8-2010

Essays on Monetary Policy

Omer Bayar
obayar@utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Omer Bayar entitled "Essays on Monetary Policy." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

William S. Neilson, Major Professor

We have read this dissertation and recommend its acceptance:

Mohammed Mohsin, Christian A. Vossler, Chanaka Edirisinghe

Accepted for the Council:
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Essays on Monetary Policy

A Dissertation Presented for
the Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Omer Bayar
August 2010

Abstract

Central banks use a series of relatively small interest rate changes in adjusting their monetary policy stance. This persistence in interest rate changes is well documented by empirical monetary policy reaction functions that feature a large estimated coefficient for the lagged interest rate. The two hypotheses that explain the size of this large estimated coefficient are monetary policy inertia and serially correlated macro shocks. In the first part of my dissertation, I show that the effect of inertia on the Federal Reserve's monthly funds rate adjustment is only moderate, and smaller than suggested by previous studies. In the second part, I present evidence that the temporal aggregation of interest rates puts an upward bias on the size of the estimated coefficient for the lagged interest rate. The third part of my dissertation is inspired by recent developments in the housing market and the resulting effect on the overall economy. In this third essay, we show that high loan-to-value mortgage borrowing reduces the effectiveness of monetary policy.

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Introduction

Central banks use a series of relatively small interest rate changes in adjusting their monetary policy stance. This persistence in interest rate changes is well documented by empirical monetary policy reaction functions that feature a large estimated coefficient for the lagged interest rate. The two hypotheses that explain the size of this large estimated coefficient are monetary policy inertia and serially correlated macro shocks.

In the first part of my dissertation, I use an ordered probit-based analysis to show that the effect of inertia on the Federal Reserve's monthly funds rate adjustment is only moderate, and smaller than suggested by previous studies. This finding indicates that the Fed's response to serially correlated factors plays an important role in policy setting. These predictions are in line with the interpretation that inertia and serially correlated shocks simultaneously affect monetary policy.

In the second part of my dissertation, I present evidence that the temporal aggregation of interest rates puts an upward bias on the size of the estimated coefficient for the lagged interest rate. Particularly, measuring the path of monetary policy by averaged interest rates leads to spuriously large parameter estimates for the lagged interest rate due to temporal aggregation effects.

The third part of my dissertation is inspired by recent developments in the housing market and the resulting effect on the overall economy. In this third essay, we use a simple partial equilibrium consumer theory model to explore the implications of high loan-to-value mortgage borrowing. We find that sufficiently large expected house price growth reduces the impact of monetary policy on aggregate demand, and that it leads to housing demand showing patterns contrary to traditional investment and consumption theories.

Part 1

An Ordered Probit Analysis of Monetary Policy Inertia

This paper is under review for publication in the *Journal of Monetary Economics*.

Abstract

The two hypotheses that explain the observed persistence in interest rate changes are monetary policy inertia and serially correlated macro shocks. In this study, I use an ordered probit-based analysis to provide evidence that the effect of inertia on the Federal Reserve's monthly funds rate adjustment is only moderate. This finding indicates that the Fed's response to serially correlated factors plays an important role in policy setting. These predictions are in line with a recent interpretation that inertia and serially correlated shocks simultaneously affect monetary policy.

1. Introduction

The two leading explanations of the observed persistence in short-term policy interest rate changes are monetary policy inertia and serially correlated macro shocks. In this paper, I use an ordered probit-based exercise to examine the Federal Reserve's monthly funds rate adjustment under the former chairmen Alan Greenspan and Ben Bernanke. The results show that inertia is present at monthly data, but its impact is not sufficient to generate the observed path of successive interest rate changes. This in turn suggests that the central bank's reaction to serially correlated factors plays an important role in policy setting.[1]

The monetary policy inertia view (also called interest rate smoothing, partial adjustment, or gradualism) is that the central bank deliberately spreads large interest rate changes over time. The inertia advocates present several motivations for such gradualism. Among them, Goodfriend (1991) discusses how reducing the volatility of interest rates and that of asset prices promote financial stability. Sack (2000) argues that the model and the parameter uncertainty inherent in macro projections warrant a sequence of small adjustments. Woodford (2003) shows how interest rate smoothing improves the bank's stabilization policy in the presence of forward-looking agents.[2] These theoretical arguments are supported by estimated monetary policy reaction functions (i.e. regressions of the interest rate on a small number of macro variables and the lagged interest rate) that produce evidence of substantial inertia.[3]

Rudebusch (2002) challenges the inertia argument by showing that a spurious finding of inertia might arise when policymakers respond to serially correlated factors that are omitted in the estimated policy rule.[4] Moreover, Rudebusch (2002), Rudebusch (2006), and Rudebusch and Wu (2008) present empirical evidence against the inertia hypothesis. They emphasize that in a highly inertial system, future interest rate changes should be largely predictable. However, the term structure evidence (built on interest rate forward and futures data) shows that the accuracy of market forecasts diminishes greatly beyond the first few months.[5]

[1] I analyze here the policy adjustment at monthly frequency. Rudebusch (2006) discusses how monthly policy inertia is independent of whether policymakers smooth interest rates over several quarters.

[2] Orphanides and Williams (2005) corroborates further the need for a restrained policy reaction by showing that activist monetary policy aimed at stabilizing unemployment tightly around a severely underestimated natural rate of unemployment led to poor macro performance in the late 1960s and 1970s. They argue that had the policy remained less aggressive the stagflation of the 1970s would have been avoided.

[3] The coefficient on the lagged interest rate is around 0.8 at quarterly frequency suggesting a very slow response to monetary shocks, with only about 20 percent of a desired adjustment achieved after a full quarter. See Judd and Rudebusch (1998), Clarida et al. (2000), and Sack and Wieland (2000) among others.

[4] These omitted serially correlated factors include episodes of financial market distress (Gerlach-Kristen, 2004), time variation in the real equilibrium interest rate (Trehan and Wu, 2007), and persistent gaps between the real-time data used by policymakers to set the interest rate and finally revised data used by analysts to estimate the policy rule (Lansing, 2002).

[5] On the contrary, Podpiera (2008) points out that the term structure evidence of limited predictable variability in future interest rates does not necessarily prove that monetary policy is non-inertial. He shows

A third line of analysis focuses on the possibility that both inertia and serially correlated factors might affect the policy setting. Using nested empirical structures, English et al. (2003) and Gerlach-Kristen (2004) present evidence that both mechanisms matter to the Fed. Carrillo et al. (2007) use a DSGE model combined with a monetary vector autoregression to show that the observed federal funds rate path is better fitted by a policy that displays moderate policy inertia and also reacts to serially correlated factors.

The customary central bank practice is to change the policy rate infrequently, and by discrete amounts. I use an ordered probit in modeling interest rate changes to account for the discrete and the censored nature of policy adjustment. Several studies consider similar monetary policy applications of the ordered probit model. Gali et al. (2004), Carstensen (2006), and Gerlach (2007) examine the interest rate setting decisions by the European Central Bank, Dueker (1992), Choi (1999), Dueker (1999), and Hamilton and Jorda (2002) by the Federal Reserve, Eichengreen et al. (1985) and Genberg and Gerlach (2004) by the Bank of England, and Huang and Lin (2006) by the monetary authority in Taiwan. Despite the large number of ordered probit applications, no previous study discusses policy inertia, with the exception of Dueker (1999).[6] The present study enters that debate proposing a novel ordered probit-based test.

Rudebusch (2006) states that the presence of substantial policy inertia in high frequency data (i.e. weekly or monthly) is generally acknowledged, and so the investigation of inertia is mostly limited to quarterly data. The main finding of the present study is that inertia is not as pronounced at monthly frequency as anecdotal evidence suggests. I demonstrate below that inertia alone is not sufficient to create the observed persistent path of monthly interest rate changes, and therefore the Fed's response to serially correlated factors must be playing a part in policy setting. This is in line with the interpretation that inertia and serially correlated shocks simultaneously affect monetary policy decisions.

The plan of paper is as follows. The second section sets out the structure of the ordered probit model. In the following section, I describe the data and present the estimation results. The fourth section describes the application of the ordered probit to measuring the impact of inertia on monthly funds rate setting. I conclude in the last section.

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that even highly inertial policymakers (i.e. Bank Board of the Czech Central Bank) are unable to predict future policy changes beyond the first two quarters, let alone market participants who tend to align their expectations with the declared policy outlook of the central bank.

[6] Dueker (1999) finds evidence of inertia in funds rate setting by choosing a proper normalization for the standard deviation of model errors, which makes the ordered probit thresholds directly comparable in size to actual funds rate changes.

2. Model

I use an ordered probit to model the Federal Reserve's monthly funds rate changes.[7] The organizing principle of the model is an extended Taylor-type rule, following Taylor (1993).[8] In the ordered probit model, ΔFFR_t^* denotes the unobserved continuous dependent variable, the desired federal funds rate change, measuring the distance between the current desired rate and the lagged actual rate (i.e. FFR_t^* - FFR_{t-1}). The desired rate change satisfies[9]:

$$(1) \qquad \Delta FFR_t^* = \beta_1 FFR_{t-1} + \beta_2\, \Delta FFR_{t-1} + \beta_3\, \Delta FFR_{t-2} + \beta_4\, \pi_{t-1} + \beta_5\, \Delta\pi_{t-1} + \beta_6\, y_{t-1} + \beta_7\, \Delta y_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0,1)$$

where π_{t-1} is the lagged inflation, $\Delta\pi_{t-1}$ is the lagged change in inflation, y_{t-1} is the lagged output gap, that is, the percentage deviation of output from its potential, Δy_{t-1} is the lagged change in the output gap, FFR_{t-1} is the lagged federal funds rate, ΔFFR_{t-1} is the lagged change in the federal funds rate, and ε_t is a stochastic error term that captures the uncertainty in policy effects and specification error.[10]

The federal funds rate changes are typically announced at the end of the Federal Open Market Committee meetings that take place eight times a year, roughly every six weeks. This institutional arrangement raises the possibility of serial correlation at the first two lags in monthly estimation depending on the timing of meetings. So, I add to the model ΔFFR_{t-2}, the second lag of the dependent variable.

The latent regression model in expression (1) underlies the maximum likelihood estimation. The conditional mean of the dependent variable ΔFFR_t^* is a linear function of

[7] Parameter stability across monetary regimes is a recurrent issue for empirical reaction functions usually preventing the use of long samples. With the fairly short samples available, a quarterly ordered probit model lacks the sufficient number of observations in different interest rate change categories necessary for estimation. Thus, the selection of the ordered probit leads naturally to a monthly analysis.

[8] Simple Taylor rules that assign positive weights on inflation and output targets are a common way of describing monetary policy on theoretical (Svensson, 1997) and empirical grounds (Judd and Rudebusch, 1998).

[9] The selection of inflation and output gap as the determinants of policy is consistent with the literature. Since the observed dependent variable is the change in the federal funds rate, I add to the model the changes in these variables. See Choi (1999) and Dueker (2000) for similar applications.

[10] One weakness of this fairly standard probit structure is that the unobserved model errors might be serially correlated if one fails to include all the relevant conditioning variables. A dynamic ordered probit specification is one way to deal with serial correlation at the expense of undertaking complicated numerical integrations (Eichengreen et al, 1985). However, the evidence presented below for residual serial independence warrants the use of the simpler model.

observed and unobserved factors, where the distribution of the latter is assumed to be normal with zero mean and unit variance.[11]

The policy rule is backward-looking in that the monetary authority is assumed to respond to the lagged values of inflation and output gap rather than to forecasts.[12] The adjustment of the current desired change ΔFFR_t^* depends on past actual rates (FFR_{t-1}, ΔFFR_{t-1}, and ΔFFR_{t-2}) rather than past desired rates, as proposed by Dueker (2000).

The central bank raises the federal funds rate in response to rising inflation and excessive output expansions. Then, the expected signs for inflation and output gap variables are positive. Provided that expression (1) is a simplified unrestricted error correction model, the expected signs on the lagged funds rate changes are positive and that on the lagged funds rate is negative.

The ordered probit maps the unobserved desired funds rate change (ΔFFR_t^*) onto the observed discrete funds rate change (ΔFFR_t) through estimated thresholds. The continuous domain of ΔFFR_t^* is divided into five regions, one for each interest rate change category observed in the sample, through six thresholds such that the first and last thresholds are $\tau_0 = -\infty$ and $\tau_5 = +\infty$ and $\tau_{k+1} > \tau_k$ for all k. The measurement model for the observed dependent variable can be formally written as:

(2) $$\Delta FFR_t = k \quad \text{when} \quad \tau_{k-1} < \Delta FFR_t^* \leq \tau_k$$

where the actual rate change falls in category $k = 1 \ldots 5$ when ΔFFR_t^* lies between τ_{k-1} and τ_k.[13]

The probability that the observed change in the policy rate falls into the k^{th} category ($\Delta FFR_t = k$) is:

(3) $$Pr\ (k) = \Phi(\tau_k - \beta X_t) - \Phi(\tau_{k-1} - \beta X_t)$$

where $\Phi(.)$ is the cumulative standard normal density function.

The probabilities in expression (3) combine for each observation to maximize the following log-likelihood function:

(4) $$\sum_{t=4}^{T} \sum_{k=1}^{6} D(\Delta FFR_t = k)\ ln[\Phi(\tau_k - \beta X_t) - \Phi(\tau_{k-1} - \beta X_t)]$$

where $D(\Delta FFR_t = k)$ is a dummy variable that equals one if $\Delta FFR_t = k$ in period t and zero otherwise.

[11] See Choi (1999) for a discussion on the normality of errors.
[12] For similar applications, see Dueker (1999), Choi (1999), and Carstensen (2006).
[13] Expression *(2)* reflects that interest rate changes occur infrequently with a threshold effect, signaling the Fed's willingness to allow deviations from the desired level in a certain tolerance range. This range might arise, for instance, from the recognition that staff projections are sensitive to data and model uncertainty.

3. Estimation

3.1 Data

I use seasonally adjusted monthly data for monetary policy under the chairmen Alan Greenspan and Ben Bernanke.[14] The sample period starts in October 1989, roughly two years after Greenspan's appointment because there were target funds rate changes of smaller than 25 basis points prior to that date, and ends in December 2007. I control for a possible shift in policy across the two chairmen by extending the model with an indicator variable for the latter period and the necessary interaction terms. The relevant results are presented below.

The federal funds rate series is available daily. I consider the observed interest rate change from the last business day of the month to that of the previous month, aggregating multiple rate changes in a single month into a larger interest rate change.[15] For the sample period 10/89 through 12/07, the Fed adjusted the federal funds rate 73 times (that is, the funds rate was cut 14 times by 50 basis points, 27 times by 25 basis points, and raised 27 times by 25 basis points, 5 times by 50 basis points) leaving it unchanged 145 times.[16]

I use a core-type inflation measure that equals the percentage growth in monthly personal consumption expenditures price index excluding food and energy prices in excess of an inflation target of 2 percent. This is in line with the original Taylor rule. Exclusion of food and energy price series serves the purpose of smoothing out temporary price fluctuations in the economy.

The monthly output gap is approximated by the percentage deviation of industrial production (IP) from its long-run trend. I run the monthly IP data through a Hodrick-Prescott filter and receive the short-run cyclical component by subtracting the long-run trend from actual IP. Accordingly, a positive output gap corresponds to an overheated economy.

3.2 Estimation Results

Although Taylor-type rules present a fairly accurate account of past monetary behavior and serve as an informal benchmark for future policy, some flexibility is required in their interpretation. For instance, deviations in the interest rate from the rule-recommended

[14] I use finally revised data rather than real-time data as advocated by Orphanides (2001).

[15] For instance, I sum up two separate 25 basis point cuts on 12/7/90 and on 12/18/90 to a 50 basis point decrease in December 1990.

[16] There are three exceptions to this categorization: I set the 75 basis point cut in December 1991 to be a 50 basis point decrease in December of 1991 and a 25 basis point decrease in January of 1992; 75 basis point raise in November 1994 to be a 50 basis point increase in November of 1991 and a 25 basis point increase in December of 1994; and 100 basis point cut in January 2001 to be two consecutive 50 basis point decreases in January and February of 2001. A small upward inertia bias that might result from these manipulations does not invalidate the conclusion that inertia has limited effects on monthly policy setting.

level occur when the central bank responds to unusual economic conditions. Rudebusch (2006) reports a list of events that the Fed seems to have responded to beyond its reaction to inflation and output gap. On this list are stock market crashes, disruptions in the flow of credit, default on debt by major borrowers, and other financial crises. In fact, several studies show that proxies for episodes of financial market distress enter significantly the Taylor-type rules estimated for the Fed.[17] So, I add an indicator variable to the estimated model to account for the monetary response to severe financial difficulty, the so-called credit crunches.[18]

The Fed's monetary policy is thought to have changed significantly over time, and a common way of controlling for the stability of coefficients in estimated rules is to divide long samples with respect to changes in the Fed chairmanship.[19] To account for a possible shift between Greenspan and Bernanke regimes, I add to the model a second indicator that equals 0 for the Greenspan period (10/89-01/06) and 1 for the Bernanke period (02/06-12/07), and the interactions between this indicator and the remaining explanatory variables.

The maximum likelihood parameter estimates for the extended policy rule including the interaction terms are reported in Table 1.1 in the Appendix.[20] I fail to reject the null hypothesis that coefficients on the interaction terms are collectively zero with a Wald statistic of 7.16 (and p-value of 0.52). This result, combined with that interaction terms are individually insignificant, supports extending the sample through the end of 2007.

The parameter estimates for the baseline model are in the fourth column. The coefficients are such that the central bank responds systematically to the level of inflation and the change in the output gap.[21] These estimates are consistent with expectations and in line with prior literature that monetary policy is carried out counter-cyclically to stabilize prices and output.[22]

[17] Among them, Gerlach-Kristen (2004) presents evidence that the Fed reacts to risk premia on corporate bonds, whereas Driffill et al. (2006) display a systematic response to interest rate futures.

[18] This variable takes the value 1 for the period 07/90-10/92 (a prolonged credit crunch where households and firms became reluctant to borrow and expend, or invest, and financial institutions to lend), 09/98-12/98 (Russian default and devaluation, Asian financial crisis), 09/01-01/02 (events of September 11, 2001), 09/07-12/07 (collapse of the housing market and resulting strain on financial markets), and 0 otherwise. Similarly, Gerlach and Schnabel (2000) and Gerlach-Kristen (2003) include dummy variables to control for the European Central Bank's reaction to intra-European exchange market pressures in the early 1990s.

[19] See Hakes (1990) or Judd and Rudebusch (1998).

[20] I take as given the stationarity of the data series in the extended Taylor rule. This is consistent with prior literature. See, for example, Clarida et al. (1998), Dueker (1999), Clarida et al. (2000), Gerlach and Schnabel (2000), Rudebusch (2002), and Gerlach-Kristen (2004), among many others.

[21] If the change in the output gap is dropped from the model, output gap becomes significant. This more closely resembles previous studies. Alternative specifications with consumer price index inflation, output gap measured by the unemployment gap, that is, the deviation of the actual rate of unemployment from the natural rate, and additional lags for the interest rate change yield quantitatively similar results, and so are not reported here for brevity.

[22] See Choi (1999) and Dueker (1999) for monthly, and Judd and Rudebusch (1998), Clarida et al. (2000), Rudebusch (2002), and English et al. (2003) for quarterly results.

The estimates on the two lags of the dependent variable (β_2 = 1.97 and β_3 = 1.54) show that funds rate changes raise the likelihood of further changes in the same direction. However, these estimates should not be taken as documenting explosive policy because their magnitudes, as with all other coefficients, depend on the normalization of the standard deviation of ordered probit errors.

In testing for serial correlation, I use the generalized residuals proposed by Gourieroux et al. (1985). I calculate the score statistics up to six lags (ξ_j, j = 1 … 6) under the null hypothesis of serial independence in the ordered probit residuals.[23] These score statistics are reported in Table 1.1. The vector of explanatory variables includes the first two lags of the dependent variable, and so I find no serial correlation at the first two lags. Although the score statistics increase in magnitude at higher lags, they remain statistically insignificant lending support to the ordered probit structure.

[23] The score statistics are asymptotic χ^2_1 variates under the null hypothesis of no serial correlation in the ordered probit residuals. In the absence of serial correlation at a given lag, they fall into the interval [0, 3.84] with 95 percent probability.

4. Inertia in Funds Rate Setting

In this section, I test for inertia in the Fed's monthly funds rate policy by measuring the extent to which an interest rate change last month affects the policy setting this month. I start by choosing values for the variables in the policy rule (X_t) to imitate a stable economic environment that requires no interest rate response from the Fed. I then impose on the system a lagged interest rate adjustment through ΔFFR_{t-1}. The expected interest rate change, defined as the impact of this counterfactual lagged adjustment on current month's policy, is used to test for inertia.

In building a stable economy, I assume that FFR_{t-1} = 4.42 (sample average), $\Delta FFR_{t-2} = 0$, $\pi_{t-1} = 0$ (in excess of the inflation target), $\Delta\pi_{t-1} = 0$, $y_{t-1} = 0$, $\Delta y_{t-1} = 0$, and the credit crunch dummy takes the value 0. The chosen values pertain to a situation in which the goal variables equal their targets, and therefore the central bank has no incentive to change the funds rate.

An alternative scenario is built on the observation that the federal funds rate was fixed at 5.50 percent from April 1997 to August 1998 for 17 consecutive months. Here, I use the average values of the explanatory variables for the period from July 1997 to June 1998, the year that corresponds to the middle of this prolonged episode of policy inactivity. The chosen values (i.e. $FFR_{t-1} = 5.50$, $\Delta FFR_{t-2} = 0$, $\pi_{t-1} = -0.57$, $\Delta\pi_{t-1} = 0.04$, $y_{t-1} = 0.50$, $\Delta y_{t-1} = 0.11$, and credit crunch dummy taking the value 0) describe a situation in which the Fed actually revealed that it did not think a change in the funds rate was warranted to attain its objectives.

Having reproduced a stable economy, I build a counterfactual on the remaining independent variable ΔFFR_{t-1}. The first lag takes one of five values observed in the sample (i.e. -0.5, -0.25, 0, 0.25, or 0.5 percentage points) one at a time. These five values represent five possible states of the world last period.

To summarize, the parameter estimates (β) and the selected values of the explanatory variables (X_t) are plugged into expression (1) to locate the conditional mean of desired rate changes, $\mu = E[\Delta FFR_t^* | X_t, \beta]$, on its continuous scale. Figure 1.1 in the Appendix provides an illustration. With the ordered probit errors distributed around μ with unit variance, the resulting probability density yields the likelihood of each response category given the estimated thresholds. The conditional mean of observed rate changes $E[\Delta FFR_t | X_t, \beta, \tau]$ is calculated as the weighted average rate of change for five discrete outcomes by multiplying each (in basis points) with its predicted probability and summing over: $E[\Delta FFR_t] = Pr\ (\Delta FFR_t = -0.50) * (-50) + \ldots + Pr\ (\Delta FFR_t = 0.50) * (50)$. I call this conditional mean the expected funds rate change.

The expected funds rate changes for five different states of the world under the two alternative scenarios are reported in Table 1.2. Columns two to six of the table show how the entire probability distribution moves with changes in the state of the world. For example, the first and the third entries in the second column of the upper panel (i.e. 0.054 and 0.005) show that a lagged funds rate cut of 50 basis points, compared to no lagged adjustment, raises the probability of observing another 50 basis point cut almost 11-fold, from 0.5 percent to 5.4 percent. Across the table, we see that lagged rate changes raise the probability of further adjustments in the same direction, and this signals inertia.

The entries in the seventh column quantify the size of the inertia implied by shifting probability densities. These entries are the interest rate changes (in basis points) expected in current period *t* following the designated rate change in previous period *t-1*. For example, the first entry in the upper panel shows that a lagged funds rate cut of 50 basis points leads to an expected further decrease of 7.80 basis points. Taken together, funds rate changes generate expectations of further changes in the same direction, and the size of these expected changes increase in the size of lagged adjustments.

The standard errors for the expected rate changes are reported in the last column. All expected changes generated by non-zero lagged adjustments are significant at 5 percent level, except the one that follows a 25 basis point cut under the first scenario that is significant at 10 percent level. The significance of expected rate changes implies that interest rate adjustments lead to further non-trivial adjustments in the future. This is evidence that inertia plays a part in the monthly setting of the federal funds rate.

As evident in expression (3), the probability of a given interest rate change category is evaluated at the values selected for the entire X_t vector, not just ΔFFR_{t-1}. Therefore, the magnitudes of expected rate changes reported in Table 1.2 depend not just on the first lag of the funds rate change but also on values chosen for other conditioning variables. To demonstrate how sensitive the expected rate changes are to small perturbations in other conditioning variables, I report in Table 1.3 the expected changes that would result from a lagged funds rate cut of 50 basis points along with a one-tenth standard deviation change (increase and decrease) in other conditioning variables.

The entry in the second row of the eight column (i.e. -10.58) shows that, when the lagged federal funds rate (i.e. FFR_{t-1}) is raised by one-tenth of a standard deviation in the calibration exercise, a lagged funds rate cut of 50 basis points leads to a further decrease of 10.58 basis points. This is very close to -10.34 reported for the baseline setting. The standard error of this prediction (i.e. 4.28) shows that it is statistically significant. Across the table, we see that although small perturbations to other conditioning variables affect the quantitative results slightly, qualitative predictions of the model remain unchanged.[24]

The contribution of inertia to the observed persistence in funds rate changes can be examined by testing whether the expected rate changes (ERCs) reported in Table 1.2 are sufficient to generate further discrete adjustments. The null hypotheses that the expected rate changes are not significantly different from 25 (or -25) basis points, the smallest

[24] The results for the remaining explanatory variables and for the other four states of the world are consistent with those reported in Table 3.

adjustment observed in the sample, are tested for four different states of the world last period, k = 1, 2, 4, and 5. The test scores for the two alternative scenarios are reported in Table 1.4. We see across the board that although expected funds rate changes are significant in size, they are never large enough to create further discrete adjustments, of even the smallest size. Therefore, inertia-driven persistence can be rejected at all conventional significance levels for all states of the world under both scenarios.

This finding has the implication that inertia plays only a limited role in generating the observed path of persistent interest rate changes. Then, a large part of such persistence must arise from the Fed's reaction to serially correlated factors omitted in policy rules. This conclusion parallels the view that inertia and serially correlated shocks jointly influence the Fed's policy.

5. Conclusions

In this study, I examine the observed persistent nature of monetary policy adjustment using an ordered probit model. The evidence shows that inertia exists in the Fed's monthly funds rate setting, but not to the extent that it could lead to consecutive interest rate changes. This finding suggests that the Fed's reaction to serially correlated factors plays an important role in policy setting.

For future research, alternative calibration values in the probit equation will help examine more deeply how the funds rate responds to varying states of the economy. Also, applications of the ordered probit-based exercise to other interest rate instruments and goal variables will reveal more about the Fed's monetary policy.

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Appendix

Table 1.1 Ordered probit estimation results for monthly target funds rate changes

Description	Extended Rule	Standard Error	Baseline Rule	Standard Error
Rule Arguments				
FFR_{t-1}	-0.11	0.06	-0.10	0.05
ΔFFR_{t-1}	2.13	0.58	1.97	0.67
ΔFFR_{t-2}	1.57	0.58	1.54	0.53
π_{t-1}	0.18	0.9	0.21	0.82
$\Delta\pi_{t-1}$	-0.08	0.07	-0.09	0.08
y_{t-1}	-0.00	0.11	-0.03	0.24
Δy_{t-1}	0.58	0.20	0.49	0.17
Credit Crunch Dummy	-1.22	0.30	-1.32	0.21
Interactions				
D1 (FFR_{t-1})	0.02	0.09		
D2 (ΔFFR_{t-1})	-3.00	2.15		
D3 (ΔFFR_{t-2})	-0.75	2.20		
D4 (π_{t-1})	0.59	0.47		
D5 ($\Delta\pi_{t-1}$)	-0.35	0.36		
D6 (y_{t-1})	0.16	0.84		
D7 (Δy_{t-1})	-1.29	1.01		
D8 (Credit Crunch)	-1.74	1.60		
Thresholds[1]				
τ_1 between-0.5 and -0.25	-3.15	0.36	-3.05	0.27
τ_2 between -0.25 and 0	-2.10	0.32	-2.05	0.41
τ_3 between 0 and 0.25	0.77	0.27	0.77	0.19
τ_4 between 0.25 and 0.5	1.88	0.31	1.87	0.28
Autocorrelation Score Statistics				
ξ_1 (p-value)	0.09 (0.76)		0.16 (0.69)	
ξ_2 (p-value)	0.27 (0.60)		0.35 (0.55)	
ξ_3 (p-value)	2.77 (0.10)		3.46 (0.06)	
ξ_4 (p-value)	2.08 (0.15)		1.13 (0.29)	
ξ_5 (p-value)	0.64 (0.42)		1.10 (0.29)	
ξ_6 (p-value)	2.31 (0.13)		2.20 (0.14)	
Wald $\chi^2_{(16/8)}$	122.64		115.34	
Prob > $\chi^2_{(16/8)}$	0.00		0.00	
Log likelihood	-163.66		-167.31	
Pseudo R^2	0.27		0.26	
Sample Size	218		218	

[1] In the extended rule, if ΔFFR_t^* is less than -3.15 ΔFFR_t is -0.50; if ΔFFR_t^* is between -3.15 and -2.10 ΔFFR_t is -0.25; and so on.

Table 1.2 Expected funds rate changes

	Pr(-50)	Pr(-25)	Pr(0)	Pr(25)	Pr(50)	Expected Rate Change (Standard Error)	p-value
First Scenario							
Δ FFR$_{t-1}$ = - 50	0.054	0.219	0.714	0.013	0.001	-7.80 (3.58)	0.03
Δ FFR$_{t-1}$ = - 25	0.018	0.118	0.821	0.041	0.002	-2.71 (1.62)	0.09
Δ FFR$_{t-1}$ = 0	0.005	0.051	0.834	0.100	0.010	1.50 (0.85)	0.08
Δ FFR$_{t-1}$ = 25	0.001	0.018	0.749	0.199	0.034	6.15 (1.74)	0.00
Δ FFR$_{t-1}$ = 50	0.001	0.005	0.589	0.315	0.091	12.27 (3.97)	0.00
Alternative Scenario							
Δ FFR$_{t-1}$ = - 50	0.079	0.263	0.650	0.008	0.001	-10.34 (4.21)	0.01
Δ FFR$_{t-1}$ = - 25	0.028	0.156	0.788	0.026	0.001	-4.60 (2.06)	0.03
Δ FFR$_{t-1}$ = 0	0.008	0.073	0.841	0.072	0.006	-0.18 (1.20)	0.88
Δ FFR$_{t-1}$ = 25	0.002	0.028	0.794	0.155	0.021	4.13 (1.84)	0.03
Δ FFR$_{t-1}$ = 50	0.001	0.008	0.660	0.269	0.062	9.58 (3.82)	0.01

Expected interest rate changes are expressed in basis points. I use the Delta method in computing standard errors and p-values for expected rate changes, which uses the variance-covariance matrix from the ordered probit estimation of the baseline model.

Table 1.3 Sensitivity analysis for expected funds rate changes

Lagged Adjustment	Controlled Variable	Pr(-50)	Pr(-25)	Pr(0)	Pr(25)	Pr(50)	Expected Rate Change	Standard Error
Δ FFR$_{t-1}$ = - 50	**Baseline**	0.079	0.263	0.650	0.008	0.001	-10.34	4.21
Δ FFR$_{t-1}$ = - 50	**+ σ/10 FFR$_{t-1}$**	0.082	0.267	0.643	0.007	0.000	-10.58	4.28
Δ FFR$_{t-1}$ = - 50	**- σ/10 FFR$_{t-1}$**	0.076	0.258	0.657	0.008	0.000	-10.05	4.15
Δ FFR$_{t-1}$ = - 50	**+ σ/10 π_{t-1}**	0.075	0.256	0.661	0.008	0.000	-9.91	4.12
Δ FFR$_{t-1}$ = - 50	**- σ/10 π_{t-1}**	0.084	0.269	0.640	0.007	0.000	-10.73	4.32
Δ FFR$_{t-1}$ = - 50	**+ σ/10 Δy_{t-1}**	0.076	0.257	0.658	0.008	0.000	-9.99	4.18
Δ FFR$_{t-1}$ = - 50	**- σ/10 Δy_{t-1}**	0.083	0.268	0.642	0.007	0.000	-10.64	4.24

Table 1.4 Hypothesis tests for inertia-driven persistence

Null Hypothesis	t-statistic	p-value
First Scenario		
$ERC_{\Delta FFRt-1 = -50}$ (= -7.80) = -25	4.80	0.00
$ERC_{\Delta FFRt-1 = -25}$ (= -2.71) = -25	13.75	0.00
$ERC_{\Delta FFRt-1 = 25}$ (= 6.15) = 25	-10.86	0.00
$ERC_{\Delta FFRt-1 = 50}$ (= 12.27) = 25	-3.21	0.00
Alternative Scenario		
$ERC_{\Delta FFRt-1 = -50}$ (= -10.34) = -25	9.41	0.00
$ERC_{\Delta FFRt-1 = -25}$ (= -4.60) = -25	9.89	0.00
$ERC_{\Delta FFRt-1 = 25}$ (= 4.13) = 25	-11.34	0.00
$ERC_{\Delta FFRt-1 = 50}$ (= 9.58) = 25	-10.57	0.00

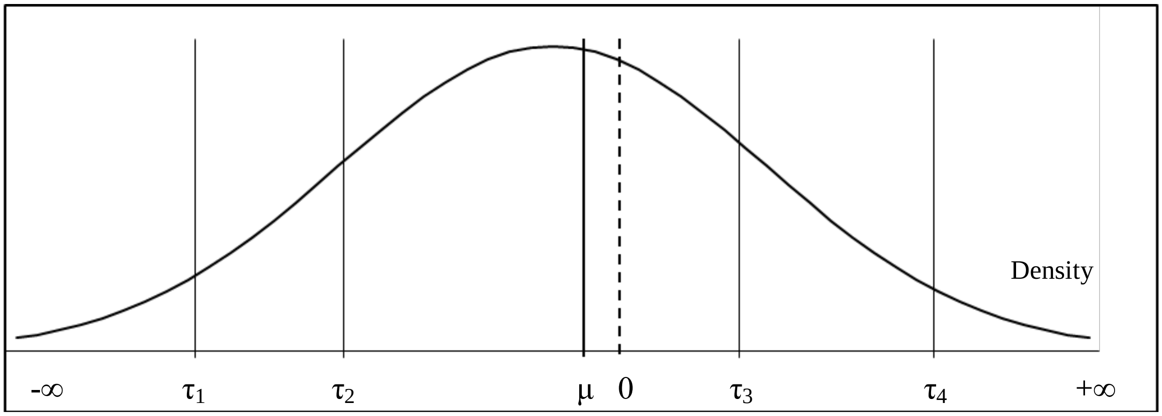

Figure 1.1 Predicted probabilities for interest rate change categories. These probabilities are determined by where $\mu = E\,[\Delta FFR_t^* \mid X_t, \beta]$ lies on its continuous scale in relation to the estimated thresholds (τ_k, for $k = 0 \ldots 5$) given $\tau_0 = -\infty$ and $\tau_5 = +\infty$. The standard normal density function is received by setting the standard deviation of ordered probit errors around μ equal to one. The area of the region beneath the density to the left of τ_1 gives the probability of a half percentage point cut in the federal funds rate, and so on.

Part 2

Temporal Aggregation and Monetary Policy Inertia

Abstract

A common feature of empirical monetary policy reaction functions is a large estimated coefficient for the lagged interest rate, which many interpret as partial adjustment or inertia. Recently, the partial adjustment hypothesis has come under criticism. It is argued that the estimated size of inertia is upward biased due to model misspecification or the use weak instruments in forward-looking policy rules. In this paper, I present evidence that the temporal aggregation of interest rates contributes to the upward inertia bias. Particularly, measuring the path of monetary policy by averaged interest rates leads to spuriously large partial adjustment coefficients due to temporal aggregation effects.

1. Introduction

Monetary policy reaction functions feature a large estimated coefficient for the lagged interest rate, which is often interpreted as partial adjustment, or inertia, by central banks.[25] This finding is difficult to reconcile with the alternative term structure evidence of low predictability in future interest rate changes.[26] In fact, Rudebusch (2002) argues that partial adjustment coefficients are considerably upward biased, and that their significance can be attributed to the central bank's reaction to serially correlated factors omitted in estimated policy rules.[27] Consolo and Favero (2009) present an alternative explanation for the upward bias focusing on the quality of instruments used in forward-looking rules estimated by the generalized method of moments.[28] In this study, I show that the temporal aggregation of interest rates is another contributing factor. In particular, measuring the path of monetary policy by averaged interest rates leads to spuriously large partial adjustment coefficients due to temporal aggregation effects.

A monetary policy reaction function is an empirical relationship that determines how strongly policymakers respond to economic conditions. Following Taylor (1993), it is common to include a short-term interest rate as the dependent variable and a few leading indicators (i.e. inflation and output gap) as explanatory variables. Often, a lagged interest rate is added to account for the dynamic nature of policy adjustment. The sampling frequency of the data on indicator variables is assumed to match the decision-making frequency of the monetary authority, which leads to the use of a temporally aggregated interest rate series. Temporal aggregation here refers to either point-in-time sampling (i.e. last day of the period interest rates) or averaging (i.e. daily interest rates averaged over each period). Although temporal aggregation is necessary for estimating the policy rule, no prior study examines its effect on the predicted speed of monetary policy adjustment.

It is well established in the literature that temporal aggregation alters the time-series properties of the data.[29] Theoretically, aggregating a data generating process over time affects not only the order of its *ARMA* representation but also the size of its parameters. Importantly, the effect of point-in-time sampling is not the same as the effect of averaging. Consequently, it is not surprising that a sampled sub-series exhibits different

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[25] Estimates on quarterly data are around 0.8 for the U.S. suggesting that only 20 percent of a desired interest rate adjustment is achieved after a full quarter, and about 60 percent after a year. See Clarida et al. (2000) and Sack and Wieland (2000).

[26] The alternative view is that large partial adjustment coefficients should make interest rate changes at horizons of longer than a quarter highly predictable, but the term structure evidence built on forward and futures rates shows otherwise. See Rudebusch (2002), Rudebusch (2006), and Rudebusch and Wu (2008).

[27] These omitted factors include episodes of financial market distress (Gerlach-Kristen, 2004), time variation in the real equilibrium interest rate (Trehan and Wu, 2007), and persistent gaps between real-time and finally revised data series (Lansing, 2002).

[28] They show that using weak instruments (instruments not sufficiently correlated with the variables that they are instrumenting) significantly inflates the partial adjustment coefficient, and that the problem can be remedied by estimating a reverse regression in which the expected inflation is the dependent variable.

[29] The important contributions to this line of research are Working (1960), Telser (1967), Tiao (1972), Wei (1981), Weiss (1984), Christiano and Eichenbaum (1987), and Rossana and Seater (1995) among others.

time-series properties than its averaged counterpart, including its degree of serial persistence.

This has direct implications for monetary policy reaction functions that are often based on averaged interest rates.[30] Suppose that an interest rate cut of 50 basis points, say, from 5 to 4.5 percent, in the middle of a quarter produces an averaged interest rate series of 5, 4.75, and 4.5 percent in three consecutive quarters. If the dependent variable is the interest rate change over the past quarter, then the 50 basis point cut is coded as two separate 25 basis point cuts in two successive quarters adding extra persistence to the averaged interest rate series. The extra persistence is spurious since it is an artifact of averaging.

This study investigates the empirical significance of this spurious persistence for estimated policy rules, especially as it pertains to the speed of adjustment coefficients. I start by describing the conditions under which an averaged sub-series displays greater serial persistence than its sampled equivalent. The former series is shown to have larger theoretical autocorrelations at all lags than the latter provided these conditions.

I then turn to the impact of the differentiated correlation patterns in the two sub-series on estimated reaction functions. An expected consequence of using a more highly serially correlated dependent variable (i.e. averaged interest rates) in the monetary policy rule is to drive up the partial adjustment coefficient. I obtain confirming results in quarterly regressions of the Federal Reserve policy under the former chairman Alan Greenspan. The partial adjustment coefficients are inflated in policy rules estimated with averaged target funds rates relative to end-of-period funds rates. The upward bias, an artifact of averaging, is significant and broadly comparable in size to the effect of omitting the serially correlated factors of Rudebusch (2002).

The plan of this paper is as follows. The second section describes the effect of temporal aggregation, both sampling and averaging, on the order of mixed *ARMA* processes. This is followed by a comparative examination of the serial correlation patterns of sampled and averaged sub-series. In the third section, I present empirical evidence that parallels the conjectures developed in the preceding section. I conclude in the last section.

[30] Most studies use averaged, rather than sampled, interest rates in reaction function estimations because inflation and output figures represent the level of economic activity throughout a given period, and so interest rates are averaged over the same period to correspond to the observations of inflation and output.

2. Theoretical Considerations

Much work has been done to uncover the effects of temporal aggregation on the time-series properties of the data. The general conclusion in this literature is that sampling and averaging change both the *ARMA* order of a time series and the size of its parameters. I start this section with a summary of findings regarding the aggregation effects on the autoregressive and moving average orders of an *ARMA* process.

Let y_t be a covariance stationary *ARMA* (p, q) process:

(1) $$y_t = a_0 + a_1 y_{t-1} + \cdots + a_p y_{t-p} + \varepsilon_t + b_1 \varepsilon_{t-1} + \cdots + b_q \varepsilon_{t-q}$$

It is assumed throughout that the underlying *ARMA* (p, q) model operates on the time interval 1, indexed by t, whereas temporally aggregated processes (both sampled and averaged) are observed at interval $m > 1$, indexed by T.

A sub-series sampled point-in-time $\{y_{sT}\}$ is generated from the original series $\{y_t\}$ by selecting the values distanced at m periods, and so $y_{sT} = y_{mt}$ for $m > 1$, an integer representing the sampling ratio between the original series and the temporally aggregated sub-series. Previous literature, see Wei (1981) and Weiss (1984) for example, shows that the sampled sub-series is an *ARMA* (p, $p + (q - p) / m$) process. The moving average component of the sampled representation, if not an integer, is rounded down to the next integer. Therefore, the number of the moving average lags can be p or $p-1$ depending on whether $q > p$ or $q < p$.

The averaged sub-series $\{y_{aT}\}$ is generated by averaging m adjacent values of $\{y_t\}$ and then choosing from this aggregated series the values distanced at m periods such that the observations from the original series do not overlap. The averaged sub-series $y_{aT} = [y_{mt} + y_{mt-1} + \ldots + y_{mt-m+1}] / m$ is shown to follow an *ARMA* (p, $p + 1 + (q - p - 1) / m$) process.

As the sampling ratio m increases, the sampled sub-series converges (for $q < p$) to an *ARMA* (p, $p-1$) model, whereas the averaged sub-series to an *ARMA* (p, p). Accordingly, the effect of averaging is to increase the moving average order of the sampled representation by one. The significance of this result is that the extra moving average term might manifest itself as additional (spurious) serial persistence in the averaged sub-series.[31]

2.1 Autocorrelations

In this sub-section, I turn to the impact of temporal aggregation on second moments. I first present a short review of aggregation effects on the theoretical autocorrelation patterns of sampled and averaged series. Then, I take the analysis one step further to

[31] A similar point is made in Christiano and Eichenbaum, section 2.C.

compare in size the autocorrelations of the sampled and the averaged series, and determine if generalizations can be made about this relationship.

2.1.1 Sampling

Ermini (1992) provides a list of closed-form solutions for the impact of temporal aggregation on model parameters. His table 2 presents the effect of both sampling and averaging on unconditional autocovariances for varying values of the sampling ratio m. In what follows, $\gamma(t)$ is the autocovariance at lag t with the subscripts sy and y denoting respectively the sampled sub-series and the original series.

Following Ermini, the autocovariances of a sub-series sampled at m equal intervals from the original series $\{y_t\}$ are:

(2) $$\gamma_{sy}(T) = \gamma_y(mT)$$

In expression (2), the autocovariance of the sampled sub-series at lag T, $\gamma_{sy}(T)$, equals the autocovariance of the original series at lag mT, $\gamma_y(mT)$. Accordingly, the autocovariance function of the sampled series for all $m > 1$ can be written as:

$$\gamma_{sy}(0) = \gamma_y(0)$$
$$\gamma_{sy}(1) = \gamma_y(m)$$
$$\gamma_{sy}(2) = \gamma_y(2m)$$
.
.
$$\gamma_{sy}(T) = \gamma_y(mT)$$

The autocorrelation at some lag t, $\rho(t)$, equals the autocovariance at that lag divided by the autocovariance at lag zero: $\rho(t) = \gamma_y(t) / \gamma_y(0)$ for all t. Then, the autocorrelations of the sampled sub-series follow from above:

$$\rho_{sy}(1) = \frac{\gamma_{sy}(1)}{\gamma_{sy}(0)} = \frac{\gamma_y(m)}{\gamma_y(0)}$$
$$\rho_{sy}(2) = \frac{\gamma_{sy}(2)}{\gamma_{sy}(0)} = \frac{\gamma_y(2m)}{\gamma_y(0)}$$
.
.
$$\rho_{sy}(T) = \frac{\gamma_{sy}(T)}{\gamma_{sy}(0)} = \frac{\gamma_y(mT)}{\gamma_y(0)}$$

where $\rho_{sy}(0)$ is 1.

2.1.2 Averaging

The averaged sub-series result from averaging *m* consecutive observations of the original series $\{y_t\}$. With the subscripts *ay* and *y* denoting the averaged and the original processes, we have:

(3) $$\gamma_{ay}(T) = \frac{|T_m(B)|^2 \ \gamma_y(mT)}{m^2}$$

$$|T_m(B)|^2 = m + \sum_{j=1}^{m-1}(m-j)[B^j + B^{-j}]$$

Here, the autocovariance of the averaged sub-series at lag T, $\gamma_{ay}(T)$, equals the autocovariance of the original series at lag mT factored by $|T_m(B)|^2 / m^2$ where B is the lag operator such that $By_t = y_{t-1}$ and $B^j y_t = y_{t-j}$.

Expression (3) is reorganized as:

(3`) $$m^2\ \gamma_{ay}(T) = \ m\,\gamma_y(mT) + \sum_{j=1}^{m-1}(m-j)[\ \gamma_y(mT+j) + \ \gamma_y(mT-j)]$$

The autocovariance function for the averaged sub-series can be written as:

$$m^2\ \gamma_{ay}(0) = \ m\,\gamma_y(0) + \sum_{j=1}^{m-1}(m-j)[\ \gamma_y(j) + \ \gamma_y(-j)]$$
$$m^2\ \gamma_{ay}(1) = \ m\,\gamma_y(m) + \sum_{j=1}^{m-1}(m-j)[\ \gamma_y(m+j) + \ \gamma_y(m-j)]$$
$$m^2\ \gamma_{ay}(2) = \ m\,\gamma_y(2m) + \sum_{j=1}^{m-1}(m-j)[\ \gamma_y(2m+j) + \ \gamma_y(2m-j)]$$
.
.
$$m^2\ \gamma_{ay}(T) = \ m\,\gamma_y(mT) + \sum_{j=1}^{m-1}(m-j)[\ \gamma_y(mT+j) + \ \gamma_y(mT-j)]$$

Then, the autocorrelations of the averaged series are:

$$\rho_{ay}(1) = \frac{\gamma_{ay}(1)}{\gamma_{ay}(0)} = \frac{m\,\gamma_y(m)+(m-1)[\gamma_y(m+1)+\gamma_y(m-1)]+\cdots+(1)[\gamma_y(2m-1)+\gamma_y(1)]}{m\ \gamma_y(0)+(m-1)[\gamma_y(1)+\gamma_y(-1)]+\cdots+(1)[\gamma_y(m-1)+\gamma_y(1-m)]}$$
$$\rho_{ay}(2) = \frac{\gamma_{ay}(2)}{\gamma_{ay}(0)} = \frac{m\,\gamma_y(2m)+(m-1)[\gamma_y(2m+1)+\gamma_y(2m-1)]+\cdots+(1)[\gamma_y(3m-1)+\gamma_y(m+1)]}{m\ \gamma_y(0)+(m-1)[\gamma_y(1)+\gamma_y(-1)]+\cdots+(1)[\gamma_y(m-1)+\gamma_y(1-m)]}$$
.
.
$$\rho_{ay}(T) = \frac{\gamma_{ay}(T)}{\gamma_{ay}(0)} = \frac{m\,\gamma_y(mT)+(m-1)[\gamma_y(mT+1)+\gamma_y(mT-1)]+\cdots+(1)[\gamma_y(mT+m-1)+\gamma_y(mT-m+1)]}{m\ \gamma_y(0)+(m-1)[\gamma_y(1)+\gamma_y(-1)]+\cdots+(1)[\gamma_y(m-1)+\gamma_y(1-m)]}$$

where, once again, for $\rho_{ay}(0) = 1$.

2.2 Comparative Autocorrelation Patterns

It is stated above that averaging affects the moving average order of a time-series differently than sampling, and thus an averaged sub-series might display additional (spurious) serial persistence compared to its sampled equivalent. I now examine the validity of this statement by building on prior work summarized in the preceding sub-section. The proposed result can be formally expressed as follows:

<u>Proposition</u>

If the underlying process $\{y_t\}$ has a convex decreasing autocovariance function, then the averaged sub-series generated from $\{y_t\}$ at some sampling ratio $m > 1$ is more serially persistent than the sampled sub-series generated from the same underlying process at the same sampling ratio. That is, the averaged process has larger theoretical correlation coefficients at all lags than the sampled process: $\rho_{ay}(T) > \rho_{sy}(T)$ for all T.

<u>Proof</u>

The strategy here is to compare the first-order correlation coefficient of the averaged sub-series, $\rho_{ay}(1)$, to that of the sampled sub-series, $\rho_{sy}(1)$, and then look for generalizations at higher-order lags. So, I start by examining if $\rho_{ay}(1) > \rho_{sy}(1)$ holds for all $m > 1$. Explicitly:

(4) $$\frac{m\,\gamma_y(m)+(m-1)\left[\gamma_y(m+1)+\gamma_y(m-1)\right]+\cdots+(1)\left[\gamma_y(2m-1)+\gamma_y(1)\right]}{m\,\gamma_y(0)+(m-1)\left[\gamma_y(1)+\gamma_y(-1)\right]+\cdots+(1)\left[\gamma_y(m-1)+\gamma_y(1-m)\right]} > \frac{\gamma_y(m)}{\gamma_y(0)}$$

Since the first terms in the numerator and the denominator of $\rho_{ay}(1)$ equal those in $\rho_{sy}(1)$ multiplied by the same factor m, the remaining terms in $\rho_{ay}(1)$ will determine whether or not expression (4) holds.

Suppose for a moment that the decrease in the autocovariance function was linear, not convex. This would allow us to rewrite every term in square brackets in the numerator of the left-hand side as 2 $\gamma_y(m)$; we would have $\gamma_y(m+1) + \gamma_y(m\text{-}1) = 2\gamma_y(m)$ for the first term, for instance. Then, with the actual convex decreasing autocovariance function, we have $\gamma_y(m+1) + \gamma_y(m\text{-}1) = 2\,\gamma_y(m) + s_1$, where s_1 is some positive surplus owing to convexity. For the second term, we have $\gamma_y(m+2) + \gamma_y(m\text{-}2) = 2\,\gamma_y(m) + s_2$, and so on. For $S = (m\text{-}1)\,s_1 + (m\text{-}2)\,s_2 + \ldots + (1)\,s_{m-1}$ and $(m\text{-}1) + (m\text{-}2) + \ldots + 1 = m\,(m\text{-}1) / 2$, the numerator adds to $m\,\gamma_y(m) + m\,(m\text{-}1)\,\gamma_y(m) + S$.

In the denominator of the left-hand side, the autocovariance pairs in each square bracket are equal since $\gamma_y(t) = \gamma_y(\text{-}t)$ for all t. Then, we can rewrite the denominator as $m\,\gamma_y(0) + (m\text{-}1)\,[2\,\gamma_y(1)] + \ldots + (1)\,[2\,\gamma_y(m\text{-}1)]$. Replacing each square bracket in this last expression with 2 $\gamma_y(1)$ the denominator adds to $m\,\gamma_y(0) + m\,(m\text{-}1)\,\gamma_y(1)$. This replacement necessarily increases the numerical value of the denominator due to the decreasing pattern in autocovariances: $\gamma_y(1) > \gamma_y(t)$ for all $t > 1$. A larger denominator reduces the ratio below $\rho_{ay}(1)$, and so the expression (4) can be rewritten as:

(4\`) $$\rho_{ay}(1) \geq \frac{m\,\gamma_y(m) + m\,(m-1)\,\gamma_y(m) + S}{m\,\gamma_y(0) + m\,(m-1)\,\gamma_y(1)} > \frac{\gamma_y(m)}{\gamma_y(0)} = \rho_{sy}(1)$$

Expression (4\`) holds if the condition $\{\gamma_y(m) + S / m\,(m\text{-}1)\} / \gamma_y(1) > \gamma_y(m) / \gamma_y(0)$ is satisfied. It is easy to see that the required condition is always satisfied because the first term has a larger numerator and a smaller denominator than the second: $S / m\,(m\text{-}1) > 0$ and $\gamma_y(1) \leq \gamma_y(0)$ respectively.[32] Subsequently, we receive $\rho_{ay}(1) > \rho_{sy}(1)$ at any sampling ratio m.

We can replicate the analysis for higher-order lags to obtain $\rho_{ay}(T) > \rho_{sy}(T)$ for all T. At lag 2, for instance, the condition $\{\gamma_y(2m) + S / m\,(m\text{-}1)\} / \gamma_y(1) > \gamma_y(2m) / \gamma_y(0)$ needs to hold, and it always does for the same reasons as above. This concludes the proof that the averaged series is more serially persistent than the sampled series if the underlying process has a convex decreasing autocovariance function. ■

Notice that the convex decrease in autocovariances is a sufficient condition, but not required.[33] Ermini (1992) draws the same conclusion that the averaged process is more serially persistent than the sampled process when the underlying model is *ARMA* (0, 2), which might have a larger autocovariance at lag two than at lag one. In fact, we can generalize Ermini's result to any *ARMA* (0, q) model. Provided $m > q$, the sampled sub-series follow an *ARMA* (0, 0) process, that is, white noise, whereas the averaged sub-series *ARMA* (0, 1), necessitating non-zero serial correlation at first lag.

[32] The autocovariance at lag zero (i.e. variance) is always positive; $\gamma_y(0) = var\,(y_t) = E\,(y_t^2) > 0$. At lag one, we have by definition $\gamma_y(1) = \rho_y(1)\,\gamma_y(0)$. Then, $\gamma_y(0) \geq \gamma_y(1)$ since $\rho_y(1) \leq 1$.

[33] The proof is based on convex decreasing autocovariances because most economic time-series are highly persistent and so display comparable autocovariance patterns.

3. Empirical Results

In this section, I illustrate the practical importance of the temporal aggregation issues discussed above for monetary policy evaluation. Particularly, I estimate quarterly reaction functions for the recent Federal Reserve policy using both sampled and averaged interest rates, and then compare the size and the significance of partial adjustment coefficients.[34]

The empirical reaction functions literature has grown substantially in recent years. Policy rules estimated in level form, in which the dependent variable is the level of the interest rate, feature large coefficients for the lagged interest rate. To some, this signals monetary policy inertia, a deliberate effort to spread interest rate changes over time. However, partial adjustment models estimated in the presence of serially correlated shocks are subject to identification and multiple optima problems.[35] This translates into an observational equivalence problem in monetary policy evaluation; it is difficult to empirically distinguish an interest rate path produced by partial adjustment under serially uncorrelated shocks from another produced by immediate adjustment under highly serially correlated shocks.[36] Thus, the evidence in favor of large policy inertia derived from level regressions is not definitive.

English et al. (2003) show that estimating the policy rule in first difference form helps overcome the observational equivalence problem, with the interest rate change replacing its level as the dependent variable. Below, I use the estimation strategies proposed by English et al.[37] The selection of the Greenspan era as the sample period is due to that they are recent enough to be relevant to present-day policymakers, and that monetary policy is thought to have remained largely consistent throughout the period.

I begin with the two specifications commonly used in the literature: partial adjustment and full adjustment under serially correlated shocks. In the traditional partial adjustment model, the lagged interest rate enters and the errors are assumed to be serially uncorrelated. The model can be written as follows:

(5)
$$i_t = (1-\lambda)\ \hat{\imath}_t + \lambda\ i_{t-1} + \varepsilon_t$$
$$\hat{\imath}_t = b_0 + b_\pi\ \pi_t + b_y\ y_t$$

[34] The theoretical findings of the preceding section and the empirical results presented in this section cover two separate but closely related issues. In particular, the proposition from above holds true unconditionally for temporally aggregated interest rates, whereas the following empirical results are conditioned on the exogenous determinants of monetary policy: inflation and output gap. This strategy is preferred to simply comparing the sample autocorrelations of the two temporally aggregated processes because sample correlations do not account for the impact of omitted serially correlated factors on interest rate setting.
[35] See Griliches (1967) and Blinder (1986). See also Rudebusch (2002) for a discussion on the implications for monetary policy reaction functions.
[36] For more on the observational equivalence problem, see Feve et al. (2007) and Carillo et al. (2007).
[37] See Castelnuovo (2003) for a similar application.

In equation (5), i_t is the interest rate, π_t is the rate of inflation, y_t is the output gap, and ε_t is an *iid* error term. This structure is referred to as the partial adjustment mechanism because the funds rate adjusts gradually to the desired Taylor-rule rate $\hat{\imath}_t$ closing $(1-\lambda)$ percent of the gap each period.

The second specification is the full adjustment model with serially correlated shocks. Here, the lagged interest rate is not included but we allow for serial correlation in model errors:

(6)
$$i_t = \hat{\imath}_t + u_t$$
$$u_t = \rho\, u_{t-1} + \varepsilon_t$$
$$\hat{\imath}_t = b_0 + b_\pi\, \pi_t + b_y\, y_t$$

In this second model, u_t is the serially correlated error term and the other variables follow from above. Equation (6) imposes no partial adjustment of the interest rate by the central bank; each period the interest rate deviates from the Taylor-rule rate by the error term u_t. The error sequence is assumed to follow a first-order autoregressive process however.[38] Accordingly, some $(1-\rho)$ percent of the gap between the actual rate and the Taylor-rule rate is closed each period.

A comparison of the two models reveals the nature of the observational equivalence problem. In the absence of new shocks, both mechanisms close each period a fraction of the gap between the interest rate and the Taylor-rule rate: $(1-\lambda)$ in equation (5) and $(1-\rho)$ in equation (6). So, it is difficult to empirically determine why interest rate changes persist over time. It might be that the central bank is partially adjusting as in equation (5), or that serially correlated factors are shaping a fully adjusting central bank's decisions as in equation (6).

The two hypotheses have different implications for the response of the interest rate to changes in the Taylor-rule rate however, and this difference can be exploited to test for consistency with data. We can, for instance, nest the two hypotheses in the same specification, and then estimate the nested model in first difference form.[39] The nested model can be written as:

[38] As stated above, Rudebusch (2002) interprets these errors as persistent factors that the central bank responds to but are omitted in reaction function estimations. Examples include financial market frictions and credit crunches, time variation in the real equilibrium interest rate or the inflation target, and discrepancies between real-time and revised economic data.

[39] Nesting is not necessary, but it is intuitively appealing because it allows for both partial adjustment and serially correlated shocks to play a role in monetary policy. English et al. have the details of the procedure.

$$(7) \qquad i_t = (1-\lambda)\ \hat{\imath}_t + \lambda\ i_{t-1} + u_t$$

$$u_t = \rho\ u_{t-1} + \varepsilon_t$$

$$\hat{\imath}_t = b_0 + b_\pi\ \pi_t + b_y\ y_t$$

In equation (7), λ is the partial adjustment parameter and ρ is the serial correlation parameter with the model simplifying to equation (5) for $\rho = 0$, and to equation (6) for $\lambda = 0$.[40]

I report the non-linear least squares estimates of the monetary policy rules (5) to (7) in Table 2.1 in the Appendix.[41] The sample includes quarterly data for Greenspan period, 1987Q4 through 2005Q4. The interest rate is the daily federal funds target rate, which is temporally aggregated in two ways: averaging over each quarter and sampling on the last business day of each quarter. Inflation is measured by the four-quarter average change in the personal consumption expenditures price index, excluding food and energy prices, in excess of an inflation target of 2 percent. The output gap is based on the difference between real GDP and potential GDP, as estimated by Congressional Budget Office.

The second column in the table reports the coefficients for the partial adjustment model (5) estimated on quarterly average funds rate, while the third reports those for the serially correlated shocks model (6). The estimates are consistent with prior literature. In both models, inflation and output gap enter significantly with positive signs.[42] The parameters of interest are those that govern the dynamic adjustment of the policy rate. Evidently, both specifications can capture the sluggish behavior of the target funds rate, via a significant λ in equation (5) and a significant ρ in equation (6).[43]

The fourth column reports the estimated coefficients for the nested model (7). The parameters are more realistic in this richer specification. Once again, inflation and output gap enter significantly with positive signs, and changes in inflation lead to greater than one-for-one changes in the policy rate satisfying the so-called Taylor-rule property.[44] A

[40] Some algebra shows that the estimated equation for the change in the interest rate is $\Delta i_t = (1-\lambda)\ \Delta\hat{\imath}_t + (1-\lambda)(1-\rho)(\hat{\imath}_{t-1} - i_{t-1}) + \lambda\rho\ \Delta i_{t-1} + \varepsilon_t$.

[41] Throughout, I follow the literature in assuming that the monetary authority set the interest rate based only on current economic conditions, and the lagged interest rate when applicable.

[42] The intercept term is estimated to be around 4 throughout. This is in line with the original Taylor rule in which the constant includes an inflation target and the real equilibrium interest rate, both of which are assumed to be 2 percent.

[43] The hypotheses that residual sequences are white noise can be rejected for both specifications at conventional significance levels. This finding implies that one of the two mechanisms alone cannot fully explain the dynamics of the funds rate. Moreover, the rejection of white noise residuals is a sign of uncontrolled autocorrelation in the (dynamic) partial adjustment model (5), which leads to inconsistent parameter estimates including λ. Nonetheless, I report these estimates to be consistent with the literature.

[44] This time we cannot reject the hypothesis that errors are white noise. This is in contrast to the rejections we had for the first two specifications, lending further support to the nested model.

comparison with the second column shows that allowing for first-order serial correlation in model errors reduces the partial adjustment coefficient, with λ falling from 0.80 to 0.72.

In the fifth column, I test for differentiated temporal aggregation effects between the averaged and the sampled interest rates. Here, I report the estimates for the nested model (7), but now I replace the quarterly average funds rate with the end-of-quarter funds rate.[45] The differences in estimates reported in columns four and five are all statistically insignificant except for the parameter of interest λ.[46] We see that using the end-of-quarter funds rate reduces the estimated degree of partial adjustment further from 0.72 to 0.64. This fall is statistically significant at 9 percent level, and similar in size to the effect of adding first-order serially correlated errors to a pure partial adjustment model.

[45] The analysis in sub-section 2.2 is meant for the levels of temporally aggregated series, while equation (7) is estimated in first difference form. This does not affect the results because equation (7) imposes the same partial adjustment mechanism for the level of the interest rate as equation (5), with parameter λ.

[46] The data sets for the two models are dependent requiring that the covariances across the two models be accounted for in cross-model comparisons of coefficients. Using the seemingly unrelated estimation of Weesie (1999), I fail to reject the hypotheses that corresponding coefficients are equal across the two models with respective p-values of 0.58 for β_π, 0.87 for β_y, and 0.56 for ρ. On the contrary, the hypothesis of equal partial adjustment coefficients is rejected with a p-value of 0.09.

4. Conclusions

This paper shows that the use of averaged interest rates in empirical policy reaction functions leads to an upward inertia bias due to temporal aggregation effects. An application to federal funds target rate reveals that using the quarterly averaged interest rates is as important in driving up the predicted size of inertia as omitting the serially correlated determinants of monetary policy.

Temporal aggregation changes the *ARMA* order of a time series and the size of its parameters. Beyond the particular aspect examined here, temporal aggregation has greater implications for empirical reaction functions. Aggregating time-series data in weekly, monthly, or quarterly terms might alter them in ways inconsistent with the underlying processes, leading to false inference. More work is needed to determine temporal aggregation's impact not only on the speed of adjustment coefficients but also on the general behavior of estimated systems.

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Appendix

Table 2.1 Estimation results for quarterly reaction functions

Coefficient	Quarterly Average Target Funds Rate			End-of-quarter Target Funds Rate
	Equation (5)	Equation (6)	Equation (7)	Equation (7)
b_0	3.68 (0.27)	3.84 (1.31)	3.85 (0.47)	3.92 (0.41)
b_π	2.16 (0.27)	0.86 (0.28)	1.88 (0.45)	1.71 (0.40)
b_y	1.09 (0.15)	0.34 (0.10)	0.89 (0.25)	0.86 (0.22)
λ	0.80 (0.05)		0.72 (0.04)	0.64 (0.03)
ρ		0.96 (0.03)	0.70 (0.13)	0.68 (0.13)
R^2	0.97	0.97	0.98	0.98
Q-stat (4) (p-value)	64.13 (0.00)	30.30 (0.00)	2.59 (0.63)	2.58 (0.63)
Q-stat (8) (p-value)	67.37 (0.00)	36.33 (0.00)	3.34 (0.91)	4.42 (0.82)
Sample Size	73	73	73	73

Equation (5) allows only for partial adjustment, equation (6) only for serially correlated errors, and equation (7) for both mechanisms to be present. Standard errors are shown in parentheses. All R^2 statistics are reported for the level of the federal funds rate to be consistent across policy rules estimated in level form and first differences. Portmanteau Q test statistics (allowing for 4 and 8 autocorrelations respectively) are reported to test for white noise residuals.

Part 3

The Peculiar Economics of Housing Bubbles

This paper has been accepted for publication in *Contemporary Economic Policy*.

My primary contributions to this paper include part of the literature review, development of the theoretical model, derivation of the policy implications, and part of the writing.

Abstract

Home values increase rapidly during housing bubbles generating large capital gains. High loan-to-value (LTV) mortgages secured by expected future home values are one way to take advantage of these capital gains. In this paper, we use a simple partial equilibrium consumer theory model to explore the implications of high LTV borrowing. We find that sufficiently large expected house price growth leads to upward sloping budget lines when households can obtain high LTV mortgages. In this environment, the demand for housing fits neither the conventional theories of consumer goods nor that of investment goods. In fact, increases in the expected future price of housing may reduce current housing demand while decreases in the effective (current) price may lead to households buying smaller homes. Moreover, high LTV loans reduce the effectiveness of monetary policy but raise the volatility of aggregate demand. Tighter borrowing standards may help lower demand volatility at the expense of shrinking the economy.

1. Introduction

Housing differs from other consumption goods in important ways. Houses are extremely durable, changing houses involves large transactions costs so that households do not move very often, and in most cases, houses are financed through borrowing. Furthermore, houses represent status and allow access to other benefits, such as parks, schools, or desirable neighborhoods. Automobiles share most of these attributes, although to a lesser extent, but housing and automobiles differ in one key feature. Automobiles, except maybe collectibles, tend to diminish in value over time. However, during several periods in recent history house prices have appreciated significantly, providing an investment motive for homeownership in addition to its consumption benefits.

Home values rise rapidly during housing bubbles, generating large capital gains. Households can take advantage of these capital gains either by selling their house or by borrowing against its increased value, either through home equity loans or new mortgages. If households are allowed to borrow against the current values of their homes, it is a small step to allow them to borrow against the expected future values of their homes, especially when both lenders and borrowers agree that house prices will keep rising. In fact, this has been happening. The Federal Reserve Act of 1913 limited the loan-to-value (LTV) ratio, that is, the fraction of the market price of a house one could borrow, to 50 percent. By 1970, that limit had grown to 90 percent, and in 1989 it rose to 100 percent. In 1997 the LTV limit increased to 125 percent allowing the mortgage loan to exceed the market value of the house, and these loans were aggressively marketed to consumers.[47] The purpose of this paper is to explore the implications of these high LTV mortgage loans secured by expected future home values.

The evidence regarding high LTV loans paints a bleak picture. Haughwout et al. (2008) report that thirty percent of subprime mortgages originated in 2006 had LTVs of at least 100 percent. These new subprime mortgages were the primary contributor to the first increase in homeownership rates in three decades (Chambers et al, 2007). The high LTV originations led to high foreclosure rates during the recent housing bust. In 2007, 40 percent of the foreclosures in Massachusetts had origination LTVs of at least 100 percent. Fifteen years earlier, in contrast, fewer than 9 percent of foreclosures had such high origination LTVs (Foote et al, 2008). Haughwout and Okah (2009) note, based on a December 2008 sample of 43 states that exclude boom and bust states, that roughly 10 percent of homes had negative equity. They report that the average origination LTV for the above-water homes was 83 percent, and that for below-water homes was 98 percent.

Our analysis presumes a particular type of market failure. If markets are efficient, expected future prices are tied to current prices through the interest rate. Specifically, if markets expect the price of an asset to be $600,000 in ten years, and the 10-year interest rate is 50 percent (that is, 50 percent over ten years and not 50 percent per year), then the

[47] High LTV borrowing often requires “piggybacking” second mortgages or home-equity loans on top of traditional mortgages, which have 80 percent LTV limitation.

present value of the asset is $400,000. Conversely, if the current value of the asset, say a house, is $400,000 and the 10-year interest rate is 50 percent, the expected future price of the house is $600,000. But, what would happen if markets forecast home prices to grow faster than the interest rate?[48] For example, what would occur if current house prices are $400,000 and are expected to rise to $700,000, but the corresponding long-term interest rate is only 50 percent? This scenario could materialize if the recent house price growth rate has exceeded the interest rate and both borrowers and lenders expect such recent price trends to persist, thereby expecting the housing bubble to continue, not burst.[49] How do these beliefs coupled with access to high LTV loans impact behavior today?

To answer this question, we use a partial equilibrium consumer theory model.[50] Consumers derive utility from housing and consumption, and current house prices, expected future house prices, and the interest rate are all given. We analyze only one period, but consumers can borrow against the expected future value of any house they buy in that period. We find that when the house prices are predicted to rise faster than the interest rate, and when consumers are allowed to borrow against these expectedly high future prices, the budget line slopes upward. The logic is straightforward. A small house leads to appreciation the consumer can borrow against. A larger house leads to greater appreciation even if house prices grow at the same rate for small and large houses. Therefore, buying a larger house now generates more income that the consumer can spend now. Essentially, the consumer chooses a larger house so that she can afford to buy more of everything else.

Other researchers have looked at the interaction of housing and consumption. Dusansky and Wilson (1993) formulate a model in which rising current house prices lead to expectations of further house price increases, in which case households increase their demand for housing to take advantage of the anticipated capital gains. This leads to an upward-sloping demand curve for housing. Dusansky and Koc (2007) treat housing as both a consumption good and an investment vehicle, and then provide empirical evidence that the investment role dominates the consumption role using data from Florida.[51] Our theoretical model goes one step further than these studies, showing that not just an upward-sloping housing demand curve, but an upward-sloping household budget line results when the expected house price growth exceeds the interest rate and households obtain high LTV loans to take advantage of the anticipated house price appreciation.

When the budget line slopes upward and consumers have monotonic preferences, no optimum exists. To get a solution, we add a constraint that limits consumer borrowing to

[48] Case and Shiller (2003) use survey evidence to document that home purchases in 2003 were driven in part by an investment motive fueled by expectations of large home price appreciation.
[49] Dusansky and Wilson (1993) also explore a similar scenario.
[50] This contrasts with the standard life cycle/permanent income approach to housing demand introduced by Artle and Varaiya (1978) and used more recently by Muellbauer (2008). In addition to simplifying the life cycle model into a single period, our paper differs from these studies by explicitly allowing housing bubbles.
[51] See also Henderson and Ioannides (1985).

a multiple of earned income. Borrowing constraints were common prior to the latest housing bubble, and one might expect them to return. For instance, before the recent housing bubble homebuyers could only borrow up to the point where their monthly mortgage payment equaled 28 percent of their monthly income, and their total debt payments equaled 36 percent of their monthly income.[52] The constraint we add to identify a solution for the household optimization problem is a fixed relationship between income and the amount to be borrowed, with a single parameter governing this relationship.

Not surprisingly, the ability to borrow against overly optimistic future house prices leads to consumers purchasing larger houses. More surprisingly, however, it leads to greater consumption spending, too.[53] Furthermore, the model shows that housing demand fits neither the conventional theories of consumer goods nor that of investment goods. Particularly, increases in the expected future price of housing may reduce the current housing demand, contrary to the typical pattern of investment goods for which rising expected prices lead to higher current demand. Similarly, a decrease in the effective (current) price of housing may lead to households purchasing smaller homes, contrary to the usual pattern of consumption goods for which lower prices lead to higher quantity demanded.

We conclude our discussion by considering issues important to policymakers: the household response to changes in the interest rate and that to shocks in earned income. The former matters to central bankers for whom housing provides a transmission channel for monetary policy and the latter to those concerned with long-term economic growth. The model shows that the ability to borrow against high house price forecasts reduces the effectiveness of monetary policy but raises the volatility of aggregate demand.[54] Tightening borrowing standards can lower such volatility and increase the marginal propensity to save at the expense of shrinking the overall activity.

The plan of this paper is as follows. The second section sets out the structure of the model describing the budget constraints and borrowing constraints. In the following section, we examine the effect of rising house price forecasts. In the fourth section, we discuss the policy implications: the effect of interest rate changes, income shocks, and lending restrictions. We conclude in the fifth section by discussing the recent developments in the housing market and macroeconomy in general in light of our model.

[52] Aron et al. (2008a, 2008b) and Williams (2008) show how financial deregulation leads to house price appreciation.

[53] Jappelli and Pagano (1994) construct an alternative model showing how financial deregulation can lead to declining national savings and slower economic growth.

[54] Edge et al. (2008) use a DSGE model of the US economy to examine house price volatility and monetary policy effects. They find evidence that monetary policy has had little impact on recent residential investment trends, in line with our findings below. On a related note, Aron et al. (2008b) show that an easing in credit conditions has led to structural shifts in the consumption-to-income ratio, breaking the pre-existing co-integrations.

2. Budget constraints and borrowing constraints

Our approach is to construct a simple model in which households can borrow against the future values of their homes. To do this, we assume that households live for a single period, purchasing a home at the beginning of the period and selling it at the end. They have preferences over housing investment *h* and consumption spending *c*, with their utility function given by $u(h, c)$. Importantly, they do not value bequests or savings since they do not live past the first period, and therefore they have an incentive to spend all of their resources and leave no equity in their homes.[55]

Earned income is given by *y*, realized at the beginning of the period. Households also earn the appreciation from the sale of their houses at the end of the period. At the beginning of the period, the price of a unit of housing is p_0 and the price of unit consumption is normalized to 1. These prices are exogenous in the model, as is the forecast future price of housing, denoted by p_f. Both households and lenders agree on the value of p_f, so that if a household purchases a house of size *h* she can borrow against its expected future value, $p_f h$, at the exogenously given interest rate *i*.

Households make all of their decisions simultaneously at the beginning of the period, choosing consumption, housing, and borrowing. They can finance current spending either through earned income or through borrowing against expected home equity. Current spending is $p_0 h + c$, and the most household can spend is:

(1) $$y + a \frac{p_f h}{1+i}$$

where *a* is the fraction of the future home value that the household borrows. Since households cannot borrow more than the expected future value of their homes, *a* falls in the unit interval.

This specification leads to immediate implications. Consider the budget constraint:

(2) $$p_0 h + c \leq y + a \frac{p_f h}{1+i}$$

Rearranging yields:

(3) $$\left[p_0 - a \frac{p_f}{1+i}\right] h + c \leq y$$

The bracketed term, which we denote as *r*, is the effective price of housing, and it is clearly smaller than the current price p_0.

[55] Together these assumptions make the model, in essence, static.

While housing shares attributes with both consumption goods and investment goods, what makes housing most different from other consumption goods is the nature of the effective price r. At one extreme, if a = 0 so that the household does not borrow at all against expected future home values, the effective price r is exactly the same as the current price p_0, and housing is no different from any other consumption good. But, if a = 1 so that household borrows fully against the future value of their house, and $\frac{p_f}{1+i} = p_0$ so that house prices are predicted to rise at the same rate as the interest rate, then the effective price of housing is zero and housing is free. If $\frac{p_f}{1+i} > p_0$ so that home prices are predicted to grow faster than the interest rate and household borrows the full amount of their expected home equity, the effective price of housing becomes negative. We explore the implications of negative effective house prices in the next section.

Households may not be able to borrow the full expected future sales value of their homes, however, perhaps because lenders are subject to regulations that relate the loan size to earned income. To account for this, we impose the borrowing constraint:

(4) $$a \frac{p_f\, h}{1+i} \leq by$$

where b represents an upper limit on the fraction of earned income that a household can borrow. Substituting (4) into (1) yields another budget constraint:

(5) $$p_0 h + c \leq (1+b)y$$

This is the budget constraint that would hold if the household could acquire an unsecured loan of b times her income y. However, households cannot get unsecured loans, and the ability to borrow by requires purchasing a house of sufficient expected future value to warrant the loan.

Figure 3.1 in the Appendix shows how the household's budget constraint works. Housing is measured on the horizontal axis and other consumption is measured on the vertical axis. The figure contains three lines. The line AB is the budget line that would hold if the household did not borrow at all against the future value of her home, that is, if a = 0. This is the budget line that is usually considered in consumer theory, and its slope is $-p_0$. We will refer to it as the "original" budget line. The line AC is the budget line that obtains when the household borrows fully against the future value of her home, so that a = 1. Borrowing reduces the effective price of housing, thereby making the budget line flatter with a slope $\left[p_0 - \frac{p_f}{1+i}\right]$ instead of $-p_0$ as with budget line AB. Evidently, this allows the household to purchase more of both housing and consumption. The remaining line ED is the budget line that would hold if the household could obtain an unsecured loan of by and spend it in any way desired. This budget constraint corresponds to expression (5), and it is referred to as the "outer" budget line. Since both expressions (2) and (5) must hold, the actual budget constraint facing the household is the curve AFD.

It is worthwhile to see how the household moves along this curve from point A to point F, and then from F to D. Begin at point A. At this point, the household spends her entire income on consumption and has no housing to borrow against. So, she does not borrow. If she purchases some amount of housing, though, she gains the ability to borrow against its expected future value. For an effective price of housing *r*, the household moves along the budget line AC toward point F, purchasing larger houses and borrowing the full discounted expected future value of those houses. When the household reaches point F, however, she has hit the borrowing constraint for a total loan size of *by*, and no bank will lend her any more than that amount. This does not mean that the household cannot buy a larger house though, it only means that she cannot borrow more than *by* against that larger house. Since the household cannot borrow against the future value of the additional housing units, the price of additional housing returns to the current price p_0 instead of the effective price *r*, and as the household purchases larger and larger houses she moves along the outer budget line from point F to point D.[56]

[56] The point F represents a situation in which the household borrows the maximum amount *by* that also corresponds to the full discounted expected future value of a house of the size $by(1+i)/p_f$.

3. The effects of rising house price forecasts

A key feature of a housing bubble is that markets expect house prices to rise rapidly. If households have access to high LTV loans secured by this expected appreciation, house price forecasts affect the household's current choices of what homes to buy and how much to consume. Figure 3.2 illustrates these issues. First suppose that $p_f = 0$, so that households cannot borrow because their homes will fully depreciate and have no value in the future. They are constrained to the original budget line. They solve the usual utility maximization problem and choose point A in the figure. Note that this is the budget constraint that would hold if housing were an ordinary consumption good.

Housing is not an ordinary consumption good, however, because home values do not fully depreciate during an individual's lifetime and homeowners can sell their houses at any time. Furthermore, homeowners may borrow against the forecast future value of their houses, especially when both borrowers and lenders agree on these forecasts. When the forecast future price of housing p_f rises, the budget line rotates outward because the effective price of housing r falls. Note that the intersection of the budget constraint with the vertical axis remains fixed at y, because when households spend all of their income on consumption and none on housing they have nothing to borrow against.

As the forecast price of housing rises and the budget line rotates outward, the household's spending opportunities increase. When the forecast future price reaches the point where $\frac{p_f}{1+i} = p_0$ so that expected growth in house prices matches the interest rate, housing becomes essentially free because the discounted expected future sales price equals the current purchase price. At this point the budget line becomes horizontal, consistent with an effective price of zero. If house price forecasts rise even further the effective house price becomes negative and the budget line actually slopes upward, meaning that by purchasing larger homes households can purchase more of other consumption goods.[57]

The bold dashed curve in Figure 3.2 is the household's expansion path, showing the optimal housing-consumption pairs for different values of the forecast future price of housing. The expansion path begins at point A on the household's original budget line, which holds when the forecast price is zero and households are unable to borrow. As the forecast price rises and the budget line rotates outward, the household increases both the housing investment and consumption spending. Eventually p_f rises to the level where the household's borrowing constraint binds, which is point B in the figure. Further increases in the expected future price of housing mean that the household does not need as many housing units to secure the maximum loan by, and so she begins downsizing. The downsizing continues until the household reaches point C, which is her utility-maximizing point along the outer budget line. At this point, the household no longer finds

[57] It is possible to modify the model to account for physical depreciation of houses, but that is ignored here in an effort to simplify the model.

it worthwhile to give up housing in favor of increased consumption. Therefore, further increases in the forecast price of housing do not lead to a behavioral response.
Looked at differently, the expansion path shows how the economy behaves as the housing bubble, defined for our purposes as a sustained increase in house price forecasts, continues to grow. Initially, both consumption and housing demand increase as households purchase larger homes to finance their consumption expenditures. Eventually, households reach a point (shown by B in the figure) at which their borrowing is constrained by their income, and further forecast price increases lead to greater demand for consumption but lower demand for housing. At some point (C in the figure) this trend ends, and further increases in the forecast house prices have no economic impact.

Importantly, the analysis identifies three different regions on the expansion path for the effect of forecast prices on household behavior. In the first region, corresponding to relatively low forecast home prices, both consumption and housing demand increase with forecast prices. In this region, housing acts like an ordinary investment vehicle, with rising expected future prices leading to higher demand. In a second region, corresponding to a middle range of forecast home prices, consumption rises but housing demand falls with forecast prices. This contradicts the typical behavior of an investment vehicle for which demand rises when expected future prices increase. Housing also differs from an ordinary consumption good in this second region, because its demand falls even though the (current) effective price decreases. In the third region, corresponding to high forecast home prices, further price increases have no effect on household spending.

4. The interest rate, saving rates, and volatility

The preceding section showed how the household's ability to take out high LTV mortgage loans secured by forecast home values leads to unusual purchasing patterns that fit neither investment nor consumption models. These patterns are only important, however, if they influence the way in which policy is formulated and carried out. This section explores the implications of the model for interest rate changes, household saving rates, economic volatility, and borrowing restrictions.

The effectiveness of monetary policy rests on its ability to promote changes in household spending. Within our model, monetary policy impacts the household through its effect on the interest rate. An examination of expression (2) shows that interest rate changes work in exactly the same manner, but in the opposite direction, as changes in the expected future price of housing, and these changes were depicted in Figure 3.2. Both interest rate decreases and forecast future house price increases lead to counter-clockwise movements along the expansion path. Unless the interest rate falls so low that households reach point C in Figure 2, monetary policy alters household behavior.

What matters for the economy, however, is not so much whether households modify their bundles of housing and consumption, but whether they change the total amount they spend on housing and consumption combined. In Figure 3.2, every bundle on the outer budget line, and in particular between B and C, costs exactly the same amount, $(1+b)y$. More importantly, this amount is completely independent of the interest rate, and so is unaffected by monetary policy. When forecast future house prices are sufficiently high or the interest rate is sufficiently low that consumers borrow all the way up to their borrowing constraints, monetary policy influences the composition of household spending, but not the total amount. Particularly, a monetary loosening leads households to consume less housing and more consumption goods, and a monetary tightening does the opposite. The directions of changes are noteworthy though. Falling interest rates reduce the demand for housing, not raise it, contrary to the monetary transmission mechanism as it was previously understood.[58] Monetary tightening, perversely, leads to greater housing demand.

Much has been made about the downward trend in the U.S. personal saving rates over the past two decades.[59] In explaining this downward trend in household savings, an essential step is to have low household marginal saving propensities. In our model, when households borrow against high forecast home values, the marginal propensity to save can become negative. To see how, suppose that future house prices are predicted to be

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[58] Traditionally, there are at least six transmission channels through which interest rate changes impact the residential investment, thus the overall economic activity. These channels include direct interest rate effects on the (1) user cost of capital, (2) expectations of future home values, and (3) housing supply, in addition to indirect (4) permanent (life-cycle) wealth effects, (5) temporary balance sheet/credit channel effects on consumer spending, and (6) temporary balance sheet/credit channel effects on housing demand. See Mishkin (2007) for an extensive discussion of the role of housing in the monetary transmission mechanism.

[59] For recent reviews of this literature, see Garner (2006) and Guidolin and La Jeunesse (2007).

sufficiently large such that households reach their borrowing constraints, and therefore consume between points B and C in Figure 3.2. Now, consider the impact of a positive income shock. An increase in earned income of Δy shifts outward both the original budget constraint and the outer budget constraint; the original budget constraint shifts upward by the amount Δy whereas the outer budget constraint shifts upward more, by $(1+b)\Delta y$. Accordingly, an income increase of the size Δy leads to a total increase in spending of $(1+b)\Delta y$. The marginal propensity to spend, then, is $1+b$, which is greater than one, and the marginal propensity to save is $-b$ which is less than zero.

A final concern for policymakers is the volatility of economic activity. Figure 3.3 examines this issue through shocks to household's earned income *y*, in two different scenarios. In the first scenario, households cannot borrow against future home values, and so must consume on their original budget constraint. The optimal point is A. An increase in earned income of Δy shifts this budget constraint upward by Δy, and the new consumption point is B. The distance between points A and B can be thought of as a rough measure of the volatility in aggregate demand.

In the second scenario, households borrow against future home values and home price forecasts are sufficiently high to make the effective price of housing negative. Prior to the income shock, households choose to consume at the kink in the budget constraint, which is at point C. An earned income shock of the same size Δy shifts the outer budget line upward by $(1+b)\Delta y$, which is a larger shift than in the first scenario. The new consumption point is D, at the kink of the outermost budget constraint. The distance between points C and D is greater than the distance between A and B, reflecting that aggregate demand would display increased variance if households were to engage in high LTV borrowing against forecast home values.

Since the effect of any income shock Δy on total demand is magnified by a factor of $1+b$ where *b* is the multiple of earned income households can borrow, regulating *b* represents a way to reduce demand variability. In particular, reductions in *b* lead to smaller adjustments in aggregate demand following an income shock, therefore a less volatile economy. Also, more restricted borrowing will help slow down the decline in household savings. The benefits associated with limitations on household borrowing come at a cost, however, since a smaller *b* also means lower levels of household spending. In particular, reductions in *b* move the outer budget line closer to the original budget line leading in general to a contraction in overall activity.

5. Conclusions

This paper examines the implications of high LTV mortgage borrowing for aggregate demand volatility and policy effectiveness. We find that households that obtain high LTV loans secured by expected high future home values purchase larger homes in order to finance other consumption spending, and that housing demand does not fit traditional consumption or investment theories. Rapidly rising home price forecasts can lead to interest rate policy having no impact on aggregate spending but only causing changes in the mixture of housing and consumption. Furthermore, high house price forecasts can generate negative marginal propensities to save and more volatile aggregate demand conditions. Restricting the household's ability to borrow can help reduce economic volatility and lead to higher marginal saving propensities at the expense of a smaller economy.

The proposed economic structure sheds light on the recent U.S. experience of a burst housing bubble and the resulting adverse macro consequences. In our model, rapidly falling home price forecasts increase the effective price of housing, moving the economy clockwise along the expansion path in Figure 3.2. In the upper part of the expansion path (that is, above point B) falling price forecasts have no impact on the overall activity; households stay on the outer budget line and the aggregate household spending remains fixed at $(1+b)y$. Below point B, however, further declines in expected home prices leads to households reducing the demand for housing. Because consumption is partly financed by purchasing large houses and borrowing against them, the decline in housing demand lowers consumption demand also. This is when the signs of recession appear with the aggregate household spending falling below $(1+b)y$.

Furthermore, changes in the economic climate in a post-bubble world may lead financial institutions to curb lending.[60] More restricted borrowing, reflected by an inward shift of the outer budget line, puts another contractionary force on the economy leading to aggregate demand declining at a faster pace than otherwise. Although policymakers respond by cutting the interest rate to support the housing demand, monetary stimulus falls short of promoting full recovery. This is because falling interest rates fail to overcome the adverse effect of the steep decline in house price forecasts, as evident in expression (3).

Our findings that house price forecasts affect macro outcomes in important ways ranging from increased aggregate demand volatility to policy ineffectiveness warrant a renewed interest in the optimal policy response to asset price bubbles. The traditional view that changes in asset prices, except their predictable impact on future inflation and output, should not be a concern for monetary policy needs to be justified in light of recent developments.

[60] The Federal Reserve Bank of Dallas has already called for lowering LTV limits; see Gunther (2009).

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Appendix

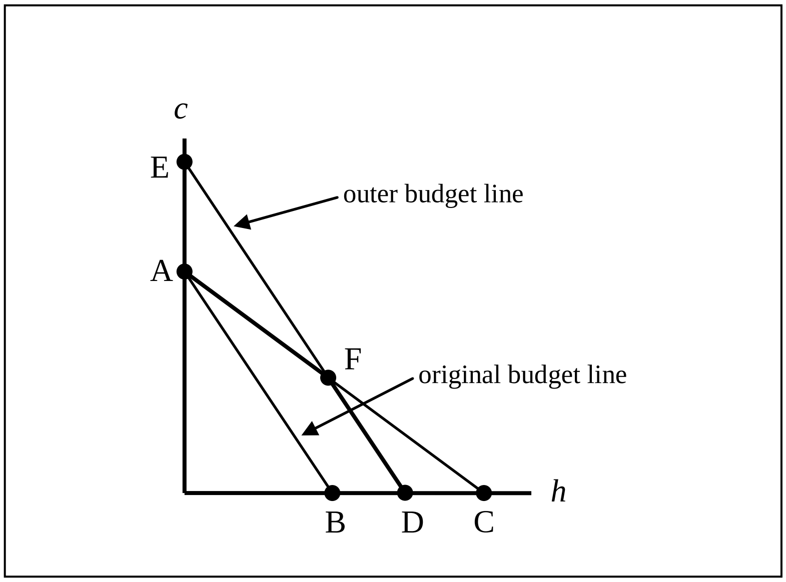

Figure 3.1 Budget and borrowing constraints

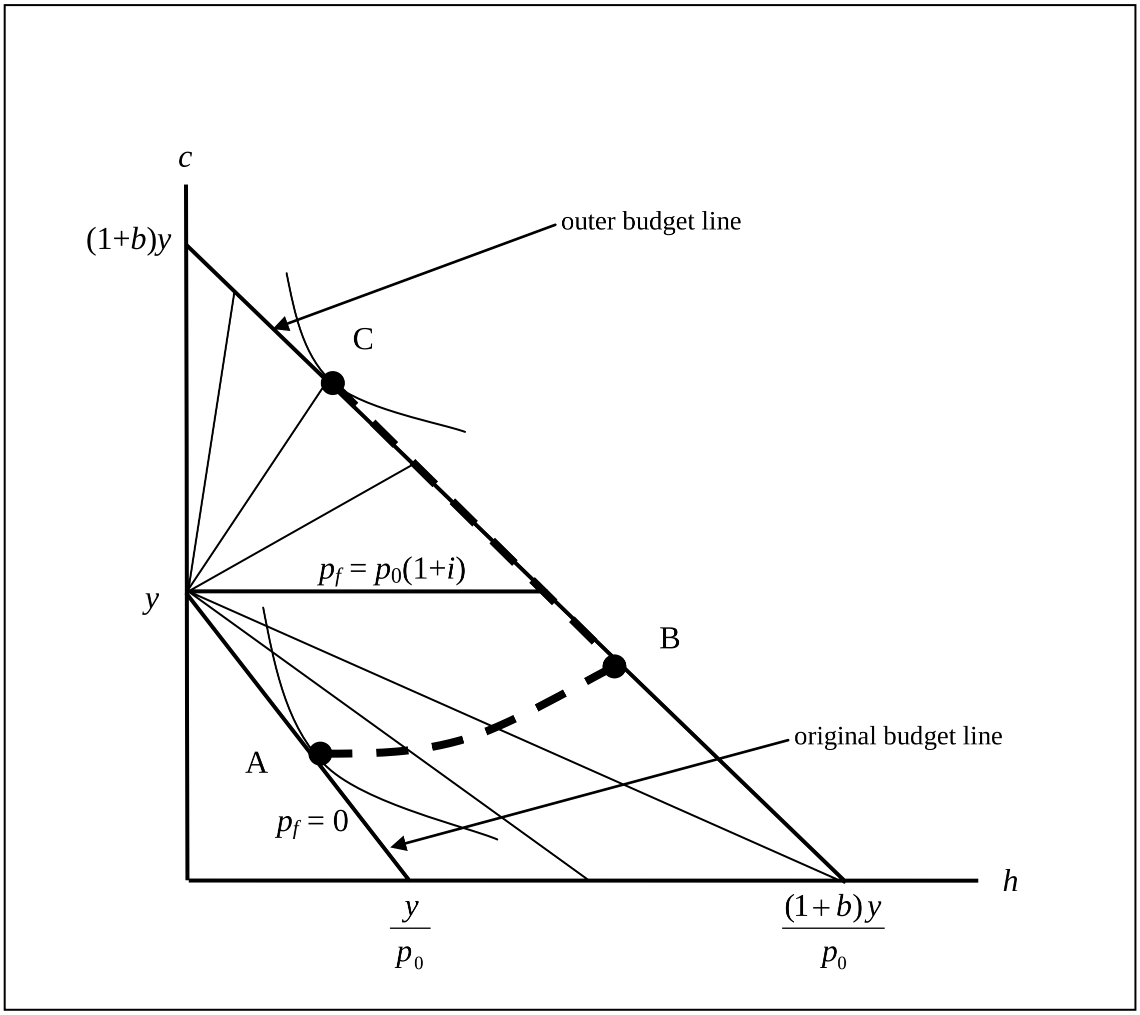

Figure 3.2 Expansion path

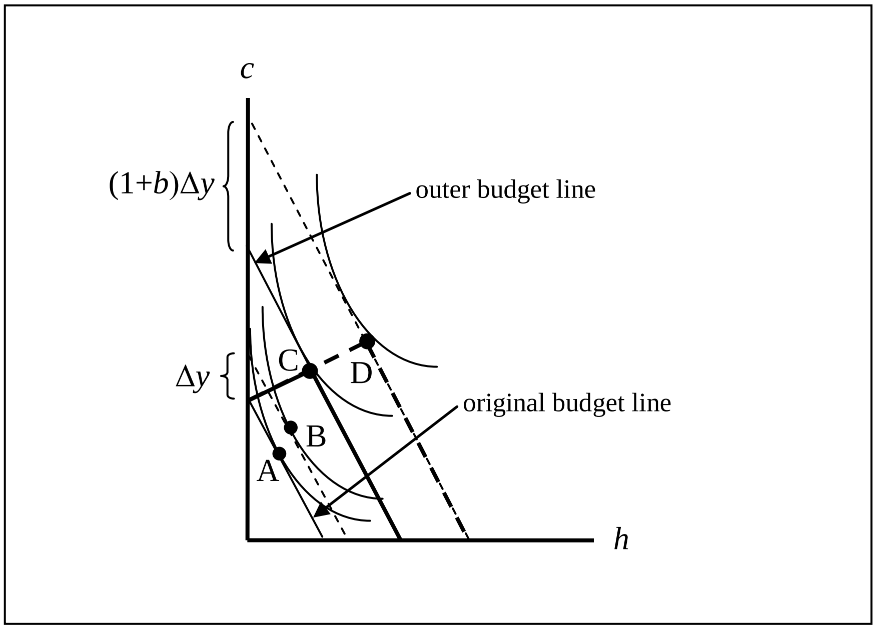

Figure 3.3 Economic volatility and borrowing restrictions

Conclusion

In this dissertation, I examine several issues regarding the conduct and the effectiveness of monetary policy. The observed monetary behavior is a preference for successive and relatively small interest rate changes. This persistence in interest rate changes is documented by empirical monetary policy reaction functions that feature a large estimated coefficient for the lagged interest rate. The two hypotheses that explain the size of this large estimated coefficient are monetary policy inertia and serially correlated macro shocks.

In the first part of my dissertation, I examine the persistent nature of monetary policy adjustment using an ordered probit model. The evidence shows that inertia exists in the Fed's monthly funds rate setting, but not to the extent that it could lead to consecutive interest rate changes. This finding suggests that the Fed's reaction to serially correlated factors plays an important role in policy setting, which is in line with the interpretation that inertia and serially correlated shocks simultaneously affect monetary policy.

In the second part of my dissertation, I show that using averaged interest rates in empirical policy reaction functions leads to an upward bias on the predicted size of inertia due to temporal aggregation effects. An application to federal funds target rate reveals that using the quarterly averaged interest rates, compared to end-of-quarter interest rates, significantly inflates the estimated size of inertia.

The third part of my dissertation is inspired by recent developments in the housing market and the resulting effect on the overall economy. This third essay examines the implications of high loan-to-value mortgage borrowing for aggregate demand and monetary policy effectiveness. We find that households with access to high loan-to-value mortgages purchase larger homes in order to finance other consumption spending, and that housing demand does not fit traditional consumption and investment theories. Furthermore, rapidly rising home price forecasts lead to interest rate policy having no impact on aggregate spending but only causing changes in the mixture of housing and consumption.

Vita

Omer Bayar was born in Zonguldak, Turkey, to the parents of Hacer and Necati Bayar. He is the younger brother Yilmaz Bayar. He attended Ankara Science High School in Ankara, Turkey, and continued to Bogazici University in Istanbul, Turkey, for a Bachelor of Arts degree in Business Administration. Omer then accepted a graduate teaching assistantship at the University of Tennessee, Knoxville. He graduated with a Doctoral degree in Economics in August 2010. He is currently an Assistant Professor of Economics at the University of Evansville in Evansville, Indiana.