Credit and Capital Markets, Volume 52, Issue 1, pp. 1–33
Scientific Papers

Applying Complexity Theory to Interest Rates: Evidence of Critical Transitions in the Euro Area

Jan Willem van den End*

Abstract

We apply complexity theory to financial markets to show that excess liquidity created by the Eurosystem has led to critical transitions in the configuration of interest rates. Complexity indicators turn out to be useful signals of tipping points and subsequent regime shifts in interest rates. We find that the critical transitions are related to the increase of excess liquidity in the euro area. These insights can help central banks to strike the right balance between the intention to support the financial system by injecting liquidity and potential unintended side-effects on market functioning.

Komplexitätstheorie auf Zinssätze angewandt: Nachweis kritischer Übergänge im Euroraum

Zusammenfassung

Wir wenden Komplexitätstheorie auf Finanzmärkte an, um zu zeigen, dass die vom Eurosystem geschaffene Überschussliquidität zu kritischen Übergängen bei der Konfiguration der Zinssätze geführt hat. Komplexitätsindikatoren erweisen sich als nützliche Signale von Kipppunkten und nachfolgenden Regimeverschiebungen bei Zinssätzen. Wir stellen fest, dass die kritischen Übergänge mit dem Anstieg der Überschussliquidität im Euroraum zusammenhängen. Diese Einblicke können Zentralbanken helfen, das richtige Gleichgewicht zwischen der Absicht, das Finanzsystem mit zusätzlicher Liquidität zu unterstützen, und möglichen unbeabsichtigten Nebenwirkungen auf das Marktgeschehen zu finden.

Keywords: interest rates, central banks and their policies, monetary policy.

JEL classifications: E43, E58, E52

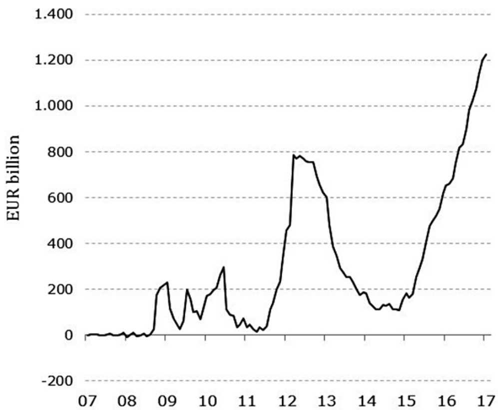
---

* Dr. Jan Willem van den End, De Nederlandsche Bank, Westeinde 1, 1000 AB, Amsterdam, The Netherlands. E-mail: w.a.van.den.end@dnb.nl (J. W. van den End). The author would like to thank Cees Diks, Christina Strobach, Christiaan Pattipeilohy, John Thoolen, Leo de Haan, Julia Körding, Marco van der Leij, Kieran James Walsh, an anonymous referee and participants at the conference 'Financial services Indices, liquidity and economic activity' (Bank of England, London 2017), participants at the INFINITI conference (Valencia, 2017) and participants at the DNB research seminar (Amsterdam, 2017), for their comments on a previous version of this article. Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

I. Introduction

Since the global financial crisis started in 2007, the Eurosystem has injected liquidity on a large scale to the financial system. Liquidity has been supplied by unconventional monetary policy measures. In the beginning of the crisis (2007–2009) this was aimed at supporting the liquidity situation of banks and alleviating the stress in financial markets, where liquidity was rapidly drying up. In a later stage (from 2011 onward) of the crisis, the liquidity injections were mainly aimed at protecting the economy from a credit crunch and low inflation.

By the liquidity operations, the intermediary role of the Eurosystem in financial markets has substantially increased. In the euro area, the interventions of the central bank in markets have become more direct, longer and more extensive. By responding to liquidity stress in the early stage of the crisis, the Eurosystem acted as backstop for system wide liquidity strains, in the unsecured interbank market in particular. In that situation the central bank was complementary to the market which failed in vital segments. With the introduction of very long-term refinancing operations (VLTROs) from 2011 onward, the monetary policy of the Eurosystem has shifted from liquidity easing in the money market to credit easing. This changed the nature of central bank financing from short-term liquidity supply to long-term funding of banks. With the introduction of quantitative easing (QE) in March 2015 in the euro area, the interventions have been further extended, in terms of size, scope and duration. By purchasing assets on a large scale, the supply of liquidity was no longer driven by the demand of banks but has been actively pushed by the central bank. This supply driven expansion of liquidity has boosted excess liquidity to record high levels (Figure 1).



Note. Excess liquidity refers to the reserves of banks on the Eurosystem's current account and deposit facility minus reserve requirements. Amounts in EUR billion, monthly average.

Figure 1: Excess Liquidity in Euro Area

By their unconventional monetary policy measures central banks have increasingly taken over critical market functions. In first instance this concerned functions where the market failed, but gradually also functions which the market could fulfill by itself. First, the Eurosystem took over maturity transformation from the market by extending long-term loans to banks and purchasing long-term bonds. Second, liquidity transformation has been taken over from the financial sector by transforming less liquid assets in central bank reserves through collateral in refinancing operations and purchases of less liquid securities. Third, the Eurosystem has taken over credit risk from the market by becoming a central counterparty in money market transactions.

By taking over critical market functions, the Eurosystem has obtained a dominant role in allocating liquidity. This has impacted on the behavior of market participants, trading volumes and price formation and so has changed the way financial markets work. The market impact increases the longer the central bank intervenes. Investors then become more dependent on central bank liquidity by adjusting their investment positions on the presumption of extended liquidity supply (e.g. by increasing leverage or reducing protection against downward risks). Market functioning so becomes endogenous on central bank measures. This can be reinforced by the perception that unconventional monetary policy is not a temporary phenomenon, but part of a new normal (*Friedman* 2014). According to *Borio* (2014), central banks have created an illusion of permanent liquidity by their unconventional monetary policy measures. As a consequence, phasing out such policy becomes harder the longer it is active.

Complexity theory provides a framework to analyze the impact of central bank interventions on the financial system. The theory describes critical transitions in complex systems that can occur due to changes in external conditions. It assumes that systems evolve as dis-equilibrium processes. In the literature, complexity theory is usually applied to research critical transitions in eco-systems (*Scheffer* et al. 2009). Some studies also apply it to financial data, by using complexity indicators to detect financial crises (*Guttal* et al. 2016; *Diks* et al. 2015; *Quax* et al. 2013). The added value of our article is that we apply complexity theory to regime shifts in the configuration of interest rates, linking them to the increase of excess liquidity. We assume that the excess liquidity created by the central bank represents a change in external conditions which fundamentally changes market functioning. The increased intermediary role of the Eurosystem went in tandem with a reduction of market liquidity and interbank trading. Thereby, the increased dependence on central bank liquidity may have weakened the resilience of markets, making them more prone to a (small) shock, such as an adjustment of market expectations about monetary policy. Feedback effects, following from the reactions by investors who readjust their portfolios, can exacerbate the shock effects. This may give rise to critical transitions in the system that will be reflected in shifts in interest rates, as key indicators of supply and demand conditions in financial markets.

We test whether indicators taken from complexity theory provide signals of shifts in financial markets, interest rates in particular, caused by excess liquidity. We find that the complexity indicators – i.c. critical slowdown, rising autocorrelation and variance, increasing skewness and flickering – indeed flag the shift to a floor system in the money market in 2009 and to a safety trap in the bond market in 2015 in advance. Moreover, there is evidence for a link between these indicators and excess liquidity. The results underline that the functioning of financial markets is endogenous on the actions of the central bank, as they influence the behavior of market participants and thereby may engender feedback effects that can lead to critical transitions in markets.

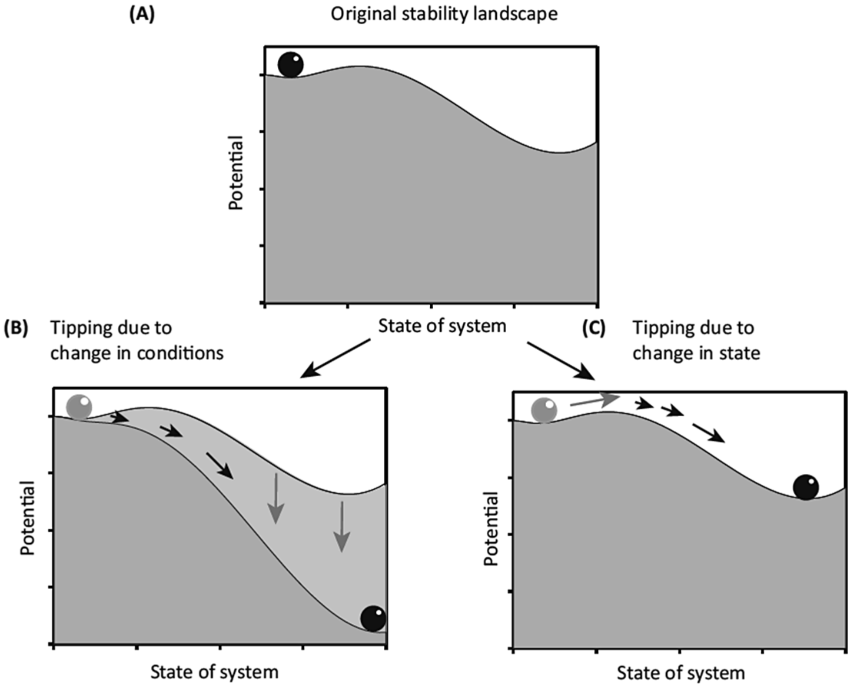
The rest of this article is organized as follows. Section II. outlines complexity theory and the indicators that may flag critical transitions. In section III. we outline the model which puts the theory in an economic context. Section IV. applies complexity theory to financial markets, interest rates in particular. In section V. we explain how tipping points are dated, after which section VI. analyzes to what extent the complexity indicators are useful signals of critical transitions in euro area interest rates. In section VII. we discuss the results and section VIII. concludes.

II. Complexity Theory

1. Literature

Complexity theory is usually applied to analyze critical transitions in eco-systems. For instance with regard to the loss of sea-ice due to temperature changes (as described by *Bathiany* et al. 2016). A complex system can suddenly shift from one equilibrium to another after a tipping point (bifurcation) where the old state becomes unstable. *Van Nes* at al. (2016) describe two ways in which such critical transitions can emerge. The first class of transitions is caused by a change in external conditions, which in models is represented by parameter changes. The change of external conditions gradually erodes the resilience of the current state by which it becomes unstable (Figure 2.B). In such a situation the system will balance between the basins of attraction of two alternative stable states. Close to a bifurcation, a small (unexpected) shock can drive the system across the boundary between the attraction basins and cause a critical transition to the new state (*Scheffer* et al. 2009).

Once a bifurcation is passed, the dynamics of the system accelerate by positive feedback effects, causing a 'runaway change' to the new state. Those feedbacks are self-reinforcing mechanisms, driven by the interaction between changes in



Note. Large arrows denote the change in external conditions (panel B), or the change of the system's state (panel C). Small arrows denote the transition path. Grey balls denote the state variable in the old – unstable – equilibrium. Black balls denote the state variable in the new equilibrium. Source: *Van Nes* et al. (2016).

Figure 2: Critical Transitions

the system and the inputs. These amplify small changes in large ones. *Van Nes* et al. (2016) define a situation where accelerating changes caused by positive feedback loops drive the system to a new steady state a 'tipping point'. Those points can potentially be detected by early warning indicators. In the second class of critical transitions, the state of the system changes by itself, which in models is represented by changes in state variables. The critical transition is then caused by a perturbation of the system's state due to a fundamental change of its character (Figure 2.C). This transition can also be a 'noise-induced' critical transition.

Scheffer et al. (2009) notice that the dynamics of a system near a tipping point have generic properties, regardless of differences in the details of each system. Therefore, sudden transitions in a range of complex systems are in fact related. The financial system as well is assumed to be a complex system, consisting of a highly connected network where dynamics are driven by interactions and feedbacks (*Battiston* et al. 2016). Following from that, the financial system fits into the first class of complex systems, in which changes in external conditions can make the system brittle and prone to a critical transition. While the cause of the transition is the change in external conditions, the trigger of the transition is usually a small (unexpected) shock which sets the transition dynamics in motion. Tipping points of such transitions can potentially be detected by early warning indicators. They are useful since the loss of resilience of a system in the run-up to a critical transition tends to develop gradually and under the surface. Once a tipping point is passed the manifestations of a critical transition come to the fore. This means that early warning indicators are important for policymakers to detect a critical transition well in advance, which can help to mitigate or prevent a regime shift.

In this article we assume that the unprecedented increase of excess liquidity caused by unconventional monetary policy represents a change in external conditions that may cause critical transitions in financial markets. Thereby we categorize this to be a phenomenon belonging to the first class of critical transitions. Several other studies have applied complexity indicators to financial data. *Guttal* et al. (2016) and *Diks* et al. (2015) use such indicators to detect critical transitions, i.c. crashes, in equity prices and report mixed results. Only some indicators (mainly the variance of equity prices) provide statistically significant early warning signals, or significance is limited to a particular episode or market segment. *Quax* et al. (2013) find early warning properties in interest rates swaps, traded among banks, prior to the collapse of Lehman Brothers in 2008. In the run up to this event, the swap prices showed an increased dependence, signaling a collective transition to a new state. These papers use complexity indicators to detect financial crises, without explicitly linking these to changes in external (market) conditions. The distinguishing feature of our approach is that it takes a fundamental switch in the configuration of interest rates (r_t) as the relevant state variable and links it to changes in excess liquidity (changing external conditions, or parameter changes).

2. *Indicators*

From the literature on complex systems we take several key indicators that signal whether a system is close to a critical transition (see *Scheffer* et al. 2009 for an overview) and apply them to the configuration of interest rates.

Critical slowing down

Critical slowing down means that a system increasingly slows down in recovering back to equilibrium from small perturbations if the state variable approaches a tipping point. *Van Nes and Scheffer* (2007) find that a slowing down typically starts far before a bifurcation point and that recovery rates decrease gradually to zero if the tipping point is reached. The recovery to equilibrium slows down due to the loss of resilience of the system. It implies that the system less easily can return to its existing (old) equilibrium after a shock. We measure critical slowdown by the decay rate (τ), which determines the speed by which deviation of state variable N from its initial state N_0 at $t = 0$ is reduced (or the speed by which N returns to N_0). The decay rate is derived from the half-life (h) of the state variable (similar to *Bathiany* et al., 2016),

(1) $$h = \frac{-t \ \ ln(2)}{ln\left(\frac{N_t}{N_0}\right)}$$

(2) $$\tau = \frac{ln(2)}{h}$$

with N_t the value of the state variable at time t. A slowdown of the recovery is reflected in an increase of h and a decrease of τ.

Autocorrelation

The slowing down usually goes in tandem with an increase in autocorrelation in the pattern of system fluctuations. Because the rates of change of the system decrease, the system's state at a given point in time becomes more and more like its past state (*Scheffer* et al. 2009). We measure the resulting increase in the persistence of the system variable N by ρ, being the coefficient of an AR(1) model,

(3) $$N_t = c + \rho N_{t-1} + \varepsilon_t$$

with parameter ρ being estimated by ordinary least squares (OLS).

Variance

Model analyses show that well before a critical transition the variance of the state variable increases (*Carpenter/Brock* 2006). Due to a slowdown in the recovery of the system, the impact of shocks do not decay so that their cumulative impact increases and thereby the variance of the state variable (N). We measure the sample variance σ^2 of N by,

(4) $$\sigma^2 = \frac{1}{n-1}\sum_{t=1}^{n}(N_t - \mu)^2$$

with n the horizon over which the variance of state variable N is measured and μ the sample mean of the state variable.

Skewness

Before a critical bifurcation the fluctuations of the state variable tend to become increasingly asymmetric (*Guttal/Jayaprakash* 2008). Close to a tipping point, the rates of change are lower, implying that the state variable stays longer in the vicinity of the unstable equilibrium (closer to the new state) than in the stable equilibrium. As a result, more observations are in the tail of the distribution of the old state and so the skewness (γ) of the distribution increases. We measure skewness of the sample of states N by the third standardized moment of the distribution,

$$\gamma = \frac{m_3}{\sigma^3} = \frac{\frac{1}{n}\sum_{t=1}^{n}(N-\mu)^3}{\left[\frac{1}{n-1}\sum_{t=1}^{n}(N-\mu)^2\right]^{3/2}} \tag{5}$$

with m_3 the third central moment of the sample, σ the standard deviation and μ the sample mean of the state variable.

Flickering

Flickering means that close to a bifurcation point the system oscillates between the old and the new state. In the unstable region there are two alternative attractors that move the system back and forth between two states. Flickering can be observed in the frequency distribution of the state variable, which before a tipping point will increasingly become a mixture of regimes. This can be measured by the bimodality of the distribution, for which we use Sarle's bimodality coefficient β,

$$\beta = \frac{\gamma^2 + 1}{\kappa} \tag{6}$$

with γ^2 the skewness and κ the kurtosis. The value of the bimodality coefficient ranges between 0 and 1. A high value of β indicates high flickering, due to low kurtosis (reflecting a flat distribution) and/or high skewness (reflecting an asymmetric distribution).

In section VI. we test whether these early warning indicators are able to detect regime shifts in the configuration of interest rates (state variable r_t) caused by changing external conditions, in particular the increase of excess liquidity in the euro area since 2007.

DOI https://doi.org/10.3790/ccm.52.1.1 | Generated on 2025-04-25 01:06:32

III. Model

By applying complexity theory to financial markets we assume that the increase of excess liquidity is equivalent to a change in external conditions (i.e. a parameter change). Initially the provision of liquidity is a desirable intervention in the system, given that the central bank intervenes to alleviate market stress and/or ward off risks to the economy. In those circumstances there are frictions in the financial system which constrain private intermediaries to obtain market funding. Friction ω is the parameter which the central bank influences through supplying liquidity. Following *Gertler/Kiyotaki* (2010) we distinguish a frictionless funding market (ω =1) from a market with frictions (ω =0), with (0 < ω <1). Frictions can be related to balance sheet constraints that limit arbitrage in the money market or bond market. As a consequence of frictions, there is an excess return (indicated by state variable r_t), with lending rate R_t^L being larger than private borrowing rate R_t^B,

(7) $$r_t = R_t^L - R_t^B$$

In an imperfect market, a crisis is associated with a rise in excess return, e.g. due to increasing risk premia. Extended liquidity supply by the central bank mitigates the friction and reduces the equilibrium lending rate. As a result r_t declines.

The level of frictions ω determines the effectiveness of central bank liquidity supply. Let C_t be the total liquidity offered to the market. Then lending by financial intermediaries is given by,

(8) $$L_t = B_t + C_t$$

With B_t the funding from the private market. The central bank chooses to fund the fraction of total lending by intermediaries.

(9) $$C_t = \varphi L_t$$

If the private intermediaries are balance sheet constrained ($r_t > 0$), the liquidity supply by the central bank expands the lending intermediated by the market,

(10) $$L_t = \frac{1}{1-\varphi}\phi \, N_t \quad \text{iff} \quad r_t > 0$$

with ϕ the leverage ratio and N_t the capital of financial intermediaries. Equation 10 implies that in a market with frictions, central bank liquidity supply has positive effects on the economy. However, if the intermediaries are not constrained (i.e. $r_t = 0$, implying the market is frictionless with ω = 1), then central bank liquidity supply merely displaces private funding and does not lead to higher lending by intermediaries. Let L_t^* be the total lending consistent with zero excess return in equilibrium, then,

$$L_t^* = B_t + \varphi L_t^* \quad \text{iff} \quad r_t = 0 \tag{11}$$

Here an increase in central bank liquidity supply beyond the liquidity demand crowds out private intermediation one for one. If the friction is close to being resolved (i.e. $r_t \rightarrow 0$), the system is closer to a bifurcation beyond which it will cease to function normally, as central bank intermediation replaces private market activity. This is detrimental for the economy, assuming that intermediation by the central bank is less efficient than by private intermediaries.

At $r_t = 0$ the market crosses a tipping point beyond which extended central bank liquidity supply has detrimental effects on market functioning. Larger and prolonged liquidity supply ($\varphi > 1$) further pushes the lending rate R_t^L (which is a broad measure of the return on intermediaries' assets, including liquidity holdings) below the private borrowing rate R_t^B. As a result, the excess return r_t becomes negative and – as reflected by that state variable – the system shifts from a good to a bad equilibrium. r_t also falls because intermediaries are forced to hold the excess liquidity $(\varphi - 1)L_t$ with zero or negative net return,

$$r_t = R_t^L - [R_t^B + ((\varphi - 1)L_t)\, \mathrm{n}_t] \quad \text{iff} \quad \varphi > 1 \tag{12}$$

The capital costs n_t of holding excess liquidity on the balance sheet by intermediaries contributes to the negative net excess return. It introduces a new friction in the financial system, to which the system may respond by a critical transition to new state.

The fold bifurcation model in Figure 3 (taken from *Scheffer* et al. 2009) depicts the dynamics to the new state. The grey arrows indicate the direction in which the system moves if it is not in equilibrium (that is, not on the curve). The arrows indicate that the curve represents stable equilibria, except for the dashed middle section. If the system is driven slightly away from this part of the curve, it will move further away instead of returning. Hence, equilibria on this part of the curve are unstable and represent the border between the basins of attraction of the two alternative stable states on the upper and lower branches. If the system is very close to a fold bifurcation point (for example point F1 or point F2), a small change in the condition may cause a large shift in the lower branch. Also, close to such a bifurcation a small perturbation can drive the system across the boundary between the attraction basins. Thus, those bifurcations are tipping points at which a tiny perturbation can produce a large transition.

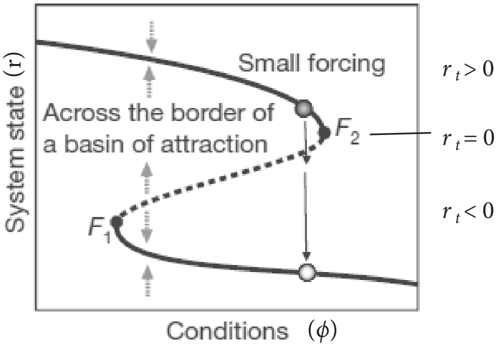


Figure 3: Fold Bifurcation Model

In our model, state variable r_t tracks the dynamics of the system (on the vertical axis in Figure 3) and φ reflects the external conditions on the horizontal axis. By providing more liquidity than the demand for it (i.e. creating excess liquidity by $\varphi > 1$), the central bank changes the parameter of the system, reflected by the decline of friction parameter ω. This goes in tandem with an increasingly negative excess return r_t. The acceleration of state variable r_t after bifurcation point F2 reflects the accelerating dynamics of the system, which are driven by positive feedback effects. The dynamics cause a 'runaway change' to the new state, in which new frictions impair private intermediation.

IV. Application

1. Critical Transitions in Interest Rates

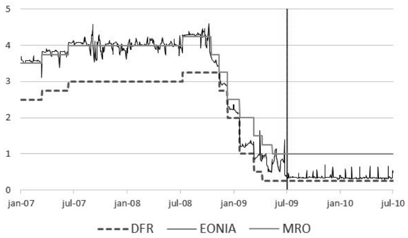
We identify two critical transitions that relate to excess liquidity in the euro area. These transitions are reflected in excess return r_t as represented by the configuration of interest rates (the state variable). The first transition is the regime shift in the unsecured money market, from the traditional corridor system to a floor system in 2009. The second is the critical transition to a safety trap in the bond market, as reflected by the fall of yields on safe assets below the central bank deposit rate in 2015. The shifts in the interest rates in both markets are illustrative for the shift in the excess return r_t to zero or negative values and the subsequent change to a bad equilibrium where private intermediation is crowded out.

With regard to the first transition, until the crisis the benchmark money market rate (EONIA) traded between the lending and deposit rate of the Eurosystem, close to the main refinancing operations (MRO) rate. With balanced liquidity conditions, money market rates in the euro area used to trade in a corridor system (*Bindseil* 2016). In response to high stress in the money market, the Eurosystem substantially extended the liquidity supply from October 2008 onward by fixed rate full allotment. This was a desirable intervention which prevented that the system collapsed (it addressed a friction in the system and led to $r_t \rightarrow 0$). However, in due course the liquidity injections were further extended in terms of size and duration. This saturated the liquidity needs in the system, by which the EONIA fell close to the deposit rate (DFR) in July 2009. So the configuration of money interest rates changed into a de facto floor system (Figure 4).

The narrowing margin between both rates is linked to the increase of excess liquidity, as indicated by the negative slope of the fitted curve in Figure 5. The regime change went in tandem with falling unsecured interbank transactions (shown in the next section), indicating that the functioning of this market segment was impaired. While it is hard to disentangle to what extent the impaired market functioning relates to the crisis (to which the Eurosystem responded) or to the prolonged liquidity provision by the central bank, literature also finds evidence for the latter. *Garcia de Andoain* et al. (2016) show that higher amounts of excess liquidity are associated with lower levels of interbank activity.

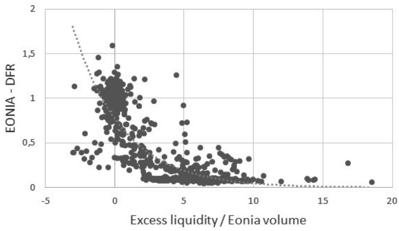
A mechanism that drives this outcome is the diminished, or even negative margin between the private borrowing rate and EONIA which makes it unattractive to lend liquidity to other market participants ($r_t < 0$, assuming that R_t^L falls with the EONIA rate below R_t^B, being the private borrowing rate which trades above the DFR). It reflects that extended liquidity supply introduced a new friction in the money market, which impaired private intermediation. The diminished appetite for lending created an even larger dependence on central bank funding by banks with a liquidity shortage. So bank behavior acts as a feedback mechanism, reinforcing the transition to a floor system. The fact that the floor system has persisted for nearly eight years now indicates that the fall of EONIA to the deposit rate looks like a 'point of no return', or a critical transition to a new equilibrium.

The second critical transition is associated with the excess liquidity created by QE since 2015. This has reinforced strong demand for safe assets, short-term bonds of AAA countries in particular. The demand mainly comes from nonbanks which have no access to the central bank deposit facility. For them, safe sovereign bonds are an alternative destination for their liquidity holdings. As a result, the interest rate on short-term AAA government bonds (proxy for safe asset) turned negative and fell below the deposit rate (DFR) in March 2015, after which the difference between both rates has accelerated (Figure 6). In terms of the model, a decline of R_t^L led to an increasingly negative excess return ($r_t < 0$, assuming that R_t^L falls with the AAA rate below R_t^B, being the private borrowing



Note. EONIA is Euro OverNight Index Average rate, based on transactions in the overnight unsecured interbank market (source Datastream). DFR is Deposit Facility rate and MRO is rate on Marginal Refinancing Operations of the Eurosystem.

Figure 4: Money Market Rates

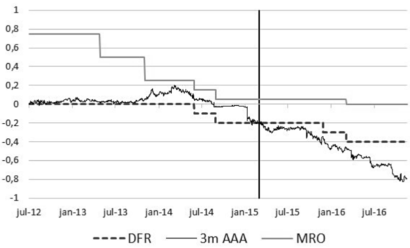


Note. Excess liquidity refers to the reserves of banks on the Eurosystem's current account and deposit facility minus reserve requirements. EONIA volume is unsecured overnight lending in the euro area interbank market (source: Datastream).

Figure 5: EONIA Margin and Excess Liquidity

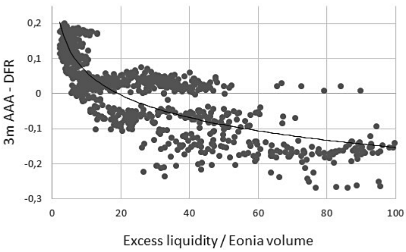
rate which trades above the risk free AAA bond rate). The capital costs n_t of banks holding excess liquidity widens the margin further, since it limits banks to arbitrage between the DFR and the AAA bond rate.

The widening margin between the AAA bond rate and the DFR is linked to the increase of excess liquidity, as indicated by the negative slope of the fitted curve in Figure 7. It reflects a critical transition from normal market conditions – in which the central bank deposit rate is the floor of short-term market rates – to a safety trap, which is characterized by a shortage of safe assets (*Caballero* et al. 2016). The difference between AAA rates and the DFR reflects a scarcity premium on safe assets, which are in short supply due to the excess liquidity. As a consequence, particular segments of the financial markets ceased



Note. 3m AAA is the yield on AAA euro area government bonds with 3 months maturity, as constructed by a yield curve model (source ECB Statistical Datawarehouse). DFR is Deposit Facility rate and MRO is rate on Marginal Refinancing Operations of the Eurosystem.

Figure 6: Yield on Safe Assets



Note. Excess liquidity refers to the reserves of banks on the Eurosystem's current account and deposit facility minus reserve requirements. EONIA volume is unsecured overnight lending in the euro area interbank market (source: Datastream).

Figure 7: AAA Rate Margin and Excess Liquidity

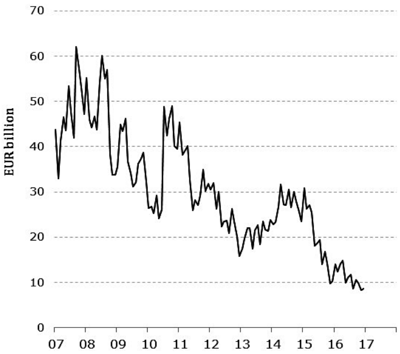
to function normally. Particularly the repo market suffered from the shortage of safe assets, which are an important asset class for collateralized lending and borrowing. The safety trap is reinforced by feedback effects, as banks tend to charge increasingly negative rates on bank deposits if excess liquidity increases. This reinforces the demand for alternative safe and liquid havens like AAA sovereign bonds and reduces bond yields even further.

2. Impaired Market Functioning

The large scale and prolonged central bank liquidity supply has crowded out private intermediation, which according to equation 11 occurs when $\varphi > 1$. In a situation of excess liquidity, private market participants have less need to trade among each other, which is exacerbated by the negative excess return r_t on private lending. Moreover, due to QE there are less tradable securities floating in the market due to the asset purchases by the central bank. This reduces trading volumes and market liquidity (IMF 2015). While the central bank creates more primary liquidity, it reduces secondary liquidity (market liquidity).

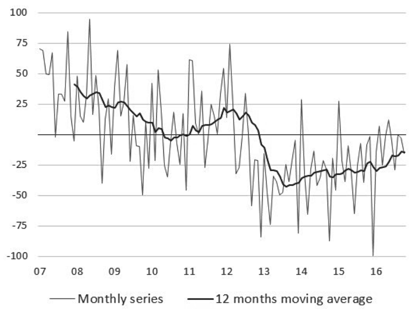
Indications of impaired market functioning in the euro area are the sharp fall in trading volumes in the unsecured interbank market (Figure 8) and the drop in debt securities issued by banks, which had little need to obtain funding from the market (Figure 9). Both examples suggest that the central bank interventions and the related expansion of liquidity have fundamentally changed the nature of financial markets.

The substitution of private market activity with central bank liquidity weakens the resilience of the financial system. At a certain level of excess liquidity the system can come in an unstable region, near a bifurcation (with $r_t \rightarrow 0$).



Note. Trading volume in euro area unsecured interbank market. EUR billion, monthly averages.

Figure 8: Trading Volume Interbank Market



Note. Net issuance of bonds by banks in the euro area (new issuance minus redemptions). EUR millions.

Figure 9: Issuance of Bonds by Banks

Since market participants increasingly position themselves on the presumption of abundant liquidity, financial markets become more vulnerable to (small) shocks, such as an adjustment of expectations about monetary policy. Feedback effects, following from the reactions by investors, may exacerbate the shock effects. Those effects can be driven by the interaction between changes in supply and demand of liquidity and the inputs, of which market prices are a critical part. Hence a 'run away' change of the system is likely reflected in market prices, interest rates in particular, as these are the ultimate price of liquidity. With interest rates as the state variable, they may indicate both the gradual change of the system before bifurcation and the critical transition beyond that point. The transition phase will likely go with (financial) instability, as interest rates may under/overshoot in search for a new equilibrium, causing high volatility in market prices.

V. Dating Tipping Points

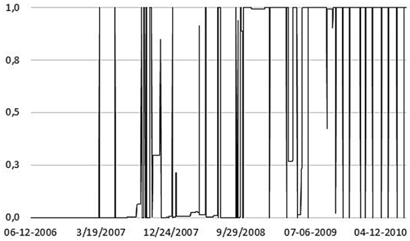
1. Markov Switching

A statistical method by which a tipping point and a related regime change could be identified is Markov switching regression. The Markov model that we estimate is a univariate autoregressive switching model with two different regimes, each of which is associated with a regime specific intercept,

$$y_t = c(s_t) + \varphi\, y_{t-1} + \varepsilon_t \qquad (13)$$
$$s_t = 1{,}2$$

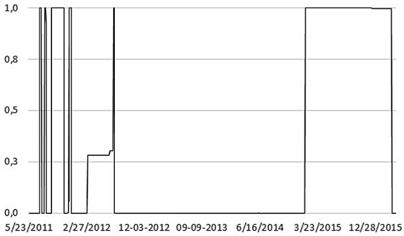
Parameter s_t is the regime indicator function that ensures that the constant term c can take two possible values, indicating either the regime before or after critical transition. The dynamics of the regime indicator is described by a two-state Markov chain with transition probability $p_{ij} = p\,(s_t = j \mid s_{t-1} = i)$ for any $i, j = 1, 2$. The latent driving discrete regime variable captures the effects of exogenous forces impacting on the observable variable via the regime allocation.

Applying the model to the critical transition to a floor system in the money market, y_t denotes the difference between the EONIA rate and the Eurosystem deposit rate (DFR). A regime switch occurs if there is a significant shift in the mean (parameter c) difference between the rates. Applying the model to the critical transition to a safety trap in the bond market, y_t denotes the difference between the rate on short-term AAA government bonds and the DFR. A regime switch occurs if there is a significant shift in the mean (parameter c) difference between the rates. The first model is estimated using daily observations covering 2006–2010 (covering the shift to the floor system in the money market) and the second model using data covering 2011–2016 (covering the shift to the safe-



Note. Probability of being in the regime with a small difference between EONIA and DFR (floor system). Estimated probability on vertical axis.

Figure 10: Regime Switches Money Market



Note. Probability of being in the regime with a large negative difference between AAA rate and DFR (safety trap). Estimated probability on vertical axis.

Figure 11: Regime Switches Safe Asset Market

ty trap). We only include autoregressive terms that are significant, implying the models are both AR(2).[1]

The parameter estimates in Tables A and B in Annex 1 shows that the two regimes are empirically required by the data, given the statistical significance of the transition probabilities and constant term $c(s_t)$ across the regimes. Figures 10–11 show the smoothed probabilities of the regimes j = 1,2. They point at a regime shift in the money market occurring between October 2008 and 2010 and in the safe asset market during 2015. While the outcomes only provide a rough indication of a regime change in interest rates, they correspond to the economic analysis in the previous section, where we date the critical transition in the money market in July 2009 and in the market for safe assets in March 2015.

To assess the link between the interest rate shifts and excess liquidity, the latter is added to the Markov switching regressions as explanatory variable. The estimation outcomes in Tables A and B in Annex 1 indicate that excess liquidity adds significant explanatory power to the autoregressive terms. The negative coefficient values of the (detrended) excess liquidity variable indicate that a rise (fall) of liquidity is associated with a fall (rise) in the interest rate margin, in line with the assumed relationship between excess liquidity and the interest rates.

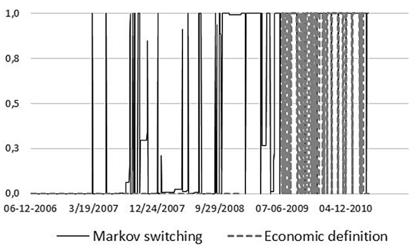
There are some well-known drawbacks of a Markov switching approach. It only identifies breaks in linear (autoregressive) relationships of data series, but

[1] Break-point unit root tests show that the EONIA – DFR margin and the AAA – DFR margin are both stationary over the full sample period as well as over the sub-sample periods for which the Markov model is estimated, once structural breaks in the series are taken into account (conventional unit root tests are biased toward a false unit root null when the data are trend stationary with a structural break). The inverted AR roots indicate that the estimated models are stationary (the absolute values of the roots lie within the unit circle).

not the driving factors behind the breaks. In other words, the switching approach is purely statistical and lacks economic foundation. Moreover, the outcomes are dependent on the model set-up and they are sensitive to changing parameter values and to the choice of the (sub)sample periods. Hence, the (explicit or implicit) assumptions in the models could be challenged. For these reasons we use the outcomes of the Markov switching model only as a rough indication, preferring an economic interpretation to date the critical transitions.

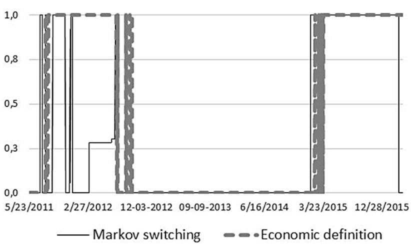
2. Economic Interpretation

In section IV.1 the critical transition in the money market was dated in July 2009 and in the safe asset market in March 2015. The transition in the money market can be more precisely identified by assuming the moment that the margin between EONIA and DFR becomes persistently smaller than 10 basis points, or in other words, as the moment from which the EONIA has fallen to the DFR within a margin of less than 10 basis points for a prolonged period of time (assuming that incidental fluctuations between 0 and 10 bp are noise). This condition was fulfilled from 1 July 2009 onward, which we therefore date as the critical transition in the money market. A likely trigger for this was the issue of long-term refinancing operations (LTROs) with a maturity of one year by the Eurosystem, of which the first operation was settled end June 2009. Figure 12 shows that the economic interpretation of the critical transition corresponds to the regime shifts identified by the Markov switching model. Dating the tipping point 10 months later than the start of the extended liquidity supply (fixed rate full allotment, October 2008) helps to disentangle the first (intended) effect of the central bank response to market stress from the (unintended) effect of extended liquidity supply.



Note. Markov switching refers to probability of being in the regime with a small difference between EONIA and DFR (floor system), with estimated probability on the vertical axis. Economic interpretation refers to a dummy that is 1 if (EONIA – DFR) < 10 bp and 0 otherwise.

Figure 12: Dating Shifts in Money Market



Note. Markov switching refers to probability of being in the regime with a large difference between AAA rate and DFR (safety trap), with estimated probability on the vertical axis. Economic interpretation refers to a dummy that is 1 if (AAA rate – DFR) < 0 bp and 0 otherwise.

Figure 13: Dating Shifts in Safe Asset Market

The critical transition in the bond market can be more precisely identified by assuming the moment that the margin between AAA safe asset rate and DFR becomes persistently negative, or in other words, as the moment from which the AAA rate has fallen below the DFR for a prolonged period of time due to (expectations on) QE. This condition was fulfilled from 11 March 2015 onward, which we therefore date as the critical transition in the safe asset market. A likely trigger for this was the purchase programme of public sector securities (QE) by the Eurosystem, which started on 9 March 2015 and was anticipated by market participants since the announcement on 22 January 2015. Figure 13 shows that the economic interpretation of the critical transition corresponds to the regime shifts identified by the Markov switching model.

VI. Outcomes

1. Methodology

In this section we test whether the indicators defined in section II. are able to detect the regime changes in the money market and safe asset market. With regard to the slowdown indicator (decay rate τ), a decline to a very low value would signal a critical transition, while for the other indicators (autocorrelation ρ, variance σ^2, skewness γ and flickering β) a rise to a very high value would signal a critical transition. The early warning indicators are calculated over a moving window of 100 days, similar to *Diks* et al. (2016)[2].

We use two statistical methods to assess whether a signal is classified as significant that are common in the literature on complexity indicators.[3] By the first method a signal is classified as significant if it exceeds the 5 % tail of the distribution within a period of 100 trading days before the critical transition. This uses the first moment of the indicator as criterion. The 5 % interval is measured as either the 5 % tail of the distribution of the complexity indicator for the difference between EONIA and DFR (shift to floor system), or the 5 % tail of the distribution of the complexity indicator for the difference between the AAA rate and DFR (shift to safety trap). The distributions cover the full sample of those

[2] Moving estimation windows smaller than 100 observations are deemed too short to obtain reliable estimates of the time-varying indicators. Besides, the moving windows over which the indicators are calculated reduce the sensitivity of the indicators to end-of-month spikes in money market rates. This is confirmed by comparing the indicators as calculated including and excluding the end-of-month data, which shows similar outcomes.

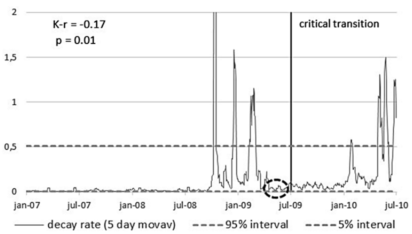
[3] *Quax* et al. (2013) consider that an indicator provides a significant signal if it exceeds a threshold of (3 years moving average) two standard deviations above the mean (threshold is a critical level of the series). *Diks* et al. (2015) and *Guttal* et al. (2016) use the Kendall rank correlation coefficient as criterion for a significant early warning signal (threshold is a significant change of the series).

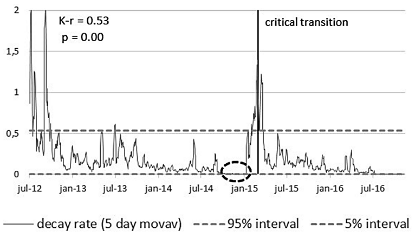
series (2005–2016). We use the 5 % percentile as threshold because the indicator series are not normally distributed, implying that thresholds based on the assumption of normality are not appropriate.

By the second method a signal is classified as significant if it has a significant trend 100 trading days before the critical transition (downward trend in case of the slowdown indicator; upward trend in case of autocorrelation, variance, skewness and flickering). This uses the second moment of the indicator as criterion. The significance of the trend is tested by the Kendall rank correlation (K-r), measuring the concordance between the indicator and a time variable (*Dakos* et al. 2008). The K-r is in the range of [–1, 1], with a value close to –1 indicating a strong downward trend (discordance between early warning indicator and time) and a value close to +1 indicating a strong upward trend (concordance between early warning indicator and time). The significance of the K-r ratio is assessed by the p-value.

2. Early Warning Signals

Figures 14–15 show that a critical slowdown occurs both before the critical transition in the money market and the safe asset market. In both cases, the decay rate touches the lower 5 % interval of the distribution within a horizon of 100 trading days before the transition (the circles in the figures). In the run-up to these lows, the decay rate falls from high levels, indicating a slowing down of the recovery. According to the negative value of the K-r ratio there is a significant downward trend of the indicator 100 days before the critical transition in the money market (Figure 14). However, the positive value of the K-r ratio in the safe asset market suggests an upward trend (Figure 15), which contradicts the information from the level of the indicator. The K-r ratio in the safe asset market is influenced by the sharp increase of the decay rate just before the critical transition, indicating that the transition took off.

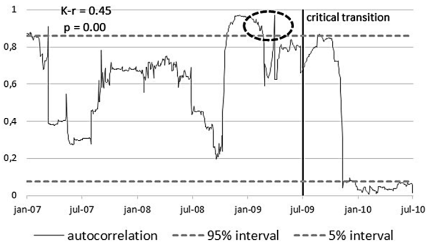


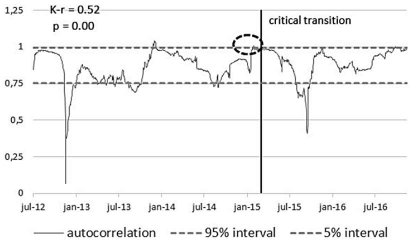


Note. A low value of the indicator signals a critical transition. Horizontal dotted line is 5 % significance interval. Vertical bold line dates the critical transition. Slowdown measured by (the absolute value of) the half-life of the margin EONIA-DFR (money market) and 3m AAA-DFR (safe asset market), over 100 days rolling window.

Figure 14: Slowdown Money Market

Figure 15: Slowdown Safe Asset Market





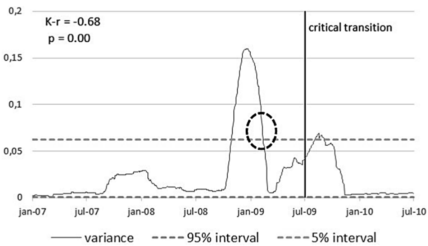
Note. A high value of the indicator signals a critical transition. Horizontal dotted line is 5 % significance interval. Vertical bold line dates the critical transition. Indicator measured by (the absolute value of) the autocorrelation of the margin EONIA-DFR (money market) and 3m AAA-DFR (safe asset market), over 100 days rolling window.

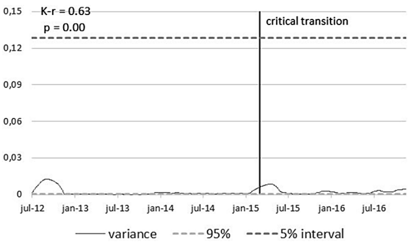
Figure 16: Autocorrelation Money Market

Figure 17: Autocorrelation Safe Asset Market

Figures 16–17 show that the memory of the system (autocorrelation) peaks both before the critical transition in the money market and in the safe asset market. In both cases, the autocorrelation measure exceeds the upper 5 % interval of the distribution within a horizon of 100 trading days before the critical transition (the circles in the figures). It confirms that the state of the market at a given point in time becomes more and more like its past state, like the signal of a critical transition in a complex system. The positive and significant values of the K-r ratios confirm the signaling property of the indicator, as they point at a strong upward trend of autocorrelation 100 days before the critical transition in both the money and safe asset market.

Figures 18–19 show that the variance of the state variable is significantly high before the critical transition in the money market, but not in the safe asset market. In the money market the variance of the EONIA-DFR margin clearly exceeds the upper 5 % interval within a horizon of 100 trading days before the critical transition (the circle in Figure 18). In contrast to that, the variance of the





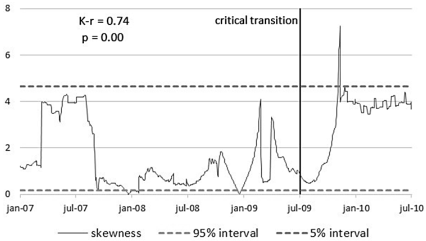
Note. A high value of the indicator signals a critical transition. Horizontal dotted line is 5 % significance interval. Vertical bold line dates the critical transition. The indicator shows the variance of the margin EONIA-DFR (money market) and 3m AAA-DFR (safe asset market), over 100 days rolling window.

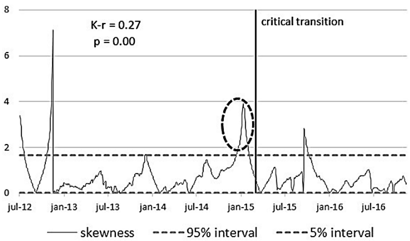
Figure 18: Variance Money Market

Figure 19: Variance Safe Asset Market

3m AAA-DFR margin remains far from the 5 % interval in Figure 19, since the tail of the distribution of that margin refers to the 2008–2009 period when financial markets were extremely volatile. The information from the Kendall rank correlation is mixed. According to the negative value of the K-r ratio there is a significant downward trend of the indicator 100 days before the critical transition in the money market (Figure 18), while the positive value of the K-r ratio flags an upward trend in the safe asset market (Figure 19). The latter is in line with the information from the level of the indicator.

Figures 20–23 show that skewness and flickering of the state variables have similar patterns. Both indicators are significantly high with regard to the 3 month AAA – DFR margin (Figures 21, 23), signaling a critical transition in the safe asset market within a horizon of 100 trading days. Skewness and flickering also peaked before the critical transition in the money market (Figures 20, 22), but they did not exceed the 5 % interval there. The similarity of the pattern of both indicators shows that they measure a similar phenomenon, namely the extent to which the system is in the vicinity of an unstable region, bordering a new

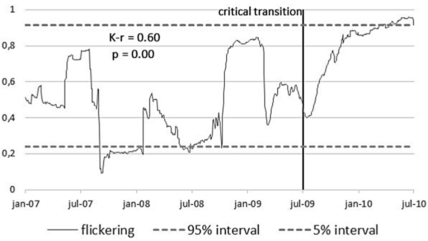


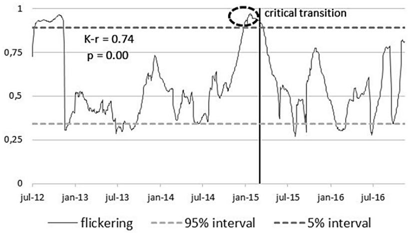


Note. A high value of the indicator signals a critical transition. Horizontal dotted line is 5 % significance interval. Vertical bold line dates the critical transition. Indicator measured by the (absolute value of) skewness of the margin EONIA-DFR (money market) and 3m AAA-DFR (safe asset market), over 100 days rolling window.

Figure 20: Skewness Money Market

Figure 21: Skewness Safe Asset Market





Note. A high value of the indicator signals a critical transition. Horizontal dotted line is 5 % significance interval. Vertical bold line dates the critical transition. Indicator measured by the flickering of the margin EONIA-DFR (money market) and 3m AAA-DFR (safe asset market), over 100 days rolling window.

Figure 22: Flickering Money Market

Figure 23: Flickering Safe Asset Market

state. The positive and significant values of the K-r ratios confirm the signaling property of the indicators, as they point at a strong upward trend of skewness and flickering 100 days before the critical transitions in both the money and safe asset market.

Above we report the naive p-values of the K-r ratios, ignoring the serial dependence of the indicator values due to the moving window. To correct for this, each K-r ratio is also calculated for a large number of bootstrap series. Following *Diks* et al. (2015) the corrected p-value is the estimated probability that a K-r ratio of the bootstrap replications is equal or smaller than the K-r ratio of the decay indicator (equal or larger than the K-r ratio of the other indicators) obtained from the original series. In other words, the corrected p-value is the fraction of bootstrap indicator values with a K-r ratio at least as low (slowdown indicator), or at least as high (correlation, variance, skewness, flickering) as the K-r ratio of the original series. For each of the complexity indicators 1000 independent bootstrap series are generated. Table 1 shows that two K-r ratios based on the original series that have the right sign and are significant, are not significant according to the bootstrap analysis (i.c. autocorrelation in the money market and skewness in the safe asset market). The significant trends that we found above in the slowdown and skewness indicators in the money market and in the autocorrelation and flickering indicators in the safe asset market are confirmed by the bootstrap analysis.

Table 1

P-values of K-r Ratio Obtained by Bootstrap Replications

	Slowdown	*Autocorr*	*Variance*	*Skewness*	*Flickering*
EONIA rate – DFR					
p-value	0.02**	0.15	0.92	0.02**	0.14
AAA rate – DFR					
p-value	1.00	0.10*	0.12	0.35	0.06*

Likelihood of obtaining a K-r ratio by chance (bootstrap series) that is equal or smaller (slowdown indicator), equal or larger (other indicators) than the K-r ratio based on the original series. Number of bootstrap replications is 1000.
*** significant at 1 % level, ** 5 % level, * 10 % level.

3. *Signaling Quality*

The quality of the early warning indicators can be assessed by analyzing how many times they provide a correct or a false signal for a critical transition. In the literature, non-parametric early warning signals are usually assessed by comparing type 1 and type 2 errors (see for instance *Comelli*, 2014). A type 1 error occurs if the indicator does not issue a signal, although the event happens later on (the crisis is missed). A type 2 error occurs if the indicator does issue a signal, although the event does not happen (false alarm). The number of type 1 versus type 2 errors depends on the threshold value of the early warning indicator. In our application we chose as threshold value the 5 % tail of the historic distribution of the complexity indicators. This rather strict threshold biases the signaling outcomes to type 1 errors and limits type 2 errors (a stricter threshold means less false alarms are issued, but more events are missed). We deliberately choose this strict threshold since our analysis in essence is an ex-post exercise to demonstrate the use of complexity theory. If the complexity indicators would be used to detect tipping points in a forward looking way, it would be useful to choose a less strict threshold, to reduce the number of missed tipping points. Table 2 confirms that the type 2 errors of the complexity indicators are small compared to the type 1 errors. The errors are based on the full sample period 2005–2016 and critical transitions in the money market are dated when (EONIA – DFR) < 10 bp and in the bond market when (3m AAA rate – DFR) < 0. The signals of the early warning indicators are taken into account only if they are issued within a horizon of 100 trading days before a critical transition. Mind that this statistical analysis of the signaling quality is less appropriate for complexity indicators, since it assumes multiple critical transitions in the sample period, which is not likely according to complexity theory.

Another method to test the signaling quality is the receiver operating characteristic curve (ROC). This non-parametric approach maps all possible trade-offs between type 1 and type 2 errors for every possible threshold value of the indi-

Table 2

Type 1 and Type 2 Errors

	*Slowdown**	*Autocorr*	*Variance*	*Skewness*	*Flickering*
EONIA rate – DFR	0.87	0.95	0.97	0.93	0.84
Type 1 error					
Type 2 error	0.08	0.05	0.06	0.04	0.00
AAA rate – DFR					
Type 1 error	0.84	0.85	0.83	0.87	0.87
Type 2 error	0.07	0.01	0.01	0.02	0.02

* For the slowdown indicator a low value implies a relevant early warning signal; for the other indicators a high value implies a relevant early warning signal (relevant in the sense that they are issued within a horizon of 100 days before a critical transition).
Note: Critical transition in money market assumed if (EONIA –DFR) < 10 bp. Critical transition in safe asset market assumed if (AAA rate – DFR) < 0. Type 1 error: (number of missed signals 100 days before critical transition/total number of critical transitions). Type 2 error: (number of false signals 100 days before critical transition/days without critical transition), taking into account the full sample period 2005–2016.

cator. The area under the ROC curve (AUROC) measures the indicator's performance in a single metric. AUROC ranges from 0 to 1. It takes the value 0.5 for uninformative indicators. AUC is larger than 0.5 if the indicator is informative and stochastically larger before a tipping point than in normal times. This applies to the autocorrelation, variance, skewness and flickering indicators. Conversely, AUROC is smaller than 0.5 if the signal is informative and stochastically smaller before a tipping point than in normal times. This applies to the slowdown (decay) indicator. To test for the early warning properties of the indicators, AUROC values have been calculated for a horizon of 0 to 100 days before a critical transition. The critical transitions are dated according to the same definition as explained above and applied to the full sample period 2005–2016.

The outcomes of the ROC analysis in Annex 2 show that the signaling quality of the indicators is mixed. The slowdown indicator (decay rate) is significantly higher than 0.5, whereas a value below 0.5 is in line with complexity theory. The autocorrelation indicator is only significantly higher than 0.5 around 20 days before the critical transitions in the safe asset market. The variance indicator is significantly below 0.5 in both the money market and safe asset market, while a value higher than 0.5 would have been expected. The skewness and flickering indicators perform best; their values are (borderline) significantly above 0.5 in both markets over the 100 days horizon. Mind that the caveat mentioned above also applies here; a ROC analysis is less appropriate for complexity indicators, since it assumes multiple critical transitions in the sample period, which is not likely according to complexity theory.

4. Link to Excess Liquidity

The scatter plots in Annex 3 link the early warning indicators to the excess liquidity in the financial system. The long tail at the right-side of Figure A.2 show that the decay rate is lowest when excess liquidity is high. It suggests that the system becomes increasingly less resilient when excess liquidity rises (the interest rate margins less easily return to their existing (old) equilibrium after a shock). This is in line with complexity theory, assuming that excess liquidity represents a change of external conditions in financial markets. While the link between excess liquidity and the autocorrelation measures is not obvious (Figures A.3–4), there seems to be a positive link between the variance indicator and excess liquidity in both the money market and the safe asset market (Figures A.5–6). The variance tends to be high when excess liquidity is high, in line with what could be expected from complexity theory. In the safe asset market, the skewness and flickering indicators have no obvious link with excess liquidity (Figures A.7 and A.9), but in the money market there is a clustering of high values of skewness and flickering at high levels of excess liquidity (Figures A.8 and A.10). Overall the findings seem to confirm the link between early warning indicators of critical transitions in the configuration of interest rates (i. e. the state variable) and excess liquidity (the external market condition).

VII. Discussion

It can be disputed to what extent the indicators of natural systems are applicable to economic and financial systems. In natural systems there are stable laws of nature that drive patterns and changes in the dynamics of systems. Hence, these dynamics are largely deterministic. However, economic and financial systems have another layer of complexity, because changes in the system interact with 'intelligent' agents. They process information and form expectations on how the system will develop in the future. Agents have the ability to learn and adapt their behavior in response to early warning signals. This drives their behavior by which the dynamics in the systems are indeterministic. *Diks* et al. (2016) mention this as a reason for complexity indicators being not suitable for financial markets data. However, the behavior of market participants have the propensities for irrational reactions and myopic foresight (*Kindleberger* 1978). This can result in trend-following and herding behavior, reinforced by positive feedbacks between market prices and investment positions. Such dynamics can lead to persistent deviations of market prices from equilibrium and make the system prone to shocks. At a tipping point market prices may crash in search for a new equilibrium. Such dynamics, driven by the behavior of interacting agents, are very similar to the dynamics in complex systems as we described before. Another argument that calls for cautiousness in applying complexity indicators as early warning signs in financial markets is that the absence of stable laws of nature implies that each financial crisis has different features. This also applies to the two regime shifts of interest rates that we describe. However this argument is not an issue for an ex-post analysis which detects patterns in past dynamics of a system, as we do in this article. We apply complexity indicators not to predict future tipping points, but to describe past regime shifts and show that the dynamics are in line with complexity theory.

Another issue with regard to the behavior of market participants is that it complicates the distinction between intended and unintended effects of central bank policies. Excess liquidity has been created by the Eurosystem for good reasons. In 2007–2009 it alleviated the liquidity stress in financial markets, while from 2011 onward the liquidity injections have protected the economy from a credit crunch and low inflation. However, applying the complexity framework to the money market and the safe asset market shows that excess liquidity can cause a critical transition in the financial system. At a certain high level of excess liquidity the functioning of market segments can fundamentally change, as reflected in regime shifts in the configuration of interest rates. The assumption underlying our analysis is that the new equilibrium is problematic, parallel to eco-systems where for instance the loss of sea ice can raise the sea level, increasing the risk of flooding. In the two interest rate configurations explored in this article, the new state seems to be problematic because it goes in tandem with impaired market functioning. If that would hamper an efficient allocation of finance in the economy it can have welfare costs. Moreover, a bifurcation can be a point of no return, after which a return to the old state is hard to realize. The fact that the floor system in the money market has been there already for many years and the fact that QE seems notoriously hard to end (because tapering may cause volatility in financial markets) are illustrative in that respect. The new state is endogenous on the interventions by the central bank, which market participants increasingly ingrain in their behavior the longer the inventions persist. This comes with the risk that at some point (of excess liquidity) the market may not be able to function on its own anymore.

For central banks the information coming from complexity indicators is useful because it shows that supporting banks and markets by injecting liquidity can change the financial system to a new state where economic relations and relative prices behave differently. In that state, private market activity may be discouraged due to the increased intermediary role of the central bank. The risk of such unintended side effects increase the longer the interventions persist and the more the excess liquidity rises. Central banks should weight the intended effects of their measures with the potential unintended side-effects. Complexity theory can help to strike the right balance here, as it provides a framework to assess the multiple dimensions of monetary policy decisions. While models are in place to estimate the intended effects (e. g. structural macroeconomic or time series models), those models are usually not developed to measure the untended effects of monetary policy. One reason for this being the difficulty to model the complex dynamics of the financial system, by which unintended effects can develop. Dynamics that go with a gradual erosion of resilience of the system and are triggered by small (unexpected) shocks are notoriously hard to measure with the models that central banks use. These are traditionally based on linearizing around the steady state to reduce computational complexity. In contrast to that, complexity indicators by nature capture non-linear and complex dynamics away from the steady state. They provide concrete metrics to assess the likelihood and potential severity of unintended side-effects of monetary policy on the financial system. For that reason they can be a useful complement to the set of indicators central banks use for the practice of policymaking. It can provide central banks for instance a tool to explain how their actions affect the working of the financial system. This can raise the understanding and awareness of policymakers and the public of the wider effects of monetary policy measures.

VIII. Conclusion

Complexity theory provides a useful framework to describe critical transitions in financial markets. The excess liquidity injected by the Eurosystem can be assumed to be a change in external market conditions, which may cause a regime shift in the configuration of interest rates. Indicators taken from complexity theory – i.e. critical slowdown, rising autocorrelation and variance, increasing skewness and flickering – appear useful instruments to describe the shift to a corridor system in the money market in 2009 and to a safety trap in the bond market in 2015. We find evidence for a link between these indicators and the level of excess liquidity.

The complexity approach provides central banks a new framework to assess the (unintended) consequences of their interventions in financial markets. It underlines that the functioning of markets is endogenous on central bank's actions, as they influence the behavior of market participants and the configuration of interest rates. This may engender feedback effects that can lead to critical transitions in the financial system which may be hard to redress. These insights can help central banks to strike the right balance between their intention to support the financial system by injecting liquidity and the potential unintended side-effects on market functioning. For that purpose, complexity indicators can be a useful complement to the set of indicators that central banks use for the practice of policymaking.

References

Bathiany, S./*Van der Bolt*, B./*Williamson*, M. S./*Lenton*, T. M./*Scheffer*, M./*Van Nes*, E. H./*Notz*, D. (2016), Statistical indicators of Arctic see-ice stability – prospects and limitations, The Cryosphere, 10, 1631–1645.

Battiston, S./*Farmer*, J. D./*Flasche*, A./*Garlaschelli*, D./*Haldane*, A. G./*Heesterbeek*, H./*Hommes*, C./*Jaeger*, C./*May,* R./*Scheffer,* M. (2016), Complexity theory and financial regulation, Science, 351, 6275, 818–819.

Bindseil, U. (2016), Evaluating monetary implementation frameworks. Presentation given at the 40th Economic Policy Symposium of the Federal Reserve Bank of Kansas, Jackson Hole, WY.

Borio, C. (2014), BIS Quarterly Review September 2014 – media briefing.

Caballero, R./*Farhi*, E./*Gourinchas*, P. O. (2016), Safe Asset Scarcity and Aggregate Demand, American Economic Review, Papers and Proceedings, 106 (5); 513–518.

Carpenter, S. R./*Brock*, W. A. (2006), A rising variance: a leading indicator of ecological transition, Ecology Letters, 9, 308–315.

Comelli, F. (2014), Comparing Parametric and Non-parametric Early Warning Systems for Currency Crises in Emerging Market Economies, Review of International Economics 22, 4.

Dakos, V./*Scheffer*, M./*Van Nes*, E. H./*Brovkin*, V./*Petoukho*, V./*Held*, H. (2008), Slowing down as an early warning signal for abrupt climate change, Proceedings of the National Academy of Sciences, 105, 14308–14312.

Diks, C./*Hommes*, C./*Wang*, J. (2015), Critical slowing down as an early warning signal for financial crisis?, CeNDEF working paper, 15-04.

Friedman B. M. (2014), Has the Financial Crisis Permanently Changed the Practice of Monetary Policy? Has It Changed the Theory of Monetary Policy?, NBER Working Paper 20128.

Garcia de Andoain, C./*Heider*, F./*Hoerova*, M./*Manganelli*, S. (2016), Lending-of-last-resort is as Lending-of-Last-Resort Does: Central Bank Liquidity Provision and Interbank Market Functioning in the Euro Area. Journal of Financial Intermediation, 28 (C), 32–47.

Gertler, M./*Kiyotaki,* N. (2010), Financial intermediation and credit policy in business cycle analysis, Handbook of monetary economics 3, 3, 547–599.

Guttal, V./*Jayaprakash*, C. (2008), Changing skewness: an early warning signal of regime shifts in ecosystems, Ecology Letters, 11, 450–460.

Guttal, V./*Raghavendra*, S./*Goel*, N./*Hoarau*, Q. (2016), Lack of Critical Slowing Down Suggests that Financial Meltdowns Are Not Critical Transitions, yet Rising Variability Could Signal Systemic Risk, Plos One, 11, 1, 1–20.

Kindleberger, C. P. (1978), Manias, Panics, and Crashes: A History of Financial Crises, New York.

Quax, R./*Kandhai*, D./*Sloot*, P. (2013), Information dissipation as an early-warning signal for the Lehman Brothers collapse in financial time series, Scientific Reports 3: 1898.

Scheffer, M./*Bascompte*, J./*Brock*, W. A./*Dakos*, V./*Held*, H./*Van Nes*, E. H./*Rietkerk*, M./*Sugihara*, G. (2009), Early-warning signals for critical transitions, Nature, 461, 53–59.

Van Nes, E. H./*Scheffer*, M. (2007), Slow recovery from perturbations as a generic indicator of a nearly catastrophic shift, The American Naturalist, 169, 6, 738–747.

Annex 1

A. Estimation Output for Money Market
Markov switching regression (2 regimes, switching in mean)
Dependent variable is difference between EONIA rate and deposit rate (DFR)
sample period 2006–2010 (daily observations)

	EONIA – DFR		*EONIA – DFR*	
	Coeff.	sign.	Coeff.	sign.
constant (1)	0.48	***	0.80	***
constant (2)	0.80	***	0.47	***
$EONIA - DFR_{t-1}$	0.88	***	0.86	***
$EONIA - DFR_{t-2}$	0.11	***	0.13	***
Excess liquidity[1]			–0.00	***
P_{11}	0.94		0.95	
P_{22}	0.95		0.93	
number of obs.	1074		1072	
AIC	–2.40		–2.41	
SIC	–2.37		–2.37	

[1] Excess liquidity is 5 days moving average of excess liquidity (detrended).
***, **, * denote p-values less than or equal to 1 %, 5 %, 10 %, respectively.

B. Estimation Output for Safe Asset Market
Markov switching regression (2 regimes, switching in mean)
Dependent variable is difference between AAA govt bond rate and deposit rate (DFR)
sample period 2011–2016 (daily observations)

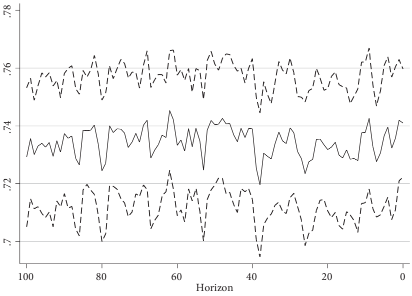
	AAA – DFR		*AAA – DFR*	
	Coeff.	sign.	Coeff.	sign.
constant (1)	–0.23	***	–0.07	*
constant (2)	–0.09	***	–0.21	***
$AAA - DFR_{t-2}$	0.86	***	0.85	***
$AAA - DFR_{t-3}$	0.12	***	0.13	***
Excess liquidity[1]			–0.03	***
P_{11}	0.98		0.99	
P_{22}	0.99		0.98	
number of obs.	1417		1225	
AIC	–4.69		–4.70	
SIC	–4.67		–4.67	

[1] Excess liquidity is 5 days moving average of excess liquidity (detrended).
***, **, * denote p-values less than or equal to 1 %, 5 %, 10 %, respectively.

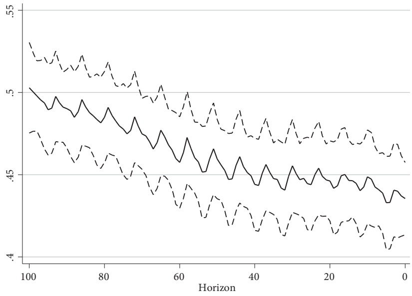
Annex 2: Outcomes of ROC Analysis

A. Switch to Floor System in Money Market

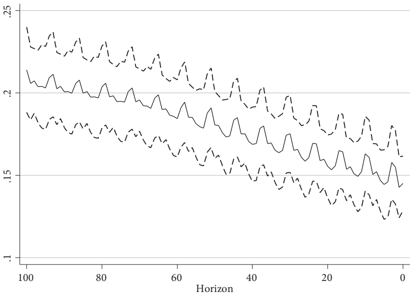
Slowdown (Decay)



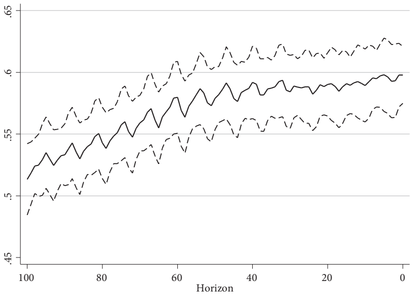
Autocorrelation



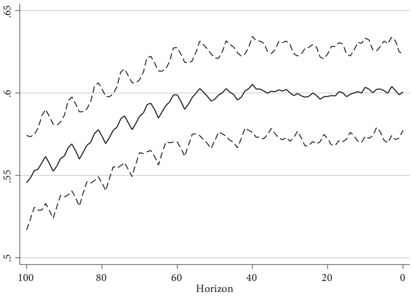
Variance



Skewness

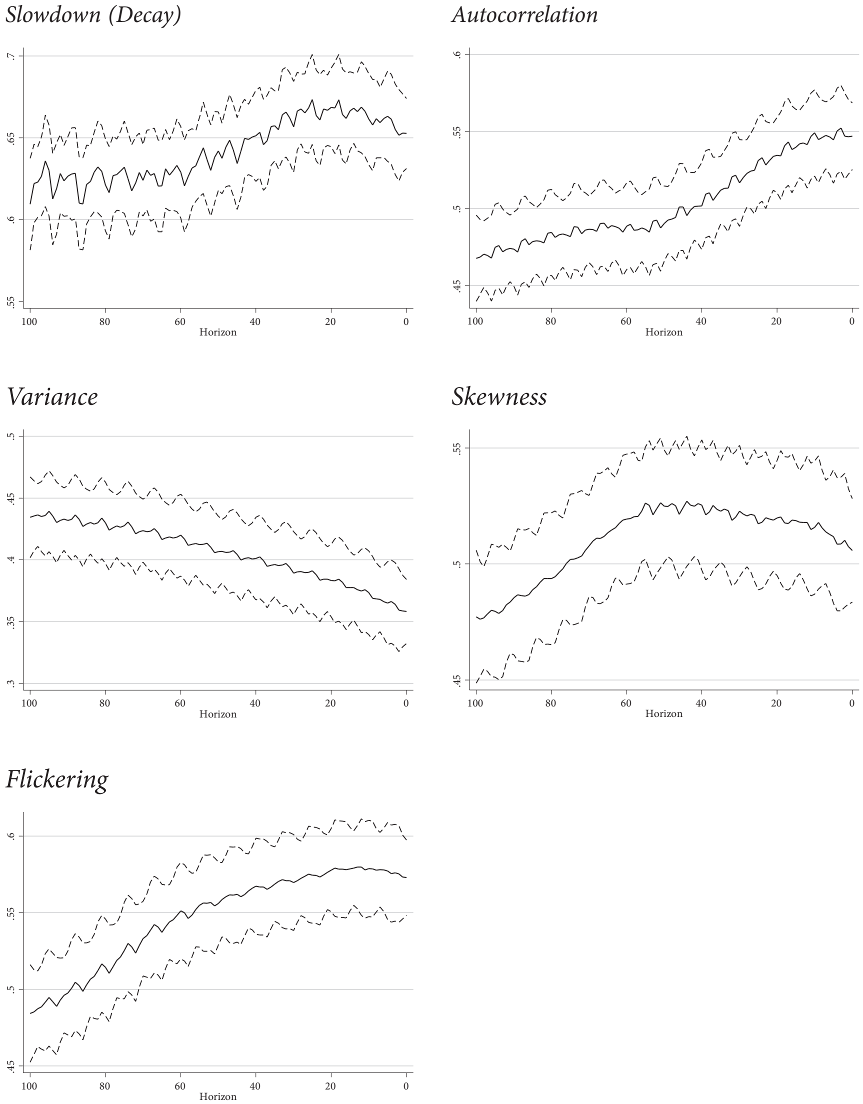


Flickering



Note: Area under the receiver operating characteristic curve (AUROC) along y-axis (solid line), Horizon: days before the critical transition in the money market (1 July 2009). Dashed lines: 95 % confidence intervals.

B. Switch to Safety Trap in Bond Market



Note: Area under the receiver operating characteristic curve (AUROC) along y-axis (solid line), Horizon: days before the critical transition in the safe asset market (11 March 2015). Dashed lines: 95 % confidence intervals.

Annex 3

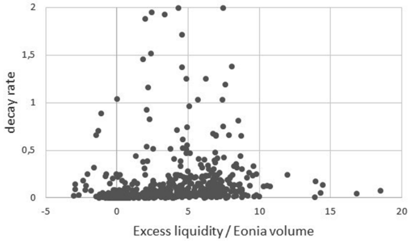


Figure A.1: Slowdown Money Market

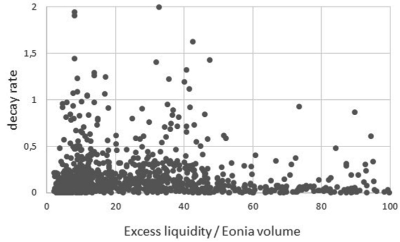


Figure A.2: Slowdown Safe Asset Market

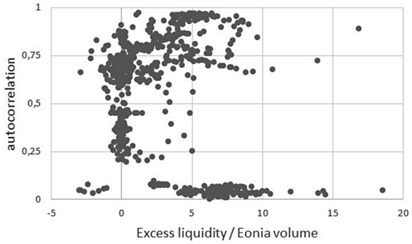


Figure A.3: Autocorrelation Money Market

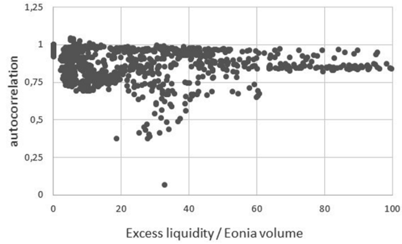


Figure A.4: Autocorrelation Safe Asset Market

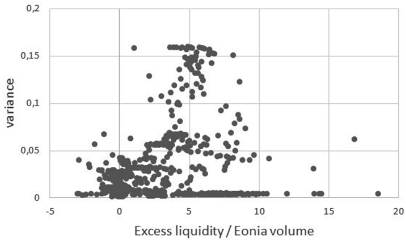


Figure A.5: Variance Money Market

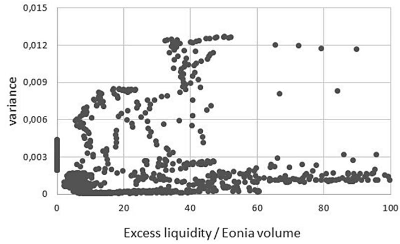


Figure A.6: Variance Safe Asset Market

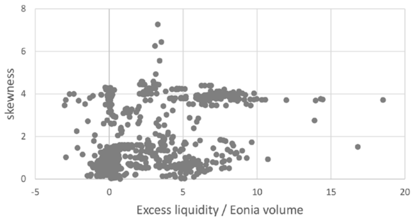


Figure A.7: Skewness Money Market

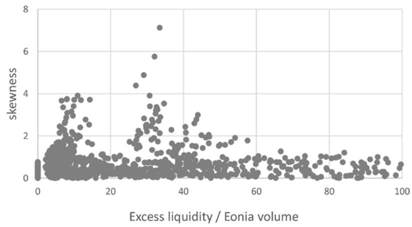


Figure A.8: Skewness Safe Asset Market

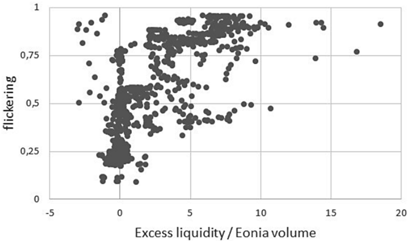


Figure A.9: Flickering Money Market

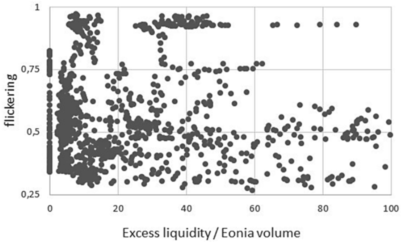


Figure A.10: Flickering Safe Asset Market