

“Does monetary policy cause randomness or chaos? A case study from the European Central Bank”

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Does monetary policy cause randomness or chaos? A case study from the European Central Bank

Abstract

Using the HICP (Harmonized Index of Consumer Prices) the author tests the series for the makeup of its dynamic components both before and after the start of stage three of the European Central Bank's (ECB) monetary policy directive. While it appears ECB is meeting its stated objective, it is perhaps more important to address the composition of the lag and volatility of monetary policy to see how a policy change alters the fundamental dynamic structure of an economic system. The HICP data provides a good natural experiment for assessing structural change. This is important because while a policy may achieve its goal(s), in doing so it may alter the fundamental nature of how that system behaves, potentially causing the system to be more volatile or more sensitive to exogenous shocks in the future. Changes to the fundamental nature of a dynamic system can mean that future policies, that are similar to the present policies, could have very different impacts on that very same system in terms of both long run and short run effects. The paper finds that while the ECB may be meeting its stated objectives, it may be potentially increasing the degree and severity of future short run deflationary/inflationary cycles from similar policies in the future due to the type of random and deterministic components in the system. More data and further study is needed to determine the long-term affects of monetary policy in economic systems as many economic cycles are indeed very long.

Keywords: dynamic systems, Hurst exponent, chaos, long-term memory, monetary policy.

JEL Classification: C50, E40, G18.

Introduction

The historical consensus is that monetary policy actions “affect economic conditions only after a lag that is both long and variable” (Friedman, 1961). Yet, we still have not been able to describe well what this entails. There has been a growing body of literature in economics about the complexity and memory of economic systems and the importance of considering the dynamic nature of the system in question. From the standpoint of deterministic systems and chaos the works of Arthur (2013), Baumol and Behhabib (1989) and Tamari (2012) are just a few of examples. The literature is also replete with the measurement of persistence and long-term memory (random or not) in dynamic process such as Fama and French (1988), Hsieh (1991) and Lo (1991). Coupling the historical precedent with the growing research in dynamic systems we have room for intriguing questions about whether or not a system is chaotic or random and what type of randomness may be involved as well as the length of cycles involved.

Due to what appears to be the increasing speed at which the dynamic nature of economic systems changes, it is becoming more and more important that we seek to describe and understand the various phenomena that occur within these systems. For instance, I have found that gold prices contain both random and deterministic components that can be separated and measured (Sanderson, 2011). Still others have shown that economic systems emerge spontaneously on their own from a decentralized state (Howitt and Clower, 2000). Along these lines, we have a good natural

experiment for testing how the structure of the Euro has been altered due to a policy change with the implementation of the third stage of the of the ECB's monetary policy.

As is the case for most central banks or monetary union, a common concern is that of inflation. In the case of the European Central Bank, the stated objective is “To maintain price stability is the primary objective of the Eurosystem and of the single monetary policy for which it is responsible. This is laid down in the Treaty on the Functioning of the European Union, Article 127 (1)” (ECB: Objective of monetary policy, 2013):

- ◆ “Without prejudice to the objective of price stability”, the Eurosystem shall also “support the general economic policies in the Union with a view to contributing to the achievement of the objectives of the Union”. These include inter alia “full employment” and “balanced economic growth”.
- ◆ “The Treaty establishes a clear hierarchy of objectives for the Eurosystem. It assigns overriding importance to price stability. The Treaty makes clear that ensuring price stability is the most important contribution that monetary policy can make to achieve a favorable economic environment and a high level of employment”.

Further, the goal of the ECB aims at inflation rates (HICP) of at or below 2 percent. Putting aside discussions of if this is an appropriate macroeconomic objective, I believe we should still ask how a policy impacts an economic system aside from meeting the stated objective. Further the ECB seeks to “reduce distortions of inflation and deflation” (ECB: Objective of monetary policy, 2013).

Given this backdrop, this paper will investigate what the total effect to the system has been, considering the change in policy with the implementation of stage three of the European Monetary Union (EMU). The start of stage three by the ECB meant that they began their implementation of a Harmonized Index of Consumer Prices for use in policy decisions. According to the ECB “The HICP aims to be representative of the developments in the prices of all goods and services available for purchase within the Euro area for the purposes of directly satisfying consumer needs (HICP Definition, 2013). It measures the average change over time in the prices paid by households for a specific, regularly updated basket of consumer goods and services”.

Fundamental changes to how the system behaves could have potential large, sector wide, impacts which could include but are not limited to: increased volatility of the business cycle, increased uncertainty

in general economic conditions, as well as a potential to increase the number of “black swans” (Taleb, 2007) that may appear. In the case of the implementation of the HICP index there has been a fundamental change in the dynamics of the system. More research and time will be needed to discover whether or not we find the change acceptable, but as you will see in the analysis, the system itself has been altered. While the ECB is most assuredly considering business cycles, market expectations, inflation and the like it is critical that we seek to fully understand the dynamics involved for a clearer picture of policy affect.

1. Analysis

To begin, let us look at how the HICP has changed. Below is a graph of the the HICP index overtime. As you can see it appears that there is a structural change that occurs after the start of stage three of the EMU policy.

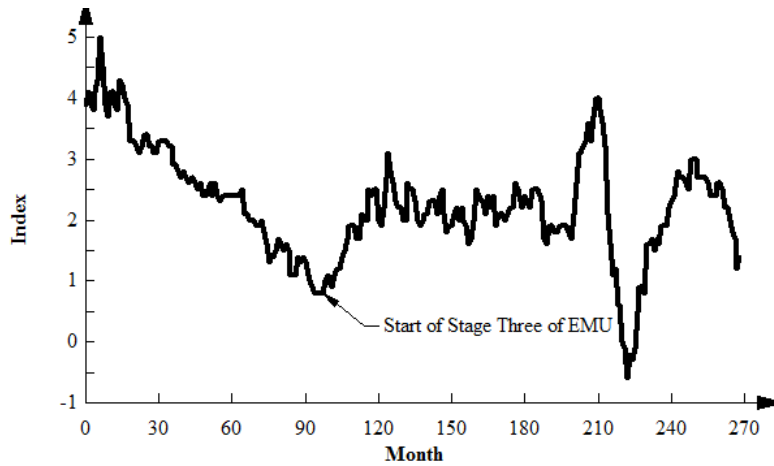


Fig. 1. HICP overall index, annual rate of change (1991-2013)

Table 1. The descriptive statistics of the HICP

	Prior to stage three	After stage three
Mean	2.62	2.06
Standard deviation	0.98	0.76
Maximum	5	4
Minimum	0.8	-0.6
Range	4.2	4.6

An *F*-test yields a result of 1.66 allowing us to conclude that the mean before and after the policy are statistically significantly different from one another. Normally this is where the authors might stop and say the policy has met its objective. Let us now dig deeper into how the system has been altered due to

the policy beyond the first and second moments of a distribution. Though the ACF is not a perfect measure, let us start with an ACF function. Using an ACF, both random phenomena and chaotic phenomena can look identical in their ACF (Sanderson, 2011).

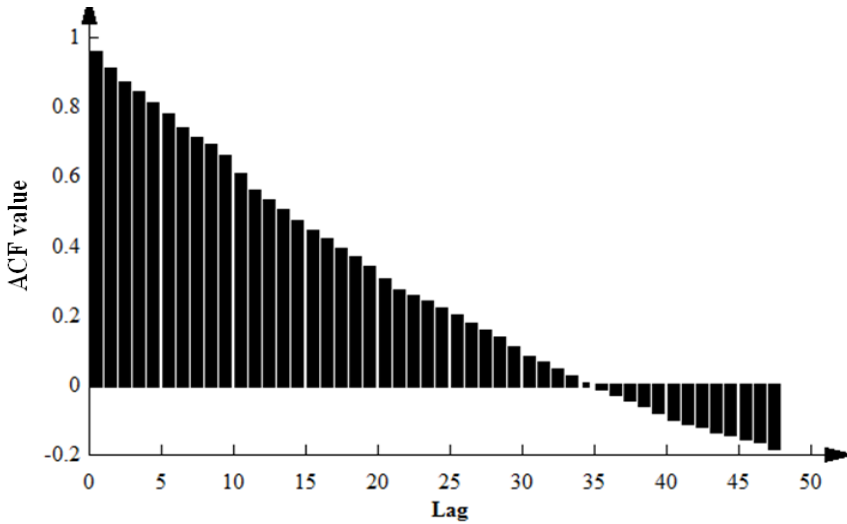


Fig. 2. ACF of HICP before ECB policy implementation

The era before the policy implementation shows relatively pretty classic auto-regressive behavior while we can see that the post policy era is showing some oscillating behavior. We now need to deter-

mine what kind of phenomena is occurring. To drill a little deeper, let us first look at a spectral analysis both before and after the policy change to get an idea of any long-term cycles that may exist.

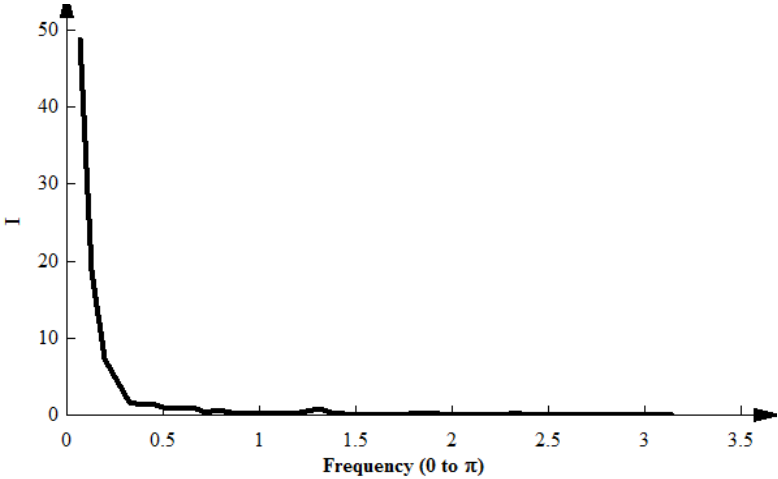


Fig. 3. Full spectrum periodogram pre ECB policy

The data before the policy implementation is not showing any cycles, or if any do exist, their wavelength is longer than the 96 months of data, which

is a possibility. In either case the authors find no cycling behavior prior to the move to the Harmonized Index of Consumer Prices.

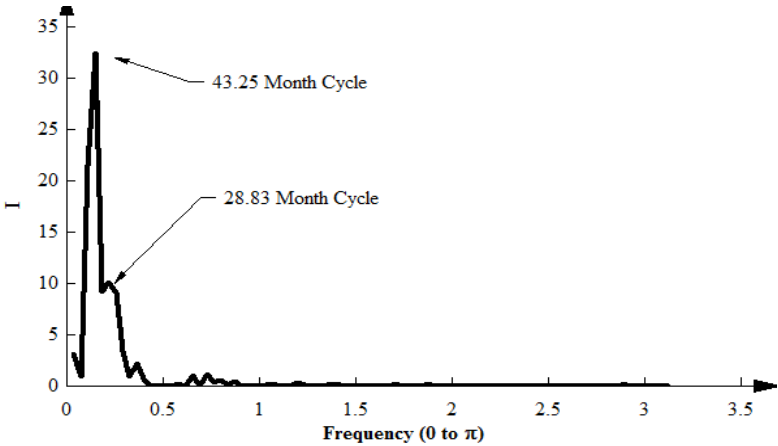


Fig. 4. Full spectrum periodogram after ECB policy implementation

The post policy data spectral analysis confers two significant cycles; one at 43.25 months and one at 28.83 months. Now that the authors have confirmed a cycle, we need to see whether or not randomness contributes to increasing or decreasing the oscillations. Recall that not all randomness is regular Brownian motion (RBM). Most is

not regular Brownian motion, but is the special type of fractal Brownian motion (FBM) where the fractal dimension is 0.5 (Sanderson, 2009). If the data is deterministic we could perhaps see it on an attractor plot (Sanderson, 2012). In the case here, we are not seeing deterministic behavior, but randomness in both cases.

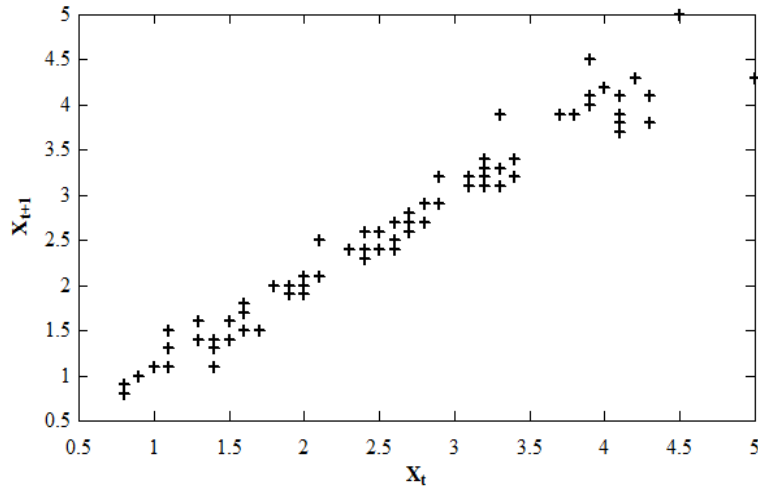


Fig. 5. Prepolicy attractor

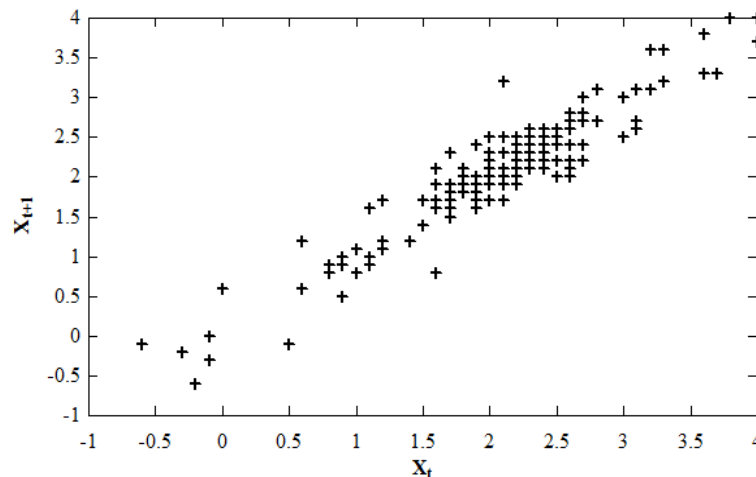


Fig. 5. Postpolicy attractor

We will confirm this by measuring the Hurst exponent (Hurst, 1951; Sanderson, 2011), the Maximum Lyapunov Exponent (LE) (Wolf, 1985) and the fractal dimension via the box counting method (Elhert, 2007). All measures help to describe the behavior of the system and their values are noted in the table below.

Table 2. Dynamic systems measures

	Before policy	After policy
Hurst exponent	0.99995	0.83131
Maximum LE	-0.0234	-0.0985
Fractal dimension	1.9056	1.9033

The Hurst exponent lets us know the amount of persistence in a system, a Hurst value of 0.5 indicates no persistence (RBM), greater than 0.5 means

persistence (events are positively correlated). The Policy had the effect of lowering the level of persistence. This however could still mean the system is either random (FBM) or deterministic (chaotic). A good measure to help with the story is the LE. An LE of zero would mean the system is conservative. A positive value would indicate chaos and a negative value would mean the system is dissipative. In this case, both systems are dissipative since the LE's are negative. Dissipative systems exhibit asymptotic stability; they are displaying randomness. With the LE of the after policy implementation data getting larger, this implies the system has become more dissipative, which implies the system is more stable (still FBM) and possibly developing an attracting orbit. Thus conferring the cycles we saw in the spec-

tral analysis are FBM. In other words, the policy change has caused the system to start orbiting around a point, but it is doing so in a random FBM manner. That is to say while the policy has stabilized the series to orbit around a point, it has also had the effect of creating persistent oscillations around that point. So the policy has had the effect of creating cycles of inflationary pressures and then deflationary ones that randomly orbit around the 2 percent target. Since the scope of the paper is not to

discuss whether or not the policy is “good”, I will leave it to the reader to decide if that is a preferred regime compared to the previous one of the fairly common AR (1) variety.

To check if there is any deterministic phenomena in the series that has gone undetected due to the size of the randomness, a space-time regression will be performed to separate the series into its random and deterministic components (Sanderson, 2011). The results are shown in the graphs below.

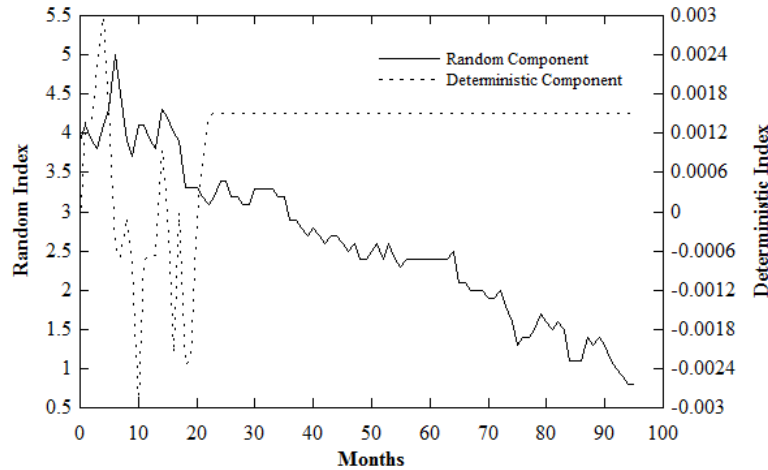


Fig. 6. Components of Index before-policy implementation

While the deterministic components both before and after the policy are small, one can still see the behavior. In the case before the policy, we see the effect of a damped oscillator that diminishes to a stationary

point. Comparing the scale of the random to deterministic parts of the series yields the result that randomness is, on average, a factor of 2332 times bigger than the deterministic component before the policy.

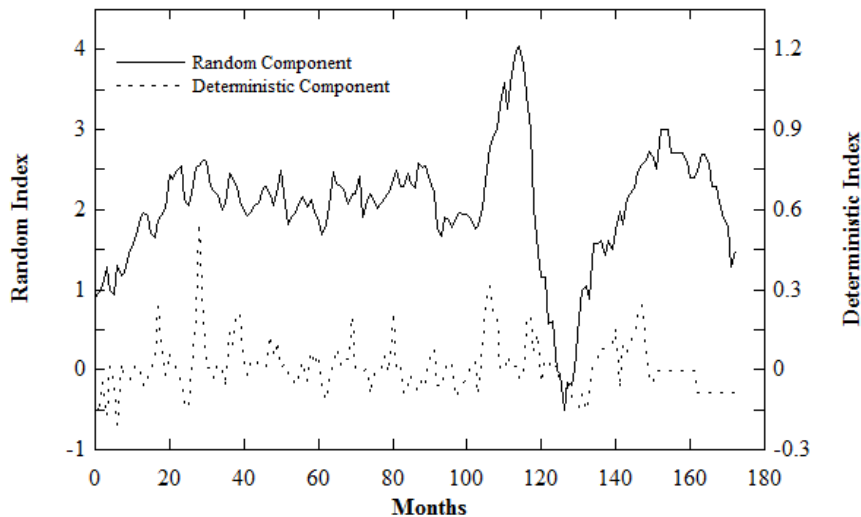


Fig. 7. Components of Index after-policy implementation

After the policy is implemented we can see that the deterministic behavior is the cyclic behavior that we saw in our spectral analysis previously with the two cycles of 43.25 and 28.83 months respectively. The deterministic component of the series has now become an oscillation that does not diminish. What this means, is that we are now starting to see a pattern of multiple equilibria start to emerge as one might see in a chaotic system where there is not one single

equilibrium but a multitude of virtually infinite equilibria. A dynamic system that is continually oscillating is always in equilibrium, just like a planet in orbit. What usually happens that is of concern, is that an oscillating system can become more sensitive to additional changes. Take a calm pond for example, once you throw in the first stone you cause some ripples and motion. As you keep throwing in stones, you can either increase or decrease the magnitude of

the waves depending on whether or not the new stone hits the water in harmony with the cycle or not. As a matter of comparison the randomness in the series before and after the policy is now only on average a factor of 170 times more than the determinis-

tic component. That is a decrease in the magnitude of randomness in the signal by 13.72 times, which is a very surprising shift indeed. A look at the attractor plot of the deterministic component after the policy reveals some of this multi-equilibrium behavior.

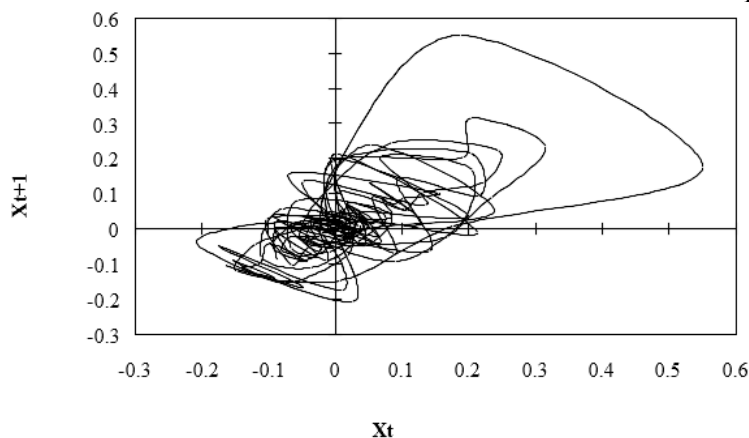


Fig. 8. Attractor plot of post policy deterministic signal

What we see in the attractor plot is that the deterministic component of the series appears to be a strange attractor. If the deterministic component gets larger the system could develop momentum of its own that may be difficult to alter. This could be either “good” or “bad” from a policy perspective. Thinking about the composition of both the deterministic and random components a system allows us to begin a new conversation about monetary policy in an ever changing system.

Conclusion

It is important that we start to further investigate, not only whether or not a policy meets its stated objective, but also how a policy can cause structural changes to the dynamic nature of an economic system. The ECB data provided a natural test for seeing the changes in the dynamic structure of a system. In the case of the implementation of Stage Three of the EMU policy, we have seen that a cursory look at the data seems to suggest, that while the ECB is meeting their objective of price stability, they may additionally be altering the structure of the economy in ways that may cause the system to be more or less sensitive to change in the future; depending on the relative size of each component. The policy has caused the signal to change from an AR(1) type of persistence, to two more pronounced phenomena: a large oscillatory random FBM and an oscillatory deterministic behavior. While this may not be surprising, as it is generally accepted that monetary policy changes cause long lags that can be highly vari-

able, the type of randomness and volatility can fundamentally alter how the system behaves in the future. This can have a twofold effect on future policy. First, it will be difficult for most economic agents to determine whether the oscillation is random or part of a deterministic cycle. The deterministic component can become very sensitive to small changes (may become chaotic). This can cause many unforeseen problems, from a policy perspective changes to the money supply or other variables could either increase the amplitude of the wave, if they are in time with both or one of components, or unintentionally we could see that either the random or deterministic component could “cancel out” the effect of a monetary policy. Monetary policy changes could also have the effect of enlarging the deterministic component more increasing the likelihood that the system may become more chaotic. As the deterministic components of a system become larger they will make a system more sensitive to changes if they become chaotic. As more data becomes available it would be prudent to continue to investigate structural changes to this dynamic system as well as others. While it appears that the general consensus on monetary policy is correct in that there are large random lags, FBM is much different from RBM. Increasing levels of persistence in a system whether they be random or deterministic can have drastically different short run and potential long run effects. We are only just beginning to appreciate the dynamic complexity of economic systems and the issues that policy decisions create in these systems warrants consideration in policy decision making.

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