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WHEN DOES MONETARY MEASUREMENT MATTER (MOST)?

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It has repeatedly been shown that properly constructed monetary aggregates based on index number theory (such as Divisia money) vastly outperform traditional measures of money (i.e. simple sum money) in empirical models. However, opponents of Divisia frequently claim that Divisia is "too complex" for little gain. And indeed, at first glance it looks as if simple sum and Divisia sum exhibit similar dynamics. In this paper, we want to build deeper understanding of how and when Divisia and simple sum differ empirically using monthly US data from 1990M1 to 2007M12. In particular, we look at how they respond differently to monetary policy shocks, which seems to be the most essential aspect of those differences from the perspective of the policy maker. We use a very rich, fairly agnostic setup that allows us to identify many potential nonlinearities, building on a smoothed local projections approach with automatic selection of the relevant interaction terms. We find, that—while the direction of change is often similar—the precise dynamics differ sharply. In particular in times of economic uncertainty, when the proper assessment of monetary policy is most relevant, those existing differences are drastically augmented.

Keywords: Local Projections, Divisia, Monetary Aggregation, Impulse Response

1. INTRODUCTION

Since the US interest rate hit the zero lower bound in 2008 and the Fed mostly had to resort to quantitative easing in its conduct of monetary policy, the analysis of monetary aggregates as measures of and in monetary policy became revitalized. Yet, that money mostly disappeared from the workhorse models used in monetary macro during the Great Moderation was not entirely without reason but driven by the poor performance of widely used (simple sum) monetary aggregates in empirical models. So it comes as no surprise that the Great Recession and the corresponding loss of information carried by interest rates also renewed the interest in the literature on monetary measurement, in particular *Divisia* money as pioneered by Barnett (1978) and Barnett (1980). Those papers developed the argument that is now known as Barnett critique, which links the empirical failure of money to the unsound measurement most commonly used, namely simple sum

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monetary aggregates, which completely ignore the different degrees of liquidity of the underlying assets.

In recent years, there has been an abundance of papers, highlighting the empirical performance of theoretically founded measures of money or monetary services in a variety of models, such as Binner et al. (2005), Barnett (2007), El-Shagi and Kelly (2014), Keating et al. (n.d.), Keating et al. (2014), El-Shagi et al. (2015), Tepper et al. (n.d.), and El-Shagi and Kelly (2016) to name just some examples.

While theoretically plausible, the magnitude and robustness of the empirical superiority of Divisia and similar monetary measures over simple sum are puzzling due to the high correlation of both measures in terms of growth rates. Thus, it might seem at first glance that simple sum—while relying on strong and undeniably wrong assumptions such as perfect substitutability between monetary assets—still is a sound approximation. Yet, some previous contributions point to the fact that the dynamics of Divisia money differ quite strongly from those of simple sum in times when it matters most. Barnett (n.d) points out that the decline of Divisia money during the so-called Monetarist experiment would have warned the Fed that the monetary contraction is far too strong and pushing the economy into a recession. El-Shagi and Kelly (2014) demonstrate that Divisia plummeted in the Euro area periphery countries, long before simple sum indicated trouble in monetary policy transmission.

In this paper, we want to build deeper understanding of how and when Divisia and simple sum differ empirically using monthly US data from 1990M1 to 2007M12. In particular, we look at how they respond differently to monetary policy shocks, which seems to be the most essential aspect of those differences from the perspective of the policy maker. The impulse response functions (IRFs) are estimated through local projections, as proposed by Jordà (2005), rather than a VAR model as done in the bulk of the literature. The key advantage of this approach is that it allows us to test the existence of asymmetries and nonlinearities in a much richer and more straightforward way. Contrary to previous papers that add the nonlinearities in an ad hoc manner, we augment the traditional local projections approach by a least absolute shrinkage and selection operator (LASSO)-based variable selection that allows to incorporate a huge range of potential interactions without running into degrees of freedom problems. Unlike a VAR, local projections require an endogenously defined shock. In our case, we use the update of the monetary policy shock measure proposed by Romer and Romer (2004) provided by Halperin (n.d.). That is, following the critique brought forward by El-Shagi and Kelly (2016), our approach uses a monetary policy measure that is based on the Federal Funds rate—which is the policy instrument actually used—rather than a monetary aggregate as sometimes found in the literature promoting the use of monetary aggregates in monetary policy.

Our study is exploratory in nature. That is, instead of testing specific hypothesis, we use a very flexible framework that allows to assess the shape of IRFs. Our contribution to the literature is twofold. First, we demonstrate when and how much the Barnett critique matters for policy makers. Second, we provide a very

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flexible nonlinear model to assess how a properly measured monetary aggregate responds to policy shocks.

The remainder of the paper is structured as follows. Section 2 outlines our method. In Section 3 we present the data and some descriptive evidence and summary statistics. Section 4 gives an in-depth description of our results, both in terms of the model chosen by the LASSO approach and the IRFs under different conditions, and Section 5 concludes.

2. METHOD

In this section, we propose an LASSO-augmented version of the smoothed local projections. Smoothed local projections have been independently developed by El-Shagi (n.d.) and Barnichon (n.d.), both building on the seminal work by Jordà (2005) and Jordà (2009) who initially proposed local projections as an alternative way to estimate IRFs.

Local projections. Rather than looking at coefficient estimates, the literature in dynamic macroeconomics has focused on analyzing IRFs in the past years. While rarely explicitly dubbed this way, IRFs are essentially differences between conditional forecasts—usually starting from the unconditional mean of all variables—with and without a hypothetical shock.

In a VAR, the underlying conditional forecasts are indirect forecasts, that is, the forecast at horizon $h+1$ is conditional on the forecast at horizon h. The estimated model only produces one step ahead forecasts.

The idea of local projections is as simple as it is ingenious. Jordà (2005) argues that the VARs have two fundamental problems. First, they are optimized to make one step ahead forecasts. Second, estimating highly nonlinear VARs is a complex undertaking because all variables that matter for dynamics have to be modeled appropriately. Thus, instead of producing indirect forecasts by iterating the VAR one step ahead forecasts, he suggests to estimate individual models for each forecast horizon. In other words, while a VAR produces IRFs for the variable Y by iterating on the model,

$$\begin{bmatrix} Y \\ Z \end{bmatrix}_{t+1} = \sum_{l=0}^{k} \hat{B}_l \begin{bmatrix} Y \\ Z \end{bmatrix}_{t-l}, \tag{1}$$

where Y is the variable of interest and Z is the vector of additional variables in the VAR, and $\hat{B}$ is the estimated coefficient matrix, local projections-based IRFs are produced using H models of the form:

$$Y_{t+h} = \hat{\mathcal{F}}(Y_t, Z_t, Y_{t-1}, Z_{t-1}, \ldots), \tag{2}$$

where H is the number of forecast horizons included in the IRF, which in most cases corresponds to the maximum horizon[1], and $\hat{\mathcal{F}}$ is a potentially highly nonlinear function projecting past data on the future.

This has two major advantages. First, and most obviously, each model is actually meant for the respective forecast horizon. Unlike VAR forecasts, the estimation errors of the one step ahead model thus do not add up. Second, because only one variable (the variable of interest Y itself) has to be modeled, the specification is much easier and allows for the straightforward inclusion of nonlinearities through higher-order polynomials and interaction terms. However, this comes at the cost of no longer being able to use the covariance matrix obtained from the VAR estimation to identify structural shocks. Therefore, local projections are only applicable where an exogenously measured shock is available as regressor. Luckily, such data are available for monetary policy shocks since the seminal paper by Romer and Romer (1989), who suggest to identify surprising changes to monetary policy through movements of the federal funds rate around meetings of the Federal Open Market Committee (FOMC).

Smoothing. Despite its advantages, there is one downside in estimating the impact of a shock over different horizons separately. More often than not, the resulting IRFs are more volatile than the—intuitively more appealing—smooth IRFs generated by a VAR. El-Shagi (n.d.) proposes a semiparametric extension of local projections that aims to combine the advantages of local projections and VAR-based IRFs by imposing smoothness as a constraint.

This is achieved by penalizing second differences between coefficients on the same regressor in regressions for adjacent forecast horizons.[2] Including this penalty, the whole system of regressions used to generate local projections can be rewritten in stacked form—as used for seemingly unrelated regressions—and estimated using feasible generalized least square estimation. The optimum degree of smoothing can be identified through standard information criteria, because said degree of smoothing can be translated into the implicit gain of degrees of freedom (compared to the unrestricted model) following Breitung and Roling (2015).

The one additional restriction that comes with this approach is identical regressors across equations. In the original local projections approach, those could be allowed to differ, although this possibility is rarely used in practice.

Identifying relevant nonlinearities. Mostly, the previous literature selects the nonlinearities considered—that is, polynomials and interactions of regressors—in a fairly ad hoc way. However, extensively testing potential nonlinearities if there is no theoretical guidance can easily be problematic or even impossible if the set of explanatory variables is large. In our particular case, with a sample of about 130 observations and a simple set of merely 6 variables, the number of possible permutations up to third-order interactions and polynomials already exceeds the number of observations substantially.

In this paper, we employ a variable selection that is based on the LASSO proposed by Tibshirani (1996). In a preselection step, the regressions for each horizon are run individually, choosing λ, the degree of shrinkage, using the C_p statistic proposed by Mallows (1973). To avoid spurious results concerning some interaction terms, the underlying basic variables are always used, whether or not they are selected by the LASSO.

However, the application of the smoothing approach requires the inclusion of identical regressors in the equations for all horizons. Using all regressors that are selected at least once can still produce a considerable number of regressors, in particular if the number of horizons included in the IRF is large. Thus, the final smoothed local projections estimator is run on a subset of regressors that are chosen in $m > \underline{m}$ models, where $\underline{m}$ is a threshold that is calibrated to allow for feasible estimation of the final system. Since the smoothing approach would remove occasional bumps created by indicators that only seem to matter at a single horizon, this change is inconsequential to the results, but greatly increases the degrees of freedom and reduces the computational demands of our procedure. Also, by removing predictors that are mostly irrelevant, we can gain a lot of efficiency in our estimation at very little cost. Generally, we find much narrower confidence bounds, when increasing the threshold $\underline{m}$ (up to a certain point), while the shape of the IRFs is barely affected. The results reported in the following sections use a threshold of 6, that is, we only consider interactions that matter in at least 25% of the forecast horizons included in our study.

Joint estimation of Divisia and simple sum IRFs. Since Divisia and simple sum exhibit a substantial degree of correlation, we choose to estimate a joint system. That is, rather than running two systems with 24 equations each (one for each forecast horizon considered), we estimate one system of 48 equations in stacked form using an seemingly unrelated regressions estimator. However, in a first step the relevant indicators are still selected individually for Divisia and simple sum. In the joint model any variable (or interaction) that is found relevant for either of the two models (i.e. Divisia or simple sum) is included. When bootstrapping the impulse response of the difference between Divisia and simple sum, we simulate said difference in every bootstrap iteration, that is, from an internally consistent set of regressors, rather than just reporting the difference of the individual median estimates. Probably driven by the high correlation between shocks to Divisia and simple sum money, this approach yields very low smoothing (while producing surprisingly smooth estimates of the difference between Divisia and simple sum). Therefore, we only use this approach where needed (i.e. when reporting the difference estimate) to not obfuscate the original IRFs with unnecessary volatility. Otherwise, we focus on the smoother individual estimates of the IRFs for Divisia and simple sum.

3. DATA

Our empirical application uses monthly US data from 1990M1 to 2007M12. The start of the time series is determined by the CBOE volatility index *VIX*, which—using the current methodology—is only available since 1990.[3] The endpoint of our sample, is determined by the availability of the monetary shock that we use [Romer and Romer (2004)]. Since it relies on surprise changes in the federal funds rate around meetings of the FOMC, it has not been updated after the Fed started approaching the zero lower bound. The monetary information we use has been provided by the Center for Financial Stability (CFS). Unless explicitly mentioned, other data used are available from the Federal Reserve Database.

Monetary aggregates. For our analysis we consider Divisia M4 as provided by the CFS and its simple sum counterpart.[4] Both are considered as log differences over the forecast horizons of interest, that is, $\Delta_h dm4 = \ln(DM4_{t+h}) - \ln(DM4_t)$ and $\Delta_h m4 = \ln(M4_{t+h}) - \ln(M4_t)$. The correlation between the two of those is high (around 0.7) but still low enough to allow for clear differences in explanatory power. More importantly, when looking at deviations from trend (based on a Hodrick Prescott filter), rather than growth rates, this correlation is reduced to merely 0.5. That is, when a longer horizon is considered, the seeming similarity between simple sum and Divisia is less clear.

Monetary policy. We consider monetary policy shocks as provided in the update of the Romer and Romer (2004) data provided by Halperin (n.d.). Additionally, we control for the current stance of monetary policy measured through the federal funds target rate. The local projections approach allows to account for asymmetric effects of expansionary and contractionary shocks, thus, rather than just using the shock indicator s_t, the model includes both $s_t^+ = s_t \mathbb{1}(s > 0)$ and $s_t^- = s_t \mathbb{1}(s < 0)$. The shock measure is only available until the end of 2007, where our sample ends.

Economic activity. While most macroeconomic research uses GDP as main indicator of economic activity, our fairly short sample necessitates the use of monthly data. Therefore, we employ the log differences of real industrial production (as an approximation of monthly growth). Inflation is measured through log differences of the consumer prices index (CPI).

Financial stability. The results in the previous literature suggest that proper monetary measurement is particularly important when there is financial turmoil and the monetary transmission is impeded. Our model includes the *VIX* as a standard measure for financial fragility in the US economy. The VIX, originally proposed by Brenner and Galai (1989), measures the implied volatility of S&P500 options over the coming 30 days. It is frequently interpreted as a measure of investors fear [Whaley (2000)]. In its latest version, the *VIX* is only available since 1990, thereby setting the earliest possible starting point for our sample.

4. MODEL AND SPECIFICATION TESTS

A preliminary VAR analysis. To assess the proper number of lags to include in our analysis, we conduct a simple VAR analysis including the log differences of simple sum money (Δm_4), Divisia money (Δdm_4), and industrial production (Δy), as well as the federal funds rate (ff), the term spread between 10- and 2-year maturity US bonds treasury bills (*spread*), inflation (π), and the *VIX*:

$$\begin{bmatrix} \Delta m_4 \\ \Delta dm_4 \\ f \\ spread \\ y \\ \pi \\ VIX \end{bmatrix}_t = c + \sum_{l=1}^{p} A_l \begin{bmatrix} \Delta m_4 \\ \Delta dm_4 \\ ff \\ spread \\ \Delta y \\ \pi \\ VIX \end{bmatrix}_{t-l} + \varepsilon_t. \tag{3}$$

Both a standard Akaike information criterion and a the finite-sample-corrected Akaike criterion clearly support the most parsimonious specification with a lag order of 1. Our baseline model will be setup correspondingly.

Model setup. For our main analysis, we use a local projections framework for forecast horizons of 1 up to 24 months. In our baseline model, we assume that monetary policy only affects interest rates immediately but has no further immediate impact on the macroeconomy at a monthly frequency. Since we include no nowcast, this implies that our explanatory variables are contemporaneous with the shock. The exceptions are the interest rate variables (ff and $r_{10} - r_2$). In spirit, this corresponds to a blockwise recursive structure in a VAR, where the growth rate of industrial production, inflation, money growth, and financial uncertainty belong to the first block, followed by the monetary policy shock, and finally an interest rate block.

That is, our model takes the form:

$$\begin{aligned}
\Delta_1 m4_t &= F_1(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_1 dm4_t &= G_1(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_2 m4_t &= F_2(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_2 dm4_t &= G_2(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_3 m4_t &= F_3(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_3 dm4_t &= G_3(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
&\vdots \\
\Delta_{24} m4_t &= F_{24}(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t), \\
\Delta_{24} dm4_t &= G_{24}(s_t^+, s_t^-, \Delta m4_t, \Delta dm4_t, \Delta y_t, \pi_t, ff_{t-1}, spread_{t-1}, VIX_t).
\end{aligned} \tag{4}$$

As a robustness test, we run an additional version of the model, where all financial market variables and monetary variables are allowed to be affected immediately.

TABLE 1. Significant interactions

	$s = s^+$		$s = s^-$	
Dependent variable	$\Delta_h dm4$	$\Delta_h m4$	$\Delta_h dm4$	$\Delta_h m4$
s				
$\Delta dm4$				
$\Delta m4$	X	X	X	X
π				
Δy	X	X	X	X
VIX	X	X		
ff_{t-1}	X	X	X	X
$spread_{t-1}$	X	X		

Note: s^+ and s^- refer to positive and negative shocks, respectively.

Thus, in this robustness test, the money growth rates and *VIX* are also included as lags rather than current values.

Selected nonlinearities and scenarios. Our results concerning nonlinearities are slightly ambiguous. From the model including all interactions up to third order, the LASSO suggests to drop all interactions. However, when only including simple interactions and squared terms, we find that the majority of those interactions matters. Given that the second-order model is nested, this rather shows some problems in the application of information criteria in LASSO, than truly reflecting the superiority of a simple linear model. Therefore, all results reported from hereon refer to models where the selection operator has been applied to the set of all potential interactions and squares, but excluding higher-order polynomials and more complex interactions.

Table 1 lists all the interactions of monetary policy shocks that are selected by our LASSO. Since the signs are not necessarily identical over all forecast horizons, we merely list whether the respective interaction is selected or not, but do not report the sign. Interestingly, we find the same interactions for simple sum and Divisia. This indicates that, while simple sum is not the adequate measurement for money, it does capture some of the relevant information.

We find some notable asymmetries in our interactions. Both the *VIX* and the interest rate spread only matter for contractionary policy but do not matter for expansionary policies. Contrarily, the interaction terms of the monetary policy stance, growth and simple sum growth, are robustly significant for shocks in both directions.

Since we use highly nonlinear models for the forecasts underlyling our IRFs, there is no such thing as *the* IRF. Therefore, rather than reporting a single IRF for both Divisia and simple sum, we report a battery of IRFs generated under different starting conditions. More specifically, we set some of the variables where we find significant interaction to one standard deviation (above) or below the mean. The descriptive statistics are found in Table 2.

TABLE 2. Descriptive statistics

Dependent variable	Mean	SD
$\Delta dm4$	0.0046	0.0031
$\Delta m4$	0.0057	0.0049
π	0.0024	0.0023
Δy	0.0022	0.0052
VIX	18.3957	6.0878
ff_{t-1}	4.4007	1.8011
$spread_{t-1}$	0.8855	0.8497

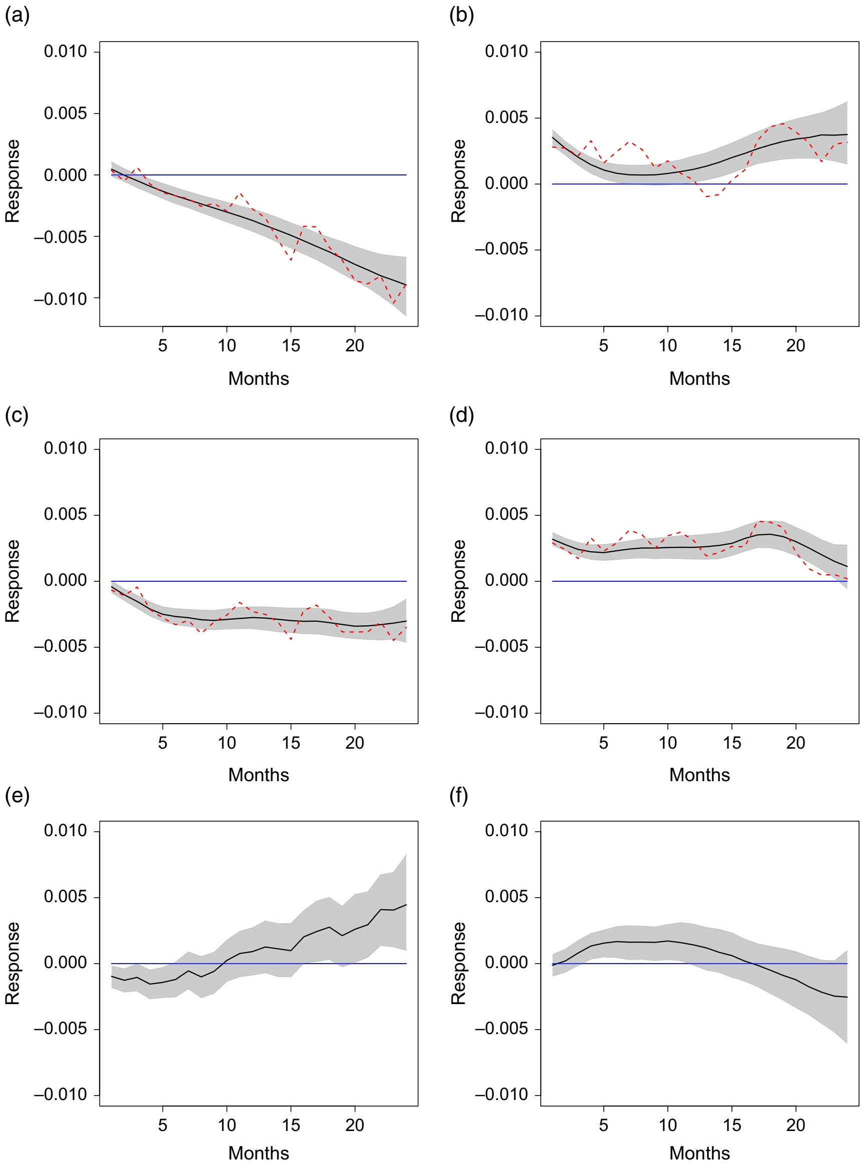
5. RESULTS

IRFs at the mean. Figure 1 summarizes the IRFs of simple sum $M4$, Divisia $M4$, and their difference for positive and negative monetary policy shocks. Both Divisia and simple sum exhibit plausible impulse responses in the sense that the respective monetary aggregate moves in the expected direction. Yet, the differences are striking.

In both cases the impact of contractionary shocks is initially small and it takes a while for monetary policy to actually decrease money supply. However, when looking at simple sum it seems as if money keeps decreasing over the entire range of forecast horizons considered. Contrarily, the impact on liquidity stabilizes about half a year after the initial shock and stays roughly constant thereafter.

The reaction to an expansionary shock happens much faster. Both simple sum money and Divisia increase immediately when the interest rate is reduced. This is highly plausible. In normal circumstances banks can easily create more liquidity by easing credit constraints. Yet, reversing their money creation process is costly and essentially depends on not renewing or replacing maturing credit.

While Divisia is mostly stable after the initial impact, simple sum significantly declines (to a point where the initial impact is almost compensated) before increasing again and eventually stabilizing. This can most likely be explained by simple sum hugely understating the role of cash and overnight deposits in liquidity provision. Unlike simple sum, Divisia correctly accounts for the fact that those components are much more liquid than other—interest bearing—assets included in broader monetary aggregates. Expansionary policy does not only affect the price of liquidity but also the relative cost of different sources of liquidity. Because low interest rates generally compress the yield curve (and thus reduce the benchmark rate), this is a plausible reaction. In this case, reducing the policy rate also reduces the relative opportunity cost of holding interest free assets (such as cash and deposits) causing a substitution into those assets. Simple sum treats one unit of—say—two-year fixed maturity debt just as it treats deposits that provide far more liquidity. Therefore, the portfolio restructuring looks as if liquidity is declining when focusing on simple sum.



Note: The solid line is the smoothed, the dashed line the unrestricted IRF.

FIGURE 1. IRFs of money to monetary policy shocks. (a) Positive shock, $M4$. (b) Negative shock, $M4$. (c) Positive shock, $DM4$. (d) Negative shock, $DM4$. (e) Positive shock, difference. (f) Negative shock, difference.

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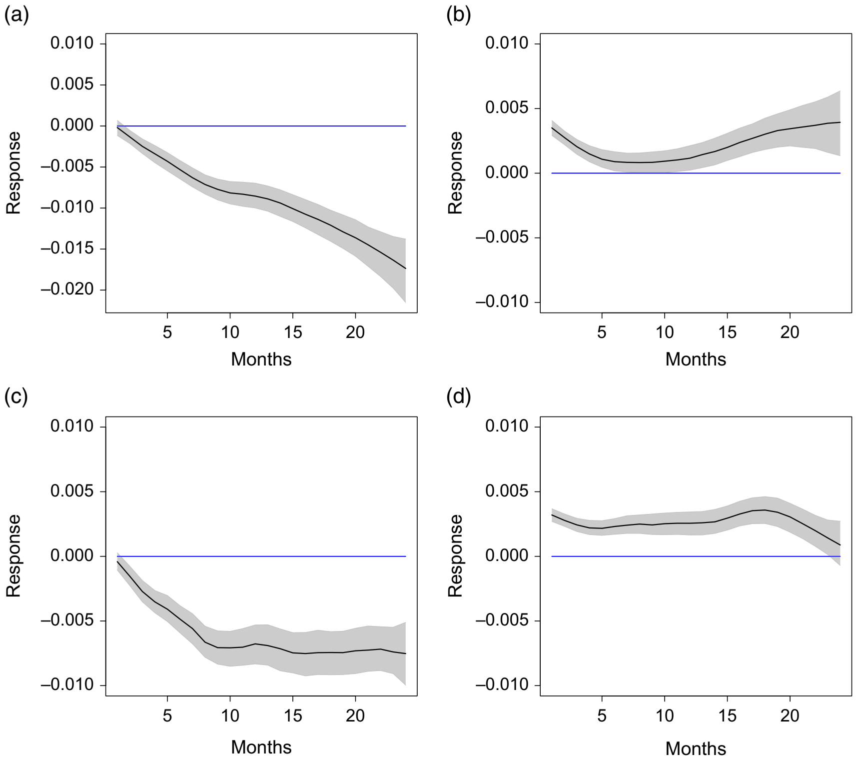

FIGURE 2. IRFs of money to MP shocks with financial uncertainty. (a) Positive shock, *M*4. (b) Negative shock, *M*4. (c) Positive shock, *DM*4. (d) Negative shock, *DM*4.

The role of financial instability. Our results suggest that the impact of interest rate hikes (i.e. contractionary monetary policy) depends strongly on financial instability (see Figure 2). Except for the first period, we find a negative interaction term for both simple sum and Divisia as dependent variable. That is, the contractionary impact of increasing the interest rate is substantially larger in times of financial uncertainty. Contrarily the impact of expansionary monetary policy does not depend on the financial conditions. While the former is intuitively appealing, the latter is in stark contrast to the narrative evidence from the most recent crisis. Due to the fear of deflationary pressure, central banks all over the world—in particular the Fed and the ECB—have attempted an unprecedented expansionary policy through quantitative easing. Yet, while the monetary base soared, money growth was barely affected.[5] However, it has to be noted that our sample does not include a financial crisis of matching magnitude of the collapse of the US real estate bubble. Unlike minor financial turmoil, the recent bust led to a temporary collapse of the interbank market and is still substantially affecting the transmission mechanism. Insofar our results should be interpreted as applying

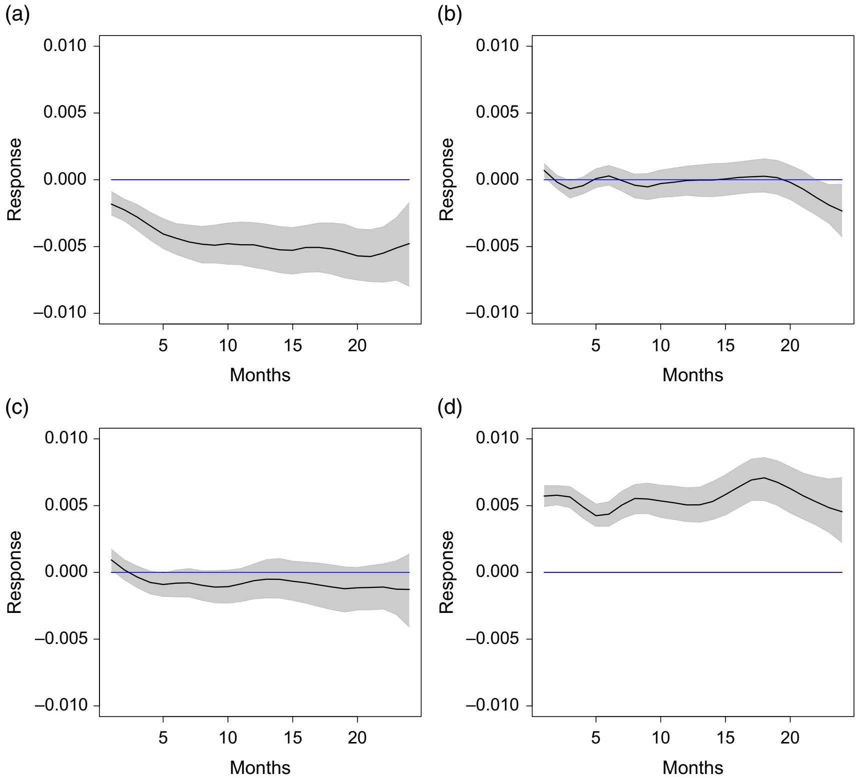

FIGURE 3. IRFs of (Divisia) money to MP shocks with a tight and loose monetary policy stance. (a) Positive shock, *DM*4, loose stance. (b) Negative shock, *DM*4, loose stance. (c) Positive shock, *DM*4, tight stance. (d) Negative shock, *DM*4, tight stance.

to financial uncertainty and recessions as they typically appear over a business cycle, rather than "black swan" events such as the Great Recession.

Monetary policy stance. Another major factor that drives the impact of monetary policy is its current stance. The IRFs for Divisia are shown in Figure 3. If monetary policy is generally accommodating with low interest rates, a further reduction of the interest rate has no additional expansionary impact. This matches expectations. At some point, the creation of more liquidity does not generate more profit for the banking sector, thus money creation fails. A more extreme example of this behavior could be observed over the past few years, when attempts to conduct a massively expansionary policy in the USA and Europe barely affected liquidity. At the same time, increasing the interest rate has a particularly strong effect in a loose policy environment. This might also help to understand the hesitation of central banks to exit the hugely expansionary policy. Past experience seems to suggest that contractions are extremely effective in a low liquidity environment, thereby making proper dosage difficult.

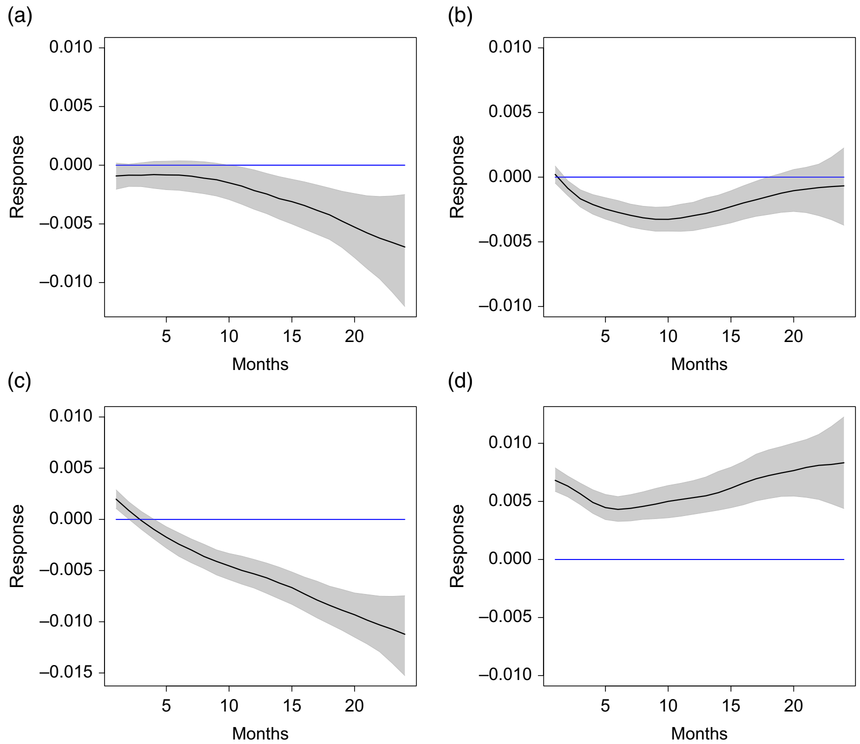

FIGURE 4. IRFs of (simple sum) money to MP shocks with a tight and loose monetary policy stance. (a) Positive shock, $M4$, loose stance. (b) Negative shock, $M4$, loose stance. (c) Positive shock, $M4$, tight stance. (d) Negative shock, $M4$, tight stance.

At the same time, contractionary shocks are ineffective when the monetary policy stance is tight. This is somewhat surprising, but not completely unreasonable. Because monetary policy no longer works through harsh restrictions (such as a binding reserve requirement), but through incentives, it is plausible that the cost for a further reduction of money creation is prohibitive at some point and cannot be overcome with the steps that the central bank is willing to take.

Finally, there is evidence for an interesting asymmetry: When looking at simple sum (Figure 4) it seems that high interest rates increase the general effectiveness of monetary policy, that is, interest rate increases are particularly effective in reducing simple sum even further if the interest rate is high. The contradicting evidence from Divisia suggests that this is mostly a portfolio rebalancing.

Business cycle effects. High growth barely affects the IRF of liquidity (measured as Divisia money). The shape of the IRF essentially remains the same. The IRF after expansionary shocks is shifted upward, the change of the IRF following contractionary shocks is quantitatively small (see Figure 5).

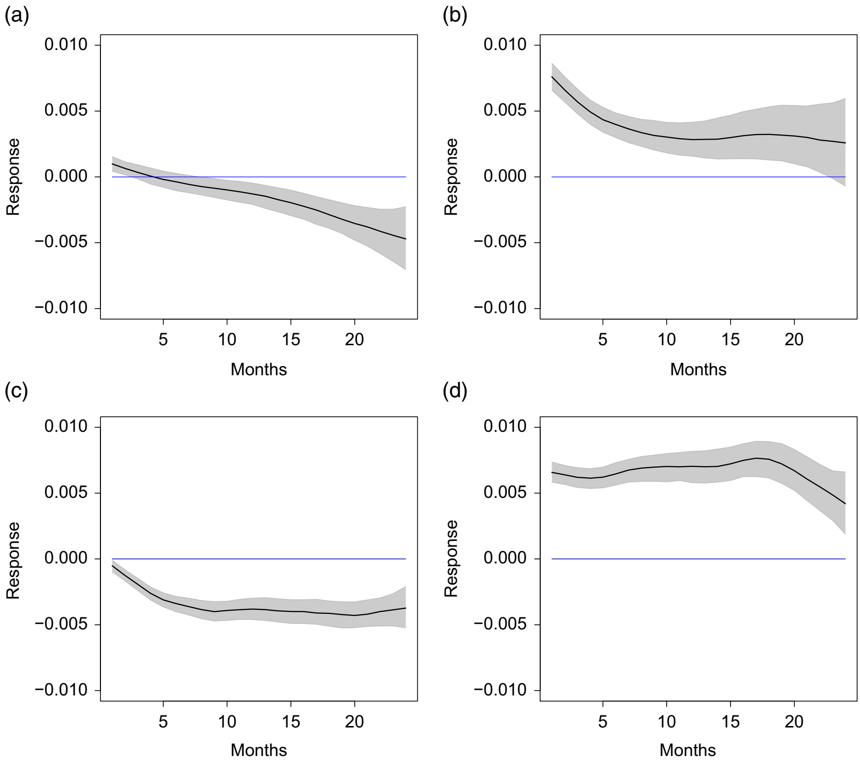

FIGURE 5. IRFs of money to MP shocks in a high-growth environment. (a) Positive shock, $M4$. (b) Negative shock, $M4$. (c) Positive shock, $DM4$. (d) Negative shock, $DM4$.

Simple sum, however, no longer responds significantly to positive interest rate shocks for many months in a high-growth environment. The confidence bounds are still fairly narrow, indicating that this lack of significance does not come from high uncertainty, but is indeed related to an economically small effect. This augments the difference between Divisia and simple sum in times of a boom. After an expansionary shock in times of high growth, we find an initially large impact on simple sum money that immediately starts declining.

Contrarily, the IRF of Divisia in response to expansionary policy changes quite drastically in times of low growth (see Figure 6). In a recession, liquidity barely responds to expansionary policy. The extremely small effect that can be observed is a contraction rather than the intended expansion. However, this contraction is so small that it seems more appropriate to treat it as zero effect despite its statistical significance. Yet, there are several channels that can explain the adverse reaction. First, measuring monetary policy shocks through market surprise might not fully remove endogeneity if the central bank has information that is unavailable to the market. If the central bank (unlike the market) anticipates a contraction,

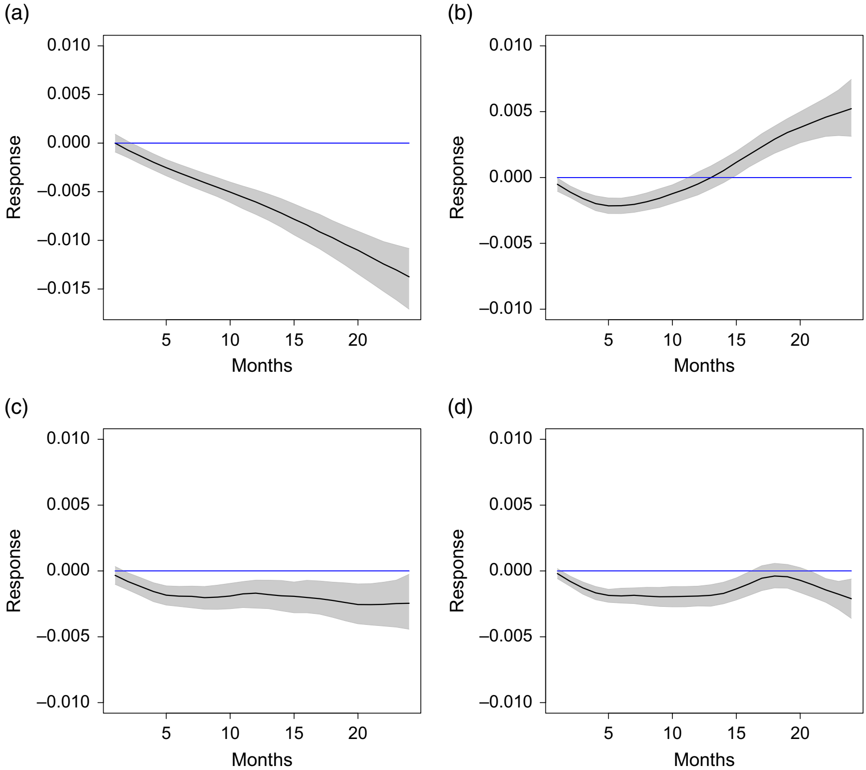

FIGURE 6. IRFs of money to MP shocks in a low-growth environment. (a) Positive shock, $M4$. (b) Negative shock, $M4$. (c) Positive shock, $DM4$. (d) Negative shock, $DM4$.

they might react to this expectation by (incompletely) preventing the contraction. Second, the market might treat the surprise action by the central bank as indicator that the central bank has hidden knowledge about (financial market) problems. Thus, the fact that the policy action is a surprise and therefore unsettling the market might (over)compensate the actual direction of the policy action itself.

Our finding casts doubt on the ability of central banks to be the major player when it comes to business cycle stabilization. Apparently, monetary policy is essentially ineffective in the most critical of times and does not even affect liquidity itself any longer.

Momentum of money growth. The last indicator included in our setup that affects the IRF of both Divisia and simple sum money supply is the growth rate of simple sum itself. In both cases, only the response to negative shocks, that is, expansionary policy is affected. We find that the impact of policy is initially dampened but increased at higher forecast horizons.

An economic interpretation here proves difficult, because it is fairly unclear what exactly simple sum measures, being a combined measure of liquidity and wealth. Yet, it has important policy implications, namely that simple sum—despite not being a proper measure of money—might contain some information that is not included in Divisia, which is clearly superior to simple sum in the intended function as monetary aggregate.

6. CONCLUSIONS

Using smoothed local projections with a LASSO-based selection of nonlinearities, we are able to show the massive nonlinearities in the response of money to policy shocks. While exhibiting some nonlinearities, Divisia—contrary to simple sum—mostly shows plausible responses. Only in most extreme cases, such as quickly declining production or very low interest rates, expansionary policy affects Divisia delayed or insignificantly. Yet, in those cases, we find plausible economic explanations. Simple sum, however, while showing the expected behavior around the mean, stops behaving economically plausible in a range of situations and usually much more erratically in the sense of substantially wider confidence bounds on average. Generally, the behavior of simple sum becomes more stochastic in extreme economic conditions, causing either extremely wide confidence bounds around the difference between simple sum and Divisia or highly significant differences. In other words, in the highly volatile times when adequate monetary policy is particularly important, the measurement problems that simple sum is prone to matter most.

Both Divisia and simple sum are highly sensitive to financial uncertainty. In particular, financial uncertainty can massively increase the response to contractionary shocks. This highlights the danger of conducting monetary policy, which merely relies on the interest rate, rather than money growth rates (based on properly measured money). By ignoring money, the New Keynesian literature fails to understand that the same interest rate change can represent huge differences in terms of monetary policy.

NOTES

1. In the case of local projections this is not necessarily the same. Since the forecasts produced do not rely on previous forecasts, it is theoretically possible to produce forecasts at specific intervals rather than for each period, as for example, done in El-Shagi (n.d.) who produces one forecast per week from a model estimated using daily data.

2. This method is inspired by the semiparametric MIDAS approach proposed by Breitung and Roling (2015) who penalizes second differences of coefficients of adjacent time lags.

3. Even including the outdated methodology would only buy another 4 years, extending the potential sample period back to 1986.

4. Among others, the recent results presented in Hjertstrand et al. (2016) give strong support to the use of broad monetary aggregates as done here.

5. This seemed to be different in the initial months of quantitative easing, when money supply did indeed sharply increase in the USA, raising concerns of inflation. See, for example, El-Shagi and Giesen (2013).

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