

Essays on the Procyclicality of Financial Cycles and the Vulnerability of Emerging Markets

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Essays on the Procyclicality of Financial Cycles
and the Vulnerability of Emerging Markets

by **Garo Garabedian**

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To Nora, Agheg, Lara and Mekhitar

Thank you notes¹

We are what we pretend to be, so we must be careful about what we pretend to be. (Kurt Vonnegut)

Think slow, act fast. (Buster Keaton)

Jusqu'ici tout va bien, jusqu'ici tout va bien. Mais l'important n'est pas la chute, c'est l'atterrissage (La Haine)

These quotes might seem strange at the commencement of a PhD dissertation on monetary and macro-financial topics. However, they do seamlessly describe many of the transitional phases I encountered during my personal path towards academic maturity. In line with Buster Keaton, during the past six years, I was instructed to take my time to think profoundly about important economic questions and many unsolvable puzzles. This was nicely contrasted with all of the submissions and deadlines, which required us to act quickly, and demanded a more realistic and head on approach.²

During a PhD, the most important characteristic one will have to rely on is probably perseverance. Being surrounded by wonderful, intelligent and supportive people enormously helps one to endure the harshest perils. I am blessed with four family members that each have their unique and unparalleled qualities. Starting with my mother Nora³, I have never met a woman with so much generosity and ability to sacrifice herself for her children. Gifted with a magical sixth sense, she has always gently guided us through all the important events in life. Gigerenzer surely must have had her in mind when he talked about the value of intuition and heuristics.⁴ My father, Agheg, a successful business man in his own right, thought

¹reference to the “Weekly Thank you notes”, featured in the Tonight Show, starring Jimmy Fallon

²sometimes even wandering into realm of the “quick and dirty”, better known as “schnell und schmutzig”

³or Vergine as she was wrongly named at birth

⁴in his book ‘Gut Feelings’ Gigerenzer describes how gut feelings can have their merit above and beyond complex rules

me to be self-reliant, follow a righteous path, and most importantly, how to become a real man.⁵ Finally, Lara and Mekhitar, my two much more talented siblings, the former being a state of the art pediatrician, specialized in neonatology; the latter a renowned artist, and talented philosopher. You both provide great examples. In the French movie *La Haine*, the protagonist Hubert tells a story about a man falling down from a high-rise building who during his fall repeatedly reassures himself that ‘up till now everything is fine’. However, Hubert sharply remarks, it is not the descent that matters, but the landing. Surrounded with such a dream team, even when I break down at times, the landing is soft on every possible occasion.

Amy Cuddy advises us to “fake it till we make it, or fake it till we become it”. I guess a lot of things we grow into are simply a result of doing them often enough. In the beginning of a PhD one has no clue of what the academic world is really about. It is only by watching and acting like a researcher, that one is slowly able to become one. However, Vonnegut provides us with a valuable warning in this context. As this process happens automatically and without full awareness, many undesirable traits we actually would not like to incorporate, might trickle through as well if we follow in the wrong footsteps. Hence, we should be careful about whom we try to emulate. I am very thankful for having had two magnificent supervisors, to whom I could mirror myself. Firstly, Koen Inghelbrecht is a role model to me, both as a researcher and as a family⁶ man. I will probably never again encounter the combination of such high competences together with such humility. A man loved by all, hated by none. Secondly, Michael Frömmel ceaselessly supported me and believed in me, and gave me valuable insight into the peculiarities of the academic world, which I will always carry with me. But the reoccurring theme is surely the importance of the family life, which makes the work life much more agreeable.⁷ In this academic context, I’m also greatly indebted to my commission members (David Veredas, Lieven Baele, Evzen Kocenda, Ansgar Belke, Franziska Schobert), for all their valuable comments and feedback, which unquestionably improved the quality of the research. Furthermore, during my years at the university of Ghent, I have been fortunate to have been surrounded by many talented, funny and warm researchers. Hence, it can come as no surprise that I have grown greatly fond of Joris Wauters, Maria Gerhard, Selien De Schryder, Xing Han, Hannes Stieperaere, Dries Heyman, Nicolas Dierick, Sarah Van Bree, Bart Defloor, Martien Lamers, Jasmien De Winne,

⁵When I think of him, I immediately hear the following verse of Public Enemy: “when the man (is) in the house and all the bullshit stops.”

⁶I would also explicitly like to thank the whole family Inghelbrecht, as I disturbed many homely moments with numerous Skype talks

⁷Both Tanya and Darina are delightful, and I enjoyed the wonderful occasions we spent together

Junior Burssens and Mustafa Disli. In this context, I also specifically want to thank Vanessa Bombeeck, Anja Van Gysegem, Nathalie Verhaeghe and Sabine Dekie for their wonderful logistical support. Finally, I also have to thank Ghent University for funding my research, as well as the Irish Central Bank for providing me with a fresh opportunity to continue my career as researcher.

There are many other people whom I have to thank, for many very divergent reasons, some more noble than others, but all very valuable in their own right. I am indebted to Gert Peersman and Gerdie Everaert for the brilliant classes they thought at Ghent University, which inspired me to become a researcher in the first place. The same goes for Carine Smolders, who provided me with the opportunity to get started on my PhD journey. Liesbet Van den Driessche, thank you for being so incredibly patient with me, and for dealing with my stubborn character, but also for providing me with valuable feedback, whenever you could. You are a brilliant researcher, and you will undoubtedly have an interesting journey in the academic world. I am much obliged to Benjamin Van Oost, Nelis Naessens, Niels Celie, Saar Swinters, and Lien Lampaert for providing me with the right level of entertainment and fun, when I was not behind my desk battling away with a paper, thus allowing me to unlearn all of the things I learned. Finally, I would like to thank Barbara Van Oost, Bram Schietecatte, Clara Van Den Broeck, Freek Van Baele, Elise Vandaele, Erik Veldhuis, Evelyne Vandenberghe, Ina Paitjan, Jeremy Godenir, Jessica Kelly, Mounia Nouda, Jessie Schietecatte, Leen Segers, Mayenne Nelen, Pieter Dekegel, Simon Gerdesman, Tatiana Geysen, Tigran Bagdasaryan, Varduhi Nanyan (and many more whom I undoubtable forget) for simply letting me be myself.⁸ Finally, I'm also grateful to (maybe not all, but at least many of) my students, who over the years kept me grounded with their whimsical (and at times crazy) questions. A lot of them have become good friends over the years, and I'm excited to see to which heights they can reach.

Garo Garabedian

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⁸“Thank you for letting me being myself, again”, song recorded by Sly and the Family Stone in 1969

General Overview of the Dissertation

The dissertation explores the procyclicality of financial cycles and the subsequent vulnerability of emerging markets, two important aspects in modern day monetary and financial economics which are closely intertwined. During recent years, many prominent institutions (the Bank for International Settlements, the International Monetary Fund, etc.) have identified credit and asset cycles as important factors which can destabilize economies. These cycles are typically characterized by irrational upswings, followed by virulent busts with huge confidence losses. The latest financial crisis highlights these vulnerabilities. Moreover, the response in many advanced economies has been very aggressive, most recently even reverting to unconventional policy in order to revitalize markets, hugely inflating their central bank's balance sheets. Through four different chapters, I try to demystify several of the mechanisms which feature in this challenging monetary environment, using different disciplines in economics, ranging from the empirical focus found in macro and finance, to the more palpable field of behavioural economics.

Chapter 1 investigates the importance of asset prices in monetary policy rules for emerging markets, and finds a role for the exchange rate in the interest rate setting behavior of several Central and Eastern European Countries (CEECs). However, the reactions of these central banks are not to the levels or the changes in their exchange rate, but comprise a nonlinear reaction to the distance of the exchange rate towards the bands which they have committed to defend. Additionally, the paper incorporates many advances in estimating monetary policy rules, thus improving the reliability of the estimated coefficients in comparison to a more traditional framework.

In Chapter 2, I unravel whether affective stimuli can have a nameable impact on our recollection, and hence shape our sentiments and expectations, even affecting our decision-making. Such a self-enforcing mechanism can lead to powerful feedback effects during downturns, when we are surrounded with negative news. This storyline allows a more behavioral underpinning of procyclicality, next to the monetary channels which focus mainly on risk-taking. The empirical setting is based on lab experiments, in which participants are primed with a certain emotion, and then subjected to memory tests in order to gauge the recall errors. In the most advanced setting, I also look whether these mnemonic disparities affect the participants' expectations differently.

Moving towards a well-known concept in finance, Chapter 3 explores the importance of liquidity (or the loss therein) over time. Such losses of confidence on the stock market are usually animal spirit driven, thus providing a close link with the behavioral outlook in chapter 2. We introduce a unified measure of liquidity that incorporates the several dimensions which are concealed within the concept. Our aggregation method not only

relies on the time-varying correlations between these dimensions, but also incorporates idiosyncratic signals. The latter focuses on nonlinear and volatile movements. Our unified liquidity measure is linked with many well-known financial and monetary concepts. Moreover, there are clear signs that purely financial shocks in liquidity can have real spillover effects, and provide forecasting value, above and beyond traditional variables.

Finally, chapter 4 examines the impact of monetary policy spillovers to emerging markets, in the recent context of advanced economies pursuing expansionary monetary policies, thus highlighting the interconnectedness (and frailty) of our modern international financial system. I find a considerable effect of shocks in EMU monetary policy on the long term yields of CEECs, while US policy shocks seem to be a more important driving force for long term yields in Asia and Latin America. In contrast, I find little influence of shocks in the policy of advanced economies on the bilateral exchange rates of emerging markets. This holds for all the geographical entities.

Table of Contents

Essays on the Procyclicality of Financial Cycles and the Vulnerability of Emerging Markets

Chapter 1: Monetary Policy Rules in Central and Eastern European Countries, Does the exchange rate matter

1. Introduction
2. Monetary Policy Rules in CEEC
3. Methodology
4. Evaluation
5. Conclusion
6. Acknowledgments

Chapter 2: Hard to let Go, The Procyclical Effect of Memory on Financial Cycles

1. Introduction
2. Memory and Negative Emotions
3. Methodology
4. Quantifying Effects of Emotions on Memory
5. Pass Through of Mnemonic Effects to Economic Expectations
6. Conclusion
7. Acknowledgments

Chapter 3: A Unified Market Liquidity Measure

1. Introduction
2. Literature
3. Statistical Design
4. Evaluation
5. Conclusion

Chapter 4: Instability Hypothesis for Small Open Economies: The Procyclical Impact of International Flows

1. Introduction
2. Literature
3. Empirics
4. Conclusion

Chapter 1

Monetary policy rules in Central and Eastern European Countries: Does the exchange rate matter?*

Michael Frömmel¹, Garo Garabedian², Franziska Schobert³

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Abstract

We estimate monetary policy rules for six Central and Eastern European Countries (CEEC) during the period when they prepared for membership to the EU and monetary union. By taking changes in the policy settings explicitly into account and by splitting up the exchange rate impact into two different components we significantly improve estimation results for monetary policy rules in CEEC. We uncover that the focus of the interest rate setting behaviour in the Czech Republic, Hungary and Poland explicitly switched from defending the peg to targeting inflation. For Slovakia, however, there still seemed to be an ongoing focus on the exchange rate. Finally, Slovenia and, after a policy switch, Romania exhibit a solid relation with inflation as well.

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Keywords: Monetary policy rules, Taylor rules, Transition economies, Exchange rate regime, CEEC, Inflation Targeting

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1 Introduction

Monetary policy in Central and Eastern European Countries (CEEC) has drawn increasing attention from academics and practitioners. While preparing for membership to the EU and monetary union, the central banks in CEEC were challenged by high inflation in the earlier periods, and then managed to disinflate fairly successfully. The way this was achieved, however, was considerably different: The Czech Republic, Hungary, Poland and Slovakia focused on exchange rate targeting during the first years, but then gradually made their exchange rate system more flexible and adopted inflation targeting as their monetary policy strategy. Romania and Slovenia never officially had a fixed exchange rate regime. While Romania adopted inflation targeting only in August 2005, Slovenia officially followed a monetary targeting strategy for most of the time before adopting a two-pillar-like strategy in the run-up to monetary union (for the official exchange rate and monetary policy regimes see Tables 1 and 2).

For these six countries, the interest rate setting behaviour of a central bank can provide important insights into the objectives which are most important in its conduct of monetary policy. A standard approach is to estimate a Taylor-like interest rate reaction function. While the empirical literature concludes that the monetary policy by most successful central banks in large industrial countries can be described by such a reaction function (Clarida et al., 1998), evidence for emerging economies and particularly transition economies is comparatively poor.

Regime shifts, however, seem to matter. Kahn and Parrish (1998), for example, find that significant structural breaks in the monetary policy reaction function occurred, after New Zealand and the UK introduced inflation targeting. In both countries the significance of the exchange rate lost importance. Neumann and von Hagen (2002) disclose the same result for a larger country set. Assenmacher-Wesche (2006) estimates reaction functions with time-varying coefficients for Germany, the United Kingdom and the US. These empirical results stress the importance of taking policy changes into account. Since CEEC are small open economies, one may argue that besides regime shifts also the exchange rate plays a major role in the reaction function. Ball (1999) argues that pure inflation targeting without explicit attention to the exchange rate is dangerous in an open economy, because it creates large fluctuations in exchange rates and output. In this context, the effects of exchange rates on inflation through import prices is the fastest channel from monetary policy to inflation, therefore monetary policy cannot neglect it. The need for considering the exchange rate will be obvious, if the monetary authorities explicitly target the exchange rate, as they (initially) did in many CEEC. However, the way the exchange

rate enters the reaction function should then be different, because monetary policy has to react on potential violations of the exchange rate band in order to keep it credible. Thus the reaction is non-linear, as it will get stronger, the closer the exchange rate approaches the intervention margins. It will also be non-discretionary, because the authorities are obliged to react, as long as they intent to sustain the peg.

In line with, e.g. Peersman and Smets (1999), our emphasis is on positive or descriptive rather than normative aspects of policy analysis. We investigate the role of the exchange rate by looking at the interest rate setting behaviour of the central bank and to which degree it has taken exchange rate developments into account. The paper thereby sheds some light on the discussion to which extent the interest setting behavior of these central banks complies with the “fear of floating” hypothesis, as analyzed by Calvo and Reinhart (2002). A central bank that changes interest rates systematically in response to inflation and also to exchange rate shocks is more likely to support evidence on this hypothesis, keeping in mind that the central bank nevertheless still may use interventions in the foreign exchange market as an instrument to steer the exchange rate.

This paper adds to the literature in five ways: First, our analysis covers a longer sample period than most previous studies. We consider a substantial part of the transition period from January 1994 till August 2008. Second, whereas most works only include the Czech Republic, Hungary, Poland and sometimes Slovakia, we add Slovenia and Romania to the sample. Thus we consider all new EU member states in CEEC which one may assume to have pursued a more or less independent monetary policy during a considerable period of time.¹

Third, the analysis takes explicitly into account shifts in exchange rate and monetary policy regimes that have occurred in all the countries of the sample. Fourth, we introduce a non-linear measure of distance to the intervention margins to identify those interest rate changes that stem from the peg. To our knowledge we are the first taking this effect into account. Fifth, we apply the cointegration methodology to interest rate rules as suggested by Gerlach-Kristen (2003), which has rarely been applied to transition economies. These innovations allow us to retrieve more realistic coefficients from our reaction function, and thus our model better describes the interest rate setting behaviour of the monetary authorities.

The paper proceeds as follows: The following Section 2 reviews the research on interest rate rules in transition economies. Section 3 introduces our empirical

¹This is not the case for the remaining CEEC that joined EU: The Baltic states and Bulgaria followed very strict exchange rate regimes and partially currency boards. This means they could not pursue an independent monetary policy.

approach and our distance measure. Section 4 describes the data and presents the empirical results, while Section 5 summarizes and concludes.

2 Monetary policy rules in CEEC

Research on monetary policy rules in the context of emerging market economies and particularly transition economies is of more recent origin and relatively scarce. An important finding of Mohanty and Klau (2004) is that central banks in emerging market economies tend to look beyond inflation and focus on other objectives as well, most prominently on exchange rate changes.

The amount of literature specifically on monetary policy rules in CEEC is limited, first because time series available are comparatively short. They usually start in the middle of the 1990s. Second, most CEEC have not followed one single strategy of monetary policy and also gradually made their exchange rates more flexible (see Tables 1 and 2). Third, it is not quite clear which target values for inflation the CEEC followed, as most countries introduced inflation targeting and explicit inflation goals only between 1997 and 2001.

Recently, there have been some attempts to describe the monetary policy in selected CEEC using interest rate rules. Maria-Dolores (2005) and Paez-Farell (2007), for example, estimate Taylor rules for the Czech Republic, Hungary, Poland and Slovakia. The latter finds that there is a reaction to exchange rate movements. Angeloni et al. (2007) set up interest rate rules for the Czech Republic, Hungary and Poland, introducing the US dollar interest rate as a proxy for inflationary pressures of global origin. Yilmazkuday (2008) and Jakab and Vilagi (2008) consider structural breaks in their estimates of monetary policy rules for CEECs. Moons and Van Poeck (2008) find that the accession countries do not differ substantially from the current EMU members with respect to the interest rate setting behavior, and that there has been increased convergence. Remo and Vasicek (2009) apply a DSGE model to Czech data, and conclude that the focus of the Czech National Bank was mainly on inflation. Finally, Horváth (2009) analyzes the policy neutral rate in the Czech Republic. The results indicate a substantial interest rate convergence to levels comparable to the euro area.

Empirical research suggests that a Taylor-like rule is helpful in understanding monetary policy of the CEEC. However, in most cases inflation coefficients are found to be far below unity, thus violating the so-called Taylor principle. If the Taylor principle holds, the policy rate should move more than proportional with increases in the inflation rate and thereby raise the real interest rate. If the monetary

policy rule violates the Taylor principle, it will mean that the central bank does not react adequately on bringing down inflation. This result is counterintuitive, as the CEEC have experienced a remarkable degree of disinflation during the last 15 years. The literature suggests mainly two explanations: Angeloni et al. (2007) argue that part of the reaction on inflation is captured by the coefficient on the US interest rate included in their equation. An increase in global inflation would then lead to a composed reaction, which is partly due to domestic inflation via the conventional inflation coefficient and partly due to foreign inflation via the coefficient on the foreign interest rate. One might similarly argue that the exchange rate included in the interest rate rule partially takes the reaction on inflation, as it anchors expectations on future monetary policy. Another argument, proposed by Golinelli and Rovelli (2005) is that the reaction to an increase in inflation may be modest, if the initial interest rate compared to inflation was set high enough. Thus a smaller coefficient means that in the course of the disinflation process monetary policy is getting even more aggressive. The scenario seems to be well applicable to the CEEC. However, one would at least expect the inflation coefficient to be close to unity during periods of autonomous monetary policy. Besides the above mentioned empirical research, the treatment of exchange rate changes in monetary policy rules is also discussed in the theoretical literature. Svensson (2000) compares strict inflation targeting, which implies a vigorous use of the direct exchange rate channel for stabilizing (CPI-) inflation at a short horizon, with flexible inflation targeting, which stabilizes inflation at a longer horizon, and thereby also stabilizes real exchange rates and other variables to a significant extent. The reaction function under inflation targeting in an open economy thus responds to more information, notably to foreign disturbances. The particular importance of the exchange rate for monetary policy rules in the case of emerging economies is also stressed by Amato and Gerlach (2002).

Taylor (2001) argues that a monetary policy rule that reacts directly to the exchange rate, as well as to inflation and output, sometimes performs worse than policy rules that do not react directly to the exchange rate and thereby avoid more erratic fluctuations in the interest rate. In Taylor (2002), however, he points out that monetary policy in open economies is different from that in closed economies. Open-economy policymakers seem averse to considerable variability in the exchange rate. In his view, they should target a measure of inflation that filters out the transitory effects of exchange rate fluctuations, and they should also include the exchange rate in their policy reaction functions.

3 Methodology

Following Taylor’s (1993) seminal paper, it has become common to describe monetary policy by a linear feedback rule linking the interest rate to the output and inflation gap

$$i_t = r^* + \pi_t + \alpha\pi_t^* + \beta y_t^*$$

where i is the short-term nominal interest rate set by the central bank, r^* the assumed equilibrium real interest rate, π_t the actual rate of inflation, π_t^* the deviation of the actual inflation rate from the (central bank’s) target rate and y_t^* the percent deviation of real GDP from its target, the output gap. The condition $\alpha > 1$, known as the Taylor principle, implies that the nominal interest rate is raised by more than one percentage point in response to an increase in inflation of one percentage point in order to increase real interest rates.

In line with Taylor (2002), we apply a monetary policy rule for open economies, which takes into account the role of the exchange rate. We extend this approach and model the exchange rate component with two variables: Δs_t representing the growth rate of the exchange rate for the whole sample period, and b_t , reflecting the exchange rates’ position in the band, if the currency is pegged to an anchor currency

$$i_t = r^* + \pi_t + \alpha\pi_t^* + \beta y_t^* + \delta\Delta s_t + \gamma b_t$$

To model the impact of the exchange rate we thus use two different tools. For countries without explicit exchange rate targets, the growth rate of monthly exchange rates to the euro (before 1999: to the D-mark) is a proxy for the central banks desire to smooth exchange rate fluctuations.²

For the countries with an explicit exchange rate target during the first subperiod, we also incorporate the band distance at which the market rates are located from either band edge.³ This measure reflects pressure on the exchange rate, as every time the market rate approaches, or actually exceeds, one of the borders the central bank is obliged to react by interventions and/or interest rate changes.⁴ Since one would expect a non-linear reaction – the closer the exchange rate approaches the intervention margins the stronger the central bank should react – we do not calculate

²We also included real and nominal effective exchange rates, this does, however, not substantially change the results. Using the exchange rates in levels (instead of growth rates) rather worsens the results.

³The correlation between Δs_t and b_t turns out to be low and insignificant.

⁴It is not unusual to add variables to capture certain pressures on the macroeconomic framework that could affect the parameters. For example, Cecchetti and Li (2008) add a measure of stress in the banking system to the original Taylor equation, which is quite close to our band distance variable. The rationale behind our band distance measure is thus similar, since it measures pressure emerging from the pegged exchange rate.

the distance between the exchange rate and the closer edge, but transform the distance by an exponential function. As long as the exchange rate is inside the band (and far away from the edges) b_t will be close to zero. However, b_t grows exponentially as the market rate approaches the borders and even explodes when it has left the band. Moreover, the measure is signed, since the impact on the central bank's interest rate policy is asymmetric. Thus, our band distance measure is:

$$b_t = \begin{cases} -\exp(l_t - s_t) & \text{if } |l_t - s_t| \leq |s_t - u_t| \\ \exp(s_t - u_t) & \text{if } |l_t - s_t| > |s_t - u_t| \end{cases}$$

with l_t the lower boundary of the band (the strong edge), u_t the upper boundary of the band (the weak edge) and s_t the exchange rate. The boundaries used for the calculation are the official bands set by the monetary authorities. In Figs. 1–4, we show the evolution of the band distance variable over time, respectively for all the countries in our sample with a pegged exchange rate. Two interesting features stand out. First, the exchange rates often have had appreciating pressure and therefore, were close to the strong edge of the narrow bands. Second, the values increase dramatically during times of crises, when boundaries are reached or exceeded.

Our band distance measure is closely related to the target zone models based on Krugman (1991). These models, such as described in Bartolini and Prati (1999), Crespo-Cuaresma et al. (2005a) or Horvath and Fidrmuc (2008), assume that monetary authorities do not intervene as long as the exchange rate is close to the central parity, but take policy actions when it is about to leave the band. However, while Krugman's target zone model describes the behaviour of the exchange rate, we focus on the policy actions themselves.

We expect that monetary policy in CEEC should exhibit different coefficients over time, reflecting the evolution of exchange rate and monetary policy regimes: The initially tight exchange rate pegs should be reflected by a focus on the band distance, combined with a limited ability to directly target inflation. Schnabl (2008) demonstrates a strong link between exchange rate stability and growth rates for the CEEC during this episode, thus motivating policy actions beyond direct interventions on the exchange rate market. However, this initial setting should change when the pegs are abolished and the central banks divert their attention more towards inflation. Nevertheless, some monitoring of the exchange rate may remain, which should be reflected by the smoothing element. The weight for output depends on the nature of the shocks and the room that the inflation target policy has left for any output goals.

In our analysis we do not incorporate the lagged interest rate as a smoothing component. Traditional explanations for smoothing interest rate changes include,

for example, fear of disrupting capital markets, loss of credibility from sudden large policy reversals or the need for consensus building to support a policy change (Clarida et al., 1998). As this approach may rather entail an econometric solution in order to get meaningful results in an environment which suffers gravely from autocorrelation, we find it more appealing to confront these problems directly, in a generalized least squares framework. According to Rudebush (2002), the increase in predictability by adding lagged interest rates may indicate inconsistency between the rule and the data.

Whereas the variables in the monetary policy rules are often treated as stationary, we follow Gerlach-Kristen (2003) and apply the cointegration methodology. Phillips (1986) claims that, if the variables are (nearly) integrated of order one, static regressions in levels are likely to produce spurious results. In this respect, Rudebush (2002) shows that such static regressions display an R-squared far larger than the Durbin Watson statistic, which may hint at a spurious regression. Therefore, results from monetary policy rules in levels are often regarded as doubtful (Carare and Tchaidze, 2005). Gerlach-Kristen (2003) states that while interest rates, inflation gap and output gap are likely to be stationary in large samples, in order to draw correct statistical inference it is desirable to treat them as non-stationary in relative short samples.⁵

We apply various unit root tests (Said and Dickey, 1984; Kwiatkowski et al., 1992; Perron, 1989) to the data. The latter is less sensitive to structural breaks. The results suggest that interest and inflation rates are integrated of order one, whereas the output gap, the exchange rate growth and the band distance can be treated as stationary. However, any results should be carefully interpreted, taking into account that the sample size is small.

For the cointegration analysis we include all variables, even the stationary ones. This has become common practice in the recent empirical literature (see e.g. Enders, 2004; Asteriou and Hall, 2007).⁶ We use the bounds testing approach by Pesaran et al. (2001) which explicitly allows for a mix of $I(1)$ and $I(0)$ variables, as standard statistical inference based on conventional cointegration tests is no longer valid. First, the optimal lag length (p) is selected through the Akaike and Schwarz' Bayesian

⁵See also empirical work: Crespo Cuaresma et al. (2005b) estimate a monetary model of the exchange rate for the same six CEEC as in our study from 1994-2002 using cointegration. In the same way Fidrmuc (2009) demonstrates for the same CEEC from 1994-2003 that money demand and all related variables are non-stationary and thus again applies cointegration techniques. This is however less common for Taylor rules.

⁶Lütkepohl (2004, p. 89) states: "Occasionally it is convenient to consider systems with both $I(1)$ and $I(0)$ variables. Thereby the concept of cointegration is extended by calling any linear combination that is $I(0)$ a cointegration relation, although this terminology is not in the spirit of the original definition."

information criteria. Because of the weight on the hypothesis of serially uncorrelated error terms for the legitimacy of the test, we set the p-value cautiously.⁷ Next, we examine the null hypothesis of no cointegration using an F-statistic for the joint significance of the lagged level coefficients in the next equation (where c_0 and c_{1t} represent drift and trend elements and ξ_t is assumed to be white noise):

$$\Delta i_t = c_0 + c_{1t} + \sum_{i=1}^{p-1} \alpha_i \Delta i_{t-i} + \sum_{i=0}^{p-1} \beta_i \Delta \pi_{t-i} + \sum_{i=0}^{p-1} \chi_i \Delta y_{t-i} + \sum_{i=0}^{p-1} \delta_i \Delta s_{t-i} + \sum_{i=0}^{p-1} \varepsilon_i \Delta b_{t-i} + \gamma_1 i_{t-1} + \gamma_2 \pi_{t-1} + \gamma_3 y_{t-1} + \gamma_4 s_{t-1} + \gamma_5 b_{t-1} + \xi_t$$

If the F-value exceeds the upper bound this indicates the existence of a long run relation. However, if the F-value is smaller than the lower bound, we cannot reject the null of no cointegration. Finally, a test statistic in between both critical values would leave us inconclusive (De Vita and Abbott, 2004). Table 3 unravels the values of the bounds test and we retrieve a cointegration relation for all the countries in our sample.⁸

In line with Gerlach-Kristen (2003), we do not estimate the full error-correction model, but instead focus on the single-equation approach discussed by Hamilton (1994). Even though cointegration yields results that are superconsistent, in small samples there may still occur a potential endogeneity bias. Hamilton postulates we can correct for this by incorporating past and future changes of the included variables. We get the following form of the Taylor rule (where we also insert the disturbance term η_t):

$$i_t = c + \alpha \pi_t^* + \beta y_t^* + \delta \Delta s_t + \gamma b_t + \sum_{k=-1}^1 (\alpha_{\pi k} \Delta \pi_{t+k} + \beta_{y k} \Delta y_{t+k} + \delta_{s k} \Delta^2 s_{t+k} + \gamma_{b k} \Delta b_{t+k}) + \eta_t$$

As the differences included in Eq. (4) only serve as a correction, we refer to the most important first part of the regression in what follows.⁹ This analysis, similar to a dynamic OLS technique, is attributed to the seminal work of Stock and Watson (1993).

Estimating Eq. (4) for the whole sample period is, however, meaningless, since the monetary policy rule is likely to substantially differ across subperiods. We therefore introduce dummy variables and allow for the coefficients to shift after the structural breaks, so that we can differentiate between the fixed and the flexible period. We also build in a dummy variable to catch any changes in the intercept. In this sense, the outer framework remains the same and the comparability between

⁷When both criteria diverge, we retain the highest lag order.

⁸We also apply the instrumental variable cointegration test by Enders et al. (2008), which is not only robust for stationary variables but also allows for dummy variables. This procedure confirms our results.

⁹For achieving a unified framework and in line with Gerlach-Kristen (2003) we set the number of leads and lags of these elements to one.

periods improves. The above tests for cointegration show that it is justified to use such a combined framework, because even though the parameters may have shifted over time, the variables involved still show a meaningful relation in the long run. This fragmentation of our sample in two separate periods gives us additional insight in the ‘fear of floating hypotheses’ (Calvo and Reinhart, 2002).

The regime switches are defined as the dates when a narrow exchange rate band is widened to $\pm 15\%$ or completely abolished, according to the official exchange rate regime.¹⁰ We regard a $\pm 15\%$ band as wide enough in order not to prevent a central bank from performing an autonomous monetary policy. This is in line with the observation that some of the countries (namely Hungary) announced inflation targeting in combination with such wide bands. The choice is also supported by the empirical observation that the band distance turns out to be close to zero for the periods with a $\pm 15\%$ band (see Fig. 2).

We thus determine the date of the regime switches by focusing on the exchange rate regime as given in Table 2, instead of the monetary policy changes as given in Table 1.¹¹ This is motivated by the crucial role the exchange rate arrangements played during the first part of the transition period.

As Slovenia and Romania never announced any official fixed exchange rate arrangement, we use the findings by Frömmel and Schobert (2006) and set the shift date for Romania to 31/12/1998. For Slovenia, we highlight a regime shift from implicit crawling band exchange rate regime before ERM2 membership to an explicit horizontal band. Due to the wide margins of the ERM2, we regard it as a shift to an (almost) floating exchange rate regime.

Since we only distinguish between fixed and flexible exchange rates and since the de facto regime switches might differ from the official ones, we tested several alternative break points around our fixed date (but also on the basis of dates retrieved through the Quandt–Andrews breakpoint test, which lay in the vicinity of our previous date) and we can state that our framework remains largely robust to the modifications.¹²

¹⁰We retrieve the following dates: For the Czech Republic we find 27/05/1997 (managed float), Hungary 1/05/2001 ($\pm 15\%$ band), Poland 25/03/1999 ($\pm 15\%$ band) and Slovakia 1/10/1998 (managed float).

¹¹For example, Poland moved already over from exchange rate targeting to inflation targeting in 1998, but only moved to a fifteen percent peg from March 1999 onwards. Nonetheless, our focus remains on the second date as the peg implies central bank intervention when the exchange rate violates one of its bands. Even though the focus of monetary policy seems to have switched to inflation, its hands may still be tied if it does not alter the peg. The same comment can be made for Slovakia. Although in both cases (we can conclude from our band distance variable that) the exchange rate troubles dwindled after the announcements of the new monetary policy.

¹²The results for these alternative dates and specifications can be retrieved from the authors

Through the above discussed changes, Eq. (4) evolves to

$$i_t = c + \psi d_t + \alpha_1 \pi_{1t}^* + \alpha_2 \pi_{2t}^* + \beta_1 y_{1t}^* + \beta_2 y_{2t}^* + \delta_1 \Delta s_{1t} + \delta_2 \Delta s_{2t} + \gamma b_t + \sum_{k=-1}^1 (\alpha_{\pi k} \Delta \pi_{t+k} + \beta_{y k} \Delta y_{t+k} + \delta_{s k} \Delta^2 s_{t+k} + \gamma_{b k} \Delta b_{t+k}) + \eta_t$$

where ψ_i is the dummy for the period i , with $i = 1$ being the fixed exchange rate period, and $i = 2$ the period with flexible exchange rate arrangement and (for most countries) inflation targeting.

Finally, we use a GLS approach¹³ to correct the standards errors for autocorrelation and apply a White correction for heteroskedasticity (MacKinnon and White, 1985).

4 Evaluation

We analyze monthly data for the Czech Republic, Hungary, Poland, Romania, Slovakia and Slovenia that covers the period between January 1994 and August 2008, thus leaving out the current financial crisis that may distort our results. Our sample includes data from the IMF’s “International Financial Statistics” database, the OECD’s “statistical compendium”, and various central banks.

For the interest rate we either implement the 3 month interbank rate or other money market rates depending on availability.¹⁴

The inflation rate is calculated as the annual rate of change in the consumer price. Considering the inflation gap, one has to keep in mind that all of the investigated countries are involved in a European integration process. These countries thus have to apply a twin inflation target. They do not only face an internal target, which is set by the domestic central bank, but they also have to comply with an external target which is embedded in the Maastricht criteria. In many publications and statements of the CEECs’ central banks a distinct focus on the inflation differential to EU countries can be observed. This strengthens our beliefs that the main attention should be on the inflation gap based on the Maastricht criterion. On a more empirical level this intuition is supported by Siklos (2006), with the external European target

¹³We prefer the method described in Johnston and Dinardo (1997), because it gives the possibility to set up a full GLS model, so we do not lose any observations compared to simply transforming the variables. Deeper analysis of the (partial) autocorrelation function of the residuals points towards a AR(1) structure. Besides the dynamic full GLS we also applied a simple OLS version and a transformed GLS estimation. The results, however, do not substantially differ. They are available from the authors on request.

¹⁴More precisely, we incorporate the three months interbank rate for the Czech Republic, Hungary, Poland and Slovakia and the money market rate for Romania and Slovenia. As a robustness check, we also include various other short term interest rates in our analysis without any substantial change in the results.

yielding more consistent results than its internal equivalent. Furthermore, there are several advantages in using the external criterion. First, not all of the countries adopted an inflation target for the whole period, thus there is only limited availability of internal inflation targets. Second, due to several reasons, e.g. the initially limited reputation of central banks or frequent changes in administered prices in CEEC or other shocks outside the control of the central bank, the official targets might substantially differ from the actual target or had to be adjusted over time. The Maastricht target, however, can be regarded as a medium to long-term objective, and therefore seems to be a more reasonable benchmark for inflation.

The output gap is calculated based on industrial production using a Hodrick–Prescott filter (smoothing parameter 14,400). The computation of the rate of potential output presents a difficult task (the same applies to the natural rate of unemployment). The results strongly depend on the way it has been conceived. If one assumes the original series to exhibit a deterministic trend, a filter is the most appropriate solution, while a stochastic trend demands differentiation of the variable.

We follow the classical Taylor rule analysis and calculate the output gap based on a filter.¹⁵ Although one may expect to retrieve better results using real-time data (Orphanides, 2001) this is not possible for our sample of countries, as internal estimates are either not available at all or not publicly available.¹⁶

As a benchmark model, we first estimate Eq. (4) as a simple open economy framework with fixed parameters over time. The results are reported in the left-hand column of each country-specific segment of Table 4.¹⁷ However, the interpretation demands caution as the coefficients will potentially be distorted and inconsistent due to the neglected structural break and the time-invariant coefficients. The long term reaction of the interest rate on inflation is above unity only for the Czech Republic and Slovenia, and at least not significantly different from 1 for Hungary. So broadly speaking, we can say that three countries satisfy the Taylor principle.¹⁸ The coefficient for output seems less convincing as only Slovenia has a significant, but counterintuitive sign. The minor role for output in the CEEC’s monetary policy also corroborates with, e.g. Vonnàk (2007) and Jakab et al. (2006) who state that

¹⁵In contrast some authors prefer to work with growth rates, although this may lead to over-differentiating (Siklos and Wohar 2005). We also estimated the model with growth rates. This does not affect the estimation output. The results are available from the authors on request.

¹⁶We also tested various specifications based on unemployment rates (both with HP-filter and MA-gap). This did, however, not affect the results. The estimation output is available from the authors.

¹⁷The constants are not reported as they are not easily interpretable in the cointegration based version of the Taylor rule and serve as an “auxiliary variable” (Gerlach-Kristen, 2003).

¹⁸However, the coefficient is uniformly smaller than 1.5, which is often taken as a benchmark measure.

(Hungarian) monetary policy has a rather limited effect on output.

The same applies to the exchange rate growth element, which solely gives meaningful results for the Czech Republic. The parameter which seems significant over all the (fixed exchange rate) countries is the band distance coefficient (although for the Czech Republic this holds for a higher level of significance). This preliminary setting already depicts a relatively realistic picture of the monetary policy stance.¹⁹ Only the equation for Slovakia does not seem to be quite stable.

As a second step, we add the dummy intercept and slice up the variables to mimic both periods more truthfully, thus estimating Eq. (5). The results are reported in the right-hand column of each country-specific section in Table 4. It is interesting to portrait the regime dependence in the components and intercept dummies and their overall impact (this uniformly applies for all countries except Slovenia, where the shift reflects a different episode).

There is a substantial change in the sliced up coefficients. These differences are most obvious for the inflation coefficient. The number of countries satisfying the Taylor principle rises remarkably in the second period (inflation targeting and flexible exchange rate). This pattern corresponds to our expectations that the central banks had more flexibility to monitor the inflation target during the second period. Moreover, the band distance element seems quite robust for the new specification and is unambiguously significant for the Czech Republic, Hungary, Poland and Slovakia during their fixed exchange rate regimes.

In contrast, the exchange rate changes Δs_t are not significant for all countries but Slovakia. Thus, central banks used the interest rate instrument in order to keep the exchange rate well inside officially announced bands, but they hardly used this instrument in order to smooth exchange rate fluctuations. These relatively high coefficients for inflation during the flexible period also are in contrast with past studies on the same or similar countries, which find insignificant or low values for inflation. This is in line with the argument by Angeloni et al. (2007) that in a Taylor rule the reaction to inflation is partially captured by other variables, in our case the band distance.

Similarly, there are some alternations over time for the coefficients of the output gap and the exchange rate growth. But the importance of these particular elements generally seems to be quite low over both periods.

As an intermediate summary, we can conclude that the interest rate setting behaviour of the respective central banks only paid attention to the exchange rate

¹⁹The Durbin-Watson statistic and the Breusch-Godfrey (BG) test indicate that the residuals do not show remaining autocorrelation.

during periods of officially fixed regimes. This consideration of the exchange rate is best embodied through the band distance. During periods of officially floating exchange rates, central banks increasingly took a more inflation minded approach. Slovakia is an exception as the coefficient on exchange rate growth is significant during its more flexible exchange rate regime. On a more empirical level, we can also state that the new specification raises the explanatory power for all the countries: The adjusted R-squared is comparable to specifications including the lagged interest rate. Therefore we can assume that our specification gives a more realistic fit of the monetary policy rules for these transition countries.

We add alternative specifications to the equations in order to include country-specific features, and in order to conduct some robustness checks. These results are listed in Table 5.

For the Czech Republic we build in an extra crisis dummy for the turbulent period in June 1997. The results show that both inflation coefficients become significant, but there is still a substantial rise. Moreover, the second period's exchange rate component is now correctly signed. Finally, the band distance element remains robust and for the output values there is little change. All of these changes cause a higher adjusted R-squared, suggesting that this may be a more accurate description.

Since in the case of Hungary and Poland the introduction of inflation targeting and the abolishment of the peg did not coincide, these countries require additional considerations. We test a different break date (based on the Andrews–Quandt test) for Hungary. The intuition behind this is that we now set the date endogenously through our data instead of imposing it externally.²⁰ The new break date becomes June 1999, which is comparatively earlier than the official date. Furthermore, we see a more distinct change in the inflation parameters, although they both remain significantly indifferent from unity.

For Poland we estimate an alternative specification to assert what happens if we let our observations for the band distance run through for a longer period (than the officially stated pegged period which ends in April 2000) as we have indications that the monitoring of the peg went on a bit longer. Remarkably, the band distance coefficient seems robust and remains significant.

Romania never explicitly announced an exchange rate policy, so no official break date is available. Nevertheless, there are good reasons to assume that a break occurred in December of 1998. Alternatively, we set the break date through the Andrew-Quandt test (August 1999). The inflation coefficient decreases slightly for

²⁰We did this check for all the countries, but only report the results in case of a considerable effect.

the later period.²¹

For Slovakia the estimation results improve with the specification allowing for the structural break, however, they remain comparatively unstable. Although the band distance element satisfies our expectations, we cannot find any realistic inflation coefficients and the adjusted R-squared is relatively low. The specification may therefore be unfit to realistically model the Slovakian data. When we add a band distance element specific for the ERM2 period to the regression, this variable is almost zero (reflected by the insignificant coefficient for γ_{2B} in Table 5), which could either be due to the absence of pressure on the Slovak koruna during this period or due to changes of the central parity at times of pressure. In fact, the latter case is more likely as the central parity of the Slovak koruna was revalued twice during its ERM2 membership, and thus relieved pressures from the exchange rate from hitting the strong edge of the band.

The Slovenian authorities officially announced a managed floating exchange rate regime for the whole period before ERM2 membership. As there was no explicit change in the exchange rate regime, the specification with breaks would not add any value for this episode. In contrast, we uncover (and model) a policy switch when the Slovenian currency joins the ERM2-system. Officially, this was a change from a managed floating regime towards a comparatively flexible peg to the euro with very wide bands. Implicitly, however, it was a more pronounced policy shift from a de facto crawling band.²² As an alternative specification, we turn our attention to the fact that Slovenia's monetary policy, in contrast to the other countries in the sample, officially focused on monetary aggregates. Until 1997 the focus was mainly on base money and M1, but later it switched to M3 (and in 2001 Slovenia even adopted a two pillar strategy). We build in these subperiods with several dummy variables and come to the following conclusion: The inflation coefficient is relatively stable over all periods, the output coefficients become significant but are wrongly signed and the coefficient of the money gap²³ is only significant in the third period. Consequently, we cannot retrieve the policy attention for monetary aggregates as it was officially stated.

²¹For checking the robustness we shortened the sample period. This does not affect the results.

²²The band distance variable in this setting only applies for the ERM2-period. Since the exchange rate during did not move close to the margins, the band distance values are negligible and were thus not included in the estimation.

²³The band distance variable in this setting only applies for the ERM2-period. Since the exchange rate during did not move close to the margins, the band distance values are negligible and were thus not included in the estimation.

5 Conclusions

Many central banks in emerging market economies may pay special attention to exchange rate movements, even though they do not officially claim to target the exchange rate. In order to influence exchange rate developments the central bank can basically use two instruments: foreign exchange interventions and interest rate changes. We focus on the later monetary policy instrument by estimating open-economy monetary policy rules, in order to analyse to which extent central banks in Central and Eastern Europe have given the exchange rate a special role in their interest rate decisions.

We estimate monetary policy rules based on a cointegration approach and explicitly take into consideration shifts in exchange rate regimes. The influence of the exchange rate on the interest rate setting behaviour of central banks in CEEC differs strongly between regimes. During periods of more rigid exchange rate arrangements the influence of the exchange rate dominates, i.e. the interest rate policy is mainly influenced by the distance to the intervention margins on which the central bank has to react in order to keep the peg working. During the time periods of more flexible exchange rate arrangements we find a stronger focus on inflation, namely, on the deviation of domestic inflation from the inflation rate set by the Maastricht criterion. This is, in particular, the case for the Czech Republic, Poland and Romania. The inflation coefficient for Slovenia also satisfies the Taylor principle, whereas for Hungary the coefficient is below, but not significantly different from unity.

Slovakia remains a special case in the sample. The inflation coefficients do not satisfy the Taylor principle, and it seems that there has been an ongoing focus on exchange rate movements after switching from a fixed exchange rate regime to a managed float. The interest rate setting behaviour indicates an implicit peg, while the two revaluations of the central parity also indicate the challenges to the implicit peg during ERM2-membership.

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Table 1: Official monetary policy strategies for Central and Eastern European Countries.

Czech Republic		Hungary		Poland	
1994–1997	Exchange rate and monetary targeting (credit volume and M2)	1994–2002	Exchange rate targeting	1994–1998	Exchange rate targeting
1998–2001	Net inflation ^a targeting	2002–	Inflation targeting (CPI annual average) ^f	1998–	Inflation targeting (end of year CPI inflation)
2002–	Headline inflation targeting with linear and declining target band				
Romania		Slovakia		Slovenia	
1994–7/2005	No official commitment to a monetary policy strategy	1994–1998	Exchange rate targeting	1994–1995	Base money targeting
8/2005–2008	Inflation targeting	1998–2008	Informal inflation targeting	1996	Base money and M1-targeting
		11/2005–12/2008	ERM-II	1997–2000	M3-targeting ^b
		2009–	Euro system		
				2001–2006	Two-pillar strategy ^d
				06/2004–12/2006	ERM-II
				2007–	Euro system

^a Headline inflation minus regulated prices and changes in indirect taxes.

^b In Slovenia also including foreign exchange deposits of private households.

^c Exchange rate targeting continues in a wide band ($\pm 15\%$).

^d Similar to the strategy of the European Central Bank the Bank of Slovenia bases its monetary policy indicators on two pillars, i.e. indicators of liquidity, and other economic indicators.

Table 2: Official exchange arrangements for Central and Eastern European Countries. Source: IMF, Annual Report of Exchange Rate Arrangements and Restrictions, various issues.

Czech Republic		Hungary		Poland	
01/01/1994– 29/02/1996	Basket peg, 65% DEM, 35%USD, Band: $\pm 0.5\%$	01/01/1994– 31/12/1996	Crawling peg ^a , 70% Ecu, 30% USD, Band: $\pm 2.25\%$	01/01/1994– 15/05/1995	Crawling peg, 45% USD, 35% DEM, 10% GBP, 5% FRF, 5% CHF Band: $\pm 1\%$
01/03/1996– 26/05/1997	Band: $\pm 7.5\%$	01/01/1997– 31/12/1999	70% DEM, 30% USD	16/05/1995– 24/02/1998	Band: $\pm 7\%$
27/05/1997– present	Managed float	01/01/2000– 30/04/2001	100% EUR	25/02/1998– 31/12/1998	Band: $\pm 10\%$
		01/05/2001– 30/09/2001	Band: $\pm 15\%$	01/01/1999– 11/04/2000	45% USD, 55% EUR
		01/10/2001– 25/02/2008	Peg to EUR, Band: $\pm 15\%$	12/04/2000– present	Free float
		26/02/2008– present	Managed float		
Romania		Slovak Republic		Slovenia	
Since 01/01/1994	Managed float	01/01/1994– 31/12/1996	Basket peg, 60% DEM, 40% USD, Band: $\pm 1.5\%$	01/01/1994– 26/06/2004	Managed float
		01/01/1997– 30/09/1998	Band: $\pm 7\%$	27/06/2004– 31/12/2006	ERM2
		01/10/1998– 24/11/2005	Managed float	Since 01/01/ 2007	Euro area member
		25/11/2005– 31/12/2008	ERM2		
		Since 01/01/2009	Euro area member		

^a Until 16.3.1995, the NBH devalued in discrete steps.

Figure 1: Statistical design of Band Distance Measure

Derivation of the band distance element from the historical exchange rate peg values. In the upper segment of each graph, the solid black lines represent the strong and weak edge, the gray line denotes the central parity and the market rate is given by the dotted line. In the lower segment, we depict the band distance.

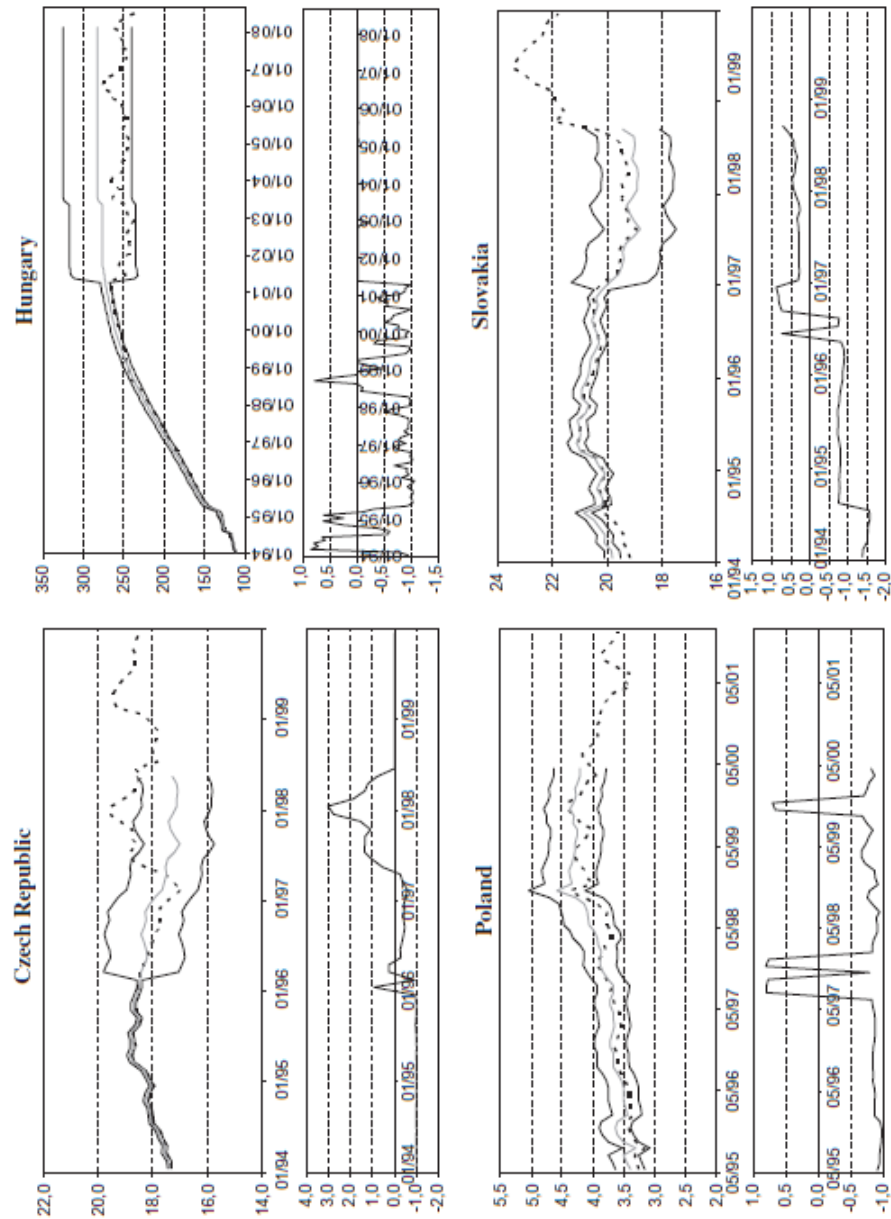


Table 3: Bounds testing approach for cointegration.

Bounds testing explicitly allows for a mix of $I(1)$ and $I(0)$ variables, as standard statistical inference based on conventional cointegration tests is no longer valid.

Table 3
Bounds testing approach for cointegration.

Country	Optimal lag length	F-statistic	Lower bound	Upper bound
Czech Republic	1	4.522	3.120	4.250
Hungary	5	4.620	3.120	4.250
Poland	1	4.507	3.120	4.250
Romania	6	5.274	3.470	4.570
Slovakia	3	5.189	3.120	4.250
Slovenia	4	4.996	3.470	4.570

Table 4: Estimates of the cointegrating vector

Coefficients	Czech Republic			Hungary			Poland			Romania			Slovakia			Slovenia		
	Time-invariant	Structural break	Time-invariant	Structural Break	Time-invariant	Structural break	Time-invariant	Structural break	Time-invariant	Structural break	Time-invariant	Structural break	Time-invariant	Structural break	Time-invariant	Structural break		
α_π	1.133 (0.000)	-0.120 (0.805)	0.878 (0.000)	0.868 (0.000)	0.685 (0.000)	0.555 (0.000)	0.324 (0.002)	0.118 (0.157)	0.239 (0.125)	0.316 (0.527)	1.306 (0.000)	0.316 (0.527)	1.306 (0.000)	0.316 (0.527)	1.453 (0.000)	0.316 (0.527)		
$\alpha_2 \pi$	-	1.021 (0.000)	-	0.903 (0.000)	-	1.134 (0.000)	-	1.120 (0.000)	-	0.344 (0.002)	-	0.344 (0.002)	-	1.050 (0.059)	-	1.050 (0.059)		
β_Y	-0.199 (0.133)	-0.093 (0.342)	-0.121 (0.119)	-0.194 (0.007)	0.031 (0.666)	0.058 (0.505)	-0.251 (0.378)	-0.940 (0.150)	0.303 (0.352)	0.118 (0.666)	-0.526 (0.001)	-0.940 (0.150)	0.303 (0.352)	-0.526 (0.001)	-0.526 (0.000)	-0.526 (0.000)	-0.526 (0.000)	
β_{2Y}	-	-0.331 (0.018)	-	-0.108 (0.170)	-	0.060 (0.465)	-	-0.006 (0.981)	-	-0.160 (0.478)	-	-0.160 (0.478)	-	-0.160 (0.478)	-	-0.430 (0.008)	-	
γ_B	1.628 (0.085)	2.619 (0.007)	1.072 (0.032)	1.695 (0.000)	1.325 (0.004)	1.381 (0.008)	-	-	3.636 (0.033)	-	-	5.908 (0.001)	-	-	-	-	-	
δ_S	0.338 (0.035)	0.285 (0.137)	0.120 (0.203)	0.152 (0.489)	-0.015 (0.044)	-0.015 (0.307)	-0.506 (0.000)	0.906 (0.554)	1.002 (0.207)	1.208 (0.163)	1.443 (0.109)	1.208 (0.163)	0.8324 (0.403)	1.208 (0.163)	1.443 (0.109)	1.443 (0.109)	1.443 (0.109)	
δ_{2S}	-	0.243 (0.210)	-	0.095 (0.418)	-	-0.000 (0.999)	-	-0.380 (0.093)	-	1.245 (0.037)	-	1.245 (0.037)	-	-3.462 (0.222)	-	-3.462 (0.222)	-	
ψ_D	-	-9.741 (0.017)	-	-1.811 (0.034)	-	-6.091 (0.000)	-	-53.466 (0.000)	-	-7.002 (0.050)	-	-7.002 (0.050)	-	-7.002 (0.050)	-	-7.002 (0.050)	-	
R_{adj}^2	0.545	0.653	0.771	0.858	0.613	0.819	0.391	0.531	0.093	0.232	0.673	0.232	0.576	0.232	0.673	0.232	0.673	
DW	1.860	1.759	1.454	1.300	1.313	0.909	1.402	1.245	2.170	1.882	2.135	1.882	2.234	1.882	2.135	1.882	2.135	

"Time-invariant" is the estimate for the benchmark Eq. (4) $i_t = c + \alpha\pi_t + \beta Y_t + \delta\Delta S_t + \gamma b_t + \sum_{k=1}^j (\alpha_{mk}\Delta\pi_{t-k} + \beta_{mk}\Delta Y_{t-k} + \delta_{mk}\Delta^2 S_{t-k} + \gamma_{mk}\Delta b_{t-k}) + \eta_t$.
 "Structural Breaks" for Eq. (5) with regime-dependent coefficients: $i_t = c + \psi d_t + \alpha_1 \pi_{1t} + \alpha_2 \pi_{2t} + \beta_1 Y_{1t} + \beta_2 Y_{2t} + \delta_1 \Delta S_{1t} + \delta_2 \Delta S_{2t} + \gamma b_t + \sum_{k=1}^{j-1} (\alpha_{mk}\Delta\pi_{t-k} + \beta_{mk}\Delta Y_{t-k} + \delta_{mk}\Delta^2 S_{t-k} + \gamma_{mk}\Delta b_{t-k}) + \eta_t$.
 We employ the following break dates: the Czech Republic (27/05/1997), Hungary (1/05/2001), Poland (25/03/1999), Romania (31/12/1998), Slovakia (1/10/1998) and Slovenia (27/06/2004). All of these represent a move into more "flexible arrangements, except for Slovenia (ERM2). P -values in parenthesis. Estimates of the auxiliary coefficient c not reported. Bold values denote the significant α of the specific coefficient (on a five percent significance level).

Table 5: Estimates of the cointegrating vector for alternative specifications

	Czech R.	Hungary	Poland	Romania	Slovakia	Slovenia
$\alpha_1 \pi$	0.799 (0.005)	0.772 (0.000)	0.528 (0.000)	0.100 (0.187)	0.298 (0.548)	1.295 (0.000)
$\alpha_2 \pi$	1.115 (0.000)	0.967 (0.000)	1.057 (0.000)	0.983 (0.000)	0.350 (0.001)	1.083 (0.002)
β_{1Y}	-0.125 (0.144)	-0.053 (0.591)	0.026 (0.774)	-1.030 (0.106)	0.110 (0.682)	-0.628 (0.000)
β_{2Y}	-0.166 (0.024)	-0.123 (0.151)	0.063 (0.464)	0.082 (0.588)	-0.171 (0.443)	-0.412 (0.005)
γ_B	1.006 (0.041)	1.085 (0.014)	1.301 (0.009)	-	5.973 (0.000)	1.196 (0.292)
δ_{1S}	0.167 (0.320)	0.168 (0.350)	-0.103 (0.001)	-0.526 (0.000)	-0.306 (0.895)	0.259 (0.929)
δ_{2S}	0.251 (0.043)	0.137 (0.177)	-0.107 (0.010)	0.324 (0.352)	1.225 (0.158)	-0.395 (0.432)
ψ_D	-1.361 (0.043)	-3.561 (0.003)	-6.683 (0.000)	-58.762 (0.000)	1.264 (0.037)	0.278 (0.179)
ψ_D	9.742 (0.000)	-	-	-	-7.184 (0.040)	-0.219 (0.008)
R_{adj}^2	0.708	0.849	0.814	0.581	0.239	0.683
DW	0.899	1.434	0.933	1.396	1.860	2.052

P-values in parenthesis. Estimates of the auxiliary coefficient c not reported. We add a crisis dummy in the equation for the Czech Republic: $\hat{k} = c + \psi d_t + \psi d_t^* + \alpha_1 \pi_{1t}^* + \alpha_2 \pi_{2t}^* + \beta_1 Y_{1t}^* + \beta_2 Y_{2t}^* + \gamma b_t + \delta_1 \Delta s_{1t} + \delta_2 \Delta s_{2t} + \sum_{k=1}^{k-1} (\alpha_{mk} \Delta \pi_{t-k} + \beta_{mk} \Delta y_{t-k} + \gamma_{mk} \Delta b_{t-k}) + \eta_t$. We opt for the classical structure of Eq. (5) for Hungary, Poland and Romania, but with their country-specific characteristics. Break date adjustments for Hungary (01/06/1999) and Romania (1/08/1999), otherwise this date complies with the information in Table 4. In Poland we examine the length of the band distance. Bold values denote the significance of the specific coefficient (on a five percent significance level). The Slovakian estimation also incorporates bands for ERM2: $\hat{k} = c + \psi d_t + \alpha_1 \pi_{1t}^* + \alpha_2 \pi_{2t}^* + \beta_1 Y_{1t}^* + \beta_2 Y_{2t}^* + \delta_1 \Delta s_{1t} + \delta_2 \Delta s_{2t} + \sigma_{3M} M_{3t} + \sum_{k=1}^{k-1} (\alpha_{mk} \Delta \pi_{t-k} + \beta_{mk} \Delta y_{t-k} + \delta_{3M} \Delta^2 s_{t-k}) + \eta_t$. Finally, for Slovenian we add monetary variables: $\hat{k} = c + \alpha_1 \pi_{1t}^* + \alpha_2 \pi_{2t}^* + \beta_1 Y_{1t}^* + \beta_2 Y_{2t}^* + \delta_1 \Delta s_{1t} + \delta_2 \Delta s_{2t} + \sigma_{3M} M_{3t} + \sigma_{3M} M_{3t} + \sum_{k=1}^{k-1} (\alpha_{mk} \Delta \pi_{t-k} + \beta_{mk} \Delta y_{t-k} + \delta_{3M} \Delta^2 s_{t-k} + \sigma_{3M} \Delta M_{t-k}) + \eta_t$.

Chapter 2

Hard to let go: The procyclical effect of memory on financial cycles

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Abstract

Abstract: Our main goal is to apply the basic idea that emotions are capable of impacting our memory in the storyline of an animal spirit driven financial cycle. We work cross-disciplinary and integrate elements from the field of psychology, neurology and evolutionary biology, in order to better understand the (economical) phenomenon of self-fulfilling and self-enhancing downward (or upward) cascades in the economy. Our analysis starts off with an investigation of general socio-economic variables, and then moves over to a more specific, financial setting. For each of these domains, we incorporate several recall tests to unravel whether affective stimuli can have a nameable impact on our recollection, and hence shape our sentiments and expectations, potentially even affecting our decision-making. Such a self-enforcing mechanism can lead to powerful feedback effects during downturns, when we are surrounded with negative news items.

JEL Classification: D87, G01, G02, E32

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1 Introduction

We provide an investigation into the role of emotions in our everyday lives. Our initial response to the environment is often affective, and although it might seem unpolished and nebulous, it has the potential to set the tone for our ensuing relations with the environment (Ittelson, 1973; Zajonc, 1980). Hence, emotions are endowed with the ability to infiltrate our run of the mill choices, even if we are unconscious about them, or unwilling to recognize them (Cohen, 2005). Seemingly irrational behaviour might therefore be better understood after evaluating the versatile functions that emotions can perform, or once performed during our evolution (Shiv et al, 2005).¹

In our study, we test the hypothesis whether such fleeting feelings could have a profound impact on our decision-making, specifically through the way our memories are being processed. If emotional events are remembered more poignantly, these experiences might also influence our subsequent behaviour more thoroughly, as they tend to overshadow our judgment when we attempt to make future plans. Such a mechanism, which transforms affective stimuli into comparatively more salient memories, could thus be an important element that reinforces the procyclicality of the economy. For example, when we are in a downward cycle, we are often confronted with gloomy news items. Since these negative stimuli are more easily remembered, they lead us to overweigh them in our subsequent decisions. As a consequence, we are prone to adapt our sentiment and our expectations accordingly, leading to a loss of confidence which can even enforce the initial crisis to become more virulent. All these components (emotions, memories, news, expectations, sentiment, confidence and decision making) seem to be innately connected with each other (creating a highly endogenous environment), and can thus propagate existing trends, and even self-enforce them.

Our framework should hence allow us to incorporate emotions into the general macroeconomic framework. However, we do not provide an all-encompassing theory on the behavioral or neural background of financial cycles, as we merely focus on one aspect (more specifically, the way our memory can be affected through emotions). Hence, we only provide a first step towards integrating different fields and adapting our way of thinking. Moreover, we are not claiming that this is the only channel (as we do not want to diminish the importance of, or to compete with, the classical economic channels, as these have their own merit).²

¹A similar narrative of looking for explanations of seemingly erratic behavior can be found in Ramachandran (2011). However, his focus lays more specifically on psychiatric anomalies.

²Borio (2012), among many others, provides an insightful analysis on the economic causes of

Nonetheless, emotions do seem to have the potential to profoundly impact sentiment and expectations, which are crucial elements in determining many micro and macro decisions, and can therefore not be neglected. We provide insight into a novel channel through which such a pass-through of emotions can be accomplished, by adapting the quality of our recollections. Such mnemonic benefits are attainable because affective stimuli have the potential to trigger cognitive and neural processes that affect the stages of memory encoding and consolidation, with the amygdala as one of the main protagonists (Hamann, 2001). Hence, we integrate several cross-disciplinary concepts (derived from the behavioral and neurologic literature) into our analysis on (economic) decision making.

The remainder of the paper is organized as follows. In section two, we describe how emotional stimuli can impact the memory, by unraveling the behavioral, neural and evolutionary mechanisms that accompany this process. Next, section three investigates the role of emotion in (economic) decision making, and introduces a procyclical effect of emotion. Our research, in section four, starts initially by examining whether emotions can truly affect our memory in every day decisions, and then (in section 5) probes more thoroughly whether emotions can also impact our decision making (through this enhanced memory heuristic). Finally, in section six, we conclude and discuss some elementary (policy) implications.

2 Memory and negative emotions

2.1 Basic Mechanism

Our ability to remember specific events depends prominently on the emotion we experience during these episodes. Typically, emotional information has a substantial comparative advantage over neutral information (Anderson, Yamaguchi, Grabski and Lacka, 2006; Buchanan and Adolphs, 2002; Hamann, 2001; Kensinger, 2009; Murray and Kensinger, 2012). Kensinger and Schacter (2008) distinguish three dimensions through which emotion can shape our memory. Firstly, the absolute number of events which are recalled increases. Secondly, there is a surge in the subjective vividness of these events. Finally, memories seem to contain a more accurate recount of the details which were encountered. This mnemonic discrepancy prevails because emotional events engage a different and more efficient mechanism when being processed to our memory, in comparison with the more traditional pathways on which neutral events depend (Kensinger, 2009; Hyde and Jenkins, 1969).

boom and bust cycles, and provides valuable answers on how to deal with them.

The memory enhancement effects of emotions have two distinct components. Emotions may intervene in our memory at two separate phases in time. On the one hand, they facilitate the encoding process, both by capturing our attention and by enhancing our perception. We tend to linger longer over these type of stimuli, thus snatching our focus away from competing (non-emotional) impulses (Brosh et al, 2013; Reisberg and Heuer, 2004; Sharot and Phelps, 2004). On the other hand, emotion stimuli have the quality to boost up memory retention by intervening at the consolidation stage, thereby allowing memories to become more permanent. However, this improvement can only be accomplished gradually, and should therefore only be tangible after an extended period (Hamann, 2001; Kleinsmith and Kaplan, 1963). Taking into consideration both of these memory-enhancing dimensions, retrieval of emotional events should be comparatively easier than their neutral equivalents (Kensinger, 2009).

However, emotion does not always enhance our recollections unilaterally over all aspect of an episode. Some elements are better remembered because of their emotional salience, while others are easier forgotten (Buchanan and Adolphs, 2002; Kensinger and Schacter, 2008; Reisberg and Heuer, 2004). While emotional salience allows some elements to be better remembered, others are more likely to be forgotten. As a result, emotion might only enhance the gist of the story, thereby losing sight of more peripheral details.³ Such a trade-off may depend on the occurrence of an attention magnet, without which the memory improvement would be more ubiquitous (Laney et al, 2004).

However, the precise impact which emotional information can have on the memory of related neutral details has been subject to much debate. Firstly, Easterbrook's (1959) cue-utilization hypothesis postulates that the presence of emotional components might thwart the recollection of peripheral details, by narrowing the scope of available attention (through a reduction of available cues which can be processed). Both positive and negative emotions receive a higher processing priority, thus draining valuable resources⁴ (Christianson, 1992; Levine and Edelman, 2009; Meinhard and Pekrun, 2003; Reisberg and Heuer, 2004). In contrast, MacKay's priority-binding theory allows the retrieval of peripheral details to be enhanced through their binding with emotional items, thus enjoying similar processing gains and taking advantage of the mnemonic benefit which are materialized by the emotional

³There are several theories that explain which elements of an event might show improvement in the retention of memories due to emotions.

⁴An intuitive way of understanding this premised is illustrated through the concept of the "weapon focus", whereby witnesses/bystanders to violent crimes are often incapable of describing the characteristics of the perpetrator, as a consequence of fixing their attention too much on the weapon.

stimuli. Such prioritized binding towards elements of the context might thus have a beneficial effect for their subsequent retrieval (Hadley and MacKay, 2006; MacKay and Ahmetzanov, 2005; MacKay et al., 2004). Both theories have been able to yield empirical validity, depending on the experimental settings. Whether or not there exists a detrimental effect of emotion on details, might therefore depend on the subjective value these elements have for the observer.

Kensinger (2007) proposes a first solution to this deadlock by distinguishing between intrinsic and extrinsic contextual details, whereby the former are closely attached to the emotional item and therefore basking in its superior attention processing, whereas the latter are conceptually, spatially and temporally removed of the emotional stimuli and therefore being pushed aside in a zero-sum fashion (Kensinger and Schacter, 2006, 2008; Kensinger, Garoff-Eaton and Schacter, 2007). Closely related is Mather’s (2007) distinction between within-item features (enhanced by arousal) versus between-item features (receiving no mnemonic benefit). Although there is no perfect match between the two theories, they both share the belief that “emotion leads to focal enhancements in memory, and these focal effects arise because of the way in which arousing info is attended and bound during encoding and consolidation” (Kensinger, 2009, p. 102). Finally, the Arousal Biased Competition (ABC) theory (Mather and Sutherland, 2011) rephrases the question in terms the amount of priority each individual element evokes within the observer, claiming an enhanced perception for high priority information and a fading perception for low priority counterparts.

2.2 Neural background

The improvement of our memory for affective stimuli is orchestrated by specific neural and hormonal mechanisms. The amygdala and related limbic areas are quintessential in this process, (and intervene at every stage, from encoding through consolidation to retrieval) (Hamann, 2001). The amygdala represents a small almond-shaped cluster of nuclei situated in the medial temporal lobe, adjacent to the hippocampus (Sharot and Phelps, 2004). The amygdala can affect memory by dispatching projections (through cables of axons rapped in myelin) to other regions of the brain involved in memorizing, most prominently the hippocampus (Sapolsky, 2011), but also by influencing the hypothalamus to release stress hormones related with the adrenergic system (McGaugh, 2000, 2004).

The more intense the activation of the amygdala is for affective experiences (in comparison to neutral events), the more pronounced the improvement is which we can monitor for the episodic memory (Anderson et al, 2006). This correlation be-

tween increased amygdala processing and efficacious encoding holds both for positive and negative high-arousal items (Kensinger and Schacter, 2008). However, a sufficient level of amygdala activation would be necessary in order to ameliorate the memory processes and achieve better recollection of emotional events (Canli, 2000).⁵ Furthermore, the impact of amygdala stimulation during encoding and consolidation on consequent recollection might hinge on the specific type of detail, with some aspects of an experience being remembered well, and others being forgotten (Kensinger, 2007).⁶

Although the amygdala is crucial in moderating the memory effects for emotional elements, it can only influence the mnemonic process through its interaction with other brain regions, most prominently through the bi-directional connections between the amygdala and the hippocampus (Anderson et al, 2006; McGaugh, 2004). Both of these limbic regions exhibit highly correlated levels of activity during the encoding of emotional content. Moreover, the amygdala, as the most abundantly intertwined subcortical region of the brain, has the potential to influence the functioning of the sensory cortices to achieve the desired level of attention (Kensinger and Schacter, 2008). Finally, the versatile connections of the amygdala also trigger the release of adrenal stress hormones (for example, epinephrine or cortisol) as well as regulate the distribution of glucocorticoids (Mackay and Hadley, 2005; Kensinger, 2009).

2.3 Evolutionary Development

An event which surpasses a certain emotional threshold is likely to have a substantial importance for our existence. From an evolutionary perspective, it would therefore be expedient, if our memory would be enhanced for such stirring occurrences, thereby providing a support for future encounters (Hamann, 2001; Brosh et al, 2013). Consequently, if emotions signal distress or danger, accentuating them in our memory could provide a valuable warning system (Stone et al 2005). Hence, the evolution of our memory mechanism has facilitated the consolidation and retrieval process of affective information (LeDoux, 1996). As both positive and negative items could possess importance for our future success, the valence of the affective flavor is trivial, and both types of stimuli should enhance attention and consequent memory channels (Kensinger and Schacter, 2008) Moreover, as we are surrounded with an abundance of external stimuli, it would be indispensable to possess such a mecha-

⁵This finding, indicating a minimal arousal threshold, bodes well with the Arousal biased Competition theory, which emphasizes that high priority stimuli succeed best at modulation the memory processes

⁶Such a focus would resonate better with Easterbrook's (1959) cue-utilization hypothesis, or Kensinger's (extrinsic/intrinsic) and Mather's (within/between) conceptualizations.

nism, which helps us keep focus, most importantly when facing perilous situations (Mather and Sutherland, 2011).

The development of our prefrontal cortex, and its ensuing ability for our cognition, has created many new technologies together with an innovative social architecture, both of which are becoming more widespread. These changes have transformed our environment in such a dramatic manner that evolutionary older mechanisms in our brain may no longer operate proficiently. Typically, emotional segments of our brain have relied on such highly conserved systems in our brain, which were once indispensable for our survival. However, due to the changed setting in which they now operate they can no longer consistently guarantee optimal outcomes (Cohen, 2005). Shiv et al (2005) refer to this phenomenon as the ‘dark side’ of emotions in decision making, and point to the fact that, albeit the neural network that sustains human emotions has evolved for survival goals, there are conditions in which a spontaneous emotional reaction could better be subdued.

“Whether you are that zebra running for your life, or that lion sprinting for your meal, your body’s physiological response mechanisms are superbly adapted for dealing with such short-term physical emergencies”⁷ (Sapolsky, 1994, p. 6). The amygdala has been evolved to provide for an immediate ‘fight or flight’ response and it was shaped during a period where there was no consequence in befuddling a false alarm (Bechara, 2005; Ledoux, 1996). If the treat of the lion seemed to be wrong, the zebra was still unharmed by running away. However, in our current developed society (and most certainly in the economic world, for example in asset markets) the amygdala might induce overreactions which could have costly consequences.

Nonetheless, the fact that economist have been able to devise the concept of the homo economicus (rational agents) could render us optimistic, as its mere creation should imply that higher cognitive capabilities might allow us to overcome such intuitive response where necessary (Cohen, 2005). In contrast, we should simultaneously be warned against the belief that we can fundamentally change our behavior by simply wearing such knowledge as a talisman (Cowen, 2009).

3 Methodology

3.1 Emotions in economics

When Bentham (1789) originally presented the concept of utility, his theory was grounded on the idea that agents conceived values of wealth by comparing the pain

⁷Both Zajonc (1980) and Bechara (2005) provide similar intuitive examples.

and the pleasure that certain actions would yield, and thus emotions had a conspicuous role in this newly developing field of economics (Loewenstein, 2000). However, neoclassical economist rapidly became disgruntled with utility's theoretical foundations, since emotions had a flawed history, both in psychology and neuroscience, with major discrepancies in their definition, value and applicability (Elster, 1998). Consequently, they purged the concept of utility from its emotional substance, and derived an ordinal measure in combination with the theory of revealed preference, thus interpreting utility as an index of preference instead of pleasure (Bechara, 2005).

Hence, it should come as no surprise that the central premise of modern economic theory generally neglects the impact of emotions on decision-making. Agents are assumed to make rational decisions which maximize their utility and are in compliance with their long-term perspectives, updating their beliefs in a Bayesian way (Cohen, 2005). However, many aspects of our behavior (ranging from consumer to investor decisions) cannot easily be understood in this framework (Barberis and Thaler, 2003; DellaVigna, 2009).

If we attempt to scrutinize why agents deviate from the prescribed optimal behavior, there are two main strains of thought. Firstly, there is the possibility that our models are not flawed but merely incomplete, and that we have not yet uncovered all elements which influence utility. Secondly, and more intimately connected to our approach, agents might simply be incapable of performing a rational maximization of their utility, and therefore economic theory might benefit from being reintroduced to the concept of emotions (Cohen, 2005). Hence, the latter assumption would imply that decision making is not dispassionate but is instead profoundly swayed by feelings (Sokol-Hessner et al, 2013). Not surprisingly, the last few decades have brought a remarkable upswing among economists in their appreciation for emotions.⁸ However, there is little research on how emotions can affect the recollection of particular events, and hence influence their salience and their impact on decision-making (Peters, 2006). With our current study we try to fill this gap, as we believe that the occurrence of affect does heavily impact our decision process.

3.2 Procyclical effect of the memory heuristic during financial cycles

We have grown accustomed to believe that every decision we take is triggered by a cognitive process, thus underestimating the impact of visceral factors (Loewenstein,

⁸Although behavioral economics had initially mainly been inspired by cognitive aspects of psychology and has remained largely untouched by the rekindled attention for emotions (Lerner and Han, 2009).

2000). However, we can find little proof to maintain this hypothesis. Instead of comparing all the costs and benefits for various substitutes, we often follow our gut feeling and simply opt for the most cherished alternative, based on our affective feelings (Zajonc, 1980).⁹ Whenever we collect information about the different options, this merely serves as a justification *ex post*. Festinger (1964) poignantly remarks that dissonance merely exists when we do not execute a detailed analysis before the judgment was made.¹⁰

Emotions have the quality of impacting us instantly, and without any effort. Additionally, emotions allow a rapid judgment about our surroundings. These transient feelings wield powerful influences on evaluative judgments. Moreover, they allow us to formulate instant answers about issues that are too complex to analyze thoroughly (Keltner and Lerner, 2010). Hence, emotions seem to trickle into a wide variety of decisions, ranging from very trivial aspects (consumer choices) to more important subjects (life satisfaction) (Peters, 2006). The underlying neural systems of decision making also rely on limbic regions, most prominently on the amygdala and the insula. This overlap hints at a common neural mechanism underlying both choice and emotion (Sokol-Hessner et al, 2013).

Feelings are thus automatically being incorporated in our daily judgment as an influential source of information (Kahneman, 2003). Even irrelevant emotional states (or stimuli we are not aware of) can have a substantial impact on subsequent choices (Han and Lerner, 2009). Therefore we need to unravel in which circumstances emotions provide a disruptive noise in our decision process, and in which cases they could actually be useful (Shiv et al, 2005). Our study attempts to answer this important puzzle, and thus shed light on the impact emotions can have subsequent (socio-)economic decisions.

We are interested in unraveling the consequences of enhanced memory effects for affective stimuli in a real life economic context, and applying this knowledge to better understand the behavioral dynamics, which seem to be implicitly present in the context of financial cycles. Such an investigation has gained substantial importance as financial cycles, after a period of great moderation, have become more prevalent again, leading up to severe asset price and credit boom-bust cycles (Borio, 2012). We start off with the observation that downturns and upswings in the economy are usually accompanied with a plethora of news items, conveying many emotional stimuli. Usually, such events, which contain a strong emotional content,

⁹Both Simon (1955) and Gigerenzer (1999) highlight the importance of rules of thumbs or heuristics in decision making.

¹⁰Hastie and Park (1986), similarly, describe a search for supporting evidence after the decision is made.

are preferentially remembered, leading to an increase in the salience and availability of these experiences in the minds of all types of economic agents (Kensinger, 2007).¹¹ Not only do these affective stimuli grab our attention more ferociously, they also receive a preferential encoding in our memory (Hamann, 2001). Consequently, we overemphasize these events when we consult our memories, and look into the past, to form our expectations about the future (Peterson, 2007).¹² This process can lead to changes in our mood, sentiment and confidence level, even influencing our subsequent decision-making. For example, during a downturn, the disclosure of news about plummeting stock prices, might lead to salient and emotional memories, which are hard to shake off. Thus leading to an even stronger drop in our sentiment, which might induce us to react even stronger to the initial signal. As a result, the memory heuristic can propagate the existing cyclical motion in the economy, and worsen its effect on many real economic variables, affecting asset prices, investment and consumption decisions, etc. The resulting financial cycle can thus reach deeper troughs and higher peaks, merely by succumbing to this behavioral bias, thus creating an additional source of procyclicality. We visualize these linkages through a simplified flow chart in figure 1. The figure also portrays the ensuing macroeconomic effects and incorporates familiar behavioral elements into the storyline of the memory heuristic.

3.3 Macroeconomic role of expectations in the pass-through mechanism of the memory heuristic

A long tradition in macroeconomics highlights the importance of expectations for aggregate economic behavior, emphasizing that swings in optimism and pessimism are a predominant factor in driving business cycles (Milani, 2013). Pigou (1927) reverts to variations in the expectations of entrepreneurs, which he characterized as faulty judgments of optimism or pessimism, as the main instigator of fluctuations in the output levels. Similarly, Keynes (1936) introduces the concept of animal spirits¹³, allowing for changes in the expectations which diverged from rational decision making, to account for the cyclical motions in the economy. Beaudry and Portier (2013) recognize three ways of integrating sentiment in the macroeconomic framework. Firstly, the cyclical behavior might be fully ascribed to psychological causes.

¹¹We all have witnessed instances where we cannot shake off certain memories of affective experiences. Here, we examine their consequences on economic behavior.

¹²Beaudry and Portier (2013, pp. 84-85): “if agents are trying to infer the future state of the economy by looking at current economic activity, this could give rise to important feedback effects that come close to creating self-fulfilling prophecies.”

¹³This notion of animal spirits was recently popularized again by Akerlof and Shiller (2009).

Such erratic behavior should eventually be corrected by a crash, as there are no underlying changes in the fundamentals. Secondly, the macro-economy might be intrinsically unstable, allowing self-fulfilling cycles wherein outbursts of optimism (or pessimism) provoke a boom (or bust) thus justifying the initial optimism. Finally, agents might occasionally make errors in their judgment of fundamentals (noise), whereby the cycles are instigated by the noise in their predictions, thus leading to news-driven business cycles.

Moreover, recent empirical studies reveal a sizeable impact of sentiment on the macro-economy, with mood swings being liable for over fifty percent of business cycle fluctuations in hours and output (Beaudry et al, 2012), and exogenous changes in sentiment accounting for forty percent of historical U.S. business cycle fluctuations. Similarly, Angeletos et al (2013) describe an animal spirit shock (closely correlated with sentiment) as the main driver of business cycles, referring to the adagio: “believe it or not, it’s all about beliefs!”. The transmission of these shocks through communication is similar to the spread of fads and rumors, thus leading to boom-bust episodes (Angeletos and La, 2012). Closely related, Forni et al (2013) unravel that a large part of the fluctuations in GDP are caused by noise shocks, which explain up to one third of the variance in GDP, consumption and investment in the short and medium term, thus allowing a large role for animal spirits. Blanchard et al (2012) similarly acknowledges an important role for noise shocks in shaping the short term dynamics in aggregate activity.

Our analysis provides a micro-economic foundation for the role of sentiment in the cyclical pattern of economic behavior, thus incorporating behavioral elements into the business cycle literature. Moreover, the above results show the empirical relevance of understanding what governs our moods, and how this is intertwined with the current stance of the economy. The above mentioned salience and availability of emotional (positive or negative) stimuli (during upswing or downturns) which are induced by our memory heuristic, fit in elegantly into this narrative.

3.4 Adjacent behavioral heuristics

Our analysis is intrinsically linked to several behavioral biases, most notably availability and representativeness¹⁴, and allows a deeper understanding of their underlying dynamics.

First of all, our memory heuristic is close in spirit with, and one of the main

¹⁴Although there are many other heuristics which can be associated with, or clarified through, we merely want to focus on those elements which are relevant in the context of financial cycles. Hence, we do not provide an exhaustive list.

drivers of, the availability bias. This phenomenon may originate as a consequence of the fluency with which certain ideas come to mind, thus leading to an exaggeration of the probability attached to emotional or well-documented events (Wärneryd, 2001). We usually assess the significance of a specific event by the ease and emotional connotation with which we can retrieve this event from our memory (Schwarz, 2010). The visions we have in our mind do not yield a flawless view of the world, because our outlook on the probability of events is biased by the pervasiveness and affective quality of the information we are surrounded with (Slovic et al, 1981). Therefore, when considering the cyclical pattern of economic behavior, it's interesting to incorporate the idea of availability cascades (Kuran and Sunstein, 1999).

According to Kahneman (2011), such a cascade usually starts off with a minor news item, seizing the attention of a certain subgroup of people, which become alarmed. Their emotional response sparks off even more attention, leading to additional coverage by the media, thus reaching a bigger audience and inciting greater distress. Moreover, as the media strive to surpass their competitors with the most conspicuous headlines, the original content is blown out of proportion and the dangers attached to the original news event are greatly exaggerated. Therefore, the influence works in both directions, as on the one hand the media outlines the public interest, but on the other hand the media is also shaped by its audience (Slovic et al, 1981). Academics who try to moderate the agitated mood are mostly neglected, or accused of concealing the truth. Due to this self-fulfilling sequence of events, a minor event becomes a salient factor in the minds of many people. At this point, policymakers are forced to intervene, in order to settle down the public sentiment, hence absorbing resources from alternative applications, which have now been demoted (Kahneman, 2011).¹⁵ Our empirical analysis can thus be interpreted as an application of an availability cascade in economic behavior, unraveling the impact our memory can have in extending and reinforcing the cyclical patterns in aggregate activity.

Kunreuther (1978) applies the concept of availability to describe the pattern of insurance acquisition and safety measures after disasters. Citizens who were suffered from, or were in the vicinity of, a calamity are very alarmed after the events. After an earthquake, Californians become more careful, acquire insurance, and adopt safety measures. However, their memories of the event fade away over time, together with their fears, and they become more careless again. Hence, the dynamics of memory

¹⁵Of course, such a news cascade will usually have a fundamental factor that triggered it from the start. People do not all wake up one morning and decide to panic. However, sometimes minor events get blown out of proportion so severely, that the minor remedies, which would have sufficed at the start, are no longer operational once the cascade has reached full power.

are useful in understanding the cycles of disaster, worry, and complacency which are ubiquitous in the literature on large scale emergencies. If we apply this narrative to the notion of risk taking on financial markets, as described by Altunbas et al (2012), we can again discern an important role for the availability and salience of memories, thus adding to the literature on the risk taking channel. Investors become (overly) careful after an eventful financial crisis. But over time, once the recollections fade away, investors become more careless again, hence yielding a procyclical effect of our memory on financial cycles.

A second type of behavioral bias which is closely connected with our memory heuristic is the representativeness bias. Gilovich (1991, p. 18) illustrates the characteristics of this behavioral phenomenon comprehensibly: “Representativeness is a tendency to assess the similarity of outcomes, instances and categories on relatively salient and even superficial features, and then to use these assessments and similarity as a basis of judgment. People assume like goes with like.” Hence, it refers to the inclination we frequently succumb to when we tend to distinguish patterns in the data that is actually completely random. A well-known example is the belief in the hot hand anomaly in basketball, where spectators (and even experienced coaches) fondly believe that players score in streaks, thus urging their team frantically to pass the ball to the player who is being successful at that instance (Tversky en Gilovich, 1989). A similar type of behavior is observed in finance, where money is often transferred into funds that have recently outperformed the average benchmark, and moves away from those that have done badly, thus abetting the existing temporary momentum effects (Taffler, 2010). In other words, we fail to allow for regression towards the mean, whereby the values return to their long term averages.

The representativeness bias originates from our tendency to overweigh salient experiences in our future forecasts (Peterson, 2007). Welch (2001) examined the estimates of professors on the expected annual equity risk premium for the next thirty years through a number of surveys. He uncovered that recent market price trends strongly influenced their future estimates. Hence, also academics seem to be vulnerable to this instinctive behavior. Barberis (2012) signals that representativeness might have played an important in the evolution of the house prices preceding the recent financial crisis, by reinforcing the belief that house prices would keep going up, because they had been mounting persistently for several years. Representativeness thus embodies a possible externality which our memory heuristic can trigger by influencing the way we form our beliefs and set our expectations, and has the potential to invigorate cyclical patterns in economic activity by reinforcing momentum effects.

4 Research

In contrast to the existing behavioral or neurologic literature related to the impact of emotions on memory, we do not test the impact of abstract emotional stimuli on memory. Classically, subjects are confronted with (pairs of) words (MacKay et al, 2004), stories (Laney et al, 2004), pictures (Kensinger and Schacter, 2007), movies (Kensinger, Garoff-Eaton and Schacter, 2007), historical events (Sharot and Phelps, 2007) with and without affective connotation, after which a recall test or a recognition test is executed, and the relative performance is analyzed. Typically, emotional stimuli are remembered more accurately, but also more vividly, both for positive and negative triggers (Mather and Sutherland, 2007). However, the improved recollection does not always hold for all the elements of the experience, and sometimes only the core (intrinsic/within) details receive the mnemonic benefits, due to a narrowing of the focus (Kensinger, 2009).

Although these experiments provide valuable information (and set out the basic framework in the field of effective memory enhancements), we attempt to adapt this setting by intervening directly in the lives of our participants, and by confronting them with personally relevant emotional news facts. Hence, a whole group of people is similarly affected by a specific event that concerns them innately, allowing us to look at the consequences in their recollection, and subsequent behavior. Specifically, we examine the impact of (socio-)economic events on the memory, as we believe that downward trends in the economy can be fortified through enhanced recollection for these type of experiences, thus affecting our sentiment and expectations, and prolonging (and even enhancing) the negative spiral.

We provide three separate experiments, each time focusing on a different socio-economic element, and each time interrogating a different group of participants. The first two are similar in nature. At the outset of the experiment, we provide our subjects information, respectively on their schooling performance or on their labor market conditions. In both cases, this material is presented as an official document, claiming to have been published by an official government body (thus putting more weight on the affective content). Both groups subsequently perform a recall test on the information they were received. The performance on this test is compared with a control group. The latter receives the exact same information, but in their case this centers around a comparable (but more distant) peer group, which should leave them neutral. Hence, both of these experiments provide us with a preliminary understanding on how real life (socio-)economic events can impact a certain group.

In the third experiment the subjects initially perform an investment exercise, which yields a specific outcome (returns, standard deviations, etc.). This allows us

to separate them in different subgroups, depending on how they performed on their investments. We grouped participants based on valence (high, neutral versus low), as well as based on arousal strength (extreme percentiles versus neutral values). We examined how these different subgroups performed on a memory test, focusing on different financial ratios. Consequently, we performed a ‘delayed’ memory test (after a one month period) in the same setting. This allows us to investigate what the precise channel is through which the mnemonic benefit is established. If we consider the consolidation process, we have to allow more time to allow these neural processes to have their full effect. Additionally, and most importantly, we investigate whether the affective event (and complementary enhanced recollection) can have a significant impact on the sentiment and expectations of the participants. Such a mechanism could lead to spill-over effects that would even affect their decision-making. Thus, emotional stimuli could influence real economic choices, simply through the impact they have on memory. Economic downturns could therefore experience self-enhancing and prolonging effects, merely through the negative emotions they create.

4.1 Quantifying Effects of Emotions on Memory

Participants

One hundred and three undergraduates from Ghent University¹⁶ (60 female and 43 male; mean age = 20.9 years, SD = 0.8) participated in the experiment. The respondents were randomly assigned to one of two conditions, either receiving emotional stimuli (n = 59), or receiving neutral stimuli (n = 44). The subjects were informed that they had to engage in reading a short segment about school performance, and subsequently answer some questions concerning this information.

Design and Procedure

The participants were presented a short official document (approximately one page) appearing to have been published by the Committee on Education of the Flemish community. It contains information on five different topics (copy behavior, grammatical level, quality of tasks, English adequacy, team work) each incorporated in a separate paragraph, with each paragraph containing two different numerical values (except the last two, which merely featured a description). We manipulated the document so that all of the presented trends were negative, thus giving the readers a dim view. The participants were randomly divided in two separate groups. The first group simply read about the educational performance of the group to which

¹⁶More specifically, from the department of applied economics

they specifically belonged (‘negative’ emotional information). The second ‘placebo’ group was confronted with exactly the same text, however, now covering the educational performance of a related (but more remote) field of study, towards which they should be more indifferent (neutral information). We allowed our subjects to take in the information during a fifteen minute interval, which was followed by another fifteen minute waiting period (as we wanted to allow some time for the different neural mechanisms to kick in), before they could precede answering.

We requested information from our respondents on three different aspects. Firstly, we examined the mood of the participants on thirteen different topics¹⁷ with scales from one to five. Secondly, and most importantly for our research question, we asked the participants to recall numerical values on copy behavior, grammatical level and the quality of tasks, as we want to examine the influence of affective versus neutral news concerning schooling on the memory performance of our participants. Specifically, we ask them to provide the best possible guess on the committee value, but additionally we also inquire what they think would be a more fitting value, in their subjective opinion.¹⁸¹⁹ Finally, we collect socio-economic and demographic information²⁰ on our subjects, which can potentially affect our research question, and thus enter our empirical framework as covariates. More specifically, we incorporate age, gender, origin, income, religion, commuter (vs. local student) dummy, and a credibility dummy (highlighting whether or not the respondent finds the document Flemish Committee in line with their beliefs) We also include our mood variables as covariates, but we apply a principle component analysis to reduce their dimension, and thus extract four components.²¹ During this procedure no communication was allowed and all participants had to perform the tasks individually. The task was performed in an university aula as we wanted to monitor our subjects during the task, as it was prohibited to take notes or collaborate with peers.

¹⁷Resentment, regret, shame, displeasure, anger, injustice, contempt, pity, confidence, calm, excitement, impatience, involvement

¹⁸Thus, next to the committee value, we also ask the participants to give a subjective value which they feel might be more appropriate, to gauge whether their own perceptions are in line of those provided by the commission. Similarly, we ask them to give an estimate of how many students will pass this year based on the document of the committee and based on their own judgment.

¹⁹Included in this segment is also a question on English adequacy, even though they did not receive any numerical value for this topics. Our motives to include such a gimmick is to test whether their perceptual difference/similarity with the Committee would persist over a fictional category.

²⁰Age, sex, place of residence, study program, family situation, income and religion

²¹Similarly, we construct simple arithmetic averages, based on the factor loadings.

Results and discussion

We investigate the recollection error for the different numerical values on the educational performance which were provided in the text, and which the participants had to process. We gauge the discrepancy with the true values in two ways, firstly through the absolute value of the difference between the recollection and the true value (referred to as AV), and secondly through the squared value of the same difference (referred to as SV), the latter assigning higher weights to stronger deviations.²² This initial test revealed that there were indeed significant differences on the AV measure for recollection precision between the two types of (emotional or neutral) information, both for the copy information ($M_{\text{emotional}} = 6.12$ vs. $M_{\text{neutral}} = 12.09$, $F(1,102) = 5.644$, $p < .02$) and the content on grammar ($M_{\text{emotional}} = 6.56$ vs. $M_{\text{neutral}} = 12.84$, $F(1,102) = 8.174$, $p < .006$). However, the recollection rates for the information on the quality of tasks were indistinguishable between both groups ($M_{\text{emotional}} = 12.95$ vs. $M_{\text{neutral}} = 15.34$, $F(1,102) = 0.49$, $p = 0.5$). We achieve comparable results using our SV measure (table 1). Moreover, both AV and SV results are confirmed by applying planned contrasts. Similarly, adding our covariates and performing an ANCOVA analysis did not profoundly change our results.²³

This exercise reveals that our participants show considerable different mnemonic patterns for different types of information provided to them, with affective information achieving the highest mnemonic advantage in comparison to neutral information. Interestingly, not all categories show such an improvement, which can be traced back to an attention narrowing effect for the more emotional aspects of the text (in casu, copy behavior and grammar content) (Easterbrook, 1959; Kensinger, 2009, Mather, 2007), or linked to the fact that the quality of tasks did stimulate not comparatively as much arousal (Sutherland and Mather, 2011). However, we can clearly see the impact on the recollection quality when participants are triggered with negative (vs. neutral information) concerning their own personal school performance. Hence, even such an artificial intervention (as we provide external news elements on something to which they are well-acquainted, and which they live through every day) can have a lasting and significant impact on the way our subjects remember events.

A comparison between the subjective values, which the participants would have expected for these different topics, and the exogenous values of the commission,

²²When comparing the means of the two groups for the different categories, this measure would yield the notorious mean squared error value (MSE) which is classically used to compare such numerical indicators (for example in the seminal paper by Meese and Rogof, 1983).

²³In this context, none of our covariates seemed important for the recollection of emotional or neutral information. These additional results can be requested from the author.

allows us to unravel that there are no significant between the neutral and the emotional group on any of the topics (table 2). Thus, participants in both affective conditions seem to perceive the information by the committee as similar. Even for the fictional category English adequacy (for which we had not provided any information) we find similar responses in both groups, with the deviations relative to the commission values being relatively high. Furthermore, our credibility dummy reveals that not many participants ($n=18$) find the report credible. When we analyze the differences concerning the credibility levels among affective groups through a multinomial logit estimator, again we find no significance influence of the underlying group (coefficient = 0.891, $p=0.115$).²⁴ Hence, these additional tests seem to highlight that across both groups we could not thoroughly adapt the beliefs of our participants, in neither affective condition. This makes sense because we merely provide exogenous information on a topic for which they have already formed their opinion. As this newly offered information is opposite to their beliefs, they do not readily incorporate this in their information set. However, despite the lack of credibility, the affective nature of the events seems to influence our neural responses, to such an extent that the subsequent memory enhancement concerning the school performance of our participants is significantly different compared to a neutral placebo group.

4.2 Study on impact of affective versus neutral information concerning labor market performance

Participants

Sixty two alumni²⁵ from Ghent University (27 female and 35 male; mean age = 24.6 years, $SD = 1.7$) took part in the experiment. Participants were randomly assigned to one of two conditions: receiving emotional stimuli ($n = 32$) or neutral stimuli ($n = 30$). The subjects were told that they had to engage in reading a short piece on the job market conditions linked with their personal educational profile (or a related, but more distant educational profile), and subsequently answer some questions concerning this information.

²⁴Moreover, our credibility dummy seems to be connected to the difference between the subjective value and the commission value only for the topic of copy behavior, but not for any of the other categories.

²⁵More specifically graduates with a degree in applied economics

Design and Procedure

The design for this second experiment is very similar in nature to our previous setup. We presented our participants a short document on the labor market (approximately one page) which appeared to have been prepared by the OECD. The document featured five different topics (salary, job satisfaction, days required to find a new job, flexibility, and career opportunities) which were structured in separate paragraphs, each featuring two numerical values about specific developments of (discussed) topic at hand, except for the last two which merely feature a description. Similarly, we had adapted the content as such to only highlight negative information, overwhelming our participants with negative news facts about the labor market. We randomly assign our participant to one of two conditions, which both rely on the same OECD text, but in the first condition the information specifically relates to labor market conditions in the sphere of their own personal educational background (negative emotion condition), while in the second condition the information alludes to labor market conditions for a similar, but slightly more remote educational background, which should affect the participants to a lesser extent (neutral condition). The participants were allowed fifteen minutes to read the OECD report, followed by a fifteen minute waiting period, after which they answered our questions.

We interrogate our participants on three different dimensions. Firstly, we have the same mood variables which featured in our first study, again on a scale from one to five. Secondly, we ask our participants to reproduce some of the numerical values, which were incorporated in the paper. More specifically, we ask them to recall numbers concerning the first three subjects. Additionally, we request for a confidence interval of the recollection values, which could be seen as a measure of vividness. Next to their best guess of the OECD, we ask them to provide the value which they personally seem most fitting (thus allowing us to scrutinize whether they follow the vision stipulated by the OECD). In a similar vein, we ask them to express their views on the representativeness of the report through a percentage, together with a (correlation) measure which indicates the affinity they feel with the specific labor market segment (neutral or emotional) they are confronted with. Thirdly, we complete our survey with several socio-economical elements concerning age, gender, commitment, work experience, income level, origin, religion. Combined with the previously mentioned mood variables, these components can markedly enrich our analysis.

Results and discussion

Similarly, we initiate our analysis with the variables which gauge the recollection error. More specifically, we compare the difference between the participants memory and the presented OECD value, expressed as an absolute value (AV) or as a squared value (SV), for our two subgroups. Starting off with the AV measure, we record significantly better recollection values for emotional stimuli both concerning salary (Memotional = 4.063 vs. Mneutral = 15.167, $F(1,61) = 10.730$, $p < 0.003$) as well as job satisfaction (Memotional = 4.314 vs. Mneutral = 14.1, $F(1,61) = 11.481$, $p < 0.002$). However, there was no mnemonic benefit for the required search days (Memotional = 15.625 vs. Mneutral = 17.133, $F(1,61) = 0.074$, $p = 0.8$). In this context, a complementary measure for the aggregate difference in recollection is provided by the total number of correct values for the different subparts (Memotional = 0.323 vs. Mneutral = 0.215, $F(1,61) = 9.602$, $p < 0.004$). All of the above results hold for the SV measure (table 3), but also remain valid when we include the covariates (which do not provide any significant influence) and augment our analysis to an ANCOVA framework.²⁶ Fully in line with our first study, emotionally tinted information leads to significantly better performance in the recall tests, in comparison with the benchmark of neutral information, at least for most of the measures in our framework.

The confidence levels we collected, alongside the recollection values of our participants, allow us to control whether the memories for affective stimuli are more vivid than their neutral counterparts. (Kensinger and Schacter, 2008). However, we do not find any significant discrepancy in the confidence levels of our two subgroups across the different categories (table 4). Thus, increased accuracy does not go hand in hand with increased vividness. However, this lack of clarity in the memories of our respondents seem to be closely linked with the lack of credibility our reports yield for both types of stimuli. We employ three different measures to gauge the overall level of credibility. Firstly, when we scrutinize the values on representativeness, we cannot report any differences between the groups (table 5). Secondly, the difference between the subjective value (which the respondents find more truthful) and the OECD value is undistinguishable between the emotional and the neutral experience (table 6). Finally, the bond which they feel (measure through the correlation) with each labor market segment (neutral or emotional), is not divergent between both groups (table 5). Therefore, each element highlights that the subjects

²⁶These additional results can be requested from the author. However, as they do not offer any additional value, and merely prove the robustness of our methodology, they were not incorporated in the paper.

did not voluntarily accept the information as being truthful. However, even without a true internalization of the given information, there is still a big mnemonic benefit for affective information over neutral stimuli.

Much in line with the results of our first study, we can only interpret the analysis on the effect of news concerning the labor market as a recall test, because there is no real impact on the respondents' decision making. The new affective information is not readily incorporated in the existing information set, as the provided information is relatively secluded from the real life situation, which our participants know and live every day. Despite this lack of coherence with one's own beliefs, it is fascinating to still witness such a remarkable divergence in the mnemonic performance as a consequence of the affective flavor which is added to the story.

Summarizing, although both experiments provide strong evidence on the memory enhancement of real life affective experiences (concerning schooling and labor market), we could not yet establish the existence of possible feedback effects, as these preliminary investigations did not allow us to markedly affect the beliefs of our participants. However, in our last experiments, we investigate a situation where the participants are confronted with the results of their own behavior, and thus allow us to endeavor a more thorough investigations into the consequences mnemonic improvements (due to the affective nature of certain news events) can have on our everyday lives.

5 Pass through of mnemonic effects to economic expectations

5.1 1 Basic experiment: an investigation of investor behavior

Participants

One hundred and thirteen undergraduate students (40 female and 73 male; mean age = 21.8 years, $SD = 0.934$) from Ghent University participated in this experiment. All respondents were enrolled in the course of investment analysis and (divided in small groups) they all took part in an investment exercise over a short term horizon (of several months), where they had to choose assets out of ten general classes (taking into account all of the practical financial considerations). After the completion of their task, they received a short report, which highlighted the performance of their investment choices through various financial ratios (return, standard deviation, beta coefficient, sharp ratio and Jensen's alpha). The students also received more general feedback on the return, risk, and performance measures of the various available

asset classes, and the individual correlations between these asset classes. At the time they received their results, we intervened with our experiments, asking those students that are willing to participate²⁷ to follow the subsequent procedure. First, we allowed fifteen minutes for the participants to take in the information, describing the outcome of their investment choices. They were instructed that they would have to answer some questions about their individual performance. Next, we incorporated a fifteen minute waiting period, to allow all of the information to be absorbed.

Design and Procedure

Based on their personal beliefs about the investment outcome, we allowed the students to indicate where they considered themselves on a hypothetical distribution that incorporates all the student performances: below the tenth percentile, below the twenty-fifth percentile, at the median (benchmark), above the seventy-fifth percentile, or above the ninetieth percentile. Such a representation allows us to separate the participants in two distinct ways (each having their own benefits). Firstly, we have the option of constructing three groups, separating the underperformers (at the low end of the distribution, combining the worst performing groups, hence inducing negative emotions), the median performers (benchmark for neutral emotions), and the best performers (at the high end of the distribution, taking together the two best performing groups, yielding positive emotions).²⁸ We refer to this first method as the ‘high-low separation’. Secondly, we create an alternative segmentation method by grouping together the extreme positive and negative percentiles (which should induce the highest arousal), similarly grouping together the positive and negative quartiles devoid of the above extreme results (which should still induce arousal, however, potentially less than the former percentiles), and finally again the benchmark of median results (representing neutral stimuli). We refer to this second method as the ‘extreme value separation’. Therefore, the groups are allowed to be fabricated endogenously (simply as a result of the exercise) and are based on their own subjective interpretation (which in real life (economic) decision-making would also be the leading inducer) and not on objective or artificially administered criteria. Moreover, our framework allows us to specifically investigate which effects the valence and the arousal strength of emotional stimuli can induce, two elements that feature prominently in the literature.

In line with the previous experiments, we divide our questionnaire in three categories. Firstly, we asked our respondents about their state of mind after receiving the

²⁷The participation to our experiment was kept voluntary. Hence, only seventy percent of the total number of subscribed students took part in our study.

²⁸Allowing us to test differences between negative, neutral and positive stimuli.

investment results, through fourteen mood characteristics, scaled from one to five.²⁹ Secondly, we perform the recollection tests for several of the financial ratios (returns, standard deviation, beta coefficient and Jensen’s alpha) concerning the personal investment results. In this section, we also inquire whether their results are due to exogenous factors or whether they are the result of an implicit strategy. Moreover, we obtain information about the subjects’ assessment on the overall riskiness of their endeavor. Finally, we collect socio-economic and demographic information³⁰, which could again enrich our further analysis.

Results and discussion

We apply the same procedure as in our previous experiments to calculate the recollection error, respectively as the deviations between the recalled value and the true outcome from their investment choices, expressed in absolute value (AV) or as a squared difference (SV). Our analysis centers on the following three variables: the return on the investments, the standard deviation, and the total amount of correct answers across all the categories (return, standard deviation, beta coefficient and Jensen’s alpha).³¹ Starting off with the high-low separation and our deviations expressed as AV, we unravel significantly lower recollection errors concerning the return values for our emotional subgroups in comparison with our neutral benchmark (Mhigh = 0.028 and Mlow = 0.017 vs. Mneutral = 0.070, $F(2,105) = 3.048$, $p=0.05$). The planned contrast analysis confirms that the emotional subgroups are not significantly different from each other ($p=0.64$), while the difference between the emotional stimuli and the neutral benchmark was significant ($p<0.04$). However, we cannot find this emotional memory enhancement for the category of the standard deviations (Mhigh = 0.103 and Mlow = 0.111 vs. Mneutral = 0.128, $F(2,87) = 0.118$, $p=0.89$). Similarly, planned contrasts do not hint at the recollection rates being distinguishably different between the emotional stimuli ($p=0.89$), nor between the emotional and the neutral stimuli ($p=0.64$). Hence, the attention of our students might be captivated by the return values, which are perceived as being more important. Young investors usually tend to focus too much on the yield they can gather, and as a result become more oblivious towards other meaningful financial

²⁹We now also add the variable ‘amazement’ to our thirteen previous mood characteristics.

³⁰Age, gender, marital commitment, income and religion

³¹We do not report the separate results for the beta coefficient and Jensen’s alpha, as there is a considerable amount of missing observations for the recollection values of the participants for these categories. In contrast to the previous experiments, we did not enforce the participants to answer. Hence, the blank values correspond with respondents who by no means could remember the true value. Consequently, the amount of correct answers, gives us a more comprehensible estimate on what the overall recollection rates were for all of our participants (not just a subgroup that answered a particular domain).

characteristics, potentially leading to several behavioral biases (Feng and Seasholes, 2005). Accordingly, this could lead to a case of attention narrowing, as originally highlighted by Easterbrook (1959). Finally, the overall percentage of correct values is significantly higher for both of the emotional experiences in comparison with their neutral counterpart ($M_{high} = 0.538$ and $M_{low} = 0.535$ vs. $M_{neutral} = 0.362$, $F(2,111) = 3.343$, $p < 0.04$). More specifically, the contrasts unravel that the emotional stimuli of different valence do not differ for this segment ($p = 0.96$), while they do differ for the different affective perceptions ($p < 0.02$).

When we perform a similar exercise for our extreme value separation, we get relatively comparable results. However, now the interpretation is somewhat different, as we compare alternating strengths of the stimuli, and no longer differences in the valence. Firstly, the recollection of the return values is remarkably better for both strengths of the emotional stimuli ($M_{10} = 0.023$ and $M_{25} = 0.022$ vs. $M_{neutral} = 0.070$, $F(2,105) = 2.936$, $p = 0.05$). The planned contrasts exhibit significant differences between the emotional and the neutral stimuli ($p < 0.04$), but not between both types of affective experience ($p = 0.94$). Recollection rates for the standard error, again are poor for all the categories alike ($M_{10} = 0.098$ and $M_{25} = 0.115$ vs. $M_{neutral} = 0.128$, $F(2,87) = 0.153$, $p = 0.86$). The contrasts exhibit no individual differences between the affective counterparts ($p = 0.77$), nor between the emotional and the impartial condition ($p = 0.63$). Finally, the all-inclusive category, given by the total number percentage of correct values, again allows us to differentiate between emotional and neutral memory enhancement ($M_{10} = 0.501$ and $M_{25} = 0.557$ vs. $M_{neutral} = 0.362$, $F(2,111) = 3.353$, $p < 0.04$). Consistent with our previous results, the contrast between the neutral and the emotional event is significant ($p < 0.02$), while this is not the case for the different arousal types individually ($p = 0.48$).

Thus, nor the valence nor the arousal strength of the stimuli to which our participants were exposed seem to have a meaningful impact on their recollection performance. The only characteristic that effectively and consistently seems to matter for the mnemonic achievements is the affective content of the experience. Using our SV measure (table 7 and 8), or applying an ANCOVA framework to incorporate our covariates, confirms the above results.³² We conclude our experiment with two remarkable observations on the high-low separation that fit well with our previous intuition. Firstly, when we inquire with our participants whether the result is due to exogenous effects, or due to their own strategic behavior³³, we find a significant

³²This final robustness check can be obtained from the author.

³³Expressed as zero being fully exogenous and one being completely a result of the chosen strategy.

difference between the valence of the stimuli ($M_{\text{high}} = 0.727$ and $M_{\text{low}} = 0.257$ vs. $M_{\text{neutral}} = 0.523$, $F(2,109) = 8.536$, $p < 0.001$). Moreover, the planned contrasts reveal that the difference is relevant for the different types of valence ($p < 0.0001$), but not for the affective versus neutral distinction ($p = 0.75$). Secondly, when we ask our respondents whether their investment decisions were risky or safe³⁴, again we discover a significant difference across the valence ($M_{\text{high}} = 1.970$ and $M_{\text{low}} = 2.657$ vs. $M_{\text{neutral}} = 2.378$, $F(2,110) = 7.258$, $p < 0.002$), with contrasts clarifying that whether or not the stimuli exhibit emotional content is not affecting this outcome ($p = 0.65$), but the valence does play an important role ($p < 0.0001$). We presume that there is an ex post evaluation of the investment outcomes which is driving both of these findings. Whenever the results are perceived to be negative, this induces cognitive dissonance, incentivizing the participants to look for explanations that could take away the responsibility for these bad outcomes (Zajonc, 1980). Thus, these additional tests emphasize that the emotional content of the stimuli in this experiment does effect the state of mind of our participants, which allows us to investigate the consequences of these stimuli both on their expectations, as well as on their subsequent behavior.

5.2 Delayed Memory Test and feedback to economic expectations

Participants

Our participants belong to the same group of undergraduate students of the University Ghent, enrolled in the investment course. However, the respondents do not perfectly match the earlier group. We now have one hundred and three participants (30 female and 73 male; mean age = 21.9 years, $SD = 0.941$). However, they have all experienced the same types of stimuli, which are connected to the investment results, and hence they are valid to be incorporated in our analysis.³⁵

Design and Procedure

We examine whether the mnemonic benefits of the emotional stimuli previously induced by the investment outcome linger on after a one month period. This allows us to infer whether the influence on the memory is merely a short term phenomenon by affecting our attention, or whether emotion can also affect deeper memory processes

³⁴On a scale from 1 to four, with one being risk free and four being very risky.

³⁵As we are simply interested in comparing the quality of the groups that experience different stimuli, such a perfect match is not mandatory for our framework. Moreover, it can be interpreted as an additional robustness check that we can reproduce our results with a slightly different sample.

at the consolidation stage and thus have long term consequences (Hamann, 2001; Sharot and Phelps, 2004). For this purpose, we use the same separations (high-low and extreme value) as in our previous test, but now we only focus on the recollection value on returns (which appeared to appropriate the most attention from our respondents in our earlier analysis).

Additionally, we ask our participants to give their expectations about the yield they could potentially achieve on the stock market in 2014³⁶, as well as their prospects for GDP growth in Europe in 2014.³⁷ This allows us to investigate whether there are spillover effects to their real life economic expectations, which are at the core of their decision making process.³⁸ Hence, we can scrutinize whether the different affective stimuli do not only enhance memory, but also affect our expectations (through a prolonged focus on the positive or negative results). This segment therefore sheds light on our initial hypothesis whether neural properties, which dictate how the brain handles emotional input and which have evolved historically, can have implications on our economic sentiment, and thus contain a procyclical quality, which can propagate downturns or upswings in the economy.³⁹

Results and discussion

Initiating the analysis with our high-low separation and considering our AV measure for the recollection error, the memory effects of emotional stimuli also hold for the long run ($M_{high} = 0.258$ and $M_{low} = 0.341$ vs. $M_{neutral} = 0.491$, $F(2,100) = 3.402$, $p < 0.04$). More precisely, the contrasts reveal that the difference between the means is only significant for the emotional content of the stimuli ($p < 0.02$), but not for the valence of the stimuli ($p = 0.4$).⁴⁰ We can therefore infer that emotional stimuli have long-term mnemonic benefits in our experimental setting, which implies that the emotional stimuli also affect the consolidation stage and not merely capture our attention.

Turning to the expectations of our participants about the future outcomes, we can start by saying that there is no significant difference in the expectations about the yield ($M_{high} = 0.055$ and $M_{low} = 0.047$ vs. $M_{neutral} = 0.051$, $F(2,100) = 0.365$, $p = 0.7$), not when we compare emotional and neutral stimuli ($p = 0.96$), nor when

³⁶Yearly nominal (without correcting for inflation) excess (above risk free market rate) return

³⁷Both forecasts are expressed by the respondents as a percentage.

³⁸We only investigate this in the long run, as it might take some time to incorporate such external stimuli in our expectations and hence in our decision making process.

³⁹Although we mainly focus on the effects of negative emotion, the reverse effect could be through during prosperous economic intervals (which might lead to bubbles).

⁴⁰This result also holds for the extreme value separation (table 9), the SV measure, and the ANCOVA framework for both (the latter can be obtained from the other).

we consider the valence of the stimuli ($p=0.4$). This result could potentially be induced by the fact that the period during which the exercise was performed was quite bear, so that all of the participants (even those getting mildly positive results) got affected similarly beyond and above our investment exercise stimuli. Another explanation could be that the expectation about yield are influenced by many other factors, which in this case seem to blur out the enhanced effects of the memory.⁴¹

However, we do find a remarkable and significant difference for the expectations which the participants have about the future GDP rates ($M_{high} = 0.039$ and $M_{low} = 0.023$ vs. $M_{neutral} = 0.017$, $F(2,100) = 7.417$, $p < 0.04$). The contrasts reveal that this difference is significant when we compare (positive) emotional stimuli with our neutral benchmark ($p < 0.003$), and also between positive and negative stimuli ($p < 0.04$). Furthermore, the difference between the successful investors as opposed to the median or unsuccessful investors also has economic significance, with yearly GDP forecasts for the former being on average two percent higher than the latter groups. The economic significance seem less ostensible when we compare the median and unsuccessful investors.

Intuitively, it might be appealing to interpret the outcomes for the different types of investors (based on the outcome of the exercise) as proxies for the macroeconomic environment in which they are typically found, which makes sense if one is willing to accept that during upswings there are comparatively more positive stimuli, and vice versa. This would imply that the prosperous investors should have rosier forecasts than the less successful groups (similarly as we uncovered), but also that the investors with negative results would have dimmer views than their neutral counterparts (which we could not retrieve). However, we have to keep in mind that all of the investors in our experiment were confronted with the same economic condition, which was characterized by stagnant growth and a bear stock market. Hence, investors with negative or neutral results may not have had any incentives to fundamentally adapt their expectations, which could explain the relative small divergence in their forecasts (at least in economic sense).⁴²

Nonetheless, this is a remarkable outcome, as the memory enhancement of emotional items, seems to have long reaching consequences, potentially affecting our expectations and hence influencing the type of economic decisions we might take. Even after one month the group of students which was affected positively merely

⁴¹However, for each separate class, the deviations of these expectation of the respective means, does seem to significantly differ over the different classes. So memory enhancement could potentially affect future volatility.

⁴²As opposed to the divergence with the forecasts of the fruitful investors, for whom the stimuli provided a good motive to adapt their beliefs.

through the results they obtained in a simple classroom investment exercise (with no monetary consequences whatsoever) led to significantly rosier GDP expectations than their counterparts which had witnessed neutral or negative results in their exercise. Consequently, considering the fact that in real life we encounter actual monetary outcomes, and we are comparatively much more surrounded with repetitive news items (which endogenously increase during upswings or downturns), this effect could be even more pronounced, and could thus prolong or even enhance certain cyclical episodes through our sentiment and our expectations.

6 Conclusions

Emotions have served an adaptive role during our historical evolution, and still provide an indispensable mechanism to provide swift responds (Ledoux, 1996). Moreover, they allow us to cope with complex situations in a proficient manner (Simon, 1955) by using simple heuristics (Kahneman, 2009). However, their strength also harbors their weakness, as their immediacy, swiftness and simplicity could provide a disruptive force when confronted with some of the aspects (ranging from financial decisions to dietary choices) which are imbedded in the complex social architecture we are surrounded with nowadays (Shiv et al, 2005). We could therefore benefit considerably from a better understanding on the way emotions may influence our cognition, and ultimately also our choices in many walks of life. In our study, we examine one such possible pass-through effect from emotions to decision making, in the context of financial markets. We build on the existing knowledge that affective information is processed, and hence remembered, comparatively more efficiently than neutral events. If emotional stimuli lead to more salient memories, these have the potential to impact our expectations and our sentiment more profoundly. These neural linkages could, in turn, affect our decision making, creating a procyclical effect, thus providing an emotional reinforcement for upswings or downturns in the economy.

We perform three experiments to analyze whether emotional stimuli can enhance the memory capacities, but also whether they trickle down into the beliefs, and possibly into the decision making framework of the participants. Our studies are specifically set in a socio-economic setting (schooling, labor market, and financial investments), and allow us to test whether we can extend the existence literature to real life applications. In the first two studies, we confront our participants with information on everyday topics which have been manipulated in order to differentiate between groups receiving neutral or emotional stimuli. This allows

us to test whether these adaptations lead to mnemonic differences dependent on the affective nature of the events. The preliminary recall tests illustrate a significantly improved recollection for affective information, both for the content on schooling and for the information on the labor market. This provides an initial intuition that the laboratory experiments which feature prominently in the existing literature, can be applied to real life situations. However, these tests did not yet allow us to dig deeper and examine the consequences of the affective information on subsequent sentiment, decision making and behavior.

For the purpose of examining whether emotions can trickle through in our decision making, we next apply our framework to a group of respondents that have participated in an investment analysis. This allows us to investigate a setting where individuals are confronted with the outcome of their own decisions. Hence, this content has a stronger impact on their beliefs, and subsequent expectations. But more importantly, we find that participants who had encountered positive results, also have more rosy views about the future GDP than their neutral or negative counterparts. This means that the emotional content (even without a real monetary loss) can impact our memory, and in turn this can influence our expectations. For example, during a downturn the salience of negative stimuli can lead to a drop in confidence, which can prolong and enhance the crisis, thus yielding a self-fulfilling and enhancing effect. In a downward spiral, which is often infected with negative news, such a mechanism could have devastating effects.

Of course, we are not claiming that this is the most important, nor that this is the only channel through which negative episodes could get more pronounced. However, we do provide a novel and valuable way of incorporating emotions into the theoretical framework of business cycles. As such, we provide an explanation to the underlying mechanisms which could be operating when there are informational cascades (Bikhchandani et al, 1992) or when agents refuse to herd (Cipriani and Guarino, 2008). Moreover, many authors (ranging from Keynes to Minsky and Kindleberger) have hinted at the potential of such animal spirits affecting, and this could be one of the channels through which they could operate. Hence, our analysis should warn policy makers that their efforts in containing crisis situations (or vice versa asset bubbles) also has an inseparable emotional aspect, next to the purely economic rationale.

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Figure 1: Pass Through and Procyclicality of Affective Stimuli

Dynamical flows and connections running from emotions to economic decision making, clarifying the pass-through mechanism of the memory heuristic and its procyclical consequences

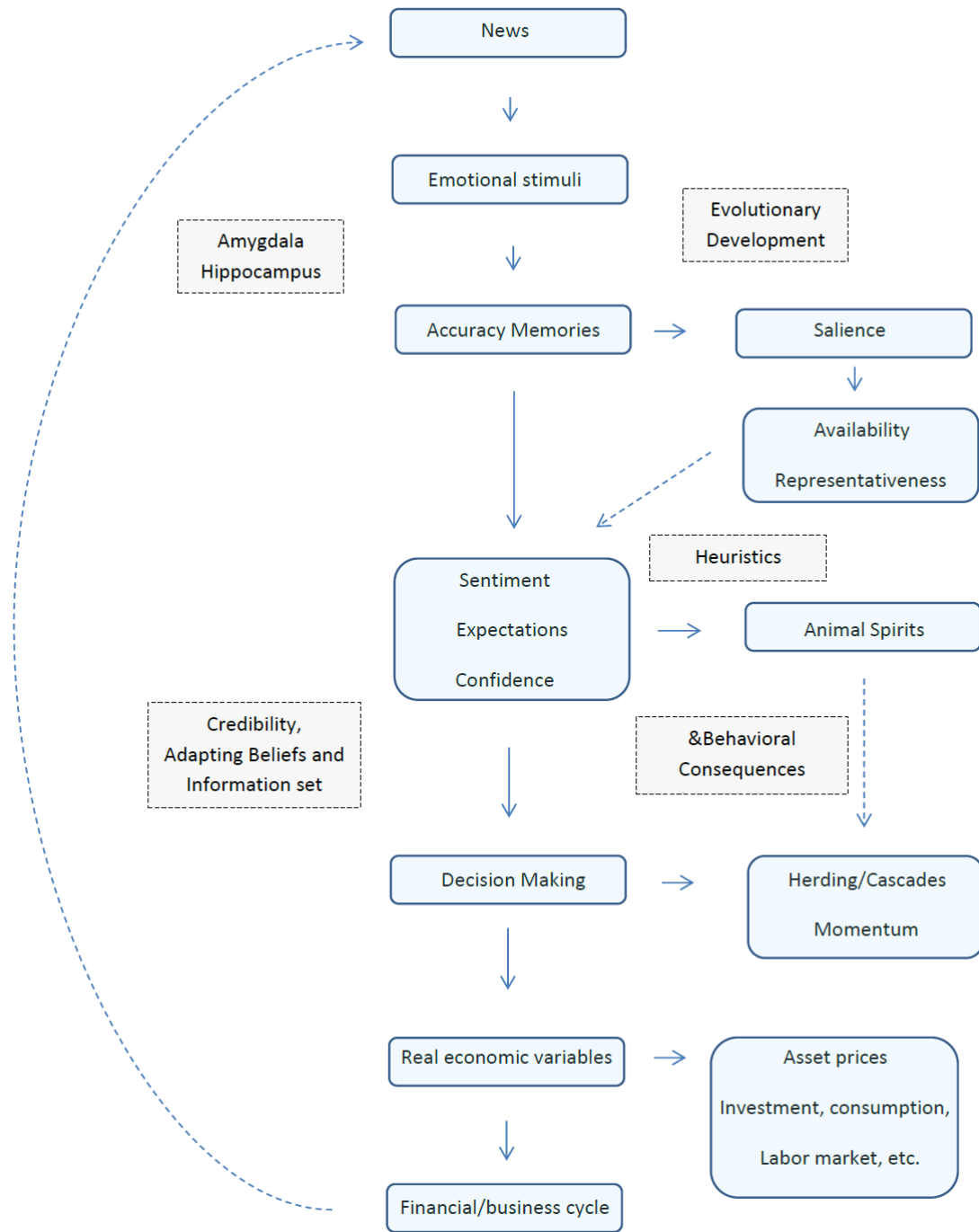


Table 1: Recollection errors for the squared value method, in study 1.

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Copy	101	3.965	0.049	151.340	359.090	0.061
Grammar	101	6.696	0.011	99.140	368.930	0.027
Task	101	1.672	0.199	358.000	656.020	0.250

Table 2: Difference between the subjective value of the participants and the exogenous value of the Commission, in study 1.

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Copy	101	0.200	0.656	12.800	11.750	0.656
Grammar	101	1.886	0.173	13.410	10.570	0.173
Task	101	0.013	0.911	9.320	9.110	0.911
English	101	0.847	0.360	12.360	14.640	0.360

Table 3: Recollection errors for squared value method, in study 2.

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Salary	61	6.725	0.012	63.063	536.233	0.018
Job Satisfact	61	6.641	0.012	47.250	426.633	0.018
Search Days	61	0.433	0.513	951.188	556.267	0.513

Table 4: Confidence levels, in study 2

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Salary	61	3.369	0.071	51.406	64.733	0.069
Job Satisfact	61	0.263	0.610	50.156	53.900	0.610
Search Days	61	0.000	0.998	67.188	67.167	0.998
Flexibility	61	0.997	0.322	35.645	28.517	0.322

Table 5: Representativeness and bond with labor market segment, in study 2

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Represent	61	1.972	0.165	50.313	59.400	0.160
Bond segm	61	0.764	0.386	58.969	53.833	0.391

Table 6: Differences between the subjective value of the participants and the exogenous value of the Commission, in study 2

	Df	Anova F	Anova Sig.	M(emo)	M(neutral)	Contrast
Salary	61	0.115	0.736	13.094	11.967	0.736
Job Satisfact	61	0.366	0.547	9.375	7.967	0.547
Search Days	61	1.763	0.189	26.875	20.033	0.189
Flexibility	61	0.056	0.814	9.643	9.000	0.814

Table 7: Recollection errors for squared value method for high low separation, in study 3a

	Df	Anova F	Anova Sig.	M(high)	M(low)	M(neutral)	Contrast High-low	Contrast emo-neut
Returns	105	2.444	0.092	0.007	0.004	0.022	0.547	0.069
St. Dev.	87	0.069	0.934	0.063	0.052	0.047	0.811	0.771
Correct Val	111	3.343	0.039	0.538	0.535	0.362	0.975	0.011

Table 8: Recollection errors for squared value method for extreme value separation, in study 3a

	Df	Anova F	Anova Sig.	M(10)	M(25)	M(neutral)	Contrast 10-25	Contrast emo-neut
Returns	105	2.374	0.098	0.006	0.005	0.022	0.966	0.068
St. Dev.	87	0.058	0.944	0.062	0.054	0.047	0.851	0.767
Correct Val	111	3.535	0.033	0.505	0.557	0.362	0.548	0.014

Table 9: General Results for extreme value separation method applying the AV measure, in study 3b

	Df	Anova F	Anova Sig.	M(10)	M(25)	M(neutral)	Contrast 10-25	Contrast emo-neut
Returns	100	3.443	0.036	0.378	0.273	0.491	0.381	0.054
Expect Yield	100	0.036	0.964	0.049	0.052	0.051	0.506	0.155
Expect GDP	100	4.925	0.009	0.023	0.034	0.017	0.131	0.012

Chapter 3

A Unified Market Liquidity Measure

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Abstract

We introduce a novel method (based on Illing and Liu (2006) and popularized by Holló et al. (2012) through the CISS measure) to aggregate different groups of liquidity measures (percent-cost proxies, cost-per-volume proxies, etc.), in order to accommodate for the ‘different dimensions of liquidity’ (Amihud et al., 2005) through a single ‘unified’ market-wide aggregate liquidity metric. The weights for the multiple dimensions are time-varying and depend on three components: the correlation between groups, the pressure conveyed through the measure (threshold), and their conditional variance. We evaluate the performance of our market liquidity measure in various ways. Most importantly, our liquidity measure succeeds in tracking the most important historic episodes of financial stress and has a close relation with many crisis indicators. Moreover, our unified liquidity measure shows the expected macroeconomic and financial relationships mentioned in the literature, and even has some predictive power for future growth rates of traditional variables. Finally, our methodology allows to gauge the individual importance of each liquidity group over time. Our results unveil the spread and effective tick liquidity groups as the main protagonist during turbulent financial periods.

JEL Classification: G01, G12, G14, E44

Keywords: Liquidity; Trading Volume; Transaction Costs; Pricing Impact; Effective Spread; Financial Crises; Macro-financial Linkages

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1 Introduction

Liquidity is a well-known concept in financial¹ and monetary² economics. It has a strong intuitive appeal and its disappearance, causing panic³, can often be linked with well-known crisis events. Moreover, liquidity has played a prominent role in the asset pricing literature over the past decades.⁴ “Investors should worry about a security’s performance and tradability both in market downturns and when liquidity dries up” (Acharya and Pedersen, 2005, p. 405). However, despite its intuitive appeal, liquidity is an unobservable, endogenous and multidimensional concept (Amihud et al., 2005). Hence, the shapes and guises which liquidity can take on are numerous, time-varying and often impalpable. These three features are central in understanding our novel approach in constructing a comprehensive, all-encompassing market liquidity measure.

Firstly, due to the fact that we are considering a latent variable, a precise and concise definition is impossible, and the literature is littered with multiple, often vaguely-defined notions of liquidity (De Nicolò and Ivaschenko, 2009). Hence, it can only be approximated through the measurement of liquidity-related quantities or proxies (Hallin et al., 2011). But because of its elusive and slippery nature (Kyle, 1985; Pástor and Stambaugh, 2003) these empirical measures can be markedly disparate (Næs et al., 2011), often relying on different methodologies.

Secondly, closely linked with the previous characteristic, liquidity is a multidimensional concept (Fong et al., 2014; Pástor and Stambaugh, 2003; Amihud et al., 2005). Most acquainted are the three quintessential dimensions advanced by Kyle (1985), namely depth, resilience and tightness, which all add up to a general feeling of liquidity. These traits describe the ability of trading a substantial amount of assets, quickly, at low cost, and at a reasonable price (Brennan et al., 2012; Harris, 2003).⁵ However, underlying the ease of converting an asset into cash (the ease of trading a security) are many different cost components and potential frictions (Hallin et al., 2011; Amihud et al., 2005), some of which are explicit and easy to

¹e.g. Sadka (2006); Mitchell et al. (2007); Roll et al. (2007); Chordia et al. (2008); Han and Lesmond (2011); Avramov et al. (2015).

²e.g. Kiyotaki and Moore (2012); Pedersen (2009); Bruno and Shin (2014).

³See Keynes (1936, p. 160) on the soothing effect of liquidity on financial markets: “For the fact that each individual investor flatters himself that his commitment is ‘liquid’ (though this cannot be true for all investors collectively) calms his nerves and makes him much more willing to run a risk”.

⁴e.g. Amihud and Mendelson (1986); Bekaert et al. (2007); Chordia et al. (2009); Asparouhova et al. (2010); Lee (2011); Brennan et al. (2012); Lou and Shu (2014).

⁵Gorton (2012, p. 48) points that “market are liquid when all parties to a transaction know that there are probably not any secrets to be known: no one knows anything about the collateral value and everyone knows that no one knows anything. In that situation it is very easy to transact.”

measure, while others are more subtle. These costs include the bid-ask spread, market-impact costs, delay and search costs, and brokerage commissions and fees (Amihud and Mendelson, 2006). A more comprehensive list is included in Table 1. The search for the true meaning of liquidity has resulted into an intricate and multi-layered concept, reminiscent of Polycephalic creatures in ancient mythology. Hence, it is unfeasible for one single measure to capture all of the layers conveyed within liquidity (Amihud et al. 2005; Hallin et al. 2011). As a result, low correlations between different individual measures do not necessarily entail that one is inferior to the other. Instead, they could simply be gauging different dimensions (Liang and Wei, 2012). Moreover, there is evidence that even different frequencies capture different phenomena (Vayanos and Wang, 2012). Unsurprisingly, we notice little consensus on the efficacy of many of the commonly used liquidity proxies. Many authors simply apply a whole spectrum of liquidity measure in their analysis to advance a broader view of liquidity (Lam and Tam, 2011; Keene and Peterson, 2007), as each proxy is considered to have its specific strengths and weaknesses, instead of being mere substitutes (Lesmond, 2005; Vayanos and Wang, 2012).

Finally, adding to the complexity, liquidity is endogenous. It arises as the outcome of trading patterns in financial markets. Hence, liquidity depends on the total volatility of the financial system (Chordia et al., 2011). Pagano (1989, p. 269) warns that “Thinness and the related price volatility may become joint self-perpetuating features of an equity market, irrespective of the volatility of asset fundamentals”. More broadly, the concept of liquidity is closely entwined with its macro-finance surroundings through many different concepts, including sentiment (Baker and Wurgler, 2006), optimism (Tetlock, 2007), the economic environment (Hameed et al., 2010; Næs et al., 2011; Rösch and Kaserer, 2013), monetary policy (Goyenko and Ukhov, 2009) and the state of the economy (Watanabe and Watanabe, 2008). Moreover, it has leading and lagging relations with credit ratings (Odders-White and Ready, 2005; Avramov et al., 2009), and strong interlinkages with the interbank market (Nyborg and Östberg, 2014). Hence, when we apply the Lucas critique (1976) to financial markets, and more specifically to the multi-layered concept of liquidity, different economic environments (with disparate shocks hitting the economy) can influence the importance and even the ability of the liquidity measures to provide a clear picture of the underlying threats.

We want to address these unique features head on, and introduce a novel multidimensional market liquidity measure which reunites the individual strengths of different groups of liquidity measures. Thus, our main goal is to construct a measure that embodies the investor’s general feeling about the liquidity (based on all of

the potential underlying costs, frictions and asymmetries) of the US stock market.⁶ We build on the recent developments made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012). Firstly, we construct eight separate groups of individual liquidity measures by taking together measures that characterize similar dimensions of liquidity. Next, we apply the portfolio approach (Illing and Liu, 2006) in order to aggregate these groups of liquidity. We allow for the time-varying correlations to determine the individual importance of every class of liquidity, as similarities over the various measures indicate that several dimensions are picking up the same signal. Up to this point, we merely provide an alternative aggregation method by applying the portfolio approach instead of more classical common factor or principal component methodologies (Korajczyk and Sadka, 2008; Hallin et al., 2011). However, we expand the existent methodology, not solely relying on the commonality across liquidity groups, by also allowing for idiosyncratic elements to affect the multidimensional or unified liquidity measure through a time-varying weighting scheme, whenever a specific group hints at extreme pressure relative to its peers. Because of the discordant backgrounds of each liquidity measure, it is not unimaginable that a single or several specific measures pick up a signal that the others ignore. Only incorporating the different dimensions as weighted by their correlations would imply that we neglect such signals (as is the case with the common factor or principal component methodology). Finally, we adjust our time-varying weights, by making the assumption that volatile liquidity groups attract more investor attention than tranquil groups, which would increase the importance of the former.⁷

Our multi-layered liquidity measure succeeds well in identifying episodes of financial crisis and recessions over a long sample period from 1957 to 2013. It is closely linked with several well-established crisis indicators, and produces comparable signal-to-noise ratios. Moreover, the novel measure exhibits a close relation with various financial and macroeconomic variables. We can additionally unravel real spillovers from liquidity droughts, even assigning some forward looking power (in the spirit of Næs et al. (2011)) for our liquidity measure above and beyond classical forecasting variables. These features are relatively more robust and significant than for the existing liquidity proxies, thus reinforcing our belief that it is important to

⁶We decide to perform our aggregate method on the market as a whole, because of the increasing importance of commonality in liquidity across stocks (Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Kamara et al., 2008; Brockman et al., 2009; Rösch and Kaserer, 2013), and because of its importance in a macroeconomic framework. However, our approach can readily be extended to the aggregation of different liquidity measures on a stock-specific level. The latter construct would be useful to incorporate in an asset pricing framework.

⁷We apply two methodologies, one by using the class specific volatility as a shrinkage factor, and another by augmenting the weighting scheme with the volatility values. Both techniques seem quite robust.

take into account all of the liquidity dimensions. Moreover, our measure is easily applicable and can be computed for long samples, as well as for many countries.

Whereas our analysis primarily consists of an aggregation method apt to handle the specific challenges surrounding liquidity, it also allows for a comprehensive inspection of the importance of the constituent liquidity groups over time, and more specifically during episodes of financial stress. We uncover that the spread and et-ick groups are the main protagonist during these turbulent periods. Depending on the type of crisis, one (or both) of these groups appears in combination with the amihud, roll and fong measure. Moreover, with the exception of the fong group, these are exactly the groups that perform well in unraveling the univariate relations with macroeconomic, financial, and crisis variables. In contrast, the flow, return and volume group seem to be more valuable in understanding liquidity during tranquil times. Hence, unifying these separate properties of each liquidity group allows for the construction of a proxy which is better equipped to handle different states of the economy.

This paper is organized as follows. Section 2 explores some strands of closely related literature, whereas section 3 describes the construction method of our multifaceted or unified liquidity measure. Next, we examine how our liquidity measure behaves over the business cycle and during financial stress in Section 4, including its interlinkages with macroeconomic and financial variables. Within this section we also gauge the importance of the separate liquidity groups. Finally, Section 5 provides some concluding remarks.

2 Literature

Our approach is similar in vein to a number of recent studies. Liu (2006) introduces a new measure that encompasses several dimensions of liquidity, including the mostly ignored aspect of trading speed. He uncovers high correlation between his novel measure and more traditional measures, which he interprets as evidence for its multidimensional property. A more explicit way of combining different attributes can be found in Holden (2009), where integrated models (combining manifold attributes) and multi-factor models (linear combinations of simpler models) have the potential of diversifying away imperfectly-correlated error terms.

Next to the outright construction of new measures, several authors have attempted principal component and common factor analyses, to crystallize the different features of liquidity into one single measure. Lesmond (2005) employs a factor analysis to unveil whether a single liquidity factor is being captured by any, or all,

of four traditional unidimensional liquidity estimators, as he is doubtful that an individual measure can capture all of the potential liquidity features. Due to concerns about scale differences between the liquidity estimators, he applies a maximum likelihood factor.

Accordingly, in the context of market liquidity, Korajczyk and Sadka (2008) attempt to assess an overall market liquidity measure based on several liquidity measures via principal component methods. Their study focuses on combining information from various sources to form a common facet of asset liquidity. Similar in vein, but technically divergent is the analysis of Hallin et al. (2011). Through a Generalized Dynamic Factor Model (with block structure to provide a data-driven definition of unobservable market liquidity and to assess the complementarity of two observed liquidity measures) they succeed in identifying commonality over different liquidity measures.

Even though all of the above mentioned techniques have their particular merits, we have to advance several remarks concerning their adaptation to this specific setting. Firstly, several of these methodologies yield an unobservable “systematic” liquidity measure, and leave no room for any measure-specific idiosyncrasy. They count heavily on the commonality over the different liquidity measures as the sole feature which concerns the investor. Such an approach is quite restrictive, as for example the return of a specific stock could also be influenced by a purely idiosyncratic liquidity measure⁸, which should therefore be kept in the equation.⁹

Secondly, these methodologies only provide a purely statistical (black box) solution for performing the aggregation exercise. There is no economic intuition behind the assemblage of the different pieces. Moreover, the selection of the included variables seems to be done on an ad hoc basis, only including a limited number of liquidity proxies, which precludes a complete account of all the potential liquidity dimensions, in addition to the difficulty of reaching an agreement on which measures to incorporate.¹⁰

Lastly, many of these studies commence by standardizing the raw liquidity measures, which are then aggregated through arithmetic averaging, principal component

⁸A individual liquidity measure is considered to be idiosyncratic if it diverges from the common trend laid out by the other liquidity measures, but still contains valuable information.

⁹Up to a certain point, our methodology (applying time-varying correlations) provides an alternative aggregation method to the more traditional principal component and common factor techniques, and similarly focuses on the systematic components. However, we extend this procedure and also allow for idiosyncratic forces within the constituent liquidity groups to have an impact. We further refine this application by weighting this idiosyncratic information set by the volatility.

¹⁰In contrast, our portfolio approach provides a more transparent way of performing the aggregation exercise. Moreover, we try to incorporate the full array of liquidity measures.

technique and common factor analysis. Holló et al. (2012) warn that standardized variables might be sensitive to irregular observations, as many customary liquidity measures violate the assumption of being normally distributed. Applying the principle component analysis might further exacerbate the problem, as this technique is also vulnerable to the presence of outliers.¹¹

The recent state of the art liquidity literature also performs horse races in order to single out the most accomplished liquidity measure, as opposed to lumping all of the liquidity measures together in order to accommodate for the different liquidity dimensions.¹² Interestingly, these studies provide valuable insight in the adequacy of low frequency proxies in capturing the features of intraday data, thus legitimizing the use of low frequency measures. However, there are also some drawbacks to this methodology.

Firstly, high frequency data is only available for a relatively short period of time in the US¹³, and is simply unobtainable for most other countries (Corwin and Schultz, 2012; Hasbrouck, 2009). In contrast, their low frequency counterparts can be formulated dating back eighty years in the US, and are available for various durations across countries around the world (Holden, 2009). When considering asset pricing tests, or similarly when performing macroeconomic analysis, researchers need to rely on long time series, to ameliorate the power of their tests (Amihud et al., 2005). More specifically, the limited availability of the high frequency data might raise questions about the stability of the results while performing these horse races. When comparing short timespans, the results might be driven by the underlying forces and shocks in the economy which can change over time (Lucas Jr, 1976). Hence, different periods might reward alternating winners, as other dimension become more important, or fade away over time.

Secondly, high-frequency benchmarks have a similar multidimensional nature comparable to its low frequency equivalent. Hence, performing the horse races only allows comparison within every dimension, resulting in a within-dimension winner, in contrast to an overall (across-dimensions) superior measure.¹⁴ Our multidimensional

¹¹We rely on conversion into order statistics using an empirical cumulative distribution function, which also provides the advantage of delivering stationary and more consistent series of the different liquidity groups.

¹²Most well-known examples are Holden (2009), Goyenko et al. (2009) and Fong et al. (2014). Moreover, Hasbrouck (2004) and Corwin and Schultz (2012) also compare their measures with high-frequency benchmarks.

¹³In the US market, transaction data provided by the Institute for Study of Securities Markets (ISSM) and TAQ databases are only available since 1983 (Chordia et al., 2009; Goyenko et al., 2009).

¹⁴For example, Holden (2009) employs the percent effective spread and the percent quoted spread as high-frequency benchmark. Goyenko et al. (2009) relies on two spread benchmarks and three price impact benchmarks. Fong et al. (2014) suggests four high-frequency percent-cost

aggregation method might therefore also be useful (to unveil the latter) for the intra-daily measures.

Finally, the use of high frequency data has its own specific micro-structural problems ranging from inventory concerns to finding a suitable aggregation interval for order flows (Chordia et al., 2011).

3 Statistical Design

3.1 Basic Setup and Data

Albeit many authors refer to the multiple dimensions of liquidity, there are few attempts at integrating this feature in an all-encompassing measure. Most of the state of the art literature refutes to running horse races in order to find the first best liquidity measure amongst its competitors. In contrast, we present a novel unified market liquidity estimator which crystallizes the disparate liquidity groups into a single value, and thus embodies the investor's general feeling about liquidity in the US stock market. We build on the recent advances made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012), and apply an advanced portfolio approach (Illing and Liu, 2006) to perform the aggregation of the separate liquidity groups.

Constructing our unified market liquidity measure consists of different steps. Initially, we standardize the rudimentary liquidity measures by converting them into order statistics using their empirical cumulative distribution function (CDF). Next, the twenty-one individual liquidity measures are grouped according to their dimension. This results in eight separate liquidity groups. Finally, we reach our unified market liquidity measure by taking into account the time-varying correlations between the different groups, but simultaneously allowing for (volatility-adjusted) time-varying weights across groups. More precisely, we implement two extensions to the traditional portfolio approach which better fit to the needs of the liquidity context under examination. Firstly, we augment our model by incorporating time-varying weights based on the relative liquidity pressures for each dimension of liquidity. This allows us to take into account the idiosyncratic signals of specific liquidity groups. Secondly, we adjust our time-varying weights to take into account the volatility of the particular group. The underlying idea is that highly volatile liquidity measures grab more attention, and hence have more impact. Practically,

benchmarks and one high-frequency cost per volume benchmark. Corwin and Schultz incorporates TAQ effective spreads. Hasbrouck (2004) simply refers to estimates derived from detailed trade and quote data.

we apply two variations on this theme which have a very similar relative impact. On the one hand we apply a ‘shrinkage factor’ to dampen the tranquil episodes, and on the other hand we incorporate an ‘augmentation factor’ reinforcing volatile outburst. Figure 1 gives a schematic overview of the different steps. The next subsections explain and motivate each step in detail.

3.1.1 Data

In our analysis, we incorporate twenty-one liquidity proxies representing eight different spheres of liquidity, based on spread measures, Roll measures, (zero) returns measures, Fong measures, effective tick measures, Amihud measures, volume measures and order flow measures.¹⁵ All measures are expressed as such to denote illiquidity, and all measures are constructed on a monthly frequency. For this purpose, we use daily data from the CRSP database, ranging from 1957 to 2013.¹⁶ We include series on prices (high, low, bid and ask), shares outstanding, shares traded and volume. An extensive survey on the construction of every individual liquidity measure can be found in Table 2. We create market aggregates for each proxy by constructing market capital weighted averages of the stock-specific liquidity measures for the five hundred stocks represented in the S&P500 in that particular month.¹⁷

3.1.2 Ordering

The rudimentary liquidity measures are standardized by converting them into order statistics using their empirical cumulative distribution function (CDF). This process is particularly critical for liquidity proxies because of differences in the unit of measurement as well as in their scale (Lesmond, 2005; Vayanos and Wang, 2012). Moreover, this transformation makes the liquidity measures robust to the influx of new information (Holló et al., 2012). We apply several alternative ordering techniques. Firstly, the ordering is done based on the full sample. Next, we apply subsamples based on changes in the underlying minimal tick size of the US stock exchange.¹⁸ Finally, we apply a rolling window method in which the ordering for each

¹⁵Of course, our list of liquidity proxies is not exhaustive. However, we have good reasons to limit our set to these variables, as it allows for long data series (hence leaving out Chordia et al., 2009), is robust for different trading periods (therefore excluding the LOT measure) and is robust at least on monthly (preferably on a daily) basis (for that reason excluding Hasbrouck, 2009).

¹⁶Initial date is chosen accordingly, as the required series for all S&P500 firms are only available from that point onwards.

¹⁷We perform robustness tests with equally weighted alternatives, but this does not change our results in a meaningful manner.

¹⁸We get three subsamples: the first from the start of the sample up to June 1997 (change in the tick size from one sixteenth to one eighth; the first time in history that an exchange had modified the minimum tick size); the second from July 1997 till February 2001 (change in tick size from

day is based on the last five years preceding that day (which shortens the sample to 1962-2013, as we lose the first five years of observations). This last approach accommodates the idea that investors have short memory. When gauging the particular impact of a liquidity measure, they would therefore mainly look at the short term window of the past five years.¹⁹ Moreover, this ‘short memory’ feature alleviates the potential problem of event reclassification which is prevalent with measures whose empirical setup thoroughly banks on stable distributional features, as is customary in limited samples (Holló et al., 2012). Additionally, we achieve a more sensible representation of liquidity over time by evaluating the variable in relation to its immediate environment. After all, over long samples, many liquidity measures show dramatic drops simply due to their construction method (often due to an increase in the activity on the stock market in recent decades), indicating that recent illiquidity pressures are negligible in comparison to historic ones. However, for the present day investor these (seemingly understated) liquidity events embody very real treats.

Finally, this local evaluation leads the variables not only to be consistent, but also stationary. Table 3 highlights that standard unit root tests cannot reject the hypothesis that several liquidity groups based on the full sample ordering technique contain unit roots. More specifically, the returns, fong, etick, amihud and volume groups appear to be non-stationary.²⁰ However, these groups all exhibit stationary time series when we apply a more local ordering, through breakpoints or with a five year rolling window. The latter has the additional advantage that we do not have to exogenously administer the breakpoint dates, which can provide additional difficulties as additional data is added to the time-series.²¹ Hence, for the remainder of the paper, we use the rolling window ordering method.

3.1.3 Liquidity Groups

In a next step, the measures for the eight separate liquidity groups, denoted by $l_{i,t}$, are then formed by taking the simple arithmetic mean of the individual measures

one sixteenth to one cent on the NYSE; this happens for all stocks in April 2001, but the choice between the two dates does not change the results); the final from March 2001 onwards till the end of the sample (Bessembinder, 2003; Goldstein and Kavajecz, 2000). Corwin and Schultz (2012) apply a comparable division in their analysis of the correlation between liquidity measures, and Holden (2009) similarly does so in the construction of the effective tick measure.

¹⁹Admittedly, the time frame of five years could be seen as arbitrary. However, the measure is robust for a time frame of ten years. The only difference is that the liquidity groups exhibit less volatility, and thus feature comparatively less idiosyncratic pressure with the ten year alternative.

²⁰With the Perron test this is limited to the etick, amihud and volume group.

²¹Moreover, as breakpoints differ across countries, this methodology does not allow a uniform approach for cross-country comparison.

$z_{i,j,t}$ belonging to each group ($i = 1, \dots, 8$):

$$l_{i,t} = \frac{1}{n} \sum_{j=1}^n z_{i,j,t}$$

with n the number of individual measures belonging to each group and t the time period. Index j refers to the individual measure of a specific liquidity group. The formation of the groups is based on the underlying dimension. A more detailed account can be obtained in Figure 1.

3.2 Time-Varying Correlations (Portfolio Approach)

We reach our multidimensional or unified market liquidity measure L_t by applying the portfolio approach to the eight groups, i.e.

$$L_t = (w_t \circ l_t) C_t (w_t \circ l_t)'$$

where C_t denotes the matrix of time-varying cross-correlations (measured with exponentially weighted moving averages with a decay factor of .94), l_t the vector of liquidity group measures and w_t the vector of weights attached to the liquidity groups, which are set equally up to this point.²² The rationale behind this approach is that every market liquidity measure can theoretically be broken down into a systematic component and its idiosyncratic counterpart (Korajczyk and Sadka, 2008). On the one hand, the different liquidity groups might represent imperfect proxies of the same true underlying concept of liquidity (Amihud et al., 2005; Lesmond, 2005). On the other hand, they might gauge different dimensions of liquidity that are interconnected with each other (thus measuring closely related concepts). By using the portfolio approach, an individual liquidity group affects our unified liquidity measure to the extent that they are correlated with the other liquidity groups. When several groups simultaneously indicate a dry spell in liquidity, we want them to receive relatively more weight, as this would point towards several dimensions picking up the same signal or characteristic.²³ This is accounted for by our matrix C_t . Hence, up to this point, we simply provide an alternative to the more traditional principal component and common factor analysis (Korajczyk and Sadka, 2008; Hallin et al.,

²² $w_t \circ l_t$ represents the Hadamard-product, i.e. element-by-element multiplication of the vector of weights and the vector of liquidity group measures.

²³Amihud et al. (1990, pp. 65-66) already acknowledged that “components of illiquidity cost are highly correlated, as stocks that have high bid-ask spreads also have high transaction fees and high search and market-impact costs, and are thinly traded. When the bid-ask spread widens, it signals that immediacy of execution is more costly, that is, asset liquidity is lower.”

2011), solely relying on the systematic liquidity elements to perform the aggregation.

Table 4 provides some summary statistics for the time-varying correlations of each specific group measure with the seven other group measures. Panel A highlights values for the mean, standard deviation and the interquartile ranges (IQ). Panel B shows sample averages for the full sample period ($n = 624$), but also differentiates between the crisis periods²⁴ ($n = 111$) and tranquil times ($n = 513$). The interquartile values in Panel A show that correlations shift considerably over time. Panel B reveals though that the timing does not exactly correspond with the crisis periods. Possibly the correlations only change after such events. Overall, the results justify the use of time-varying cross-correlations in our methodology.

3.3 Time-Varying Weights

3.3.1 Methodology

Up to this point, we have mainly followed the approach by Holló et al. (2012). However, we customize the existing approach to better fit the needs of the liquidity context that we are examining. As our groups consist of imperfect proxies that gauge the same concept from different viewing points (fundamental and distinct aspects of illiquidity, as pointed out by Vayanos and Wang (2012)), it is possible that a single or several specific measures pick up a signal that the other groups (because of their specific construction method) do not pick up on. Merely incorporating the different dimensions as weighted by their correlations would imply that we interpret this signal as noise, and hence would be weighted less relative to the other groups. However, if this signal is strong, it could be hinting at an important feature that the other groups are not able to pick up on. We would therefore also like to account for these idiosyncratic signals, in our weighting scheme. For this purpose, we enhance our model by incorporating time-varying weights based on the relative illiquidity pressures in every group.²⁵ The weighting function $w_{i,t}$ of group i at time t is modeled as an exponential function of the deviation of the group-specific liquidity

²⁴Crisis periods are defined as historic financial stress events (as explained in Section 4.1), combined with the recession periods during the sample from January 1962 up to December 2013.

²⁵The CISS methodology only incorporates fixed weights for the full sample, based on the impact of each group on the economy. However, this could introduce endogeneity issues in the identification of the importance of every group.

value $l_{i,t}$ at time t minus an arbitrary threshold T ²⁶:

$$w_{i,t} = \frac{\exp(l_{i,t} - T)}{\sum_{i=1}^8 \exp(l_{i,t} - T)}.$$

This function ensures that higher deviations (which point at stronger signals or higher pressure) get higher weights. We force the weights to sum to one over the different groups, and are therefore only interested in the relative pressures which are present in our system of liquidity groups. If all the groups are similarly exceeding their threshold, they simply receive equal weights.

3.3.2 Volatility Adjustment

We also include another explicit aspect of investor behavior based on the literature about limited attention (Kahneman, 1973) and the use of heuristics (Gigerenzer, 2008).²⁷ Closer to our story, there are several studies examining limited attention in the stock market (Corwin and Coughenour, 2008; Huang and Liu, 2007). With the full spectrum of information, we cannot expect an individual investor to pick up all the relevant signals to make his decision. We suspect that signals that are more volatile will also attract more attention.²⁸ More specifically, investors will be affected more by episodes of high relative idiosyncratic pressure in a specific group, if this relative pressure reveals itself in an irregular, unexpected manner. For example, if the illiquidity pressure in the group is comparatively high, this would yield a high weight in the previous setting. But if it has been that high for the past five months, then the investor would be accustomed to that stance, and would have already taken the necessary precautionary steps, thus being less affected by it lingering. In contrast, a similar amount of pressure, brought about virulently, with high volatility, will bring about a more pronounced impact. Attention grabbing “liquidity groups” may have a similar impact as attention grabbing stocks (‘all that glitters’), when there are many to choose from (Barber and Odean, 2008). We therefore adjust our weighting function to take into account the volatility of the particular group.²⁹

²⁶As our liquidity proxies are between zero and one, imagine a threshold of 0.75, where values above the threshold are weighted more strongly (see formula). However, as we force the respective weights over all the groups to sum to one, we simply examine relative values, and the outcome becomes independent of the chosen threshold.

²⁷We do not want to construct an abstract theoretical construct that relates to the real life investor experience, as for example Goyenko et al. (2009) remark that there is little evidence that any liquidity measure is related to the investor experience.

²⁸Including a threshold and integrating a volatility metric is reminiscent of option pricing models, something already noticed by Copeland and Galai (1983).

²⁹The downside is that the weights of the groups do not sum up to one, due to the shrinkage, so we lose some comparability with the previous weighting schemes. However, this approach is

Using volatility as a weighting factor for different groups is not uncommon. For example Gerdesmeier et al. (2011) apply weights based on the volatility of different asset classes in setting up their early warning indicator. Practically, we apply two variations on this theme which have a very similar relative impact. Firstly, we apply a ‘shrinkage factor’ to dampen the tranquil episodes:

$$ws_{i,t} = \frac{\exp(l_{i,t} - T) * \sigma_{i,t}^2}{\sum_{i=1}^8 \exp(l_{i,t} - T)}$$

where $\sigma_{i,t}^2$ is the volatility (measured with exponentially weighted moving averages with a decay factor of .94) of liquidity measure $l_{i,t}$ of group i at time t . Secondly, we built an alternative version where volatility interacts with the liquidity measure itself, leading to a volatility augmented approach:³⁰

$$wa_{i,t} = \frac{\exp(l_{i,t} - T) + (\sigma_{i,t}^2 * l_i)}{\sum_{i=1}^8 [\exp(l_{i,t} - T) + (\sigma_{i,t}^2 * l_i)]}$$

According to this model, volatility outbursts are reinforced for higher levels of illiquidity. Both volatility-adjusted weighting functions $ws_{i,t}$ and $wa_{i,t}$ allow us to account for the heuristic approach many investors rely on.³¹

3.3.3 Descriptive Statistics

To get a full understanding of the different weighting functions, we look closely at the dynamics of our unified liquidity measure and the underlying time-varying weighting schemes. Table 5 reports the average values for our unified liquidity measure based on the four different weighting schemes, namely fixed weights w , basic time-varying weights $w_{i,t}$, volatility shrinkage time-varying weights $ws_{i,t}$ and volatility augmented time-varying weights $wa_{i,t}$. We present the average values over the full sample period, but also differentiate between crisis periods and tranquil times (as explained in Section 3.2). As the different construction methods do not allow a clear-cut comparison across methodology for the absolute values, we merely focus on the relative changes (expressed as percentage) in the average illiquidity values for the different weighting options. Moving from the full sample to the tranquil subsample, illiquidity values based on $w_{i,t}$, $w_{i,t}$, and $wa_{i,t}$ exhibit comparable fluctuations whereas the drop for their $ws_{i,t}$ based counterpart is comparatively larger.

intuitively appealing and yields the most powerful results.

³⁰With the additional advantage that this methodology allows the weights to sum to one again.

³¹An additional feature for future work could be to allow the threshold to change for up and down markets.

This difference is even more pronounced when we switch from the full sample to the turbulent sub-period. While this increase is above fifty percent for the $ws_{i,t}$ methodology, it only amounts to thirty-three percent with the other options. This suggests that the preferred volatility shrinkage methodology succeeds best at capturing the expected pattern of higher relative illiquidity values during crisis times (and conversely lower values during tranquil times) in comparison with its full sample counterpart. For the remainder of the paper, we focus on this specific application of our unified liquidity measure, unless we mention it explicitly.

A more detailed understanding of the driving forces for the above mentioned shifts can be obtained by looking more closely at the dynamics in the underlying time-varying weighting schemes. This allows us to unravel how our unified liquidity measure is built up (for the different alternatives), and how the importance of the different groups can shift over time. In Table 6 we can clearly distinguish three different trends among the weights of the constituent groups. Firstly, for some groups these weights markedly increase during the crisis timespan, and decrease (slightly) during the tranquil period. This is most pronounced for the spread, etick and amihud group, and holds to a lesser extent for the roll group. Secondly, the opposite trend, where the weights decrease noticeably during crisis and increase (moderately) in tranquil times, is present for the returns group, and to a lesser extent for the fong and volume group. The third group merely consists of the order flow, which is visibly unaffected but the different subsamples. These results are further refined in Section 4.4 where we analyze in detail which groups contribute more/less during well-known historic episodes of financial stress.

4 Evaluation

4.1 Identifying Financial Stress

4.1.1 Financial Stress Events

Since the eighties, we have witnessed several market crisis which were closely associated with liquidity spirals, focusing the attention of researchers and policymakers towards understanding the dynamics of liquidity (Brennan et al., 2012; Liang and Wei, 2012). Figure 2 displays our unified market liquidity measure together with the NBER recessions and a list of episodes that are linked with financial pressure.³² Many of the upswings in illiquidity systematically coincide with market downturns,

³²The list is based on Hubrich and Tetlow (2015), who document financial events affecting the US Economy from 1986 till 2012, which we expand for our full dataset.

consistent with the existing literature (Chordia et al., 2001; Jones, 2002; Amihud and Mendelson, 2006; Næs et al., 2011). Chronologically, we can discern following major events.³³ Firstly, we can discern a brief episode of domestic political unrest in 1970, matched with a spike in illiquidity. The second major hike in the multi-dimensional liquidity measure corresponds with the oil embargo in November 1973. Moreover, illiquidity remained relatively high in the seventies (Chordia et al., 2001; Jones, 2002). Thirdly, the early eighties witnessed a double dip recession. During the aftermath of the second oil crisis, a recession was triggered due to Paul Volcker’s shift in monetary policy (Rotemberg, 2013), which was followed with a debt crisis in Latin American. Fourthly, we highlight the stock market collapse in October 1987, during which the financial markets were highly illiquid (Grossman and Miller, 1988; Brennan et al., 2012). The crash was partly attributable to a decline in investors’ awareness of the general market liquidity in comparison to pre-crash level (Amihud et al., 1990). Fifthly, after witnessing spurts of illiquidity during the Iraq invasion (and ensuing recession) as well as during the Mexican Peso crisis, we reach the Asian crisis in 1997, shortly thereafter succeeded by the collapse of Long Term Capital Management (LTCM) combined with the Russian debt crises. Both of these events can be separately discerned by means of our liquidity proxy (Chordia et al., 2001; Lesmond, 2005). Sixthly, a remarkable feature about the tech bubble burst in 2000 is that the illiquidity levels already skyrocketed just before the recession really kicked in. Finally, the most recent financial crisis witnessed a twenty percent drop in stock markets around the world in the second week of October 2008 due to the scarceness in liquidity (Brennan et al., 2012). Concerns about liquidity kept global equity markets tumbling until March 2009. Hence, shortage or abundance of liquidity can ravage or buttress stock markets (Liang and Wei (2012)).

The behavior of liquidity during financial distress highlights that market liquidity evaporates when it is most necessary, during market turmoil and in periods of crisis. Market risk and liquidity risk seem therefore to be closely connected, with investors simultaneously being hit by both factors (Rösch and Kaserer, 2013). Our multifaceted liquidity measure succeeds well in capturing these rich dynamics and succeeds proficiently in identifying historical episodes of financial stress.

Table 7 shows that our constructed liquidity measure also has some rapport with other well-known crisis indicators. Certainly, during the past decades, market crises seem to have been closely associated with financial pressures and liquidity spirals (Liang and Wei, 2012). The regression results reported underpin what we presented

³³We merely want to provide the reader some examples, as we do not want to dissect this anecdotal analysis in too many details.

visually in Figure 2. However, this relation does not hold uniformly over all the incorporated crisis measures. Whereas liquidity seems to be connected to certain elements of the Cleveland Financial Stress Index (CFSI), namely the contribution of the interbank or funding markets (CFSI-IB-FUND) and the interbank liquidity spread (CFSI-IB-LIQ), this relation cannot be retrieved with the overall CFSI itself.³⁴ However, our unified market liquidity measure does show kinship with the concepts of the National Financial Conditions Index (NFCI), the Kansas City Financial Stress Index (KCFSI)³⁵, Smoothed U.S. Recession Probabilities (REC P), the St. Louis Fed Financial Stress Index (SLFSI), Aruoba-Diebold-Scotti business conditions index (ADSBCI)³⁶ and the Financial Stress index measured by the International Monetary Fund (IMF FSI).³⁷

4.1.2 Signal-to-Noise Ratio

Even though our unified liquidity measure is merely constructed with the goal of capturing all of the dimensions of liquidity simultaneously and hence not primarily set up to retrieve financial stress events, we can use the close association between such events and the disappearance of liquidity as a general indication of its performance.³⁸ In order to uncover the historic dates necessary for the calculation of our signal-to-noise ratios, we follow Christensen and Li (2014) in describing a financial stress event as the moment when the financial stress index (FSI) exceeds an extreme value:

$$fin\ stress_t = \begin{cases} 1 & \text{if } FSI_t > \mu_{FSI} + k\sigma_{FSI} \\ 0 & \text{otherwise} \end{cases}$$

where μ_{FSI} is the sample mean of the FSI and σ_{FSI} the sample standard deviation. However, as we do not want to be reliant on a single financial stress index, we apply this methodology to several well-known FSI's.³⁹ In order to detect the stress events,

³⁴Similarly, there is no significant relation with the Flight-to-Safety measure constructed by Baele et al. (2015).

³⁵Albeit, only at a higher significance level.

³⁶All these financial stress indicators and (business or financial) condition indices were obtained from the FRED database, which is provided by the St. Louis Fed.

³⁷Gibson and Mougeot (2004) also find evidence that the time-varying liquidity risk premium in the U.S. stock market is associated with a recession index.

³⁸However, the occurrence of illiquidity with such stress events does not necessarily have to be simultaneous. The dynamics in liquidity could have a leading or lagging pattern, depending on the type of event, and underlying causes.

³⁹We employ the following stress indices: the St. Louis Fed Financial Stress Index (STLFSI), the Kansas City Financial Stress Index (KCFSI), the Cleveland Financial Stress Index (CFSI), the International Monetary Fund U.S. Financial Stress Index (IMF FSI); in combination with the following condition indices: the National Financial Conditions Index (NFCI), the Bloomberg Financial Conditions Index (BFCI), the Citi financial conditions index (CFCI) and the Aruoba-

we set $k = 1.5$, similar to Christensen and Li (2014).⁴⁰ In our analysis, we focus on the signal-to-noise ratio, as well as the number of financial stress events which were distinguished correctly, and similarly the number of no stress events unraveled appropriately. When we analyze the data, the following four situations can be discerned, as described in Panel A of Table 8: a financial stress event signaled by our measure (A), a financial stress event not signaled by our measure (C), a no financial stress event miscorrectly signaled as stress event (B), and a no financial stress event correctly not being signaled (D). The signal-to-noise ratio can then be summarized by $[B/(B+D)]/[A/(A+C)]$, the number of crisis events signaled correctly by $[A/(A+C)]$, and the number of non-crisis events signaled correctly by $[D/(D+B)]$.

Panel B of Table 8 compares the signal-to-noise ratio for our unified market liquidity measure with those for two established financial conditions indicators, more specifically the National Financial Conditions Index (NFCI) and the Aruoba-Diebold-Scotti business conditions index (ADSBCI).⁴¹ The values are similar to the NFCI index, and slightly worse than the ADSBCI. We can therefore conclude that our measure performs comparatively well.⁴² We have to keep in mind that our liquidity construct only takes into account one very specific market, namely the stock market (S&P500 stocks), it merely incorporates a very limited amount of data series on these stocks, and it is not designed with the aim of detecting crisis events, but solely with the purpose of unraveling illiquidity. In contrast, the financial conditions index looks at very many different markets, and combines the information of many data series, specifically in order to optimally detect the specific conditions of the economy.

Panel C of Table 8 examines the signal-to-noise ratios for the several different weighting methods underlying our liquidity measure. The liquidity measure with the volatility adjusted weights ($ws_{i,t}$ and $wa_{i,t}$) perform relatively better than their more basic counterparts.⁴³ Hence, this provides additional evidence that the volatility corrections are valuable extensions in constructing a sensible liquidity measure.

Diebold-Scotti business conditions index (ADSBCI). We identify the stress events based on each of these indices and then evaluate an observation to contain financial stress when the average exceeds .5, hence when at least half of the available indices for that observation hint at stress.

⁴⁰Alternatively, Illing and Liu (2006) set $k = 2$, whereas Cardarelli et al. (2009) apply $k = 1$. However, these adjustments do not change the identified crisis moments profoundly.

⁴¹We limit our comparison to the ADSBCI and the NFCI, as these have long-running data series.

⁴²As a robustness test, we perform a similar exercise with dates based on anecdotal evidence, as given by the important historical financial stress events discussed in Section 4.1.1. For our unified measure and NFCI the results are still comparable. In contrast, the ADSBCI is slightly superior in this setting. These results can be obtained from the authors upon request.

⁴³Similarly, we perform this exercise with the anecdotal dates. The results are comparable, with the distinction of the $ws_{i,t}$ now also being superior to $wa_{i,t}$, thus reaffirming our choice as the preferred metric.

4.2 Link with Financial and Macroeconomic Variables

In this section, we examine the basic comovement of our unified market liquidity measure with a large number of financial and economic variables (as conducted in Baele et al., 2015; and specifically for liquidity measures in Brennan et al. (2012)). We learn that our measure behaves in accordance to general financial and macroeconomic theory and intuition. We find similar interlinkages for the alternative weighting methods of our unified liquidity measure, albeit these relations are considerably less pronounced, uniformly exhibiting lower R^2 values for all of the subcategories. The results are summarized in Tables 9 to 11.

When looking at the comovement of illiquidity with confidence indicators (see Panel A of Table 9), we retrieve the expected negative relation, where higher illiquidity coincides with lower levels of confidence (Baker and Stein, 2004). This relation holds for the business tendency survey, consumer opinion survey and inventory sentiment index. The sign is different for the inventory sentiment index, as an increase in this index leads to a greater degree of discomfort with current levels of inventory. Similarly, we would expect illiquidity to match with higher uncertainty. However, we cannot retrieve a significant relationship in this context (see Panel B of Table 9).

“A number of empirical studies have found that thin speculative markets are *ceteris paribus* more volatile than deep ones” (Pagano, 1989, p. 269). More recently, Brennan et al. (2012) unravel that their market wide illiquidity proxies are significantly positively correlated with TED spread as well as with implied market volatility measure (VIX).⁴⁴ In a similar vein, Nyborg and Östberg (2014) report that the market share of volume for more liquid stocks expands with Libor-OIS spread, above and beyond what can be explained by the VIX.⁴⁵ Correspondingly, on a stock specific level, Han and Lesmond (2011) report a robust positive correlation between idiosyncratic volatility and liquidity. The same type of interdependence between liquidity and total volatility is highlighted in Chordia et al. (2009). We detect a similar positive relation between illiquidity and the market specific variants of implied volatility, with the highest adjusted R-squared for the market indices most closely related to the construction of our unified market liquidity index (see Panel A of Table 10). The same story holds for the TED spread, as well as for the different modalities of the option adjusted spreads (ranging from AAA to higher yielding spreads), as visualized in Panel B of Table 10.

When we examine the relation of our market liquidity measure with measures indicating the capacity of the economy, we get a mixed picture (see Table 11).

⁴⁴Both values are typically associated with funding liquidity (Asness et al., 2013)

⁴⁵The market share of volume of more liquid stocks is also increasing in the VIX itself.

Whereas the linkages between illiquidity and the growth proxies are robust and even forward-looking (see next section), the evidence for particular variables seem weaker. For example, with the coincident index, there seems no clear-cut association. However, for capital utilization and (on a higher significance level) for labor market conditions, we do retrieve a closer relation. A potential reason for the weaker bond might be that these variables are more sluggish, and we should thus build in richer dynamics to get the true linkages. House prices have played an important role during financial crises (Case and Shiller, 2003), and are quintessential in identifying financial cycles (Borio, 2014). Hence, it is no surprise that higher illiquidity seems to coincide with lower levels of house price inflation. Evaluating the connection with monetary policy⁴⁶, we can discern that higher illiquidity is associated with higher short term interest rates. Moreover, higher illiquidity levels concur with a flattening yield curve. When incorporating monetary aggregates in our analysis, we rely on the concept of real money gap, based on the construction method by Calza et al. (2003), and implemented by Hofmann (2009) and Drescher (2011). As such, we retrieve the real money gap proxy from a recursive long-run M3 demand function. Illiquidity seems to be negatively connected with the real money gap.⁴⁷ Because financial crises usually coincidence with flights to home and flights to safety, we also examine the relationship with exchange rates. Both for the US-Euro as for the US-UK exchange rate, there seems to be a flight to home effect, where higher illiquidity levels concur with higher relative values for the US dollar. The same effect is measurable through the real trade-weighted exchange rate (towards a broad range of currencies).⁴⁸

4.3 Impact on Future Economic Growth

Both De Nicolò and Ivaschenko (2009) and Næs et al. (2011) hint at the potential of illiquidity to affect the real economy. More specifically, illiquidity is presumed to have a forward looking effect on a country's growth opportunities. Hence, we incorporate an update of the empirical exercise featured in Næs et al. (2011), and look at the forecasting abilities of illiquidity on future economic performance, in a multivariate setting, with a number of control variables.⁴⁹ In Table 12, we conduct an in-sample forecasting exercise where we gauge the effect of illiquidity on the one-quarter ahead industrial production growth (Panel A), as well as on the

⁴⁶Goyenko and Ukhov (2009) advance that monetary policy shocks can impact stock and bond market illiquidity.

⁴⁷Our results are robust for estimates of the monetary overhang and the change in p-star.

⁴⁸The sign is different, as this measure is expressed conversely to the other exchange rate measures, i.e. the foreign exchange value of the U.S. dollar.

⁴⁹We incorporate the term spread, excess market return and corporate bond yield as control variables.

one-quarter ahead industrial production gap measure, constructed using a HP filter (Panel B).⁵⁰ Our results are comparable with Næs et al. (2011), as we detect that higher illiquidity levels lead to lower growth levels.⁵¹

To further investigate the causality of the relation, we apply Granger causality tests, to analyze whether the impact on future growth rates is generated by illiquidity, and not vice versa. Table 13 reports p -values for the Granger Causality tests between brackets. A value below .05 implies proof in support of Granger causality. We find consistent evidence for our unified liquidity measure Granger causing output growth, while the reverse causality is not present.⁵² When looking at the control variables, the excess market returns and the term spread (on a higher significance level) Granger cause output growth, while output growth also Granger causes the latter, but not the former. No causality is found with the spread measure.

We get a similar outcome when performing a simple Vector Autoregressive estimation with 5 lags (based on the lag selection criteria), and a choleski ordering consisting of our unified market liquidity measure, year-on-year money growth, federal funds rate, month-on-month CPI inflation, and year-on-year industrial productions growth. A shock in illiquidity leads to a lower rate of growth in industrial production. The impulse response functions are summarized in Figure 3.

To complement our previous in-sample analysis in Table 12, we perform a small out-of-sample forecasting exercise for economic growth. Table 14 presents the out-of-sample forecasting performance for future economic growth over different horizons, respectively 3, 6 and 9 months. We estimate our forecasting models through a rolling window technique (Næs et al. (2011)). The initial estimation sample is set to 45 years (1962-2007) in order to obtain stable estimation parameters. The out of sample estimation covers the period 2008-2013. We evaluate our model, which includes term spread, excess market return, corporate bond yield and our unified liquidity measure, and compare this to a benchmark model without liquidity. We report the relative mean squared forecasting error and the relative out-of-sample R -squared value for our four different unified liquidity measures. Despite the full-fledged crisis period, the model which incorporates liquidity performs markedly better at fore-

⁵⁰We use industrial production as proxy for output, since we conduct our analysis on a monthly level.

⁵¹Our unified market liquidity measure seems even capable of explaining a markedly higher proportion of variation of future growth values than its unidimensional counterparts, indicating that incorporating our novel methodology might improve on capturing the existent macroeconomic relations. These results can be requested from the authors.

⁵²This causal relation is absent for the unified liquidity measure with the basic time-varying weighting function, and the causality even reverses (with output growth Granger causing illiquidity) for the fixed weight alternative. This further supports our model using time-varying weights combined with the volatility shrinkage.

casting out of sample, than a model that neglects liquidity.⁵³ Moreover, the results are comparatively robust for the different forecasting horizons ($h = 3, 6, 9$).

4.4 Evaluation of Individual Groups

4.4.1 Importance of Constituent Liquidity Groups

We link back the properties of our multidimensional liquidity measure to its founding elements in Table 15 by analyzing the correlation of our measure with the individual group measures (Panel A), together with the results for the unconditional variance decomposition of our measure into the underlying group measures (Panel B). Panel A indicates that the most important associations can be found with the etick group, followed by the spread, roll, fong and order flow groups (which are comparable). The return and volume group generally have low correlations with our unified liquidity measure. Panel B reports the results for the unconditional variance decomposition. Firstly, we convey the unconditional variance decomposition making abstraction of the covariance terms ('Var1' and 'Var2' provide two separate options in this context⁵⁴). However, we also calculate the unconditional variance decomposition including the covariance terms ('Cov'). All three techniques give a general idea on the influence of each underlying group on our multidimensional liquidity measure. In this exercise, the etick, roll and spread group seem to be the most important. Admittedly, our framework lacks a theoretical framework, a feature it shares with most of the empirical work on liquidity, and with the widespread crisis measures which provided us with the inspiration to take on this exercise (Vayanos and Wang, 2012; Chordia et al., 2009). A theoretical foundation could provide valuable insights, not only for our understanding of the financial concept, but also in its interlinkages with the macroeconomic world, especially in the financial and monetary world we have come to live in (Borio, 2014). However, in this particular setting, we merely aspire to create a measure, which takes into account all of the dimensions of liquidity (allowing a sensible aggregation), and which is not susceptible to any fad or fashion concerning the particular measures.

4.4.2 Contributions of the Constituent Liquidity Groups to Stress Events

This section analyzes the contributions of the constituent liquidity groups for specific historic crisis moments. A supplementary feature of our methodology is that it does

⁵³This improvement is most pronounced for our preferred volatility shrinkage methodology.

⁵⁴Whereas for the latter methodology the weights are treated as being exogenous; this is not the case for the former.

not only allow to aggregate the different liquidity groups into a unified measure, but also allows us to gauge the individual importance of each group over time, and more specifically during periods of financial stress.⁵⁵ To give a comprehensive overview, we group the historic stress events based on their most important contributing liquidity groups. This classification allows us to discern some general characteristics that these events might have in common. The results are reported in Figure 4. Each panel groups stress events of a specific type which relates to a certain category of liquidity group measures.

Firstly, in Panel A, we focus on the category that contains the spread, etick, amihud groups as its main protagonists, and which entails the following dates: The 1966 credit crunch (10/1966), the peak during the first oil shock (10/1974) and the Iraq invasion (08/1990).⁵⁶ These periods were characterized by some sort of foreign contamination (increase in spending due to the Vietnam war, the Yom Kippur war, and the Iraq Invasion). Similarly, they all witnessed a credit crunch⁵⁷ and are related to a stock market crash (only 1990 saw a mini crash). Moreover, these specific episodes of financial stress were preceded by a tightening of the Federal Reserve rate. Finally, we can discern no (1966) or only a slight (1990) recession, except for 1974 when there was a severe recession.⁵⁸

The second class (Panel B) most prominently features the spread, etick, fong group, and portrays the peak of the 1970s crisis (06/1970), the peak during the 1980s crisis (04/1980)⁵⁹ and the Tech Bubble burst (03/2000). Interestingly, there was a credit crunch both in 1970 and 1980 (1982), but not in 2000, as this event seems to have a slightly different physiology than its peers. Additionally, there was a stock market crash in 1970 and 2000, however, not in 1980 or 1982. Furthermore, each of these crisis periods tends to occur after a tightening of the Federal Reserve rate. Finally, there was no banking crisis, nor a major recession.⁶⁰ Admittedly, this specific class of events shows close resemblance with the first cluster, both for the features of these events (credit crunch, Fed tightening, stock market crash; only the

⁵⁵Hubrich and Tetlow (2015) provide an extensive historical account of such financial stress events. We further refine and extend this list using similar tables provided in Brave and Butters (2010) and Bordo and Haubrich (2013). Hence, our analysis mainly builds on their classification and interpretation of these events.

⁵⁶The peak during the Russian crisis (08/1998) could also be added to these events, but only has the spread and amihud group as its main protagonists.

⁵⁷Albeit for 1998 the not full blown credit crunch might explain a divergent pattern.

⁵⁸Both the event in 1974 and in 1990 are also associated with a banking crisis (although this was minor for 1974).

⁵⁹The peak of the 1982 crisis (08/1982) can be closely linked to this event and has similar dynamics.

⁶⁰Except 1982, which actually witnessed both a banking crisis and was characterized as a severe recession.

foreign component disappears), as well as for the most important groups it contains (the spread and etick group now simply go together with the fong group, instead of with the Amihud group). Hence, both can be seen as subclasses of a more general class of events.

For the third category (Panel C), the lion's share of the contributions can be attributed to the spread and roll group. This composition seems useful to describe the 1987 stock market crash (10/1987), the decline of LTCM (05/1998)⁶¹ and AIG-Lehman (09/2008). We can observe a minor⁶² or a more full-fledged (during the 2008 financial crisis) stock market crash. We cannot ascertain any underlying recession for earlier crises (1987 and 1998), in comparison to their more recent counterpart (which featured a major recession, banking crisis and housing bust). A subcategory of these events, more specifically focusing on their aftermath, can be constructed by grouping together the aftermath of the 1987 stock market crash (corresponding with its peak in illiquidity, 01/1988), together with the aftermath of the 2008 financial crisis (the TALF announcement, 11/2008; the stress test announcement 02/2009). The composition (see Panel D) is logically very similar to the above mentioned events, only with the addition of the etick group. Hence, this cluster again shows a close association with the first two groups, where the etick and spread groups are similarly playing a prominent role, but this time together with the roll group.

Finally, in Panel E, we describe a more dispersed category which contains the returns, fong, etick, and order flow group⁶³, which is useful for describing the 1977 dollar crisis (10/1977), the second oil shock (01/1979) and the Mexican crisis (12/1994). All three events can broadly be described as an external crisis (the dollar declines against major currencies in 1977, the second oil shock in 1979, and huge losses on the Mexican stock market in 1994 leading to rebalancing portfolios). However, there were no severe disruptions of the financial markets, and no real domestic stock market crash. Moreover, we cannot observe any tightening of the Federal reserve rate. Finally, there was no recession associated with these events.⁶⁴ Hence, we could potentially describe these events as being the least impactful.

The most prominent liquidity groups in our analysis of historical crisis events, are the spread group, closely followed by the etick group. Both groups seem to feature

⁶¹Similarly, the closely linked events of the Asian Crisis (07/1997), and the Hong Kong speculative attack (10/1997).

⁶²In 1987 there was black Monday, as well as the savings and loans crisis; while in 1998 the US witnessed a mini crash due to the Asian financial crisis, together with the demise of LTCM, which brought the country almost on the verge of a liquidity crash.

⁶³The only class of events where the return group or the order flow group come into play.

⁶⁴At least not preceding the respective crisis events. For example there were interest rate hikes starting from 10/1979.

prominently at times when the financial stress skyrockets. These protagonists are often combined with the roll, fong and amihud group, which tend to be useful at portraying specific subclasses with their own characteristics.⁶⁵ In contrast, the flow, returns and volume group seem to be less important liquidity categories when examining these crisis events specifically. We can discern a similar pattern when we perform the same analysis for the recession periods as a whole, instead of the mere crisis dates. Hence, our conclusions are more broadly applicable than for the historic snapshots analyzed above.

Of course, these categories can, to a certain extent, be considered as being anecdotal or somewhat arbitrary. Moreover, many characteristics of these financial pressure episodes can be debated upon, and have been the focus of numerous academic studies. However, our only purpose is to show that specific liquidity groups are more important during financial stress periods than others, and that there are some similarities over time between different stress events. For this objective, our current distinction between the different types of crisis events or their underlying causes should be sufficient.⁶⁶ Finally, our results might be mainly driven by the construction method of our unified liquidity measure. Logically, as portrayed in Table 6, the most prominent groups during financial stress events are also the groups that exhibit the largest increase in weights when comparing the full sample with the sub-period of stress (and conversely the groups least prominent during the crisis events, are those which exhibit the largest increase in their weights when comparing the full sample with the tranquil period).⁶⁷ However, we find proof that our conclusions are not solely model-dependent. The univariate regressions for the eight liquidity groups (which will be discussed in Section 4.4.3) show us that the liquidity groups which have strong interlinkages with many confidence and uncertainty; spread and volatility; crisis; productivity; monetary and exchange rate variables (which can be mainly retrieved with the spread and etick group, but to a lesser extent also with the roll and amihud group) coincide with the protagonist liquidity groups during the financial stress events, as mentioned in our pie charts.⁶⁸ Hence, the contributions

⁶⁵Due to presence of the two dominant groups, these subclasses tend to have many similarities.

⁶⁶We acknowledge that the groups can be formed differently. However, this would not fundamentally change the conclusion of this section. The same holds for different identification methods, criteria and definitions of the financial stress events.

⁶⁷The only special case is the fong group, which features prominently in at least two of the crisis categories. An explanation can be that the fong group (which has increasing weights during the tranquil period in comparison to the full sample) succeeds in capturing liquidity movements during tranquil periods, but also plays its part in certain crisis events. Both aspects might also explain its prominent role in the variance decomposition or the decomposition based on the group contribution.

⁶⁸But also perform best in signaling financial stress moments, when looking at their signal-to-noise ratios or the amount of correct crisis events they signal.

of the different groups into our unified model, simply reflect their intrinsic qualities, and our model seems to perform the aggregation in a desirable fashion. We can therefore conclude that specific groups are better equipped at capturing the more volatile episodes in liquidity, while others are more useful to model its relative tranquil counterparts. Hence, if we would solely focus on a subgroup of them, we would have to sacrifice on the richer dynamics we can portray within our framework.

4.4.3 Univariate Regressions for Constituent Liquidity Groups

Similarly to our analysis in Section 4.2, we again look at linkages between the liquidity measure (but now for the underlying groups) and the following four main categories: confidence and uncertainty indices; spread and volatility measures; crisis indicators; productivity and monetary/exchange rate variables. The main results are summarized in Tables 16 to 19. We report the R -squared for the univariate regressions. Moreover, whenever the coefficients have a counterintuitive sign, we add brackets to the R -squared value.

The spread and the etick group perform best at untangling the univariate relations, posting comparable and at times higher R -squared values than the unified measure.⁶⁹ However, the spread group is not able to unravel the monetary interlinkages, while the etick group shows little or no connections with the option-adjusted spreads and productivity subcategories. The performance of the roll and amihud group is more mixed. Whereas the former unveils a close relation with the option-adjusted spreads, variants of implied volatility as well as with some crisis indicators, the latter succeeds for the monetary, and some of the implied volatility and crisis variables. However, both perform worse in detecting relationships with many of the other categories. Finally, the fong, volume and order flow groups exhibit many counterintuitive signs and feeble relations with the investigated categories, which should normally be closely linked to liquidity. A possible explanation might be that these groups mainly seem important for liquidity during tranquil times, and hence are not able to catch the richer dynamics necessary to unravel such connections.

⁶⁹For several of these categories, the spread and etick group show an even higher R -squared value than for our unified liquidity measure. Hence, a hasty conclusion might be to dismiss the unified measure (and its more complex aggregation methodology) and simply use one of the (adequately performing) constituent groups as well. However, this cannot be seen as a surprising result. As the unified liquidity measure is merely the sum of the underlying groups. Hence, its performance, de facto, has to be comparable with its building blocks. It cannot suddenly outperform them. In contrast, it will often be outperformed by many of its constituent elements, as it incorporates all of the different qualities (for example, necessary to identify illiquidity both during stress events and tranquil times). However, whereas the underlying groups perform inadequately in at least one or several of the categories we are investigating, the unified measure finds all of the expected monetary, macroeconomic, financial and crisis linkages consistently over all of the domains.

Moreover, their relationship with the investigated categories might have changed over time, leading to the lack of coherent interlinkages. Because of its multidimensional properties our novel market liquidity measure succeeds better in catching a much broader array of dynamics with its macroeconomic surroundings than its unidimensional siblings, where interlinkages are more confined to certain subcategories.

5 Conclusions

Liquidity is an unobservable, endogenous and multidimensional concept. Hence, it is unfeasible for one single measure to capture all of the layers conveyed within liquidity. We want to address each of these challenges directly, and introduce a novel multidimensional market liquidity measure which unifies the individual strengths of the constituent liquidity groups. Albeit there are many authors that refer to the multiple dimensions of liquidity, there have been few attempts at integrating this feature in an all-encompassing measure. Most of the state of the art literature re-futes to running horse races, in order to find the first best liquidity measure amongst its competitors. In contrast, our novel liquidity measure incorporates all of the individual groups through a mechanism of time-varying correlations and time-varying weights. We augment the latter with a volatility component to reflect the effects of limited investor attention. For this purpose, we build on the recent advances made on financial crisis indicators (Oet et al., 2011; Holló et al., 2012), and apply several extensions on the portfolio approach (Illing and Liu, 2006) to perform the aggregation of the separate liquidity groups.

Looking back over the sample period, our unified liquidity measure is capable of tracking episodes of financial strains. It is closely linked with several prominent crisis indicators. Moreover, it exhibits a close relation with its macro-financial surroundings. Additionally, we can detect spillovers to the real economy from liquidity droughts. These features are relatively more robust and meaningful than for the existing liquidity proxies, thus reinforcing our belief that it is important to take all of the liquidity dimensions into account. Finally, next to aggregating our constituent liquidity groups, our methodology also allows closer inspection of the importance of these groups over time, and specifically during crisis periods. The protagonists during these latter periods are mainly the spread and etick group.

Given the importance of illiquidity during downturns (due to the increasingly financial nature of our economy) and the endogenous nature of the concept, it is necessary to have such an all-encompassing measure, with respect to all of the existing layers and dynamics. Moreover, our measure is easily applicable and can

be computed for long samples, as well as for many countries.

Interesting paths for future research would be to examine the performance of our multilayered liquidity measure in an asset pricing framework, by also constructing its counterpart on an asset-specific level. The same adaptations could be also done for high frequency data. Moreover, it would be useful to further examine the rich dynamics of liquidity with the macroeconomics surroundings, potentially building a more general theoretical framework. Moreover, our adaptation to the well-established portfolio approach could be useful for other markets as well, besides the stock market, and hence can be suitable for constructing more elaborate crisis or early warning indicators.

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Table 1: Overview of underlying costs and frictions reflecting the different dimensions of liquidity

This table reports several typologies for the costs and frictions underlying the concept of liquidity.

Year	Author	Background Measures	Measures/Explanation
1985	Kyle	Resiliency	Time dimension
		Tightness	Cost
		Depth	Volume
2005	Lesmond	Direct trading costs (tightness)	Bid-ask spread (quoted or effective)
		Indirect trading costs (depth,resiliency)	Costs based on price behavior (price impact)
			From firm-level data Occurrence of zero returns
2005	Amihud et al.	Exogenous transaction costs	
		Demand pressure, Inventory risk	
		Private info	
		Difficulty locating counterparty	
		Imperfect competition	
2006	Amihud;Mendelson	Price-impact costs	Bid-ask spread, Depth
		Search and delay costs	
		Direct trading costs	Exchange fees, Taxes, Brokerage commissions
2009	Holden	Proxy for effective spread	
		Proxies for price impact	
2012	Vayanos;Wang	Price impact	Coefficient of returns on signed volume
		Price reversal	(-) Autocovariance returns
		Participation costs	
		Transaction costs	
		Funding constraints	
		Asymmetric info	
		Imperfect competition	
Search frictions			
2013	Fong et al.	Percent-cost	Price concession required to execute trade
		Cost-per-volume	Price concession per currency unit of volume

Table 2: Eight liquidity groups representing the different dimensions in our analysis
This table reports all of the different groups which are incorporated in the multidimensional liquidity measure. The table provides the most important formulas for their construction.

Reference	Proxy
1. Spread Group	
Korajczyk, Sadka (2008)	$Qspread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{Ask_{i,j} - Bid_{i,j}}{m_{i,j}}$ $m_{i,j} = (Ask_{i,j} + Bid_{i,j})/2$ $Espread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{ p_{i,j} - m_{i,j} }{m_{i,j}}$ <p>(Both spreads also calculated with high and low prices)</p>
Corwin, Schultz (2012)	$S = \frac{2(e^\alpha - 1)}{1 + e^\alpha}$ with $\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$ where β is sum (over 2 days) of squared daily log(high/low) γ is squared log(high/low) but where high (low) is over 2 days
De Nicolò, Ivaschenko (2009)	$L_t = \frac{2 \left(\left \sum_{i,j \in K, i \neq j} cov_t(R_i, R_j)_- \right + \left \sum_{i,j \in K, i \neq j} cov_t(R_i, R_j)_+ \right \right)}{\sum_{s \in K} var_{t(R_s) + 2 \left(\left \sum_{i,j \in K, i \neq j} cov_t(R_i, R_j)_- \right + \left \sum_{i,j \in K, i \neq j} cov_t(R_i, R_j)_+ \right \right)}$
2. Roll Group	
Roll (1984)	$S = 2\sqrt{-cov(\Delta P_t, \Delta P_{t-1})}$ $\frac{1}{n} \sum_{t=1}^n \Delta P_t \Delta P_{t-1} - \Delta P^2$ (Harris, 1990)
Holden (2009)	$\begin{cases} \sqrt{\frac{-Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**})}{\hat{\mu}}} & \text{when } Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) < 0 \\ 0 & \text{when } Cov(\Delta P_t^{**}, \Delta P_{t+1}^{**}) > 0 \end{cases}$ $\Delta P_t^* = ar_t \cdot P_{t-1}$ with ar_t : adjusted returns $\Delta P_t^* = z_t \cdot P_{t-1}$ $ar_t - r_f = \alpha + \beta (r_{mt} - r_f) + z_t$ <p>Corwin and Schultz (2012) provide extensions on how to treat positive covariances (hence 2 versions of each Roll measure)</p>
3. Zero Return Group	
Lesmond, Ogden, Trzcinka (1999)	$Zeros = \frac{\text{Number of days with zero return}}{\text{Number of trading days in month}}$ $Zeros PV = \frac{\text{Number of positive volume days with zero return}}{\text{Number of trading days in month}}$
4. Fong Group	
Fong, Holden, Trzcinka (2013)	$FHT \equiv S = 2\sigma N^{-1} \left(\frac{1+Z}{2} \right)$ $\sigma : \text{Std}(\text{returns}), z : \text{Zero return days / total days}$ $N^{-1} : \text{Inverse function of cumulative distribution function}$
5. Effective tick (etick) Group	
Holden (2009)	<p>based on observed probabilities of special trade prices correspondent to the jth spread (N_j) dependent on fractional 1/8, 1/16 system or decimal which are then transformed to constrained probabilities</p> $F_j = \frac{N_j}{\sum_{j=1}^J N_j}$

Reference	Proxy
6. Amihud Group	
Amihud (2002)	$\frac{1}{TradingDays} \sum Abs(DailyReturns)/DailyDollarvolume$
Goyenko, Holden, Trzcinka (2009)	$SpreadProxy/DailyDollarvolume$ in casu: $High - low Spread Measure/DailyDollarvolume$
Sarr Lybeck (2002)	Hui-Heubel ratio: $L_{HH} = [(P_{max} - P_{min}) / P_{min}] / [V/S * \bar{P}]$ V: total dollar volume, S: number of instruments outstanding \bar{P} : Average closing price of instrument
Breen, Hodrick, Korajczyk (2000)	$r_{i,t}^{AR} = \theta_t + \phi_t r_{i,t} + BHK_t sign(r_{i,t}^e) * vol_t + \epsilon_t$ $r_{i,t}^{AR} = \theta_t + \phi_t r_{i,t} + BHK_t sign(r_{i,t}^e) * turn_t + \epsilon_t$
Liu (2006)	$(VolumezeroPreviousXmonths + \frac{1/PreviousXmonthsTurnover}{Deflator}) * \frac{21X}{NoTD}$ $\frac{21X}{NoTD}$: Standardizes amount of trading days in a month to 21
7. Volume Group	
	<i>Dollar Volume</i>
Datar (1998)	$SharesTraded/SharesOutstanding$
8. Order Flow Measures	
Pastor, Stambaugh (2003)	$r_{i,t+1}^e = \theta_t + \phi_t r_{i,t} + \gamma_t sign(r_{i,t}^e) * vol_t$ $r_{i,t+1}^e = \theta_t + \phi_t r_{i,t} + \gamma_t sign(r_{i,t}^e) * turn_t$

Table 3: Augmented Dickey-Fuller test: Testing stationarity of the eight different liquidity groups

This table reports the test statistic and the accompanying p -value (between brackets) of the augmented Dickey-Fuller test, performed for our eight liquidity group measures, according to the three ordering techniques (as explained in Section 3.1.2). ‘FS’ refers to the full sample ordering technique, ‘BP’ to the subsamples or breakpoint ordering technique, and ‘5y RW’ to the 5-year rolling window ordering method.

	Spread	Roll	Returns	Fong	Etick	Amihud	Volume	Flow
FS	-4.64 (0.00)	-5.37 (0.00)	-2.15 (0.22)	-1.97 (0.30)	-1.48 (0.54)	-1.54 (0.51)	-1.47 (0.55)	-3.30 (0.02)
BP	-5.40 (0.00)	-6.89 (0.00)	-7.08 (0.00)	-3.49 (0.01)	-3.55 (0.01)	-3.69 (0.00)	-3.12 (0.03)	-5.65 (0.00)
5y RW	-5.05 (0.00)	-7.30 (0.00)	-5.27 (0.00)	-4.82 (0.00)	-5.14 (0.00)	-6.56 (0.00)	-5.63 (0.00)	-23.27 (0.00)

Table 4: Summary statistics for the time-varying correlations over the eight different liquidity dimensions

This table reports summary statistics for the time-varying correlations among the eight liquidity group measures. Each column refers to the correlation of the specific group measure with the seven other group measures. Panel A highlights values for the mean, standard deviation and the interquartile ranges (IQ). Panel B shows sample averages for the full sample ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

Panel A: Descriptive statistics

	Spread	Roll	Return	Fong	Etick	Amihud	Volume	Flow
Mean	0.81	0.84	0.79	0.84	0.81	0.83	0.79	0.83
Stdev	0.07	0.05	0.09	0.08	0.11	0.06	0.09	0.06
IQ0 (min)	0.56	0.67	0.43	0.54	0.45	0.63	0.46	0.59
IQ1	0.77	0.80	0.74	0.80	0.73	0.79	0.73	0.80
IQ2 (med)	0.82	0.84	0.81	0.86	0.84	0.84	0.81	0.84
IQ3	0.87	0.88	0.86	0.89	0.90	0.88	0.85	0.88
IQ4 (max)	0.95	0.94	0.95	0.95	0.96	0.94	0.93	0.94

Panel B: Subsample analysis

	Spread	Roll	Return	Fong	Etick	Amihud	Volume	Flow
fs	0.81	0.83	0.79	0.84	0.81	0.83	0.79	0.83
tranq	0.81	0.84	0.80	0.84	0.80	0.83	0.79	0.84
% Δ	-1%	0%	1%	1%	0%	0%	0%	1%
crisis	0.85	0.82	0.75	0.80	0.82	0.83	0.78	0.81
% Δ	4%	-1%	-6%	-4%	2%	0%	0%	-3%

Table 5: Descriptive statistics for unified liquidity measure over different weighting methods

This table summarizes descriptive statistics for our unified liquidity measure, respectively based on equal weights (w) and based on three different weighting schemes as explained in Section 3. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i). We report the results for the full samples ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

	w	w_i	ws_i	wa_i
fs	0.21	0.28	0.12	0.35
tranq	0.19	0.26	0.11	0.33
% Δ	-7%	-7%	-11%	-7%
crisis	0.27	0.37	0.18	0.46
% Δ	33%	33%	52%	33%

Table 6: Descriptive statistics for the weights

This table summarizes the average value of the weights used in our unified liquidity measure, based on the three different weighting schemes as explained in Section 3. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i). We report the results for the full samples ('fs'), as well as for two sub-periods where we discern tranquil times ('tranq'), versus financial stress periods ('crisis'). Additionally, we convey the relative changes of the subperiods in comparison to the full sample.

Panel A: Spread and Roll

spread	w_i	ws_i	wa_i	roll	w_i	ws_i	wa_i
fs	0.13	0.08	0.14	fs	0.13	0.07	0.13
tranq	0.13	0.07	0.13	tranq	0.13	0.07	0.13
% Δ	-4%	-11%	-8%	% Δ	0%	-2%	0%
crisis	0.16	0.13	0.20	crisis	0.13	0.08	0.13
% Δ	20%	57%	40%	% Δ	1%	13%	4%

Panel B: Returns and Fong

ret	w_i	ws_i	wa_i	fong	w_i	ws_i	wa_i
fs	0.12	0.06	0.12	fs	0.15	0.11	0.19
tranq	0.13	0.07	0.13	tranq	0.16	0.12	0.20
% Δ	5%	9%	8%	% Δ	3%	4%	5%
crisis	0.09	0.04	0.07	crisis	0.13	0.09	0.14
% Δ	-23%	-45%	-41%	% Δ	-15%	-21%	-26%

Panel C: Etick and Amihud

etick	w_i	ws_i	wa_i	amih	w_i	ws_i	wa_i
fs	0.12	0.06	0.11	fs	0.11	0.04	0.09
tranq	0.11	0.05	0.10	tranq	0.11	0.04	0.09
% Δ	-4%	-13%	-9%	% Δ	-2%	-11%	-4%
crisis	0.14	0.10	0.16	crisis	0.12	0.07	0.11
% Δ	21%	61%	43%	% Δ	12%	54%	20%

Panel D: Volume and Order Flow

vol	w_i	ws_i	wa_i	flow	w_i	ws_i	wa_i
fs	0.10	0.04	0.09	fs	0.13	0.08	0.13
tranq	0.11	0.04	0.09	tranq	0.13	0.08	0.13
% Δ	2%	3%	4%	% Δ	1%	0%	2%
crisis	0.09	0.03	0.07	crisis	0.13	0.08	0.12
% Δ	-9%	-18%	-19%	% Δ	-4%	1%	-9%

Table 7: Univariate regressions for unified liquidity measure: Crisis indicators

This table reports estimated intercept and slope coefficients from regressions of our unified liquidity measure (constructed with the volatility shrinkage weighting method) on a number of widespread crisis indicators. We employ the following crisis indicators: the Cleveland Financial Stress Index (CFSI), the contribution of the interbank or funding markets (CFSI-IB-FUND), the interbank liquidity spread (CFSI-IB-LIQ) and the liquidity spread (CFSI-LIQ) to this index, the National Financial Conditions Index (NFCI), the Flight-to-Safety measure constructed by Baele et al. (2015) (FTS), the Kansas City Financial Stress Index (KCFSI), Smoothed U.S. Recession Probabilities (REC P), St. Louis Fed Financial Stress Index (STLFSI), the Aruoba-Diebold-Scotti business conditions index (ADSBCI) and the International Monetary Fund U.S. Financial Stress Index (IMF FSI). The sample size depends on the available data series (and is mentioned in the left column). P -values are denoted between brackets. The last column shows the adjusted R -squared.

Crisis Indicators	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adj R^2$
CFSI (n=268)	-0.106 (0.626)	1.515 (0.502)	0.005
CFSI-IB-FUND (n=267)	4.528 (0.000)	17.150 (0.000)	0.255
CFSI-IB-LIQ (n=267)	0.790 (0.000)	8.777 (0.000)	0.325
CFSI-LIQ (n=267)	2.313 (0.000)	-4.665 (0.041)	0.074
NFCI (n=492)	-0.804 (0.000)	7.112 (0.000)	0.213
FTS (n=386)	0.012 (0.550)	0.169 (0.351)	0.008
KCFSI (n=287)	-0.645 (0.020)	6.722 (0.070)	0.151
REC P (n=559)	-0.108 (0.008)	1.850 (0.000)	0.213
STLFSI (n=241)	-0.715 (0.003)	8.131 (0.004)	0.265
ADSBCI (n=624)	-0.415 (0.007)	3.555 (0.014)	0.069
IMF FSI (n=349)	-2.611 (0.000)	22.701 (0.001)	0.185

Table 8: Signal-to-noise ratio

This table reports the results for the signal-to-noise ratio analysis. Panel A summarizes the methodology, based on Christensen and Li (2014), to calculate signal-to-noise ratios, as explained in Section 4.1.2. Panel B reports the signal-to-noise ratio, as well as the number of crisis respectively non-crisis events signaled correctly (in %), for our unified liquidity measure L_t , the National Financial Conditions Index (NFCI), and Aruoba-Diebold-Scotti business conditions index (ADSBCI). Panel C reports the same statistics for our unified liquidity according to the four different weighting schemes, as explained in Section 3. w refers to the constant weighting scheme; w_i denotes the basic time-varying weighting scheme; the other two include a volatility adjustment, respectively the shrinkage method (ws_i) and augmented method (wa_i).

Panel A: Four situations

	Financial stress event	No Financial Stress event
Signal	A	B
No signal	C	D

Panel B: S/N for unified measure

	S/N	fin stress correct	No fin stress correct
L_t	0.13	0.34	0.95
NFCI	0.16	0.37	0.94
ADSBCI	0.05	0.56	0.97

Panel C: S/N for different weighting schemes

	S/N	fin stress correct	No fin stress correct
w	0.12	0.10	0.99
w_i	0.11	0.15	0.98
ws_i	0.13	0.34	0.95
wa_i	0.09	0.34	0.97

Table 9: Univariate regressions for unified liquidity measure: Confidence and uncertainty measures

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (constructed with the volatility shrinkage weighting method) on confidence measures (Panel A) and uncertainty measures (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P -values are denoted between brackets. The last column shows the adjusted R -squared.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adj R^2$
Panel A: Confidence Measures			
Business Tendency Survey ($n = 624$)	100.653 (0.000)	-5.700 (0.008)	0.071
Consumer Opinion Survey ($n = 624$)	100.592 (0.000)	-5.228 (0.010)	0.051
Inventory Sentiment Index ($n = 198$)	61.426 (0.000)	11.165 (0.014)	0.045
Consumer Sentiment ($n = 430$)	88.030 (0.000)	-26.366 (0.251)	0.013
Panel B: Uncertainty Measures			
Economic Policy Uncertainty ($n = 348$)	101.737 (0.000)	24.454 (0.772)	0.000
Equity Market Uncertainty ($n = 348$)	69.894 (0.000)	256.980 (0.136)	0.029

Table 10: Univariate regressions for unified liquidity measure: Volatility and spread Measures

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (constructed with the volatility shrinkage weighting method) on volatility measures (Panel A) and spread measures (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P -values are denoted between brackets. The last column shows the adjusted R -squared.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adjR^2$
Panel A: Volatility Measures			
CBOE 10Y Treasury (n=132)	5.387 (0.000)	19.785 (0.001)	0.259
CBOE DJIA Vol Index (n=195)	15.333 (0.000)	60.974 (0.005)	0.206
CBOE Russel 2000 Vol Index (n=120)	16.521 (0.000)	119.575 (0.000)	0.400
CBOE SP500 (n=73)	14.769 (0.000)	101.461 (0.001)	0.428
Panel B: Spread Measures			
TED Spread (n=336)	0.291 (0.000)	3.320 (0.000)	0.204
ML AAA O-A Spread (n=204)	0.403 (0.015)	5.078 (0.044)	0.235
ML BBB O-A Spread (n=204)	1.359 (0.000)	8.592 (0.064)	0.177
ML CCC O-A Spread (n=204)	8.799 (0.000)	35.888 (0.060)	0.121
ML High Yield II O-A Spread (n=204)	4.236 (0.000)	18.981 (0.079)	0.141

Table 11: Univariate regressions for unified liquidity measure: Macroeconomic and monetary variables

This table reports estimated intercept and slope coefficients from univariate regressions of our unified liquidity measure (constructed with the volatility shrinkage weighting method) on a series of macroeconomic and monetary variables.. The sample size depends on the available data series (and is mentioned in the left column). P -values are denoted between brackets. The last column shows the adjusted R -squared. The values used for money are equilibrium values obtained through estimation of recursive money demand function. The last column shows the adjusted R -squared.

Dependent Variable	$\hat{\alpha}$	$\hat{\beta}^{liq}$	$adjR^2$
Panel A: Output			
Coincident Index (n=408)	2.209 (0.000)	-0.183 (0.966)	0.000
Capacity Utilization (n=552)	1.955 (0.014)	-17.083 (0.014)	0.061
Labor Market Conditions (n=449)	4.184 (0.031)	-34.965 (0.070)	0.047
Panel B: Housing Prices			
CS HP Real Δ YOY (n=408)	3.111 (0.009)	-23.670 (0.013)	0.069
Panel C: Interest Rate			
Interest Rate FFR (n=624)	3.176 (0.000)	19.790 (0.000)	0.125
Panel D: Interest Rate Spread			
Term Spread 10Y-FFR (n=624)	1.655 (0.000)	-5.420 (0.014)	0.041
Term Spread 10Y-2Y (n=451)	1.419 (0.000)	-4.408 (0.001)	0.083
Panel E: Money (equilibrium values)			
M3 Real Mgap (n=598)	0.0225 (0.000)	-0.1185 (0.006)	0.0674
Panel F: Exchange Rate (flight to home effect)			
ER US Euro Δ YOY (n=168)	9.275 (0.000)	-87.839 (0.000)	0.264
ER Real TW Broad Δ YOY (n=408)	-3.739 (0.017)	37.634 (0.003)	0.088
ER US UK Δ YOY (n=408)	4.141 (0.038)	-42.205 (0.037)	0.057

Table 12: Multivariate regressions for unified liquidity measure: Future economic growth

This table reports univariate regressions capturing the effect of the multidimensional liquidity measure on future industrial production growth (in the spirit of Næs et al., 2011). We test the specification for one-quarter-ahead industrial production growth (Panel A), as well as for a one-quarter-ahead industrial production gap measure (constructed with a HP filter) (Panel B). The sample size depends on the available data series (and is mentioned in the left column). P -values are denoted between brackets. The last column shows the adjusted R -squared.

$\hat{\alpha}$	$\hat{\beta}^{liq}$	$\hat{\gamma}^{term\ spread}$	$\hat{\gamma}^{excess\ mkt\ ret}$	$\hat{\gamma}^{Moody's\ spread}$	$adjR^2$	$adjR^2$ (excl. liq)
Panel A: ΔIP 3m ahead						
9.066 (0.000)	-25.829 (0.000)	0.531 (0.090)	0.038 (0.429)	-4.020 (0.000)	0.264	0.144
Panel B: IPGap3m ahead						
2.611 (0.001)	-10.167 (0.003)	-0.343 (0.029)	-0.042 (0.043)	-0.899 (0.024)	0.199	0.085

Table 13: Granger causality test, accompanying in-sample forecast of ΔIP

This table reports the Granger causality tests which complement the in-sample forecasting exercise. Firstly, we perform a Granger causality test for our liquidity measure based on equal weights (w) and based on three different weighting schemes. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: ws_i is based on the shrinkage method; wa_i is based on the augmented method. Additionally, we apply a Granger causality test for the control variables which are incorporated in our in sample forecasting exercise. TS denotes the term spread between 10 year and 3 month rate; EMR represents the excess market return; SPR is the corporate bond yield versus 10 year rate. We test the null hypothesis that market illiquidity (or the control variable) does not Granger cause industrial production growth, and whether industrial production growth does not Granger cause market illiquidity (or the control variable). We report the F-value and p-value (in parentheses) for each test. We choose the optimal lag length for each test based on lag length selection criteria .”

	$LIQ \rightarrow \Delta IP$	$\Delta IP \rightarrow LIQ$		$CON \rightarrow \Delta IP$	$\Delta IP \rightarrow CON$
w	1.31 (0.26)	2.88 (0.01)	TS	2.32 (0.07)	4.49 (0.00)
w_i	1.81 (0.11)	1.80 (0.11)	EMR	7.83 (0.00)	1.86 (0.14)
ws_i	2.96 (0.01)	1.61 (0.16)	SPR	1.64 (0.18)	1.88 (0.13)
wa_i	2.07 (0.07)	1.52 (0.18)			

Table 14: Out-of-sample forecasting performance for future economic growth

This table presents the out-of-sample forecasting performance for future economic growth over different horizons, respectively 3, 6 and 9 months. The forecasting models are estimated through a rolling window technique (Naes et al, 2011). The initial estimation sample is set to 45 years (1962-2007). The out of sample estimation covers the period 2008-2013. Our forecasting model includes the term spread, the excess market return, the corporate bond yield and our unified liquidity measure, and is compared to a benchmark forecasting model without liquidity. RMSE is the mean squared forecasting error of our model including the unified liquidity measure, relative to the mean squared forecasting error of the benchmark model excluding the unified liquidity measure. ΔR_{OS}^2 is the out-of-sample R -squared value relative to the benchmark. We report the results for the unified liquidity measure based on the four different weighting schemes. w refers to the measure based on equal weights. w_i denotes the basic time-varying weighting scheme, while the other two include a volatility adjustment: ws_i is based on the shrinkage method; wa_i is based on the augmented method.

	RMSE ($h = 3$)	ΔR_{OS}^2	RMSE ($h = 6$)	ΔR_{OS}^2	RMSE ($h = 9$)	ΔR_{OS}^2
w	0,95	0,10	0,96	0,07	1,00	-0,01
w_i	0,93	0,14	0,93	0,13	0,98	0,04
ws_i	0,83	0,30	0,85	0,29	0,92	0,15
wa_i	0,91	0,18	0,88	0,22	0,92	0,16

Table 15: Unified liquidity measure: Correlation with liquidity groups and variance decomposition

This table shows the impact of each liquidity group in the unified liquidity measure. Panel A reports the average correlations of our unified market liquidity measure with the groups employed for the construction of the measure. P -values for the correlation test are reported between brackets. Panel B reports the results for the unconditional variance decomposition of the multidimensional liquidity measure into the underlying liquidity group measures. Firstly, we convey the unconditional variance decomposition making abstraction of the covariances ('Var1' and 'Var2' provide two separate options in this context). However, we also calculate the unconditional variance decomposition including the covariance terms ('Cov'). All three techniques gives a general idea on the influence of each underlying subgroup on our multidimensional liquidity measure.

	Spread	Roll	Returns	Fong	Etick	Amihud	Volume	Flow
Panel A: Correlation with liquidity group measures								
L_t	0.349 (0.000)	0.339 (0.000)	0.193 (0.000)	0.355 (0.000)	0.722 (0.000)	0.298 (0.000)	-0.150 (0.000)	0.321 (0.000)
Panel B: Variance decomposition								
Var1	0.192	0.097	0.146	0.239	0.149	0.060	0.056	0.061
Var2	0.178	0.097	0.132	0.299	0.135	0.042	0.034	0.082
Cov	0.183	0.122	0.081	0.191	0.320	0.087	-0.064	0.079

Table 16: Univariate regressions for individual group measures: Confidence and uncertainty

This table reports the adjusted R -squared values from univariate regressions of the individual liquidity group measures on confidence and uncertainty measures. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R -squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	Spread	Roll	Return	Fong	Etick	Amihud	Volume	Flow
Business Tend Sur (n=624)	-	0.07	0.11	0.02	(0.00)	0.01	0.03	(0.01)	(0.01)	0.02
Cons Opinion Sur (n=624)	-	0.05	0.03	(0.01)	(0.01)	0.00	0.05	(0.01)	(0.01)	0.02
Inventory Sent Ind (n=198)	+	0.05	0.09	0.05	0.00	(0.02)	0.13	0.11	0.08	0.07
Con Sent (n=430)	-	0.01	(0.01)	(0.02)	0.00	(0.03)	0.01	0.00	0.00	(0.00)
Econ Policy Uncert (n=348)	+	0.00	0.01	0.00	(0.01)	(0.02)	0.00	(0.00)	(0.01)	0.00
Equity Mkt Uncert (n=348)	+	0.03	0.09	0.00	0.02	(0.13)	0.18	0.19	0.12	(0.01)

Table 17: Univariate regressions for individual group measures: Volatility and spread measures

This table reports the adjusted R -squared values from univariate regressions of the individual liquidity group measures on volatility and spread measures. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R -squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	Spread	Roll	Return	Fong	Efick	Amihud	Volume	Flow
CBOE 10Y Treasury (n=132)	+	0.26	0.46	0.24	(0.16)	(0.10)	0.24	0.06	-0.01	0.01
CBOE DJIA Vol Index (n=195)	+	0.21	0.54	0.28	(0.05)	(0.17)	0.20	0.12	0.04	0.01
CBOE R2000 Vol Index (n=120)	+	0.40	0.55	0.34	(0.30)	(0.07)	0.13	0.00	(0.06)	0.00
CBOE SP500 (n=73)	+	0.43	0.55	0.29	(0.20)	(0.09)	0.58	0.25	-0.01	0.04
TED Spread (n=336)	+	0.20	0.08	0.02	0.04	(0.04)	0.13	0.13	0.07	(0.03)
ML AAA O-A Spread (n=204)	+	0.24	0.14	0.11	(0.21)	(0.01)	(0.00)	(0.02)	(0.07)	0.00
ML BBB O-A Spread (n=204)	+	0.18	0.11	0.09	(0.31)	(0.00)	(0.01)	(0.06)	(0.15)	0.01
ML CCC O-A Spread (n=204)	+	0.12	0.35	0.14	(0.10)	(0.05)	0.10	0.02	0.00	0.04
ML HY II O-A Spread (n=204)	+	0.14	0.26	0.12	(0.24)	(0.03)	0.00	(0.00)	(0.04)	0.02

Table 18: Univariate regressions for individual group measures: Crisis indicators

This table reports the adjusted R -squared values from univariate regressions of the individual liquidity group measures on a number of widespread crisis indicators. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R -squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	Spread	Roll	Return	Fong	Etick	Amihud	Volume	Flow
CFSI (n=268)	+	0.01	0.18	0.05	(0.26)	(0.00)	(0.15)	(0.09)	(0.19)	0.00
CFSI IB FUND (n=267)	+	0.26	0.13	0.08	0.06	(0.01)	0.12	0.17	0.11	0.00
CFSI IB LIQ (n=267)	+	0.33	0.12	0.10	0.12	(0.01)	0.16	0.28	0.17	0.00
CFSI LIQ (n=267)	+	0.07	(0.02)	(0.02)	(0.32)	0.01	(0.31)	(0.49)	(0.43)	0.00
NFCI (n=492)	+	0.21	0.04	(0.02)	0.05	(0.22)	0.20	0.24	0.20	0.01
FTS (n=386)	+	0.01	0.12	0.08	(0.10)	0.00	(0.05)	(0.04)	(0.06)	0.02
KCFSI (n=287)	+	0.15	0.38	0.14	(0.14)	(0.03)	(0.03)	(0.00)	(0.05)	0.00
REC P (n=559)	+	0.21	0.11	0.00	(0.00)	(0.03)	0.04	0.02	0.01	0.00
STLFSI (n=241)	+	0.27	0.47	0.24	(0.00)	(0.07)	0.05	0.07	0.01	0.01
ADSBCI (n=624)	+	0.07	0.13	0.03	(0.04)	0.01	0.00	(0.02)	(0.02)	0.02
IMF FSI (n=349)	+	0.19	0.18	0.02	(0.01)	(0.04)	0.00	0.00	(0.00)	(0.01)

Table 19: Univariate regressions for individual group measures: Macroeconomic and monetary variables

This table reports the adjusted R -squared values from univariate regressions of the individual liquidity group measures on a series of macroeconomic and monetary variables. When the sign of the slope coefficient is contrary to what is expected (first column) the adjusted R -squared value is featured between brackets. The sample size is dependent on the available data series (and mentioned in the left column).

	sign	L_t	Spread	Roll	Return	Fong	Etick	Amihud	Volume	Flow
Coincident Index (n=408)	-	0.00	0.07	0.00	(0.09)	0.00	(0.03)	(0.03)	(0.03)	0.00
Capacity Utilization (n=552)	-	0.06	0.11	0.00	(0.01)	0.01	0.01	0.01	0.00	0.00
Labor Market Conditions (n=449)	-	0.05	0.12	0.02	(0.00)	0.01	0.00	0.00	(0.00)	0.00
CS HP Real Δ YOY (n=408)	-	0.07	0.01	0.00	0.01	0.00	0.02	0.00	0.00	(0.00)
Interest Rate FFR (n=624)	+	0.12	0.02	0.06	0.18	0.02	0.51	0.08	0.07	(0.00)
Term Spread 10Y-FFR (n=624)	-	0.04	(0.00)	(0.02)	0.03	(0.11)	0.06	0.15	0.13	(0.02)
Term Spread 10Y-2Y (n=451)	-	0.08	(0.00)	(0.01)	0.16	(0.09)	0.16	0.25	0.21	(0.01)
M2 Real Mgap (n=598)	-	0.07	(0.00)	(0.02)	0.09	(0.07)	0.18	0.17	0.17	(0.00)
ER US Euro Δ YOY (n=168)	-	0.26	0.00	0.03	0.02	0.03	0.04	0.02	-0.01	(-0.01)
ER R TW Broad Δ YOY (n=408)	+	0.09	0.00	0.00	0.04	(0.01)	0.01	0.04	0.02	(0.00)
ER US UK Δ YOY (n=408)	-	0.06	0.00	(0.00)	0.04	(0.00)	0.01	0.01	0.01	0.00

Figure 1: Statistical design of unified market liquidity measure
 This figure gives a schematic overview of the different steps in the statistical design of our unified market liquidity measure.

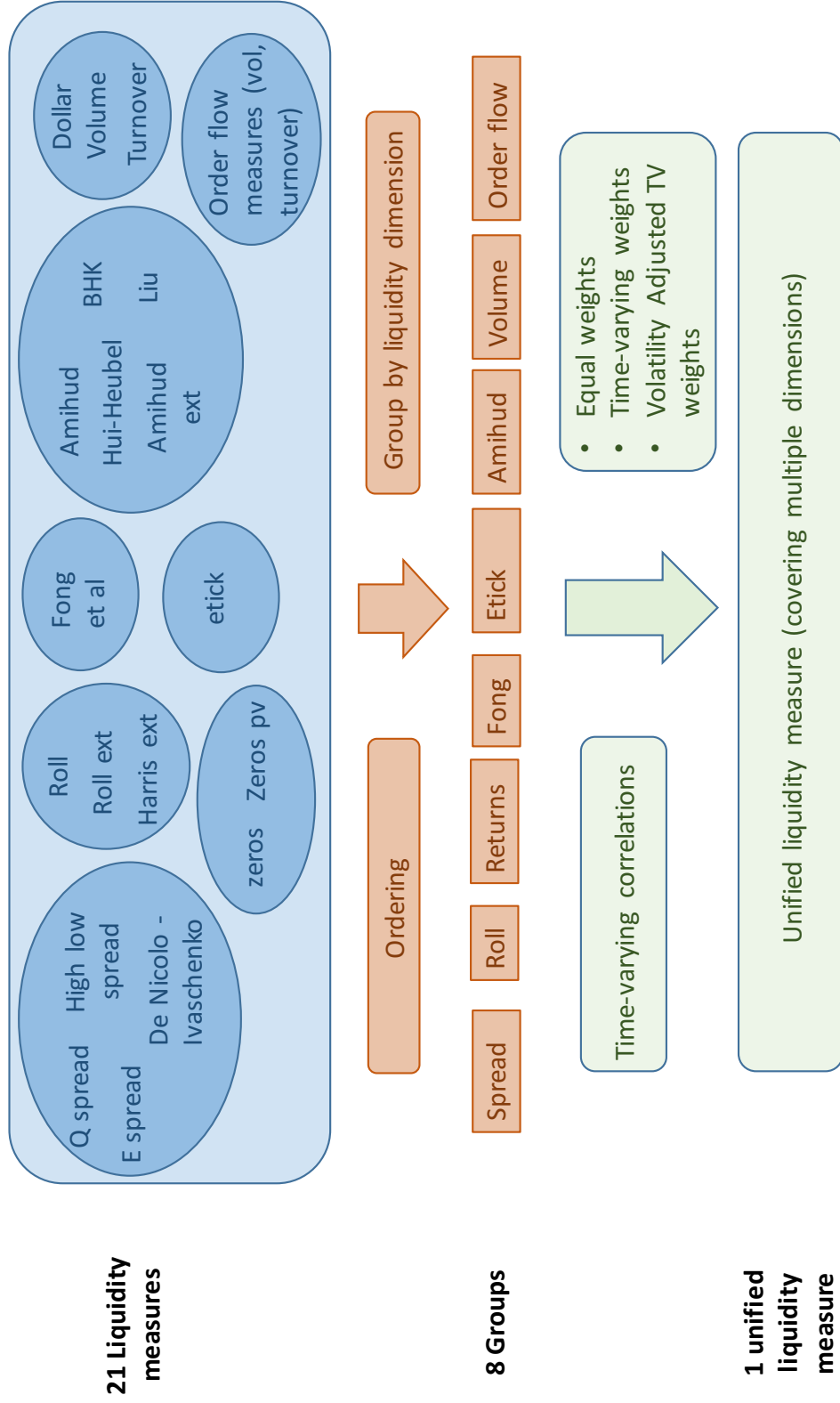


Figure 2: Unified market liquidity measure and financial stress events

This figure plots the unified market liquidity measure (constructed with the volatility shrinkage weighting method). The dotted lines denote financial pressure. The bars denote NBER recessions.

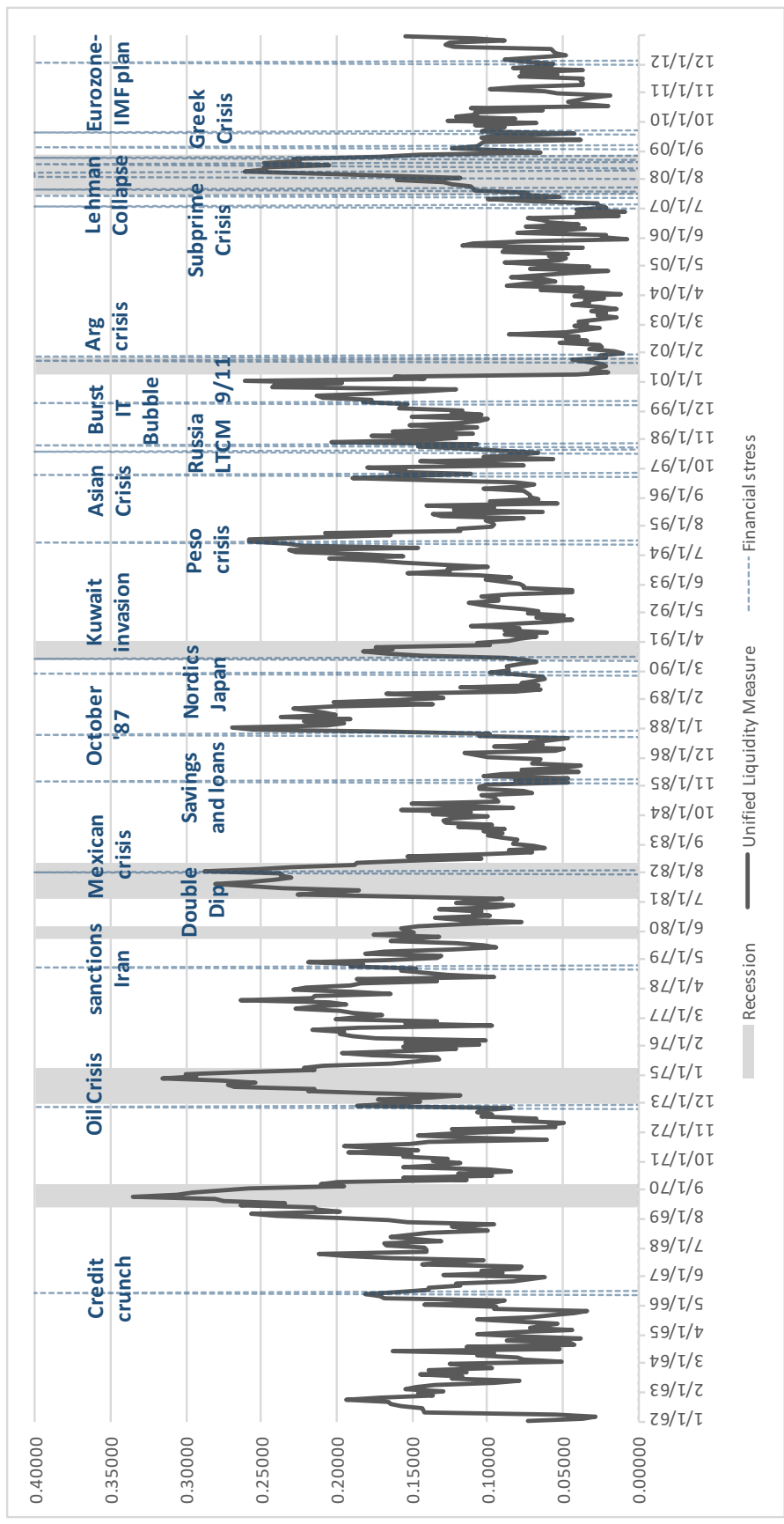
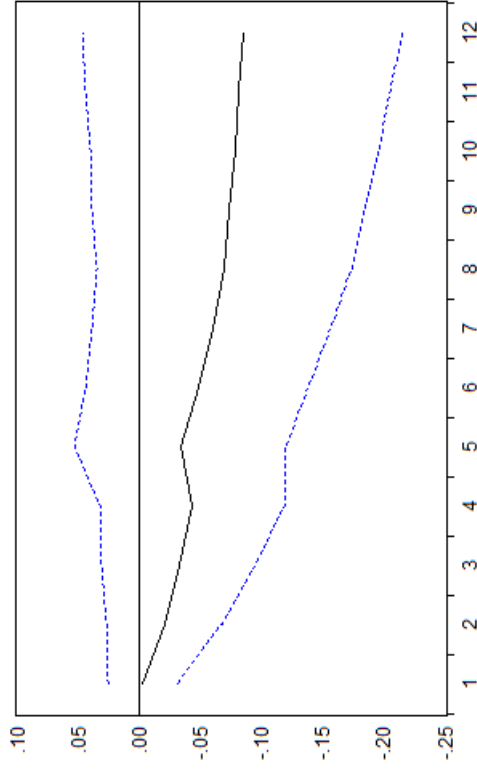


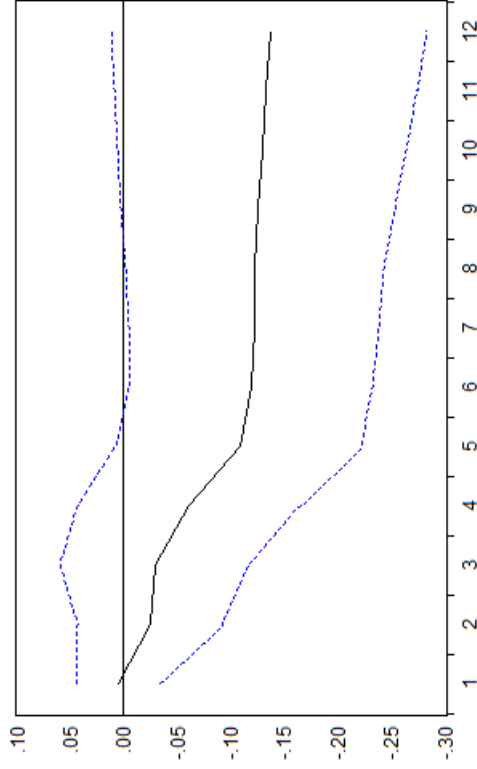
Figure 3: Impulse responses

This figure plots impulse responses of a VAR with 5 lags (based on lag selection criteria) and the following choleski ordering: unified liquidity measure, M3 (YoY money growth), federal funds rate, CPI (MoM CPI inflation), IP growth (YoY industrial production growth). The panels show the effect of a shock in illiquidity on respectively inflation (CPI), federal funds rate, IP growth and M3.

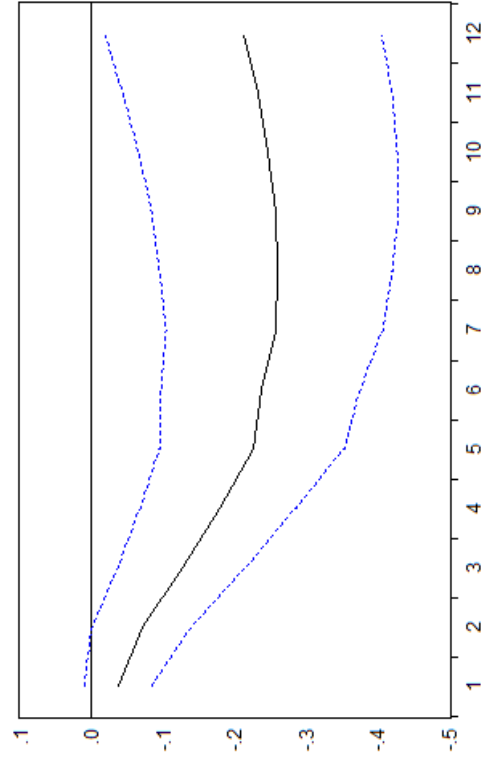
Panel A: Effect of illiquidity on CPI



Panel B: Effect of illiquidity on federal funds rate



Panel C: Effect of illiquidity on IP growth



Panel D: Effect of illiquidity on M3

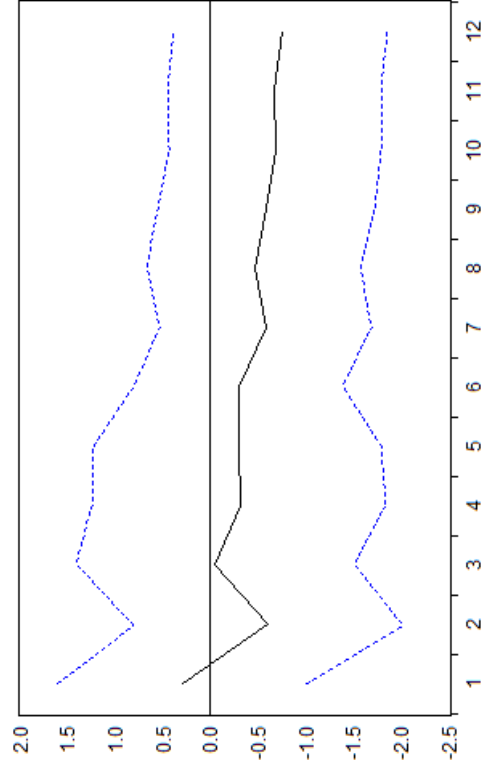
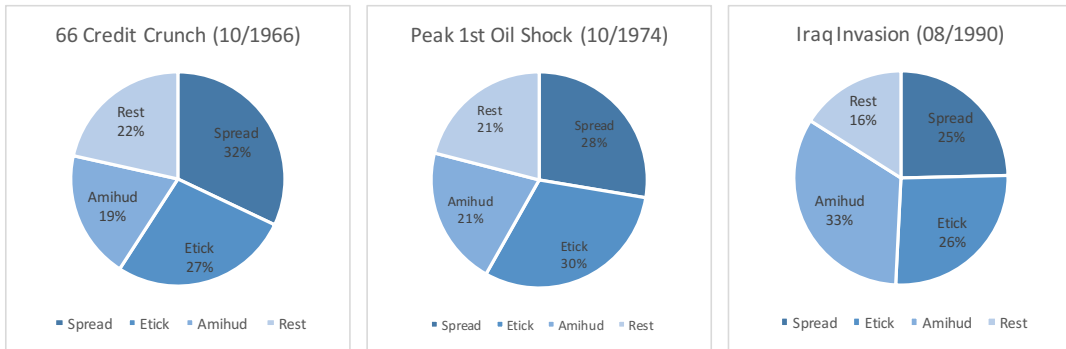


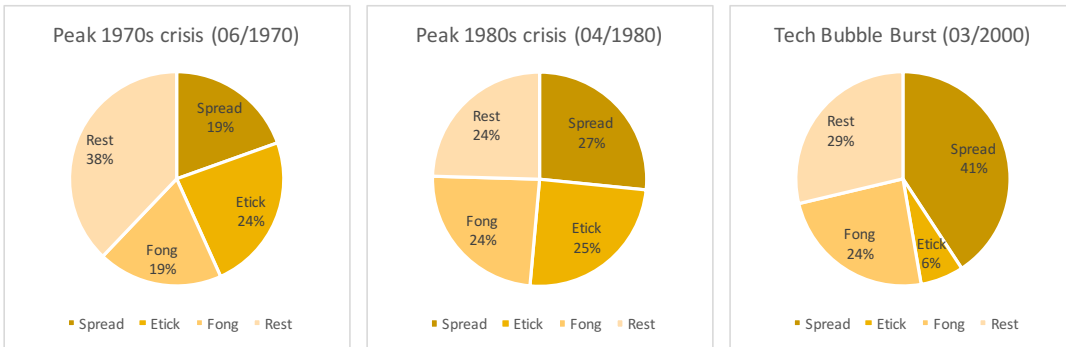
Figure 4: Decomposition of unified liquidity measure and financial crises

- This figure shows the contribution of the individual liquidity group measures to our unified liquidity measure for specific historic stress events. Each panel groups stress events of a specific type which relates to a certain category of liquidity group measures.

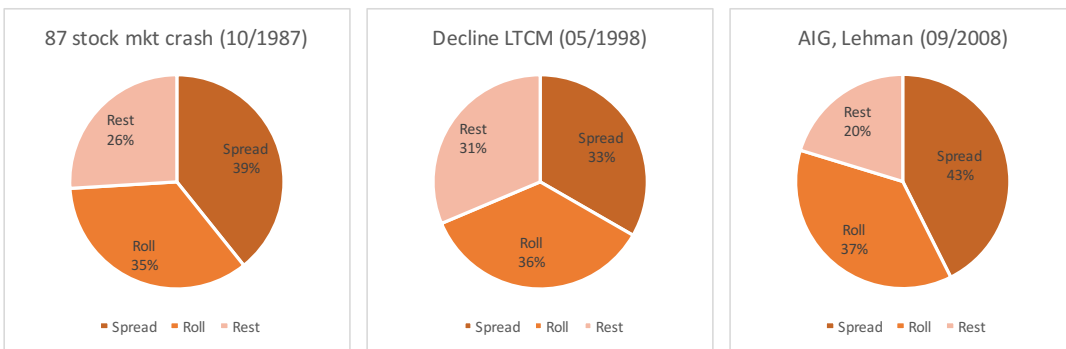
Panel A: Crisis Type 1



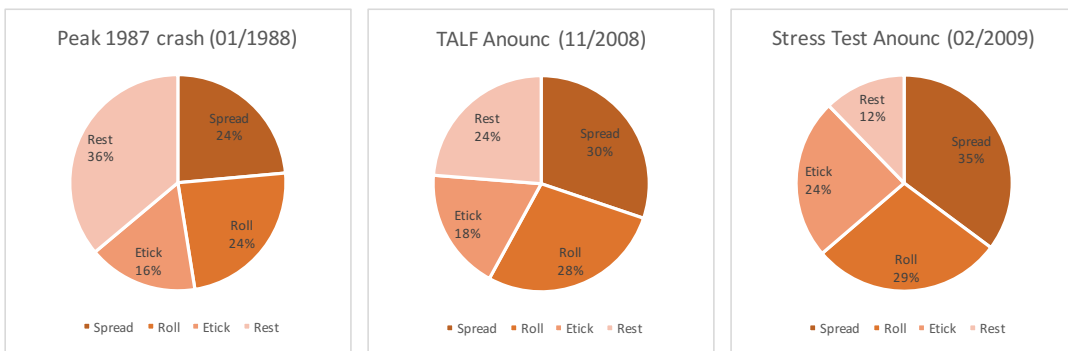
Panel D: Crisis Type 2



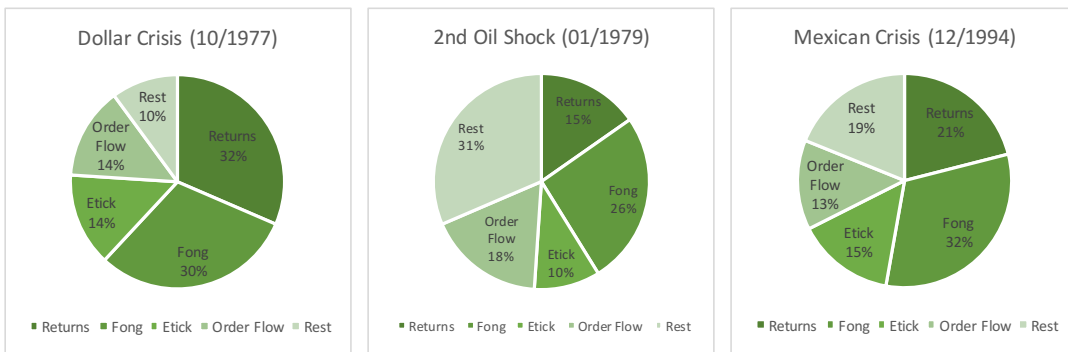
Panel C: Crisis Type 3A



Panel D: Crisis Type 3B



Panel E: Crisis Type 4



Chapter 4

Instability hypothesis for small open economies: The procyclical impact of international flows

Garo Garabedian¹

November 2015

Abstract

We investigate the impact of monetary policy spillovers to emerging in the recent context of advanced economies pursuing expansionary monetary policies. We unravel many channels through which such international transmission could occur. Moreover, the buildup of maturity and currency mismatches has regained importance as emerging market non-financial firms have picked up the original sin of issuing foreign denominated debt, thus leading to many hidden vulnerabilities in the international financial system. Therefore a shift in the expansive stance of advanced central banks could trigger considerable capital flows. In our empirical analysis we measure the impact of US monetary policy on emerging markets in Central and Easter Europe (Bulgaria, the Czech Republic, Hungary and Poland), as well as in Latin America (Chile and Mexico) and in Asia (Indonesia and Malaysia). We find considerable effect of shocks in EMU monetary policy on the long term yields of CEECs, while US policy shocks seem to be a more important driving force for long term yields in Asia and Latin America. Moreover, we unravel a significant difference in the transmission of shocks before and after the financial crisis, with the latter being significantly more prolonged.

JEL Classification: E52, F32, F44

Keywords: Monetary policy spillovers, emerging markets, capital flows, quantitative easing

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1 Introduction

In addition to traditional trade linkages among countries, the recent global financial crisis has highlighted the critical role of growing financial and institutional interdependences in explaining business cycle fluctuations. More specifically, we can discern connections between the occurrence of boom and bust cycles in different geographical context over time. Each successive crisis seems to be related. Kindleberger (2008, p. 7) already described this process very vividly: “One of the themes of this book is that the bubbles in real estate and stocks in Japan in the second half of the 1980s, the similar bubbles in Bangkok and the financial centers in the nearby Asian countries in the mid-1990s, and the bubble in US stock prices in the second half of the 1990s were systematically related.”

Moreover, we can unravel similar patterns in different types of crisis, whether the culprit can be found in the banking sector, the government sector, the external balance, etc. The boom period is typically characterized by capital inflows, overconfidence, abundance of credit, overvaluation of assets (housing or stock), underestimation of risk, and overleveraging. In the meantime, macroeconomic imbalances, such as current account deficits and currency appreciations, are building up (Brunermeier et al., 2012). We can thus unravel an important interaction between credit creation and the perception of risk, which enhances the procyclicality of credit flows which further excavates the frailty of the international financial system. The implosion of the bubble in one country leads to an increase in the flow of money to another country; consequently, playing an important role in explaining imbalances of that country. More integrated financial markets have increased the return opportunities for mobile capital; which in turn makes more countries prone to another crisis. Minsky (1982, p. 5) highlights this phenomenon as: “The economic instability so evident since the late 1960s is the result of the fragile financial system that emerged from cumulative changes in financial relations and institutions over the years following World War II.”

In our analysis we focus on the impact of recent unconventional monetary policy in the US and the Euro Area on emerging markets. More specifically, we gauge the impact of US and EMU long term government yields on their counterparts in four Central and Eastern European countries (CEECs). We find that policy shocks from advanced economies have comparatively more impact on long term yields than their domestic policy yields. We also examine whether these spillovers have increased over time by comparing a pre and post crisis sample. We find that most effects are persistent. However, the duration and strenght of the spillovers seems to increase during the unconventional monetary policy phase of the advanced

economies under investigation. As a robustness check, we apply our methodology to two Latin American and two Asian countries, where we find similar results.

2 Literature

Increased financial globalization can have conflicting impacts on emerging markets. On the one hand, foreign investors generally acquire more financial products with longer maturities, thus broadening the maturity structure of local bond markets (Barroso et al, 2015). Moreover, the deepening of EME financial markets, leads to improved price discovery and has the potential to limit the price impact of capital flows (Rafiq, 2015). On the other hand, short term (sentiment driven) flows to emerging markets can cause excessive pressures on their currency, and lead to unwarranted credit expansion, thus exposing its financial fragility (Agosin and Huaita, 2011). Additionally, heightened levels of global financial integration are shaping an environment where many developing countries are importing financing conditions from several prominent advanced economies, despite the exchange rate they administer. Rey (2015, p. 2) admonishes us “for a world with powerful global financial cycles, characterized by large common movements in asset prices, gross flows and leverage. It is also a world with massive deviations from uncovered interest parity.” Under such conditions, the possibility arises that the conditions chosen in several prominent advanced economies can be transmitted around the globe.

When credit cycles and capital flows are thus governed by worldwide phenomenon they can prove unfathomable for the country-specific conditions in many emerging countries, thus leading to procyclical effects, with abundance of credit during good times and extreme draughts during downturns (Rey, 2015). We can therefore unravel interconnectedness between the monetary policy of advanced economies and global financial conditions in many emerging countries, through changes in risk aversion and uncertainty (Bekaert et al, 2012; Bruno and Shin, 2014). Minsky (1982, p. 118) similarly argues that “the structural characteristics of the financial system change during periods of prolonged expansion and economic boom and that these changes cumulate to decrease the domain of stability of the system.”

2.1 Monetary Policy Transmission to Emerging markets

Chen et al (2014) apply a global vector error correction model (GVECM) to investigate the effects of reductions in the US term and corporate spreads, thus uncovering a more prominent role for the latter. Additionally, spillovers to emerging economies vary significantly, but are larger in size than for developed economies. While aid-

ing their recoveries, pass through of US monetary policy had procyclical effects in Brazil, China, etc. in the post crisis period. Relying on a recursive VAR analysis, Rey (2015) advocates that monetary conditions are diffused from advanced financial centers to the rest of the world through gross credit flows and leverage. Fluctuating exchange rates are not capable to shield against the global financial cycle when capital flows move freely, thus shrinking the trilemma to a mere dilemma.

Miyajima et al (2014) examine the impact of a very low US term premium on comparatively small open Asian economies using panel VAR model. Pass through of US monetary policy to Asia primarily seems to occur through low local bond yields and swift growth of domestic bank credit. While national monetary authorities can retain control over their short term policy rates in this context of financial interconnectedness, however, they do concede control over the long term rates, which are important factors in consumption and investment decisions. Asia, Jain-Chandra and Unsal (2012) find similar results for Asia by incorporating a dynamic factor model and an SVAR model. More specifically, they unravel a weaker role for domestic short term interest rates during surges of capital inflow. Correspondingly, Bowman et al (2014) acknowledge that US policy shocks that drive down US sovereign yields have a kindred effect on the sovereign yields in most EMEs, sometimes even outsizing the domestic impact. More specifically, this vulnerability of EMEs is driven by country-specific variables, most prominently by interest rates, cds spreads, inflation rates, current account deficits and banking systems.

In contrast to the previous studies, Ahmed and Zlate (2013) focus on the determinants of capital flows to emerging markets. Unconventional US monetary policy expansion does not seem to affect the total net inflows of capital into EMEs. There has only been a shift in the composition toward portfolio flows. Furthermore, most other determinants of EME flows keep their relevance with the addition of variables associated with unconventional policy regime.

2.2 Emerging market economy corporate debt

In previous decades, emerging markets in Latin America and Asia were often tempted by the original sin, and simultaneously borrowed extensively in the international capital markets (with the debt denominated in foreign currency), while upholding rigid exchange rate regimes. Most of these debts remained unhedged, and left these economies vulnerable to exchange rate and sovereign risk. In such a setting, any change in the appetite of investors leads to capital reversals, hot money pouring out of the emerging economies, often initiating full-fledged crises. (Acharya et al, 2015)

Conversely, since 2000 numerous emerging markets succeeded in issuing long-

term debt denominated in their national currency instead of dollars, thus shirking a currency mismatch. However, these last years, have reacquired the taste for foreign denominated debt. The main culprit in these international bond markets this time are not the governments, but emerging market corporations, many of which are constrained by their local markets (Turner, 2014). More specifically, we have witnessed a sharp hike in the external borrowing of non-financial firms through offshore issuance of debt instruments (Avdjiev et al, 2014), the majority of which went through subsidiaries of the “local firms “ which are situated abroad. This foreign denominated debt, which is mostly expressed in dollars, is one of the main drivers of domestic credit growth in emerging markets (Cabballero et al, 2014) (footnote: There is a strong link between offshore borrowing and credit growth in Latin America and East Asia, which strengthens cross-border financial Linkages (Lane, 2015)). Moreover, these securities are not hedged by proceeds in foreign currency, thus creating a currency mismatch on the consolidated balance sheets of these non-financial emerging market firms (Shin, 2013). These flows are mainly driven by carry trade strategies (Bruno and Shin, 2015; Hofmann). Simultaneous with the off shore issuance of debt, we can discern an increase in corporate deposits in the local banking system which can potentially be withdrawn in the occurrence of financial stress events, thus exposing the firms involved also to a maturity mismatch. (Acharya et al, 2015).

All these vulnerabilities lead to a Financial systems which can be at serious risk when Fed begins to raise rates. More importantly, supervisors in these emerging markets, or even globally, are not endowed to face these challenges, as their focal points, which were crucial during previous crisis, are not as useful to detect the current risks, most of which remain undetected with the current measuring systems (Cabballero et al, 2014). However, even the current flows leave a mark on the local financial system, because the higher rate of international borrowing will coincide with a greater holding of cash as deposit with the banks or short-term securities with the shadow banks (Shin, 2013).

Finally, the increased integration of emerging markets in the international debt markets has led to yields on debt instruments of these markets in local currency dropping in chorus with those of advanced economies, even co-moving more aligned to each other (Turner, 2014). This adds further to the vulnerability of emerging economies to a reversal of the current expansionary monetary policy stance of advanced economies. (Turner, 2014).

2.3 Tapering Talks

The prospects of lower interest rates in many advanced economies have motivated investors to search for yields on international financial markets. Hence, it should come as no surprise that the relative resilience of emerging markets to the recent episodes of financial stress and their subsequent rapid recovery has lured in many foreign investors.¹ find that foreign flows into many developing economies have skyrocketed during this post-crisis period, translating into sharp increases in credit, unwarranted hikes in the prices of many asset classes and pressures towards an appreciation of their currency (Calderon and Kubota, 2012). This process coincided with a swift build-up in leverage creating contributing to the financial fragility of markets which have historically been fragile, and only recently have begun setting up the necessary macroprudential framework.

These vulnerabilities became painfully clear in the summer of 2013 when a flood of volatility submerged the global financial markets, following some signals that the U.S. Federal Reserve would slow down its large scale asset purchase program and move into a less accommodative monetary policy stance ² (Mishra et al, 2012). This environment severely disrupted emerging markets, affecting asset prices and currency values, and even raising doubt about the growth prospect of emerging markets. These corrections came to many commentators as a surprise and was surprisingly large in size (Eichengreen and Gupta, 2014)

Some patterns can be discerned in the reaction of emerging markets during the 2013 taper-tantrum episode. Finally, albeit monetary policy spillovers were clearly present well before the taper-tantrum, the size of emerging market asset price and capital flow shocks was markedly higher during the latter episodes, particularly for bond yields and exchange rates (Sahay et al, 2014). Secondly, in contrast to the initial reaction which was similar across most emerging markets, we soon saw clear disparities between the way individual countries were affected, which prevailed during the whole period (Calderon and Kubota, 2012). Thirdly, emerging markets that exhibited more healthy economic fundamentals suffered less from the increased volatility (Ahmed et al, 2015; Rai and Suchanek, 2014). For example, current account balances, inflation rates, growth prospects, and central bank reserves were important protagonists in the market reactions to U.S. monetary policy shocks. However, Eichengreen and Gupta (2014) refute the idea that strong fundamentals are causing the cross-country disparities, and hint at size of financial markets as the most discerning characteristic. Investors would thus favor large and liquid platforms

¹Many authors Bruno and Shin, 2014; Obstfeld, 2012; Borio and Disyatat, 2011

²This episodes got labelled as the tapering talk

as these allow relatively costless and swift movements of capital (Sahay et al, 2014). Finally, conditions worsened most dramatically in countries that had witnessed large capital inflows and more severe exchange rate appreciation during the earlier phase expansionary monetary policy by the Fed reserve (Ahmed et al, 2015). In contrast, countries that relied on their internal policy to limit these trends, also experienced the smallest setbacks. Hence, macroprudential policy can function as a buffer against such international spillovers (Eichengreen and Gupta, 2014)

This episode also emphasises an important lesson for monetary policy in advanced economies which focuses mainly on their internal goals, and has little attention for global effects of their policies. Hence, for the future, central banks in advanced economies should revert to clear and effective communication in order to limit such volatile episodes (Draghi, 2013). As both the US and the EU are facing future exists from quantitative easing programs, we will learn soon enough whether they will also have picked up the lessons from the tapering tantrum.

3 Empirics

3.1 Data and preliminary tests

We collect our data from datastream, together with the respective national central banks, as well as the FRED database provided by the Federal Reserve Bank of Saint Louis and the EMU statistical data warehouse.³ We use monthly data and our sample runs from 2000 till 2015. If we deviate from these general settings, we report this explicitly. Our analysis focuses on four geographically dispersed emerging markets. More specifically, we investigate US monetary policy spillovers into four Central Eastern European Countries, (Bulgaria, the Czech Republic, Hungary, and Poland). As a robustness check, we also look at pass-through to two Latin American countries (Chile and Mexico) and two Asian countries (Indonesia and Malaysia).

With many advanced economies stuck in a liquidity trap due to the financial crisis, the long term yield has attracted much attention as a potential channel for monetary policy transmission. Figure 1 shows the trends in long term government bond yields for nine Central Eastern European Countries (Bulgaria, The Czech Republic, Hungary, Poland, Slovakia, Lithuania, Latvia, Romania and Croatia), together with their US and EMU counterpart. Similar to Turner (2014) we see an increased alignment of these yields due to a heightened integration of these CEECs in the international financial framework. Such comovement in these yields expose

³We assemble data on prices, output, money, interest rates, government bonds, asset prices, confidence indicators and volatility indices

the vulnerability of these CEEC to monetary policy in advanced economies. According to Obstfeld (2014), long term interest rates provide one of the most powerful channels for international transmission. If advanced economy policy can be passed through via bond markets, the mere focus on short term interest rates and exchange rate can lead us to misinterpret the policy stance for the CEEC under investigation (Miyajima et al, 2014).

When we compare the common factor in the government bond yield for several⁴ of these CEECs with the US term premium⁵, there seems to be a connection over time, visualized in figure 2. The correlation between both series amounts to 0.57. However, compared to Miyajima et al, 2014, who applies a principle component methodology for several Asian countries, the fit between both series looks to be relatively more loose. Based on this anecdotal first evidence, we wonder whether the flexible exchange rate might perform its task as stabilizer more efficiently in these CEECs (Barosso et al, 2015) thus making domestic shocks more important, or whether EMU government bond spillovers could be distorting the above described relation.

Whereas Fratzscher (2012) claims domestic monetary policy shocks in emerging market economies have been trivial in comparison to the spillovers from US monetary policy shocks, Barroso et al (2015) question this and assert that despite the influence of international spillovers, domestic policy should be the primary focus, due to the shock absorbing abilities of a floating exchange rate. In order to answer this question more rigorously, we perform a Granger Causality test. More specifically, we check whether EMU, US long term government yields and domestic policy rates Granger cause the domestic long term government yield in each of the CEECs under investigation. Figure 3 reports p -values for the Granger Causality tests between brackets. A value below .05 implies proof in support of Granger causality. We can conclude that long term yields in the mentioned CEEC are mainly driven by their European equivalent (except for Poland). The domestic policy rate merely seems important for the Czech Republic (and on a higher significance level in Hungary and Poland), while the US yields only significantly Granger cause the Czech yields (and on a higher significance level the Hungarian yields). However, in order to look at the specific magnitude and duration of the shocks resulting from advanced economy monetary policy spillovers we revert to a Vector autoregression set up, as is common

⁴For this exercise we focus on the Czech Republic, Hungary, Latvia, Lithuania and Poland, as these countries have the longest timeseries available for their government bond yields

⁵Provided by the New York Federal Reserve

in the related literature.⁶

3.2 Methodology

For the estimation procedure, we follow Miyajima et al (2014), and apply a vector autoregressive (VAR) estimation procedure to gauge the relationship between the emerging market variables and the US monetary policy:

$$Y_t = A_0 + \sum_{i=1}^p AY_{t-i} + BZ_t + \epsilon_t$$

The Y-vector incorporates our endogenous variables: industrial production (ip), consumer prices (cp), the short term interest rate (ir), the domestic government bond yield yield (gov) and the bilateral nominal exchange rate against the US dollar (er). The US monetary spillovers (US) are captured by the X-vector. When incorporating the US policy effects in our model we rely on the long government bond yields. At the zero lower bound, in the context of forward guidance and large scale asset purchases, these values provide an interesting proxy for the policy stance.⁷

We rely on a Choleski decomposition to obtain our structural identification. The ordering is as follows: {US, IP, CP, IR, YLD, NER}. After performing extensive stationary testing (through Augmented Dicky Fuller and Phillips-Perron tests) we decide only to take (year on year) growth rates for industrial production and consumer prices. The other variables are simply expressed in levels.⁸ Furthermore, we rely on several lag length criteria to decide on the optimal dynamic structure of our vector autoregressive procedure.⁹ We estimate our VAR procedure separately for the pre (from 2000 till 2007) and post crisis period (from 2008 till 2015), individually for each country, so we can unravel shifts in the monetary spillovers for these emerging markets due to the financial crisis. In the discussion of our results, we focus on the impulse responses from a rise in US and EMU long-term bond yields on EME long term bond yields and exchange rates.¹⁰ These results are depicted from figure 5 till figure 11.

⁶Although there is also a burgeoning literature that employs event study techniques in order to analyse such pass through effects.

⁷We also look at the concept of real money gap, based on the construction method by Calza et al. (2003), and implemented by Hofmann (2009) and Drescher (2011). As such, we retrieve the real money gap proxy from a recursive long-run M3 demand function. However, these results are less convincing.

⁸We find that overdifferencing often leads to the elimination of valuable information about the relation of the variables under investigation.

⁹Aikake's information criterion (AIC), Schwarz information criterion (SIC), Hannan-Quinn criterion (HQC), final prediction error (FPE), and Bayesian information criterion (BIC). We chose the lag length at which comparatively most of these measures are hinting.

¹⁰However, many other asset prices could be incorporate in this framework.

3.3 Results

3.3.1 CEEC

For the pre-crisis era in Bulgaria, we find a meaningful influence of shocks in both EMU as well as in US long term yields on domestic yields, although this is very short-lived for the latter. The sign for both is as expected. An increase in the yield of the advanced economies leads to an increase in the domestic yield. After the crisis only the EMU yield remains significant. In contrast, the exchange rate is not important for both the US and EMU shocks for both periods, except for a short period with the EMU shocks (in both subsamples) around six months after the shock. An increase in the EMU yield hence leads to a brief depreciation of the Bulgarian Lev.

The shocks to the Czech long term yields are remarkably similar, with both EMU and US shocks leading to a positive shift in the domestic yield in the first subsample. After the crisis, however, only shocks in the US yields affect their Czech counterpart. The effect on the exchange rate is generally trivial. Except the post-crisis shock in the EMU yield seems to lead to a slight appreciation in the long run.

Interestingly, a shock in the pre-crisis period to the US and EMU long term yields does not seem to affect the Hungarian yields. This is still the case for a US shock in the latter period. However, a shock in the EMU yield now does yield the expected positive effect. The impact of these shocks on the exchange rate seems less important, except for very brief devaluating episodes.

Finally, for shocks in the advanced economy yields on Polish yields, we find the expected positive effect for both periods. However, for the US this is very brief during the pre-crisis periods, and extends somewhat in the latter period. However, shocks in the EMU yields seem to be more persistent. Again, the effect of these shocks on the exchange rate, seems to be less meaningful.

Hence, we can conclude that shocks in EMU and US long term yields affect the domestic long term yields in most of these CEEC, with the former being both more consistent and more persistent. The impact on the exchange rate of the CEECs seems less important. To gauge whether our results are driven by country-specific effects, or merely by proximity or interconnectedness of these Central and Eastern Economies to the EMU, we also apply our methodology to two Latin American and two Asian countries.

3.3.2 Latin America

While the impact of advanced economy policy shocks on the Chilean long term yields is significant for both EMU and US in the pre-crisis period, this is only the case for the US after the crisis. In contrast, the policy shocks of the advanced economies do not seem to matter for the Chilean exchange rate. For Mexico, only the shocks in the US policy seem to matter for the long term yield after the crisis. The same shock leads to a very brief appreciative episode.

3.3.3 Asia

Whereas shocks in both EMU and US long term yields have a positive and significant impact on Malaysian long term yields, this is merely the case for the latter shock (albeit for a blip in the EMU shock after 2 months). The impact on the exchange rate is less eventful, with only a brief appreciative impact of a pre crisis EMU shock.

The shocks in the long term government bond yields in the advanced economies do not seem to influence the Indonesian long term yields, except for the US shocks in the post crisis period, which have the expected positive sign. The exchange rate does not show any persistent effects from shocks in the advanced economies.

Hence, we can conclude that both for the Latin American and Asian impulse responses, US policy shocks seem to lead to more meaningful results, in comparison to the earlier discussion of the CEEC (where the EMU policy shocks seemed to be more dominant).

4 Conclusion

Due to the increasing integration of global financial markets, emerging markets are increasingly vulnerable to spillover from monetary policy stance in advanced economies. More specifically, the recent episodes of quantitative easing have left their marks on financial systems in emerging economies. A remarkable episode in this context was the taper tantrum in 2013, when huge volatility spillovers were caused due to the fact that US monetary policy was hinting at a potential exit out of their expansionary policy.

Recently, emerging markets non-financial firms have been employing foreign denominated debt to acquire funds which are not available on their local markets, thus creating exposures to exchange rate and maturity mismatches. These flows are mainly driven by carry trade strategies. Hence, a reversal in the policy rate of advanced economies could unravel many potential vulnerabilities.

We start off our empirical analysis with Granger Causality tests, through which we unravel that CEEC long term government yields are more influenced by EMU government yields than their domestic policy rates (or US government yields). However, to analyse the effect of advanced economy spillovers more rigourously, we decide to look at shocks in the long term yields and their effect on the domestic long term yield and the exchange rate.

Our VAR analysis focuses on the impact of EMU and US monetary policy on several emerging markets in Central and Eastern Europe and in Latin America. We can discern clear spill-over effects from both advanced economies on emerging market variables. For the CEEC the impact of EMU shocks seems more persistent and consistent than their US counterpart. For Latin America and Asia, the persistence and importance of the latter increases considerably. Moreover, these spillovers have gotten significantly stronger after the recent financial crisis. We mainly focus on the impact of advanced economy policy shocks on long term government bond yields, since the effect on the exchange rate seems to be much more trivial in comparison. Finally, we can extend several methods to gauge the US policy shocks, and investigate the impact of monetary policy pass through on long term government bond yields and exchange rates in emerging markets.

Policymakers in these emerging markets therefore should revert to macroprudential policy to shield their economies from external pressures that reinforce the countercyclical nature of their economies. Moreover, many countries are applying capital controls to limit the impact of short term capital reversals.

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Figure 1: Long Term Government Bond Yields in Emerging Markets and the US

This figure shows the evolution of the long term government bond yields in several Central and Eastern European Emerging Markets together with the long term government bond yield in the US and for the EMU.

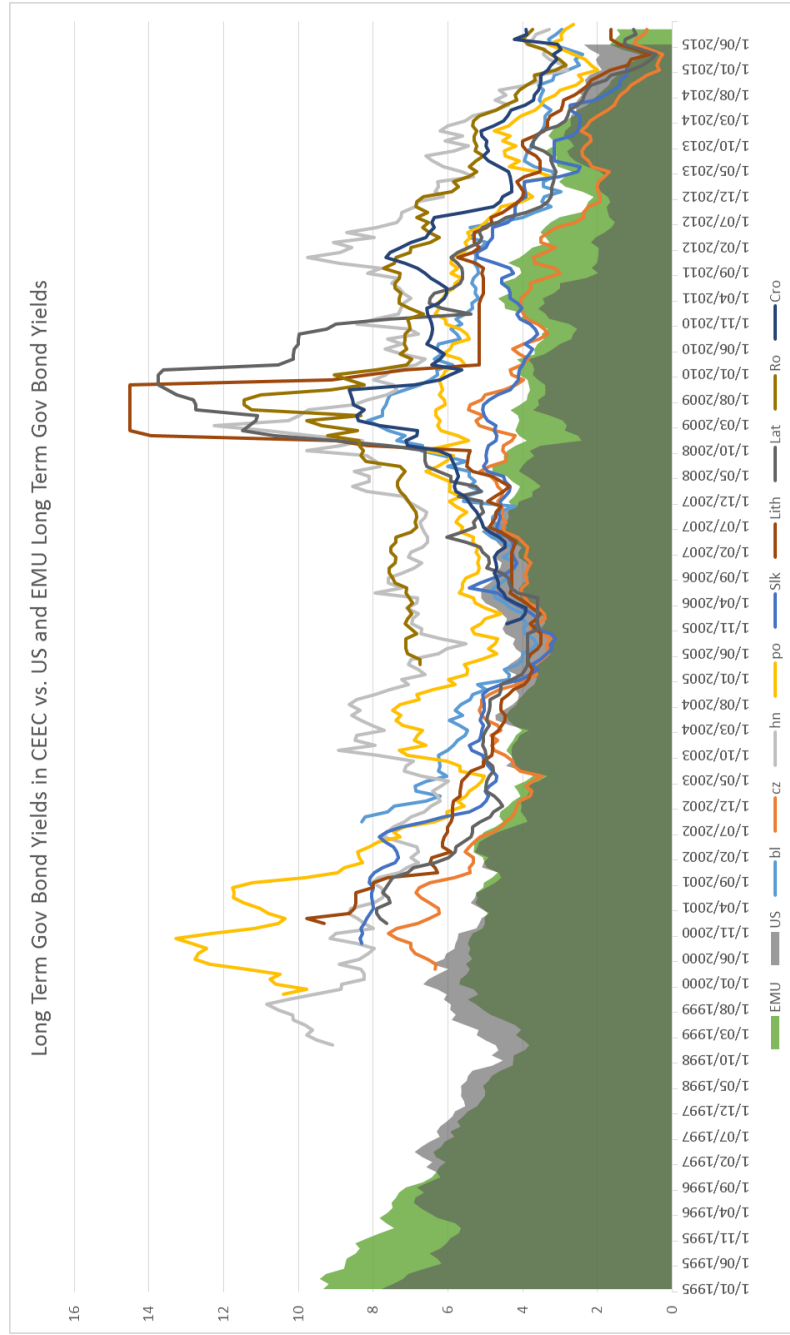


Figure 2: Long Term Government Bond Yields in Emerging Markets and the US

- This figure depicts a common component in the long term government bond yield of several CEECs (the Czech Republic, Hungaria, Poland, Latvia and Lithuania) together with the Term premium for the US (retrieved from the NY Federal Reserve)

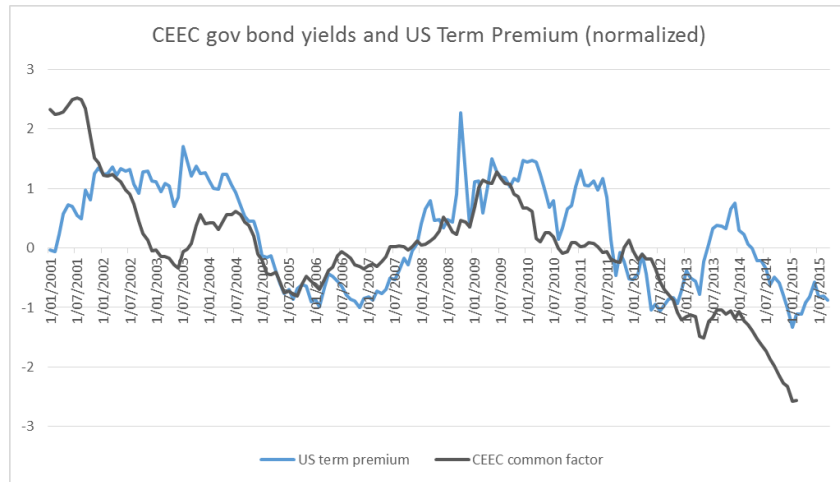


Figure 3: Granger Causality, analyzing domestic long term government yield for CEECs

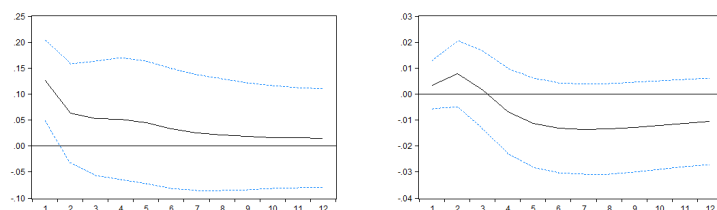
- This table shows the Granger Causality test running from US government bond yields, EMU government bond yields and domestic EME policy rates to EME government bond yields. P-values are denoted in brackets. * and ** respectively denote 5 and 10 percent significance levels.

	$USGB \rightarrow EMEGB$	$EMUGB \rightarrow EMEGB$	$EMEPLR \rightarrow EMEGB$
<i>BL</i>	0.68 (0.51)	3.52** (0.03)	1.64 (0.20)
<i>CZ</i>	4.55** (0.01)	3.12** (0.05)	4.80** (0.01)
<i>HU</i>	2.50* (0.08)	4.38** (0.01)	2.74* (0.07)
<i>PO</i>	0.95 (0.39)	0.85 (0.43)	2.84* (0.06)

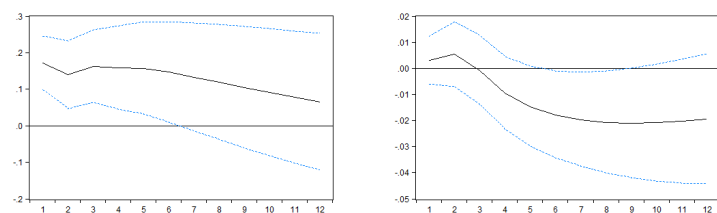
Figure 4: Full Sample VAR impulse responses for Bulgaria

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Bulgaria, in response to shocks in EMU and US long term government bond yield

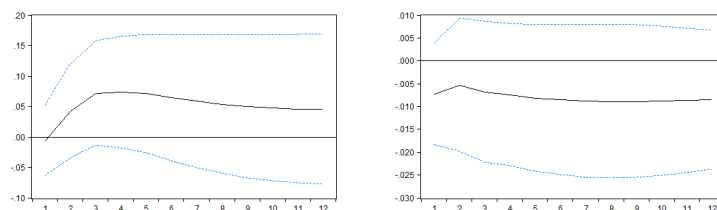
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Bulgarian long term government bond yield (left panel) and Bulgarian bilateral exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Bulgarian long term government bond yield (left panel) and Bulgarian bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Bulgarian long term government bond yield (left panel) and Bulgarian bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Bulgarian long term government bond yield (left panel) and Bulgarian bilateral exchange rate (right panel)

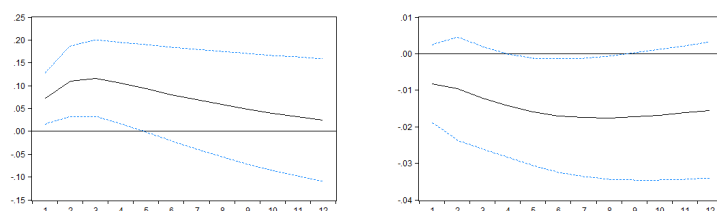
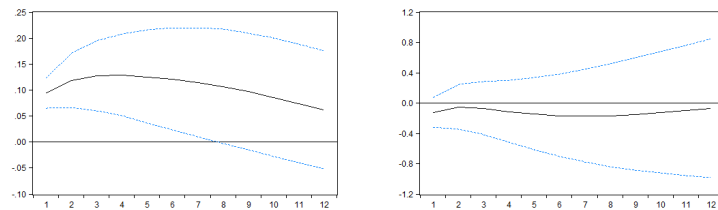


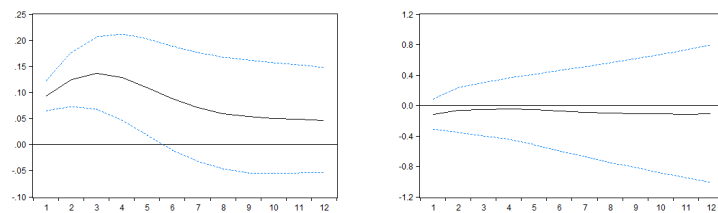
Figure 5: Full Sample VAR impulse responses for the Czech Republic

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for the Czech Republic, in response to shocks in EMU and US long term government bond yield

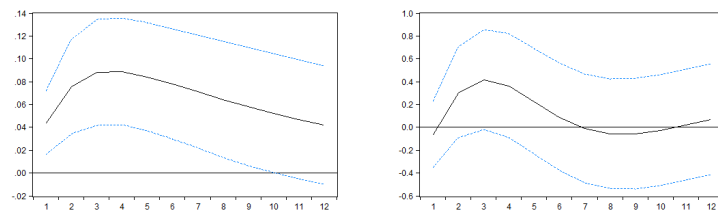
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Czech long term government bond yield (left panel) and Czech nominal exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Czech long term government bond yield (left panel) and Czech nominal exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Czech long term government bond yield (left panel) and Czech nominal exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Czech long term government bond yield (left panel) and Czech nominal exchange rate (right panel)

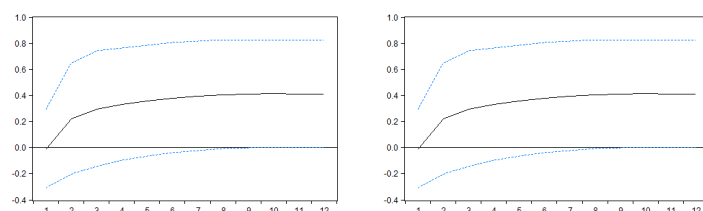
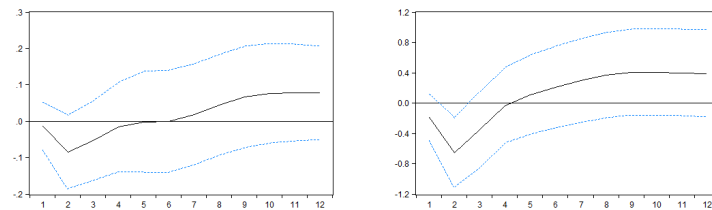


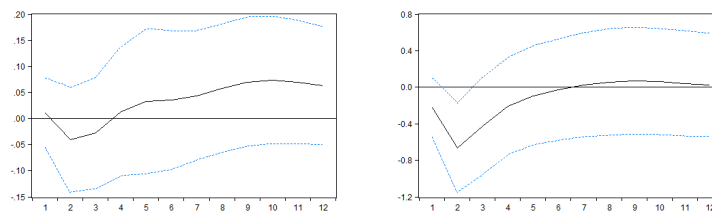
Figure 6: Full Sample VAR impulse responses for Hungary

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Hungary, in response to shocks in EMU and US long term government bond yield

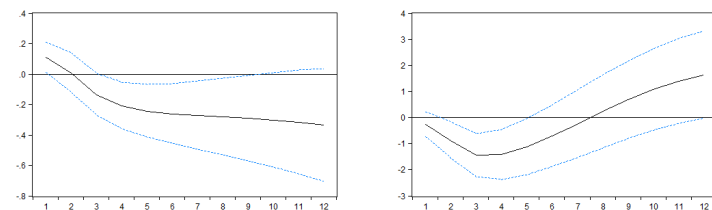
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Hungarian long term government bond yield (left panel) and nominal Hungarian exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Hungarian long term government bond yield (left panel) and nominal Hungarian exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Hungarian long term government bond yield (left panel) and nominal Hungarian exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Hungarian long term government bond yield (left panel) and nominal Hungarian exchange rate (right panel)

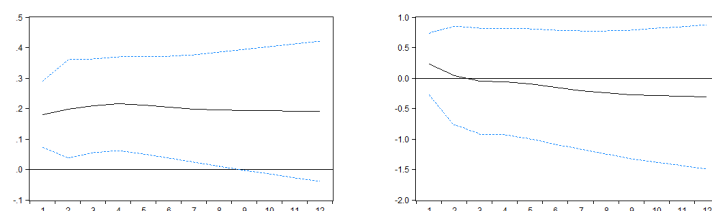
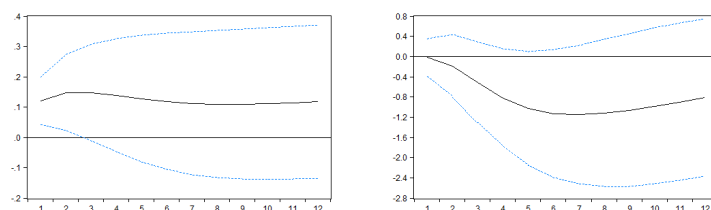


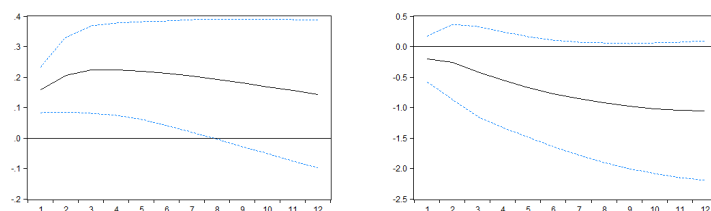
Figure 7: Full Sample VAR impulse responses for Poland

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Poland, in response to shocks in EMU and US long term government bond yield

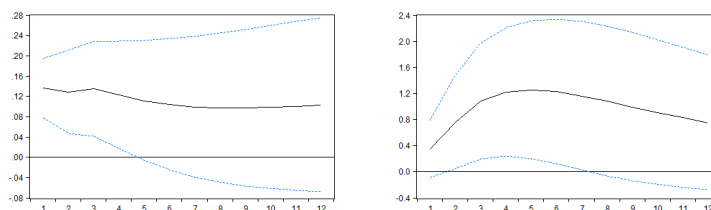
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Polish long term government bond yield (left panel) and Polish nominal exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Polish long term government bond yield (left panel) and Polish nominal exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Polish long term government bond yield (left panel) and Polish nominal exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Polish long term government bond yield (left panel) and Polish nominal exchange rate (right panel)

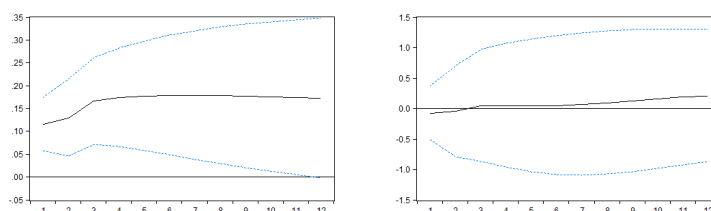
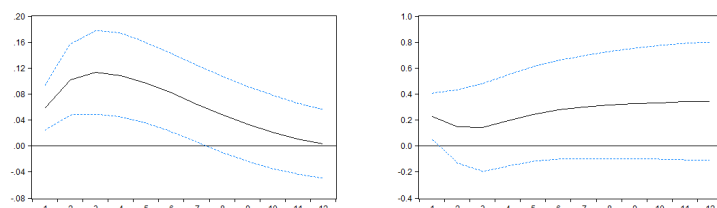


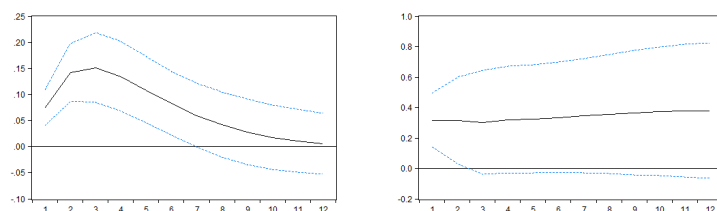
Figure 8: Full Sample VAR impulse responses for Malaysia

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Malaysia, in response to shocks in EMU and US long term government bond yield

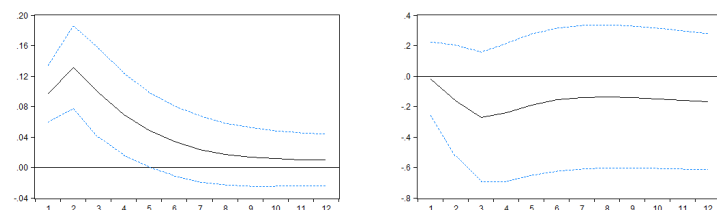
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Malaysian long term government bond yield (left panel) and Malaysian nominal exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Malaysian long term government bond yield (left panel) and Malaysian nominal exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Malaysian long term government bond yield (left panel) and Malaysian nominal exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Malaysian long term government bond yield (left panel) and Malaysian nominal exchange rate (right panel)

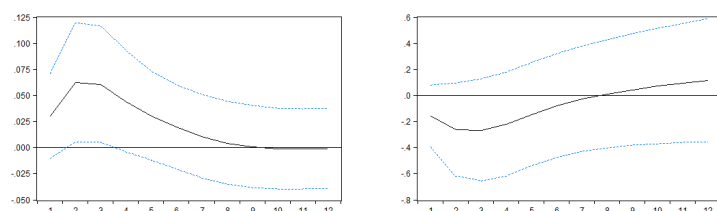
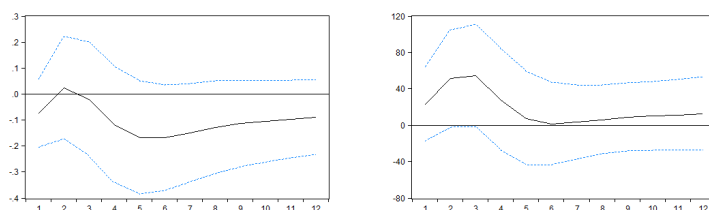


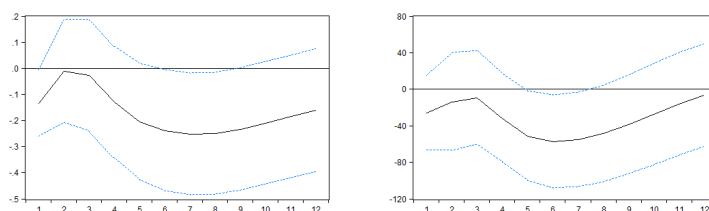
Figure 9: Full Sample VAR impulse responses for Indonesia

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Indonesia, in response to shocks in EMU and US long term government bond yield

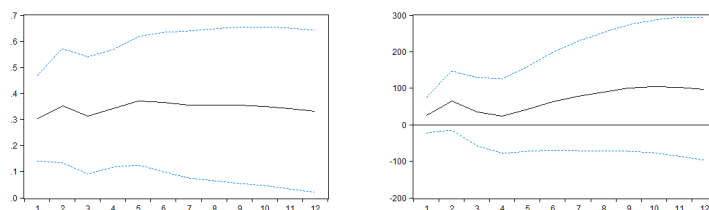
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Indonesian long term government bond yield (left panel) and Indonesian bilateral exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Indonesian long term government bond yield (left panel) and Indonesian bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Indonesian long term government bond yield (left panel) and Indonesian bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Indonesian long term government bond yield (left panel) and Indonesian bilateral exchange rate (right panel)

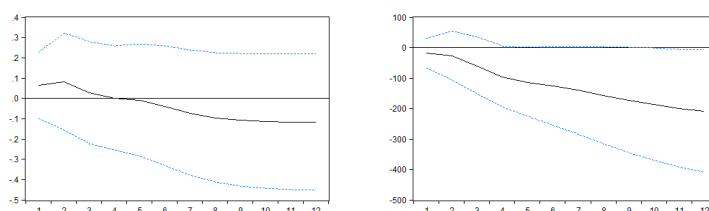
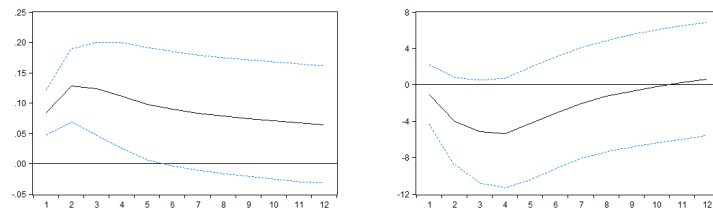


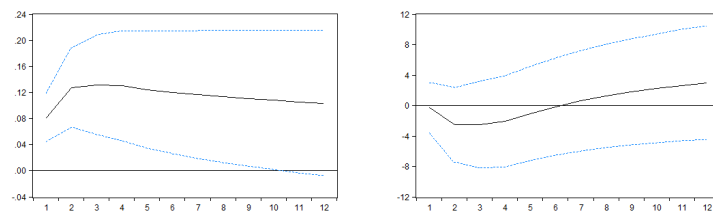
Figure 10: Full Sample VAR impulse responses for Chile

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Chile, in response to shocks in EMU and US long term government bond yield

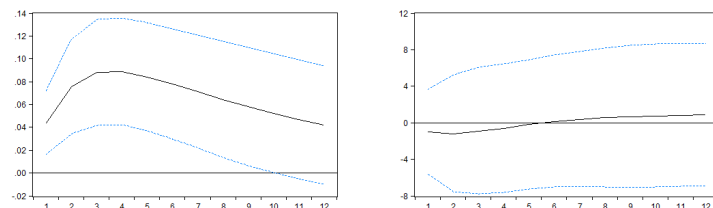
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Chilean long term government bond yield (left panel) and Chilean bilateral exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Chilean long term government bond yield (left panel) and Chilean bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Chilean long term government bond yield (left panel) and Chilean bilateral exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Chilean long term government bond yield (left panel) and Chilean bilateral exchange rate (right panel)

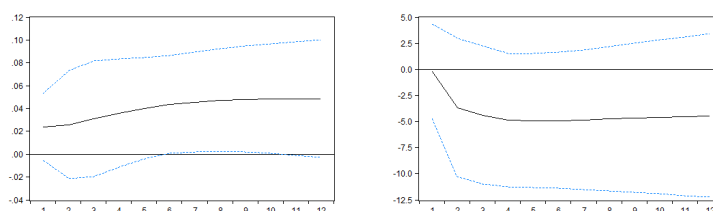
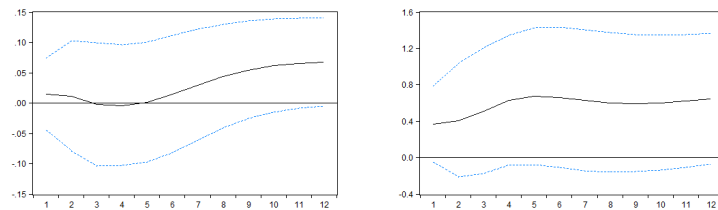


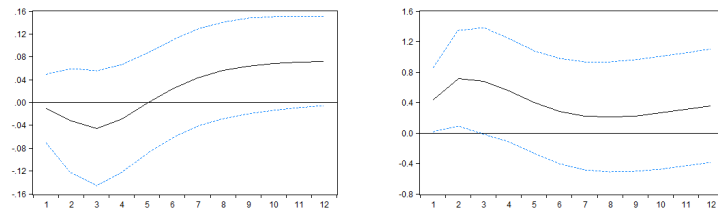
Figure 11: Full Sample VAR impulse responses for Mexico

- This figure shows the impulse responses for the full sample Vector Autoregressive estimation procedure for Mexico, in response to shocks in EMU and US long term government bond yield

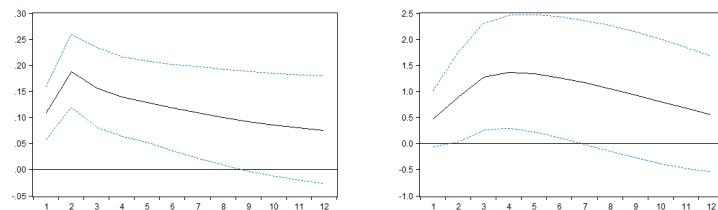
Panel A: Pre-crisis, shock in US long term government bond yield and respons in Mexican long term government bond yield (left panel) and Mexican nominal exchange rate (right panel)



Panel B: Pre-crisis, shock in EMU long term government bond yield and respons in Mexican long term government bond yield (left panel) and Mexican nominal exchange rate (right panel)



Panel C: Post-crisis, shock in US long term government bond yield and respons in Mexican long term government bond yield (left panel) and Mexican nominal exchange rate (right panel)



Panel C: Post-crisis, shock in EMU long term government bond yield and respons in Mexican long term government bond yield (left panel) and Mexican nominal exchange rate (right panel)

