample performance when compared to nested baseline alternatives, giving accurate out-of-sample forecasts for the 1990-1991 recession. We also show that forecasts including the new indicator outperform those reported in the survey of professional forecasters, suggesting that other variables would not undo the contribution of the new indicator.

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Table of Contents

To Michael for his unwavering love, immeasurable wisdom, remarkable patience, and offbeat humor. He makes me a better person and a better researcher.

Chapter One

Marginal Product of Capital, the Business Cycle, and Forecasting Economic Growth

1.1 Introduction

Forecasting GDP growth plays an important role for the present and future state of the economy. A more precise prediction of the health of economic activity will reduce the cost associated with late or inaccurate forecasts and strengthen the pulse of the economy. A better performing forecast allows the policymakers to judge the right amount of "medicine" needed to heal the US economy more quickly. The credibility of the policymaker is strengthened when decisions are based on better information of the economy's health. Thus, better forecast performance will lead to better decisions.

Our analysis focuses on improving the predictability of real GDP growth forecasts. To this end, we create a new indicator based on the correlation of residential and non-residential marginal product of capital (MPK) and test how well models including the new indicator perform in-sample and out-of-sample compared to nested baseline models. To our knowledge, the newly created indicator is original to this paper.

There is a vast literature on the prediction of GDP growth using a multitude of methods to determine predictive ability. One strain of literature has examined numerous contemporaneous and leading indicators that improve forecasts of the business cycle. Short-term interest rates attracted considerable attention in predicting output changes, beginning with the influential study of Sims (1980), who found that that upward innovation in interest rates were followed by a decline in GDP growth with a two-quarter lag, and later confirmed by Bernanke and Blinder (1992). Yield spreads between short-term and long-term interest rates were effective enough in predicting economic activity to be included in the index of leading economic indicators created by Stock and Watson (1989), and also the inverted yield curve was found to be a good indicator of recessions by Estrella and Mishkin (1998).

Hamilton and Lin (1996) and Taylor (1999) asses the importance of asset prices and asset price volatility on GDP growth. Finally, the study of oil shocks can also help to predict economic slowdowns as shown in the seminal paper of Hamilton (1983), where he finds that a large increase in crude oil prices generally preceded US recessions until the beginning of the 1980s.[1]

Using a novel measure based on the correlation of the marginal product of capital (MPK) between residential and non-residential sectors, we attempt to improve existing forecasts of real output growth.[2] We create an indicator based on a pattern observed through the business cycle: negative correlation of the series during recessions, weak positive correlation during recoveries, positive during expansions, and close to zero between one and three quarters before the following recession. This indicator is largely driven by residential investment being much more interest rate sensitive and less income sensitive than non-residential investment. The correlation changes in a predictable way because of fluctuations in income and real interest rates. We then test our proposed models' performance both in-sample and out-of-sample against their nested baseline alternatives.

The correlation between residential and non-residential MPK is strongly negative in a recession. Leading up to a recession, interest rates are relatively high and generally increasing. Looking at the non-residential and residential sectors, the responses to interest rate changes are different, and so are the marginal products of capital. Non-residential capital is not terribly sensitive to the interest rate variation, and does not see major changes from

[1] For the following periods, Hamilton (1996, 2003) uses a nonlinear transformation of oil prices suggesting a strong relationship from oil to output growth. Nonetheless, Bernanke, Gertler, and Watson (1997), Edelstein and Kilian (2009), and Blanchard and Gali (2010), present a fading predictive content from oil to economic activity. Hamilton and Herrera (2004) show that Bernanke's et. al (1997) results are not robust to the inclusion of longer lags. Hamilton (2009) uses several of Edelstein and Kilian's (2009) models and discovers that energy prices explain a large fraction of the forecast errors.

[2] The two sectoral MPKs were first analyzed by Mulligan and Threinen (2010), utilizing a different framework.

expansion to recession. Non-residential income, however, falls considerably during a recession, causing non-residential MPK to fall as well. Residential MPK is much different. Residential income adjusts very slowly to market conditions, while, because housing is more interest rate sensitive, residential capital takes a much bigger hit, causing residential MPK to increase during recessions.

In the recovery phase, following the end of the recession, the correlation between residential and non-residential capital switches from being highly negative to weakly negative and, shortly after, weakly positive. When the economy is weak, the Fed loosens monetary policy by decreasing interest rates in an attempt to stimulate the economy. This affects the MPK of each sector differently. Non-residential income increases quickly, while residential income remains sticky. Capital also reacts differently based on how sensitive investment in each sector is to the interest rate. Non-residential capital increases, but at a rate that is slower than non-residential income growth. Residential capital, on the other hand, shoots up at a rate that is faster than residential income growth.

As the recovery matures, it evolves into an expansion where we observe a strong positive correlation between residential and non-residential MPK. Expansions are generally much longer and more stable than recoveries, thus, residential income is no longer sticky because it has enough time to adjust to current market conditions. Furthermore, when the economy is heating up, the Fed generally starts to run tighter monetary policy, increasing interest rates and depressing investment. Non-residential income and capital are both increasing during expansions and the effect on non-residential MPK is somewhat ambiguous. Over the entire recovery and expansion period, both residential and non-residential MPK are almost constant, with only short-term movement. As a result of the interest rate’s behavior, between one and three quarters before most recessions, the correlation becomes essentially zero.

There are two episodes that do not fit the observed pattern of correlations. First, the expansion of 2002-2007 is an anomaly, likely due to the global savings glut flowing to the US, providing firms with "cheap money", which led to overinvesting and a falling MPK. The second exception is the Great Recession, which has a very different pattern from the other post-war recessions, because it was not “caused” by the Fed in an attempt to fight inflation, but occurred as a consequence of the financial crisis. For these two episodes the correlation between residential and non-residential MPK never reaches zero. Our model has a high predictability of output growth for a typical business cycle, but does not work as well for financial crises.

We perform forecasts of GDP growth using an indicator based on the correlation between residential and non-residential MPK as an explanatory variable. We add this new indicator to two well established models, an autoregressive model and an autoregressive model including lags of Hamilton's (2003) peak oil variable, and compare in-sample fit and out-of-sample predictability. We find moderate improvement over the autoregressive model for both metrics. When the new variable is added to the model including peak oil, the results are much stronger. This suggests that not only does our indicator improve forecasts of output growth, but it is also a complement rather than a substitute to the well established leading indicator peak oil.

We use rolling and recursive regressions to forecast output growth starting in 1947:4, with 100 observations in each regression for the rolling specification, and a minimum of 100 observations for the recursive specification. Keeping the number of observations constant (rolling), or having an increasing number of observations (recursive), we report results beginning in 1973:4, through 2011:1.

The most common econometric method of identifying a potentially useful predictor is to rely on in-sample significance tests such as comparison of the adjusted R-squared ($\overline{R}^2$) and Granger causality tests. When we compare the proposed models to their nested baselines, we find that the $\overline{R}^2$ is always higher for our models than for the nested baseline models with the recursive framework, and generally higher for the rolling framework, except between 1987-1997. Additionally, for both proposed models, the Granger causality on our indicator is usually significant, except during the 1990s, when it is insignificant for all models.

The period 1987 to 2000 is generally considered a great success for monetary policy, considering that the Fed closely followed the Taylor rule. Due to this success, inflation was kept near its target, hence, there were rather small fluctuations in the real interest rate. The relatively stable real interest rate suggests that our model is unlikely to perform well during this time, or other times of exceptionally good monetary policy, because the correlation of the MPKs is largely driven by changes in the real interest rate.

We report two out-of-sample test statistics which are appropriate for nested models: the DMW test of Diebold and Mariano (1995) and West (1996) with McCracken's (2007) critical values and the CW test of Clark and West (2006). We test the model including our indicator against the nested baseline autoregressive model, and find that there is strong evidence in favor of our model through 1990:2 for both the rolling and recursive specifications. The rolling specification has mixed results from 1990:3 until 1997:2 when the evidence becomes strong again, and remains so for the rest of the sample. Similarly, the recursive specification also has mixed results until 1996:2, however it exhibits no evidence from 1996:3 to 1998:2, then mixed evidence from 1998:3 until 2009:1, when the evidence finally becomes strong again, and remains so for the rest of the sample. When adding our indicator to the autoregressive and peak oil model, we always find strong evidence that our model outperforms the nested baseline alternative.

In the following section, we construct the sectoral MPKs and analyze their trend. Next, we examine the post-war business cycles. We then present and discuss the in-sample results, that are both illustrative and useful in model selection. Lastly, we test for increased out-of-sample predictability, which constitutes the main focus of the paper, and report the out-of-sample results. Finally, we conclude on the usefulness of the new indicator.

1.2 Marginal Product of Capital for the Residential and Non-Residential Sectors

According to economic theory, the marginal product of capital (MPK) is as a good predictor of real economic activity (e.g., Feldstein and Summers (1977), Auerbach (1983)). We show that when analyzing business cycle conditions, the sectoral marginal product of capital can improve forecasts of GDP growth. We present the method of constructing quarterly marginal products and discuss their evolution during the representative sample periods, pointing out the commonalities and dissimilarities between them.

1.2.1 Sectoral MPKs

Consider the standard neoclassical model for a two-sector economy, residential and non-residential, featuring all of the standard assumptions of constant returns to scale and perfectly competitive domestic capital markets. The marginal product of capital equals the rental rate of capital for each of the two sectors. We assume a Cobb-Douglas production function given by: $Y_t^R = A_t^R K_t^{R^{\alpha_R}} L_t^{R^{1-\alpha_R}}$ for the residential sector, where Y_t^R is the total income for the residential sector at time t, A_t^R is the Total Factor Productivity (TFP) at time t, K_t^R represents residential capital and L_t^R is the labor utilized for the residential sector.

Similarly, the production function for the non-residential sector is: $Y_t^{NR} = A_t^{NR} K_t^{\alpha_{NR}} L_t^{1-\alpha_{NR}}$, where Y_t^{NR} is the income of the non-residential sector at time t, A_t^{NR} is Total Factor Productivity at time t, K_t^{NR} is non-residential capital, and L_t^{NR} is the labor utilized for the non-residential sector.

Following growth theory, it is easy to derive the value of sectoral MPKs:

$MPK_t^R = \alpha_{R,t} \frac{Y_t^R}{K_t^R}$ for the residential sector, and

$MPK_t^{NR} = \alpha_{NR,t} \frac{Y_t^{NR}}{K_t^{NR}}$ for the non-residential sector.

In a competitive market with constant returns to scale, the sectoral marginal product of capital is given by the income accruing for each sector divided by the amount of capital employed. In calculating the sectoral marginal product of capital, we first start by describing each term in the order they are presented in the equations.

We make several observations when calculating capital shares for the two sectors, and construct them by closely following methods presented in the literature, by backing out the capital share as 1 – labor share. For the residential sector, we assume that there is too little labor involved in owning and living in a house to affect the labor share, and as a result the labor share for the residential sector approaches zero, leaving the capital share, α_R, trending to a value not significantly different than 1. For simplicity of calculation, we consider $\alpha_{R,t} = 1$. For the non-residential sector, the labor share takes a value of one third.[3]

[3] The results are robust when using Mulligan and Threinen's (2010) measure of labor share. In this case, the capital share is: $\alpha_{NR,t} = 1 - \frac{\text{Compensation of Private Sector Employees}_t}{\text{National Income}_t - \text{Compensation of Governement Employees}_t - \text{Proprietors' Income}_t}$

The measure for residential income comes from the NIPA tables on Gross Value Added for Households and Institutions and comprises the rental of tenant-occupied non-farm housing and the imputed rental value of owner occupied nonfarm housing. The non-residential income, called Gross Value Added of the Business Sector in the NIPA tables, is backed out from GDP – Residential Income and Gross Value Added of Government.

The standard measure of the capital stock is calculated using the perpetual inventory method from residential and non-residential real investment flows, using a depreciation rate of 6% per year for the non-residential sector and 2% for the residential sector.[4] Following standard practice, we compute the initial value of the capital stock for the residential sector as $K_0^R = \frac{I_0^R}{(g_R+\delta)}$, where I_0^R is the value of residential investment for the first year of available data (1948:1), where g_R is the average of the geometric mean growth rate between the first year of data available and last year.[5] In the same manner, the initial value of the capital stock for the non-residential sector is $K_0^{NR} = \frac{I_0^{NR}}{(g_{NR}+\delta)}$, with I_0^{NR} representing the initial value of the non-residential investment, where g_{NR} represents the geometric mean growth for non-residential investment for the whole sample.[6] We follow the same practice for the residential sector. The next step involves constructing each period's "t" residential and non-residential capital: $K_t^i = K_{t-1}^i + (1-\delta)I_t^i$, where i = {residential, non-residential}.

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[4] These are the values most commonly used in the literature. When we perform robustness checks, results do not change for values of 10% for non-residential and 5% residential.

[5] Also from NIPA tables and comprises construction put in place, single-family housing starts, sales of new homes and sales of existing homes.

[6] Unit auto and truck sales, construction put in place, manufacturers' shipments of machinery and equipment other than aircraft, shipments of civilian aircraft, exports and imports of machinery and equipment.

1.2.2 Trends and Features

Figure 1.1 shows the evolution of both series over time, created as described above. Over the whole sample period, 1948:1 to 2009:4, the trend of the residential MPK is rising, while non-residential MPK is declining over time. The convergence toward the same value (5.3%) is satisfactory from the growth theory perspective. One would expect that, if properly calculated, the MPKs would converge to the same value over time. It is surprising that it took so long for the two series to come closer together and even more unanticipated that it happened toward the end of the Great Recession.

On average, the marginal product of residential capital for the whole sample is 4.4% and 8.9% for the non-residential. There are multiple reasons why these values are not equal to each other. For one, we can think that the differences may arise from a risk premium. If the public receives information that the housing sector could be affected, the risk-premium increases, the capital for the housing sector will decrease, and investors will reallocate their money to the non-residential sector, which implies a higher value of MPK for the non-residential sector. Another reason stems from the fact that flows of capital do not account for land values or for the price of capital, both of which have been shown to reduce these differences.[7] Mismeasurement in constructing the capital estimates in the two sectors could also be erroneous.[8] Indirect taxes and income taxes make marginal product of non-residential capital higher than marginal product of residential capital, as discussed in Mulligan and Threinen (2010). Rented homes, new homes, and imputed services for owner occupied housing are not subject to any of the taxes mentioned previously.

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[7] Caselli and Feyrer (2007) show that financial markets allocate capital efficiently if we distinguish between the prices of capital goods versus consumption goods

[8] Griliches (1981) shows that we exclude intangible capital from capital stock measure.

For a more clear understanding of the evolution, we graph the residential MPK on the left axis and non-residential MPK on the left axis with grey shades representing the NBER recession dates, as shown in Figure 1.2. It is visible in the graph that during expansions, the MPKs have a tendency to move away from each other. When "good times" occur, the economy is booming and the residential and non-residential income is also intensifying, explaining the upward trend and the positive correlation of the two series. During "bad times", the economic activity experiences a slowdown, putting downward pressure on the interest rates, which will affect the residential sector more quickly than the non-residential sector. As a consequence, the non-residential MPK declines while residential MPK stagnates or even increases. It is not surprising in these circumstances that the two MPKs are negatively correlated. The correlation of the two series is negative (-0.75). Around 1969, there is a switch in the evolution of the series, when non-residential MPK started to go down and residential MPK went up, with the switch completed around 1980. The residential MPK series has a smoother appearance, while non-residential MPK is more volatile by nature. This was highly expected considering the nature of the capital involved and the duration of repaying the initial investment. Between 1970:1 and 1980:1, both series fluctuate slightly around their trend, keeping an almost constant value of 4.27% in the case of residential MPK and an exactly double value of 9.45% for non-residential MPK. Throughout the same period, the correlation of the series was still negative (-29.2%), but significantly lower than for the whole interval. The time before 1970:1 was characterized by a positive correlation of 40.4%, but this could be erroneously calculated and interpreted considering the flaws in the perpetual inventory method regarding the initial value of capital. However, the period after 1980:1, displays negative correlation of -42.16%, which is consistent with the finding for the whole sample. Visually, one might think that recessions are associated with slowdowns in non-residential investment and non-residential MPK lower at the troughs, and expansions with recoveries in residential investment, higher residential MPK at the peak.

Figure 1.3 depicts the evolution over time of the growth rates of residential and non-residential MPK. The most striking feature of the growth rates is the noticeable divergence during most recessions, with residential MPK growth moving very slowly down, and non-residential declining very abruptly. This behavior is explained by the evolution of capital and income for each sector. Residential income is sticky, especially in recessions which are short, so the movement in residential MPK comes from decreased residential investment during a recession. Recessions generally begin because the Fed induces them, in order to fight inflation, by raising the interest rate. Residential investment is highly sensitive to the interest rate partially because it is generally made using long-term collateralized loans. Thus, during a recession, the residential MPK generally increases. Non-residential MPK on the other hand is much more volatile. Non-residential income is not sticky, and decreases rapidly during a recession, pushing the non-residential MPK down. Non-residential investment also falls, pushing the MPK up, but generally not by as much as income.

There is strong evidence that the Great Recession was different. Residential investment dropped to its lowest value in 30 years. Part of the decline in residential investment is almost certainly due to the credit crunch that accompanied the Great Recession. Banks were hesitant to lend in a time of such turmoil, due to rising costs from having a "risk premium" on all new investments; this is consistent with the increasing MPK. Non-residential investment is likely to follow the same pattern, although the likelihood of the credit crunch affecting investment is much lower than in the residential sector. This is because labor is complimentary to non-residential capital. Thus, as labor decreases with the crisis, the demand for non-residential capital also decreases, leading to falling investment, and an increasing MPK.

1.3 Zero correlation measure and economic activity

Forecasting the growth of output is of great interest to policymakers and market participant, and any way to improve our ability to do better is an important contribution to the literature. Therefore, we suggest a new variable for forecasting real GDP growth and test it against a variety of more restricted models, including the results of previously successful forecasting models.

1.3.1 The correlation indicator

The variable proposed in this study is constructed based on the correlation of MPK for residential and non-residential sectors, based on the pattern observed for the business cycle. First, there are some necessary annotations about the way correlations were calculated. For each recession and following expansion, we will be calculating the correlation for that sample period after the rule: for the beginning of any recession, specifically, for the first three quarters the correlation will include the past four previous observations, and from quarter four onward, we exclusively pick only the previous observation of that particular recession. As an example, if we calculate the correlation for MPK residential and non-residential for the beginning of 1960 recession (1960:2), it will include three of the observations from the previous expansion: 1959:03, 1959:04, 1960:01 and the first observation of the recession, 1960:2. The four-quarter rule is compulsory, because of statistical properties of correlation. A correlation with less than three observations would be meaningless, and exactly three tends to give no useful information, beside the direction of the relationship between two variables. Hence, four observations is the minimum number that could be selected. We apply exactly the same logic for the expansions, and of course, in this case we register a higher number of correlation values, based on the fact that expansions are approximately six times longer than recessions. As a last observation, we would like to emphasis the importance of the last one and three correlations from an expansion, calculated with all the previous values recorded for that expansion.

In the data, between one to three quarters before the onset of a recession, the above-mentioned correlation takes values close to zero. These are not are not the only times when the correlation takes very low values, however there are a few scarce appearances at the beginning of 1990s. Our indicator consists in creating a dummy variable, ZEROCORR, that takes value one if the correlation is less than 7%, and zero otherwise.

Our proposed indicator performs better than the unaltered correlation because it focuses solely on predicting turning points. The result of forecasting GDP is a continuing trend, and to obtain a better forecast we need to be able to predict the actual switch from peak to through. Therefore, our indicator improves the forecast of economic activity when the economy is entering a recession. Our indicator is very similar to Hamilton's (2003) nonlinear transformation called oil price shock, with the only difference that the latter takes the maximum value of the previous three years window and zero for the rest.

1.3.2 Forecasting Models

We study four regression models with the purpose of analyzing the predictive content of zero correlation measure in various models for future GDP growth. We explore how sensitive the results are for both recursive and rolling windows. We analyze the predictive content up to 16 quarters. The finding of this exercise is that the zero correlation measure has important predictive content for real activity.

Because current and lagged rates of GDP growth may be useful for forecasting GDP, the first model used is a simple AR(4) specification, which will be the baseline specification for comparing forecasts. The lag order for the estimated model is set to four, following Hamilton (2003).[9] Specifically, consider regressing each quarter of GDP growth (y_t) on a constant and four lags of GDP growth. The regression equation is:

$$y_t^k = \alpha + \sum_{i=1}^{4} \beta_i \, y_{t-i} + \varepsilon_t \qquad \text{(Model 1)}$$

where $k \ \frac{400}{k}(\ln(Y_{t+k}) - \ln(Y_t))$ is annualized quarterly GDP growth at time t with Y_{t+k} real GDP in quarter $t+k$, and ε_t is the error term, $\varepsilon_t \sim N(0,1)$. As expected, the estimates of the autoregressive model indicate that past values of GDP growth help predict future GDP growth, but for a very short horizon. Model 1 is the nested model and serves as the benchmark for making comparisons with all the other models.

The second model builds on the first by including four lags of Hamilton's (2003) nonlinear oil shock measure. There is a vast and very influential literature on the benefits of including oil prices to forecast economic activity. Hamilton (1983) documented and exploited the significant negative relationship between oil price changes and future GDP growth. He documented the quarterly symmetric oil price changes significantly affecting the quarterly growth rate from 1948:2 – 1980:3. A symmetric relationship implies a growth spurt with the decline of oil prices. This explanation suffers from omitted variables, but works fairly well before 1986 due to positive oil price changes. However, the effect can also be

[9] Cochrane (2005) mentions that a few extra lags were added to make sure when identifying the lag order for time series models.

asymmetric, and as a result, a dramatic increase in oil prices might be followed by slow future growth. As a result, Hamilton's (1983) specification is appropriate until 1986, but flawed after as a cause of the increased nonlinearity induced by large negative oil price movements. This issue was fixed in Hamilton's (2003) paper, using a transformation of the raw oil price. The new measure of the transformed oil price shock exhibits a stable, negative relationship with future GDP growth.[10]

We are not interested in confirming this fact, but rather, we take it as given and use the peak oil model as a second baseline model. The model is a regression of each quarter's GDP growth (y_t) on a constant, four lags of GDP growth and four lags of the net increase in oil prices (OIL_{t-i}). The regression equation for the peak oil model is described as a linear regression model, even though the transformation of oil price changes is non-linear:

$$y_t^k = \alpha + \sum_{i=1}^{4} \beta_i \, y_{t-i} + \sum_{i=1}^{4} \gamma_i \, \mathrm{OIL}_{t-i} + \varepsilon_t \qquad \text{(Model 2)}$$

where OIL_t is the net percentage increase in oil prices over the previous twelve quarters if positive, and zero otherwise. In other words, to account for asymmetric effects of oil prices, the positive changes for the definition of an oil shock are used as follows:

$$\mathrm{OIL}_t = \begin{cases} o_t & \text{if } \{o_t - \max(o_{t-1}, o_{t-2}, \dots, o_{t-12})\} > 0 \\ 0 & \text{if } \{o_t - \max(o_{t-1}, o_{t-2}, \dots, o_{t-12})\} \leq 0 \end{cases}$$

where o_t is the natural log of the oil price given by the producer's price index (PPI). This nonlinear transformation restored the true relationship between oil and GDP growth for the complete chosen sample, avoiding a spurious forecast of a non-existent GDP growth increase when oil prices decline. Hamilton (2003) found the coefficient on the fourth oil lag to be negative and significant at the 1% level.

[10] An oil shock is equal to the difference between the current oil price and the maximum price in the past 4 or 12 quarters if the difference is positive and is equal to zero otherwise

The third model, once again builds on the baseline autoregressive model, and takes advantage of the new zero correlation variable. The regression equation for the zero correlation model is regressing each quarter of GDP growth (y_t) on a constant, four lags of GDP growth and four lags of the zero correlation measure ($\mathrm{ZEROCORR}_{t-i}$):

$$y_t^k = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \lambda_i \, \mathrm{ZEROCORR}_{t-i} + \varepsilon_t \qquad \text{(Model 3)}$$

We compare this model (Model 3) with the autoregressive model (Model 1) to see which fits the data better and which model better forecasts GDP growth. The univariate model provides just a benchmark for our analysis, allowing for the evaluation of whether the newly integrated indicator explains changes in economic activity and improves the fit for the nesting models.

The final model that we consider is a model with both Hamilton's peak oil measure (2003), and the zero correlation measure created in this paper. We are interested in showing that the inclusion of the zero correlation measure can improve the predictability of GDP growth over the oil model or the autocorrelation model. We proceed by regressing each quarter's GDP growth (y_t) on a constant, four lags of GDP growth, four lags of the net increase in oil prices (OIL_{t-i}), and four lags of the zero correlation measure ($\mathrm{ZEROCORR}_{t-i}$). The regression equation for model with zero correlation and the oil model measure included is then:

$$y_t^k = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i \, \mathrm{OIL}_{t-i} + \sum_{i=1}^{4} \lambda_i \, \mathrm{ZEROCORR}_{t-i} + \varepsilon_t \qquad \text{(Model 4)}$$

Figure 1.4 plots oil and ZEROCORR on the same graph.

In order to see if our indicator truly helps explain the variation in GDP growth, we need to have a statistically significant negative coefficient on at least one of the lags of ZEROCORR. The criterion is met for Model 4, the one-quarter ahead recursive regression, with the coefficient on $\mathrm{ZEROCORR}_{t-2}$ negative and significant until 1990 and $\mathrm{ZEROCORR}_{t-3}$ negative and significant (almost all the time) from 1990 to the end of the sample. The only drawback is that the significance is generally only at the 10% level. In contrast, the Model 3 one-quarter ahead recursive regression only satisfies this condition between 1982 and 1990, still at the 10% level. It is important to note that the coefficients change over the sample and the fit or $\overline{\mathrm{R}}^2$ also varies notably, so it is necessary to analyze the indicator using a rolling specification.

The one-quarter ahead results for Model 4 are not as strong as the recursive in this case, with $\mathrm{ZEROCORR}_{t-2}$ being negative and significant at the 10% level (almost always) until 1986, and then loses its significance between 1986 and 1998, after which $\mathrm{ZEROCORR}_{t-3}$ becomes significant at the 1% level and keeps the significance through the end of the sample period. Model 3, once again performs not desirable, especially at the end of the sample, where $\mathrm{ZEROCORR}_{t-3}$ is negative and significant at the 1% level through 1991 and at the 10% level through 1996. Afterwards, it becomes insignificant for the remainder of the sample. The only other place a negative significant coefficient is found is $\mathrm{ZEROCORR}_{t-2}$ from about 1975 to 1978, generally at the 10% level. As a final observation, $\mathrm{ZEROCORR}_{t-1}$ is rarely significant, which seems to suggest that this is a leading indicator, even with data lag times factored in. Tables 1.1 and 1.2 summarize the results for Model 4.

1.3.3 In-sample predictive content

We examine the in-sample predictive content of the zero correlation measure between the residential and non-residential MPK. The sample period of our analysis begins in 1947:1 and extends to 2011:1 using exclusively calculated data according to the specification from Section 2. Data for economic activity is represented by quarterly GDP growth rates from the St. Louis FRED database, and the measure for oil is calculated using Hamilton's (1998, 2003) methodology. To evaluate in-sample fit, we use the adjusted R-squared ($\bar{R}^2$), where higher values are preferred. We check the value of $\bar{R}^2$ for each of the models using two types of regressions, rolling (Table 1.3) and recursive (Table 1.4). The rolling regressions utilize a fixed window to set the coefficients used to build the forecast. In this case the window is 25 years, meaning that each time the regression moves forward by one quarter, one quarter is trimmed off from the beginning of the sample. The recursive regression, on the other hand, has an expanding window. The first recursive window is 25 years (the first forecast is the same for both the rolling and recursive regressions) and then one observation at a time is added to the end of the sample, increasing the sample size. We report the $\bar{R}^2$ separately for each regression type, but put all four models on one graph for ease of comparison, as depicted by Figures 1.5 and 1.6. The $\bar{R}^2$ is generally higher for models with zero correlation, with the exception of a period in the mid 1980s to the mid 1990s, and again after 2006, for the rolling regression. The recursive regression $\bar{R}^2$ is strictly higher for the models including zero correlation as compared with the baseline models.

1.3.4 Granger Causality

Previous studies have scrutinized Granger causality among oil measures and GDP growth. Hamilton (1983) showed that US recessions are systematically preceded by large crude oil price boosts and, consequently, the crude oil price Granger-causes real output on the sample ending in 1980.[11] Hooker (1996) criticized the linear time-series approach previously described, due to the fact that oil prices no longer Granger-cause real output. In response, Hamilton (1996, 1998) created a new nonlinear transformation of oil prices, which sustains the initial result on Granger causality even when more recent data are included.

Granger causality tests prove useful when OLS fails to determine the direction of the relationship between oil and the zero correlation measure with GDP. The argument made is that if the two measures lead to changes in output growth, we can rule out the possibility of real output changes causing the oil and zero correlation changes. The test is set to estimate the regressions for Model 3 and Model 4 both including and excluding the zero correlation measure as an explanatory variable. The causal association between the zero correlation measure and output is verified by Model 3 and Model 4 better explaining GDP growth relative to Model 1, Model 2 respectively. Both Model 3 and 4 Granger cause real GDP growth.

We start by testing the hypothesis that the zero correlation measure helps forecast GDP. The null hypothesis in this case states that all coefficients on the zero correlation measure equal zero; if we reject the null, then the unrestricted Model 3 is reduced to the restricted Model 1 and $\mathrm{ZEROCORR_t}$ Granger causes y_t. In addition, the unrestricted Model 4 reduces to Model 2, with $\mathrm{ZEROCORR_t}$ and $\mathrm{OIL_t}$ is Granger causing y_t. All usual OLS t-statistics and F-tests on the regression estimates are valid when drawing the conclusions. A more formal way to write this is:

$$\mathrm{H_0}: \lambda_\mathrm{i} = 0 \text{ for all i}\{1,2,3,4\}$$

[11] The positive correlation between an oil price increase and US recessions was noticeable after the OAPEC embargo, the Iranian revolution in 1978, and the outbreak of the Iran-Iraq war in 1980.

$$H_1\text{: At least 1 } \lambda_i \neq 0$$

We perform Granger causality tests for both models containing the ZEROCORR variable and both regression types. The p-values of the F-test are provided on the graph, so it is clearly visible when ZEROCORR Granger causes real GDP growth. For the rolling window, comparing Model 3 with Model 1, the null hypothesis is generally rejected, often at the 1% level, with the exceptions of 1989-1997 and 2001-2003, where the p-value spikes, causing a failure to reject the null. Comparing Model 4 with Model 2 yields similar results, except at the beginning of the sample, where we can only reject the null hypothesis at the 10% level, and from 1983-1997, where we fail to reject the null. From 1998 on, the rejection is at least at the 5% level, and generally at the 1% level. The recursive regression does not change these basic results much. When comparing Model 4 with Model 2, we reject the null at the 1% level until 1990, after which there is a sharp increase in the p-value, which does not return to acceptable levels for the remainder of the sample. Figures 1.7 and 1.8 plot the p-values for these results. Model 3 fares much better then Model 1, and is significant at the 5% level at the beginning of the sample, with the p-value spiking up again around 1990; however, this time it returns to 10% significance around 2002. The results are presented in Figures 1.9 and 1.10. This is discouraging, of course, but not unexpected given the results from the rolling regressions and the $\overline{R}^2$ results. It seems that ZEROCORR struggles to explain GDP growth in the 1980s and 1990s, and this trouble persists in the recursive regressions because of the expanding window, though it is removed in the rolling window regressions.

1.4 Out-of-Sample predictability

When making forecasts, it is important to compare the out-of-sample predictability. It is often the case that a model may provide excellent in-sample fit (high $\bar{R}^2$ and low p-values for Granger causality leading to rejection of the null hypothesis), but this does not guarantee significant out-of-sample predictability, leading to a dreadful forecast.[12] The in-sample forecasts always present the danger of spurious predictability, with out-of-sample forecasts becoming imperative for the accuracy of a prediction. The model of interest for our investigation, for which we use oil shock and the zero correlation measure, is quite the opposite. There are some issues with the Granger causality, but the out-of-sample predictability is significantly better than for the alternative models.

We now look at the out-of-sample forecast accuracy of one-quarter-ahead output growth for the Models 1 to 4 defined in the previous sections. An out-of-sample comparison involves estimating the model parameters for a predetermined subsample, and using them in the forecasting equation for the latter part of the sample. The forecasts and actual data are presented for both rolling and recursive regression in Figures 1.11 to 1.18. The forecasts are made over the period from 1973:1 to 2011:1, but the comparative predictive accuracy of the forecasts is presented over a more recent period of 1985:1 to 2011:2 using competing methodologies, well-established in the literature.

To examine the predictive power of the zero correlation measure and oil shocks for real output growth, we use evaluation statistics for point estimates, previously proposed in the literature. We compare the point forecasts in terms of mean square prediction errors (MSPEs) for Model 4 versus Model 2, and Model 3 versus Model 1 for different out-of-sample periods. Under the null hypothesis that the parsimonious benchmark (Model 1 and 2)

[12] For more information, see Granger (1990).

is the true data generating process (DGP), the use of estimated non-benchmark models (Models 3 and 4) that nest the benchmark induces noise for the out-of-sample forecasts. The Clark and West MSPE, which we will discuss later, is an attempt to reduce the noise when making forecast comparison for nested models.

Testing if the output growth is equally linearly predictable with nested and non-nested models requires, as a first check, a comparison of the mean square prediction error (MSPE) for each model. The model with a lower than one ratio of MSPE, is said to have a better out-of-sample predictability. The ideal case would be for the unrestricted model to outperform the restricted model.

To test the out-of-sample predictability, we use two tests. First, we use the DMW test, introduced by Diebold and Mariano (1995) and West (1996), and CW test, introduced by Clark and West (2006). The CW test is actually an adjustment to the DMW test, making it applicable to nested models. Since we are comparing nested models, the DMW test using standard critical values is inappropriate, therefore, we will use the appropriate asymptotic critical values as explained in McCracken (2007). These considerations are central in forecasting GDP growth, because Model 1 is nested in Model 3, and Model 2 in Model 4. It is important to note that for both tests of out-of-sample predictability, one-quarter-ahead forecasts are used, and both are based on the mean squared prediction error (MSPE).

For the DMW test, we test the null hypothesis that the nested baseline model, without the zero correlation measure, has the lower MSPE:

$$\mathrm{H}_0\colon \mathrm{MSPE}_1 - \mathrm{MSPE}_2 = 0$$

$$\mathrm{H}_1\colon \mathrm{MSPE}_1 - \mathrm{MSPE}_2 > 0$$

where forecasting equation 1 is the nested forecast and equation 2 is the nesting forecast. For example, consider Model 1 and Model 3 from above:

$$\text{Model 1:}\ \ y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \varepsilon_t$$

$$\text{Model 3:}\quad y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \lambda_i\, \mathrm{ZEROCORR}_{t-i} + \varepsilon_t,$$

and

$$\mathrm{MSPE} = \frac{(y_t - \mathrm{FORECAST}_t)^2}{P}$$

Model 1 is nested in Model 3, so we compare whether the MSPE of Model 1 is greater than the MSPE of Model 3, or not. This is a one sided test, because if the MSPE of Model 3 is greater than or equal to MSPE of Model 1, then Model 1 is preferred.

Likewise, Model 2 is nested in Model 4:

$$\text{Model 2:}\quad y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i\, \mathrm{OIL}_{t-i} + \varepsilon_t$$

$$\text{Model 4:}\quad y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i\, \mathrm{OIL}_{t-i} + \sum_{i=1}^{4} \lambda_i\, \mathrm{ZEROCORR}_{t-i} + \varepsilon_t$$

Thus, we compare whether the MSPE of Model 2 is greater than the MSPE of Model 4, following the steps outlined above.

To get the test statistic for the DMW test, the first step is to construct a series of the squared prediction error differential as follows:

$$\hat{f}_{\mathrm{DMW}} = (y_t - \mathrm{RESTRICTFOR}_t)^2 - (y_t - \mathrm{UNRESTRICTFOR}_t)^2.$$

Then, we regress $\hat{f}_{\mathrm{DMW}}$ on a constant, and the t-statistic on the constant is the DMW test statistic, which is also known as MSE-t. When comparing nested models, such as those we examine in this study, using the standard normal critical values causes the DMW test to be severely undersized, to correct for this we use McCracken (2007)'s critical values. We perform the DMW test for both rolling and recursive forecasting regressions, comparing Model 3 to Model 1, and Model 4 to Model 2. The results are presented in Table 1.5. The rolling regression performs better than the recursive regression for both model comparisons. Model 4 is always superior to Model 2, and Model 3 is always superior in the rolling regression, but is insignificant for much of the later part of the sample.

The Clark West statistic is very similar to the DMW statistic, but makes an adjustment to the MSPE in order to achieve proper size when the restricted forecast is nested. For the CW test, the hypotheses are:

$$\mathrm{H_0: MSPE_1 - (MSPE_2 - \ adjustment) = 0}$$

$$\mathrm{H_1: MSPE_1 - (MSPE_2 - \ adjustment) > 0}$$

Much like the DMW test, the first step in getting the test statistic involves constructing a series of the squared prediction error differential adjusted

$$\hat{\mathrm{f}}_{\mathrm{CW}} = (\mathrm{y_t} - \mathrm{RESTRICTFOR_t})^2 - ((\mathrm{y_t} - \mathrm{UNRESTRICTFOR_t})^2 - (\mathrm{RESTRICTFOR_t} - \mathrm{UNRESTRICTFOR_t})^2).$$

We then regress $\hat{\mathrm{f}}_{\mathrm{CW}}$ on a constant and the test statistic is the t-stat on the constant. The CW test has already been adjusted, so standard asymptotic critical values for the t distribution are applicable.

As with the DMW test, we perform the CW test for both rolling and recursive regressions, and for both Model 3 versus Model 1, and Model 4 versus Model 2. The results, reported in Table 1.5, are quite similar to the DMW test, where Model 4 is always preferred to Model 2, for both rolling and recursive regressions. The results on Model 3 versus Model

1 are not nearly as strong, the majority of the time Model 3 is preferred (rejection of the null), but from 1990:4 to 1998:3 Model 1 is preferred (failure to reject the null) for both rolling and recursive regressions.

Another important way of comparing forecasts is to use the ratio of MSPEs, where $\mathrm{MSPE}_{\mathrm{unrestricted}}/\mathrm{MSPE}_{\mathrm{restricted}}$ should be less than one. For the rolling regressions, one quarter ahead, this is always the case Model 3 versus Model 1 approaches, but never reaches or exceeds one. The one-quarter-ahead recursive regressions do not do quite as well, with Model 3 versus Model 1 occasionally exceeding one, and a value very close to or equal to one from 1991 onward. Model 4 vs. Model 2 fares better, once again, never equaling or exceeding one, but approaching one very closely. The ratio of MSPEs is shown in Figures 1.19 to 1.22. Comparing Model 4 to Model 2, using the rolling regression, it is quite evident that the MSPE for Model 4 is smaller than that of Model 2 with a ratio of only 0.934 throughout the entire sample, but does not perform nearly as well under a recursive framework with a MSPE of 0.996. Model 3 does not perform nearly as well against Model 1 when the entire sample is considered, with a value of 0.993 for the rolling regression and 0.999 for recursive. Selected results are presented in Table 1.6.

1.5 Conclusions

We have constructed a new indicator of economic activity involving the correlation between residential and non-residential marginal product of capital and demonstated its usefulness in economic forecasting. The in-sample fit and out-of-sample performance of standard forecasting models are improved by the inclusion of our indicator. To examine in-sample fit we perform Granger causality tests and compare the adjusted R-squared. We test out-of-sample predictability using the DMW test with McCracken critical values and the CW test, as well as examining the ratio of MSPEs. The in-sample fit shows more improvement in the recursive framework compared to the rolling framework, while out-of-sample performance exhibits the opposite trend, improving more in the rolling framework than in the recursive.

The current empirical analysis leads to several important conclusions about the relationship between GDP growth and our indicator. First, the model's explanatory power is visibly improved when including the zero correlation measure of the non-residential and residential sectors. Second, our indicator improves upon a strict autoregressive model. The evidence is much stronger for the model with both an autoregressive and oil component, where inclusion of our indicator always improves out-of-sample predictability. The increase in out-of-sample predictability is striking for the autoregressive model both, with both DMW and CW tests generally, but not always, significant. However, for the model also including oil, both the DMW and CW tests are always significant.

Although a myriad of factors could be related to GDP growth, our indicator significantly improves forecasts of GDP growth, especially when Hamilton's (2003) peak oil measure is also used. The complementarity between these two measures is remarkable, as many things could improve the GDP growth forecasts on their own, but most fail to add anything when well-established explanatory variables such as oil are used. Not only does our indicator not lose its significance when oil is included in the forecasting equation, but it is enhanced.

1.6 Figures and Tables

Figure 1.1 Residential and Non-residential MPKs

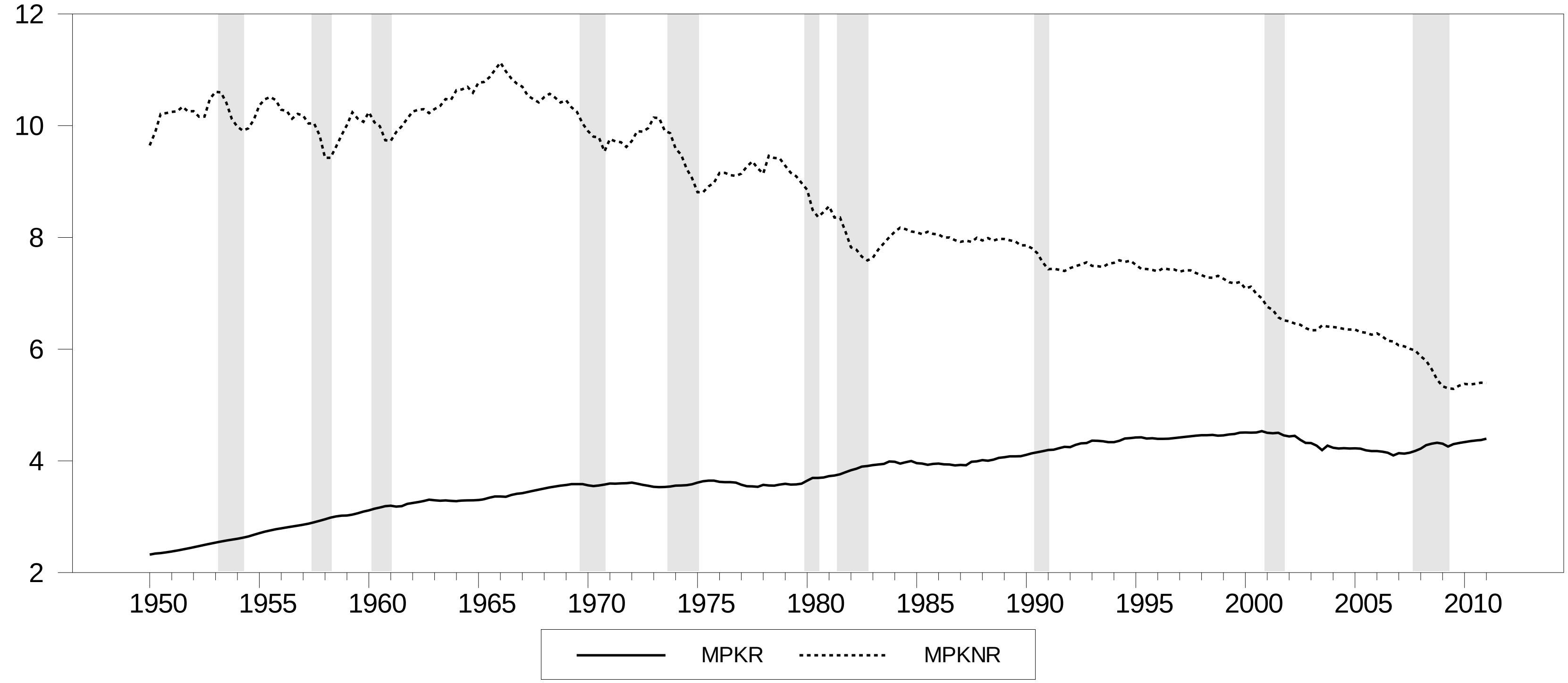
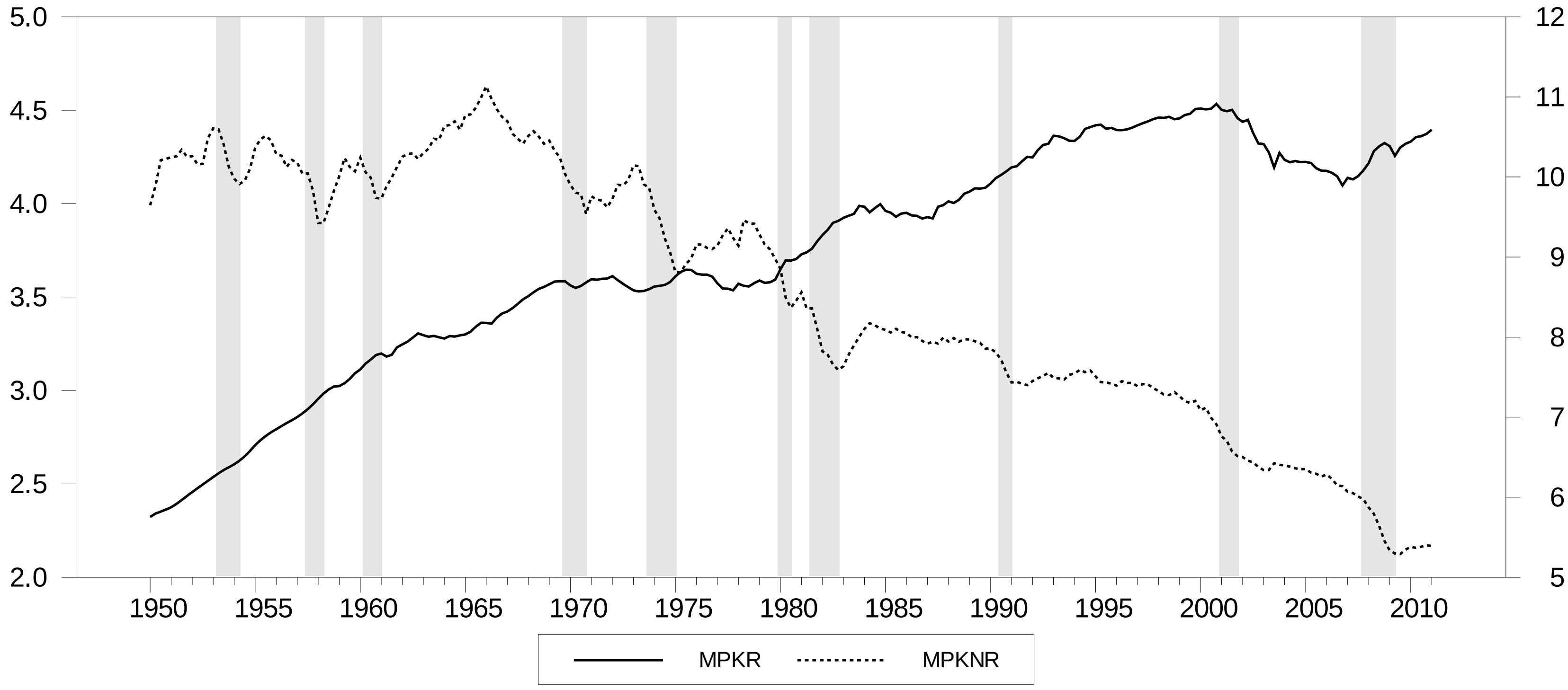
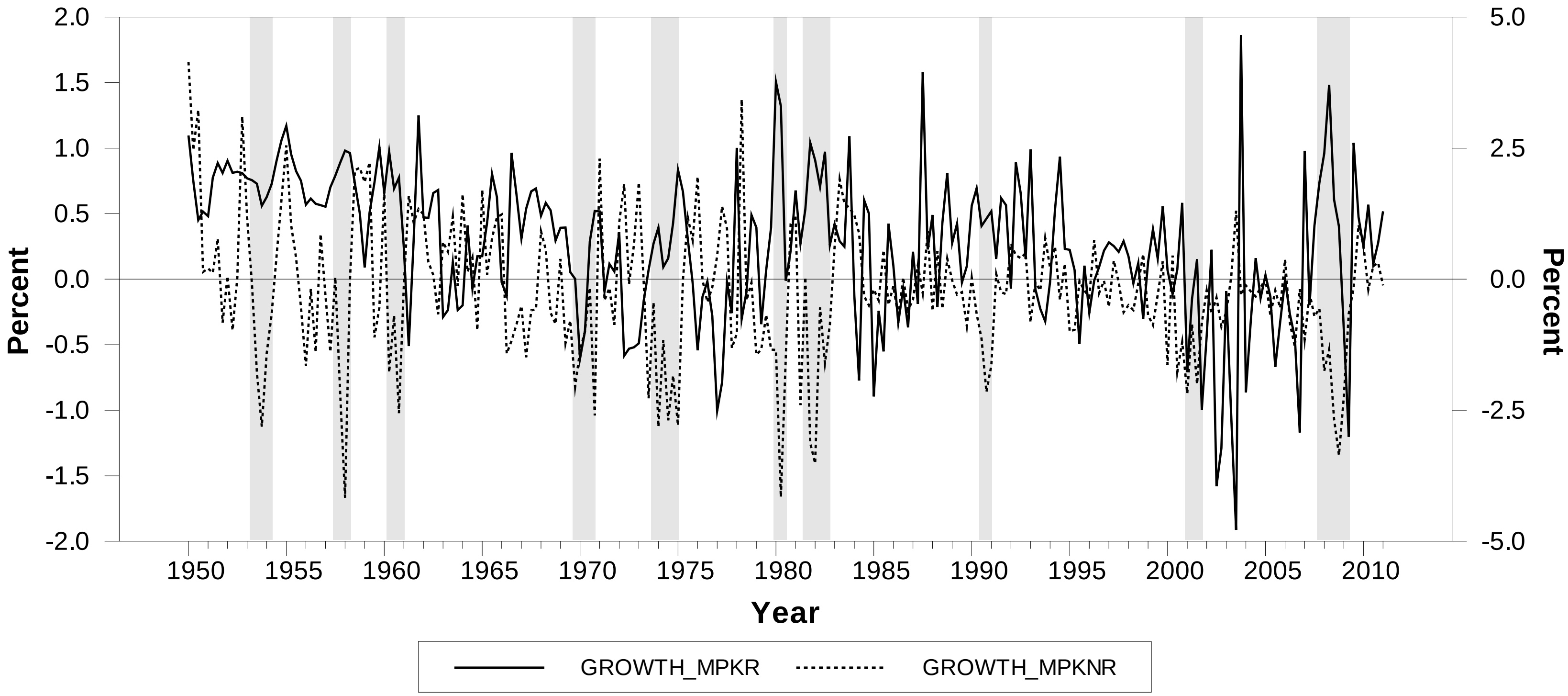


Figure 1.2 Residential and Non-residential MPKs



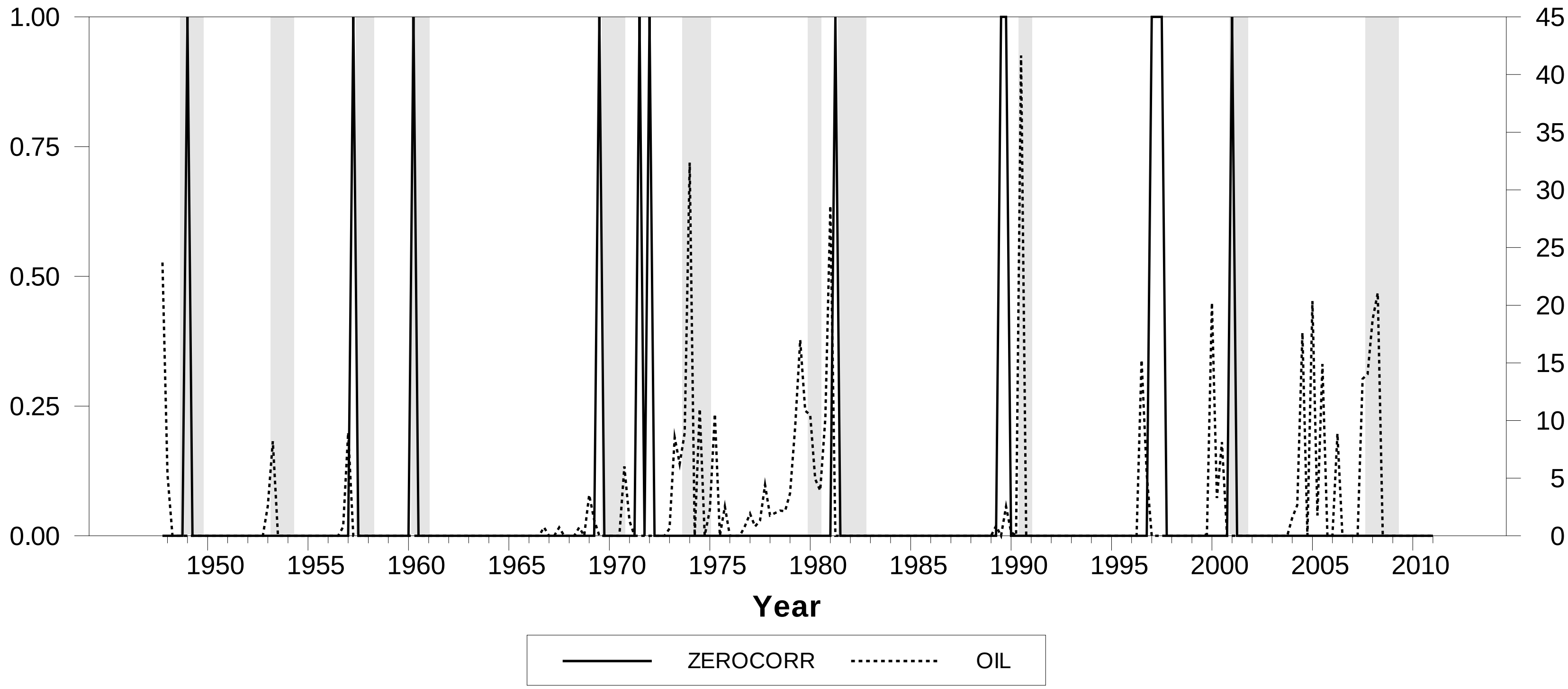
Note: MPKR left axis, MPKNR right axis

Figure 1.3 MPK Residential and Non-residential Growth Rates



Note: GROWTH_MPKR left axis, GROWTH_MPKNR right axis

Figure 1.4 ZEROCORR and Oil with NBER Recession Dates



Notes: Zerocorr on left axis, Oil on right axis, NBER recession dates shaded

Figure 1.5 Adjusted R-squared for Rolling Regression

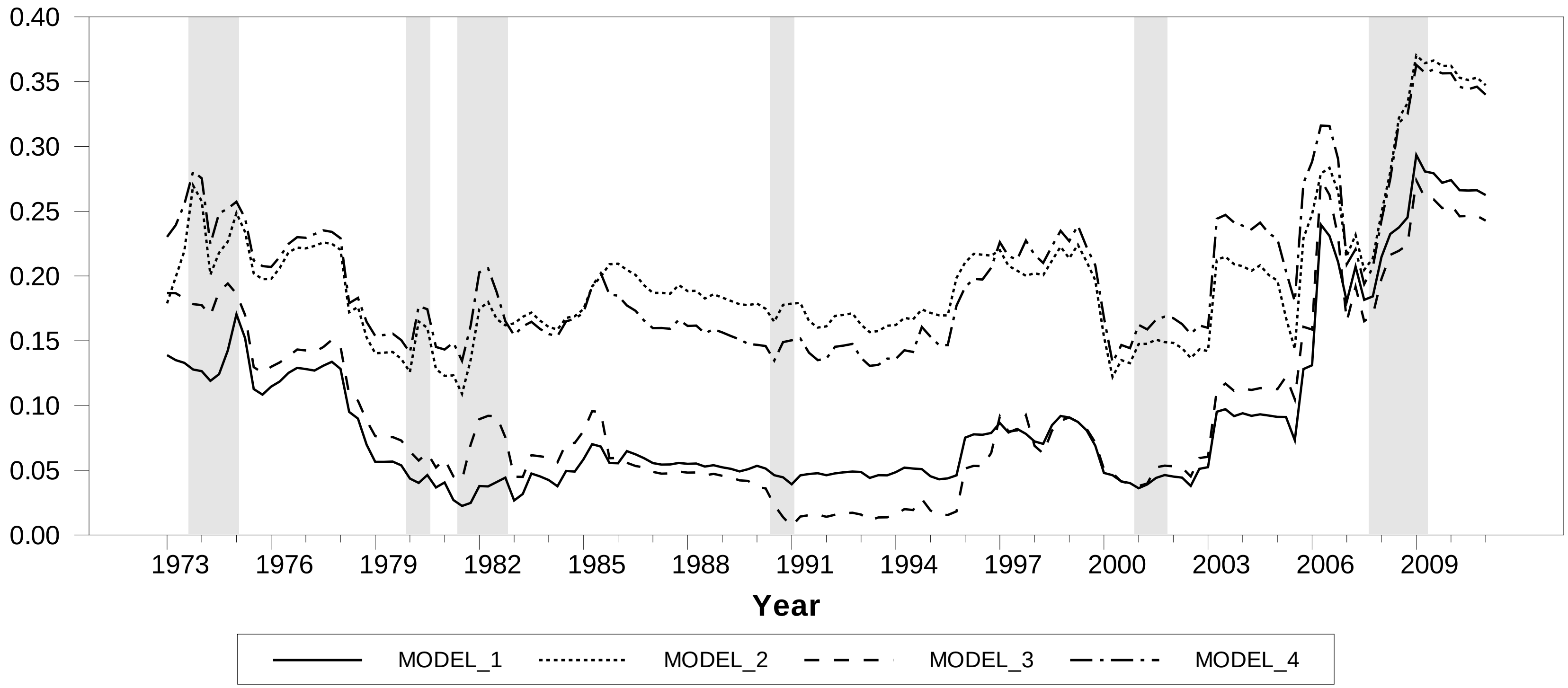


Figure 1.6 Adjusted R-Squared for Recursive Regression

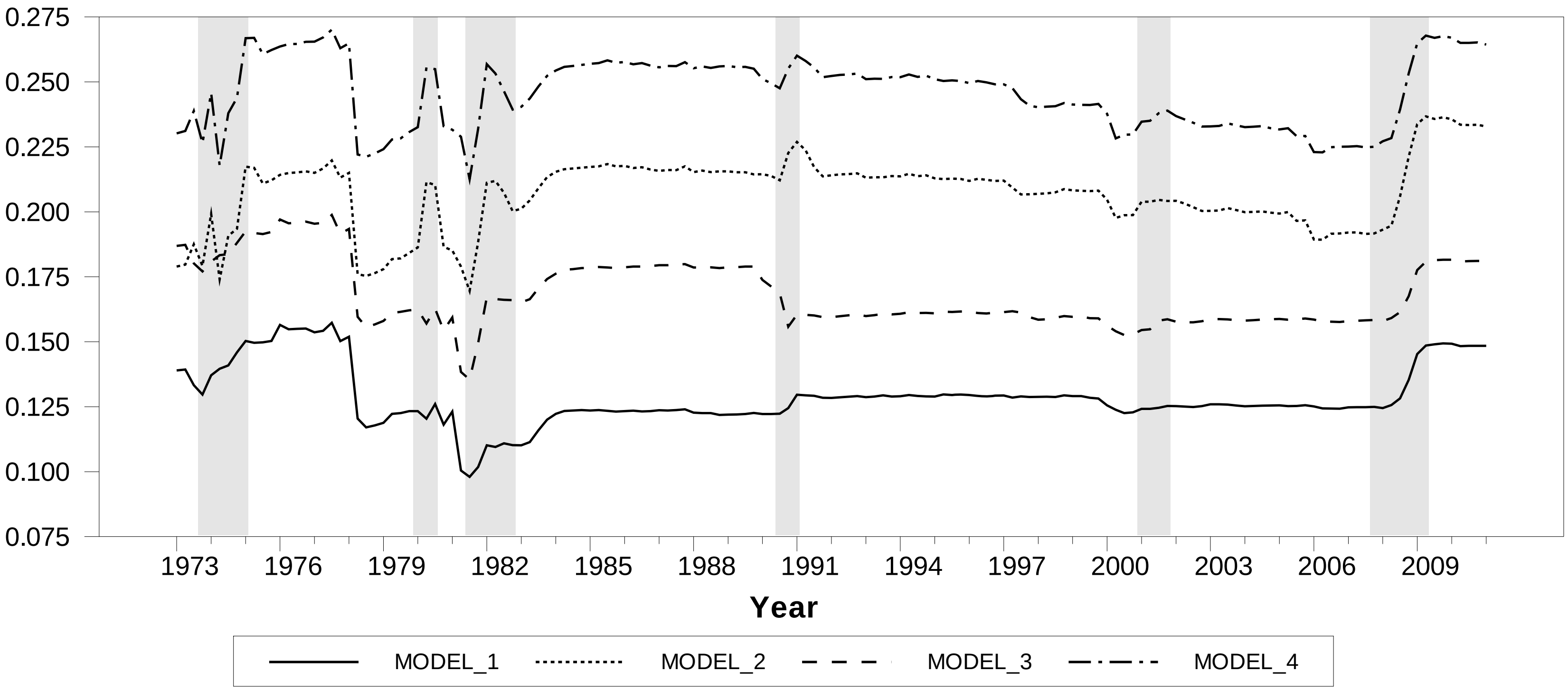


Figure 1.7 Granger Causality Model 4 vs. Model 2

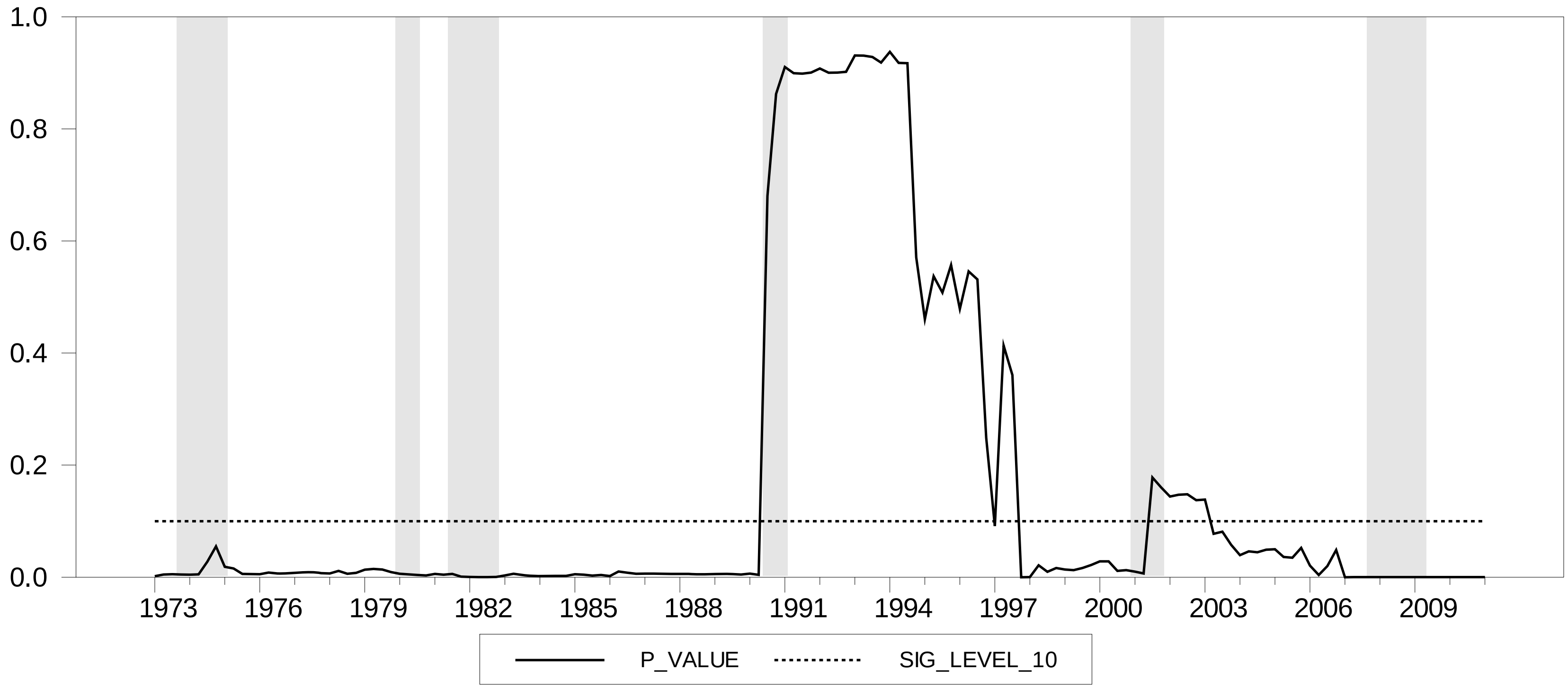


Figure 1.8 Granger Causality Model 4 vs. Model 2 Recursive

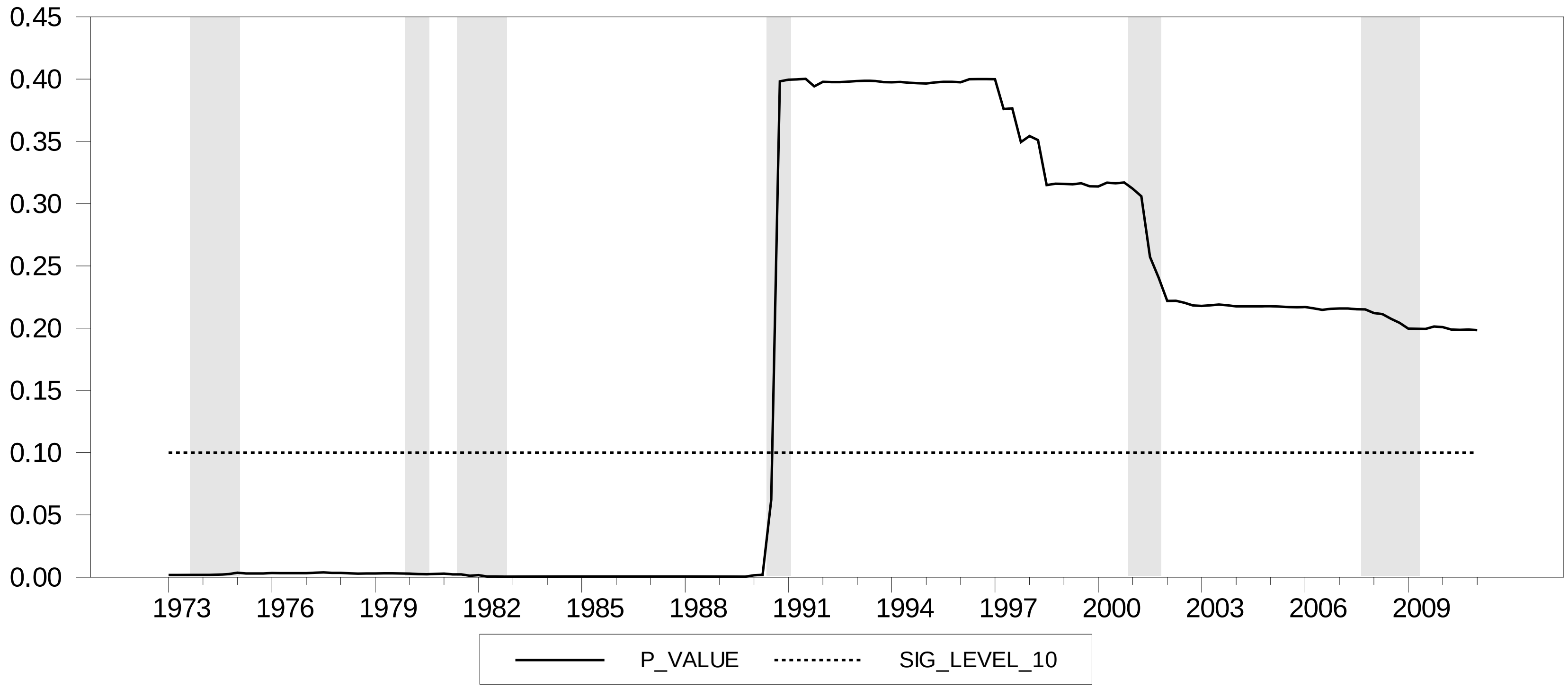


Figure 1.9 Granger Causality Model 3 vs. Model 1 Rolling

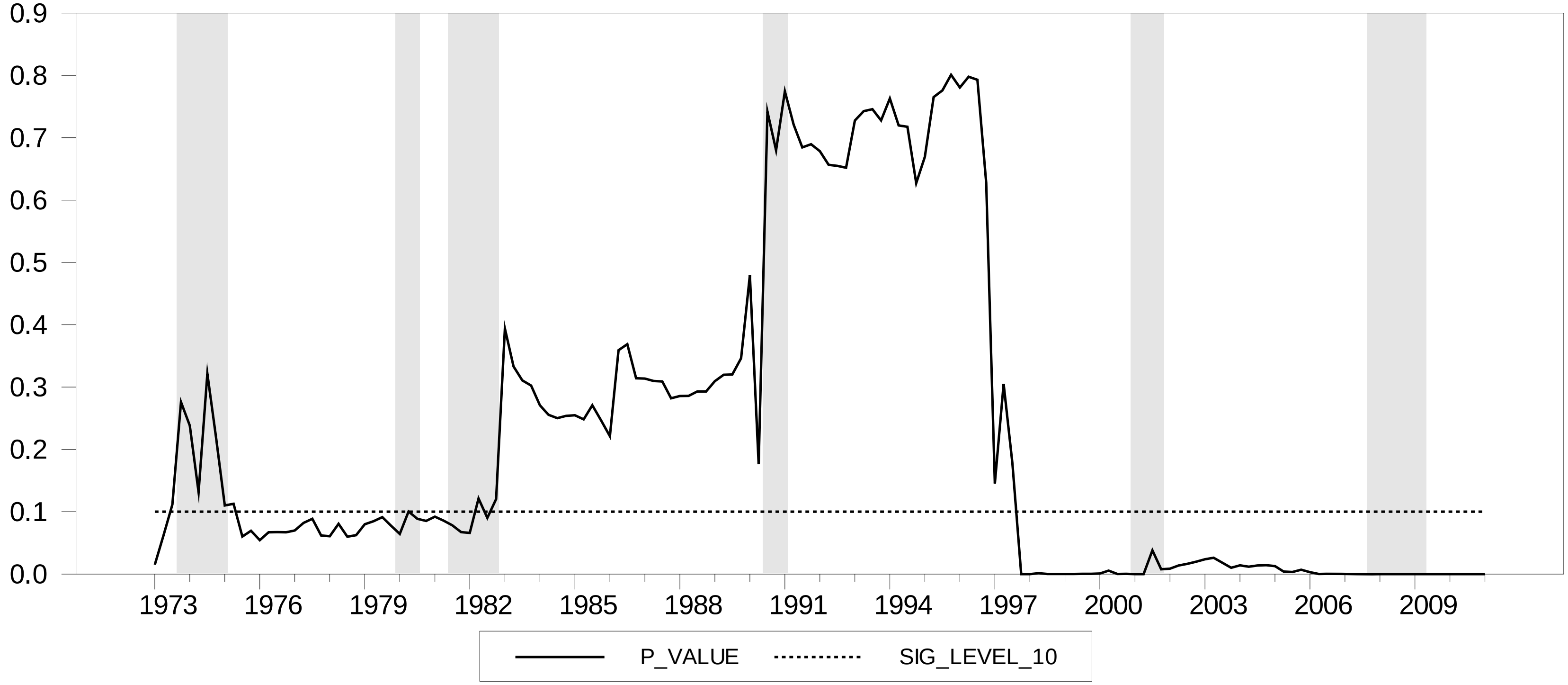


Figure 1.10 Granger Causality Mdoel 3 vs. Model 1 Recursive

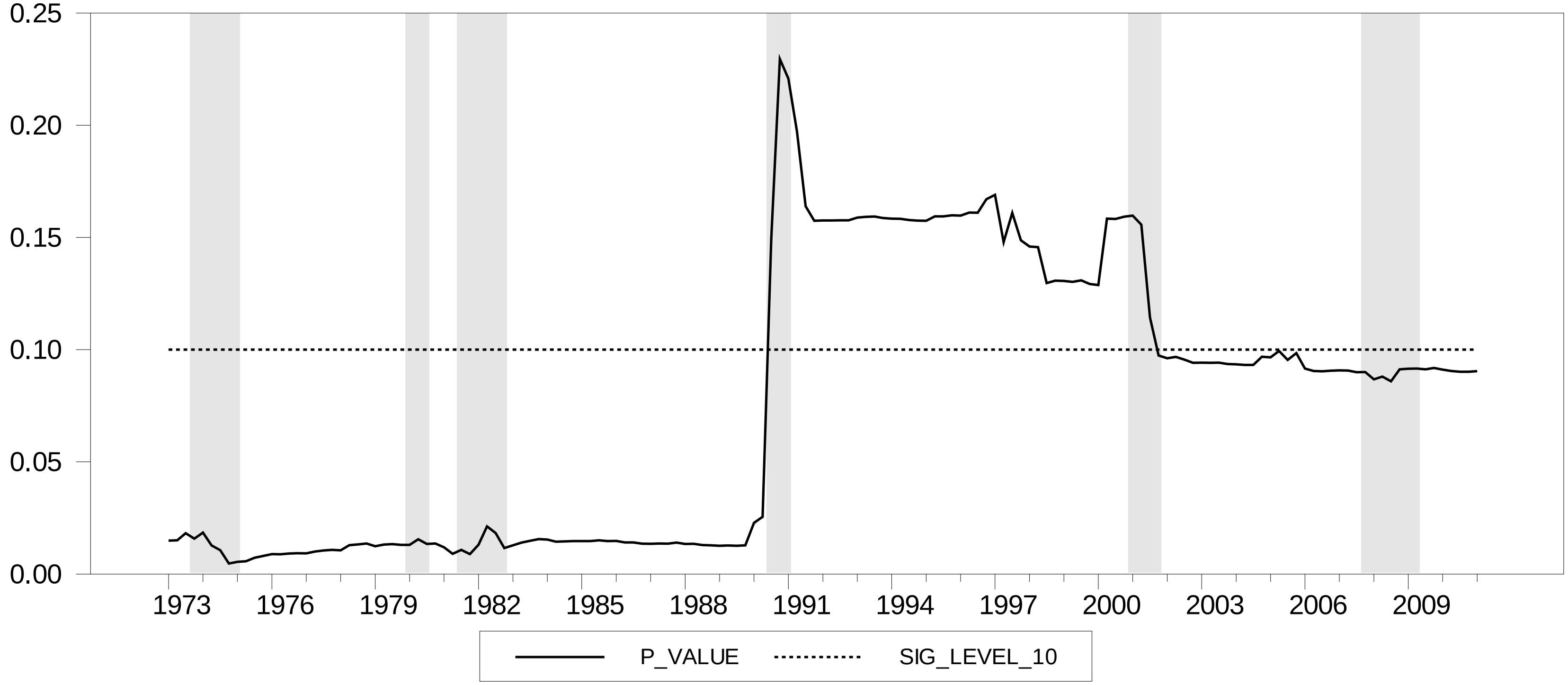
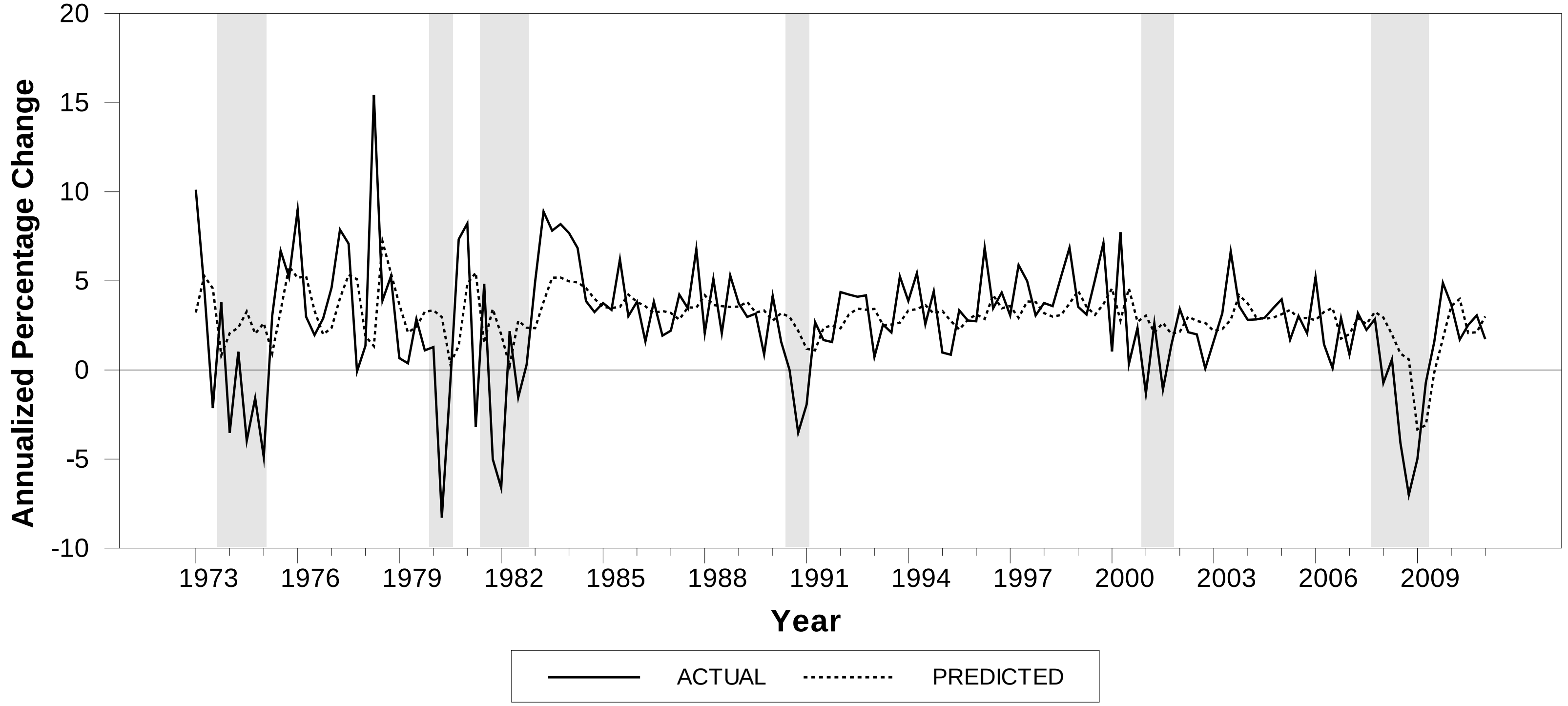


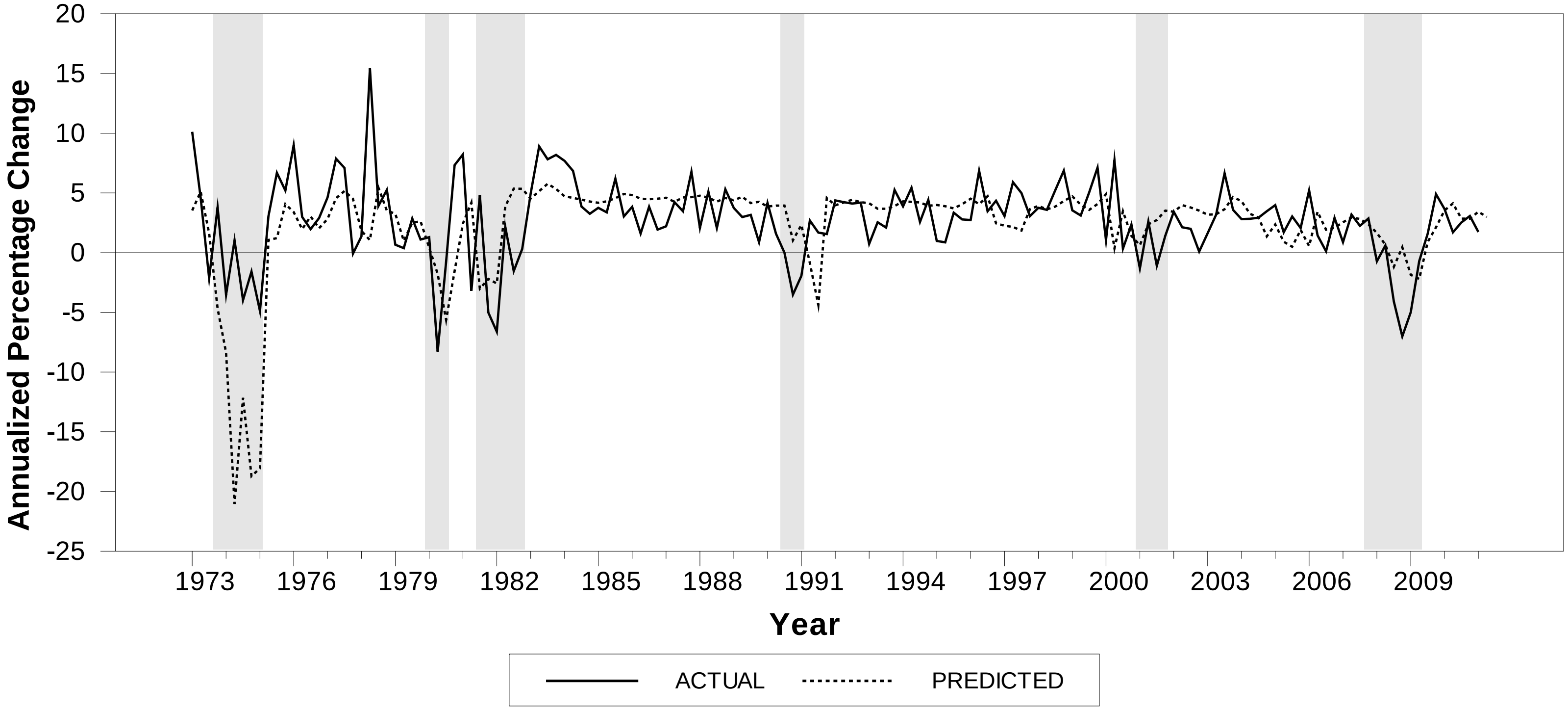
Figure 1.11 Actual and Annualized Quarterly Growth, Model 1 Rolling



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$$

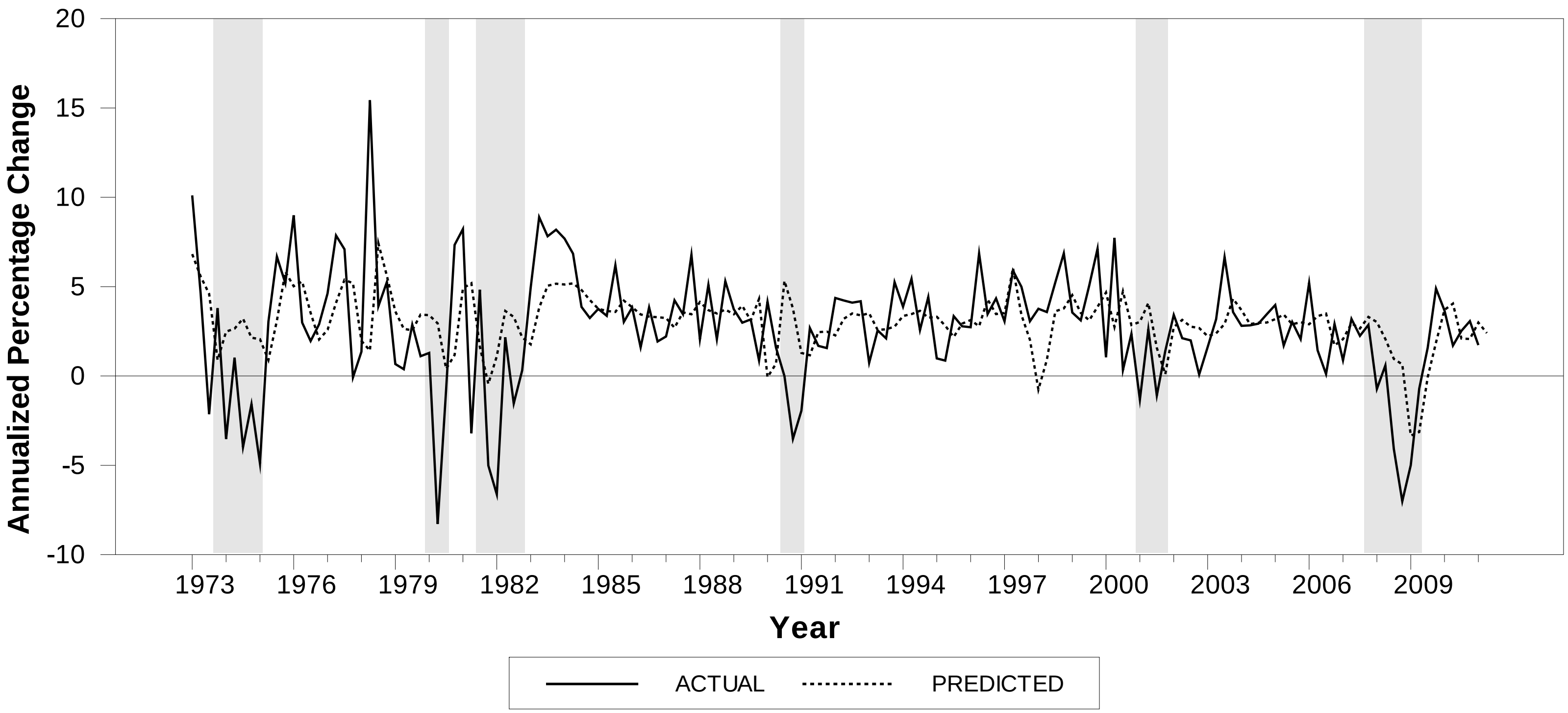
Figure 1.12 Actual and Predicted Annualized Quarterly Growth, Model 2 Rolling



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$$

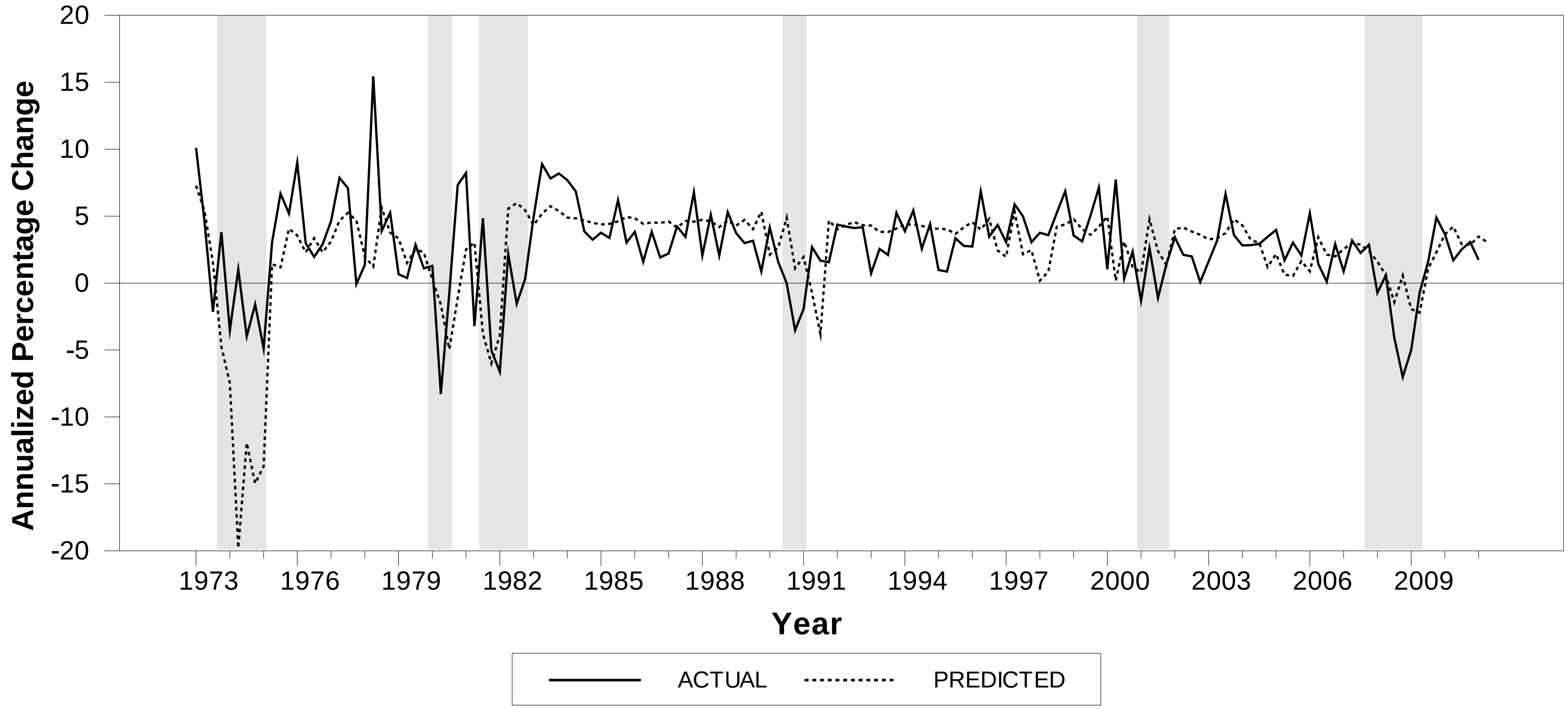
Figure 1.13 Actual and Predicted Annualized Quarterly Growth, Model 3 Rolling



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$$

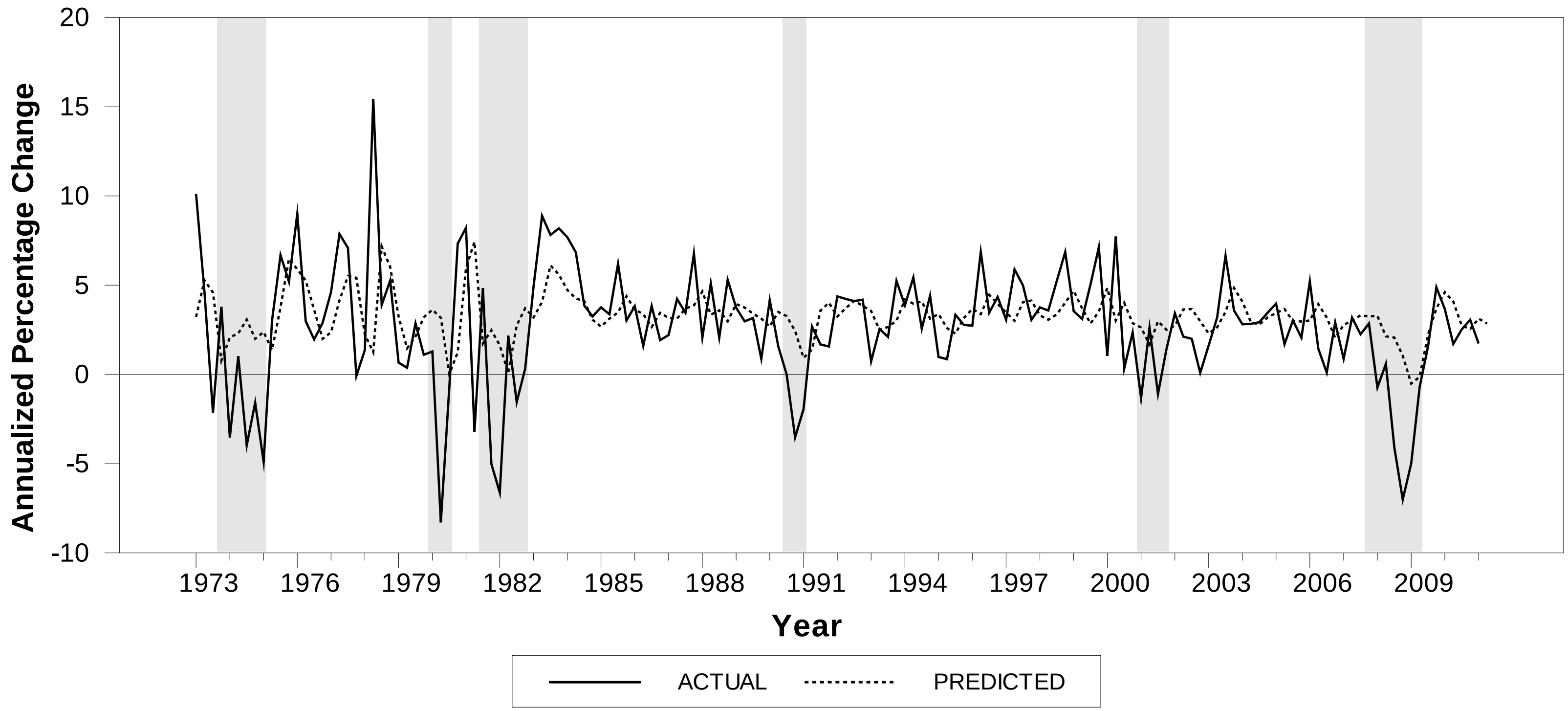
Figure 1.14 Actual and Predicted Annualized Quarterly Growth, Model 4, Rolling



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$$

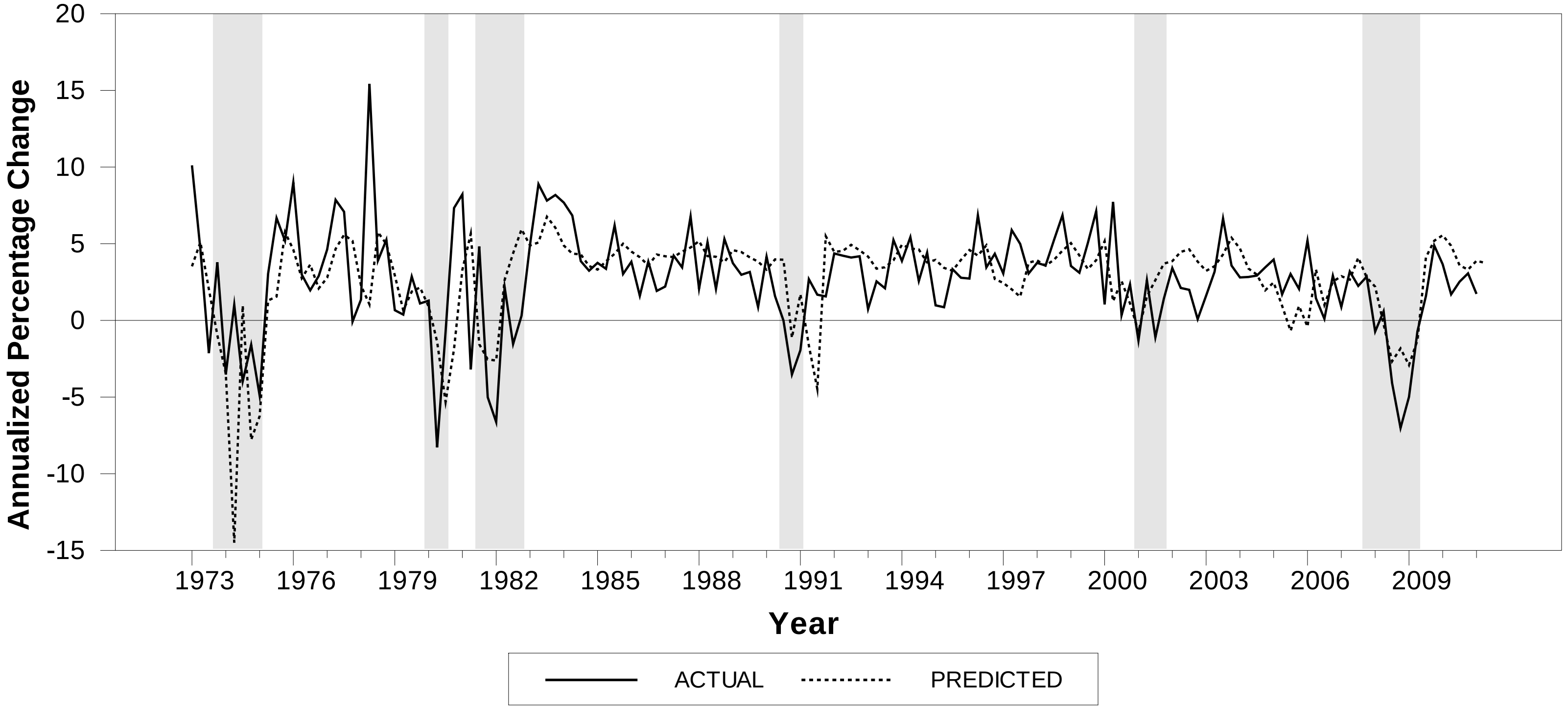
Figure 1.15 Actual and Predicted Annualized Quarterly Growth, Model 1 Recursive



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$$

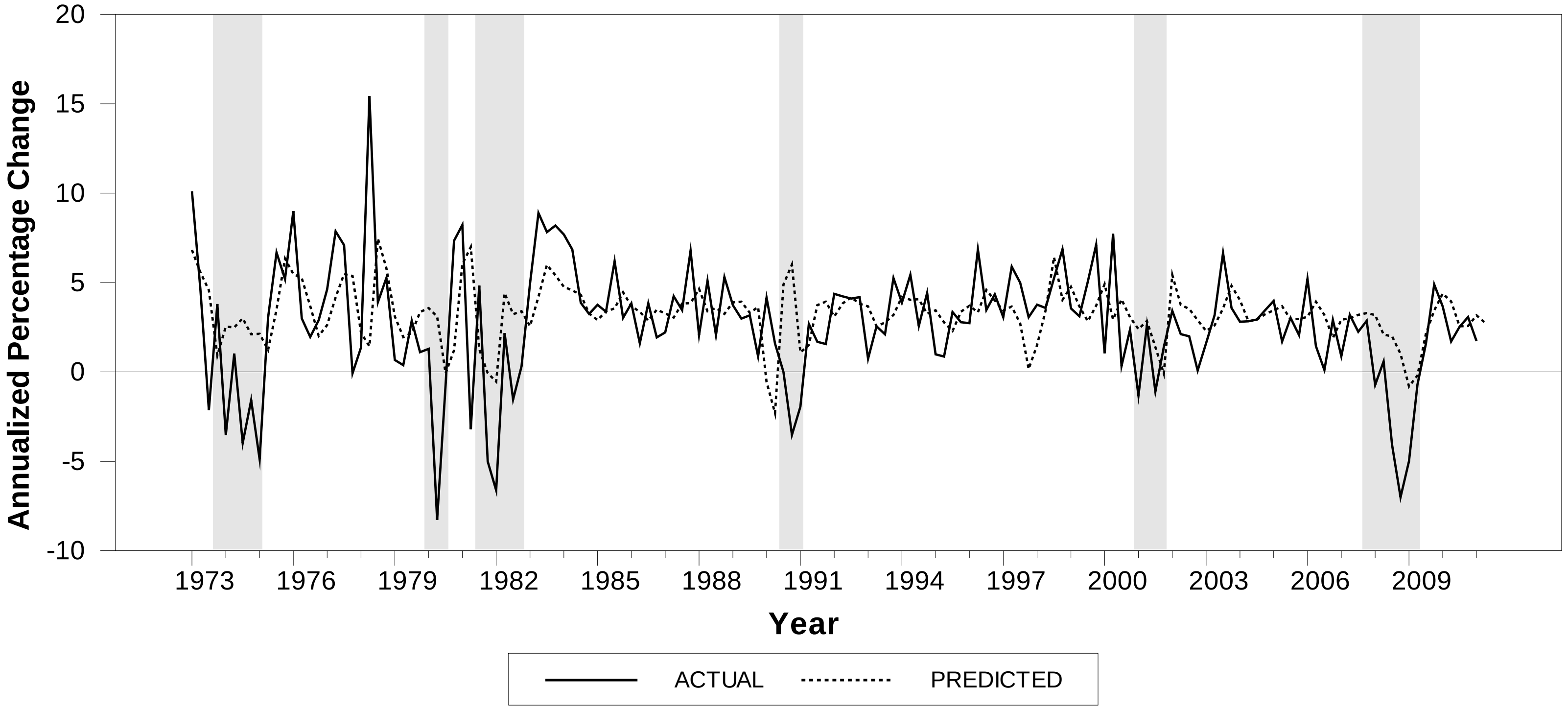
Figure 1.16 Actual and Predicted Annualized Quarterly Growth, Model 2 Recursive



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$$

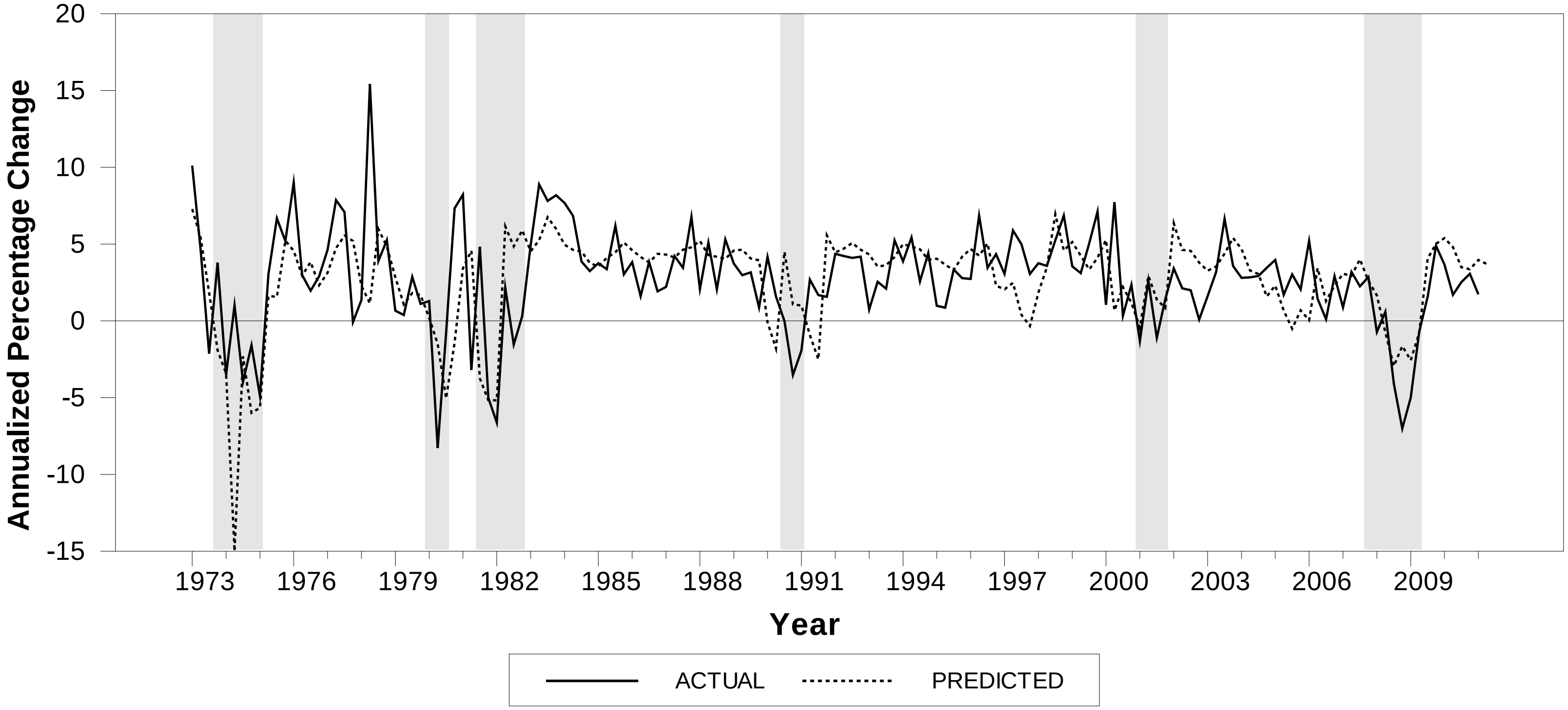
Figure 1.17 Actual and Predicted Annualized Quarterly Growth, Model 3 Recursive



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$$

Figure 1.18 Actual and Predicted Annualized Quarterly Growth, Model 4 Recursive.



Note: Predicted is one quarter ahead forecasts, based on a recursive regression, with an initial sample period of 25 years, of the equation:

$$y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$$

Figure 1.19 Model 3 vs. Model 1 Rolling MSPE Ratio

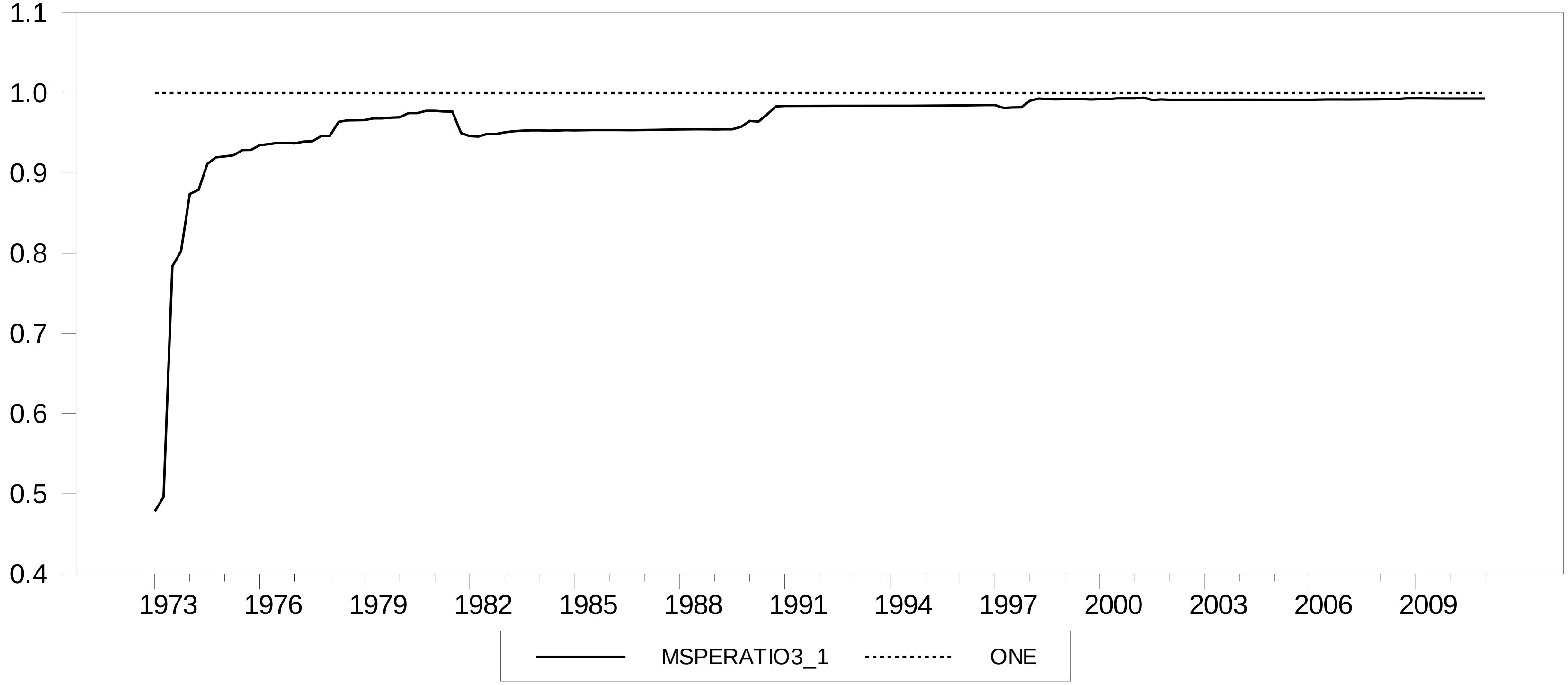


Figure 1.20 Model 3 vs. Model 1 Recursive MSPE Ratio

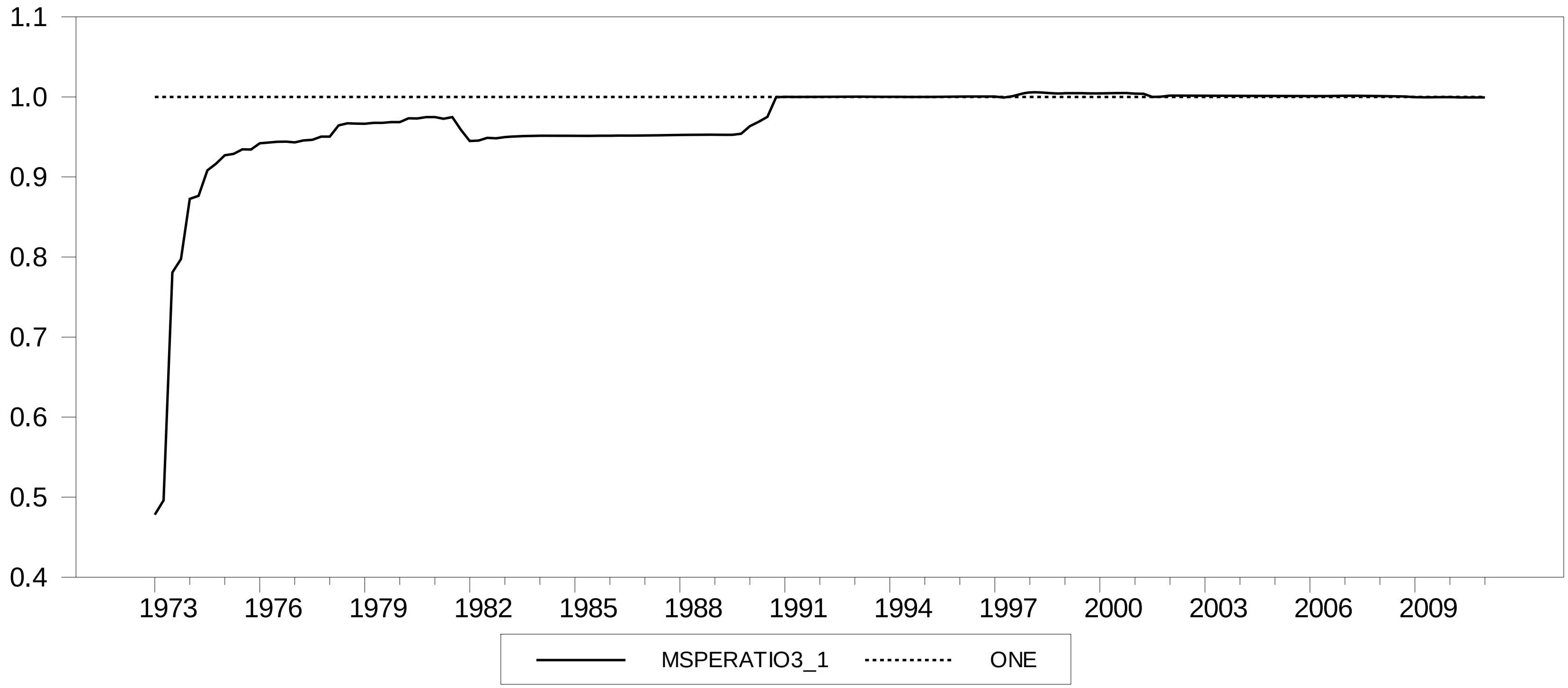


Figure 1.21 Model 4 vs. Model 2 Rolling MSPE Ratio

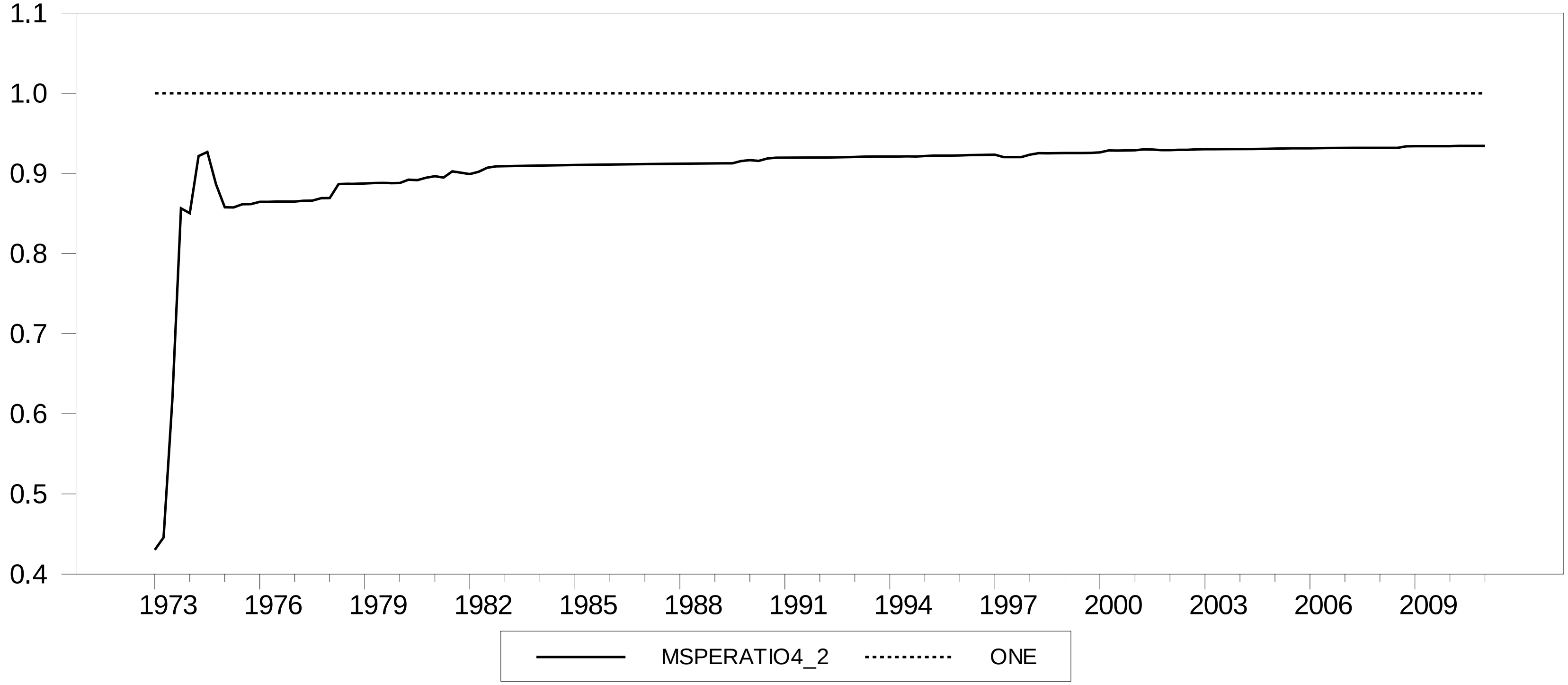


Figure 1.22 Model 4 vs. Model 2 Recursive MSPE Ratio

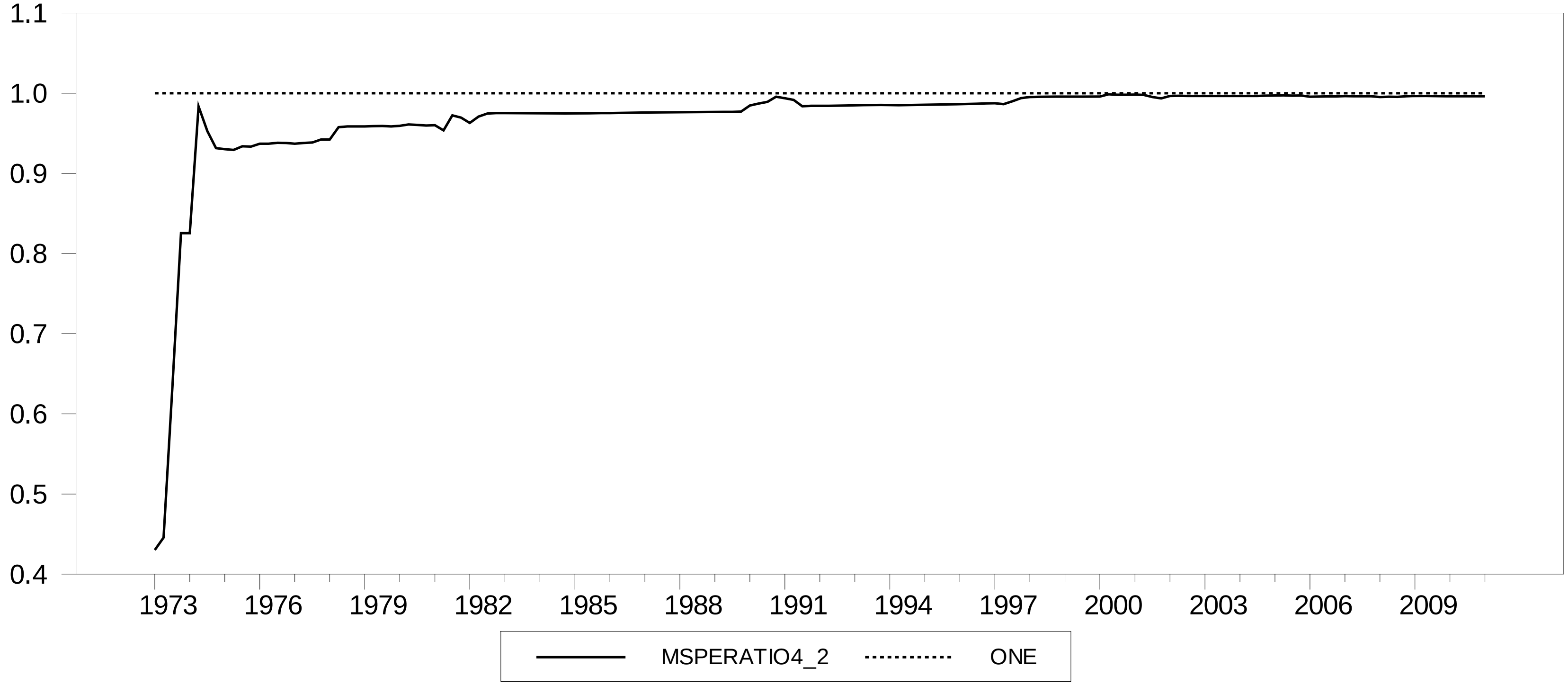


Table 1.1 OLS Estimates of GDP growth (y), using lagged growth, lagged OIL, and lagged ZEROCORR

Recursive regression always starting at 1947:4										
End Date	k	Constant	y{1}	y{2}	y{3}	y{4}	OIL{1}	OIL{2}	OIL{3}	OIL{4}
1983:1	1	4.17***	0.22***	0.08	-0.13**	-0.11*	-0.12	-0.06	-0.1***	-0.18***
		(0.551)	(0.063)	(0.074)	(0.053)	(0.063)	(0.097)	(0.083)	(0.037)	(0.041)
	2	2.80***	1.01***	-0.80***	0.51***	-0.36***	-0.05**	-0.08***	-0.1***	-0.04
		(0.305)	(0.043)	(0.069)	(0.089)	(0.053)	(0.023)	(0.027)	(0.023)	(0.043)
	3	1.43***	1.0***	-0.04	-0.59***	0.27***	-0.07***	-0.08**	-0.03	0.03
		(0.241)	(0.055)	(0.088)	(0.079)	(0.051)	(0.020)	(0.030)	(0.021)	(0.033)
1991:2	1	4.22***	0.22***	0.1	-0.15***	-0.13**	-0.16***	-0.07	-0.07**	-0.18***
		(0.452)	(0.060)	(0.074)	(0.050)	(0.057)	(0.060)	(0.045)	(0.028)	(0.039)
	2	2.80***	1.02***	-0.80***	0.48***	-0.35***	-0.06***	-0.06***	-0.09***	-0.04
		(0.270)	(0.041)	(0.063)	(0.083)	(0.049)	(0.015)	(0.023)	(0.016)	(0.042)
	3	1.4***	1.02***	-0.06	-0.6***	0.29***	-0.06***	-0.06***	-0.04***	0.03
		(0.201)	(0.056)	(0.086)	(0.080)	(0.050)	(0.018)	(0.021)	(0.013)	(0.028)
2002:1	1	3.77***	0.24***	0.12*	-0.15***	-0.11**	-0.12**	-0.09**	-0.06**	-0.14***
		(0.374)	(0.056)	(0.072)	(0.046)	(0.053)	(0.060)	(0.037)	(0.028)	(0.030)
	2	2.47***	1.03***	-0.76***	0.46***	-0.32***	-0.05***	-0.06**	-0.07***	-0.04
		(0.235)	(0.040)	(0.058)	(0.073)	(0.046)	(0.013)	(0.023)	(0.016)	(0.024)
	3	1.3***	1.02***	-0.03	-0.64***	0.31***	-0.04**	-0.05***	-0.03***	0.01
		(0.170)	(0.055)	(0.081)	(0.077)	(0.051)	(0.018)	(0.018)	(0.011)	(0.019)
2009:3	1	3.44***	0.26***	0.13*	-0.14***	-0.08	-0.10**	-0.07**	-0.08**	-0.13***
		(0.354)	(0.055)	(0.069)	(0.045)	(0.054)	(0.049)	(0.035)	(0.032)	(0.026)
	2	2.25***	1.05***	-0.77***	0.46***	-0.30***	-0.05***	-0.06***	-0.06***	-0.03
		(0.233)	(0.041)	(0.056)	(0.072)	(0.048)	(0.017)	(0.021)	(0.014)	(0.021)
	3	1.16***	1.04***	-0.04	-0.64***	0.33***	-0.04***	-0.05***	-0.03***	0.01
		(0.159)	(0.053)	(0.078)	(0.075)	(0.050)	(0.015)	(0.015)	(0.009)	(0.016)

Note: The regression takes the form of $y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i \, OIL_{t-i} + \sum_{i=1}^{4} \lambda_i \, ZEROCORR_{t-i} + \varepsilon_t$.

Significance is represented by *, **, and *** representing 10%, 5%, and 1% significance, respectively.

In Parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors corrected with twelve lags.

Table 1.1 Continued OLS Estimates of GDP growth (y), using lagged growth, lagged OIL, and lagged ZEROCORR

Recursive regression always starting at 1947:4					
End Date	k	ZERO CORR{1}	ZERO CORR{2}	ZERO CORR{3}	ZERO CORR{4}
1983:1	1	-0.05	-3.12*	-3.29	3.3***
		(1.589)	(1.601)	(2.603)	(1.267)
	2	-2.07***	-1.81	1.93**	-0.15
		(0.717)	(1.735)	(0.774)	(1.066)
	3	-0.2	0.27	-0.02	1.33*
		(0.806)	(0.630)	(0.689)	(0.724)
1991:2	1	-0.07	-2.2	-3.34	2.46*
		(1.211)	(1.397)	(2.058)	(1.370)
	2	-1.48*	-1.75	1.06	-0.72
		(0.765)	(1.389)	(0.918)	(0.911)
	3	-0.3	-0.06	-0.66	1.15***
		(0.690)	(0.518)	(0.722)	(0.562)
2002:1	1	1.02	-1.57	-2.82*	2.39**
		(1.080)	(1.082)	(1.488)	(1.149)
	2	-0.64	-1.46	1.2*	-0.47
		(0.738)	(1.041)	(0.682)	(0.662)
	3	-0.26	0.05	-0.37	0.88**
		(0.493)	(0.399)	(0.491)	(0.413)
2009:3	1	1.14	-1.49	-2.75*	2.52**
		(1.056)	(1.055)	(1.478)	(1.148)
	2	-0.57	-1.45	1.31*	-0.4
		(0.727)	(1.044)	(0.691)	(0.658)
	3	-0.24	0.07	-0.35	0.96**
		(0.491)	(0.400)	(0.496)	(0.409)

Note: The regression takes the form of $y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i \, OIL_{t-i} + \sum_{i=1}^{4} \lambda_i \, ZEROCORR_{t-i} + \varepsilon_t$.

Significance is represented by *, **, and *** representing 10%, 5%, and 1% significance, respectively.

In Parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors corrected with twelve lags.

Table 1.2 OLS Estimates of GDP growth (y), using lagged growth, lagged OIL, and lagged ZEROCORR

Rolling regression always starting 25 years prior to the End Date										
End Date	k	Constant	y{1}	y{2}	y{3}	y{4}	OIL{1}	OIL{2}	OIL{3}	OIL{4}
1983:1	1	4.554***	0.112*	0.025	-0.093	-0.036	-0.09	-0.065	-0.106**	-0.216***
		(0.856)	(0.058)	(0.076)	(0.062)	(0.087)	(0.081)	(0.093)	(0.051)	(0.036)
	2	3.132***	0.961***	-0.852***	0.606***	-0.407***	-0.043**	-0.103***	-0.116***	-0.025
		(0.525)	(0.070)	(0.068)	(0.088)	(0.049)	(0.018)	(0.032)	(0.034)	(0.048)
	3	1.594***	0.91***	0.028	-0.586***	0.268***	-0.072***	-0.088***	-0.025	0.041
		(0.355)	(0.058)	(0.100)	(0.103)	(0.065)	(0.020)	(0.022)	(0.016)	(0.033)
1991:2	1	4.143***	0.091	0.046	-0.082	-0.033	-0.104***	-0.087*	-0.072*	-0.201***
		(0.746)	(0.072)	(0.090)	(0.064)	(0.077)	(0.037)	(0.048)	(0.037)	(0.032)
	2	2.635***	0.96***	-0.806***	0.579***	-0.356***	-0.044***	-0.073***	-0.091***	-0.011
		(0.423)	(0.067)	(0.066)	(0.105)	(0.078)	(0.013)	(0.026)	(0.030)	(0.047)
	3	1.365***	0.9***	0.041	-0.534***	0.24***	-0.056***	-0.058**	-0.026***	0.049**
		(0.284)	(0.060)	(0.124)	(0.114)	(0.070)	(0.021)	(0.025)	(0.008)	(0.025)
2002:1	1	3.508***	0.157	0.048	-0.047	-0.007	-0.109**	-0.074*	-0.062	-0.118***
		(0.652)	(0.098)	(0.130)	(0.078)	(0.079)	(0.053)	(0.038)	(0.056)	(0.042)
	2	2.027***	0.98***	-0.774***	0.534***	-0.25***	-0.035*	-0.051	-0.064**	-0.006
		(0.313)	(0.075)	(0.101)	(0.097)	(0.084)	(0.021)	(0.037)	(0.027)	(0.024)
	3	1.208***	0.911***	-0.01	-0.524***	0.308***	-0.032	-0.034**	-0.019**	-0.009
		(0.275)	(0.091)	(0.120)	(0.143)	(0.096)	(0.028)	(0.017)	(0.008)	(0.015)
2009:3	1	2.023***	0.211**	0.296***	-0.138*	0.077	-0.071*	-0.077*	-0.037	-0.055**
		(0.204)	(0.107)	(0.077)	(0.076)	(0.072)	(0.041)	(0.041)	(0.057)	(0.025)
	2	1.309***	1.102***	-0.701***	0.35***	-0.117	-0.044	-0.028	-0.029**	-0.027*
		(0.218)	(0.078)	(0.108)	(0.121)	(0.099)	(0.027)	(0.028)	(0.012)	(0.015)
	3	0.626***	1.072***	0.046	-0.871***	0.57***	-0.018	-0.03*	-0.023***	0.007
		(0.187)	(0.103)	(0.132)	(0.100)	(0.077)	(0.020)	(0.017)	(0.004)	(0.011)

Note: The regression takes the form of $y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i \, OIL_{t-i} + \sum_{i=1}^{4} \lambda_i \, ZEROCORR_{t-i} + \varepsilon_t$.

Significance is represented by *, **, and *** representing 10%, 5%, and 1% significance, respectively.

In Parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors corrected with twelve lags.

Table 1.2 Continued OLS Estimates of GDP growth (y), using lagged growth, lagged OIL, and lagged ZEROCORR

Rolling regression always starting 25 years prior to the End Date					
End Date	k	ZEROCORR{1}	ZEROCORR{2}	ZEROCORR{3}	ZEROCORR{4}
1983:1	1	-0.246	-3.226	-0.503	1.208
		(1.917)	(1.962)	(1.649)	(1.181)
	2	-2.505***	-0.043	1.346	-1.443
		(0.696)	(1.537)	(0.819)	(0.900)
	3	0.887*	-0.088	-0.972	0.775
		(0.513)	(0.535)	(0.794)	(0.676)
1991:2	1	0.468	-1.138	-0.974	-0.191
		(1.463)	(0.907)	(1.427)	(1.257)
	2	-1.240**	0.178	-0.073	-2.132**
		(0.539)	(1.321)	(0.746)	(0.837)
	3	0.481	-0.605*	-1.546**	0.55
		(0.662)	(0.319)	(0.741)	(0.490)
2002:1	1	2.055	-1.307	-2.093***	0.353
		(1.537)	(1.286)	(0.608)	(0.971)
	2	0.515	-1.897***	0.967	-1.339
		(0.467)	(0.569)	(0.773)	(1.213)
	3	-0.273	-0.249	-0.806	0.457
		(0.248)	(0.371)	(0.667)	(0.304)
2009:3	1	0.58	0.245	-1.622***	0.368
		(1.182)	(1.105)	(0.488)	(0.876)
	2	0.697**	-0.993***	0.109	-0.167
		(0.342)	(0.259)	(0.835)	(0.806)
	3	-0.554**	0.172	-0.682	0.594*
		(0.274)	(0.286)	(0.673)	(0.329)

Note: The regression takes the form of $y_t = \alpha + \sum_{i=1}^{4} \beta_i y_{t-i} + \sum_{i=1}^{4} \gamma_i \, OIL_{t-i} + \sum_{i=1}^{4} \lambda_i \, ZEROCORR_{t-i} + \varepsilon_t$.

Significance is represented by *, **, and *** representing 10%, 5%, and 1% significance, respectively.

In Parentheses are the Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors corrected with twelve lags.

Table 1.3 Rolling Regression Adjusted R-Squared

End Date	k	Model 1	Model 2	Model 3	Model 4
1983:1	1	0.027	0.163	0.045	0.154
	2	0.561	0.637	0.591	0.657
	3	0.694	0.725	0.695	0.724
	4	0.761	0.797	0.765	0.796
1991:2	1	0.046	0.179	0.014	0.152
	2	0.571	0.62	0.583	0.637
	3	0.698	0.712	0.695	0.722
	4	0.783	0.803	0.782	0.806
2002:1	1	0.045	0.148	0.053	0.167
	2	0.562	0.596	0.586	0.617
	3	0.704	0.709	0.701	0.707
	4	0.77	0.788	0.776	0.793
2009:3	1	0.279	0.366	0.259	0.359
	2	0.714	0.744	0.714	0.744
	3	0.814	0.823	0.816	0.825
	4	0.862	0.863	0.86	0.861

Note: Rolling regressions are based on a 25 year window ending at the date provided. The forecast horizon, in quarters, is represented by k.
Model 1: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$,
Model 2: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$
Model 3: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$
Model 4: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$

Table 1.4 Recursive Regression Adjusted R-Squared

End Date	k	Model 1	Model 2	Model 3	Model 4
1983:1	1	0.110	0.201	0.165	0.240
	2	0.606	0.658	0.639	0.679
	3	0.746	0.766	0.750	0.768
	4	0.774	0.800	0.784	0.804
1991:2	1	0.129	0.224	0.160	0.258
	2	0.620	0.661	0.640	0.678
	3	0.756	0.768	0.756	0.772
	4	0.786	0.803	0.791	0.807
2002:1	1	0.125	0.204	0.158	0.237
	2	0.618	0.655	0.636	0.667
	3	0.754	0.764	0.755	0.766
	4	0.784	0.799	0.791	0.804
2009:3	1	0.149	0.236	0.181	0.267
	2	0.636	0.677	0.652	0.688
	3	0.769	0.783	0.771	0.786
	4	0.799	0.813	0.806	0.818

Note: Recursive regressions all start in 1947:4.
The forecast horizon, in quarters, is represented by k.
Model 1: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$,
Model 2: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$
Model 3: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$
Model 4: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$

Table 1.5 Out of Sample Predictability

	Rolling				Recursive			
	Model 4 vs. Model 2		Model 3 vs. Model 1		Model 4 vs. Model 2		Model 3 vs. Model 1	
Date	CW	DMW	CW	DMW	CW	DMW	CW	DMW
1983:01	2.205**	2.077***	1.670**	1.513***	1.511*	0.798**	1.989**	1.725***
1991:02	2.136**	1.965***	1.166	0.514***	1.626*	0.291**	1.169	0.001*
2002:01	2.338***	1.925***	1.441*	0.295**	2.009**	0.135*	1.621*	-0.053
2009:03	2.328***	1.916***	1.416*	0.265**	2.033**	0.150*	1.687**	0.016*

Note: Significance is represented by *, **, and *** representing 10%, 5%, and 1% significance, respectively.
CW and DMW stand for the Clark West, and Diebold Mariano West test statistics, respectively.
Model 1: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$,
Model 2: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$
Model 3: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$
Model 4: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$

Table 1.6 Ratio of Mean Squared Prediction Errors

Recursive MSPE ratio				
	1983:1	1991:2	2002:1	2009:3
Model 3 vs. 1	0.950	1.000	1.002	1.000
Model 4 vs. 2	0.975	0.991	0.996	0.997

Rolling RMSE ratio				
	1983:1	1991:2	2002:1	2009:3
Model 3 vs. 1	0.951	0.984	0.992	0.993
Model 4 vs. 2	0.909	0.920	0.929	0.934

Note: Formula is always nesting model/nested model
Recursive regressions start in 1947:4.
Rolling regressions start 25 years prior to the given date.
Model 1: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \varepsilon_t$,
Model 2: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \varepsilon_t$
Model 3: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$
Model 4: $y_t = \alpha + \sum_{i=1}^{4} \beta_i * y_{t-i} + \sum_{i=1}^{4} \gamma_i * OIL_{t-i} + \sum_{i=1}^{4} \lambda_i * ZEROCORR_{t-i} + \varepsilon_t$

Chapter Two

Forecasting U.S. Recessions Using the Marginal Product of Capital

2.1 Introduction

Forecasting turning points remains of great interest for all market participants, the challenge being if one can identify an impending recession. Recessions inflict an enormous cost on society: businesses risk bankruptcy, factories stay idle, workers are affected by unemployment, and policymakers deal with a greater apprehension. However, when forecasters choose to report probabilities, rather than point estimates, these forecasts are more informative and easy to use when quantifying the stance of the economy. Thus, better forecasts of turning point have the potential to improve standard model forecasts. Even though in the Unites States recessions have become milder and less frequent and expansionary periods more stable with the onset of the Great Moderation, the recent events show that recessions are as perilous as before. Therefore, any improvement in predicting recessions is highly valuable for the numerous economic agents.

It is common knowledge that recessions happen unexpectedly as a sudden decrease in economic activity, inflicting a high cost to the society.[1] Economists find themselves put through a challenge when predicting recessions: they need to find a reliable indicator that mimics the movements of the business cycle reference series that has a significant and stable relationship, and improves the predictive power over time.

In this paper, we use a newly constructed indicator based on the correlation between marginal product of capital (MPK) in non-residential and residential sectors as an explanatory variable to a probit model to predict the likelihood of a recession in United States up to five quarters ahead both in-sample and out-of-sample. We consider two probit models for forecasting the binary variable that takes value 1 if there is a recession in the subsequent h quarters, and 0 otherwise. The baseline model uses the famous yield spread,

[1] Tichy (1994)

and we build a second model with both yield spread and zero correlation indicator. The probit regression including the correlation indicator provides a better in-sample fit and is able to predict the 1990 recession out-of-sample. We then compare these forecasts with recession predictions based on the probability forecast provided by the Survey of Professional Forecasters (SPF). We find that SPF probability forecasts are worse at forecasting recessions for horizons beyond two quarters, with the implication that the indicator adds tremendous value to the standard yield curve model.

The literature on predicting recessions had given somewhat pessimistic results: Diebold and Rudebusch (1991) found the index of leading indicators performing subpar, Stock and Watson (1993) dynamic single index modeled could not identify 1990 and 2001 out-of-sample recessions, and Zaranowitz and Braun (1993) concluded that the largest prediction errors accompany recessions. The more optimistic strand of literature focuses on different variables that perform well in the predictability of recessions, namely, the slope of the yield curve as the difference between long- and short-run interest rates. The ability of yield spread in predicting recession was shown since late 1980s – early 1990s by Stock and Watson (1989), Estrella and Hardouvelis (1991), Hu (1993), Harvey (1991, 1997). The seminal work of Estrella and Mishkin (1998) has shown that yield spread is an excellent indicator in predicting US recessions and also dominates the index of leading indicators. Their work was strengthen by a series of papers on the predictive power of the yield spread by Chauvet and Potter (2005), Ang, Piazzesi, and Wei (2006), Wright (2006), and Rudebusch and Williams (2009).

Unfortunately, the spread failed to predict the 1990-1991 recession, even though the spread narrowed and predicted somewhat weaker activity. Haubrich and Dombrosky (1996) found that the yield spread is a relatively accurate predictor of four-quarter economic growth, except over the period 1985 to 1995. Also, the yield curve seems to have difficulty in predicting milder recessions, as shown in Dueker (1997).

The focus of this paper is to examine the ability of the yield curve together with a new indicator in predicting recessions. We anticipate the new model to capture the controversial recession of 1990-1991 and also the milder recessions, harder to detect with the yield curve alone. The indicator presented in Stoica (2012) is based on a recurrent pattern observed across the business cycle beginning with the 1953 recession: between one to three quarters to the following recession, the correlation of sectoral MPK registers values close to zero, positive values in recoveries and expansions, and strongly negative across recessions. This behavior is likely due to the different response of the non-residential and residential sectors to monetary policy. The addition of this new indicator of monetary policy helps refine the signal in predicting a weakening in the economy.

The rationale of why an indicator based on the correlation of residential and non-residential MPK might be useful is because it reacts to the movements in interest rates. For example, the higher the interest rates, the more restrictive the monetary policy, and more likely for a recession to follow.

When the economy is growing quickly, the Federal Reserve (Fed) adopts a more restrictive monetary policy by increasing interest rates in order to keep inflation around its target, in this case, a recession to materialize is very likely. The increasing interest rates are depressing investments in both sectors, but the real hit is going to be taken by the residential capital, rather sensitive to interest rates movements, so the residential MPK is going up toward the end of the expansion, while non-residential MPK starts going gradually down, with a major drop at the beginning of the recession. This movement creates with approximately two quarters before a recession a close to zero correlation.

We provide new evidence that the yield curve is a very reliable indicator, performing even better when associated with the zero correlation measure. We proceed further by examining the information content of the probability forecasts provided by the respondents in the SPF, compare these forecasts to the yield curve, and zero correlation indicators. The SPF forecasts are considered by the literature to perform extremely well in evaluation exercises, estimating the probabilities of a negative growth in GDP in the current quarter through four quarters ahead quite accurately.

It became necessary to improve upon the standard yield curve model when it failed to predict the 1990 recession. This led many practitioners to discontinue the use of the yield curve, which may have worsened their forecast ability. Our indicator helps improve the predictive power of the yield curve in- and out-of-sample and picks up the 1990 recession, demonstrating that the yield curve is not obsolete. Even more, for longer horizons, the new model seems to do better than the yield curve alone.

We also provide evidence that the out-of-sample SPF probability forecasts perform better for one and two-quarters ahead than our probit model including the yield spread and zero correlation indicator. The predictive power of the SPF, however, disappears at three-, four-, and five-quarter ahead forecasts. Conversely, the probit model with yield spread and zero correlation indicator is performing significantly better than SPF forecasts probability at longer horizons, but for shorter horizons, SPF predicts the likelihood of a recession better.

The paper proceeds as follows. In the next section, we define and provide a short history on US recessions. In section 3, we describe the models and assess the in-sample accuracy. Section 4 evaluates the out-of-sample forecast performance and provides a comparison of the models incorporating the zero correlation indicator as an explanatory variable with those of SPF forecasts, and we conclude in section 5 about the usefulness of our indicator in improving the likelihood of forecasting recessions.

2.2 Defining Recessions

The first step in our analysis is to define what we call "recession". A very common use of the word recession was introduced by Arthur Okun and widely used since is that the beginning of a recession is defined by two consecutive quarters of decline in real GDP or what we call a "peak". However, the authority in dating recessions in US, the National Bureau of Economic Research (NBER) *does not define a recession in terms of two consecutive quarters of decline in real GDP. Rather, 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. A recession is a period between a peak and a trough, and an expansion is a period between a trough and a peak; most recessions are brief and they have been rare in recent decades.* – (July 2003)

The NBER's Business Cycle Dating Committee determines the peaks and troughs of the business cycle, considering a collection of variables known as Leading Economic Indicators (LEI). Initially, Burns and Mitchell (1938) identified 21 series as reliable indicators out of 487 total chosen on their ability to forecast in-sample. The LEI list is periodically revised, some of the series could not forecast future recessions, or out-of-sample.

The current list has changed from the one originally proposed to about 10 variables.[2] Following Burns and Mitchell, Moore (1950, 1961) construct a new list of indicators by searching also for indicators of business contraction in addition to the expansion indicators. More recently, Stock and Watson (1989) used modern econometric techniques in revisiting the list of indicators. There are several papers discussing on NBER methodology of maintain US chronology of the business cycle, Diebold and Rudebusch (1989, 1992, 1996) and Aruoba, Diebold, and Scotti (2008).

Faithful to Burns and Mitchell's definition of business cycle, the NBER defined recessions tend to be longer than those defined by the two-quarter rule, as a consequence of the fact that NBER considers the months with very low growth as belonging to recessions rather than expansion.

In our analysis, we use the NBER's simple rule that links decline in GDP to recessions: *The committee views real GDP as the single best measure of aggregate activity. In determining whether a recession has occurred and identifying its approximate dates of peak and the trough, the committee therefore places considerable weight on the estimates of real GDP issued by the Bureau of Economic Analysis of the U.S. Department of Commerce.*

2.3 The Models

In this section, we study the ability of the yield curve and zero correlation indicator to predict recessions. Empirically, we would like to construct a model that translates the steepness of the yield curve at present time into a likelihood of a recession in the future and also connects it with the NBER definition of a recession. Our approach is to employ a probit model that converts the stance of monetary policy into a probability of a recession.

[2] For a history if the revisions, see Conference Board (1997)

First, we estimate probit models and obtain the probability of a recession occurring 1 to 5 quarters ahead, with information from the candidate series. Then, we analyze the in-sample predictive content by examining the $pseudo - R^2$. We also include information about the SPF probability forecasts, which will be used later in our analysis.

2.3.1 Yield-curve and zero-correlation probability forecasts

We consider alternative probit models to forecast NBER recessions at time t, with a forecast horizon of h periods. In a probit model, the variables included are chosen based on their likelihood to forecast recessions, rather than their ability to track past movements of economic indicators. The main strength of this approach is that it focuses solely on turning points, which might also be considered a weakness considering that recession are relatively rare events.

Historically, the term spread or the slope of the yield curve has exhibited negative statistical correlation with real GDP growth over subsequent quarters, and a positive with the start of a recession. The term spread also constitutes part of several important indexes used in forecasting, such as the Conference Board and the Leading Economic Indicators(LEI). However, the yield curve did not signal the 1990 recession, causing it to lose a lot of its credibility, and also showed itself almost flat and modestly inverted in the eve of Great Recession. Nevertheless, the yield curve is still among the most performing recession indicators.

The term spread is a useful indicator of the state of monetary policy. The reason behind this is that, theoretically, the term spread measures the difference between current and the average expected short-term interest rates under the expectations hypothesis. The higher the spread, the tighter the monetary policy, and more likely for a recession to occur in the following quarters.

Neglecting the effect of the term premium, it is not clear that the spread of short-term interest rates over the yield on a long-term bond should necessary capture all the information available about the likelihood of a recession.[3] We believe that if this affirmation is right, we need a less complicated and more straightforward measure of the stance of monetary policy. The measure that we propose and previously used as a successful indicator in forecasting GDP growth comes as a complement to the yield curve, rather than a substitute. The indicator is based on the correlation between MPK in residential and non-residential sectors, which becomes significantly close to zero before a recession, excepting the 2007-2009 recession.

We believe that the indicator is appropriate when dealing with the likelihood of a recession because is largely driven by residential investment being much more interest rate sensitive and less income sensitive than non-residential investment. The best example is to think about the end of an expansion. Commonly, when the economy is heating up and the inflation starts being of concern, the Fed increases interest rates and depresses investment in order to keep inflation near its target. As a consequence of the interest rates' behavior, between one to three quarters preceding recessions, the correlation of the non-residential and residential MPK becomes essentially zero. A graphical representation of the two variables used in this study can be visualized in Figure 2.1.

The exception from this rule is the Great Recession of 2007-2009. One possible explanation would be that it did not come as a result of high and increasing interest rates, or a Fed "induced" recession, but more likely as a outcome of the Financial Crisis.

[3] Jonathan Wright (2006)

Data on the yield curve is obtained from the St. Louis Federal Reserve Database. Following Estrella and Hardouvelis (1991), we define the spread, $YS_t \equiv i_t^L - i_t^S$, as the difference between the yield on a 10-year Treasury note, i_t^L, and the yield on a 3-month Treasury bill, i_t^S. Our first model then is one of the baseline specifications for comparing probability forecasts and it comprises the value of yield spread:

$$P(NBER_t = 1) = \Phi(\alpha + \beta YS_{t-h}) \qquad (Model\ 1)$$

$$\text{where } \mathrm{NBER}_t = \begin{cases} 1, \text{if there is an NBER defined recession in quarter t} \\ 0, \text{otherwise.} \end{cases}$$

$\Phi(.)$ is the standard normal cumulative distribution function, y_t is the annualized GDP growth at time *t*, and the forecast horizon *h* = 1, 2, 3, 4, 5. The information at time *t-h* includes the information of *t-h-1*. The fitted values can be interpreted as the probability that a recession will occur, conditional on the observed value of the yield spread.

A second model builds on the first with the inclusion of the zero correlation variable, described in Stoica (2012). We include the new indicator based on the predictive power of real economic activity in- and out-of-sample specification and also on its ability to capture the explicit turning point from trough to peak. This indicator is very similar to Hamilton's (2003) oil price shock, the only difference being that it takes 0 and 1 values.

$$P(NBER_t = 1) = \Phi(\alpha + \beta YS_{t-h} + \gamma ZEROCORR_{t-h}) \qquad (Model\ 2)$$

$$ZEROCORR_t = \begin{cases} 1, & \textit{if the absolute value of the correlation between} \\ & \textit{non-residential and residential MPK} \leq 7\% \\ 0, & \textit{otherwise.} \end{cases}$$

2.3.2 SPF probability forecasts

Forecasts are vital for economic conditions. Dean Croushore (1993) suggested that "one easy way to get forecasts is to subscribe to a survey of forecasts, such as the Survey of Professional Forecasters." Every quarter beginning with 1968:4, the American Statistical Association (ASA) together with National Bureau of Economic Research (NBER) survey various professional forecasters on subjective estimates of real GNP/GDP declines during the current quarter and four subsequent quarters.[4] In 1990, Federal Reserve Bank of Philadelphia took over the survey and invited new forecasters, boosting the number of respondents to 36.[5]

We are mostly interested in the particular question that asses the probability of a decline in GDP. The question is phrased as follows: "indicate the probability you would attach to a decline in real GDP (chain-weighted basis, seasonally adjusted) in the next five quarters. Write in a figure that may range from 0 to 100 in each of the cells (100 means a decline in the given quarter is certain, 0 means is no change at all)." By notation, in response to this question asked at time *t-h*, we call the mean probability forecast at time t $P_{t|t-h}^{SPF}$.

If one were to graph the SPF probability forecasts, with a high degree of certainty we can comment that SPF forecasts do not give any relevant information for four- and five-quarter ahead forecasts, but perform extremely well in identify negative growth for the next quarter.

2.3.3 In-sample results

The in-sample results are based on probit models for the yield curve model and the yield curve and zero correlation indicator estimated over the whole sample, 1953:2 through

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[4] The forecasters in the Survey of Professional Forecasters come largely from the business world and Wall Street.
[5] See Croushore (1993)

2011:1. The fitted values are then compared with the actual NBER recession dates. We are interested to show that the second model has higher predictive power across all horizons.

In the classical regression model, the in-sample predictive power is analyzed by comparing the $adjusted\ R^2$ for each regression model. The model with the highest value of $adjusted\ R^2$ is said to have the best explanatory power. However, in a probit model, the simple $adjusted\ R^2$ is biased toward 1.[6]

The measure of comparison is a modified McFadden's R^2 called $pseudo-R^2$ developed to correspond intuitively to the widely used coefficient of determination in a standard linear regression. The $pseudo-R^2$ takes value between 0 and 1, with the interpretation of no fit for 0, and perfect fit for 1.

$$pseudo-R^2 = 1-\left(\frac{\log L_u}{\log L_c}\right)^{-(2/n)\log Lc}$$

where L_u is the unconstrained maximum value of the likelihood function L, L_c its maximum value under the constraint that all coefficients are zero except for the constant, and n is the number of observations.

As in the linear regression case, the measure of goodness of fit is not sufficient for statistical hypothesis testing for horizons over two quarters. The longer the forecast horizon than the observation interval, the more likely the forecast errors to be correlated. To correct this bias, we use the Newey-West (1987) technique and present t-statistic calculated using robust errors adjusted for autocorrelation.[7]

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[6] To bias is discussed more in Estrella (1998)
[7] Estrella and Rodrigues (1998)

Concretely, to compare the in-sample performance, we estimate a 25-year rolling regression, with the first one starting in 1948:1, and moving forward by one quarter at a time. We forecast the probability of the economy being in a recession at time t for horizons one to five quarters ahead. We compute the $pseudo-R^2$ statistic for both Model 1 and Model 2 comparing them with higher values indicating a better in-sample performance. The $pseudo-R^2$ statistics are reported as occurring in the last quarter of the associated regression, for example, if the regression is from 1975:1-2000:1, then $pseudo-R^2$ from this regression is reported as the pseudo-R-squared for 2000:1. It is important to note that $pseudo-R^2$ does not penalize for model size, so very small differences from Model 1 to Model 2 indicate no improvement in fit

Table 1 presents the $pseudo-R^2$ for Model 1 and Model 2 with lags ranging from 1 to 5 quarters. The $pseudo-R^2$ is visibly higher for Model 2 than Model 1 until 1990 and from 1995-1999 for one and two quarter ahead forecasts, until 1990 for three quarters ahead, until 2006 for four quarters ahead and from 1987-2003 for five quarters ahead. A better representation could be seen in Figure 2.2.

The advantage of using a probit model is that it allows us to estimate the probabilities that the economy will be in recession in the following quarters on the basis of the interest rate spread and interest rate sensitivity to activity in different sectors of the economy, observed some quarters ago. Figure 3 graphs these fitted probabilities using the spread and zero correlation measure. The probability forecasts should be 1 in a recession, shaded in the figure, and zero for the rest of the time. The estimated probabilities increases during recession periods and remains low during in non-recession quarters. For the 1990 recession, Model 2 gives a fair warning, the estimated probability increases to the value of 0.57 in

1989:4 for one quarter ahead horizon, 0.63 in 1990:1 for the two quarter ahead horizon, likewise, 0.64 in 1990:2, 0.61 in 1990:3, and 0.60 in 1990:4 for three, four, and five quarters ahead, respectively. The model seems to perform fairly well.

As seen in Figure 2.3, the yield spread itself predicts the in-sample probability of a recession fairly well, except the 1990-1991 recession. Adding the zero correlation indicator that incorporates tight monetary policy helps in forecasting recessions.

2.4 Out-of-sample results

The main drawback of in-sample forecasting is that it is using information not available at the time of the forecast. For example, the probability of a recession in 2001 was calculated estimating the model on the whole period, from 1953:2 to 2011:1. Moreover, the in-sample forecast always performs better when including more explanatory variables. In order to avoid the overfitting problems that might arise and misleading indicators of the true ability of predicting recessions, we perform an out-of-sample forecasting exercise. The out-of-sample forecasts are improved by using only information available to market participants at the time of the forecast.

First, we estimate the likelihood of a recession for out-of-sample forecasts. Next, we assess the forecasting performance of the probit models looking at forecast errors. Finally, we compare the accuracy of our best model (Model 2) with the SPF forecasts.

2.4.1 Assessing probability forecasts

In this section, we evaluate the performance of yield curve and zero correlation indicator when used to predict turning points. We evaluate each type of forecast in terms of accuracy at an *h* quarters horizon using three common measures:

1. Mean absolute value (MAE)

$$MAE(h) = \frac{1}{T}\sum_{t=1}^{T}\left|P_{t|t-h} - NBER_t\right|$$

2. Root mean squared error (RMSE)

$$RMSE(h) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(P_{t|t-h} - NBER_t\right)^2}$$

3. Log probability score (LPS)

$$LPS(h) = -\frac{1}{T}\sum_{t=1}^{T}(1 - NBER_t)\ln(1 - P_{t|t-h}) + NBER_t \ln(P_{t|t-h})$$

These measures evaluate the probability forecasts by looking at the average closeness of the predicted probability to the observed realization as measured by the NBER dummy variable denoting the NBER recession quarters. The first two measures, MAE and RMSE, provide standard summary measures of forecasting performance. The third measure, LPS, corresponds to the loss function that assigns more weight to larger forecast errors. The range of LPS is [0,∞], with the interpretation that a value closer to 0 indicates perfect accuracy. The MAE has the clear advantage of performing better in-sample and out-of-sample, while LPS and RMSE loss function penalizes the predictive ability of yield curve and zero correlation indicator over SPF.

Table 2 provides accuracy evaluations for each of the models, Model 1, Model 2, and SPF reported forecasts, at each of the available horizons (h= 1, 2, 3, 4, 5) for the sample beginning in 1973:4 through 1998:1. The results show that Model 2 yields smaller forecast errors than both Model 1 and SPF for all three criteria (RMSE, MAE, and LPS) for the four- and five quarter ahead forecasts. For two and three quarter ahead horizons, Model 2 forecasts are more accurate with MAE, but Model 1 seems to outperform Model 2 and SPF when using RMSE and LPS. The SPF forecast does better than the considered models for the short horizon of one-quarter ahead.

2.4.2 Comparing yield curve and yield curve plus zero correlation forecasts

To compare the forecasting ability of the model including the yield curve (Model 1) and the model augmented by zero correlation indicator (Model 2), we use Diebold-Mariano (1995), and West (1996) test, hence DMW. We test the null hypothesis that the forecasting performance of this two models, measured in MAE, RMSE, LPS, is equally good against one-sided alternative, or in other words, we test the null hypothesis of the DMW test is of equal predictability for both forecasts (we test the hypothesis of equal expected absolute errors).

We first calculate the loss differential for the three accuracy measure at a horizon h as follows:

$$LossDifferential_t(MAE) = \left|P^{YS}_{t|t-h} - NBER_t\right| - \left|P^{YSZC}_{t|t-h} - NBER_t\right|$$

The DMW test cannot be computed for an RMSE loss function, so instead we report the results for the Mean Square Error (MSE) test:

$$LossDifferential_t(MSE) = \left(P^{YS}_{t|t-h} - NBER_t\right)^2 - \left(P^{YSZC}_{t|t-h} - NBER_t\right)^2$$

The Loss Differential function for the Log Score Probability measure conveys better results as shown is West (1996), because the parameter estimation error disappears when the in-sample objective corresponds with the out-of-sample loss function:

$$LossDifferential_t(LPS) = (1 - NBER_t)(\ln(1 - P^{YS}_{t|t-h}) - \ln(1 - P^{YSZC}_{t|t-h})) + NBER_t(\ln(P^{YS}_{t|t-h}) - \ln(P^{YSZC}_{t|t-h}))$$

Next step is to compute the DMW test statistic by regressing each loss function differentials on a constant and test the significance using robust standard errors for heteroskedasticity and autocorrelation corrections. If the parameter uncertainty is accounted for, the asymptotic distribution of DMW may depend on nuisance parameters, and the standard theory does not apply. Because the models are nested, we cannot use the standard critical values, instead we use McCracken (2007) critical values.

The comparison between Model 1 and Model 2 leads to mixed results, often with the models not being significantly different from each other. The five-quarter ahead forecast horizon is the most consistent across measures of performance with Model 2 significantly outperforming Model 1from 1988 to 1999 for MAE, 1990 to 2002 for MSE, and 1990 to 2001 for LPS. Table 3 displays these results for 1998:1. Similarly, for four quarters ahead we find that Model 2 performs significantly better from 1990 to1998 for LPS, and MSE, and from 1983 to 1998 for MAE. Three quarters ahead forecasts are very mixed with Model 2 always significantly better with MAE, never significantly better with LPS, and with MSE it is only significantly better for one quarter in 2007. The two-quarter ahead horizon has Model 2 performing significantly better from 1983 to 1990 and in 1998 for MAE, but never for LPS or MSE. Finally, for the one-quarter ahead horizon, Model 2 is always significantly better than Model 1 for the MAE, never for the LPS, and from 1987 to 1989 for MSE.

2.4.3 Comparing yield curve plus zero correlation indicator and SPF forecasts

For the comparison of our better model and SPF forecasts, we are going to employ exactly the same method as for the previous comparison, DWM test.

Again, the loss differential functions for each of the proposed measures at a horizon:

$$LossDifferential_t(MAE) = \left|P_{t|t-h}^{SPF} - NBER_t\right| - \left|P_{t|t-h}^{YSZC} - NBER_t\right|$$

$$LossDifferential_t(MSE) = \left(P_{t|t-h}^{SPF} - NBER_t\right)^2 - \left(P_{t|t-h}^{YSZC} - NBER_t\right)^2$$

$$LossDifferential_t(LPS) = (1 - NBER_t)(\ln(1 - P_{t|t-h}^{SPF}) - \ln(1 - P_{t|t-h}^{YSZC})) + NBER_t(\ln(P_{t|t-h}^{SPF}) - \ln(P_{t|t-h}^{YSZC}))$$

As previously, we compute the DMW test statistic by regressing each loss function differentials on a constant and test its significance using robust standard errors for heteroskedasticity and autocorrelation corrections (HAC), or Newey-West HAC. When comparing Model 1 and Model 2 against the SPF standard critical values are a good approximation because we do not know what goes in to the SPF forecasts, so the assumption is that they are not nested in Model 1 or Model 2, and likewise the models are not nested in the SPF forecasts.

Comparing Model 2 with the SPF forecasts, we find that for five-quarters ahead Model 2 always performs better than the SPF for all three metrics. Four-quarters ahead is similar, with Model 2 outperforming the SPF for MAE and MSE for the entire sample, and for LPS between 1989 and 2009, with no significant difference otherwise. For the three-quarter ahead forecasts, MAE is still always significantly better than the SPF, MSE is also performing better, except for one quarter in 2009, while LPS is only significantly better from 2001 to 2009. Two quarters ahead Model 2 outperforms the SPF until 2009 according to the MAE, but with the MSE and LPS there is no significant difference. Finally, for the one-quarter forecasts ahead the SPF performs significantly better for all three metrics.

Predicting the 1990 recession is one of the places where the yield curve comes up short. It fails to capture the 1990 recession at any of the considered forecast horizons. However, when the zero correlation indicator is included we are able to capture the 1990 recession. Figure 2.4 displays the forecasted probabilities for both models and the SPF. For the four- and five-quarter ahead horizons, we are no more than one quarter off at either the beginning or end of that recession. Considering the three quarters ahead forecast, we predict that the will begin recession shortly before it starts, and that it will end shortly before its conclusion. Finally, one- and two-quarter ahead forecasts predict that the 1990 recession starts in 1989 and ends before the onset of the actual recession. While the timing is a little inaccurate for one- to three-quarter ahead forecast horizons, we still view this as adding important information about the state of the economy, picking up that there is trouble before it actually happens.

2.5 Conclusion

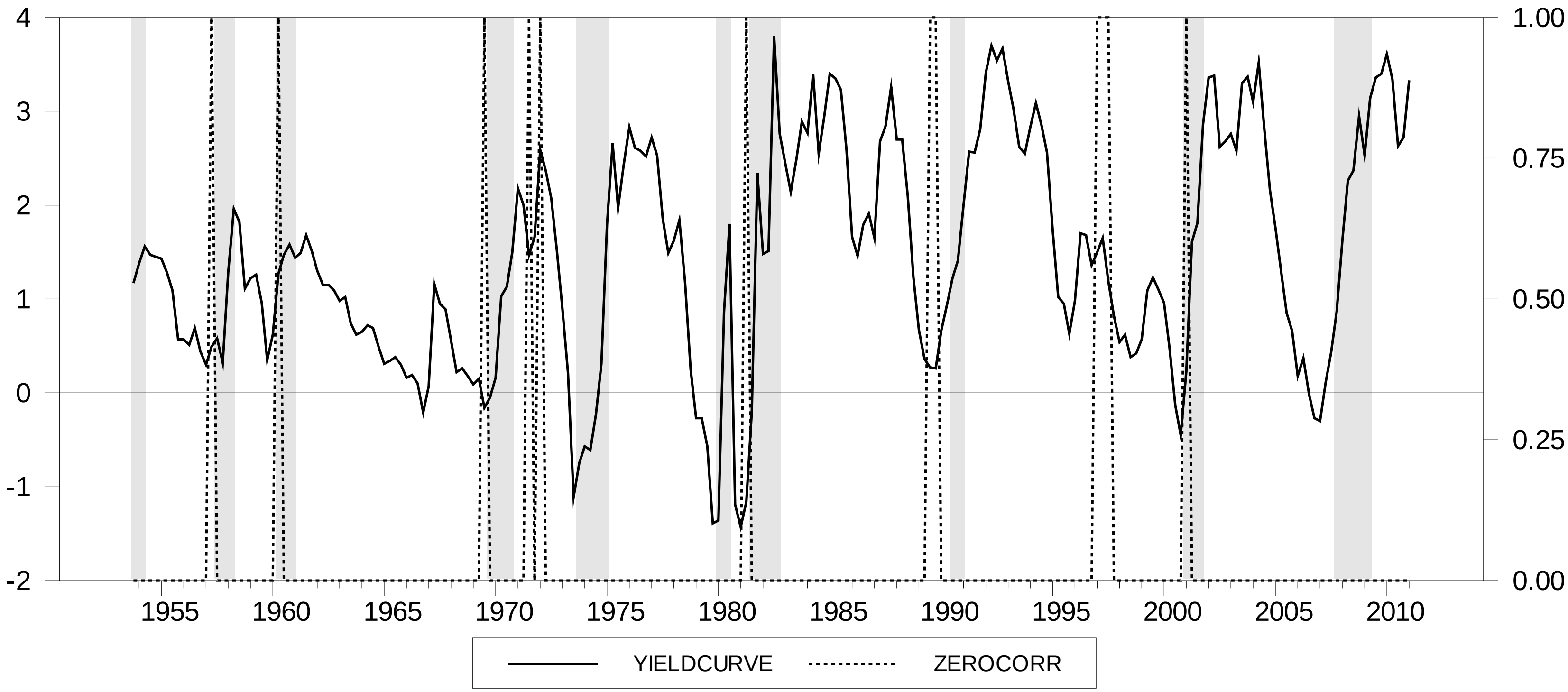
There is a great deal of interest in forecasting recessions**,** but the profession has not always kept a flawless track record when detecting their likelihood. The main shortcoming reported was that the 1990-1991 recession was not captured using the usual forecasting indicators. This view, however, is contradicted by new evidence on the usefulness of the yield curve. In this paper, we confirm the importance of the yield curve when we also include an indicator of monetary policy based on the non-residential and residential MPK correlation. We show that the predictive power of this model is superior to the predictions of professional macroeconomic forecasters on longer forecast horizons.

We first employ two non-linear model specifications to forecast the probability of a recession: the standard probit model proposed by Estrella and Mishkin (1998) of the yield curve and a modified model of the yield curve augmented by the zero correlation indicator. Both in-sample and out-of-sample results conclude that the second model is superior and it appears to contain useful information about the monetary policy, including for the difficult to forecast period of 1989-1999.

Second, in order to provide evidence on the importance of the new indicator as a complement to the yield spread, we compare the predictive ability of the model with the Survey of Professional Forecasters probabilities for one to five-quarter ahead horizon. We find that our model produces better forecasts of recessions than the SPF at horizons beyond two quarters, and especially for four- and five-quarters ahead. This conclusion is still current and stayed true for the past 20 years.

2.6 Figures and Tables

Figure 2.1 Yield Curve and Zero Correlation



Note: Recession Dates are shaded

Figure 2.2 Model 1 and Model 2 Pseudo R-Squared

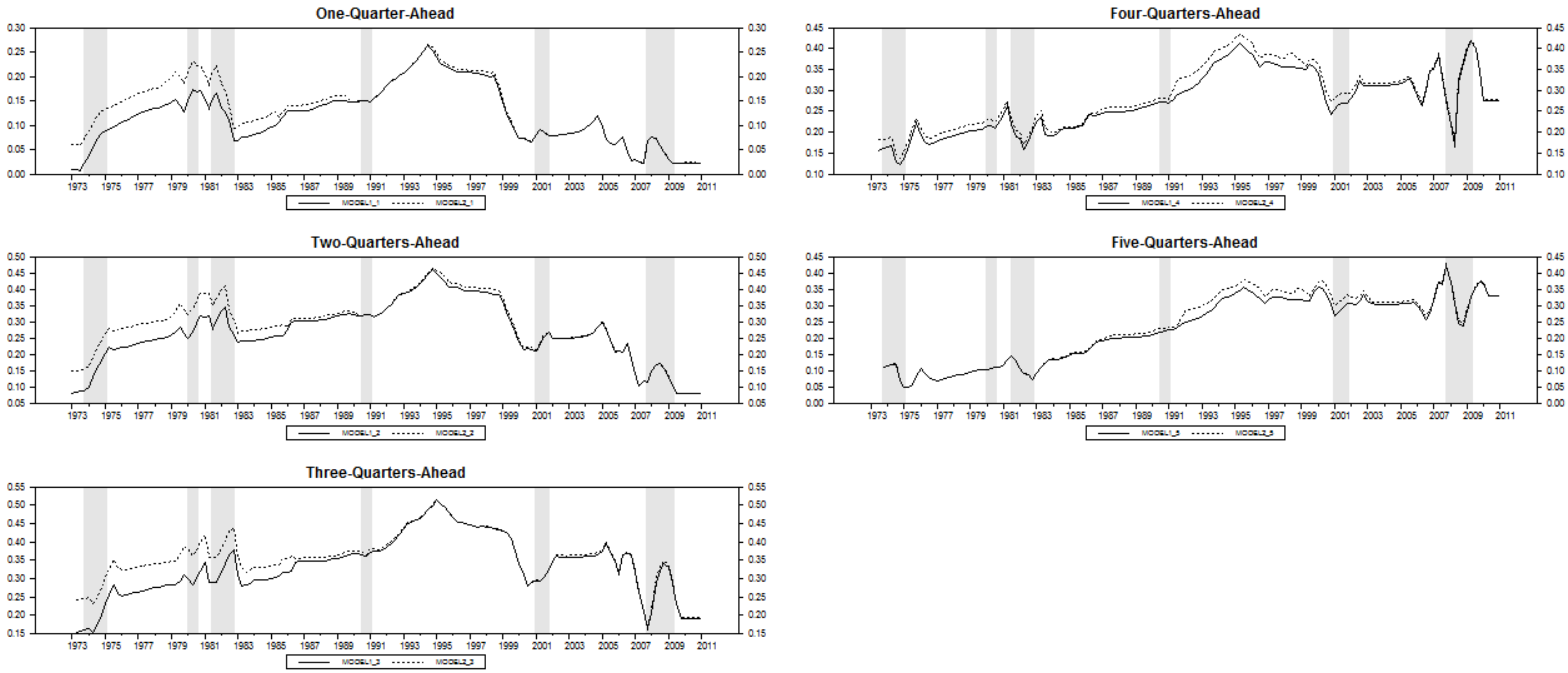


Figure 2.3 Model 1 and Model 2 Fitted Recession Probabilities

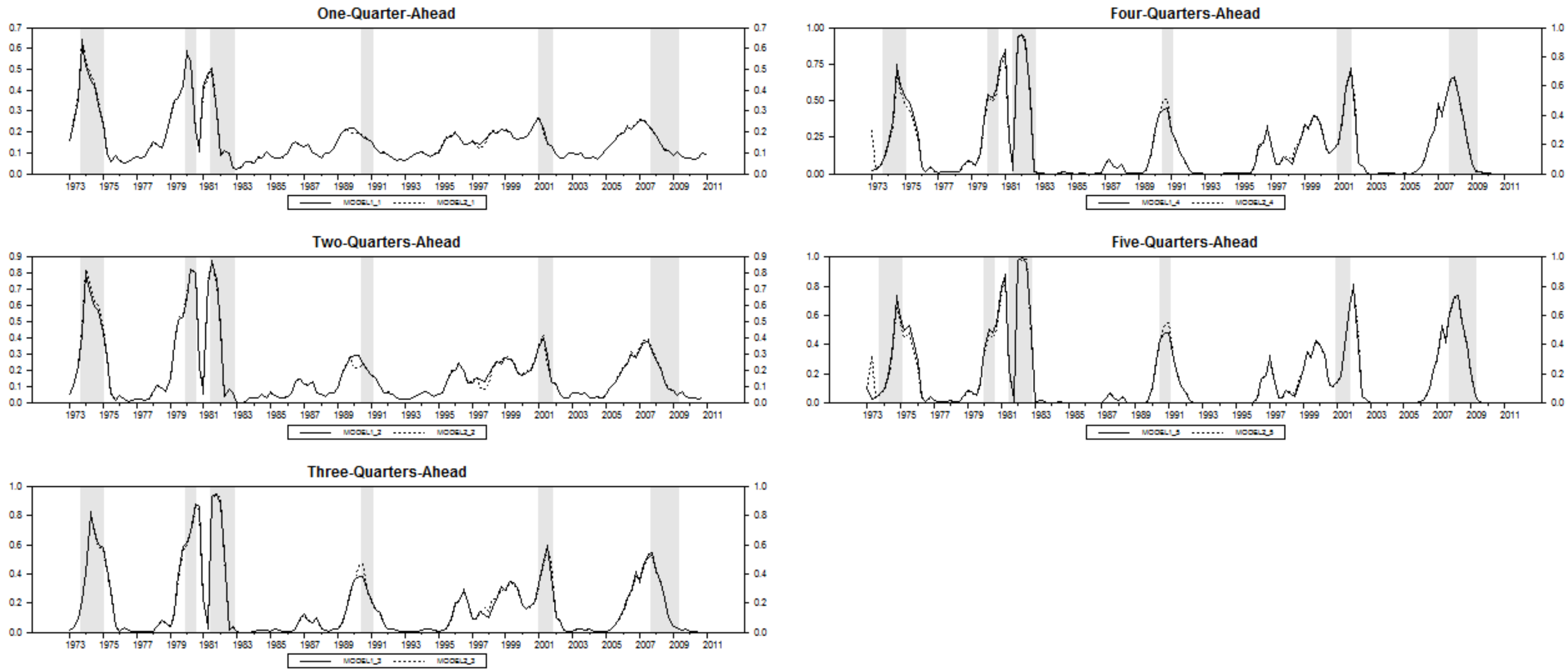


Figure 2.4 SPF, Model 1, and Model 2 Forecasted Recession Probabilities

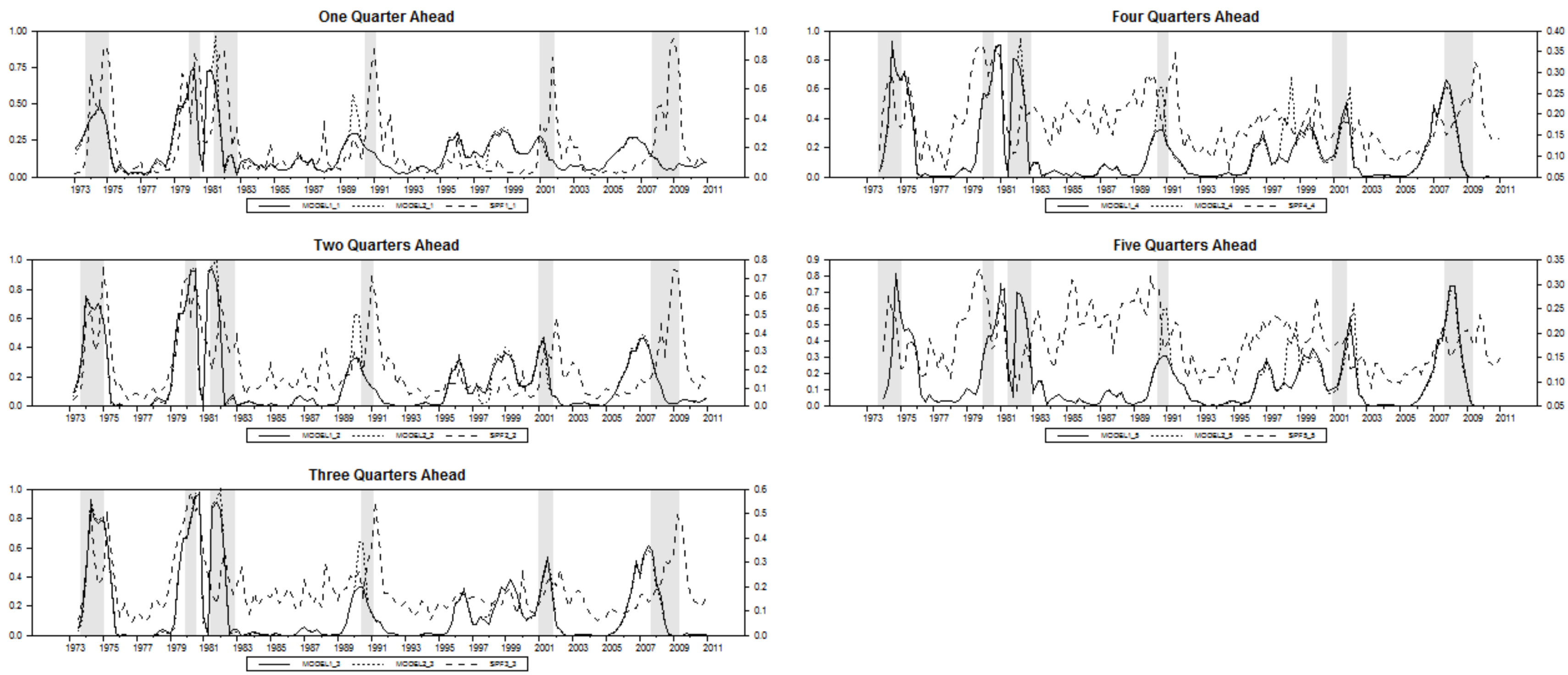


Table 2.1 In Sample Performance

	h=1	h=2	h=3	h=4	h=5
Model 1					
Pseudo R-squared	0.023	0.081	0.192	0.276	0.331
t-stat (yield curve)	-1.287	-2.169	-2.743	-3.467	-3.909
Model 2					
Pseudo R-squared	0.023	0.083	0.194	0.277	0.331
t-stat (yield curve)	-1.367	-2.283	-2.868	-3.61	-4.179
t-stat (zero correlation)	-0.163	-0.417	0.65	0.253	0.25

Note: Larger Pseudo R-Squared is better and significant t-stats are desirable.

Table 2.2 Probability Forecast Evaluation 1998:1

	RMSE	MAE	LPS
	1 QUARTER AHEAD		
MODEL 1	0.346	0.235	0.393
MODEL 2	0.350	0.230	0.400
SPF	**0.271**	**0.180**	**0.247**
	2 QUARTERS AHEAD		
MODEL 1	**0.298**	0.165	**0.311**
MODEL 2	0.308	**0.164**	0.333
SPF	0.325	0.239	0.340
	3 QUARTERS AHEAD		
MODEL 1	**0.286**	0.147	**0.291**
MODEL 2	0.287	**0.142**	0.311
SPF	0.367	0.277	0.423
	4 QUARTERS AHEAD		
MODEL 1	0.319	0.182	0.342
MODEL 2	**0.311**	**0.174**	**0.333**
SPF	0.393	0.298	0.482
	5 QUARTERS AHEAD		
MODEL 1	0.319	0.198	0.319
MODEL 2	**0.308**	**0.189**	**0.303**
SPF	0.410	0.313	0.527

Note: The smaller the statistic, the better the forecast.
The smallest statistic for each horizon is in bold.

Table 2.3 Diebold Mariano West Test Results 1998:1

	MSE	MAE	LPS
	1 QUARTER AHEAD		
MODEL 1 VS SPF	-2.561	-2.687	-2.647
MODEL 2 VS SPF	-2.594	-2.358	-2.573
MODEL 2 VS MODEL 1	-0.855	0.959	-0.766
	2 QUARTERS AHEAD		
MODEL 1 VS SPF	0.563	3.658	0.288
MODEL 2 VS SPF	0.233	3.445	-0.049
MODEL 2 VS MODEL 1	-1.434	0.208	-1.636
	3 QUARTERS AHEAD		
MODEL 1 VS SPF	2.535	7.009	1.825
MODEL 2 VS SPF	2.329	6.600	1.248
MODEL 2 VS MODEL 1	-0.126	0.934	-1.188
	4 QUARTERS AHEAD		
MODEL 1 VS SPF	2.129	5.900	2.065
MODEL 2 VS SPF	2.286	6.000	2.109
MODEL 2 VS MODEL 1	1.142	1.373	0.859
	5 QUARTERS AHEAD		
MODEL 1 VS SPF	2.830	6.078	3.592
MODEL 2 VS SPF	3.032	6.379	3.766
MODEL 2 VS MODEL 1	1.527	2.018	1.682

Note: When one Model is Nested in the other, use McCracken Critical Values, otherwise (for SPF comparisons) standard critical values are appropriate.

Appendix: Business Cycle. Recessions and Expansions.

Before each of the past six out of seven recessions, the interest rates rose, with the exception of Great Recession, when interest rates hit historic lows. Often, Fed engages in contractionary monetary policy when the expected inflation is higher than their target, by increasing short-term interest rates, and initially long-run interest rates also rises, but not as much as the short-term rate. The result of Fed's policy of monetary tightening is often generating recessions.[1] On the other hand, when the economy is weak, Fed loosens monetary policy by decreasing interest rates. Below is a succinct characterization of the behavior of interest rates for both recessions and expansions for seven of the last cycles. This is necessary for a better understanding of the comportment of the marginal products of capital and their evolution across the business cycle. In a recession, we are expecting to see a decrease in the non-residential MPK as a result of the decline in non-residential income. The non-residential capital does not see major changes, because it is not appallingly sensitive to the interest rates increase. The best way to think of this scenario is to consider businesses and the fact that they are driven by their returns. The residential MPK during a recession behaves differently. First, the residential income is quite sticky due to the measurement issues. Second, the residential capital is highly sensitive to the movement in interest rate, because households are more credit constrained. Therefore, an increase in interest rates leads to a decline of residential capital. The outcome of these two facts put together is an increase in residential MPK, mostly as a consequence of unadjusted income.

We start chronologically by characterizing the interest rates' behavior and sectoral marginal product of capital evolution during both recessions and the following expansions

[1] See Goodfriend (1993)

and graph them in figures A1 through A6. We are particularly interested in proving that there is a pattern associated with each recession and expansion, that will allow me to use a new measure for forecasting real GDP growth.

The 1960 recession lasted 4 quarters and followed only 8 quarters after the previous one. It was one of the mild monetary recessions, with a fall in GNP of 1.6% starting after FED raised the interest rates in 1959 to tackle huge inflation and gold outflows. The reserve requirement and discount rate were both cut in August, both successful measures in ending the recession in February. The correlation between Residential and Non-residential marginal product of capital was highly negative, featuring a value of -0.85. Marginal product of non-residential capital went down 1 percentage points from a value of 10.43% to 9.46%, as opposed to the marginal product of residential capital which went up by just a very little from 3.78% to 3.85%.

The expansion that followed was the second longest (1961:2 – 1969:3) lasting for 8 years. The policy directive was moderate, exhibiting rapid growth and the federal funds rate started rising after the trough. Inflation stayed at low values until 1965, when it began rising and so did the interest rates, but the Fed could not control the inflation growth. Further increases in interest rates caused the "credit crunch" of 1966, which happily was only a growth slowdown. This expansion was somewhat atypical from the point of view of correlation of marginal product of residential and non-residential capital, with a negative correlation of -0.19 strongly driven by the last 2 quarters of data. For most of the following expansions, the two series moved together for the whole sample. Both of the series had the same upward course until the mid of the expansion, after which the non-residential marginal product went by a very little bit down and the residential went up. For the whole expansion time, the growth in MPK residential (12%) was almost double than for the non-residential MPK (6.2%). The values for MPK non-residential in 1961:2 was 10.13% and 3.83% for MPK non-residential, reaching in 1969:3 10.76%, respectively 4.29%. If we go back two quarters before the next recession starts and measure the correlation again, we find a value remarkably closer to zero.

The **1969 recession** was relatively mild and followed a long expansion. The end of the expansion was characterized by high inflation. The Fed attempted monetary tightening and fiscal tightening was also used for closing the deficit caused by the Vietnam War. The result was slow money growth, declining interest rates and a very slow reduction in inflation rate. Real GNP fell only by 0.6%. The correlation between MPK residential and non-residential unlike for the rest of the recessions is positive, 0.62. The main reason for this is the length of the recession, only 5 quarters, being considered not only short, but the public got the information of a recession happening after the recession ended and did not react to the market uncertainty. As a general trend, MPK residential stayed unchanged at a value of 4.29%, while MPK non-residential fluctuated, reaching a value of 9.67% at the end of the recession.

The 1971:1 to 1973:4 expansion was short, but settling lower interest rates and higher money growth, even though the recovery was sluggish and unemployment did not pick up until 1971:3. The expansionary period was an effort of keeping unemployment under control and at a lower level, the Nixon administration imposing unsuccessful wage control. The result was a crazy increase in inflation. Not surprisingly, the expansion is too short for a clear interpretation of the agent's behavior in residential and non-residential sector, and from the perspective of the correlation in marginal product of capital, it seemed like investors acted with a lag, as if the recession never ended.

The recession of 1973 was significantly worse than the previous ones and even more aggravated by the quadrupling of oil prices in 1973 and stock market crash 1973 - 1974. It lasted 6 quarters, and registered the highest drop in GDP (-3.2%) and increase in both inflation and unemployment. In the first quarter on 1975, Fed adopted a more aggressive policy continued even after the recession ended, cutting federal funds rates, discounts rate and reserve requirement, desired for a higher money growth, because the problem of high unemployment was very pressing. The government spending was higher than before because of the Vietnam War, leading to stagflation. The recession also significantly affected the non-residential sector, with a declining marginal product of capital from 10.8% in 1973:4 to 8.02% in 1975:1. MPK of residential sector stayed almost constant with a very small increase from 4.21% to 4.30% for the same time frame. The correlation of the two was -0.74.

The expansion started in 1975:2 and lasted until 1977:4 and continued with worrying level of inflation. The evolution of the MPKs was somewhat stagnant, with a very slight decrease in the residential MPK and almost no overall change for the non-residential sector, even though it registered quarter-to-quarter fluctuations of almost 1%. Again, we are interested to see when is the first time that we can see a zero correlation between the series, and not surprisingly, we find it two quarters before the preceding recession.

The NBER considers the **1980 Recession** a short recession, followed by a short period of recovery and another deep recession. This period is known in the literature as the "double-dip" recession or "W-shaped" recession. The first part of the double-dip recession was mainly about lowering the 1970s high inflation and fighting 1979's energy crisis. The newly appointed chairman of Federal Reserve, Paul Volker, declared war against inflation, raising the interest rates dramatically. This was the largest increase in federal funds rate since the beginning of the Fed, which had to be abandoned in the third quarter of 1980 in the light of decelerated economic activity. FOMC imposed the necessary credit controls, leading to a decline in consumer credit, which caused a chain reaction of low consumption and decrease in GDP. At beginning of the very short expansion, Fed reversed the strategy (expansionary monetary policy) by decreasing the federal funds rate and increasing the money base. There is not too much to be said about the correlation of the marginal products of non-residential and residential capital, considering the short span of only 3 quarters for both recession and expansion. The non-residential MPK stayed constant during recession, but increased exactly at the switch between recession and expansion by 13.7%, to go down again until the end of the expansion. Residential MPK increased at a steady low step in both stages of the business cycle. The recovery in the expansion was surprisingly rapid, but the inflation rate got again under control in the second quarter of 1981, causing the second wave of recession from 1981:3 to 1982:4.[2] Fed adopted contractionary monetary policy, increasing the federal funds rate and discount rate. This new wave of measures accomplished the desired result of reducing the inflation rate, from about 10% in early 1981 to about 4% in 1983, but at the cost of a sharp and very prolonged recession. Although the rate of inflation was at a low value, there was more concern regarding solvency, especially in the light of new debt default in the Latin America. In the last 6 quarters of double dip recession, the marginal product of residential capital went constantly up from 4.50% to 4.71%, while the non-residential went up for two quarters, and down in the last 4 from 8.84% to 7.78%. The correlation was -0.79. After a new reduction in interest rate, a lengthy expansion started with most indicators

[2] Fed raised the federal funds rate from 14.7% in March to 19.1% in June.

growing rapidly, including undesirable unemployment. Monetary policy tightened again somewhat, but nothing so radical as in the 1981 recession. The marginal product of both residential and non-residential capital went up, from 4.73% to 4.98%and 7.15% to 8.06% respectively. This is very much in line with Fed's monetary policy. For the whole length of the expansion, the correlation is MPK series was highly positive, recording a value of 4% in the last quarter. This time, we do not see the zero correlation two-quarter rule before recession, but in the last quarter of the expansion, the value of the correlation is close to zero.

After a long expansion of 26 quarters, the contractionary monetary policy led to the mild and short 1990 recession.[3] The increasing interest rates for a three year period (1986 – 1989) might not have caused a recession this time, if they wouldn't have been accompanied by another oil shock, after Iraq invaded Kuwait in August 1990. The new bank regulations after the Savings and Loan Crises of 1980s, the accumulated debt and the consumer pessimism contributed to the 3 quarter recession. The evolution of MPK is too short to make any certain affirmation, but we do see a slight decrease in non-residential and a slight increase in residential. The following expansion was the longest and most prosperous in American history that lasted for ten years. Fed played an impressive role in keeping inflation under control, especially in 1993:1, when a tighter policy was put in place for almost a year. The residential and non-residential sectors commoved most of the time, with several occasions when marginal product of residential capital went up and the non-residential down. The correlation for the whole expansion period was -0.22, driven mostly of the last three quarters before recession. MPK residential increased to 5.49% from a previous value of 5.08, and non-residential MPK decreased at 7.02% from 7.60%As always, our main focus is

[3] The decrease in real GDP was only 1.4%

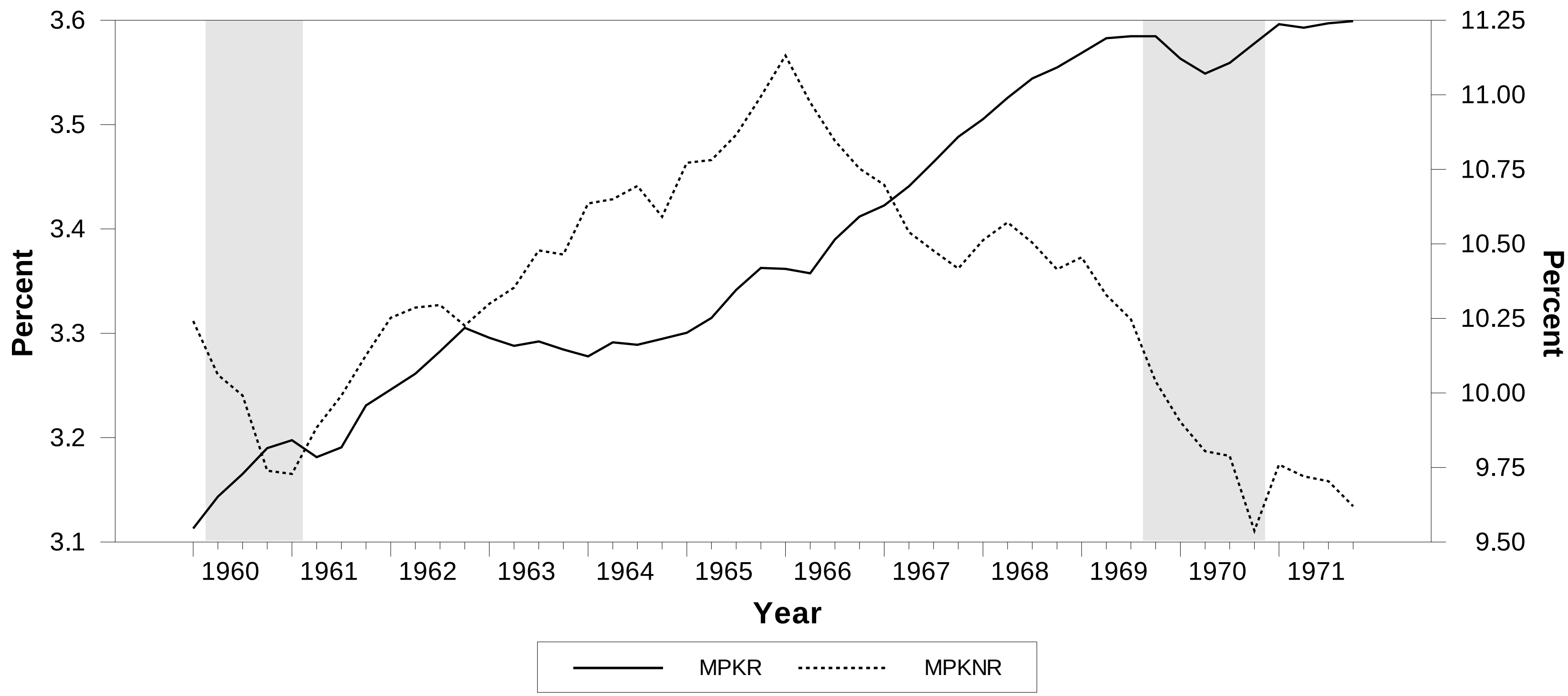
the correlation right before the following recession. This time, we can see the zero correlation of the series with 3 quarters ahead of the recession, but the story still holds.

Several factors facilitated **2001 recession**: the tragedy of September 11th attacks, the speculative dot-com bubble, and a decrease in business investment. Fortunately, the recession was brief (4 quarters) and didn't affect the growth of main indicators notably. Like the previous recession, there were concerns about a "jobless recovery" employment not being able to pick up. A contractionary course of action could not be avoided on time, and the federal funds rate decreased to a historical low of 1% in 2003:2, accompanied by the real short-term interest rates reaching almost 0% in 2002:2. From the point of view of correlation of non-residential and residential MPK, this recession looked very much like the one in 1969, recording a positive value of 0.46. Both MPKs decreased in the 4 recession quarters by 1% in residential sector, and 3% in non-residential. Naturally, Fed started to be apprehensive about deflation during this expansion and alarmed to the perspective of an inflationary future, federal funds rates had been risen 0.25 percentage points until 2007:3. This expansion is totally unusual from all the others if we are looking at the evolution of residential and non-residential MPK, the residential in decreasing by 7% for the whole expansion's duration, which is not unexpected considering that we were in a housing bubble, while the MPK residential increases just a half of the increase in residential, from 6.25% to 6.41%. Consequently, the correlation in -0.51 and it stays negative for the whole sample period. This is the only expansion that does not conform to the story of recession predicted by the correlation between residential and non-residential MPK. No matter how many quarters we go back, we never find the desired zero correlation, hence the last expansion was different and it only could have led to a "different" recession.

The Great recession of 2007 or subprime mortgage crisis is probably the most severe postwar event. It led to the end of housing bubble and caused a financial crisis dangerous for the health of global economies. It was the longest postwar recession and caused the higher drop in real GDP (4.1%) and alarming high rates of unemployment (10.2% as of July 2010). One of the major factors that headed toward this direction was the lack of prudent lending. Prior loose monetary policy ending in 2004 and alarmingly slow growth of employment is believed to only aggravate the falling housing related assets and create the credit crunch. Tight monetary policy was reflected in the escalating federal funds rate, which was replaced by expansionary policy, cutting the federal funds rates close to 0%. For now, we know only that the correlation of MPK in residential and non-residential sector were highly negatively correlated (-0.87), with descending values in the non-residential sector and ascending in the residential.

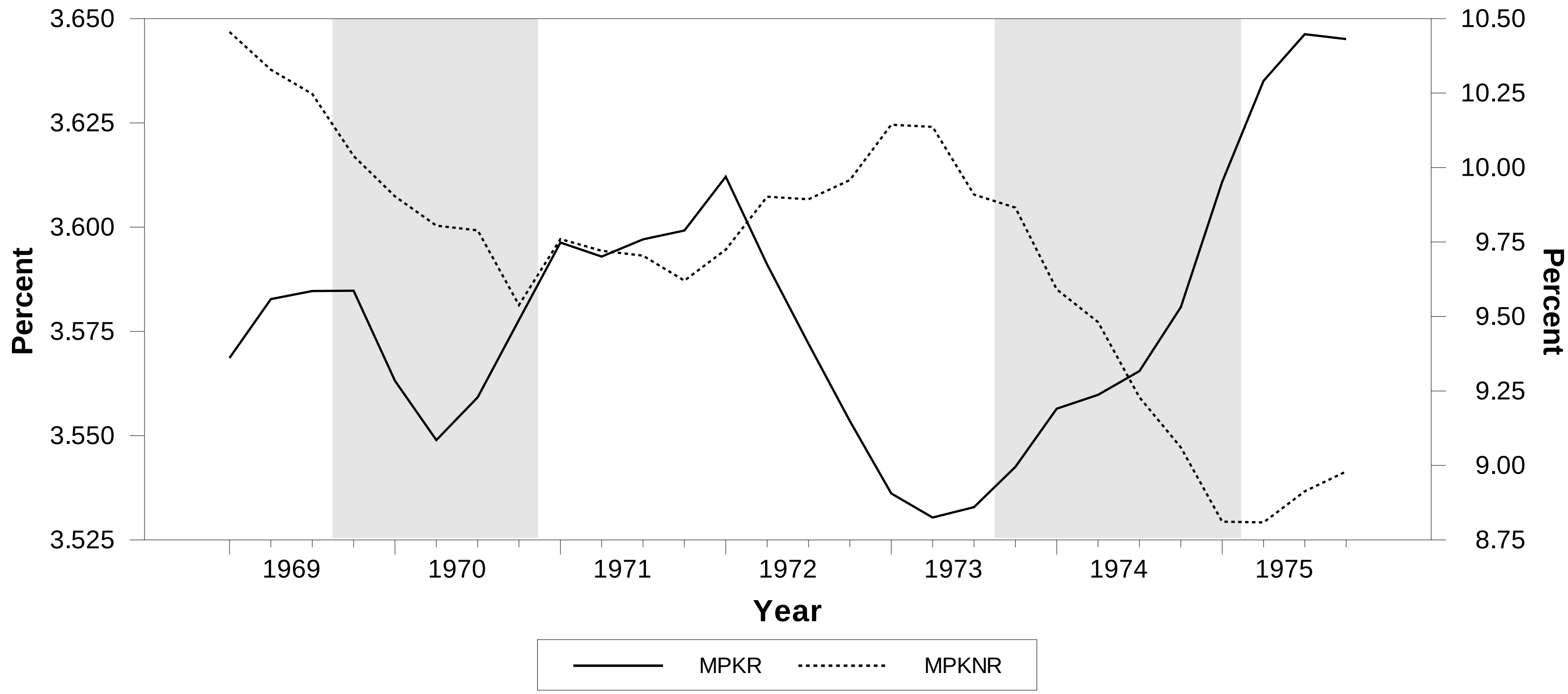
Appendix: Figures

Figure A1 MPK Residential and Non-Residential 1960-1971



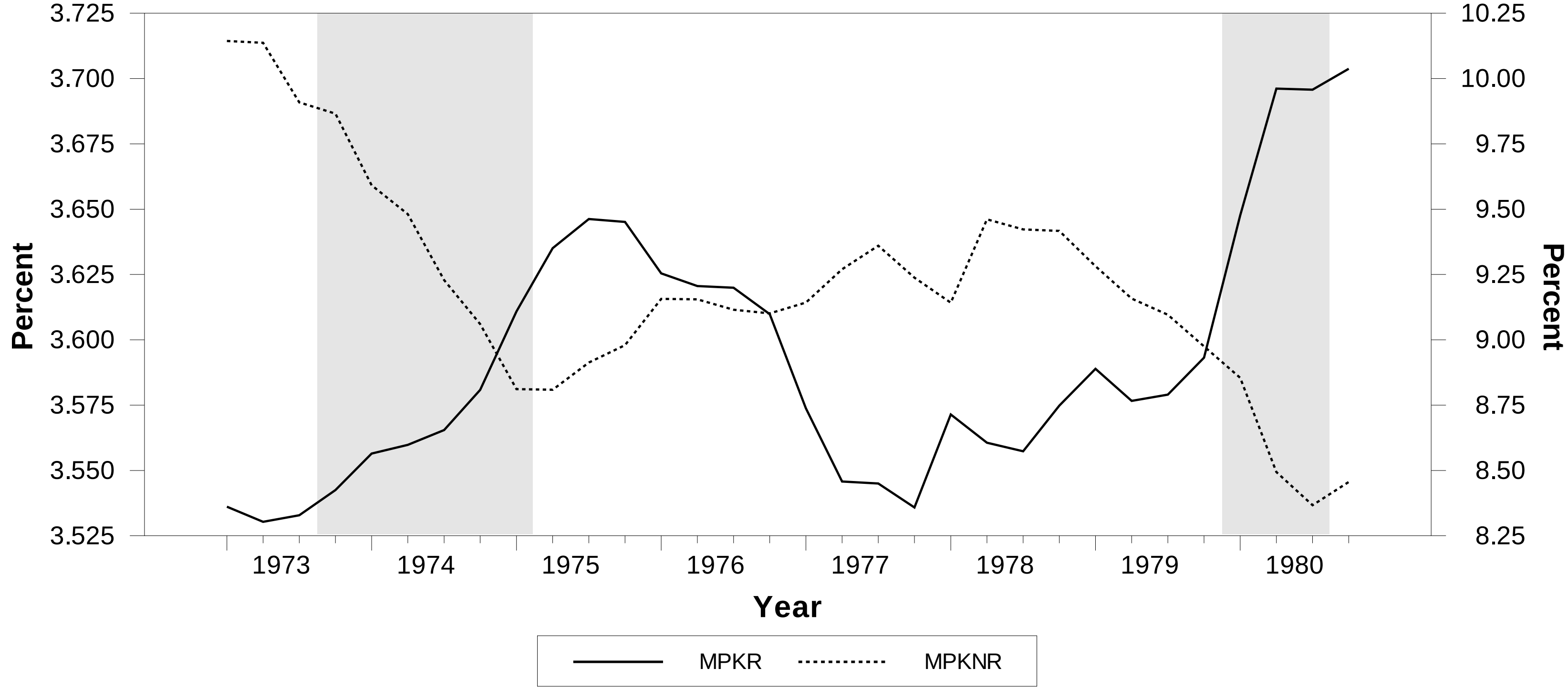
Note: MPKR left axis, MPKNR right axis

Figure A2 MPK Residential and Non-residential 1969-1975



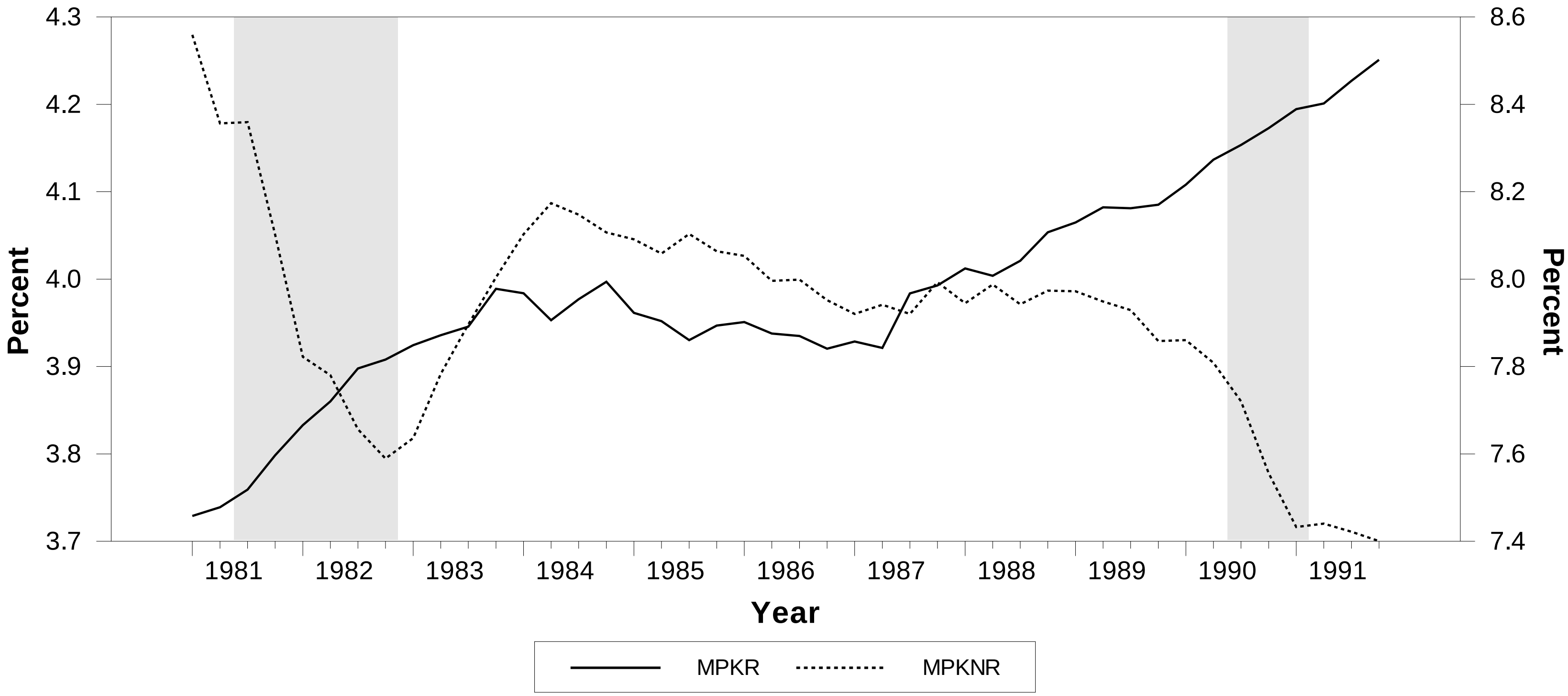
Note: MPKR left axis, MPKNR right axis

Figure A3 MPK Residential and Non-residential 1973-1980



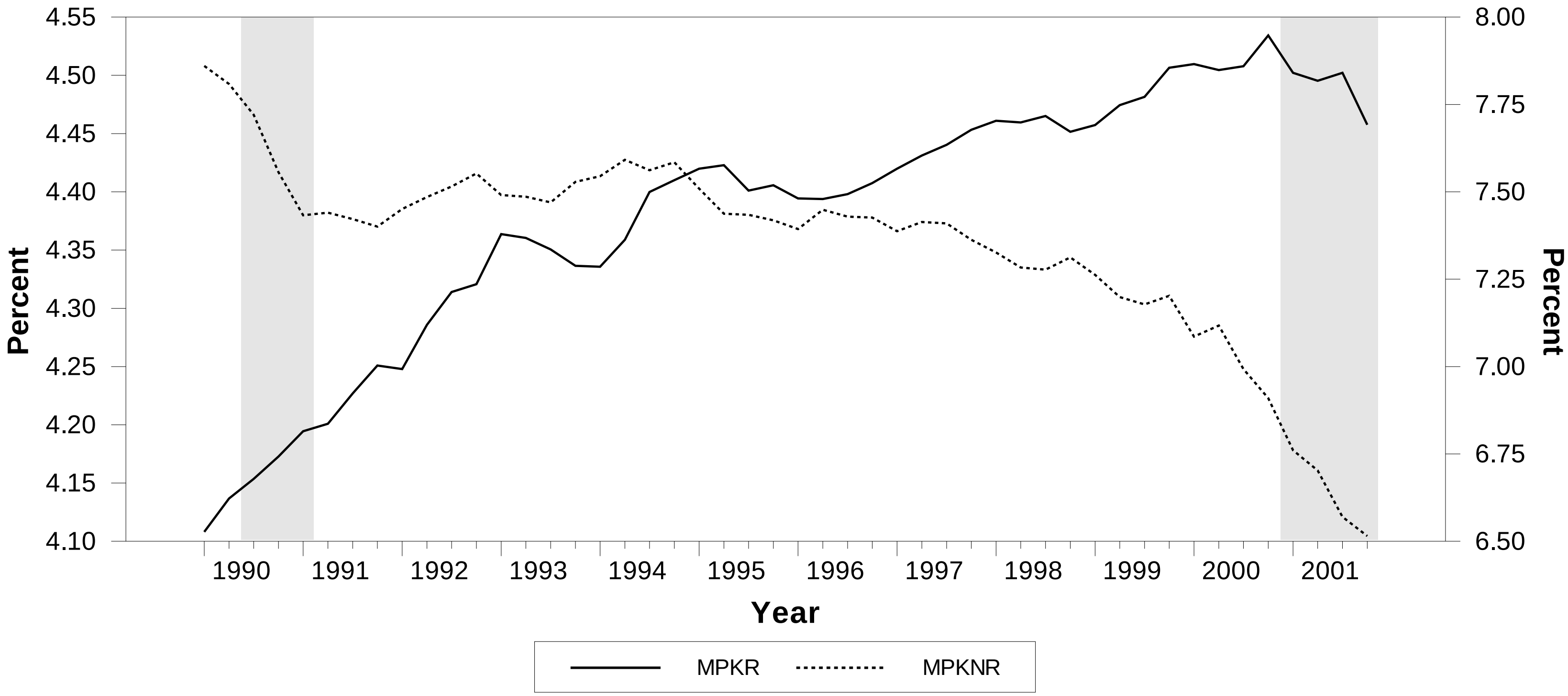
Note: MPKR left axis, MPKNR right axis

Figure A4 MPK Residential and Non-residential 1981-1991



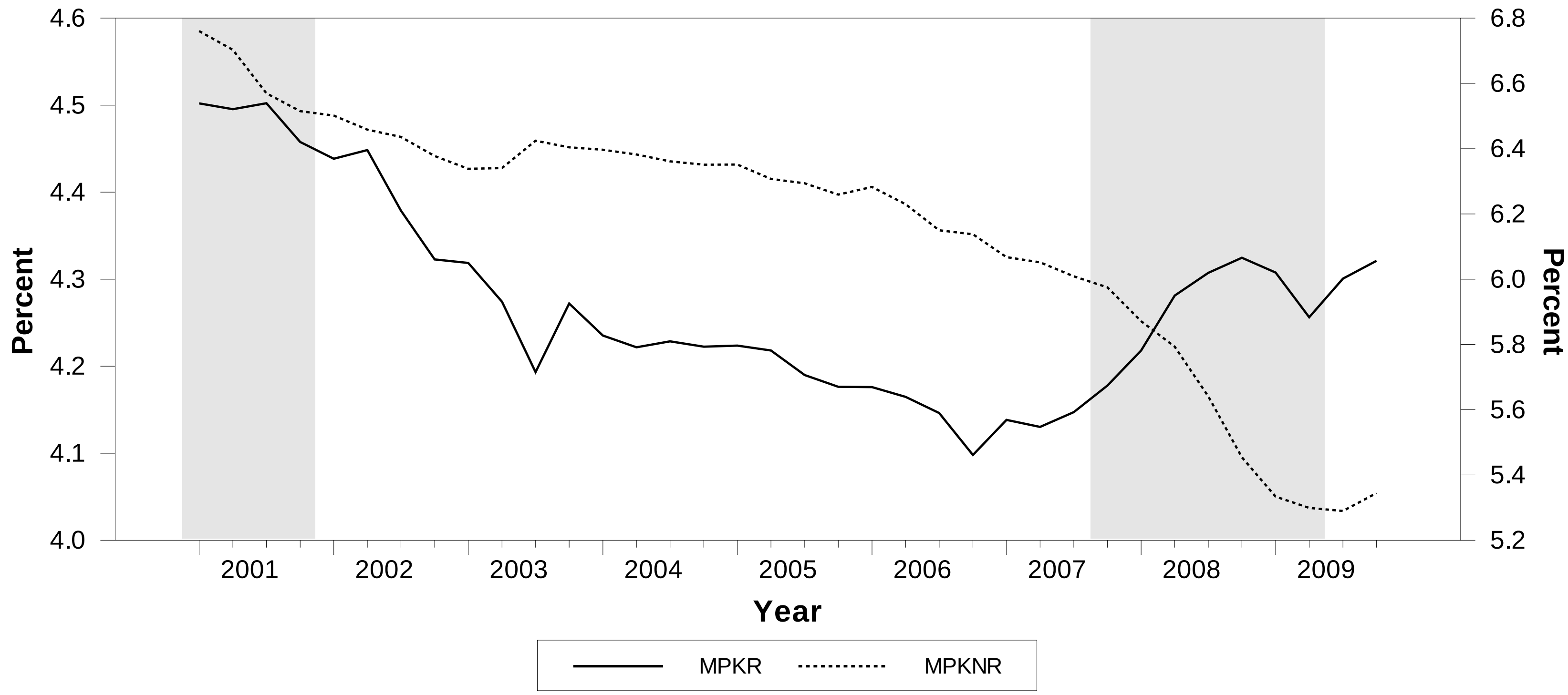
Note: MPKR left axis, MPKNR right axis

Figure A5 MPK Residential and Non-Residential 1990-2001



Note: MPKR left axis, MPKNR right axis

Figure A6 MPK Residential and Non-Residential 2001-2009



Note: MPKR left axis, MPKNR right axis

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