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Highlights

- The contribution of Money Market Funds to the Systemic Risk is analysed.
- The liquidity mismatch contributes to systemic risk during ordinary periods.
- The liquidity mismatch mitigates systemic risk during crisis periods.

Money Market Funds, Shadow Banking and Systemic Risk in United Kingdom[1]

Carlo Bellavite Pellegrini†, Michele Meoli**[,c], Giovanni Urga***

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Abstract

Shadow banking entities have been repeatedly charged with the breaking up of the recent financial crises. This paper examines the contribution of the money market funds, an important part of the shadow banking entities, to the systemic risk in United Kingdom by using the CoVaR methodology (Adrian and Brunnermeier, 2016). Using a sample of 143 money market funds, continuously listed between 2005Q4 and 2013Q4, we investigate the impact of institutional corporate variables on the systemic risk. Our results show that liquidity mismatch increases the average systemic risk over the whole period, but decreases the risk during the Great Financial Depression.

Keywords: Money Market Funds, Shadow banking, Global Financial Crisis, Panel Data.
J.E.L. Classification: G01, G15, G21, G23, C23.

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1. Introduction

Financial literature has recently devoted an increasing attention to the issue of shadow banking, exploring institutional features in the United States (Poszar et al. 2012, Adrian and Ashcraft 2016), United Kingdom (Jackson 2013), and the Euro area (Bakk-Simon et al. 2012).

In particular, the supposed involvement in the triggering of the recent financial crisis[2] has been investigated by considering the relationships between shadow banking and the traditional banking system during the financial crisis (Hsu and Moroz 2010, Meeks, et al. 2014). The main differences between the two lie in the distinction between relationship based lending versus actuarially based lending (Hancock and Passmore 2015) and the nature of core liabilities in the traditional banking system versus the noncore liabilities in the shadow banking system (Harutyunyan et al. 2015). Despite the significant bulk of research dedicated to this issue, many distinguishing features of the shadow banking activities are still unexplored, and an empirical assessment of their contribution to systemic risk is yet to come.

In particular, Money Market Funds (MMFs henceforth), ascribed by financial literature as a part of the external and independent shadow banking entities, according to the definition introduced by Poszar (2008), Poszar et al. (2012) and Adrian and Ashcraft (2016), and representing a significant part of the listed shadow banking entities, have been often criticized for having contributed to spread systemic risk. Kodres (2015) notices that during the crisis we observed runs - not the usual retail runs but wholesale funding runs - on MMFs that had provided funding to commercial and universal banks (both in United States and in Europe).

MMFs are collective investment schemes which invest in “money market” instruments, with a very negligible risk, such as short-term high credit quality and liquid debt instruments, government securities, commercial paper, certificates of deposit and short-term securities or provide repurchase agreement (repo) financing. The returns to investors in the mutual fund are a straightforward function of the gain and losses of the mutual fund’s investment portfolio. Money market mutual funds are a sort of “open end” funds in which investors get back their funds redeeming their shares[3].

The main aim of this paper is to identify the main determinants of MMFs contribution to systemic risk. There are several reasons of why focusing on MMFs is of interest. On the one hand, these shadow entities are directly involved in a revised form of risk and maturities transformation,

[2] According to *The Economist*’(10/5/2014, p. 9), Mark Carney, Governor of the Bank of England and head of the Financial Stability Board (FSB), identifies the shadow banking in emerging markets as “the greatest danger to the world economy”.

[3] The value of a share in a mutual fund can be identified in the “Net Asset Value” of the fund. The Net Asset Value of a mutual fund is the net value of all of its assets divided by the number of shares outstanding. Thus the NAV approximates the liquidation value of an investor’s shares in a fund. It is the price at which investors can buy fund shares or sell them back to the fund. The fund managers calculates the NAV of the fund each day, and when an investor wants his money back, the fund buys (or redeems) the investor’s shares at the price per share (Macey, 2011).

and are therefore likely to be identified as financial devices potentially increasing systemic risk of the financial sectors. On the other hand, they are typically seen as entities with very negligible risk, because their assets are not characterized by maturity mismatch. Therefore, following the arguments in previous literature (Macey 2011; Kodres 2015), in this paper we investigate whether the liquidity mismatch characterizing these entities lead to a positive or negative contribution to systemic risk, discriminating what we can observe during ordinary periods or during financial crises.

To this purpose, in this paper we adopt the Conditional Value-at-Risk (CoVaR) measure introduced by Adrian and Brunnermaier (2016). The CoVaR quantifies the contribution of a financial institution to systemic risk and its contribution to the risk of other financial institutions. CoVaR indicates the Value-at-Risk (VaR) of financial institution *i*, conditional on financial institution *j* being in distress. Adrian and Brunnermeier (2016) argue that this is a more complete measure of risk since it is able to capture alternative sources of risk which affect institution *i* even though they are not generated by it. Furthermore, if we consider that institution *i* is the whole financial system, then ΔCoVaR is defined as the difference between the CoVaR and the unconditional VaR and it captures the marginal non-causal contribution of a particular institution to the overall systemic risk.

In this paper, we build on the CoVaR methodology, which allows us to generate time-varying estimates of the systemic risk contribution of MMFs as a specific sector of the financial industry. We employ micro data from 143 MMF listed on the London Stock Exchange from 2005Q4 to 2013Q4 While our time span allows us to cover the different phases of the recent financial crises, namely the Subprime crisis and the Great Financial Depression, the United Kingdom's context is chosen because it represents one of the most developed shadow banking system among the European countries with a relevant presence of listed money market funds.

To anticipate some findings, our empirical applications allow us to identify what institutional features of shadow entities are correlated to systemic risk. As a contribution to previous literature, we find that liquidity mismatch plays a major role as determinant of ΔCoVaR: it increases systemic risk over the whole period, while mitigates risk during the Great Financial Depression.

The reminder of the paper is organised as follows. Section 2 describes the nature and the main features of the shadow banking system and its relationship with the systemic risk literature. Section 3 introduces the methodology and the data used in our analysis. Section 4 reports the main empirical findings. Section 5 concludes.

2. The contribution of MMFs to systemic risk

2.1 Shadow banking entities and systemic risk

One of the main challenges of recent financial literature on the topic has consisted in the identification of shadow banking activities and of features that banks do not have.

Even if "shadow banks are easier to define by what they are not than by what they are" (*The Economist*, Special Report International Banking, May 10th 2014), recent banking and financial literature provides different definitions of shadow banking. McCulley (2007) introduces the notion of shadow banking as an unregulated financial institution characterized by high leverage without to benefit from a safety net or other official guarantees. According to Adrian and Ashcraft (2016), the shadow banking system is a web of specialized financial institutions that conduit funding from savers to investors through a range of securization and secured funding techniques, while Claessens and Ratnovski (2014) define shadow banking as all financial activities, except traditional banking, requiring a private or public backstop to operate. For Mehrling et al. (2013) shadow banking is simply money market funding of capital market lending, sometimes on the balance sheets of entities called banks and sometimes on their balance sheets. Moreover, the Financial Stability Board (2011) defines the shadow banking system as the system of credit intermediation that involves entities and activities outside the regular banking system. In addition, revealing its prejudice about the role of shadow banking in financial turmoil, it states that shadow banking encompasses all financial activities and entities that increased systemic risk owing to maturity/liquidity transformation and/or leverage and/or showing indications of regulatory arbitrage as well.

This issue has been developed by the Poszar's (2008) and Poszar et al. (2012), providing a classification of the different natures and features of shadow banking entities. The authors define shadow banking as a chain of financial intermediaries that conduct credit intermediation, decomposing the same credit intermediation "into a chain of wholesale-funded, securitization-based lending" and defining seven steps of shadow bank credit intermediation. Moreover, Pozsar et al. (2012) identifies for different kind of shadow banking. The first is defined as *internal shadow banking* and consists of activities that are conducted by subsidiaries of banking holding. Hence these activities are included in the traditional banking's structure. For instance, a banking holding company may own wealth management unit or may provide liquidity to entities belonging to shadow banking system. Moreover, in many cases the largest non-bank subsidiaries of banking groups are finance companies, broker-dealers and wealth management unit, such as mutual funds, hedge fund and money market funds. For these reasons, the authors stress that the shadow banking system is organized around securitization and wholesale funding. The second category, denominated as *external shadow banking*, consists of independent and regulated institutions that conduct shadow banking activities, but these do not represent their primary business. They refer to stand-alone broker-dealers, independent wealth management institutions, credit hedge funds and finance companies, like auto loan subsidiaries. The third category, defined as *independent shadow banking*, consists of entities which are specialized only in shadow banking, such as structured investment vehicle, stand-alone money market funds, independent collateralized debt obligation, collateralized debt obligation and the majority of asset backed securities. The fourth group, defined as *government sponsored shadow banking*, includes government-sponsored enterprises, such as Fannie Mae and Freddie Mac in the United States (see also the European Commission 2012).

These four categories are partially overlapping because, for example, a money market fund may be ascribed to the first typology as a subsidiary of a banking holding, or to the third one, being an independent entity, potentially listed, and involved in shadow banking activity.

From the overview of the definitions of shadow banking, an important issue clearly emerges. In comparison with the traditional banking system, shadow banking would transform risk and maturities (Diamond and Dybvig 1983) without the presence of direct and explicit public sources of liquidity and of any sort of public deposit insurance (Adrian and Ashcraft 2016). This fact suggested that shadow banking is intrinsically fragile (Pozsar et al. 2012), and is at the basis of the exploratory researches analysing the relationship with systemic risk, as in Duca (2015), stressing the role of reserve and other regulatory requirements that induced shifts from bank loans to other sources of finance, boosting shadow banking activity in the past decade.

2.2 Money Market Funds and their contribution to Systemic Risk

The financial literature highlights, within the shadow banking sector, the wholesale funding channel as one of the potential device triggering systemic risk (Paltalidis et al. 2015). For this reasons, Poschmann (2012) focuses on mutual funds, money market funds, hedge funds and finance companies like consumer and commercial finance companies, leasing companies and factors or captive financing subsidiaries of non-financial corporations like auto or equipment lease financing related. The main mission of these companies is to provide loans to consumers and businesses; therefore, they are important suppliers of credit. Finance companies do not take deposits from public as funding source, but they issue commercial paper and other short and medium term debt instruments in order to raise funds. The increasing relevance of the above mentioned typologies of shadow banking entities is witnessed by Jackson (2013) who highlights that in Europe many small and medium enterprises are principally financed by leasing and factoring companies rather than traditional banks. Thus, it is reasonable to assume that the above described typologies of shadow banking entities, involved in a revised form of transforming risk and maturities, may be ascribed as financial devices potentially increasing systemic risk of the financial sectors.

We focus our attention on continuously listed money market funds, being a part of "external and independent" listed shadow banking entities: they are linked with the systemic risk issue and it is possible to obtain reliable data of corporate variables both in accounting and financial measures.

The main aim of this study is to test whether money market funds have contributed to increase systemic risk or to decrease systemic risk. The theoretical argument follows Hsu and Moroz (2010), suggesting that the liquidity mismatch does not necessarily imply that the assets have longer term than liabilities. For example, a money market fund can be compelled to a fire sale of assets, because of a request of an immediate liability redemption. In other words, money market funds do not have any problems connected with the existence of a maturity mismatch between assets and liabilities, because they do not have liabilities as the commercial banks financing the assets, but investors' shares. Conversely money market funds may experience an issue linked with liquidity mismatch in periods of financial crisis, because they could not have an immediate cash availability to tune the request of an investors' shares redemption with the sale of assets on the market. Therefore, while their liquidity mismatch can generally add to systemic risk in ordinary conditions, a reverse effect is likely to be observed in periods of crisis, such as during the recent Great Financial Depression.

We can formalize our expectation as follows:

Hypothesis 1: The higher is the liquidity mismatch of a MMF, the higher will be the contribution to systemic risk.

Hypothesis 2: During a financial crisis, the higher is the liquidity mismatch of a MMF, the lower will be the contribution to systemic risk.

2. Methodology and Data

Our paper makes use of the *CoVaR* measure of Adrian and Brunnermeier (2016). The most common measure of risk used by financial institutions is the value-at-risk (*VaR*), which focuses on the risk of an individual institution in isolation. The q%-*VaR* is the maximum dollar loss within the q%-confidence interval. Formally, the q-*VaR* for an institution *i* can be defined as:

$$Prob(X^i \leq VaR_q^i) = q\% \quad (1)$$

where X^i is the variable of institution i for which the VaR^i is defined that we set X^i to be the growth rates of market-valued total financial assets. Note that VaR^i is typically a negative number and, while in practice the sign is often switched, we will not follow this convention, in accordance to Adrian and Brunnermeier (2016).

The indicator of systemic risk, $CoVaR$, is defined as the VaR of the financial system as a whole conditional on some event $C(X_i)$ of institution i. That is, $CoVaR_q^{system|C(X^i)}$ is defined by the q-th quantile of the conditional probability distribution:

$$Prob(X^{system}|C(X^i) \leq (CoVaR_q^{system|C(X_i)}) = q\% \quad (2)$$

where X^i is the market-valued asset return of institution i, and X^{system} is the return of the portfolio, computed as the average of the X^i's weighted by the lagged market value assets of the institutions in the portfolio. Adrian and Brunnermeier (2016) measure the contribution of each single institution to systemic risk by the *ΔCoVaR*, namely the difference between *CoVaR* conditional on the institution being in distress and *CoVaR* in the median state of the institution.

As far as the estimation method is concerned, quantile regressions are employed to estimate *CoVaR*. First, one can estimate the predicted value of a quantile regression where the financial sector losses $X_q^{system|X^i}$ is determined given the losses of a particular institution i for the q%-quantile:

$$\hat{X}_q^{system|X^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \quad (3)$$

where $\hat{X}_q^{system|X^i}$ denotes the predicted value for a particular q%-quantile of the system conditional on a return realization X^i of institution i. From the definition of *VaR*, in equation (1), we have that:

$$VaR_q^{system|X^i} = \hat{X}_q^{system|X^i} \quad (4)$$

In practice, the predicted value from the quantile regression of the system losses on institution i losses gives the value at risk of the financial system conditional on X^i, because the $VaR_q^{system|X^i}$ is simply the conditional quantile. Using the particular predicted value of $X^i = VaR_q^i$ yields the $CoVaR_q^i$ measure. More formally, within the quantile regression framework, the $CoVaR_q^i$ measure is:

$$CoVaR_q^i = VaR_q^{system|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \quad (5)$$

The $\Delta CoVaR_q^i$ is therefore given by:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_{50}^i = \hat{\beta}_q^i (VaR_q^i - VaR_{50}^i) \quad (6)$$

In order to simplify the notation, in what follows q is always set to be 5%, so that $CoVaR^i$ identifies the system losses predicted on the 5% loss of institution i, while $\Delta CoVaR^i$ identifies the deterioration in the system losses, when the institution i moves from its median state to its 5% worst scenario.

These measures are defined as time-varying, and in practice, in order to estimate the time-varying VaR_t, as in equation (3) and CoVaR_t, as in equation (5), we include a set of state variables to capture the time variation in conditional moments of asset returns. With references to these specific market's factors, we also follow the implementation adopted by Lopez-Espinosa et al. (2012) to take into account the peculiarities of the European institutional environment. In practice, in our analysis we use the following variables:

1. *FTSE-Vol:* is the weekly price of the index of the FTSE 100 as a volatility index; ii)
2. *Liquidity Spread:* is the liquidity spread calculated as the difference between the three months UK repo rate and the three months UK T bill;
3. *T-bill change:* indicates the change in UK T bill 3-month rate;
4. *Y-Curve slope:* indicates the change in slope of the yield curve represented by UK 5-year minus three-months interest rate on government bonds;
5. *Credit spread:* indicates the change in credit spread represented by the difference between BBB corporate bonds and the ten year German government bonds;
6. *Equity Return:* indicates the weekly equity returns from the FTSE 100.

Our analysis is performed on a sample of 143 British MMF continuously listed between 2005Q4 and 2013Q4, thus covering the Subprime Crisis and the Great Financial Depression. Table 1 shows the total market capitalization of the sample. Over the period 2005Q4-2013Q4, money market funds represent an average capitalization of roughly 76% of listed shadow banking entities in the United Kingdom, being the remaining part constituted by finance companies. In terms of capitalization the whole sector was severely hit between 2007 and 2009 by the Great Financial

Depression, registering in 2011 the recovery of 2007's market capitalization and a further significant increase since then.

[INSERT HERE TABLE 1]

Table 2 reports the mean, median, minimum, maximum and standard deviation values of 95%-risk measures, computed for 143 entities on weekly data for the period 2005Q4-2013Q4 and financial market losses X(i). Indicating with ME_t^i the market value of a money market fund and with LEV_t^i the ratio between total assets and common equity, we can define:

$$X_i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i} \quad (7)$$

where the sum of all the X_i of the sample givesX_{system}, namely the growth rate of the market value of the total asset of financial sector under analysis. The values of *VaR* are obtained by performing the quantile regressions (95%) of weekly lagged returns of market variables and computing the expected value of the regression. The *CoVaR* is the expected value of the quantile regression (95%) of the capital losses of the financial system on the financial losses of the individual institution and delayed market variables. The *ΔCoVaR* is the difference between the *CoVaR* with a quantile regression to 95% and that to 50%.

Table 2 shows that money market funds of our sample went through some turbulent period. Indeed, during 2005Q4 and 2013Q4, the VaR was almost equal to -2% (on average), while the CoVaR and ΔCoVaR were equal to -2.1% and -2%, respectively. However, whenever we observe the values of the same quantities for the European traditional banking (Bellavite Pellegrini et al. 2015), we find a different picture: i.e the VaR is equal to -9% (on average), CoVaR equal to -5.2% (on average) and a ΔCoVaR equal to -3.6%, which are considerably larger values than those found for the UK money market funds.

[INSERT HERE TABLE 2]

Once estimated the *ΔCoVaR*, our analysis implies the identification of the institutional determinants correlated. For the U.K. money market funds, we take into analysis the corporate variables as described by Adrian and Brunnermaier (2016) and by Lopez Espinosa et al. (2012) and adapt them to the money market funds specificities. For this mentioned reason we take into consideration a modified variable of maturity mismatch and we define it as "liquidity mismatch", as mentioned above, according to (Hsu and Moroz 2010; Poschmann 2012), as an effective main potential source of systemic risk.

1. *Leverage* indicates the leverage calculated as the total assets to equity ratio of the money market fund i at quarter (t-1);
2. *Liquidity Mismatch* indicates the relative level of short term funding as the total short term debt minus cash to total liabilities ratio of money market fund i at quarter (t-1);
3. *ERV* indicates the equity return volatility;
4. *Beta* is the equity market beta ;
5. *M-t-B* is the market to book ratio of money market fund i at quarter (t-1);
6. *Size* represents the total assets of money market fund i at quarter (t-1).

In Table 3, we report the descriptive statistics both for the institutional variables and for the state variables to capture the time variation in conditional moments of asset returns. If we compare the values with those of the UK traditional banking system (as reported in Bellavite Pellegrini et al. 2014), we notice that the average value of leverage, 1.54, is more than ten times lower than the traditional banking system one of 22.34, while the liquidity mismatch experiences a negative value of -3.70 which may be only partially compared with the maturity mismatch for the traditional banking system which shows a value of 7.17. Only a slight difference arises regarding the market to book value being 0.94 for money market funds as compared to 1.01 for the traditional UK banking system, while the beta coefficient in the traditional banking system is 1.26, which is more than double than in our money market funds of 0.56.

[INSERT HERE TABLE 3]

3. Empirical Results

We estimate a panel predictive regression model with fixed effects, where the full specification can be described as follows:

$$\Delta CoVaR_{it} = \beta_{i0} + \beta_1 \Delta CoVaR_{it-1} + \beta_2 VaR_{it-1} + \beta_3 Leverage_{it-1} + \beta_4 MM_{it-1} + \beta_5 ERV_{it-1} + \beta_6 Beta_{it-1} + \beta_7 MBV_{it-1} + \beta_8 Size_{it-1} + \beta_{c1} Crisis_1 + \beta_{c2} Crisis_2 + \sum_{k=1}^{m-1} \beta_k Time_k + \varepsilon_{it} \quad (8)$$

Table 4 reports the results of several estimated equations, where the specification described above has been simplified according to the following rules. Column (1) represents our baseline specification considering the full sample period, without crisis and time dummies. In column (2), we report the regression containing time dummies. Specification (3) considers crisis dummies: in particular, the dummy variable Crisis 1 captures the characteristics of the Subprime Crisis, containing period between the outbreak of subprime loans crisis in 2007Q3 and the outbreak of crisis in 2008Q3; the dummy variable Crisis 2 captures the effects of the Global Financial Crisis running since 2008Q4 (the bankruptcy of Lehman Brothers) to 2010Q2.

[INSERT HERE TABLE 4]

Model (1) highlights that equity return volatility has a negative and statistically significant impact on systemic risk, meanwhile liquidity mismatch has a negative impact on systemic risk. This latter results confirms our Hypothesis 1. As far as the other corporate variables are concerned, money market funds' beta and market to book value are likely to mitigate systemic risk. Model (2) confirms former finding when controlling for time-specific effects. Model (3) documents a negative and statistically significant impact of the dummy Crisis 1 while Crisis 2 dummy has a positive impact. This latter finding suggests that money market funds have contributed to decrease and not to increase systemic risk during the Global Financial Crisis in United Kingdom, being otherwise their role much more detrimental during the Subprime Crisis. In broad terms, Black et al. (2013) document a similar result about the contribution of the British banking system to the systemic risk of the European ones.

Table 5 reports the marginal effect of money market funds corporate variables over Crisis 1 and Crisis 2. Column (4) reports the main coefficients, while column (5) and column (6) report the marginal effects, i.e. the interactions between the money market funds' corporate variables and Crisis 1 and Crisis 2, respectively.

[INSERT HERE TABLE 5]

The results listed in Column (5) show that none of the money market funds corporate variables was moderated by the Subprime Crisis, while Column (6) reports a positive impact of liquidity mismatch and beta coefficient on systemic risk during the Global Financial Crisis. This results confirms our Hypothesis 2, and represent a contribution with respect to former literature, where the maturity mismatch is identified as negatively related to risk, especially in a context of crisis. Indeed, empirical evidence on traditional banking (Bellavite Pellegrini et al. 2015; Betz et al., 2016), suggests that the traditional banking system maturity mismatch represents a proxy of interconnectedness among financial institutions, being extremely beneficial in normal times and very detrimental during the financial turmoil. As far as the shadow entities are concerned, Hsu and Moroz (2010) stress that money market funds liquidity mismatch has not too much to share with traditional banks maturity mismatch, because it does not imply that assets have a longer average duration than liabilities. A money market funds has to sell off its assets whenever none of the liabilities can be rolled over.

The different results that we report with respect to MMFs may be interpreted according to the different institutional features of liquidity mismatch for money market funds and for maturity mismatch in the traditional banking system. In this respect, Table 2 shows how the average value of liquidity mismatch for money market funds is negative and how these entities are featured by a low level of leverage. If we combine these two pieces evidence, it emerges that money market funds are characterized by the existence of a potentially satisfying level of liquidity. For money market funds, this corporate variable is likely to represent a proxy of liquidity endowment which is useful in lowering systemic risk during the financial turmoil. Similar evidence occurs for the beta coefficient being likely to respectively decrease systemic risk in the Great Financial Depression for money market funds and to increase for traditional banks.

4. Conclusions

This paper evaluated the impact of the corporate variables of 143 continuously listed money market funds, a considerable part of shadow banking entities, on systemic risk in United Kingdom over the period 2005Q4-2013Q4 covering both the Subprime Crisis and the Great Financial Depression. Corporate and financial descriptive statistics suggest that UK money market funds are featured by an average value of leverage more than ten times lower as compared with traditional UK banks, as well as by a negative average value for the liquidity mismatch. An important result of our study is related to the different impact of liquidity mismatch on systemic risk on the whole period and during the Global Financial Crisis, being first negative (implying increasing systemic risk) and the second positive (decreasing systemic risk). As comparison, the results for the European traditional banking system reported by Bellavite Pellegrini, et al. (2015) show that maturity mismatch have an opposite impact. In this respect, UK listed money market funds are likely to have decreased rather than increased systemic risk during the Global Financial Crisis.

These results are confirmed when we introduce in our specification two Crisis dummies, documenting a negative impact during the Subprime Crisis and a positive impact during the Global Financial Crisis. Most likely this finding depends on the different endowment of liquidity of these entities had in comparison with traditional banks.

It will be interesting to extend this research to other shadow banking entities, such as finance companies for instance, also considering other European countries, in particular continental Europe. We leave this development to future research.

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TABLES

Table 1. Market capitalization for the full sample of money market funds (mln £). The table reports the average market capitalization, calculated year by year, for the sample of 143 money market funds continuously listed in the UK over the period 2005Q4-2013Q4.

Capitalization/Years	2005	2007	2009	2011	2013
Money market funds	30,263.00	41,275.90	29,272.29	39,291.51	46,448.25

Table 2. Summary Statistics. The table reports the average and median values, and the standard deviation of the corporate variables, for the sample of 143 money market funds continuously listed in the UK between 2005Q4 and 2013Q4, and of the variables used to estimate the $\Delta CoVaR$, calculated over the period 2005Q4-2013Q4.

	Average	**Median**	**Standard Deviation**
Leverage	1.547	1.101	6.679
Liquidity Mismatch	-3.704	-0.104	32.768
ERV	0.013	0.011	0.007
Beta	0.568	0.577	0.353
M-t-B	0.948	0.900	0.906
Size (mln£)	212.439	184.427	109.737
FTSE-Vol	0.012	0.010	0.006
Liquidity Spread	0.086	0.073	0.070
T-Bill Change	-0.010	-0.002	0.049
Credit Spread	2.687	2.714	0.555
Y-Curve Slope	0.005	0.003	0.034
Equity Return	0.009	0.026	0.076

Table 3. Summary Statistics for *X(i), VaR, CoVaR and* Δ*CoVaR*. The table reports average, median, min and max values, standard deviation, for the growth rate in market value of the total asset (*X(i)*), for the Value at Risk (*VaR*), for the *CoVaR* and the Δ*CoVaR* measures, calculated for the 143 money market funds listed in UK over the period 2005Q4-2013Q4.

	Average	**Median**	**Minimum**	**Maximum**	**Standard Deviation**
X(i)	0.00173	0.00116	-32.242	61.409	0.2878
VaR	-0.0173	-0.0103	-32.242	12.662	0.1379
CoVaR	-0.0213	-0.02145	-0.2663	0.4236	0.0157
Δ*CoVaR*	-0.0196	-0.0185	-0.2304	0.39123	0.01540

Table 4. Regression Analysis of ∆Covar Determinants. The table reports the results of Fixed Effects Panel Model regressions for the ∆Covar of 143 UK money market funds over the period 2005Q4-2013Q4. Robust standard errors in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10%, respectively.

VARIABLES	(1)	(2)	(3)
∆CoVaR (-1)	0.673***	0.692***	0.678***
	(0.014)	(0.015)	(0.014)
VaR (-1)	0.014	0.013	0.012
	(0.010)	(0.008)	(0.009)
Leverage (-1)	-0.001	-0.000	-0.001
	(0.000)	(0.000)	(0.000)
Liquidity Mismatch (-1)	-0.004**	-0.002	-0.003*
	(0.002)	(0.002)	(0.002)
ERV (-1)	-1.729***	-0.346	-1.678***
	(0.281)	(0.222)	(0.310)
Beta (-1)	0.015**	0.015**	0.012
	(0.008)	(0.008)	(0.008)
M-to-B (-1)	0.009**	0.006*	0.008**
	(0.004)	(0.003)	(0.004)
Size (-1)	0.002	0.002	0.020
	(0.013)	(0.011)	(0.013)
Crisis 1			-0.022***
			(0.003)
Crisis 2			0.006*
			(0.004)
Constant	-0.065	-0.037	-0.154**
	(0.071)	(0.058)	(0.067)
Time dummies	No	Yes	No
Observations	4,719	4,719	4,719
R-squared	0.550	0.611	0.557
Number of id	143	143	143
AIC	-11740	-12337	-11814
BIC	-11689	-12087	-11750

Table 5. Regression Analysis of ∆Covar Determinants (Marginal effects for money market funds over the financial crisis). The table reports the results of a Fixed Effects Panel Model regression for the ∆Covar of the 143 UK money market funds over the period 2005Q4-2013Q4. Column (4) reports the baseline coefficients, Column (5) the coefficients of the variables interacted with Crisis 1, and Column (6) the coefficients of the variables interacted with Crisis 2. Robust standard errors in parentheses. ***, ** and * represent the statistical significance at 1%, 5% and 10%, respectively.

VARIABLES	(4) Baseline coefficients	(5) Marginal effects over Crisis 1	(6) Marginal effects over Crisis 2
∆CoVaR (-1)	0.666***	0.095***	0.000
	(0.018)	(0.023)	(0.024)
VaR (-1)	-0.008	0.003	0.035**
	(0.011)	(0.025)	(0.016)
Leverage (-1)	-0.002**	-0.005	0.004
	(0.001)	(0.005)	(0.003)
Liquidity Mismatch (-1)	-0.006***	0.013	0.012***
	(0.002)	(0.027)	(0.004)
ERV (-1)	-1.687***	-0.757	-0.050
	(0.355)	(0.550)	(0.501)
Beta (-1)	0.009	0.019	0.022*
	(0.008)	(0.013)	(0.013)
M-to-B (-1)	0.017**	-0.005	-0.024
	(0.008)	(0.014)	(0.015)
Size (-1)	0.020	0.004	-0.007
	(0.012)	(0.006)	(0.008)
Crisis 1	-0.015		
	(0.033)		
Crisis 2	0.054		
	(0.040)		
Constant	-0.060*		
	(0.036)		
Observations	4,719		
R-squared	0.562		
Number of id	143		
AIC	-11828		
BIC	-11662		

Appendix

Table A1. Average and median values of balance sheet variables by year (mln £). The table reports the average and median values of some balance sheet values, calculated year by year for the sample of 143 money market funds listed in UK over the period 2005Q4-2013Q4.

	2005	2007	2009	2011	2013
Total Asset					
Average	268.33	353.81	259.12	338.00	398.16
Median	143.42	177.80	126.17	180.05	202.81
Common Equity					
Average	235.29	317.52	227.16	299.32	355.81
Median	114.07	158.08	114.07	158.84	175.35
Short Term Debt					
Average	6.92	10.23	7.34	13.33	15.59
Median	0.05	1.41	-	0.37	4.15
Cash&Equivalent					
Average	11.20	14.65	16.38	15.31	17.37
Median	3.03	2.90	3.93	3.45	3.10
Total Liabilities					
Average	31.72	35.03	30.68	38.60	42.20
Median	12.76	12.70	9.42	11.29	14.66