Should Monetary Policy Target Asset Bubbles?
– A Machine Learning Perspective

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Abstract

In this project, I will discuss the limitations of macroeconomic studies on asset bubbles from a machine learning perspective. While theory models rely exclusively on ad hoc assumptions of investors' psychology and trading behavior, quantitative results from lab experiments have limited predictive power. I will highlight the challenge of obtaining externally valid quantitative results, using data generated from my economic experiments conducted on Amazon Mechanical Turk platform. At the end, I will outline follow up research for my 2nd year Ph.D. I believe machine learning promises a quantitatively accurate description of investors' psychology and trading behavior, the holy grail of macroeconomic studies.

Introduction

Should monetary policy target asset bubbles? The conventional wisdom is "no". In the 2002 seminal paper *Monetary Policy and Asset Price Volatility*, Federal Reserve chairman Ben Bernanke and his co-author Mark Gertler argued that, as long as asset bubbles pose no threat to Federal Reserve's dual mandate of maximum employment and stable consumer prices, central bankers should not be concerned.

Do asset price affect the real economy? If so, what is the design of an optimal monetary policy that would contain its damage? To investigate these questions, Bernanke relied upon reflections of historical evidence, and a modified standard dynamic new Keysian simulation model. He concluded that asset price stability is a byproduct of consumer price stability. This became the famous Jackson Hole consensus that dominated macroeconomic profession until the financial crisis of 2007.

In light of recent events, it is tempting to walk away from this paper and never look back. However, the challenges of incorporating asset price fluctuations into monetary policymaking outlined in this paper remain. In this project, I would investigate the nature of these challenges and evaluate recent development in Economics from a machine learning perspective. I would then go on to outline how machine learning can improve Economists' understanding on asset bubble dynamics, and inform optimal monetary policy design.

Challenges of Combating Asset Price Bubbles Using Monetary Policy

Detecting a bubble in real-time

What is an asset bubble? For economists, a bubble is defined relative to the fundamental value of an asset, calculated as the expected net present value of this asset. If the market price of an asset is greater than its fundamental value, we are in a boom; if the market price of an asset is less than its fundamental value, we are in a crash. Detecting a bubble in real time is challenging, in part because fundamental value is hard to pin down. For example, if we observed a young company growing at a meteoric rate, should we extrapolate this growth rate into the future when we calculate the fundamental value? If so, how long can this growth rate be sustained? There are no easy answers to these questions, and different investors may form different judgments. Moreover, when we are calculating fundamental value as the infinite sum of discounted earnings, slight changes to expected growth rate would generate drastically different fundamental values.

Bluntness of Monetary Policy and the Industry Specific Nature of Asset Bubbles

Conventional monetary policy promotes macroeconomic stability by adjusting interest rates in response to inflation, unemployment and other macroeconomic indicators. When the Fed increases interest rate, borrowing become more expensive. This leads to lower investment, relieving upward pressure on prices and wages. Hence, conventional monetary policy is suitable for economy-wide problem. Meanwhile, most asset bubbles originate in specific industries (e.g. housing, technology, savings and loans, etc.). Is monetary policy the appropriate instrument to target asset bubbles?

"Inability" to Observe Expectation of Future Asset Prices and the Quantitative Nature of Monetary Policy

When introducing asset bubble into a standard dynamic new Keysian model, we need 3 additional equations. The first equation describes how investors form expectation of future asset prices; the second equation describes how investors trade, given their expectation of future asset prices; and the third equation describes how fluctuation in asset prices will feed into the real economy. And without a good characterization of how people form their expectation, no quantitative models will give quantitatively valid results.

Current Approaches in Economics: Theory

Most macroeconomic theory model assumes an ad hoc expectation formation process. For example, in Bernanke and Gertler's 2002 paper, they model investors' expectations as follows:

A bubble exists if the market price of capital, S_t, is greater than its fundamental value Q_t. They do not rationalize why market participants do not arbitrage away this difference. If a bubble exists at date t, it persists with probability p and grows at an exgoegnous rate of g with probability p. With probability (1-p),the bubble crashes, and market price reverts to its fundamental price and stay there forever.

Bernanke and Gertler justify their modeling technique with the following quote:

> "By treating the probability that the bubble bursts as exogenous, we rule out the possibility that monetary policy can surgically prick the bubble. Although it is certainly possible to endogenize this probability, so little is known about the effects of policy actions on market psychology that any modification along these lines would necessarily be ad hoc."

Why is this approach problematic?

- We do not observe (p,a). The best thing we can do is to simulate a macro model, using different pairs of (p,a); but then the quantitative results may be very different. Since monetary policy requires highly accurate quantitative results, this kind of simulation exercise will only be useful for qualitative thought experiment.
- (p,a) may be market context dependent, as implied by the quotation.
- We can certainly try to elicit (p,a) in a laboratory; but there's the question of external validity. It is highly unlikely that average undergrads and Wall Street research analysts would have quantitatively similar results.

<u>Current Approaches in Economics: Experimental Evidence</u>

Experimental findings on asset bubbles cluster around the 2002 Nobel Economist Vernon Smith's two famous papers *Bubbles, Crashes and Endogenous Expectations in Experimental Spot Asset Market* (1988), and *Thar She Blows: Can Bubbles be Rekindled with Experienced Subjects?* (2008). The typical experimental set up involves an asset that generate earnings with a known distribution, and having subjects trade with each other. The main conclusion is that given a specific earnings distribution, more experienced subjects are less likely to generate a bubble. However, once the underlying earnings distribution change, even experienced subjects can generate bubble.

<u>Experiment Set-Up and Data</u>

For reasons that are irrelevant to this discussion, I replicated Smith's experiment with a twist on Amazon Mechanical Turk's platform. Here's my experimental set-up and the data I elicited:

In each round, I provide 100 subjects with past information of a stock. Specifically, they will see the stock's past price, earnings per share, rate of return, and price earnings ratio. To keep my experiment sharp, I choose a time series where the company does not pay dividend. Once a subject click on a specific financial metric, the associated graph and table are revealed. If he/she clicks on another financial metric, the existing graph and table would be closed, and the associated graph and table with this new financial metric would be revealed. A computer program is installed so that I can monitor subjects' clicking sequence, unbeknown to them. In each round, a subject is prompted for his/her best guess for the stock price in the upcoming round, and a range within the best guess will occur. At the end of each period, subjects learn the true price, the accuracy of their guesses, and the latest earnings announcement. The forecasting game continues for 19 periods. The time series I choose is Yahoo's quarterly data from September 1996 to June 2002. The first five periods are given as initial information.

The use of 100 subjects and 19 periods would make any computer scientist laugh. But this is already a drastic improvement upon Smith's 7 subjects and 15 periods set-up, which is the current standard for economic experiments. I capped the number of subjects at 100 due to my limited graduate research funding, and the number of periods at 19 because any experiment longer than that would result in non-sensible forecasts due to boredom.

Methodology and Results

I use logistic, linear regression (with variations) and SVM to study how people's forecasts change in response to latest update on earnings, prices and market sentiments. The results are highly sensitive to different feature selection, a problem that plague Economic experiment work but is rarely, if ever discussed. To illustrate my point, I've included my regression result using weighted least squares with individual fixed effect and clustered standard errors. Notice how the signs flip from table 1 to table 2 on the next page.

I then use reinforcement learning to investigate how long it takes for people to learn a fixed, unknown distribution of an asset price distribution. The most successful configuration requires 50 iterations.

Future Work

The empirical part of this project shows why economists should not rely on laboratory experiment for quantitative description of investors' forecasting behavior. This is because the size of the data set is necessarily limited by the number of participants and time periods. Unfortunately, this represents the frontier of quantitative research on asset price bubbles and investors' forecasts.

A reading of a 2012 CS229 project suggests echo state neural network being a suitable candidate for accurately forecasting high frequency cycles in Foreign Exchange Market. I plan to learn and implement this approach on I/B/E/S data set It contains comprehensive global information on individual analyst's estimates of earnings, and on a more limited basis, revenue, cash flow, FFO, and long-term growth. It currently covers over 63,000 securities for more than 50,000 companies in more than 150 countries. U.S. data dates back to 1976, and international data back to 1987. I am cautiously optimistic about this project, due to its large data size, and because of the increasing adoption of machine learning in the investment and trading profession.

Dependent variable	$\frac{\text{Forecast}_{it+1}-P_t}{P_t}$		
	(1)	(2)	(3)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_1$	-0.097	-0.182	-0.108
	(0.093)	(0.118)	(0.102)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_2$	-0.313	-1.058***	-0.166
	(0.362)	(0.298)	(0.401)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_3$	1.770***	1.810***	0.624
	(0.344)	(0.416)	(0.581)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_4$	0.551	0.042	1.328***
	(0.370)	(0.301)	(0.329)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_1$	0.129***	0.119***	0.127***
	(0.023)	(0.021)	(0.023)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_2$	0.194***	0.008	0.230***
	(0.018)	(0.013)	(0.019)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_3$	- 0.207***	-0.031	-0.061*
	(0.036)	(0.029)	(0.034)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_4$	0.055	-.132**	0.005
	(0.035)	(0.060)	0.028
$\left(\frac{\text{Forecast}_{it}-P_{t-1}}{P_{t-1}}\right)D_1$	0.254***	0.242***	0.247***
	(0.036)	(0.046)	(0.046)
$\left(\frac{\text{Forecast}_{it}-P_{t-1}}{P_{t-1}}\right)D_2$	0.128	0.156	0.126
	(0.213)	(0.184)	(0.247)
$\left(\frac{\text{Forecast}_{it}-P_{t-1}}{P_{t-1}}\right)D_3$	-0.349	0.535	-0.073
	(0.380)	(0.468)	(0.407)
$\left(\frac{\text{Forecast}_{it}-P_{t-1}}{P_{t-1}}\right)D_4$	0.216	0.190	0.256
	(0.201)	(0.221)	(0.242)
Constant	0.506***	0.714	0.466***
	(0.027)	(0.036)	0.027
Observations	404	404	404
R^2	0.41	0.44	0.41
Person Fixed Effects	Yes	Yes	Yes

Dependent variable	$\frac{Forecast_{it+1}-P_t}{P_t}$			
	(1)	(2)	(3)	(4)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_1$		0.183***	0.110***	0.160***
		(0.037)	(0.040)	(0.038)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_2$		0.036	- 0.647***	0.171*
		(0.104)	(0.116)	(0.101)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_3$		1.297***	1.973***	0.727***
		(0.165)	(0.214)	(0.176)
$\left(\frac{P_t-P_{t-1}}{P_{t-1}}\right)D_4$		0.548	0.136	1.360***
		(0.505)	(0.299)	(0.269)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_1$		0.135***	0.128***	0.133***
		(0.029)	(0.026)	(0.029)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_2$		0.204***	0.011	0.242***
		(0.014)	(0.013)	(0.016)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_3$		- 0.193***	-0.003	-0.093**
		(0.025)	(0.014)	(0.036)
$\left(\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}\right)D_4$		0.079**	-0.076	0.032
		(0.033)	(0.063)	(0.021)
$\frac{P_t-P_{t-1}}{P_{t-1}}$	0.183***			
	(0.033)			
$\frac{EPS_t-EPS_{t-1}}{EPS_{t-1}}$	0.132***			
	(0.025)			
Constant	0.322***	0.372***	0.545***	0.333***
	(0.025)	(0.019)	(0.027)	(0.020)
Observations	447	447	447	447
R^2	0.32	0.41	0.36	0.35
Person Fixed Effects	Yes	Yes	Yes	Yes