THE MACROECONOMIC EFFECTIVENESS OF
UNCONVENTIONAL MONETARY POLICY IN THE EURO AREA:
A STRUCTURAL VAR ANALYSIS

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Abstract

Ever since the Global Financial Crisis unfolded in the euro area and a near-zero lower bound was reached, the way in which the ECB conducts monetary policy has radically changed. We investigate the macroeconomic effects of unconventional monetary policy in the euro area using a structural vector autoregression (VAR) with two different identification approaches. The aims of this paper are threefold. First, and most importantly, we show that it is possible to orthogonalize structural shocks in the euro area using identification through heteroskedasticity based on the framework provided by Brunnermeier, Palia, Sastry and Sims (2019) for the US economy. This method identifies the structural shocks on the premise that their variance changes across different time periods and thereby does not require the imposition of any strict short- or long-run restrictions on the structural VAR’s coefficients. Nonetheless, we are able to interpret one of our emerging shocks as a contractionary monetary policy shock whose characteristics are largely consistent with the previous literature. A rise in our policy tool, the shadow short rate, leads to a significant decline in output and a smaller, and less significant, decline in prices. Additionally, we find that the shadow short rate appears to be endogenously driven by financial stress, aggregate demand and aggregate supply shocks. Next, we employ the standard identification approach in the literature, namely a combination of sign and zero restrictions, to confirm our previous results and shed some new light onto the cross-period heterogeneity of unconventional monetary policy effectiveness. While we find that the ECB’s unconventional monetary policy has positively affected the real economy throughout the full time period from 2008 to 2019, our more nuanced analysis shows that it has reaped larger benefits during non-crisis times since 2013. Instead, during crisis times, it has been more effective in reducing financial stress without generating the desired spillover into the real economy. Overall, our findings have important implications for the policy debates surrounding the ECB’s controversial unconventional monetary policy measures, while also contributing an alternative identification framework that can be applied to future eurozone macro studies.
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1. Introduction

Historically, the standard response of central banks to downturns in the economy has been to lower interest rates in order to stimulate output and fulfil the mandate of price stability. However, over the past two decades, central banks have been forced to rethink the way they conduct monetary policy; benchmark interest rates in many developed economies reached the zero lower bound (ZLB) thus further loosening was no longer an option. Instead, central bankers have increasingly turned to unconventional monetary policy (UMP) measures, mainly consisting of large-scale asset purchases (LSAP), also referred to as quantitative easing (QE), and forward guidance. Originally used by the Bank of Japan in 2001, the Federal Reserve (Fed), the Bank of England (BoE) and the European Central Bank (ECB) followed suit and adopted unprecedented levels of UMP in the aftermath of the Global Financial Crisis of 2007.

Naturally, as the way central banks conduct policy has transformed, so has the way monetary policy and its effects are studied from an empirical perspective. This new era of monetary policy has raised a multitude of relevant questions, most importantly concerning the effectiveness of UMP in achieving its predominant aims of stimulating the real economy in terms of output and inflation. Particularly in the eurozone, these questions are as pertinent as ever. Despite the ECB’s use of UMP for over a decade, its benchmark interest rates still remain at the ZLB. The ECB reintroduced monthly asset purchases just recently in September 2019 as well as an unprecedented pandemic-related purchasing program in March 2020 to help combat the next crisis. This demonstrates that UMP measures are likely to remain in the ECB’s toolbox for the years to come and are considered both crisis and non-crisis measures, making an evaluation of their effectiveness vital. Given the difficulty of identifying UMP shocks from an empirical perspective as well as the substantial transmission lag of its effects onto the real economy, there are considerable gaps in this field that we aim to bridge. We therefore (re-)assess the macroeconomic impacts of the ECB’s UMP using a structural vector
autoregression (SVAR) in which we solve the identification problem with a previously unused approach using identification through heteroskedasticity and update existing estimates with the most recently available data.

The ECB’s initial reaction to the Global Financial Crisis was to utilize conventional measures by cutting the policy rate, namely the Marginal Refinancing Operations (MRO) rate, from 4.25 percent in October 2008 to 1 percent in early 2009. At this point, conventional monetary policy was largely exhausted even though the seeds for the next crisis had already been sown as financial market stress began spilling over into sovereign debt markets. Unlike the US and the UK, the euro area faced a second devastating crisis, the Euro Crisis, soon thereafter starting in 2010. Finding itself at the effective lower bound, the ECB had to take a different approach in restoring financial market stability and generating a robust recovery of the eurozone. Therefore, it turned to more unconventional measures. In contrast to the Fed and the Bank of England, who began their QE programs in November 2008 and March 2009 respectively, the ECB did not pursue a LSAP program in the immediate aftermath of the two crises. Instead, the ECB initially implemented a host of alternative UMP measures that also significantly changed the size and composition of its balance sheet prior to the introduction of its own QE program, the Asset Purchase Programme (APP) in January 2015. In the immediate aftermath of the crisis, the ECB introduced a number of liquidity and financing measures such as longer-term refinancing operations (LTROs) and switching from variable-tender to fixed-tender rates with full allotment (FRFA) in October 2008. With the LTROs, banks were able to buy government bonds and exchange them with the ECB for a loan of reserves, essentially fostering the same effects as QE whilst circumventing the fact that the ECB was not legally mandated to buy government bonds directly. In addition, it introduced several smaller-scale asset purchasing programs including the Covered Bond Purchase Programs (CBPP), the Securities Market Programme (SMP) for purchases of longer-term sovereign bonds and the Outright Monetary Transactions (OMT) program.
for short-term sovereign bonds in specific euro area countries with financial difficulties, aiming at removing euro denomination risk. Thereby, the ECB essentially became a lender of last resort for several EMU members during crisis times.

When the immediate crises were over, the euro area found itself at a point with sluggish aggregate demand and deflationary risks despite historically low interest rates. Therefore, the ECB intervened once more. The goal on this occasion was not so much to restore liquidity into financial markets and undo an immediate crisis, but rather to conduct loose monetary policy when they found themselves operating at the effective lower bound. Additionally to using forward guidance to instill credibility and confidence in the euro area’s future trajectory, the ECB announced that it would adopt a negative deposit rate and asset purchase programs for asset-backed securities and once more covered bonds. These measures were soon thereafter extended to form the APP under which the ECB could also purchase sovereign bonds, officially launched in January 2015. As a result of these measures, the balance sheet of the ECB grew from €1.2 trillion in 2007, to €2.8 trillion at the end of 2015 and €4.7 trillion in December 2019. A timeline detailing the ECB’s monetary policy since the crisis in 2007 until its most recent announcement can be found in Table 4 of the Appendix.

Thus far, the majority of the literature around UMP has focused on financial market effects since they are easier to measure and occur on impact or in the short term without a substantial lag. Generally, these studies have found that yields and spreads were compressed (see Andrade, Breckenfelder, Fiore, Karadi and Tristani, 2016), equity prices rose (see Haitsma, Unalmis and de Haan, 2016) and the euro depreciated (see Bulligan and Monache, 2018) in response to the ECB’s UMP measures. However, the much more important and interesting question is whether and how well these positive financial market effects were able to spill over into the real economy to give the EMU member states a much-needed boost and fulfil the ECB’s original policy goals. Since the ECB evidently relies on these unconventional measures to this day and will continue to do so in the future,
especially in light of the upcoming grave economic difficulties triggered by COVID-19, their effects on the real economy are a worthy topic of study. However, given how difficult it is to isolate these real effects, they have generally been understudied in relation to their potentially powerful implications, with only a relatively scarce literature existing around the macroeconomic effects of the ECB’s UMP.

The central challenge faced by empirical researchers is disentangling UMP shocks from other cyclical shocks in the economy to make them truly exogenous in the SVAR setup. This paper employs two different identification schemes. First, we contribute to the literature by successfully adopting Brunnermeier, Palia, Sastry and Sims’s (2019) identification through heteroskedasticity approach from the US, which – to our knowledge – has not previously been attempted in the euro area. Without requiring strict assumptions on the coefficients of the VAR, this method is able to orthogonalize structural shocks based on the premise that their variance changes across different time periods. To confirm the robustness of our results and carry out subsample analyses, we also conduct the status quo identification scheme in this literature, a combination of sign and zero restrictions, based on Boeckx, Dossche and Peersman (2017).

The next difficulty faced in the literature is how to best measure the unconventional policies given that the traditional instrument – simply the policy rate – is no longer representative of the central bank’s monetary policy stance at the ZLB. While there is no scholarly consensus, most studies opt for the central bank’s balance sheet as a proxy. However, balance sheet movements fail to include expectations that are created by announcements of UMP, making them a problematic measure especially for the APP purchases that were fully expected in advance. An alternative measure that has gained traction more recently is the shadow short rate that can take on negative values when the policy rate is zero. Since it is derived from the yield curve and thus financial market data, it also incorporates
expectations. We follow Elbourne, Ji and Duijndam (2018) in using the shadow rate in our paper, making it one of few studies in this field to do so and enabling us to offer a fresh perspective.

Lastly, given the lagged effect of UMP on the real economy, the main drawback of most existing studies is limited data availability. There are no studies thus far that factor in post-2016 data points even though a significant portion of the APP was carried out afterwards. Here, our study uses data until December 2019 in hope of capturing lagged effects and the impact of more recent UMP recalibrations. Given the breadth of data available to us, we also compare the effectiveness of UMP in crisis times versus non-crisis times in the euro area, following Hesse, Hofmann and Weber’s (2018) study on diminishing returns of QE in the US and UK.

Therefore, this study presents a new identification method that provides a platform on which future studies can build, while giving both a holistic and more nuanced overview of the UMP program and making use of the shadow short rate as a persistent policy tool throughout our whole time period from 2007 to 2019. We find that, overall, the ECB’s monetary policy has been successful in stimulating the economy since 2007 for both of our identification methods. However, our split sample analysis indicates that the effect on the real economy was stronger in post-crisis times than during the crises, during which it more effectively reduced financial stress. The effect on inflation relative to output was less pronounced throughout. We also make the conclusion that the shadow rate was largely endogenously driven by financial stress, aggregate demand and aggregate supply shocks throughout, suggesting that monetary policy surprises did not represent the major source of variation.

The paper proceeds as follows: Chapter 2 discusses related literature to establish a backdrop and framework for this study. Next, Chapter 3 describes the data and variables we use in our methodology that is outlined in detail in Chapter 4. The results and robustness analyses are reported in Chapter 5 and discussed in a broader context in Chapter 6. Lastly, our concluding remarks can be found in Chapter 7.
2. Literature Review

An extensive literature exists on the macroeconomic impacts of conventional monetary policy as determined by traditional interest rate movements. However, much less is known about the dynamics between macroeconomic variables like output and inflation and UMP measures. These have become the predominant tool used by the central banks of many developed economies in the low-interest environment we have witnessed since the advent of the Global Financial Crisis. Alongside the shift from conventional to unconventional monetary policy, empirical research has also evolved – the UMP literature has proliferated throughout the last decade. While the pre-crisis literature on conventional monetary policy generally came to the consensus that expansionary shocks in the form of interest rate cuts lead to hump-shaped temporary rises in output and a more persistent rise in inflation, as shown by Christiano, Eichenbaum and Evans (1999) in the US and Peersman and Smets (2003) in the euro area, the real effect of UMP is more ambiguous and debated among scholars. Most studies in the US find a significant and lasting positive impact on output and inflation, however, some studies conducted in the euro area find no significant or only transitory impacts on the real economy, implying that there is still room for further research that we aim to address. The following section includes i) an overview of the financial market effects of UMP in order to shed a light on the transmission mechanisms to the real economy, ii) an explanation of the evolution of this paper’s methodology as well as iii) existing evidence that this paper will build on.

2.1 The Transmission Channels of UMP

First off, given the short-term and rapid responsiveness of financial market variables to monetary policy announcements, financial market studies have dominated the UMP literature thus far. The macroeconomic effects of UMP, on the other hand, only materialize over a longer time period, usually with a lag, and are more difficult to model econometrically. Even so, we can learn
important lessons from financial market studies that elucidate the potential transmission mechanisms of UMP on the real economy, thereby helping us determine the relevant variables for the setup of our macroeconomic model. Therefore, even though the methodologies of these studies – namely event study approaches with high-frequency data from a narrow time window around announcement events – will be irrelevant for this paper’s methodology, the findings are nonetheless useful to establish why and through which channels output and prices might be affected by UMP.

Numerous studies on financial market effects of UMP in the eurozone focus on the impact on yields, which provide evidence for the so-called portfolio rebalancing channel and the signaling channel. The relevant studies hailing from the eurozone suggest that UMP has led to a compression of sovereign and corporate bond yields, as well as a reduction in spreads and risk premia, even for securities not directly purchased by the ECB (Altavilla, Carboni and Motto 2015; DeSantis, 2016; Andrade et al., 2016). Bulligan and Monache (2018) show that UMP announcement affected long-term sovereign bond yields significantly. This subsequently triggered reductions in corporate bond yields through the portfolio rebalancing channel. This channel theorizes that central bank asset purchases cause the sellers of assets to rebalance their portfolios towards riskier assets in terms of asset class or maturity, causing a spill over into other asset classes, driving up prices of a wider range of assets than those originally purchased. In turn, external financing costs are lowered, the supply of bank lending rises, and investment is stimulated. This idea is supported by Haitsma et al. (2016), who find an overall positive effect of UMP surprises on equity prices, with the strongest effect on highly leveraged firms who rely more on debt and particularly bank funding. Similarly, lower yields provide evidence for the signaling channel in which bank purchase announcement affect market expectations, signaling that the central bank will retain an expansionary stance for longer than expected, reducing expectations of short-term interest rates. A concept first identified by Bauer and Redebusch (2013) in the US, Gern et al. (2015) makes the same argument for the euro area, claiming that asset purchases
strengthen the credibility of the low-interest rate policy. In addition, there is also an exchange rate channel that materializes itself through the depreciation of the effective exchange rate as a result of rebalancing euro-denominated portfolios towards external assets (Bulligan and Monache, 2018).

The question that follows from the high-level overview of these channels is whether they successfully transmit financial market effects of UMP to the real economy. Answering this question is particularly salient since the ECB has continued to employ these measures in a non-crisis era where its aims go far beyond restoring liquidity and stability into malfunctioning financial markets. Turning to existing studies on the effects of unconventional monetary policy on output and inflation, VARs offer a more suitable approach to systematically capturing the dynamics of multiple time series and incorporate lagged effects of endogenous variables compared to event study methodologies.

2.2 The Use of SVARs in the Monetary Policy Literature

As aforementioned, the literature concerning the macroeconomic effects of UMP is considerably more limited than that on microeconomic effects. Naturally, the closest literature to borrow from is conventional monetary policy, which has been studied extensively pre-Global Financial Crisis. With his seminal work, Sims (1980) provided a novel framework, namely the VAR, that has become the standard tool in macroeconomics as well as monetary policy analysis to identify the relationship between different variables and their lagged values. In order to obtain causal interpretations of impulse responses, we need a structural representation of the VAR model whose innovations are orthogonal to other shocks in the economy – these can be recovered from the reduced-form shocks by imposing certain restrictions, thereby solving the so-called identification problem. There are a handful of different identification approaches provided to us by the literature, each with respective advantages and disadvantages. These include the Cholesky decomposition, a recursive scheme initially proposed by Sims (1980), as well as non-recursive methods such as short-
run restrictions (Sims, 1986; Bernanke, 1986) and long-run response restrictions (Blanchard and Quah, 1989). Since the Cholesky identification and long-run restrictions rely on assumptions that are often difficult to justify from a theoretical perspective, a more recent method of identification has become prevalent in monetary policy studies, namely sign restrictions as proposed by Faust (1998) and Uhlig (2005). This method restricts the impulse responses of variables to structural shocks to be either negative or positive, driven by theoretical and empirical findings.

The majority of the UMP literature has combined two approaches to impose both sign and zero restrictions to solve the identification problem. Combining these two schemes adds an additional layer of identification that is meant to lower the chance of several separate structural shocks being conflated, thereby reducing the number of accepted draws and sharpening the identification of structural shocks. Initial applications of this combination were carried out by Jarocinski and Smets (2008) to identify housing supply and housing demand shocks as well as Mountford and Uhlig (2009) to disentangle fiscal shocks. However, it also can be, and has been, used for the purpose disentangling monetary policy shocks. Whilst Eickmeier and Hofman (2013) utilize this method for conventional monetary policy shock identification, it has also become the standard identification scheme used in the bulk of the UMP literature, where the interest rates are replaced with different indicators of monetary policy stance such as central bank reserves or the shadow short rate. The intuition behind using this strategy in monetary policy studies is as follows; on the one hand, contemporaneous zero restrictions are useful to account for the notion that effects on output only materialize with a lag and prices are assumed to be sticky (Bernanke and Blinder, 1992; Christiano et al. (1999); Peersman and Smets, 2003). Sign restrictions, on the other hand, represent the idea that financial market variables respond contemporaneously to monetary policy shocks in a specific direction that has been determined by microeconomic studies as demonstrated in Section 2.1. A summary of existing empirical evidence using this mainstream identification method is provided in Section 2.3.
In addition to making use of this widespread approach, this paper attempts a novel identification method, identification through heteroskedasticity, that has not yet been used in macroeconomic UMP studies in the euro area, but only in a macro VAR in the US by Brunnermeier et al. (2019). Pioneered by Rigobon (2003) in a study of sovereign bond contagion in a General Methods of Moments estimation framework, this method relies on the heteroskedasticity of structural shocks. It assumes that even though the pattern in which the shocks affect the economy is the same across different time periods, their relative volatility and size differs across periods. This method originates from and has been mainly used in financial market studies, including monetary policy studies such as Rigobon and Sack’s (2004) who rely on the heteroskedasticity of high-frequency data to estimate the impact of monetary policy on asset prices. Similarly, it has been used by some UMP studies which assume that the variance of monetary policy shocks is larger on days where there are central bank announcements – Wright (2012), for instance, carries out a SVAR with identification through heteroskedasticity to find that UMP shocks lead to a temporary yield compression, while Ghilchrist and Zakrajsek (2013) use it to find a reduction of private sector risk in the US. While all these studies use daily data, Lütkepohl and Netšunajev (2018) studied the effect of monetary policy on the stock market in Europe using a SVAR with monthly data, modeling the volatility changes with a Markov-switching mechanism. They find that a contractionary monetary policy shock leads to a persistent decline in real stock prices.

However, as Brunnermeier et al. (2019) demonstrate, identification through heteroskedasticity is not only useful for financial market studies, but it can also be adapted to suit a macroeconomic analysis. Their use of this method in a large-scale SVAR that investigates the interaction between credit conditions, monetary policy and real activity in the US inspired this study’s use of the same identification approach. Brunnermeier et al. (2019) exogenously specify six different variance regimes whose innovations have different covariance matrices based on prior knowledge about monetary
policy changes and observations in the time series instead of using a Markov-switching mechanism as previous studies have done. Given the evident time-varying variances of shocks in the data, Brunnermeier et al. (2019) argue that this identification method is more suitable for their data than short-run zero and sign restrictions or long-run response restrictions. They manage to find a contractionary monetary policy shock that behaves as we would expect: a positive response of the interest rate on impact, a gradual reduction of industrial production and prices as well as correctly-signed responses for their financial market variables. Building on this approach, we attempt to apply this novel identification approach to the euro area and compare these findings with our results following the aforementioned status quo method that combines sign and zero restrictions. Since the euro area can be characterized by two distinct macroeconomic conditions since 2007: crisis versus post-crisis, our data seemed to comply with the assumptions made by Brunnermeier et al. (2019). We hence evaluate the usefulness of this method for the euro area going forward, providing a foundation upon which future studies can build.

2.3 Empirical Evidence of UMP’s Effect on the Real Economy

Now that we have outlined the prevalent methods in the literature and specifically those used in our study, we turn to the existing empirical evidence on the effectiveness of UMP in stimulating the real economy. Most studies have hailed from the US and the UK since the Fed and BoE carried out their QE policies much quicker and aggressively than the ECB following the Global Financial Crisis. These studies largely use a combination of sign and zero restrictions and replace interest rates as monetary policy indicator with different variables such as interest rate spreads and central bank reserves or purchases. For example, Baumeister and Benati (2013) use a time-varying parameter SVAR model with sign restrictions and a single zero restriction, determining a UMP shock through interest spread shocks, to find that QE counteracted deflation and raised real GDP by 0.9 percent in the US,
with similar results in the UK. Weale and Wieladek (2016) use a Bayesian VAR with central bank asset purchases as the UMP instrument and four different identification schemes including a Cholesky ordering, sign restrictions and a combination of zero and sign restrictions, finding that an asset purchase equal to one percent of nominal GDP leads to a 0.62 percent increase of real GDP and 0.58 percent increase of the CPI in the US (0.25 and 0.32 respectively for the UK). In Japan, on the other hand, Schenkelberg and Watzka (2013) who consider a UMP shock as increase in reserves, use a combination of sign and zero restrictions in an SVAR to find a significant, yet only transitory positive impact of QE on output and inflation. These empirical findings are in line with the theoretical effects found using Dynamic Stochastic General Equilibrium (DSGE) models following Cúrdia and Woodford (2011). The overall conclusion of DSGE studies is that output and inflation are both stimulated in response to a QE shock (Chen and Macdonald, 2012; Falagardia, 2014; Quint and Rabanal, 2017). Overall, we can conclude that the studies in the US, UK, and Japan indicate that unconventional measures have been similarly effective as conventional measures in terms of stimulating output and prices.

Over the years, the euro area research has been ever-growing even though the analysis in a monetary union is comparatively more difficult than in a singular country with monetary policy authority. Since the EMU consists of 19 fiscally independent countries with different monetary policy needs, who are nonetheless all subject to the ECB’s decisions, we cannot assume that the positive effects found in the US and UK will be mirrored in the euro area. In addition, the nature of UMP in the euro area was fundamentally different in the euro area. Specifically, the ECB introduced a wider variety of UMP instruments prior to LSAPs, including LTROs, TL TROs and FRFA prior to its APP program. The latter was only launched in late-2015. Nonetheless, we can draw from a handful of existing studies to aid setting up our own analysis. Most of these studies focus on the effect of UMP prior to the APP, using data up to 2015. They use the balance sheet of the ECB as a UMP
measurement tool since even the UMP measures introduced prior to the APP more than doubled it (see Figure 4 in Appendix). In order to identify a UMP shock, these studies apply a positive sign restriction to the balance sheet assets on impact, zero restrictions on output and prices, and varying sign restrictions for different financial market variables. Unlike the consensus for the US and the UK, the euro area studies provide quite mixed evidence on the effectiveness of UMP, making this paper’s contribution important.

The first paper to analyze the macroeconomic effects of the ECB’s non-standard policies by Gambacorta, Hofmann and Peersman (2014) included the euro area in a panel VAR next to three other countries. They concluded that, on average, a 3 percent increase in the balance sheet leads to an output expansion of 0.06 to 0.15 percent and inflation of 0.06 to 0.11 percent. However, while providing the groundwork for future UMP studies in the euro area, the sign and zero restrictions applied were generalized to suit all four economies in the panel and not geared towards euro area dynamics. Accordingly, the reported responses were also pooled averages from all four regions. Boeckx et al. (2017) criticizes Gambacorta et al. (2014) for failing to distinguish between policy-induced and demand-driven innovations to the balance sheet as well as not including financial market variables to help identify exogenous UMP shocks. Additionally, Gambacorta et al. (2014) were unable to factor in the effect of UMP policies after 2011 due to the limited time period at their disposal. Hence, Boeckx et al. (2017) addressed these shortcomings with a Bayesian SVAR geared to assess the ECB’s pre-APP UMP measures from 2007 to 2014. The authors attempt to disentangle the exogenous balance sheet shock representing UMP by restricting the contemporaneous response of the balance sheet to be positive and that of the main policy rate, the MRO, to be zero to exclude any conventional monetary policy shocks. In addition, they impose negative restrictions on the money market spread (between the MRO and the Euro Overnight Index Average [EONIA]) and a measure of systemic financial stress to rule out an endogenous expansion of the balance sheet. Boeckx et al.’s (2017) study
finds that a 1.5 percent increase in the ECB’s balance sheet stimulates both output and prices by about 0.1 percent. Burriel and Galesi (2018) extend Boeckx et al.’s (2017) study by incorporating cross-country interdependencies into a global VAR that accounts for panel variation among euro area economies, using the same identifying restrictions (with one additional variable new credit growth) and a comparable time period. They find a heterogenous effect throughout euro area countries which dampened the overall effect on the real economy on aggregate. This led them to the conclusion that UMP effects are significantly smaller and less persistent than those of conventional monetary policy. Overall, they find a one percent increase in growth of ECB assets increases output by nearly 0.1 percent and inflation by 0.05 percent.

While these papers focused on a time period up to 2015, the literature around the APP is scarce. There are only two macroeconomic studies that focus on the APP. However, they fail to consider the longer-term lagged effects on macroeconomic variables that likely exist as well as any recalibrations because they were conducted shortly after APP’s introduction. The balance sheet identifications used by Boeckx et al. (2017) and Burriel and Galesi (2018) are no longer applicable – the balance sheet does not reflect market expectations that were influenced by APP announcements made long in advance before their implementation. The first attempt to study the effectiveness of QE in the euro area is Wieladek and Garcia Pascual (2016), who use data from mid-2012 until 2016. They identify asset purchase shocks through QE announcements, scaling the total amount of euro area sovereign debt purchases announced at each meeting by pre-announcement GDP. Using the same four different identification schemes in a Bayesian VAR as the aforementioned Weale and Wieladek (2016), including sign and zero restrictions that keep inflation and output unrestricted though; they find statistically significant peak responses between 0.07 and 0.15 percent on output and 0.05 to 0.1 percent on inflation in reaction to an asset purchase shock. Gambetti and Musso (2017), who, to our knowledge, conducted the only other study on the macroeconomic impacts of APP restrict their
analysis to the initial announcement effect of APP. Using quarterly data from 2009 to 2016, they focus on the APP shock in the first quarter of 2015 by only setting restrictions on effects of Eurosystem security purchases that took place in said quarter. Through a novel combination of sign, timing and magnitude restrictions based on financial market studies, they estimate a peak impact on real GDP of 0.18 in the first quarter of 2015 and on inflation of 0.36 in the fourth quarter of 2016. Notably, they claim that these effects are relatively small compared to the empirical impact of QE in the US and the UK. These effects are also quite small compared to those found in theoretical approaches. Sahuc (2016), for example, finds peak responses of 0.9 percent on output and 0.6 percent on inflation in 2015. Generally, the studies seem to suggest a more immediate and higher impact on output, with a more subtle and delayed or even insignificant impact on prices.

Overall, even though there seems to be a general positive consensus concerning the effectiveness of UMP in stimulating the real economy in the euro area, there is strong quantitative variation among estimates. The presentation of the relevant studies has helped identify a gap in the literature – the most recent existing studies do not use data beyond mid-2016 and we now have 3.5 more years of data available in which asset purchases were continued and lagged effects that both Weale and Wieladek (2016) and Gambetti and Musso (2017) acknowledge may have materialized. Our study attempts to bridge this gap by both giving a holistic overview of UMP effectiveness in the euro area since 2007 as well as a specialized analysis of subperiods to investigate whether the policies were more effective during or after crisis episodes. In doing so, we follow the setup of Hesse et al. (2018) in the US and UK who compare their full sample results (November 2008 to October 2014 for the US and January 2009 to November 2016 for the UK) with sub-sample results with the split occurring in June 2011 for both countries. They apply the same sign and zero restrictions as Weale and Wieladek (2016) in their Bayesian VAR and find a reduced effectiveness of QE in both countries in the non-crisis period. Following this methodology, we will assess whether these diminishing effects can also
be seen in the euro area or whether the APP was effective even in a non-crisis time period. However, in order to get consistent estimates throughout both subperiods, we can no longer use the balance sheet as an indicator of UMP since the exact amount of APP purchases was expected before their implementation. Instead, we use a different measurement tool of UMP, namely the shadow short rate. This alternative approach has been developed by several scholars in recent years to incorporate expectations; it is explained in Section 2.4.

2.4 Measurement of UMP Shocks in the Euro Area

An alternative to using the balance sheet as UMP indicator is the shadow short rate that has only been used by a limited number of studies but is very useful for the purposes of this study. The construction and usage of shadow short rates have become more popular recently. Policy rates around the world have reached the ZLB for a sustained period of time and thus can no longer be used to model monetary policy. First introduced by Black (1995), shadow short rates differ from short-term interest rates since they are not bound by the ZLB; they can freely take on negative values. They represent the short rate that would prevail in the absence of physical currency, taking on negative values when interest rates are at the ZLB (von Borstel, Eickmeier and Krippner, 2015). Therefore, they have been proposed as a metric to quantify the stance of a central bank’s UMP by several scholars once conventional policies run into their constraints. Intuitively, the idea behind using a shadow short rate is that since it is derived from market bond rates, it should price in all expectations about the future size of the central bank’s balance sheet, assuming that markets are efficient.

The shadow rate is a more suitable indicator of monetary policy than the balance sheet for two main reasons. First, it is particularly useful for the latter half of our time frame that includes the APP program whose exact quantities and recalibrations were announced well in advance as seen in Appendix Table 4. It thereby overcomes the limitation in Boeckx et al. (2017); they themselves claim
that their identification scheme is not plausible for beyond 2014 since the expectation of the APP is not accounted for in the ECB’s balance sheet positions at a given point in time. The balance sheet fails to wholly reflect the total impact of the expected future stream of asset purchases as determined by prior announcements (Meinusch and Tillman, 2015). Second, it also gives us an edge over the balance sheet even prior to the APP since other UMP measures were also announced in advance – for example, the 12-month LTROs and CBPP1 announced in May 2009 but not started until June and July respectively. Therefore, the shadow rate offers us a solution to the time inconsistencies between announcement and executions for the full time period and allows us to consistently compare the effects of UMP.

From a theoretical point of view, shadow rates are a decomposition of the yield curve into a shadow yield curve plus a call option that offers a payoff to holding a physical currency. While scholars have use different methods to calibrate the shadow rate, the most widely used ones carried out by Krippner (2015) and Wu and Xia (2016) extract information such as the level and the slope from the yield curve through term structure modelling. In times where the ZLB is neared, the term structure models must be adjusted in order to factor in the presence of the ZLB (Damjanovic and Masten, 2016). The ZLB-adjusted yield curve, denoted as \( \overline{R}(t, \tau) \), at time \( t \) as a function of time to maturity \( \tau \), can be defined as:

\[
\overline{R}(t, \tau) = R(t, \tau) + Z(t, \tau)
\]

where \( R(t, \tau) \) represents a shadow yield curve without the possibility of holding a physical currency at the ZLB, while \( Z(t, \tau) \) represents the call option. The shadow short rate characterizes the short-term end of that shadow yield curve with the shortest maturities, with parameters estimated in the ZLB-adjusted framework (Damjanovic and Masten, 2016). There is a main difference underlying the Wu and Xia (2016) and Krippner (2015) estimation techniques. Krippner (2015) uses a more restrictive specification by incorporating two latent factors in the lower bound term structure model, while Wu
and Xia (2016) use a three-factor model that has one fewer constraint. Both have been shown to successfully model monetary policy and its macroeconomic effects at the ZLB; therefore, we will use both to check for the robustness of our results.

Shadow rates are a relatively recent phenomenon. The majority of existing research has hailed from the US and, to a lesser extent, Japan, while there is much more room for research in the euro area. Wu and Xia (2016), for example, use their shadow rate in a factor-augmented VAR and show consistent impulse responses in a pre-ZLB and ZLB period, indicating that their shadow rate successfully identifies UMP shocks in the US. In the euro area, on the other hand, most of the existing research focuses on financial market effects such as von Borstel et al. (2015) who utilize Krippner’s (2015) shadow short rate measure to evaluate the effect of the ECB’s UMP on bank lending rates and interest rate passthrough effects during the Euro Crisis. Nonetheless, several studies have verified the plausibility of using shadow rates as a measure of UMP in a EMU macroeconomic context, both from an empirical and a theoretical perspective. Using quarterly data from 1996 to 2013 in a basic three variable VAR with Cholesky decomposition, Damjanovic and Masten (2016) show that a 100 basis point contractionary shock to the Krippner (2015) shadow short rate lowers EMU output by 0.7 percent and prices by 0.2 percent. They claim that shocks to the shadow short rate produce similar macroeconomic responses as standard policy rate shocks and demonstrate that the shadow short rate is a useful and consistent measure of the ECB policy stance. Furthermore, Mouabbi and Sahuc (2019) use a Bayesian DSGE with shadow rates for the euro area. Their counterfactual analyses show that without UMP measures, inflation and GDP growth would have been 0.61 and 1.09 percent below their actual levels since the Great Recession.

In addition, there are two empirical studies using the shadow short rate that explicitly focus on the macroeconomic effectiveness of UMP, but both have shortcomings that this paper aims to address. One subsection of Antilla’s (2018) study runs a VAR with Cholesky Decomposition and data
from mid-2011 to late 2016, using the Wu and Xia (2016) rate as UMP measurement. Antilla (2018) finds that UMP shocks lead to small yet significant and persistent increases in output with no significant response of prices though. Like Wu and Xia (2016) in the US, they show that the effects of conventional and unconventional monetary policy are largely very similar in terms of their macro impact. The other relevant study is Elbourne et al. (2018), who also use the Wu and Xia (2016) shadow rate in a zero- and sign-restricted VAR with a time period from 2009 to 2016. They find that an expansionary UMP shock reduces the shadow rate by 20 basis points on impact, returning to baseline after 10 months. In terms of output, the peak response is 0.5 percent yet insignificant and the price level response is negligible. Interestingly, the results of both studies are much more pessimistic than those of balance sheet studies, contributing to the overall lack of consensus in the literature.

Overall, the existing literature around the shadow rate justifies this study’s usage of it. We expand on the existing literature by applying a new identification approach and extending the time period as a significant amount of asset purchases (over 42%) was carried out since the end of 2016 when Elbourne et al. (2018) terminates (see Figure 3 in the Appendix). Additionally, we use two different shadow rates; the Wu and Xia shadow rate for our benchmark results, following Elbourne et al. (2018) and Antilla (2018), and the Krippner (2015) rate in line with Damjanovic and Masten (2016) for robustness check of our results. This is important since shadow short rates are sensitive to the specifications of the models.

2.5 Contribution to Literature

Overall, this paper provides a threefold contribution to the literature concerning macroeconomic effects of the ECB’s UMP in terms of identification method, time period and UMP measurement tool used. The first part of our study applies Brunnermeier et al.’s (2019) identification through heteroskedasticity method for a macro VAR not implemented before in the euro area.
Successfully identifying the main shocks in a system, we thereby build a foundation for future papers to adapt the methodology for other macro studies in the euro area. Second, we use the status quo identification method of sign and zero restrictions to evaluate the plausibility of our previous results and conduct a subperiod analysis of our different variance regimes to observe whether the effectiveness of UMP in the euro area has changed over time as it transitioned from an acute crisis to a non-crisis environment and introduced new UMP tools including the APP. Analyzing the effectiveness of UMP in non-crisis times is highly important given that recent studies suggest that UMP will likely remain in the toolkits of central bankers (Blinder et al., 2017). Lastly, in order to consistently compare the effectiveness of UMP throughout the whole sample period and address the shortcomings of existing balance sheet studies, it uses the shadow short rate as a policy tool.
3. Data and Variables

In order to successfully disentangle a monetary policy shock, it is important to absorb other shocks in the economy and carefully select appropriate variables. In our variable selection we largely follow the foundational study by Boeckx et al. (2017), except in their choice of the policy tool. We replace the ECB assets with the shadow short rate for reasons outlined in Section 2.4. We conduct our methodology using monthly data ranging from January 1999 to December 2019, though our main focus is 2008 onwards, when the Global Financial Crisis took hold and UMP became the ECB’s predominant tool of monetary policy. The use of monthly data follows the vast majority of studies in this field and allows us to maximize the number of observations in our time series given the limited time period available since the inception of UMP measures. Our data set ends with the most recently available data and conveniently encompasses both crises faced by the euro area (the Global Financial Crisis and the sovereign debt crisis) as well as the post-crisis and APP period. To our knowledge, this paper is the first macroeconomic UMP study in the eurozone to incorporate data beyond 2016. We first run our identification through heteroskedasticity methodology on the full sample period starting in 1999 as well as a restricted one from 2008 onwards. This ensures that the method yields viable results and is robust to the differing time periods. Once turning to the combination of sign and zero restrictions, we focus our analysis on 2008 onwards in order to capture the effects of UMP. In addition, we conduct a split sample analysis to investigate the time-varying effect of UMP by separating our sample in March 2013, which largely marks the end of the Euro Crisis and a return to relative normalcy in financial markets. Furthermore, we alter the split date for robustness checks and analyze the APP separately by limiting our time frame to start in July 2014, right before expectations for APP were first raised by Draghi’s speech in Jackson Hole in August 2014.

For the SVAR analysis there are several relevant variables that aim to capture the monetary policy stance of the ECB as well as macroeconomic and financial market dynamics during the sample
period. The five euro area level variables used in the specification of our VARs are (1) the shadow rate, (2) log of real GDP, (3) log of the Harmonized Index for Consumer Prices (HICP) and two financial market variables: (4) the spread between the EONIA and the MRO (what we call the money market spread) and (5) the level of financial stress measured by the CISS indicator by Holló, Kremer and Lo Duca (2012). See Table 5 for a summary of the relevant variables, Table 6 for their descriptive statistics, as well as Figures 5 and 6 for a graphical interpretation of each variable and their first differences, all of which are located in the Appendix. Apart from the shadow short rates, the data for all variables was obtained from the ECB Statistical Data Warehouse. The data for the Wu and Xia (2016) rate was kindly provided by Cynthia Wu while the time series of Krippner’s (2015) shadow rates are publicly available on his website.\(^1\) In some of our robustness analyses we added additional variables including the log of real equity prices and an alternative measurement of financial stress.\(^2\)

We elect the shadow short rate as our measure of UMP since interest rates are no longer a viable representation of monetary policy stance in a near-ZLB environment and the balance sheet has the foresight problem of not including expectations. The shadow rate has been demonstrated to be an appropriate approximation of the ECB’s monetary policy stance. The benchmark identification scheme will include the Wu and Xia (2016) shadow rate, while we use Krippner’s (2015) rate to test for robustness. Observing the trajectory of both shadow rates in Figure 4 of the Appendix, we see that prior to the Global Financial Crisis they closely follow the EONIA and MRO. However, once the MRO hits one percent in early 2009, the EONIA and MRO barely move despite the extensive UMP measures taken since, while the shadow rates begin to diverge. For example, both rates become negative towards the end of 2011 when a number of policies to combat the Euro Crisis such as CSPP2 and LTROs were introduced in November and December. From then on, both shadow rates are

\(^1\) Krippner’s (2015) shadow rate series is available on: [https://www.ljkmsa.com/test/test/international-ssrs/](https://www.ljkmsa.com/test/test/international-ssrs/)

\(^2\) Equity prices were based on the EURO STOXX 50 Index obtained from the ECB’s Statistical and Data Warehouse and the VSTOXX obtained from Bloomberg was used as alternative measure of stress.
largely negative for the rest of time while the MRO and EONIA hover around zero. It should also be
noted that the shadow rates move inversely to the balance sheet, meaning that an expansionary
monetary policy shock is recognized by a reduction in the shadow rate.

Next, the main variables of interest for the purpose of a macroeconomic analysis are output
and inflation. Output is proxied by monthly real GDP, interpolated using the Chow Lin (1971)
procedure since only quarterly data is reported. The monthly industrial production index (base year
2015) is used as the high-frequency reference series to construct a monthly GDP measure from the
quarterly seasonally and calendar adjusted real GDP for the euro area. The Chow Lin approach follows
the other major studies in this field including Boeckx et al. (2017) and Elbourne et al. (2018) and is
crucial for the use of monthly data. While it is an imperfect indicator of output, the lack of availability
of monthly GDP data makes this method the next best alternative given that the relatively short
sample period favors monthly data. The price levels are represented by the level of the seasonally-
and working-day adjusted overall HICP (base year 2015), provided at monthly frequency. Both GDP and
HICP measures are taken as their natural logarithms. Further, the Composite Indicator of Systemic
Stress (CISS) indicator developed specifically for the euro area by Holló et al. (2012) will be included
in the VAR to account for financial turbulence and economic risk at euro area level. Studies like
Gambacorta et al. (2014) and Kremer (2016) suggest that there is a high correlation between UMP
shocks and the CISS, demonstrating the importance of regarding the endogenous response of UMP
to systemic stress in our model. Moreover, our VAR incorporates the spread between EONIA and
the MRO rate, also referred to as money market spread for purposes of this study. We incorporate
this variable because a host of financial market empirical studies have shown that the spreads respond
to UMP shocks (Beirne et al., 2011; Baumeister and Benati, 2013).

3 The CISS is a unit-free index that takes on values between 0 and 1, incorporating different market information (money
markets, bonds, equity, forex, financial intermediaries, commodity market risks, etc.) as well as global uncertainty.
4 The MRO is the rate at which the ECB lends to banks at 28 days while the EONIA is the overnight bank lending rate.
4. Methodology

4.1 Bayesian SVAR Framework

This paper uses a Bayesian SVAR model with two different approaches to identification – identification through heteroskedasticity and a combination of sign and zero restrictions. In order to get to the structural form of the VAR, we must begin with the reduced form as follows:

\[ y_t = \sum_{j=1}^{p} B_j y_{t-j} + D + u_t \]  

(1)

where \( y_t \) is a \( n \times 1 \) vector of \( n \) endogenous variables, \((B_j)_{j=1}^{p}\) are \( n \times n \) matrices of coefficients at each lag \( j \) capturing the lagged effects of the endogenous variables, \( D \) is a vector of constant terms and \( u_t \) is a vector of the reduced-form residuals at time \( t \), assumed to be normally distributed with variance covariance matrix \( \Sigma \) i.e. \( u_t \sim N(0, \Sigma) \). As explained in Section 3, the \( y_t \) vector contains log of GDP as a measure for output, log of HICP as a measure for price level, the CISS measure of financial stress, the EONIA-MRO spread, and the measure of the ECB’s monetary policy modeled either by the Wu and Xia (2016) or the Krippner (2015) shadow short rate (SSR), for robustness:

\[ y_t = [SSR_t, GDP_t, HICP_t, CISS_t, Spread_t] \]  

(2)

The reduced-form VAR in Equation (1) is not suitable for establishing causal relationships as required for this paper since the impulse response functions result from correlated shocks; the variance covariance matrix \( \Sigma \) of the reduced-form error terms \( u_t \) is not diagonal. Instead, in order to recover the mutually uncorrelated structural error term, \( \varepsilon_t \), we must obtain the structural form of Equation (1). In order to do so, we write the reduced-form errors as a linear combination of structural shocks. The inverse contemporaneous impact matrix \( A_0 \) relates the reduced-form forecast errors \( u_t \) and the structural shocks \( \varepsilon_t \) in the following way:

\[ u_t = A_0^{-1} \varepsilon_t \]  

(3)
Therefore, the structural and reduced form VAR equations are related through \( \Sigma = A_0^{-1}A_0^{-1}' \).

Combining the reduced-form VAR in Equation (1) and the linear transformation in Equation (3), we obtain the following structural model:

\[
A_0y_t = \sum_{j=1}^{p} A_j y_{t-j} + C + \varepsilon_t
\]  

(4)

where \( A_0 \) denotes an \( n \times n \) matrix containing the contemporaneous reactions of the variables to the structural shocks, \( (A_j)_{j=1}^{p} \) are \( n \times n \) matrices of structural coefficients at each lag \( j \), \( C \) is an \( n \times 1 \) vector of constants, and \( \varepsilon_t \) is an \( n \times 1 \) vector of independent structural innovations. The diagonal elements of the impact matrix \( A_0 \) are equal to one, while the off-diagonal elements capture the contemporaneous interactions across the endogenous variables \( y_t \).

The main challenge of performing a SVAR is to disentangle the orthogonal, structural economic shocks \( \varepsilon_t \) from the correlated reduced-form shocks \( u_t \). There are multiple approaches to solving the identification problem, as outlined in Section 2.2, including the imposition of restrictions on the impact matrix \( A_0 \) or the sum of coefficients in \( (A_k)_{k=1}^{L} \). We make use of two different methods: first, identification through heteroskedasticity (Section 4.2), which relies on time variation in \( \Sigma \), and second, sign and zero restrictions (Section 4.3). Once the mutually orthogonal shocks in the SVAR are identified, we can analyze the impulse response functions as the effect of a shock on a variable, holding all other shocks constant.

This paper employs Bayesian methods of inference for purposes of identifying the parameters of interest, following Boeckx et al. (2017), Elbourne et al. (2018) as well as Brunnermeier et al. (2019). In the Bayesian framework, unknown parameters are treated as random variables characterized by an underlying probability distribution. Instead of trying to identify the ‘true’ values of parameters and solely relying on the data, as the traditional frequentist approach does, the Bayesian approach
combines prior knowledge with evidence from the data to identify the entire distribution of parameters. It begins with a prior that represents the beliefs we have about the distribution of the parameters of interest. Combining the prior with the so-called likelihood function, containing the evidence provided by our observed data, we produce the posterior distribution. This is done using Bayes Rule, as formalized below:

$$
\pi(\theta | y) = \frac{f(y | \theta) \pi(\theta)}{f(y)}
$$

The probability density function of our prior that captures our beliefs on $\theta$, a stochastic vector of parameters, is given by $\pi(\theta)$. The likelihood or the probability density function of our sample data conditional on $\theta$ is denoted by $f(y | \theta)$. When these two are multiplied and divided by the density of the data $f(y)$, we obtain the posterior distribution of $\theta$ given by $\pi(\theta | y)$. This is then used as the central object for inference about parameter values as it contains all the information we have about $\theta$ (Dieppe, 2016). We choose different priors for our two identification procedures that are outlined in their respective sections below.

4.2 Identification Through Heteroskedasticity

4.2.1 Econometric Framework and Methodology

For the identification through heteroskedasticity approach we entirely follow Brunnermeier et al.’s (2019) methodology and notation. We nonetheless use the same variables as we do for our other identification scheme, following Boeckx et al. (2017), to adapt the model to the euro area and retain consistency and comparability for our emerging impulse response functions. This identification method is based on the exogenous assumption that the variance of our structural shocks changes at pre-specified dates in our sample period. We start with the SVAR Equation (4) above, in which the structural shocks $\varepsilon_t$ are independent across equations and time. This methodology assumes that the
variance of the structural shocks $\varepsilon_t$ varies across different time periods. We separate our full sample period into $\mathcal{M} = \{1 \ldots M\}$ subperiods, each with structural shocks that have constant variance, where the function $m : T \rightarrow \mathcal{M}$ maps the different monthly time series observations to their respective variance regimes.\(^5\) For each regime, the variance of the structural shocks is a different diagonal matrix $\Lambda_m$, so that:

$$\mathbb{E}[\varepsilon_t \varepsilon_t'] = \Lambda_{m(t)}$$

(6)

While the variance of structural shocks differs in each regime, the matrices of contemporaneous and lagged coefficients, $A_0$ and $(A_j)_{j=1}^P$, are held constant throughout, implying that the dynamic relationship amongst the variables remains unchanged in the full sample period. This means that the economy reacts to a shock in the same way in each subperiod even though the relative magnitude of the shocks and their effects vary. As a result, even though the scale of the resulting impulse response functions will be different for each period, depending on differing variances of the structural shocks, the shape of the responses will be the same.

In order to be able to compare our impulse response functions we must normalize the variances of the structural shocks. Since the rows of $A_0$ and $\Lambda$ can be multiplied by a scale factor without affecting the implied behavior of the data, we can make the cross-period average variance of structural shocks equal to one in each equation applying the following restriction:

$$\frac{1}{M} \sum_{m=1}^{M} \lambda_{i,m(t)} = 1 \quad \forall i \in \{1 \ldots n\}$$

(7)

where $\lambda_{i,m(t)}$ is the $i$th diagonal element of $\Lambda_{m(t)}$, i.e. the vector of variances in each equation. The normalization restriction of the variances is key for identification – in combination with the assumption that each pair of equations differs in variance in at least one time period, it infers that all

\(^5\) For our specification of the model, $M = 3$ or $2$, depending on whether we run it for the full sample (from 1999) or for the restricted sample (from 2008). See Section 4.2.2 for the determination of the variance regimes.
\( n^2 \) free parameters of \( A_0 \) can be uniquely identified, at least up the signs of an entire row or a permutation in the row ordering. The intuition behind the proof is demonstrated by Brunnermeier et al. (2019), with a formal proof in Lanne, Lütkepohl and Maciejowska (2010). Therefore, as long as we have heteroskedasticity over the time periods, our model can be fully identified without having to impose strict linear restrictions such as contemporaneous short-run restrictions on \( A_0 \) or long-run restrictions on the sum of \((A_j)^p_{j=1}\), whose plausibility have been previously questioned. Similarly, we also do not have to impose sign restrictions as we do in our other identification scheme. Identification through heteroskedasticity thereby generates a more flexible identification of impulse responses. However, it must be noted that unlike other identification methods, the structural shocks in the resulting impulse response function plots are not labeled, but we must apply our qualitative beliefs and prior assumptions to interpret each shock, by similar virtue as sign restrictions.

As previously mentioned, we use a Bayesian estimation method to create posterior distributions for our unknowns. Equations (4), (6) and (7) together imply that our model has \( n^2 \) free parameters in \( A_0 \), \( n^2p \) free parameters in \((A_j)^p_{j=1}\) and \((M-1)n\) free parameters in \( \Lambda_m(t)\). We follow Brunnermeier et al. (2019) for the choices of our prior as well as the relevant hyperparameters. For \( A_0 \), we use a Gaussian prior that has means of zero off the diagonal and 100 on the diagonal \((A_0 = 100I)\). This prior treats each element as independent with a standard deviation of 200, implicitly scaling each equation to an expected residual variance of 0.01.\(^7\) Next, for the vector of variances in each equation, in order to ensure normalization of the average variance, we use a Dirichlet prior on

\(^6\) For example, assuming that constancy of \( A_0 \) holds, the reduced-form residual variance covariance matrices \( \Sigma_i \) from two different variance regimes can be expressed as \( \Sigma_1 = A_0^{-1}A_1(A_0^{-1})' \) and \( \Sigma_2 = A_0^{-1}A_2(A_0^{-1})' \). This means that \( \Sigma_1^{-1}\Sigma_2 = A_0^{-1}\Lambda_1^{-1}A_2(A_0^{-1})' \) has the form of an eigenvalue decomposition with the columns of \( A_0^{-1} \) being eigenvectors. If the eigenvalues are unique, as determined by the diagonal elements of \( \Lambda_1^{-1}A_2 \), we can find \( A_0 \). Therefore, as long as the central assumption of this identification method (that variances differ across time periods) holds, this will be the case.

\(^7\) While this was an appropriate assumption for our data expressed in logs (GDP and HICP) and our shadow rates, we had to divide our CISS and spread measures by 10 to properly scale them. Therefore, the Y-axis of the impulse response functions for these two variables must be multiplied by 10 to attain the values in proportions (i.e. where 0.01 is 1%).

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\[ \frac{\lambda_i}{M} \] with \( \alpha = 2 \). This means that each variance must lie between \([0, M]\), centering the prior on equal variances for each period and normalizing the cross-period variances to one. Lastly, for the reduced-form coefficients \( (B_j)_{j=1}^p \) in Equation (1), we use two different priors described in Sims and Zha (1996). The first consists of a set of Minnesota prior dummy observations that center around the belief that there are independent random walks in each variable, with prior precision around a mean of zero, increasing for further lags. The second one is a unit root prior, according to which each variable will stay at mean level, independently of each other, as constant terms do not interact with unit roots to imply rapid growth. These two priors on the reduced-form coefficients \( (B_j)_{j=1}^p \) are turned into priors on the structural coefficients \( (A_j)_{j=1}^p \) by multiplying the dummy data and the actual data by \( A_0 \).

Next, we use a standard Random Walk Metropolis algorithm to sample the elements of \( A_0 \) and \( \{A_1 \ldots A_M\} \) from the marginal posterior distribution. For each \( A_0, \Lambda \) draw from our large Markov Chain Monte Carlo sample, we can sample the matrix \( (A_k)_{k=1}^L \). In order to ensure that we have reached convergence and stabilized around the highest density area of the posterior, we observe the trace plots of the log posterior density. Once convergence is achieved, we use a subsample of 1,000 \( A_0 \) and \( \Lambda \) pairs to generate the impulse response functions of each variable to the structural shocks. The error bands in the impulse response functions show the highest 68 and 90 percent of the posterior density regions, following Sims and Zha (1999). Since these plots have unnamed shocks, we must impose our prior knowledge on them to interpret each of the shocks.

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8 For the Minnesota prior, we set tightness to 1 and decay to 0.3.
9 For the unit root prior, persistence (i.e. weight on prior pulling toward non-stationarity) is set to 1 and tightness (i.e. weight on prior pulling toward variable-by-variable random walk behavior) to 5.
10 For further details on the implementation of the method see Brunnermeier et al. (2019); we carry out our estimation using Christopher Sims’s R programs for identification through heteroskedasticity.
4.2.2 Determination of Variance Regimes

In the literature of identification through heteroskedasticity, the variance regime changes have been determined in different ways depending on the type of study and the frequency of data. These include a vector generalized autoregressive conditional heteroskedasticity (MGARCH) process, the Markov-switching mechanism and, most importantly for our study, an exogenous determination of the variance regimes (Lütkepohl, 2012). For a low-frequency macro setup such as ours, we can exogenously determine our variance regimes based on historical events, monetary policy era changes and as well as observed variation in the data, following Brunnermeier et al. (2019). We divide our sample into either three or two variance regimes depending on whether we are considering the full sample starting in 1999 or a restricted sample starting in 2008 to focus on UMP analysis. These are outlined in Table 1 below.

The first regime of our full sample goes from January 1999 to September 2008, ranging from the formation of the eurozone and earliest data available to the start of the Global Financial Crisis taking hold in the euro area. In this pre-crisis phase, the ECB largely used conventional monetary policy through the benchmark interest rate and financial market disturbances were limited. The second regime for the full sample (and therefore first regime of our restricted sample) ranges throughout both the Global Financial Crisis and the Euro Crisis, from October 2008 to March 2013. The latter date marks the end of the sovereign debt crisis and the extreme volatility that had been characteristic of much of Europe’s financial markets since the onset of the Global Financial Crisis. We can observe this volatility in Figure 6 of the Appendix, in which we see quite drastic fluctuations in the first differences of particularly our market variables (the CISS and the spread). In addition, we see a much more volatile shadow short rate as it started diverging from the MRO and entering negative territory in light of UMP measures being introduced – one of the first major UMP announcements by the ECB came in October 2008 with the FRFA being introduced. Hence, we see a breakpoint in terms of
monetary policy regime, but also in terms of the state of the economy. Finally, our last variance regime lasts from April 2013 to the end of our sample in December 2019. During this time period, we no longer see a crisis permeating the euro area and therefore much more tranquil financial markets. In addition, it is also a convenient breakpoint in terms of ECB policy, since it marked a shift to new UMP measures including forward guidance, a negative deposit rate as well as the APP that was of a much larger scale than any previous asset purchases and implied monthly purchases up to €80 billion. Due to these unprecedented purchases in conjunction with multiple recalibrations and tapering, we see more extreme fluctuations in both of our shadow rates in the third variance regime relative to the crisis period. Therefore, we believe that the driving factors of economic fluctuations had comparatively different weights in each regime, generating structural innovations with different covariance matrices, appropriate for heteroskedasticity-based identification.

Our chosen regimes are consistent with the limited literature that is available. Brunnermeier et al. (2019), who study the US economy, also have a separate regime for the financial crisis followed by a regime encompassing the economy’s recovery from the Great Recession at the ZLB. Likewise, Guidolin and Pedio (2019) establish three separate regimes in the euro area based on the variance of residuals, where the highest-variance regime, the crisis state, covers both the 2008 crisis and the euro area sovereign debt crisis in 2010 and 2011, confirming the notion that the variance of shocks is largest in crisis periods, thereby supporting the idea of combining them into one high-variance regime.

<p>| Table 1: Variance Regime Changes for Identification Through Heteroskedasticity Approach |</p>
<table>
<thead>
<tr>
<th>Start</th>
<th>End</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Jan 1999</td>
<td>Pre-Crisis Environment, Conventional Monetary Policy</td>
</tr>
<tr>
<td>2</td>
<td>Oct 2008</td>
<td>Global Financial Crisis &amp; Sovereign Debt Crisis, pre-QE UMP</td>
</tr>
<tr>
<td>3</td>
<td>Apr 2013</td>
<td>Post-Crisis Environment, APP Program and UMP continuation</td>
</tr>
</tbody>
</table>
4.3 Identification Through Sign and Zero Restrictions

4.3.1 Econometric Framework and Methodology

Next, in order to validate the plausibility of our identification through heteroskedasticity results and carry out further sub-sample analyses, we carry out the status quo identification in the literature—a combination of sign and zero restrictions. We again carry out Bayesian inference for our parameters of interest, this time the reduced-form coefficients and the variance covariance matrix of the reduced-form residuals as we no longer assume heteroskedastic structural shocks as we did before. Following the relevant studies in this field who also impose sign and zero restrictions (Boeckx et al., 2017; Elbourne et al., 2018; Schenkelberg and Watzka, 2013), we choose a prior distribution from the Normal-Wishart family. The Normal-Wishart prior is also referred to as the natural conjugate prior since it yields a posterior distribution in the same family as the prior, which is then used to generate the impulse response functions. It assumes that both the vector of coefficients and the variance covariance matrix are unknowns. We follow the notation of Dieppe et al. (2016).

For the vector of coefficients, $\beta$, we assume a multivariate normal distribution for the prior:

$$\beta \sim \mathcal{N}(\beta_0, \Sigma \otimes \Phi_0)$$ (8)

We adopt a conventional Minnesota scheme for $\beta_0$, which is a vector of zeros, apart from the entries for the first lag of each endogenous variable, which are one, following Litterman (1986). This represents the idea that each endogenous variable in the model presents a unit root in its first own lags and coefficients zero for further lags and cross-variable lag coefficients. Next, $\Phi_0$ characterizes the variance for the parameters of a single equation in the VAR model that is then scaled by the variable-specific variance contained in $\Sigma$ in the Kronecker structure, to ensure that the variance-covariance matrix of each equation is proportional to that of the others. ¹¹

¹¹ The hyperparameters of the prior are chosen according to what we commonly see in the literature. We set overall tightness ($\lambda_1$) to 0.1, lag decay ($\lambda_3$) to 2 and the autoregressive coefficient of the prior to 0.8 (Dieppe et al., 2016).
The variance covariance matrix parameter has an inverse Wishart distribution with \( n \times n \) scale matrix \( S_0 \) and \( \alpha_0 \) prior degrees of freedom:

\[
\Sigma \sim IW(S_0, \alpha_0)
\]

(9)

By combining the priors with the likelihood function from our data, we obtain our posterior distribution – the kernel of a multivariate normal distribution for \( \beta \), conditional on \( \Sigma \), multiplied by the kernel of an inverse Wishart distribution for \( \Sigma \). This way, our posterior distribution takes on the same form as the prior, making the Normal-Wishart prior a conjugate prior. This joint posterior is then used to draw inference by becoming subject to our sign and zero restrictions to generate impulse responses with structural economic interpretation.

In order to collect draws from the posterior distribution of the structural parameters that satisfy our sign and zero restrictions, we use the Gibbs sampling algorithm developed by Arias, Rubio-Ramirez and Waggoner (2014). A sign restriction limits the response of a variable to a structural shock to be either positive or negative, while zero restrictions force it to be zero for a specified number of periods. The aim of the methodology is to find a structural matrix \( A = A_0^{-1} \) so that the structural impulse response functions will satisfy the predetermined sign and zero restrictions (see Section 4.2.2 for our specific restriction scheme). The difficulty with the Gibbs sampling framework is that it does not allow to draw directly from the posterior distribution of the SVAR coefficients, but instead draws from the posterior distribution of the reduced-form VAR coefficients and variance covariance matrix. Arias et al.’s (2014) second theorem demonstrates that it is possible to use the draws from the reduced-form posterior distribution to obtain draws from the SVAR posterior distribution with the implementation of an additional orthogonalization step. The vector of reduced-form VAR coefficients

\[\text{In choosing the hyperparameters } S_0 \text{ and } \alpha_0, \text{ we follow the literature around Karlsson (2012), who proposes that } S_0 \text{ is obtained from univariate AR regressions where the degrees of freedom } \alpha_0 \text{ are set to } n + 2, \text{ the minimum possible to obtain a well-defined mean and variance for } \Sigma. \text{ As a result, the expectation of } \Sigma \text{ is the diagonal covariance matrix obtained from individual AR regressions, which is then used as an estimate for } \Sigma \text{ in Equation (8) above.}\]
\( \beta \) and the residual variance covariance matrix \( \Sigma \) are drawn from their posterior distributions to recover the reduced-form VAR model in Equation (1). Next, we obtain our first set of structural impulse response functions using the Cholesky factor, which are combined into a preliminary stacked matrix. However, since these are drawn from the incorrect distribution, we must carry out the additional orthogonalization step. The Cholesky decomposition of the reduced-form variance covariance matrix is extended by an orthonormal matrix \( Q \) that satisfies our zero restrictions. The matrix \( Q \) is then applied to the preliminary structural impulse response functions to create the candidate stacked structural impulse response function matrix. We define the stacked structural matrix for all periods \( p \) to which the restrictions are applied to as \( f(A, A_1, \ldots, A_p) \). Since \( Q \) fulfilled our zero restrictions, so does this candidate stacked structural matrix, which then undergoes an additional selection process to determine whether the sign restrictions are also verified.

The selection process is carried out using selection matrices that determine whether the sign restrictions are realized in a specific iteration. A selection matrix is denoted as \( S_j \) for each structural shock \( j = 1, 2, \ldots, n \). Its number of columns is equal to the number of rows of \( f(A, A_1, \ldots, A_p) \) and its number of rows is equal to the number of sign restrictions of shock \( j \). Each row represents a single sign restriction; all entries are zero except for the one corresponding to the sign restriction, which is equal to one or negative one, respectively. The restrictions for shock \( j \) are satisfied if:

\[
S_j \times f_j(A, A_1, \ldots, A_p) > 0 \tag{10}
\]

where \( f_j(A, A_1, \ldots, A_p) \) represents column \( j \) of the stacked structural matrix. If the inequality in (10) holds for all \( n \) shocks, the sign restrictions are verified and the draw of matrix \( Q \) is retained. Otherwise, it is discarded, a new \( Q \) is created and the selection process is repeated until all sign restrictions are fulfilled. This procedure is repeated until a sufficient number of iterations are obtained. In our case, after a burn-in of 5,000 draws, a total of 10,000 successful draws from the posterior are utilized to
produce the impulse response figures. These display the median response of an endogenous variable to a shock over 60 periods with error bands denoting the 68\% posterior probability regions.\textsuperscript{13}

4.3.2 Determination of Identifying Sign and Zero Restrictions

In order to follow the methodology proposed in 4.3.1, we must come up with the corresponding sign and zero restrictions that have to be met in the selection procedure. It is vital to determine truly orthogonal UMP shocks since a fluctuation in the shadow rate could also represent an endogenous response to other systematic shocks in the economy. Therefore, in addition to the monetary policy shock, we also define sign and zero restrictions for an aggregate demand shock, aggregate supply shock, and financial stress shock, in order to determine how these endogenously impact the shadow short rate and to help us recover truly exogenous UMP shocks. We also leave one shock undefined to capture any additional variation. Isolating truly orthogonal UMP shocks allows us to evaluate their macroeconomic impact and draw conclusions from our impulse response functions.

We borrow from the existing eurozone UMP literature to ensure that our identification scheme in Table 2 is valid and our results are comparable. We mainly draw on the identification approach of the foundational study on eurozone UMP, namely Boeckx et al. (2017), however adapt it for use of the shadow rate. Here, we borrow from Elbourne et al. (2018) who uses a similar set of variables in their shadow-rate-specific identification scheme which we deem more appropriate for our time series that includes post-2014 data. Following Elbourne et al. (2018), all restrictions are imposed only on impact while the model is left unrestricted for the subsequent months. We also vary the restriction length to test for robustness of our findings.

\textsuperscript{13} We carry out the estimation procedure using the Bayesian Estimation, Analysis and Regression toolbox by Dieppe et al. (2016). For additional details on the estimation refer to Dieppe et al. (2016).
Table 2: Benchmark Sign and Zero Restriction Identification Scheme

<table>
<thead>
<tr>
<th>Variable</th>
<th>Monetary Policy</th>
<th>Financial Stress</th>
<th>Aggregate Demand</th>
<th>Aggregate Supply</th>
<th>Undefined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shadow Short Rate</td>
<td>-</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>?</td>
</tr>
<tr>
<td>Output</td>
<td>0</td>
<td>0</td>
<td>+</td>
<td>+</td>
<td>?</td>
</tr>
<tr>
<td>Prices</td>
<td>0</td>
<td>0</td>
<td>+</td>
<td>-</td>
<td>?</td>
</tr>
<tr>
<td>CISS Index</td>
<td>?</td>
<td>+</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>EONIA-MRO Spread</td>
<td>-</td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
</tbody>
</table>

Note: identifying restrictions are based on Elbourne et al. (2018). Zero restrictions are denoted by 0, sign restrictions by ‘+’ and ‘-’ and unrestricted responses by ‘?’. Restrictions are binding for the impact month in our benchmark identification scheme.

The most important shock for purposes of this study is the monetary policy shock, characterized by a reduction in the shadow short rate and spread on impact as well as a lagged response of the real macroeconomic variables. CISS is left unrestricted. The contemporaneous zero restrictions on output and prices follow studies of conventional (see Bernanke and Blinder, 1992; Christiano et al., 1999; Peersman and Smets, 2003) and unconventional monetary policy (see Boeckx et al., 2017; Elbourne et al., 2018, Wieladek and Pascual, 2016; Burriel and Galesi, 2018) and are plausible for monthly data given that prices are considered sticky and output responses occur with a lag. These zero restrictions allow us to orthogonalize monetary policy shocks from endogenous real economy disturbances to aggregate demand or supply. We place a negative sign restriction on the contemporaneous response of the EONIA-MRO spread since, as mentioned in Section 2.1, there is significant evidence that spreads decline on impact of an expansionary UMP shock. The intuition behind this restriction is that an expansionary UMP shock tends to increase the liquidity surplus, in particular under the FRFA, placing downward pressure on the EONIA rate and thus the spread (Boeckx et al., 2017). Next, following Elbourne et al. (2018), we are agnostic towards the response of our financial stress variable CISS to a UMP shock and leave it unrestricted. This will enable us to determine whether UMP was successful in reducing systemic stress, which is particularly relevant for the crisis years when this was a major component of the ECB’s objectives.
The aggregate demand and supply shocks, on the other hand, aim at capturing the drivers behind macroeconomic fluctuations. They are defined to ensure that monetary policy shocks are not endogenous responses to changes in the real economy. The responses to these shocks have been widely established in the literature and follow basic macroeconomic theory. A positive demand shock leads to an increase in output and prices, coinciding with a shift in the aggregate expenditure or IS curve (Peersman, 2005). A positive supply-side shock, on the other hand, moves prices and output into opposite directions. In addition to these sign restrictions, we place a zero contemporaneous restriction on the response of the shadow rate to both in order to account for the notion that monetary policymakers do not observe output and prices in real time within a month but can only react contemporaneously to their best estimates of output growth and inflation, which often differ significantly from the data that we use in empirical studies (Elbourne et al., 2018). The assumption that policymakers are only able to react with a lag is in line with other monetary VAR studies such as Kim and Roubini (2000) for conventional monetary policy and Wieladek and García Pascual (2016) for UMP. The responses on CISS and the spread are unrestricted for the aggregate shocks.

Lastly, a financial stress shock increases the CISS index on impact. It is particularly important to include this shock since studies have shown that UMP and the CISS are highly correlated and a substantial component of UMP is endogenously driven by changes in the CISS (Kremer et al., 2016; Gambacorta et al., 2014). We restrict the response of the shadow rate to be negative since, unlike real economic disturbances, financial stress shocks can be observed and counteracted in real time by central bankers. However, due to the stickiness of prices and the lagged response of output to financial disturbances, we place a zero restriction on the real variables again, like we did for the UMP shock.
5. Results

5.1 Identification Through Heteroskedasticity

The first part of this study applied Brunnermeier et al.’s (2019) heteroskedasticity-based identification approach on euro area data in order to investigate the effects of UMP on the real economy. We report results for both the full sample period starting in 1999 and the restricted period from 2009 onwards, where we focus on UMP, both extending until December 2019. We follow Brunnermeier et al. (2019) in our lag selection of 10 for this identification scheme. The impulse responses of our variables to the structural shocks over a time horizon of 60 months can be found in Figures 7 to 10 in the Appendix; the first two use the Wu and Xia (2016) shadow rate and the latter two use the Krippner (2015) shadow rate. The black lines in the plots represent the posterior median, the red lines the 68 percent error bands and the green lines the 90 percent error bands. Given the normalization restriction imposed on the variances of structural shocks in our methodology, the impulse response functions show an average response across the pre-specified variance regimes (see Table 1). Moreover, since this method constructs the impulse responses without strong prior assumptions, the resulting shocks are not explicitly named. Therefore, we must interpret them using our economic intuition and based on findings from other studies.

First, and most importantly for the goal of this study, we look for a monetary policy shock in our impulse response functions and, hence, a shock that is strongly associated with the contemporaneous reaction of the shadow short rate. This will help us determine whether identification through heteroskedasticity is useful for purposes of our analysis of monetary policy and, more broadly, whether it is a solid framework to model the macroeconomic dynamics in the euro area. One of our shocks emerges as a clear monetary policy shock for both shadow rates and time periods covered, exhibiting the expected characteristic responses of all endogenous variables. More specifically, we label Shock 1 in the first column of the figures a contractionary monetary policy shock since it leads to an
immediate and sustained rise in the shadow short rate of approximately 20 to 40 basis points depending on the shadow rate and time period used. Next, the movements of other variables are also in line with findings from the surrounding literature and economic theory. Neither of our main variables of interest, output or prices, reacts contemporaneously to Shock 1. This is exactly what we would expect due to the transmission lag of monetary policy, corresponding to the zero restrictions we impose on these variables in our sign and zero restriction scheme. Notably though, the response of these variables on impact is zero even though we did not place any such restrictions on their impact matrix in this heteroskedasticity-based approach. In addition, our real variables’ longer-run responses behave according to expectations. A contractionary monetary policy shock leads to a gradual decline in GDP with median responses between 10 to 40 basis points, exhibiting significance at the 68 percent, or even the 90 percent level, depending on time period and shadow rate used. The response of prices, as indicated by the HICP, is weaker and less significant (within the 68 percent but not the 90 percent error bands in most cases), with median impulse responses between 0 and -10 basis points. If we flip the sign of our impulse responses, these findings imply that an expansionary monetary policy shock would lead to an increase in output and a weaker increase in inflation over time, which corresponds to the general consensus in the literature. Next, we turn to our financial market variables, namely the CISS and the money market spread, to further confirm the feasibility of our identification approach. Both variables’ responses increase over time in line with our expectations, with varying significance though. The rise in the CISS variable corresponds with the idea that contractionary monetary policy would lead to heightened stress in financial markets. The tendency for the money market spread to increase is reasonable too, as outlined in Section 4.3.2, since expansionary UMP puts downward pressure on the EONIA and thereby the spread.

Next, comparing the different configurations of our model, we first notice that the impact of Shock 1 on the shadow rate is not symmetric for each time period and shadow rate estimation.
Specifically, we see that the shadow rate increases approximately 10 basis points more for the Krippner (2015) rate versus the Wu and Xia (2016) rate for each sample length, before gradually decreasing to a similar long-run level. The Krippner (2015) rate increases by up to 40 basis points in the shorter sample period and 30 basis points in the longer one, while the Wu and Xia (2016) rate moves just 30 and 20 basis points, respectively. This is a first indicator that the Krippner (2015) rate showed stronger variation than its counterpart, as we can also tell from the plots in Figure 6 of the Appendix. The impact of Shock 1 on the other variables is therefore also larger for the Krippner (2015) versus the Wu and Xia (2016) rate. Comparing the two time periods, we see larger movements in variables in the restricted time period, indicating that there may have been more fluctuations in the economy since 2008. Despite these differences, we can conclude that the responses of all discussed variables are at least marginally significant at some point for all configurations, apart from the longer sample for the Wu and Xia (2016) rate. Unfortunately, Wu and Xia (2016) only begin their shadow rate estimation in September 2004 and suggest using the MRO as a proxy prior to that, which likely distorted our results and caused the impact on both output and inflation to be insignificant, or just marginally significant. The median responses nonetheless show a negative tendency as per our economic intuition.

Disregarding the Wu and Xia (2016) full sample results, we can claim that this method has successfully identified an exogenous monetary policy shock that exhibits expected characteristics across the board, even though some responses are stronger in a certain sample length or using a certain shadow rate. More important for the conclusion of this study is the second time period starting in 2008 since most of the variability in the shadow rate stemming from UMP began showing then. In this subsample, output decreases significantly in response to a contractionary monetary policy shock up to the 90% error bands for both shadow rates at some point throughout the 60-month horizon. Prices, on the other hand, show a negative and marginally significant response only for the Wu and Xia (2016) rate, while its response is flat and insignificant for the Krippner (2015) rate. Therefore, this
identification suggests that, overall, UMP was successful in stimulating output, while its effect on prices is more ambiguous.

In order to put our responses to a monetary policy shock into context, we compare our findings with the existing literature. We start by looking to the results of Brunnermeier et al. (2019) who inspired the heteroskedasticity-based approach we take this study. The monetary policy shock they identify is associated with similar characteristics compared to ours, even though their study uses different variables and covers a different time period and region. Their contractionary monetary policy shock causes the interest rate to increase on impact and leads to a negative and delayed response of industrial production as well as a negative response of prices in the long run. Therefore, with prices reducing less, and less significantly, than output, Brunnermeier et al.’s (2019) findings largely confirms ours. Next, due to a lack of other eurozone studies using the identification through heteroskedasticity approach, we turn to studies who apply other identification methods but nonetheless use the shadow rate as UMP measurement tool. Even though the magnitude of the estimated responses varies quite strongly from study to study, the overall consensus is that output tends to respond more than inflation, in line with our results.

First, we can look at Damjanovic and Masten (2016) who use the Krippner (2015) shadow rate in a Cholesky decomposition VAR and cover a similar time period as our extended one, with quarterly data from 1996 to 2014. Their study finds that after an initial positive but insignificant response of output to a 50-basis point contractionary monetary policy shock, output declines steadily with a peak negative response of around 35 basis points. Prices show a much weaker and consistently insignificant decline of up to roughly 10 basis points, consistent with the limited effect of a monetary policy shock on inflation in our impulse responses. Next, Elbourne et al. (2018) focus on post-2008 data and make use of the Wu and Xia (2016) shadow rate in a sign- and zero-restricted identification scheme. They find that a 20-basis point drop in the shadow rate leads to a median GDP response of
50 basis points and a negligible impact on prices, both responses being statistically insignificant with very wide error bands though. Next, Anttila (2019) reports a persistent and marginally significant increase of real economic activity of up to 40 basis points in response to a 25-basis point drop in the Wu and Xia (2016) rate, while HICP shows a negative median response with very wide error bands. Additionally, the stronger response of output relative to inflation is also consistent with studies using the balance sheet as UMP indicator and a combination of sign and zero restrictions for identification (Boeckx et al, 2017; Burriel and Galesi, 2018; Gambacorta et al., 2014). For example, Boeckx et al. (2017) who use a very similar set of variables as us show a flatter impulse response function for prices than for output. The overall comparability of our results to those of the existing literature is another indicator that our method successfully orthogonalized the monetary policy shocks, attaining expected responses without having to impose stringent restrictions on the coefficients of the VAR.

Now that we established our monetary policy shock, we try to interpret the remainder of shocks in our model based on prior assumptions about the characteristics of the responses. In fact, identifying the additional shocks in the economy also helps us determine what other systematic fluctuations drove the behavior of the shadow rate in our time periods. We label the other shocks as follows. Shock 2 can be interpreted as an expansionary aggregate demand shock not arising from monetary policy since we see a jump of GDP on impact as well as an increase of inflation. Shock 3, on the other hand, shows output and prices moving in opposite directions, denoting a contractionary aggregate supply shock since output declines. We refer to the fourth shock as a financial stress shock, with the CISS increasing substantially on impact before returning to its baseline level prior to the end of the 60-month horizon. The short-term nature of the CISS shock is in line with our expectation since it is a financial market not a macroeconomic shock. We also see output decline in the long run after a CISS shock. The last shock is a money market spread shock, with the EONIA-MRO spread increasing on impact. The EONIA-MRO spread is not a standard spread shock as found in other
studies, but instead represents an increase in the difference between the overnight lending rate and the policy rate. This was included in the VAR as an additional UMP indicator since the FRFA meant that additional UMP measures would place downward pressure on the EONIA and cause the spread to decline (Boeckx et al., 2017; Hristov, Hülseweg and Scharler, 2020). Therefore, seeing the spread and CISS move into opposite directions is sensible. Interestingly, they only move in opposite directions for the restricted time period, whose monetary policy shocks are likely dominated by UMP, which makes sense given that most movement of the spread was initiated by UMP policies.

Next, having identified the remaining structural shocks in our system, it is worthwhile to assess how the shadow rate variable is influenced endogenously by them. In particular, the shadow rate seems to be quite responsive to the respective state of the economy as it reacts significantly to a number of other orthogonal shocks – aggregate demand, aggregate supply and financial stress shocks. The shadow rate generally rises in response to both an expansionary aggregate demand shock (Shock 2) and a contractionary aggregate supply shock (Shock 3), with a stronger and more significant reaction to aggregate demand shocks. Intuitively, these reactions are interpretable as policymakers trying to counteract the inflationary effects of these shocks. Vice versa, flipping the signs implies that the ECB reacts with policy easing to both a negative aggregate demand shock to stimulate output and to a positive aggregate supply shock to prevent deflation from taking hold. Since policymakers cannot observe these values in real time, we would expect them to react to these shifts in the economy with a lag, explaining the zero contemporaneous reaction of the shadow rate. Additionally, we can also analyze the reaction of the shadow rate to a structural innovation in financial stress, as denoted by Shock 4. The shadow rate reacts with a persistent decline to this shock up to 25 basis points. This, again, is expected as the ECB tries to offset the effects of financial market disturbances by loosening its monetary policy stance, in particular during a crisis. Overall, the significant and plausible endogenous responses of the shadow rate to other systematic shocks on average suggest that monetary
policy surprises were not necessarily a dominant source of variation in this period, but that the variability in the shadow rate was largely driven by shocks to other variables. This might help explain the relatively muted response of the real economic variables to the monetary policy shock.

In addition to our reported results in the Appendix and the use of two different shadow rates, we performed several sensitivity analyses to determine the robustness of our findings to alternative specifications. In particular, we changed the break dates for our variance regimes to ensure that we captured the different variances of structural shocks across periods as best as possible, thereby achieving stronger identification. We varied the start and end dates of our crisis regime on both ends, however, were unable to yield any substantially different results that are worth reporting.¹⁴ This is not surprising given that Brunnermeier et al. (2019) explain that the results should not be sensitive to modest changes in the breaks of variance regimes and that reduced variation in cross-period variance would only lead to larger error bands but not inconsistent estimates. Our variance regimes appear to exhibit enough variability for this identification method to succeed nonetheless, particularly given the changes in financial market volatility around the crises and the changes in monetary policy by the ECB from conventional to unconventional measures. We also varied the number of lags and were able to obtain robust results using up to 5 fewer lags.

Overall, the plausibility of our results for both sample specifications suggests that the variances of our structural shocks do differ substantially between the pre-specified variance regimes, thereby fulfilling the central assumption of the heteroskedasticity-based identification approach. As a result, this identification method successfully managed to orthogonalize the different structural shocks, including monetary policy, aggregate demand, aggregate supply and financial stress shocks, and yielded sensible results for them. We find that a contractionary monetary policy shock leads to a slight

¹⁴ For example, we tried changing the end of the sovereign debt crisis date to June 2014 right before the APP program was announced and we modified the exact start dates of the financial crisis by using an earlier date from 2007.
reduction in output and prices, while it is endogenously driven by aggregate and stress shocks. The subtle effect of monetary policy on our real economic variables might also be related to our relatively short time period in which we use less than half of Brunnermeier et al.’s (2019) 42 years. Nonetheless, our finding is a very important contribution to the literature since we manage to produce these results without imposing any short- or long-run identifying restrictions on the structural VAR coefficients as the other identification approaches used thus far rely on. Unlike the sign restriction approach, we make fewer assumptions and manage to provide point identification. Therefore, this paper provides a useful framework for macroeconomic analysis in the euro area based on Brunnermeier et al. (2019) for future research. Especially once further eurozone data is available than the 20 years it has been in existence for, the sample can be split into an increasing number of variance regimes. This method could prove to be very useful for other macroeconomic studies that investigate the relationship between different variables over a long period of time, not necessarily limited to monetary policy effectiveness as our study.

At this point, having interpreted our findings with the identification through heteroskedasticity approach, our next step is to carry out the more commonly used identification method, sign and zero restrictions, with the exact same variables and time period in order to compare our findings. In addition, since the identification through heteroskedasticity approach reports the average responses across all variance regimes, we use the sign and zero restrictions method to dissect the different sub-periods and investigate the potential time-varying effects of UMP. The results are reported in the following Section 5.2 and generally seem to confirm some our findings from this section, while also shedding some additional light on the nuances of UMP effectiveness.
5.2 Identification Through Sign and Zero Restrictions

5.2.1 Benchmark Results

We first estimate our SVAR with sign and zero restrictions for the same time period as we did for our identification through heteroskedasticity approach in order to generate a plausible comparison to our results in Section 5.1. From now on, our focus is on data from the Global Financial Crisis onwards in order to ensure that we largely evaluate the effectiveness of UMP and not conventional monetary policy in general. The reason we used data starting in 1999 in our identification through heteroskedasticity approach was to ensure that it was yielding valid results since it had never been used in the euro area before. Now, we focus on a time period in which the shadow short rate started deviating significantly from the MRO. After the first major UMP measures were introduced in October 2008, these began to be reflected in the shadow short rate’s trajectory. The set of impulse response functions to all our identified shocks can be found in Figure 11 of the Appendix. Overall, these results can be reconciled with those using a heteroskedasticity-based identification approach, highlighting the fact that we were able to achieve identification through heteroskedasticity without having to make strong prior assumptions in the form of sign and zero restrictions as we do now.

According to our identifying sign and zero restrictions (see Table 3 in Section 4.3.2), we specified our monetary policy shock to be expansionary, not contractionary, as indicated by a decline in the shadow rate. Our results using the Wu and Xia (2016) shadow rate indicate that a monetary policy shock is now associated with a 15-basis point decline of the shadow rate on impact, gradually moving towards the baseline over the 60-month horizon. After the zero contemporaneous response of our real economic variables as pre-specified in our identification scheme, we see a significant

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15 We report our results using two lags as indicated by the AIC selection criteria and in line with existing studies (Elbourne et al., 2018) for this identification method. The BIC criterion indicates a use of only one lag, but to prevent misspecification, we use two lags. Again, to test for robustness, we ran our model with up to 10 lags as in our heteroskedasticity-based approach and did not find any substantial difference in the median responses.
increase in output of around 50 basis points that peaks after one year before stabilizing at around 20 basis points. The response of prices is correctly signed, with a peak median response of 12 basis points; however, due to the wide error bands we see no significance during the full horizon. Both of these responses can be reconciled with those of our identification through heteroskedasticity approach where we also saw a significant and persistent decline in output as well as a smaller and less significant response of prices. Next, even though we were agnostic towards the response of CISS and purposely left it unrestricted, we find that CISS reduces by around 2 percent on impact and remains significantly impacted for around 20 months. The response of the money market spread was restricted on impact to aid with the identification of UMP shocks and shows a decrease of around 2 basis points. It then returns to baseline rapidly after one year. Based on these findings, we can conclude that our results from both identifications techniques show similar tendencies and same-signed reactions, even for those left unrestricted. The magnitude of the responses seems to be slightly stronger for the sign and zero restriction approach, but the relative responses are comparable.

The sign and zero restriction results are also largely in line with those of other studies that apply the same restrictions. Just like Elbourne et al. (2018), we find no significant effect on prices and, in addition, the shape of our output and inflation trajectories is also very similar compared to balance sheet studies such as Boeckx et al. (2017). The main difference is that their peak impacts seem to occur slightly earlier than ours, which can be explained by the nature of the shadow rate that already captures balance sheet innovations on announcement, not only at implementation. For robustness, we also considered the Krippner (2015) shadow rate as seen in Figure 12 of the Appendix – here, the 20 basis point reduction of the shadow short rate is associated with a marginally significant, peak median response of output of around 50 basis points after 15 months, gradually decreasing thereafter. The price response is again not significant with very wide error bands. For this shadow rate, the median response is actually negative. This is a very interesting finding since in our other approach, we also
were not able to find any significance in terms of price response for the 2008 to 2019 period, while were able to for the Wu and Xia (2016) rate. Therefore, overall, the Krippner (2015) results further confirm our heteroskedasticity-based identification findings.

Furthermore, we compare the remaining identified shocks in our system with those we obtained through identification through heteroskedasticity in order to determine how the shadow rate was endogenously driven by other orthogonal shocks (Figure 11). Again, we see that the shadow rate responds strongly to a CISS shock, with a 20-basis point reduction, in order to offset the financial market disturbances. The directions of the responses of the shadow rate to our aggregate shocks are sensible and consistent with those of identification through heteroskedasticity, however, the large error bands make it difficult to interpret a causal relationship here. The median shadow rate response to an expansionary aggregate demand shock is largely neutral in the short run and increases slightly after around 20 months. The supply shock is followed by stronger and persistent decrease in the shadow rate, though this reaction is also not significant. Either way, the direction that we see the shadow rate move is in line with our identification through heteroskedasticity results. This is further evidence for our assertion that the shadow rate is moved endogenously by shocks to other variables and thereby confirms our interpretation of the identification through heteroskedasticity results that, in this period, monetary policy surprises were only a limited source of variation.

One more place to look to confirm this hypothesis is the historical decomposition and forecast error variance decomposition of the shadow rate. The historical decomposition captures the cumulative effects of the different shocks on movements in the shadow rate throughout the sample period, as demonstrated in Figure 13 of the Appendix. Looking at the four main shocks in our model (namely monetary policy, financial stress, aggregate demand and aggregate supply) displayed, we see that the shadow rate was largely driven by financial stress shocks, in particular throughout the first half of our sample that includes the two crises. In the latter half of our sample, there seem to be more
exogenous UMP shocks, corresponding with the fact that there was no longer a financial crisis that generated excessive financial stress that the ECB had to explicitly counteract. The relative importance of supply shocks in driving the shadow rate is also plausible, given that much of the APP program was aimed at countering the threat of disinflation – a positive supply shock causes output to increase while prices decrease, hence, causing the central bank to counteract with loose measures to stimulate inflation. Similarly, looking at the forecast variance error decomposition in Figure 14 that takes into account the magnitude of the shocks, the financial stress shocks identify large proportion of variation in the shadow rate. After the shadow rate’s zero contemporaneous response to aggregate demand and supply shocks, they also begin to gradually contribute to more variability of the shadow rate over time.

These findings are important in two ways: one, they confirm that the shadow rate was substantially driven endogenously by other shocks in the system and that the number of identifiable monetary policy surprises was limited in the time period, in particular during the two crises, which may explain the limited impact on the real macroeconomic variables we have determined. Two, they also indicate that within our sample, there was significant variation in terms the main drivers of the shadow rate over time, making it necessary to further dissect the time period, which we do in the following section.

5.2.2 Subsample Analysis – Crisis versus Non-Crisis

The results from our sign and zero restriction identification scheme largely confirm those of the identification through heteroskedasticity scheme – both indicate that the ECB’s policies had a positive effect on output and a smaller effect on prices. However, we are clearly dealing with two strikingly different time periods in terms of the volatility of our variables and the nature of ECB policy. As a result, we carry out a more in-depth analysis of subsamples to determine the relative and potentially time-varying effectiveness and importance of ECB policies. Since identification through heteroskedasticity shows us the average results over the two (or three) subperiods, we again use sign
and zero restrictions to apply our model to shorter subperiods. In doing so, we first want to compare the effectiveness of UMP in crisis times to non-crisis times following the method of Hesse et al. (2018) for the US and UK. This has not yet been studied on eurozone-level given that most existing studies have been constrained by data availability. The only other study to conduct a subsample analysis is Panizza and Wyplosz (2018), however, their time periods overlap and are split in the middle of the sovereign debt crisis, making it hard to analyze differential effectiveness in a crisis versus non-crisis environment. We therefore follow Hesse et al. (2018) by splitting our sample right after the crisis episode ends. Our first subsample begins in January 2009, to exclude as many of the MRO movements as possible, and ends in March 2013, largely seen as the end of the sovereign debt crisis. The second subsample lasts from April 2013 to December 2019 to encompass the non-crisis time during which UMP measures continued and evolved. In this division, the first subsample contains the original UMP measures by the ECB including the LTROs, SMP and OMT, while the second one includes more recent innovations in ECB policies including forward guidance, negative deposit facility rates and the APP.

Our findings summarized in Table 3 and Figure 1 are very interesting as they suggest some differentiated effects of the ECB’s policies over time. We use red color to denote the median responses and error bands of the crisis subsample and blue for the non-crisis subsample. By placing the impulse responses on the same chart, we can conveniently compare them. The overarching conclusion of our results is that UMP was more successful in reducing financial stress in the first subperiod but had a substantially higher effect on output in the second subperiod, with impact on prices being negligible throughout. Importantly, the shadow rate response (in this case Wu and Xia [2015]) to a positive UMP shock is identical on impact – it reduced by 15 basis points, which means that we can directly compare the responses of other variables.
First, we turn to our variables of interest, output and inflation. Our results suggest that UMP has been more successful in non-crisis times to raise output. The median peak response of real GDP to a UMP shock is 66 basis points in the second subperiod, while it reaches a positive peak of just 1 basis point before reaching negative values up to 3 basis points. Even though the error bands do overlap for most of the horizon, they do not overlap in the first six months, indicating a significant
difference. The response of GDP in the first time period is also never significantly different from zero, while the lower 68 percent error band in the second subsample does not cross zero until 15 months, indicating a substantial positive response. Overall, we can conclude that the ECB’s UMP measures functioned better in stimulating output during the non-crisis subsample than during the crises. Next, turning to the impact on inflation, we cannot make any definite conclusions about a differentiated impact. The error bands of the first time period are very wide and the reaction of prices is not significantly different from zero in either time period. The median responses do point in the right direction though, suggesting that there is a gradual and persistent impact on inflation as we have also seen in most of our other specifications so far.

Further, it is also relevant for our analysis to look at the differential impact on financial market variables of a UMP shock. The effect on the shadow rate is markedly shorter in the first subsample, as it returns to baseline after half a year, while it takes the whole 60-month horizon to return to baseline in the second subsample. This might provide further evidence of the more short-term, financial stress-driven monetary policy during the crisis period, in which policymakers tried to mitigate immediate stress that threatened to impair market functioning. This is confirmed by the reaction of the financial stress variable CISS – a UMP shock reduces financial stress significantly more in the crisis period versus the non-crisis period, namely 3 versus 1.2 percent, with non-overlapping error bands for the first year. The reduction of financial stress is also much more prolonged in the crisis period. It is again important to note that we were purposely agnostic towards the response of CISS and let the data speak freely, confirming that financial stress reduced significantly in response to a positive UMP shock in both time periods. The result that the second subsample is denoted by a stronger decline in CISS as a response to the fall in the shadow rate is indicative of the idea that even though the effect on real variables may have been more muted, the UMP policies succeeded in tranquilizing financial stress that surged during both of the crisis in the time period as seen in the time series of CISS in Figure 5 in the
Appendix. The high volatility of stress may have also impaired the transmission mechanism to the real economy in the first time period. In comparison, the financial stress in the second period was markedly lower. Our finding here is consistent with the notion that the ECB was more concerned with the stability and functioning of the financial system in this immediate crisis period than generating long-term effects on real macroeconomic activity. The impact on the money market spread being stronger in the first compared to the second period is also intuitive given that a decline in the spread is an indicator of downward pressure on the EONIA due to the FRFA, which was a policy applicable to the LTROs that made up a larger part of monetary policy in the first period.

Again, it is useful to look at the difference in the forecast error variance decomposition of our variables of interest, particularly those of output, prices and CISS, to determine what were most important in driving their fluctuations. These are found in Figure 17 of the Appendix. In terms of output, we see that the UMP shock identifies a higher percentage of variation in output in the second time period than the first time period. The impact on inflation, on the other hand, is higher in the first period. Due to the wide error bands, however, it is difficult to make a conclusion about the definite impact of UMP on inflation. Next, in terms of CISS, we see that the relative importance of the UMP shock is reduced in the second subsample, consistent with the idea that UMP was more important in reducing stress during crisis times than non-crisis times.

As a robustness check for our UMP measurement tool, we also re-ran the same subsamples with the Krippner (2015) shadow rate. The difficulty for the Krippner (2015) rate is that the since it undergoes much higher fluctuations in the second subsample, the reduction of the shadow rate associated with a UMP shock is much higher in the second subperiod (19 basis points) than the second one (10 basis points). Since we refrained from scaling the shocks to show their differential impact on the shadow short rate, the responses to the shock cannot be compared directly by virtue of placing them in the same plots, but the impulse response functions for the individual subperiods can be found
in the Appendix Figures 18 and 19. Interestingly, these large differentials relate to the stronger impact a monetary policy shock had on the Krippner (2015) shadow rate for our identification through heteroskedasticity approach as well. Overall, nonetheless, the results still largely confirm our findings about time variation in the effectiveness of UMP – even though the shadow rate shock is almost half that of the second subperiod, it reduces CISS and the spread more than in the first subperiod. The impulse response functions are qualitatively similar as those using Wu and Xia (2016), in particular that of output, which again barely increases in the first subsample and then shows a larger decline in the median response than it did a positive peak.

Next, we compare our findings with the existing literature that analyzes effectiveness over time. Even though this is the first study to split the sample based on crisis versus non-crisis for the euro area, there are still a few relevant studies to consider. Since we base our comparative study on Hesse et al. (2018) it is a good starting point even though they analyze the US and UK. Hesse et al. (2018) find the opposite result to ours, meaning that the effectiveness of later QE programs in non-crisis times decreased significantly. On the other hand, it does confirm our findings for inflation as their error bands also overlap as well as for stress variable. They find that the measure for financial stress in the US reduces more in the crisis period in response to a positive UMP shock compared to the non-crisis period. Overall, our study shows though that the diminishing return phenomenon of QE that has been found in the US and the UK is not applicable to the euro area. There are several reasons why this might be the case, including the inherently different nature of UMP by the ECB in early years, the fact that there were two crises in the EMU, and the different nature of corporate financing in the EMU versus the US – these will be discussed in detail in Section 6.

A perhaps better metric to compare our study with is Panizza and Wyplosz (2016) who examine whether the claim that UMP has diminishing returns is valid for four different regions, including the EMU. Similar to Hesse et al. (2018), they find diminishing returns for the US and the
UK when using the shadow rate as indicator, while they do not find a significant difference between their subperiods in the eurozone. If anything, they claim, the GDP response might be slightly higher in the second period. Even though their error bands overlap, there is a positive effect in the 2011 to 2016 time period, but none in 2008 to 2012. Their subperiods are not ideal since they overlap and dissect the sovereign debt crisis due to limited data availability and, further, they do not restrict the contemporaneous impact of prices and output to be zero as we do – this might explain why our differences between our time periods were more pronounced. They even acknowledge that the breakpoint might not be appropriate for the eurozone. Additionally, they carry out linear projections using balance sheet data for the EMU for which. Further, they carry out a linear projections method following Jordá (2005) using the balance sheet as UMP indicator – this time they are able to split their sample in January 2013, with the second period extending until December 2015. While they find a negative GDP response in the first period (2009 to 2013), they find an insignificant and rather neutral response in the second period, with prices insignificant in both periods. The relative difference shows an increased effectiveness, again supporting our findings. Likewise, Finck (2018) uses the shadow rate as well to compare the reactions to it in 1999, 2007 and 2015 and finds no significant difference and hence no evidence that monetary policy has become less effective in the eurozone. Their counterfactual analysis also suggests that a lack of the ECB’s expansionary monetary policy would have not resulted in a significantly less severe recession and lower inflation in the crisis period, indicating a lack of effectiveness in crisis periods. Further, Filardo and Nikajima (2018) use a time-varying parameter VAR framework and find that the counterfactual responses of output growth to a UMP shock for (pre-crisis) Q2 2007 differs little from that in Q2 2016 (post-crisis) while the response of inflation is muted. Prior to the crisis, a 10-basis point UMP shock would have caused a significant and persistent increase in inflation, while post-crisis in 2016 it no longer leads to a significant reaction
to inflation at all. They attribute this to a flattening of the Phillips Curve, which might be an explanation for the lack of any impact on inflation we have found.

5.2.3 Subsample Analysis – APP

So far, we have only differentiated between crisis and non-crisis, but we have the external knowledge of the vast new ECB asset purchase program that was announced in the second half of 2014 before being implemented early-2015. In order to test for robustness of our results as well as provide an overview of the effectiveness of APP in an isolated manner, we provide the results for an alternative specification of subperiods and vary our structural break. This time we split our sample in July 2014 in order to ensure to include the entirety of APP effects in the second time period, including Draghi’s speech at Jackson Hole in August 2014, that is seen to have increased the expectations of the APP, according to Gambetti and Musso (2017), and the September announcements of the CBPP3 and the Asset-Backed Securities Purchase Programme (ASBPP) that were incorporated into APP. Simultaneously, we exclude the announcement of the TLTROs and initial negative deposit facility rate cut in June 2014 as best as possible. It is not ideal how close these policy announcements are, but we hope that with the short-term response of the shadow rate (compared the ECB assets) we were able to separate these effects based on our subsample split. In addition, this means that first use of forward guidance in July 2013 now falls under the first subperiod instead of the second.

The results in Figure 2 are very similar to our other specification – both qualitatively and quantitatively. Looking at our first variable of interest, output, the error bands tangentially touch, even though the median peak responses still differ strongly. This is not a result of the peak response of the second time period being lower now (67 basis points vs 66) but can be attributed to the error bands being minimally wider, causing the error bands of both subperiods to touch even though they still do not overlap significantly. Neither responses for inflation are significant again, with very wide error bands. The lack of a positive significant response of inflation is not too worrisome in terms of whether
our model is well-identified given that most other studies do not find a significant effect on inflation, some even finding a negative effect. We still find a significant difference in terms of the CISS response.

**Figure 2: Impulse Response Functions to UMP Shock Split Sample (Alternate Specification)**

![Impulse Response Functions](image)

*Notes: Solid line denotes the median response, shaded areas the 68% posterior credibility bounds. Subsample I runs from January 2009 to March 2013 and Subsample II from April 2013 to December 2019.*

Our alternative subsample specification implies that the blue impulse response functions above represent the endogenous responses to an APP shock since basically all ECB announcements after July 2014 were related to the APP, apart from very few related to the TLTROs, which would be impossible to isolate though because the announcement month overlapped with APP announcements. The results using the Krippner (2015) shadow rate are reported in Figure 22 of the Appendix, demonstrating that our APP conclusions are largely robust, even though the impact on output is only marginally significant. Either way, from the impulse response functions themselves, we cannot determine whether we have managed to successfully isolate the APP shocks. In order to do so, we follow Boeckx et al. (2017) who inspect the time series of the structural balance sheet shocks to assess whether they coincide with the major UMP measures taken by the ECB from a narrative perspective. Figure 20 in the Appendix shows the median cumulative time series of the UMP shocks identified in
our model measured in standard deviations for the first subperiod (January 2009 until June 2014) and Figure 21 that of the second subperiod (July 2014 until December 2019). A rise of the cumulative shock series is indicative of an expansionary UMP shock while a negative movement implies a contractionary UMP relative to the average endogenous response to the other shocks impacting the economy. By observing the behavior of the structural shocks at known policy announcements, we can get a sense of how well our identified shocks reflect actual UMP announcements, that are expected to immediately impact the shadow rate and are largely unexpected for market agents.

We first look at the major positive shocks in the 2009 to 2014 subperiod. The first occurs in May 2009, which is the month that the ECB announced its first UMP policy in our sample period – three LTROs with 12-month maturity as well as CBPP1. The positive shock is extended into June where we see an extension of LTRO maturity and July when CBPP1 is implemented. Next, we see a number of positive shocks between May 2010 and the end of 2010 which can be associated with the start of the SMP as well as the announcement of several LTROs throughout the second half of the year. This episode is followed by little movement until our next large announcement – the CBPP2 in November 2011 when we see a large spike again, with another positive shock with LTROs announced in March 2012. In summer 2012 we see several positive shocks that might correspond to the announcement that FRFA will be continued for as long as necessary, Draghi’s ‘Whatever it takes’ speech in July, and the OMT announcements were announced in August. The last large spike occurs in July 2013, when the ECB uses forward guidance for the first time indicating that key interest rates will remain low for “an extended period of time”. Of course this does not imply that every single announcement is identified, especially because the shadow rate is also impacted endogenously, as previously specified, but it does give the overarching impression that the time series of shocks includes the main policy announcements for the first subperiod. Next to the positive shocks, the negative shocks may be reflective of the ECB not announcing any new policy measures despite worsening
economic conditions and financial stability – for example in the first half of 2011 we see largely negative structural shocks, coinciding with a lack of rapid intervention in light of the sovereign debt crisis.

Next, we look at our APP shocks between June 2014 and December 2019. Again, most positive shocks can be associated with UMP announcements. In September 2014, we see a positive shock when CBPP3 and ABSPP were announced. In March 2015, we see a positive shock when APP is launched, while the positive shocks in December 2015 and March 2016 can be associated with the announcements of APP extension and expansion. In December 2016, the continuation of purchases for at least another year is announced, also associated with a positive shock. On the other hand, we see a significant negative shock in October 2017 when the ECB announced that it would lower purchases from €60 to €30 billion. The announcement of the gradual end of APP in June 2018 is followed by several months of negative shocks. The other two positive announcements in our sample – the TLTRO III in March 2019 and the restart of monthly APP purchases in September 2019 – are also associated with positive shocks. Again, there are movements that cannot be explained, but overall, we believe that our identification has been able to filter out the most important announcements and is therefore plausible.

Having confirmed the plausibility of our structural shocks for both subperiods, we can infer that our second time period reflects the APP announcements and the impulse response functions therefore the effects of it. A reduction in the shadow rate in this period is associated with a positive and significant hump-shaped effect on output, a negligible yet slightly positive increase of prices at least of the median response, a significant reduction in financial stress and spreads. We can now compare our APP-specific results with the other two studies that have thus far investigated the effectiveness of APP. Our findings can largely be reconciled with the literature that exists so far, even though no study has taken the sample period as far as 2019. First, we can look at the empirical studies
explicitly focusing on APP, including Wieladek and Garcia Pascual (2016) and Gambetti and Musso (2017). Wieladek and Garcia Pascual refer to the APP as “a new hope” as they find that in the absence of the first round of QE by the ECB that goes until April 2016 in their time period, real GDP would have been 1.3 percent lower and core CPI 0.9 percent lower. Even though they find a much more marked effect on inflation, the relative magnitude of these effects confirms our findings, with a stronger impact on output than prices. Gambetti and Musso (2017) on the other hand, find a very similarly shaped response of output, with the effect mainly concentrated in the short run and an initial peak that gradually fades out – it is significant for only three quarters. Counter to our results, though, they find a higher impact of inflation in the long run that only peaks after two years and remains significant for five. The differences here might be explained by the fact that Gambetti and Musso (2017) solely try to isolate the effect of the first announcement of APP and not any recalibrations of it, their use of quarterly data, their lack of zero restrictions on output and prices and their time period ending three years before ours.

From a theoretical perspective, Mouabbi and Sahuc (2019) use a DSGE model starting in 2014 and find that without UMP, the reduction in GDP growth would have been much more extreme than that of inflation (0.99 versus 0.66 percent), again confirming the relative differences we found. Similarly, Hohberger, Priftis and Vogel (2018) who study the QE program from 2015 to 2018 in a DSGE model and finds that QE contributed positively to both inflation and GDP growth. Overall, even though there is mixed evidence regarding the relative response of inflation, our study is the first to use data until 2019, which might explain any differences.
5.2.4 Sensitivity Analysis

In addition to varying the structural breaks as discussed above, we also use a number of other methods to test the robustness of our results with sign and zero restrictions. First, we also follow one robustness check in Hesse et al. (2018) who re-estimate their model using industrial production in lieu of Chow-Lin interpolated GDP data. We also changed the indicator of financial stress to the VSTOXX, a measure of volatility of the EURO STOXX 50. Both of these are relevant for our studies given the host of conclusions we draw about the effects of and on output and financial stress. These results did not significantly alter the impulse response functions we obtained. Even adding an addition variable such real equity prices did not provide any additional insights, except for a short-term positive significant response that faded out relatively quickly in result to an expansionary monetary policy shock.

Next, we varied the lag length, but even when extending it to 10 as we used for our identification through heteroskedasticity model, we were unable to find a significant difference in response that would be worth responding. In a similar vein, we also varied the restriction horizon on the sign restrictions. Following Elbourne et al. (2018), we initially only restricted the variables on impact, however, as a robustness test, we varied this length. Other studies in the euro area extend the imposition of the sign restrictions to one month after impact (Boeckx et al., 2017; Weale and Wieladek, 2016). When our sign restrictions (not zero restrictions) are imposed upon impact and one additional month, our results prove to be robust, both quantitatively and qualitatively.
6. Discussion

Since the effectiveness of UMP in the euro area is still widely disputed and previous studies often contradict one another, our paper fits in nicely within the academic (and policy) debates surrounding this topic and can add some valuable insights. While we manage to largely support the claims from pre-existing studies, also with the application of a novel identification method that places no prior restrictions on the coefficients, we also highlight some new findings based on more recently available data to contribute to existing literature around this salient topic. This section will attempt to place our empirical findings into broader context and try to find potential reasons behind the time-varying effectiveness of APP we have explored.

6.1 Explaining the Time-Variation in UMP Effectiveness

As shown in Section 5.2, we find that UMP has been more effective in stimulating output in non-crisis than crisis times, while the UMP’s ability to reduce stress was higher in crisis times. The effect on prices was negligible for both our time periods. Similarly, when restricting our time period to solely the APP program starting in July 2014, we also find that it managed to increase output, but not inflation, significantly. These findings are the exact opposite of the decreased effectiveness of UMP that scholars such as Hesse et al. (2018) have found for the US and UK and we now aim to find reasons for this geographic discrepancy. In order to reconcile our findings with Hesse et al.’s (2018) we must look at the differences in the programs carried out by the Fed and BoE versus the ECB as well as the economic conditions faced in each geography. The largest difference exists in the timeline and magnitude of policies implemented – while especially the Fed is seen to have taken a very proactive and aggressive approach in stimulating the US economy in the immediate aftermath of the Global Financial Crisis, the ECB was more hesitant and did not implement an LSAP program until many years later. Especially considering the first subsample in our baseline specification, during which the
entire monetary union faced two severe crises, the policy actions conducted by the ECB to counteract these differed quite strongly to those of the Fed and the BoE, who rapidly initiated large QE programs. The more gradual intervention by the ECB in response to the immediate threat of the Global Financial Crisis has been widely criticized as being ‘too little’ and ‘too late’ (Lombardi, Siklos and Amand, 2018, 1242). Part of the delayed reaction of the ECB can be attributed to its legal mandate that originally included to never act as a lender of last resort for individual members of the monetary union, hindering its ability to purchase sovereign bonds (Brunnermeier and Reis, 2019; Lombardi et al, 2018). While such a policy intended to prevent fiscal dominance on monetary policy in the monetary union, it put the ECB in a position where it was unable to pursue a LSAP program as vast as the Fed or BoE.

The other early programs by the ECB were largely aimed at and succeeded in easing tensions in financial markets. For example, one of the first UMP measures announced in our sample, the Enhanced Credit Support Program consisting of 12-month LTROs, was able to reduce spreads (Reichlin, 2014) and avert a major credit crunch (Cahn, Matheron and Sahuc, 2017) while the CBPP1 increased the liquidity in financial markets and caused a term rate recline (Beirne et al., 2011). Therefore, although these measures were able to reduce financial system stress, as confirmed by the stronger CISS reaction to a reduction in the shadow rate in the first subperiod of our findings, the transmission mechanism to the real economy appears to have been impaired during the crisis. Bech, Gambacorta and Kharroubi (2014) confirm this notion with their finding that monetary policy transmission is less effective during crisis episodes. Hartmann and Smets (2019) agree, while also highlighting that the uneven passthrough of these policies to EMU member countries weakened the effectiveness of ECB monetary policy. In addition, the absence of strong institutions and tools available to address unprecedented financial and fiscal instabilities in the monetary union undermined

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16 Article 123 of the Treaty of the Functioning of the EU prohibits the direct purchase of government debt instruments and other types of credit facilities by the ECB (Hartmann and Smets, 2019).
ECB policymaking. Only once sufficient reforms were made during the June 2012 European Summit did the ECB gain enough credibility for its programs to be more effective (Hartmann and Smets, 2019).

The first outright purchasing program was the SMP, which however was largely seen as temporary and limited and failed to stem the euro redenomination risk, leading to further spillover of the sovereign debt crisis into other countries (Pill and Reichlin, 2014). The ECB’s initial purchasing programs have been widely criticized as too limited to restore confidence, incomparable to the US QE1 program, for example. Instead, the hesitation of the ECB may have contributed the euro area’s spiral into a second crisis as well as the low-inflation trap afterwards, and the much weaker recovery compared to other developed economies, as also demonstrated by our pessimistic findings for the first subperiod. It must be noted, that we see an important change in the stance of the ECB in summer 2012. First, the OMT is introduced, which was considered a very powerful program and its announcement tranquilized markets and decelerated further spiraling of the sovereign debt crisis. However, the ECB never actually applied this program which may explain why the stimulus was unable to reach the real economy even though it sent a positive signal to markets initially. In addition, Draghi famously stated that the ECB would do ‘whatever it takes’ to preserve the euro in summer 2012. Panizza and Wyplosz (2018), who also find a larger output response in their later period, attribute this difference to the delay in policies implemented by the ECB and the more active stance taken on after Draghi’s speech. Lombardi et al. (2018) similarly regards this speech as a turning point in ECB policy, after which became more proactive and aggressive, more comparable to what we had seen by the Fed and BoE in the immediate aftermath of the crisis.

The APP was launched in a very different environment than the initial UMP measures, which may explain its higher effectiveness that we find. The financial disruptions had largely evaporated but instead the ECB tried to counter a contractionary aggregate demand shock and the weakened
economic sentiment that followed from the ‘double dip’ of the two recessions, as well as fiscal policy tightening across members states. This time it was not dealing with the malfunctioning of markets. The mere scale of this program might explain the increased effectiveness, but also a restructuring of the financing system in the euro area. The central role of banks diminished in the aftermath of the crisis, which may have contributed to increased effectiveness of the interventions in capital markets through the LSAP. Prior to the crisis in 2007, bank loans made up 37 percent of total debt financing of eurozone companies, which shrunk to only 28% in 2017 (ECB Annual Report 2017). This shift shows that non-bank financing directly from debt capital markets has become a lot more important for corporate funding, which might explain part of the APP’s effectiveness in stimulating investment and hence output. At the same time, the APP came at a point when the ECB also lowered their deposit facility rate below zero, which may have further contributed to a favorable investment environment and a stimulus to aggregate demand. In addition, the ECB successfully linked its APP announcements to forward guidance on the interest rate, strengthening the signal sent to the markets (Hartmann and Smets, 2019). Hence, the policies employed post-2014 may have helped stem the strong recovery and a period of more resilient growth in the eurozone since.

In terms of inflation, on the other hand, we never really saw a robust rebound in the eurozone, which might explain our negligible finding on prices. Even though these results might be puzzling, they are consistent with the findings of Aßhoff, Belke and Osowski (2020) who investigate UMP’s impact on inflation expectations between 2009 and 2018 – they find that UMP leads to a short-term rise in inflation expectations, which fades out in the medium term though. Therefore, they cast some doubt on UMP’s ability to re-anchor and stabilize inflation expectations in the euro area, which may have contributed to the inability of UMP to stimulate HICP directly.
6.2 Limitations and Future Research

Even though our study managed to bridge some gaps in the existing literature, we must address some of its shortcomings as well as important questions that are left unanswered and might be relevant for future research. One main limitation of our study is that there is no ideal way to measure the ECB’s monetary policy stance and that even the shadow rate is not a perfect measurement of UMP. It is not directly set by the ECB as the MRO is, for example, and it also reflects both conventional and unconventional measures, making it hard to isolate UMP effects when the interest rate is not yet at the ZLB. Even though most of the shadow rate’s variability from 2009 onwards stems from UMP, given its strong fluctuations despite the MRO barely moving, we likely ended up including some interest rate movements as well. Therefore, while our results give a good indication of the overall effectiveness of ECB policymaking in the time period, we might be conflating some unconventional and conventional monetary measures in our estimates. We tried to limit the effect of conventional monetary policy by running subsamples starting in 2009, however, even these inevitably incorporate some MRO movements. Most notably (and highly controversially), the ECB hiked rates in April and July 2011 by 25 points each time to 1.5 percent, before cutting it back to one percent by the end of the year, thereby creating additional headwinds for the sovereign debt crisis. In addition, the ECB gradually cut the MRO from one percent in July 2012 to zero in March 2016 – however, since the ECB was also conducting forward guidance at the same time and market participants expected the rates to remain low regardless of the cuts, we do not expect these to have impacted our estimations drastically. Nonetheless, our results must be analyzed with caution and perhaps be considered as an upper bound of estimates, even though they paint an overall picture of the effectiveness of ECB policymaking regardless and no other measure would have enabled us to consistently compare the full sample period due to the aforementioned issues of balance sheet problems as well as the changing nature of ECB UMP.
On a related note, another limitation regarding the shadow rate measure is that there are several different measures that differ depending on their specifications. We see quite a strong difference in the development of the Wu and Xia (2016) and Krippner (2015) rates and scholars have disagreed on which one is a better approximation for monetary policy stance in the eurozone. We try to mitigate this by testing for robustness using both shadow rates, which largely confirms our results, despite some differences. Nonetheless, there are a number of other shadow rates that take a different approach to its estimation that could be used by future research to further test robustness.

Next, since we ended up carrying out subsample analyses, some of these time periods were quite short, which could have contributed to the wide error bands we saw for some variables. It will be particularly interesting for future research to include new data that will emerge within the next few years. Particularly in light of the new crisis approaching, our conclusion that UMP is less effective during crisis than non-crisis periods could be re-tested using a third and different type of crisis. Another shortcoming regarding the short time period is that we had to interpolate data for our GDP measure, which is one of our main variables of interest. However, when testing for robustness with industrial production, our results did not differ substantially.

Furthermore, a limitation inherent to euro area studies is that the changing composition of members as well as the potentially deepening integration among members might create parameter instability. In a similar vein, our results indicate eurozone-wide effects without taking into account potential asymmetries. Generating country-by-country results is a difficult task from an econometric perspective since even though monetary policy is determined by the ECB for all 19 eurozone countries, individual eurozone countries also generate feedback into the euro-area-wide shadow rate variable. However, it a vital subject of research in a monetary union given that the central bank needs to cater to all countries regardless of differing economic conditions and while a certain policy measure might be beneficial for one country, it might be counterproductive for another country, and vice versa.
For future research, it would be very interesting to dive deeper into the cross-country heterogeneity of UMP and establish whether this may have contributed to the time-varying effectiveness of UMP we found evidence of. Several studies have shown this to be true for the pre-APP UMP so it would be useful to look at asymmetries of APP effectiveness (Burriel and Galesi, 2018; Serati and Venegoni, 2019; Dominguez-Torres and Hierro, 2020). In a similar vein, a natural extension of our study would be to analyze the importance of differing transmission channels that may have contributed to the changing effectiveness of monetary policy.
7. Conclusion

This paper uses a Bayesian structural VAR approach with two different identification methods (identification through heteroskedasticity and a combination of sign and zero restrictions) to investigate the effectiveness of monetary policy in the euro area since 2008, an area of research that has remained quite inconclusive. We contribute to the literature with several interesting findings.

First, we show that identification through heteroskedasticity following Brunnermeier et al. (2019) can be applied to macro VARs in the euro area as it yields interpretable results without imposing strict restrictions on the structural coefficients as most other identification methods used thus far do. The results using identification through heteroskedasticity suggest that a contractionary monetary policy shock, characterized by an increase in the shadow rate, has led to a significant and persistent decline in output and a smaller and less significant decline in prices between 2008 and 2019. Our results indicate that unexpected changes in monetary policy were not a dominant source of variation in this time period, but that the shadow short rate was largely endogenously driven by orthogonal shocks in the system, most notably financial stress, but also aggregate demand and aggregate supply. Overall, the plausibility of our results suggests that this novel identification method can successfully orthogonalize different macroeconomic and financial market shocks in the euro area, including a monetary policy shock, without making strict assumptions – therefore, our paper provides a solid foundation for future empirical research on the macroeconomic dynamics in the euro system.

Second, we confirm our results using a sign and zero restriction identification scheme. We further use this method to analyze different subperiods in our sample and thereby time-varying effectiveness of UMP in the euro area. While our full sample results indicate that the ECB was successful in stimulating output and to a lesser degree inflation with their monetary policy measures since 2008, we find important nuance. In our first subsample that spans over the two crises episodes until March 2013, we find that even though an exogenous UMP shock succeeds in lowering financial
system risk, this effect fails to spill over into the real economy as indicated by a negligible effect on output and inflation. On the other hand, during our non-crisis subperiod ranging from April 2013 to 2020, UMP shocks have a positive significant effect on output even though the impact on inflation is still slightly subdued, suggesting that ECB was more effective in stimulating the economy in non-crisis times. A separate subsample analysis starting in July 2014 further demonstrates that the APP program contributed to the eurozone’s robust recovery from the sovereign debt crisis yet failed to significantly stimulate prices.

These findings have very important implications for policymaking in the euro area. First off, given UMP’s successful dampening of financial stress during the crisis time period, it might be useful for future crises to restore the functionality and inject liquidity into financial markets. However, since the transmission mechanism to create spillovers from financial markets into the real economy was impaired, according to our findings, monetary policy alone is not sufficient to reach policy goals in a crisis and the ECB must find ways to more directly drive aggregate demand during a crisis. Alternatively, the inability of UMP to stimulate output during the crisis might imply the need for a fiscal union to accompany the monetary union, allowing for the pooling of a centralized budget with a solidarity mechanism when a crisis takes hold, in particular if this crisis is as asymmetric as the sovereign debt crisis was. Lastly, while our study shows that the APP program was successful in driving output, the effects on prices were negligible. Given the controversy of QE in the euro area with regards to its conflation of monetary and fiscal policy as well as its unsustainability, the EMU might have to find a more effective solution to stabilizing prices.
8. Appendix

Table 4: Key ECB Announcements between August 2007 and March 2020

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
<th>Policy Measure / Announcement</th>
</tr>
</thead>
<tbody>
<tr>
<td>August-September 2007</td>
<td>Financial market turmoil begins in euro area and euro money market</td>
<td>Non-standard liquidity providing and funding measures (liquidity injections, more use of fine-tuning operations, etc.); Announcement of two 3-month longer-term refinancing operations (LTROs), one in August and one in September</td>
</tr>
<tr>
<td>February-March 2008</td>
<td>Lehman Brothers bankruptcy, exacerbation of Global Financial Crisis</td>
<td>Announcement of 3-month LTRO in February; Announcement of first 6-month LTRO in March</td>
</tr>
<tr>
<td>September 2008</td>
<td>Lehman Brothers bankruptcy, exacerbation of Global Financial Crisis</td>
<td>Liquidity and funding measures including overnight fine-tuning operations (FTOs) and maturity extensions</td>
</tr>
<tr>
<td>October 2008</td>
<td>Sovereign debt crisis; Economic Adjustment program for Greece (followed by one for Ireland in December 2010 and Portugal in May 2011)</td>
<td>Announcement of fixed-rate tender procedures with full allotment (FRFA) for MROs and LTROs; Expansion of collateral LTROs; Interest rate cut of 50 bps, followed by additional 275 bps cuts in six steps until May 2009 to 1 percent</td>
</tr>
<tr>
<td>May 2009</td>
<td>Sovereign debt crisis; Economic Adjustment program for Greece (followed by one for Ireland in December 2010 and Portugal in May 2011)</td>
<td>Announcement of the ‘Enhanced Credit Support Programme’ to include three LTROs with 12-month maturity with FRFA starting in June; Announcement of the first Covered Bond Purchase Programme (CBPP1) to launch in July</td>
</tr>
<tr>
<td>May 2010</td>
<td>Re-intensification of sovereign debt crisis</td>
<td>Securities Markets Program (SMP I) started (purchase of private and public debt securities mainly from peripheral countries); Announcement of swap lines with the Fed; Announcement of 6-month LTRO; Several LTROs with 12-, 13- and 26-month maturities announced in the second half of 2010 as well</td>
</tr>
<tr>
<td>August 2011</td>
<td>Re-intensification of sovereign debt crisis</td>
<td>Reactivation of government bond purchases under SMP (SMP II)</td>
</tr>
<tr>
<td>November 2011</td>
<td>Re-intensification of sovereign debt crisis</td>
<td>Second covered bond purchase program (CBPP2); Interest rate cuts down to 0.15 percent in June 2014</td>
</tr>
<tr>
<td>December 2011</td>
<td>Re-intensification of sovereign debt crisis</td>
<td>Announcement of two 3-year liquidity-providing LTROs with full allotment (first one offered in December and second one in February 2012)</td>
</tr>
<tr>
<td>March 2012</td>
<td>Private sector involvement (PSI) debt restructuring deal for Greece</td>
<td>Financial assistance program for Spain; ‘Whatever it takes’ Speech by ECB president Mario Draghi in July</td>
</tr>
<tr>
<td>Summer 2012</td>
<td>Financial assistance program for Spain; ‘Whatever it takes’ Speech by ECB president Mario Draghi in July</td>
<td>Outright monetary transactions (OMTs) announced in August, allowing ECB to undertake OMTs in secondary sovereign bond markets</td>
</tr>
<tr>
<td>Date</td>
<td>Event</td>
<td>Description</td>
</tr>
<tr>
<td>------------</td>
<td>-----------------------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>July 2013</td>
<td>Forward Guidance</td>
<td>Communicated that it “expects the key ECB interest rates to remain at present or lower levels for extended period of time”</td>
</tr>
<tr>
<td>June 2014</td>
<td>Announcement of targeted long-term refinancing operations (TLTRO1)</td>
<td>And of Preparatory work on asset-backed securities purchases; Deposit facility rate becomes negative (i.e. -0.10%)</td>
</tr>
<tr>
<td>August 2014</td>
<td>Jackson Hole Speech by Mario Draghi</td>
<td>Speech is seen to have increased expectations of APP</td>
</tr>
<tr>
<td>September</td>
<td>Announcement of CBPP3 and an asset-backed securities purchase program (ABSPP)</td>
<td>Further interest rate cut</td>
</tr>
<tr>
<td>January 2015</td>
<td>Announcement of APP, encompassing existing purchasing programs (CBPP3 &amp; ABSPP)</td>
<td>A Public Sector Purchasing Program (PSPP), with monthly purchases of €60bn, intended to be carried out until end of September 2016</td>
</tr>
<tr>
<td>March 2015</td>
<td>Start of purchases under APP (euro-denominated IG securities issued by euro area governments, agencies and institutions in secondary market)</td>
<td></td>
</tr>
<tr>
<td>December 2015</td>
<td>First APP recalibration</td>
<td>Extension of APP duration (until end of March 2017 or beyond) and ECB to reinvest principal payments on securities purchased under APP as they mature</td>
</tr>
<tr>
<td>March 2016</td>
<td>Second APP recalibration</td>
<td>Expansion of monthly purchases to €80bn, including a new Corporate Securities Purchase Program (CSPP) in which IG bonds of non-financial corporations are eligible; Forward guidance: policy rate well beyond APP; Announcement of second series of TLTROs (TLTRO II), starting in June 2016 Further cut of deposit facility rate to -0.40%</td>
</tr>
<tr>
<td>December 2016</td>
<td>Third APP recalibration</td>
<td>Maintain €60bn monthly purchases until end of March 2017 and then reduce pace to €60bn until end of December 2017 or beyond, if necessary</td>
</tr>
<tr>
<td>October 2017</td>
<td>Fourth APP recalibration</td>
<td>Lower purchases to €30bn monthly starting from January 2018 until September 2018</td>
</tr>
<tr>
<td>June 2018</td>
<td>APP Transition Announcement</td>
<td>Lower purchases to €15bn from October 2018 to December 2018, followed by end of APP.</td>
</tr>
<tr>
<td>March 2019</td>
<td>Third series of TLTROs (TLTRO III) announced, starting in September 2019 at quarterly frequency</td>
<td></td>
</tr>
<tr>
<td>September 2019</td>
<td>APP Restart Announcement</td>
<td>Restart monthly purchases at pace of €20bn starting in November 2019, lasting as long as necessary.</td>
</tr>
<tr>
<td>March 2020</td>
<td>Announcement of Pandemic Emergency Purchase Programme (PEP)</td>
<td>Purchases of €750 billion of private and public sector securities until the end of 2020 in light of COVID-19</td>
</tr>
</tbody>
</table>

Source: ECB / Author’s Research
Figure 3: Net Monthly APP Purchases by Asset Class

Source: ECB Data and Statistical Warehouse
Notes: Asset-backed Securities (ABSPP), Covered Bond (CBPP), Corporate Sector (CSPP) and Public Sector (PSPP)

Figure 4: Measures of Monetary Policy in the Eurozone Since 1999

Source: ECB Statistical Data Warehouse, Leo Krippner’s website and directly obtained from Cynthia Wu.
Note: Wu and Xia (2016) estimates start in September 2004.
Table 5: Variable Names and Descriptions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSR</td>
<td>Shadow Rate as determined by Wu &amp; Xia (2016) or Krippner (2015)</td>
</tr>
<tr>
<td>Output</td>
<td>Log of monthly real GDP, Chow-Lin interpolated with IP (base year = 2015)</td>
</tr>
<tr>
<td>Prices</td>
<td>Log of monthly Harmonized Index of Consumer Prices (base year = 2015)</td>
</tr>
<tr>
<td>Money Market Spread</td>
<td>Spread between policy rate (MRO) and overnight index average rate (EONIA)</td>
</tr>
<tr>
<td>CISS Index</td>
<td>Composite Indicator of Systemic Stress (Holló et al 2012)</td>
</tr>
</tbody>
</table>

Table 6: Descriptive Statistics of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations</th>
<th>Mean Value</th>
<th>Standard Deviation</th>
<th>Minimum Value</th>
<th>Maximum Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wu and Xia (2016) Shadow Rate</td>
<td>252</td>
<td>0.200</td>
<td>3.318</td>
<td>-7.636</td>
<td>4.917</td>
</tr>
<tr>
<td>Log of Real GDP</td>
<td>252</td>
<td>13.58</td>
<td>0.0703</td>
<td>13.42</td>
<td>13.71</td>
</tr>
<tr>
<td>Log of HICP</td>
<td>252</td>
<td>4.506</td>
<td>0.106</td>
<td>4.305</td>
<td>4.658</td>
</tr>
<tr>
<td>CISS (Holló et al., 2012)</td>
<td>252</td>
<td>0.179</td>
<td>0.160</td>
<td>0.0331</td>
<td>0.778</td>
</tr>
<tr>
<td>Money Market Spread</td>
<td>252</td>
<td>-0.178</td>
<td>0.266</td>
<td>-0.743</td>
<td>0.314</td>
</tr>
</tbody>
</table>
Figure 5: Monthly Variation in Variables over Time (January 1999 to December 2019)

Note: Vertical lines represent sample breaks in October 2008, March 2013 and June 2014.
Figure 6: First Differences of Variables over Time (January 1999 to December 2019)

Note: Vertical lines represent sample breaks in October 2008, March 2013 and June 2014.
Figure 7: Identification Through Heteroskedasticity Impulse Response Functions using the Wu and Xia Shadow Rate (October 2008 to December 2019)

Notes: Shadow short rate (SSR) variable is expressed in proportions; output and inflation are in natural logs; CISS and Spread must be multiplied by 10 to get proportion. Break in variance regimes occurs in March 2013. The black lines represent the median impulse responses over a 40-month horizon, the red lines are the 68% credible set and the green lines the 90% credible set.
Figure 8: Identification Through Heteroskedasticity Impulse Response Functions using the Wu and Xia Shadow Rate (January 1999 to December 2019)

Notes: Shadow short rate (SSR) variable is expressed in proportions; output and inflation are in natural logs; CISS and Spread must be multiplied by 10 to get proportion. Breaks in variance regimes occur in October 2008 and March 2013. The black lines represent the median impulse responses over a 40-month horizon, the red lines are the 68% credible set and the green lines the 90% credible set.
Figure 9: Identification Through Heteroskedasticity Impulse Response Functions using the Krippner Shadow Rate (October 2008 to December to December 2019)

Notes: Shadow short rate (SSR) variable is expressed in proportions; output and inflation are in natural logs; CISS and Spread must be multiplied by 10 to get proportion. Break in variance regimes occurs in March 2013. The black lines represent the median impulse responses over a 40-month horizon, the red lines are the 68% credible set and the green lines the 90% credible set.

Figure 10: Identification Through Heteroskedasticity Impulse Response Functions using the Krippner Shadow Rate (January 1999 to December 2019)

Notes: Shadow short rate (SSR) variable is expressed in proportions; output and inflation are in natural logs; CISS and Spread must be multiplied by 10 to get proportion. Breaks in variance regimes occur in October 2008 and March 2013. The black lines represent the median impulse responses over a 40-month horizon, the red lines are the 68% credible set and the green lines the 90% credible set.
Figure 11: Sign and Zero Restriction Impulse Response Functions using the Wu and Xia Shadow Rate (October 2008 – December 2019)

Notes: Shadow short rate (SSR), spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
Figure 12: Sign and Zero Restriction Impulse Response Functions using the Krippner Shadow Rate (October 2008 – December 2019)

Notes: Shadow short rate (SSR), spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
Figure 13: Historical Decomposition of Wu and Xia Shadow Rate (2009 – 2019)

Notes: Remaining variability of the shadow rate is generated by unidentified shocks.

Figure 14: Forecast Error Variance Decomposition of Wu and Xia Shadow Rate (2009 – 2019)
Figure 15: Sign and Zero Restriction Impulse Response Functions using the Wu and Xia Shadow Rate (January 2009 – March 2013)

Notes: Shadow short rate (SSR), spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
Figure 16: Sign and Zero Restriction Impulse Response Functions using the Wu and Xia Shadow Rate (April 2013 – December 2019)

Notes: Shadow short rate (SSR), spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
Figure 17 Forecast Error Variance Decomposition in Split Sample for Output, Prices & CISS
Figure 18: Sign and Zero Restriction Impulse Responses to a UMP Shock using the Krippner Shadow Rate (January 2009 – March 2013)

Notes: Shadow short rate, spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.

Figure 19: Sign and Zero Restriction Impulse Responses to a UMP Shock using the Krippner Shadow Rate (April 2013 – December 2019)

Notes: Shadow short rate, spreads and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
Figure 20: Identified Structural UMP Shocks Time Series Subsample I (2009-2014)

Figure 21: Identified Structural UMP Shocks Time Series Subsample II (2014-2019)
Figure 22: Sign and Zero Restriction Impulse Responses to a UMP Shock using the Krippner Shadow Rate (July 2014 – December 2019 i.e. APP Period)

Notes: Shadow short rate, spread and CISS expressed in percentages; Output and Prices in logs. Solid lines denote the median impulse responses, shaded area indicate 68% credible set.
9. References


PLEDGE:

This paper represents my own work in accordance with University regulations.

Carlotta von Gierke