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# On the role of the ECB's collateral framework in preventing fire sales

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## Abstract

*In this paper, I analyze the impact of the extension of the ECB's collateral framework on securities sales. In addition, I evaluate the impact of different macroeconomic and bank-specific characteristics on banks' selling behavior. At this, I distinguish between healthy banks and banks rescued from the German government hypothesizing that distressed banks manage sales of their assets differently. My analysis is based on quantile regressions for panel data containing securities holdings of 27 German banks, which allows an assessment of extremely large sales. Such selling behavior could cause a collapse of prices and lead to fire sales adversely impacting other financial institutions. I find clear evidence that the ECB's collateral framework has a stabilizing impact on sales of assets, especially for impaired banks' and during the crisis the relationship is significant.*

*Key words:* Fire Sales, ECB's collateral framework, Banks, Quantile Regressions

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\* The paper represents the authors' personal opinion and not necessarily those of the Deutsche Bundesbank. All remaining errors are of course my own. This paper contains very preliminary results; please do not circulate or cite the paper.

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## 1 Introduction

After the fall of Lehman the volume of the Eurosystem's eligible marketable assets increased materially. In this paper, I assess the impact of this extension on extreme securities sales by large German banks. In addition, I evaluate the impact of different macroeconomic and bank-specific characteristics on banks' selling behavior. For this purpose I distinguish between healthy banks and banks supported by the German government hypothesizing that distressed banks manage sales of their assets differently.

One of the most potent contagion channels - the fire sales channel - has been at the core of the policy discussions also in the current financial crisis. Banks that experience high demand for liquidity owing to unusual demands of banks' customers or even panic withdrawals could be forced to sell assets in order to raise money very quickly. Such distressed sales can cause a collapse of prices in certain market segments, indirectly forcing other financial institutions with exposures to these markets to adjust the valuations of their assets.

In normal market environments, an adjustment mechanism would set in, since investors would have an increased interest in buying undervalued assets. However, in a crisis, with potential buyers sustaining losses of their own, this mechanism does not take place. Given that demand by potential buyers is limited, financial institutions may be forced to sell assets at fire sale prices. Shleifer and Vishny (1992) and Duffie et al. (2007) show that forced asset selling could cause transaction prices to significantly deviate from fundamental prices. However, this mechanism of fire sales will not be set in motion if banks are able to find alternative sources of funding. Such alternative sources include secured borrowing from the central banks and capital injections from the government.<sup>1</sup> Therefore, as the global financial crisis unfolded and the support

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<sup>1</sup> The pressure on balance sheets can also be relieved by issuing new debt, raising equity capital, scaling back of loan growth, cutting dividends and reducing stock repurchases. However, these sources of liquidity may not be available in times of stress and typically take more time in comparison to asset sales.

of banks became paramount, the Eurosystem widened its collateral framework to support bank lending and the liquidity in euro-area money market. In addition, national governments including Germany provided rescue schemes such as capital injections and guarantees in order to restore financial stability (Stolz and Wedow, 2010).

Even though this risk transmission channel has gained much attention from policy makers and the academic community, the empirical and theoretical evidence is controversial with regard to the existence and causes of fire sales, their contagious impact and the meaning of the potential amplification mechanisms such as low market liquidity, fair value accounting, regulatory capital requirements and securitized banking.

Brunnermeier and Pedersen (2009) provide a theoretical model where assets' market liquidity is linked to traders' funding liquidity. They formulate an amplification mechanism where in an environment of increasing market illiquidity and rising haircuts, a trader who experiences funding problems is forced to reduce his securities positions. However, the greater the amount of securities sales, the more prices for this security will deteriorate and move away from their fundamental level. As a consequence, the trader experiences losses on his remaining positions. Decreasing market prices drive haircuts to increase further forcing the trader to reduce his positions by selling larger amounts. Similarly, Allen and Carletti (2006), Adrian and Shin (2010), Krishnamurthy (2009) argue in favor of the hypothesis that liquidity shortages could force banks to sell assets at the times when securities markets are illiquid. In addition, Acharya et al. (2011) and Shleifer and Vishny (2011) observe assets diminishing in size in response to bank's funding problems. The importance of fire sales is further underpinned by two empirical studies which investigate the existence of fire selling for insurance companies. Ellul et al. (2011) find that firms which are capital constrained by regulation are more likely to sell downgraded bonds at prices which deviate from fundamentals. Such deviations are pronounced especially when the whole insurance industry is distressed, im-

plying that many insurance companies experience capital constraints. Merrill et al. (2012) find that if an insurance company applies fair value accounting, it improves its regulatory capital position by selling impaired assets even if it has to accept a liquidity discount.

On the other hand, empirical studies by Chari et al. (2008) and He et al. (2010) show evidence of asset growth during the last crisis rather than a curtailed banking activity. In addition, Diamond and Rajan (2011) explain theoretically that asset sales during periods when markets are illiquid are irrational from the perspective of an individual illiquid institution. They argue that expected future fire sales, which could lead to a bank insolvency, will be priced into the current value of assets. To put it differently, potential buyers of the assets would immediately demand a higher return if they expect that assets will be sold at fire prices very soon. Hence, for the buyer it is rational not to buy but to hold on their cash. For the selling bank it is thus irrational to sell the asset at the non-optimal price, especially if this bank expects the asset price to recover. Furthermore, the authors argue that the higher the number of distressed banks in the system which are under pressure to sell illiquid assets the higher the downward pressure on asset prices and the less interested distressed banks are to sell. Three empirical studies which analyse asset sales by commercial and investment banks, and hedge funds (Boyson et al. (2013), Boyson et al. (2012b), Boyson et al. (2012a) do not find empirical evidence for asset fire-selling into falling markets. Furthermore, financial institutions prefer to sell liquid assets in crises, when they need to raise cash. Moreover, banks' funding needs are significantly related to positive deposit growth and issuance of equity rather than to asset sales.

With my study, I aim to contribute to the literature by evaluating the Eurosystem's response to the crisis in form of an extension of collateral framework. Particularly, I aim to answer the question whether the level of eligible assets held by banks in Germany has a stabilizing effect on extremely large sales, distinguishing in subsequent steps of the analysis between sales of ECB eligi-

ble and non-eligible assets. I expect that having ECB funding as an extended alternative source of liquidity, banks will sell fewer assets. Against the theoretical background that especially funding shortages are the most important driver for banks to sell their assets, I include CDS spreads as a proxy for bank's funding costs. In addition, I answer the following questions. First, is there a significant relationship between banks' asset sales and their liquidity needs? Is a bank's capitalization and its selling behavior related? Second, do market liquidity conditions matter for banks' asset sales? More specifically, I analyze these questions by distinguishing between 16 healthy banks and 9 banks which received support from the German government during the global financial crisis.

In my analysis, I rely on quantile regressions for panel data, which allow me to assess the impact of the explanatory variables on different quantiles of the dependent variable. This is particularly useful for understanding the drivers of extremely large amounts of securities sales.

My analysis is based on a unique data set on securities holdings of large German banks, including all D-SIFIs (domestic systemically important financial institutions). The sample includes 27 banks representing 52% of total assets of all German banks. The data are available on a quarterly basis from the end of 2005 until the end of 2011. The dependent variable consists of all negative changes in the security holdings.

With regard to my findings, I find evidence that the amount of available central bank eligible assets has a stabilizing effect on sales for the ECB non-eligible assets. The relationship is significant in particular for distressed banks and during the crisis. The relationship is even stronger when considering the extreme quantiles of sales. In addition, I find evidence confirming a positive relationship between funding costs and the amount of assets sold. In contrast, the capitalization of a bank measured with Tier 1 capital seems not to be a robust explanatory variable for asset sales.

The paper is structured as follows. In the next section, I describe the vari-

ables and provide descriptive statistics, followed by a model specification. The subsequent results section is subdivided into three parts: the basic specification, capital constraints, funding shortage and liquidity needs, and the ECB's eligible assets and distressed banks.

## 2 Descriptive statistics

### 2.1 Data sources

The data for the analysis are obtained from various sources. The main source is the Securities Deposits Statistics (SDS) - *Depotstatistik* of the Deutsche Bundesbank, which contain detailed quarterly information on all securities holdings of all German banks in terms of volume (i.e. a euro total) excluding derivatives. Thereby, the observation unit is the amount (in euros) that bank  $i$  holds from security  $j$  at the time  $t$ . The data is available from 2005Q3 until 2011Q4, both on the nominal and market value. For the purpose of my analysis, I eliminate those observations from the sample that banks hold for their customers and those observations where the holder is equivalent to the issuer. Despite the uniqueness of the SDS, it inhibits some notable shortages. First, the holdings of banks' branches located in foreign countries are not included. Second, banks are not asked to provide information on derivatives and finally, the quarterly frequency is not totally optimal for my analysis. Higher frequency would enrich the understanding on bank's selling patterns, but on this stage this data source is the best to get.

In addition to the securities holdings, the information on issue and maturity date of bonds is obtained from the Centralised Securities Database (CSDB). Using this information I distinguish between actual sales and the normal expiry of the bonds. Quarterly data on the eligibility of securities for European System of Central Banks (ESCB), corresponding valuation haircuts and bank

specific information are available at the Deutsche Bundesbank. The single name 5-year senior CDS spreads for banks are from Markit Group. The indicators on the liquidity of different market segments are obtained from the ECB.

### *2.1.1 Variables description and stylized facts*

For the construction of the indicators for banks' selling/purchasing patterns, I use nominal values from SDS in order to exclude pure price effects. The dependent variable is the overall sales, the sales of ECB eligible and non-eligible assets.<sup>2</sup> All measures of banks' selling/purchasing patterns are constructed as an aggregate of all negative/positive changes of all securities held by bank  $i$  for each period of time  $t$  in comparison to the previous period  $t - 1$ . Securities whose maturity date is equal to the respective quarter are not included in the aggregated measure, to better capture actual sales and to avoid distorting the measure by maturing assets. If security  $j$  has a positive value in the period  $t - 1$  and the value disappears in the period  $t$ , I assume that the security has been sold in the period  $t$ . The value of the holding for the specific security is negative/positive if a bank sold more/less than it bought of this specific type of security. Therefore, these measures stand for net sales/net purchases with regard to the specific security.

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<sup>2</sup> For my analysis the different types of securities are not at major importance. For more details on the asset classes and how banks changed their investment strategies over time, see Hildebrand et al. (2012). The major share of banks' portfolios in my sample are different types of bonds including Floating Rate Notes, Pfandbriefe/Covered Bonds and Government Bonds. Their overall share equals to approximately 64%. From the sample I drop retail investment certificates, since for them the nominal and market values are not available, only the number of the securities held by bank is registered instead. Their share is equal to 6%. The remaining assets classes are Asset Backed Securities and shares, which represent approximately 28% of total securities.



Figure 1. Average measures based on portfolio holdings, from 2005 to 2011

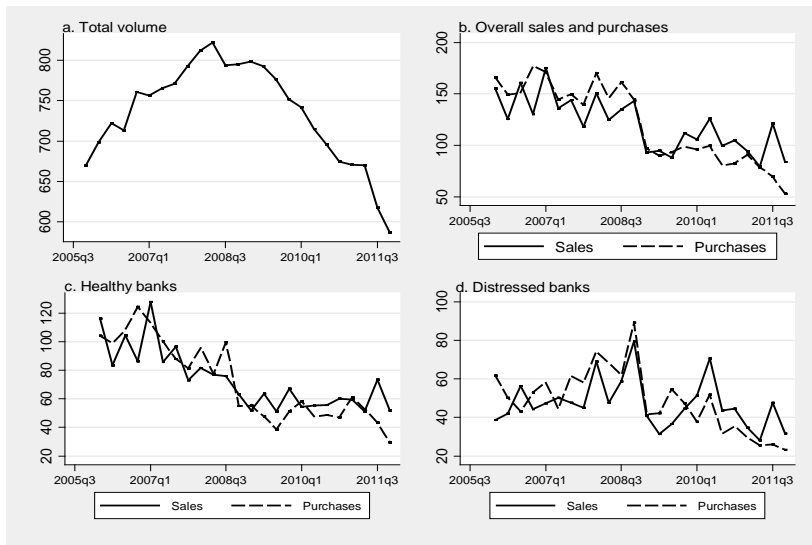
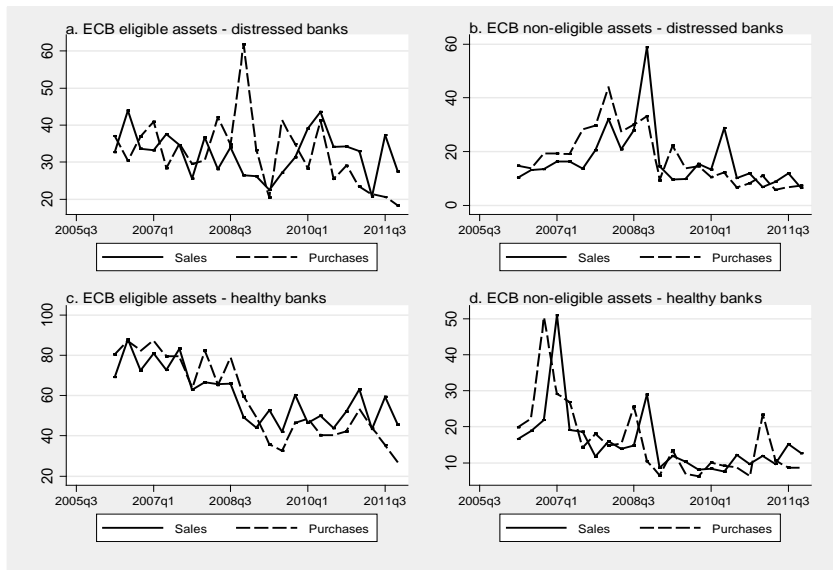


Figure 1a shows that the aggregated securities holdings were at their maximum in the second quarter of 2008 and were approximately equal to Euro 822 billion, while at the end of the period under review (2011 Q4) the volume was down to approximately Euro 583 billion. It becomes clear that from the end of 2008 the banks under review started to reduce their overall securities positions and became less active, both with regard to their selling and purchasing behavior (see Figure 1(b.)). I expected to see such a development, since during the crisis and its aftermath banks were put under pressure (came from markets, policy makers, regulators) to reduce their leverage. The first interesting feature emerging from my data is that the selling and purchasing behavior of healthy banks in terms of sold/bought volumes differ from that of distressed banks. While healthy banks reduced their activity gradually (see Figure 1(c.)) throughout the period under review, distressed banks were very active with regard to both sold and bought volumes around the Lehman event in 2008 Q3 (see Figure 1(d.)). Starting in 2010 Q1 both groups of banks sold more assets than they bought at the same time, though for healthy banks this difference is less pronounced.

Figure 2 illustrates the selling and purchasing patterns for healthy and dis-

tressed banks broken down by ECB eligible and ECB non-eligible assets. The second interesting feature is that one quarter after the Lehman bankruptcy in 2008 Q4 distressed banks sold ECB non-eligible securities valued at approximately 60 billions Euro and purchased approximately the same volume of ECB eligible securities. By contrast, healthy banks exhibit high volumes of ECB eligible assets bought from the beginning of the period under review. The ratio (see Figure 3 a.) of ECB eligible assets to total holdings confirms that healthy banks held more ECB eligible securities in their portfolios over the entire period. The ratio of ECB eligible securities decreased gradually for distressed banks to its minimum of 67% in 2008Q3. It started to increase for the first time after the Lehman bankruptcy.

Figure 2. Selling and purchasing patterns in volumes (bn), from 2005 to 2011



Furthermore, I use both nominal and market asset values to assess changes in asset market prices relatively to its nominal values proceeding as follows:

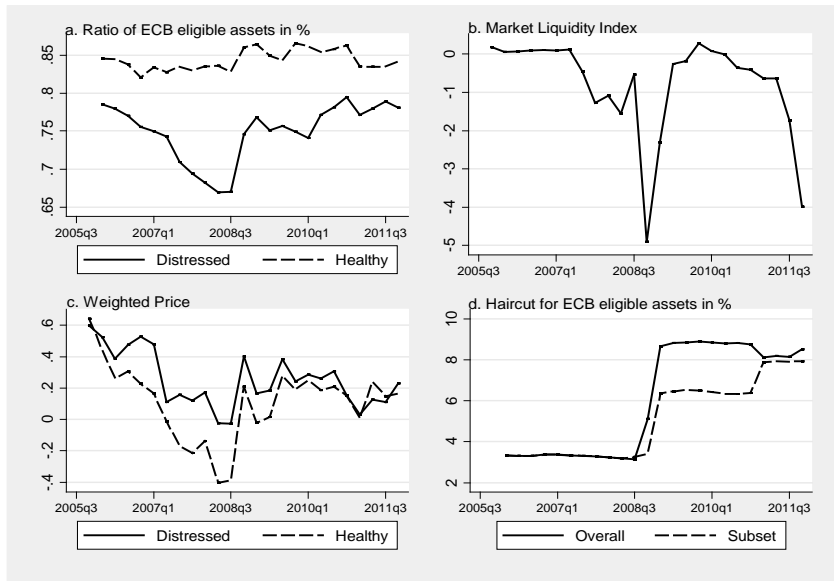
$$P_{it}^{Dev} = \sum_{j=1}^K \omega_j \frac{MV_t^j}{NV_t^j} \quad (1)$$

where  $\omega_j$  is the weight of the security  $j$  relative to the whole portfolio held by the bank  $i$  at the time period  $t$ . If the relation of the market value  $MV$  to nominal value  $NV$  is less than 1, I assign a negative sign. The ratio stays positive if it equals or is higher than 1. The higher the overall value, the more favourable is the market price development of the whole portfolio is for the bank  $i$ . I call the variable "weighted price". Figure 2(c) points to a substantial drop in relative prices on average during the period between 2007 Q2 and 2008 Q3, with a minimum in 2008 Q2 and 2008 Q3. Interestingly, for distressed banks the weighted price does not seem to decrease by the same degree around the fall of Lehman as it is the case for healthy banks. In 2008Q4 the relative price of bank portfolios improves considerably. This could be due to two possible factors or a combination of both: banks could have sold securities, with unfavorable relative prices or the market prices of securities started to recover. The latter argument is supported by the development of the market liquidity indicator (Figure 2(b)), which shows an improvement in the overall market liquidity in 2008Q4. This liquidity indicator includes liquidity sub-measures for bond, equity, money market and foreign exchange liquidity and is calculated as a simple average of all liquidity sub-measures normalised over the period 1999-2006.<sup>3</sup> The variable "haircut" (Figure 2(d)) is defined as an average valuation haircut across all securities which are eligible for the ECB at the time  $t$ . The valuation haircuts reflect specific characteristics of the assets, including liquidity risk. The average haircut increased noticeably from 3.14% in 2008Q3 to 5.12% in 2008Q4 and to 8.65% in 2009Q1, peaking in 2009Q4. Since then the value has remained roughly unchanged. The valuation haircut for a sub-sample shows how an average haircut would have developed if the ECB had not extended its collateral framework after the fall of Lehman.

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<sup>3</sup> For additional details see, Box 9 in ECB, Financial Stability Review, June 2007 and Bank of England, Financial Stability Report, April 2007.

Figure 3. Market indicators and statistics on ECB eligibility, from 2005 to 2011



In Table 1, I summarize variables which display different bank-specific characteristics for the two groups of banks separately. It is a common knowledge that CDS spreads directly reflect the risk of failure of the underlying entity. In my analysis, the purpose of including the CDS is not directly to acknowledge a bank's credit risk, but rather to approximate the ease with which it can access funding. The logic behind this is the following: the higher a bank's CDS, the tighter the conditions at which this bank would receive funding. Thus, I include CDS as proxies for banks' funding costs. Thus, the mean value and the maximum of the funding costs for distressed banks are higher than the same statistics for healthy banks. The liquidity ratio shows the number of times by which the short-term debt obligations are covered by the liquid assets. If the value is greater than 1, it means the short-term obligations are fully covered. In general, banks with liquidity ratios that are higher than 1 are considered to be in good financial health. On average considered banks exhibits high degree of safety to meet their current liabilities, while on an individual basis values of less than 1 appear. Again, the statistics show that healthy banks are more liquid than their distressed peers. The average leverage level, which is defined as assets to regulatory capital, indicate a higher leverage on average for healthy

banks. The Tier 1 ratio seems to be higher on average for distressed banks, whereas the maximum value is higher for healthy banks.

Table 1  
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Distressed Banks</i>					
CDS	174	153.32	238.72	6.27	1860.53
Weighted Price	225	0.26	0.32	-0.53	1.80
Tier 1 Ratio	208	0.1	0.05	0.05	0.28
Liquid Assets Ratio	229	1.42	0.31	0.75	2.57
Leverage	208	34.76	15.16	14.26	95.72
<i>Healthy Banks</i>					
CDS	275	77.50	58.15	4.28	273.03
Weighted Price	388	0.11	0.38	-0.95	1.12
Tier 1 Ratio	387	0.09	0.04	0.02	0.46
Liquid Assets Ratio	422	1.64	1.17	0	15.36
Leverage	387	42.52	19.94	5.00	135.05
Val. Haircut	586	5.81	2.62	3.14	8.89
Market Liquidity	613	-0.74	1.25	-4.90	0.28
Herding	613	-231.78	2883.16	-6656	8192

Lakonishok et al. (1992) introduce a measure for herding. According to the authors, herding is defined as the tendency of traders to accumulate on the same side of the market in a specific stock at the same time, relative to what would be expected. Following his idea I simplify and adapt his measure substantially and calculate approximately a measure for the "herding" behavior of the banks under review in terms of their aggregated selling volume, which is given as:

$$HM_{it} = |\sum_{k \neq i}^N sv_{kt} - \bar{sv}_t| - E|\sum_{k \neq i}^N sv_{kt} - \bar{sv}_t| \quad (2)$$

The measure is calculated without including the volume sold by the bank  $i$ . The first term captures the deviation from the average sold volume and the

volume sold at the period  $t$ , which could be understood as an excess of the volume sold in comparison to the expected value. The second term is the expected value of the difference between the volume sold at the time  $t$  and the period average. The measure equals zero if there is no evidence of dependent selling. The higher the measure, the more evidence of herding. On average the value for herding behavior is negative, thus there is no evidence for dependent selling. However, the measure is extremely volatile and includes periods where the measure is positive.

In sum, the descriptive statistics reveal a couple of interesting patterns in the data. First, I find a pronounced difference in the selling and purchasing patterns of healthy and distressed banks. While healthy banks reduced their activity gradually throughout the period under review, distressed banks were very active around the Lehman event in 2008 Q3. Second, distressed banks replaced ECB non-eligible securities with ECB eligible securities one quarter after Lehman collapsed. Third, healthy banks exhibit high ratios of ECB eligible assets from the beginning of the period under review. Finally, distressed banks seem to be better capitalized (on average) and exhibit lower leverage ratios than healthy banks.

## *2.2 Model specification*

Methodologically, I rely on dynamic fixed-effects panel estimation in the spirit of Kiviet (1995) and Bruno (2005) and on the two-step quantile regression analysis for panel data in the spirit of Canay (2011). Since the LSDV estimator requires strict exogeneity assumptions  $E(\nu_{it}|x_i, \alpha_i)$ , the inclusion of a lagged dependent variable in the standard fixed-effect estimation would lead to a bias in the estimated coefficients. The estimator from Bruno (2005) corrects this bias by using preliminary consistent estimator and is especially good for small

$N$ . The dynamic fixed-effects panel estimation model has the following form:

$$y_{it} = \rho y_{i,t-1} + \beta x_{it} + \gamma s_t + \alpha_i + \nu_{it} \quad (3)$$

where the  $y_{it}$  is the dependent variable of interest at the time  $t$  of bank  $i$ ,  $\alpha_i$  are the fixed effects,  $x_{it}$  is a set of bank-specific variables of bank  $i$  at the time  $t$ ,  $s_t$  is a set of systematic factors, which vary only over time  $t$ . Furthermore,  $\beta$  and  $\gamma$  are the corresponding regression coefficients, and  $\nu_{it}$  is an error term. I define the dependent variable  $y_{it}$  as overall sales, as sales of ECB eligible assets and ECB non-eligible assets.

Since I am particularly interested in extreme sales, I use quantile regression techniques to estimate conditional quantiles of the dependent variable. In the first step of the quantile regression analysis, the fixed effects estimated with the equation 3 are subtracted from the dependent variable. In the second step the impact of the covariates on the transformed dependent variable is estimated with the quantiles regression methodology for the quantiles of interest.

More technically, let me first define  $\hat{\alpha}_i$  which is equal to  $[y_{it} - X'\hat{\theta}]$ , where  $X'\hat{\theta}$  equals a vector including all covariates from the equation (3) and  $\hat{\theta}$  is a consistent estimator of  $\theta$ . Moreover, the transformed dependent variable  $\hat{y}_{it}^{\tau}$  is defined as  $y_{it} - \hat{\alpha}_i$ . The two-step estimator for the  $\tau$ th sample quantile is then defined as:

$$\hat{\theta}_{\tau} = \underset{\theta}{\operatorname{argmin}} E_{nT}[\rho_{\tau}(\hat{y}_{it}^{\tau} - X'\hat{\theta})] \quad (4)$$

I run quantile regressions for  $\tau$  equalling 99%, 95% and 90%.

## 2.3 Results

### 2.3.1 Basic specification

The results of the basic specification of models are presented in Table 2. Here, the dependent variable  $y_{it}$  in column (1) represents the volume of overall sales

for bank  $i$  in quarter  $t$ . The higher the indicator the higher the volume sold (log). Columns (1), (5) and (9) of the table provide results for the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 in the spirit of Bruno (2005) for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results for quantile regressions for the respective quantiles in the spirit of Canay (2011) are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in model specification above. The dynamic term is significant, which underlines the right choice of model type. The positive and significant coefficient for purchases indicates that the more banks buy, the more they are able to sell.

Brunnermeier and Pedersen (2009) show that haircuts and reduction of assets position are positively correlated. If for a bank borrowing money against securities is unattractive due to high haircuts, then the bank would rather decide to sell this security. The variable "haircut" is negative and not significant in the majority of the cases. It turns significant only in column (8), where the extreme sales of ECB eligible securities are explained. The negative sign could indicate that banks are rather reluctant to sell in an environment in which haircuts are high and market liquidity is usually low. The insignificance of the indicator could also mean that the valuation haircuts by the ECB for the ECB eligible assets are not representative for haircuts which markets require for securities.

The findings regarding market liquidity confirm that banks sell more assets in an environment where liquidity is high. I find the opposite for sales of ECB non-eligible assets, which possibly indicates that banks also sale ECB non-eligible when market liquidity is low. This feature could be the first indication of bank selling assets into falling markets with the purpose of raising money very quickly. The result remains significant at the 10% level for the quantiles equal to 90% and 95%.

The variable "size" is positive and significant in all columns. The stronger a bank's balance sheet, the higher the amounts it is able to sell. I include



leverage to control for the well documented fact, that banks have de-leveraged during the financial crisis. Thus, theoretically the higher the leverage ratio, the higher the pressure on a bank to sell assets. The relationship is unclear. The variable is only significant for the selling patterns of ECB eligible assets. The relationship seems to be negative and thus not plausible at this stage of my analysis.

In addition, the variable "Weighted Price<sub>*t,i*</sub>" which is significant and positively correlated with overall sales (gaining significance in the most extreme quantile), again underlines the fact that large sales are more likely to be driven by positive development of market values relatively to the nominal values in banks' portfolios.

The impact of the herding measure is very clear. The higher the indicator, reflecting dependent selling in the system, the higher the volume sold by the individual bank. The dummy variable "Crisis" which equals 1 in the period from 2007 Q3 to 2011 Q4 is only significant in column (12), indicating higher volumes of the most extreme sales of ECB non-eligible assets during the crisis.

### **3 Capital constraints**

Brunnermeier and Pedersen (2009) show that banks' capital constraints work as an amplification mechanism between banks' difficulties in obtaining funding and selling assets in a falling market. In an environment of increasing haircuts which allied with low market liquidity, it is less attractive for a bank with capital constraints to borrow against securities than to sell them.

Table 2  
Baseline Model

	(1) Overall	(2) Quantile Regression $\alpha = 10\%$	(3) Quantile Regression $\alpha = 5\%$	(4) Quantile Regression $\alpha = 1\%$	(5) Eligible	(6) Quantile Regression $\alpha = 10\%$	(7) Quantile Regression $\alpha = 5\%$	(8) Quantile Regression $\alpha = 1\%$	(9) Non-eligible	(10) $\alpha = 10\%$	(11) Quantile Regression $\alpha = 5\%$	(12) Quantile Regression $\alpha = 1\%$
$Sales_{t,i}$	0.25*** (5.940)				0.16*** (3.004)				0.10*** (2.678)			
$Purchases_{t,i}$	0.06*** (2.612)	0.09* (1.842)	0.10** (2.045)	0.04 (0.689)	0.05 (1.363)	0.05* (1.914)	0.06 (1.620)	0.01 (0.330)	0.09** (2.265)	0.11*** (2.837)	0.12* (1.815)	-0.04 (-0.318)
Haircut <sub>t</sub>	0.05 (0.179)	-0.18 (-0.753)	-0.30 (-1.471)	-0.35 (-1.302)	-0.06 (-0.189)	-0.32 (-1.460)	-0.41 (-1.635)	-0.60** (-2.113)	0.13 (0.319)	0.61 (1.147)	0.23 (0.527)	-0.56 (-1.129)
Market Liq <sub>t</sub>	0.08* (1.845)	0.04 (0.401)	-0.09 (-0.961)	-0.07 (-0.685)	0.13*** (2.769)	0.05 (0.986)	0.08 (1.325)	0.07 (0.984)	-0.16** (-2.272)	-0.15* (-1.732)	-0.21* (-1.657)	-0.12 (-0.489)
Size <sub>t,i</sub>	0.65*** (4.271)	0.72*** (6.700)	0.65*** (8.149)	0.66*** (6.477)	0.63*** (2.922)	0.63*** (9.946)	0.58*** (7.091)	0.53*** (5.162)	0.52** (2.079)	0.33*** (4.114)	0.29** (2.234)	0.45* (1.929)
Leverage <sub>t,i</sub>	-0.08 (-0.500)	-0.01 (-0.098)	0.04 (0.510)	0.22 (1.405)	-0.31 (-1.356)	-0.23** (-2.317)	-0.29** (-2.335)	-0.26* (-1.722)	-0.03 (-0.102)	0.22* (1.929)	0.12 (0.624)	0.14 (0.422)
Weighted Price <sub>t,i</sub>	0.11 (1.228)	0.32** (2.410)	0.38*** (2.937)	0.55** (2.257)	0.07 (0.670)	0.24* (1.862)	0.28 (1.551)	0.19 (0.998)	-0.06 (-0.424)	0.21 (1.103)	0.37 (1.574)	1.04*** (3.304)
Herding <sub>t,i</sub>	0.53*** (3.849)	0.74*** (3.311)	0.93*** (4.108)	1.01*** (2.923)	0.50*** (3.350)	0.75*** (3.752)	0.91*** (3.354)	1.25*** (3.333)	1.23*** (6.356)	0.67* (1.924)	1.04** (2.092)	2.22* (1.933)
Crisis <sub>t</sub>	0.07 (0.978)	0.08 (0.686)	0.05 (0.374)	0.29 (1.409)	-0.06 (-0.675)	-0.10 (-0.872)	0.13 (0.613)	-0.29 (-1.220)	-0.08 (-0.586)	0.04 (0.348)	-0.00 (-0.014)	0.65** (2.260)
Obs.	482	482	482	482	451	451	451	451	424	424	424	424
R-squared	0.195	0.4756	0.4526	0.4506	0.133	0.4020	0.3617	0.3328	0.180	0.2130	0.2261	0.3499
Banks	27	27	27	27	27	27	27	27	22	22	22	22

Note: The dependent variable in column (1) represents the volume of overall sales for bank  $i$  in quarter  $t$ . Column (1), (5) and (9) of the table provides results from the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results from quantile regressions for the respective quantiles are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in the model specification above. Five banks in my sample do not have ECB non-eligible assets; therefore the sample shrinks to 22 banks.

In this section, I expand the baseline model discussed in the previous section by including a measure for regulatory capital - Tier 1. The variable is often negative and significant. A decreasing capital ratio increases the volume of assets sold, which could reflect the bank's inability to finance the difference between the security price and its collateral value with its own capital. However, the significance partially disappears due to possible multi-collinearity when I add dummy variables and interaction terms as shown in Table 3.

In the first step, I define a dummy for banks which have been supported by the German government, which is equal to 1 for the period prior to the government measure. The upper part of the table provides the results for the baseline specification with Tier 1 and a dummy for weak banks, which is significant for the 1% of the extreme overall sales at significance level equalling 10%. The second part of the table shows that the relation between asset sales and capitalization for weak banks is rather positive. This evidence holds true for the 10% of the extreme sales of overall assets and the ECB non-eligible assets.

Even though the dummy variable for weak banks is positively correlated, indicating higher sold volumes for weak banks, the interaction term  $WeakB * Tier1_{t,i}$  is positive.

To further assess the possible non-linearities in the impact emanating from the Tier 1, I define a dummy which equals 1 if a bank exhibits a capital level lower than median of the considered sample. Subsequently, I interact this dummy with Tier 1 capital ratio. The dummy is positive and significant for sales of ECB eligible assets. Banks with Tier1 under the median level have sold more ECB eligible assets in comparison to the periods where these banks exhibit high Tier1 ratios. The impact emanating from the interaction term  $Tier1 * Dummy'_{t,i}$  is positive, meaning that decreasing capital levels under median do not cause higher volumes of sold assets.

Table 3  
Capital Constraints

	(1) Overall	(2) Quantile Regression $\alpha = 10\%$	(3) Quantile Regression $\alpha = 5\%$	(4) Quantile Regression $\alpha = 1\%$	(5) Eligible	(6) Quantile Regression $\alpha = 10\%$	(7) Quantile Regression $\alpha = 5\%$	(8) Quantile Regression $\alpha = 1\%$	(9) Non - eligible	(10) Quantile Regression $\alpha = 10\%$	(11) Quantile Regression $\alpha = 5\%$	(12) Quantile Regression $\alpha = 1\%$
<b>Sales<sub>t,i</sub></b>	-0.36** (-2.054)	-0.18 (-1.402)	-0.28** (-2.305)	-0.09 (-0.428)	-0.27 (-1.340)	-0.18 (-1.188)	-0.12 (-0.768)	-0.49*** (-2.912)	-0.13 (-0.495)	-0.30 (-1.233)	-0.21 (-0.731)	0.63 (1.250)
Tier <sub>t,i</sub>												
WeakB <sub>t,i</sub>	-0.01 (-0.111)	0.03 (0.322)	0.03 (0.223)	-0.60* (-1.753)	0.04 (0.319)	0.05 (0.488)	-0.08 (-0.557)	0.16 (0.811)	0.13 (0.726)	-0.03 (-0.134)	-0.38 (-1.216)	-0.26 (-0.760)
R-squared	0.1898	0.5260	0.5023	0.4875	0.1292	0.4332	0.3923	0.3588	0.1765	0.2442	0.2522	0.3653
Tier <sub>t,i</sub>												
WeakB <sub>t,i</sub>	-0.53** (-2.076)	-0.58** (-2.215)	-0.41 (-1.171)	1.07 (0.650)	-0.03 (-0.107)	-0.30 (-0.593)	0.07 (0.117)	-0.24 (-0.248)	-0.51 (-1.191)	-1.18** (-2.106)	-0.51 (-0.632)	-1.05 (-0.867)
WeakB*Tier <sub>t,i</sub>	0.52 (0.835)	1.17* (1.792)	0.43 (0.517)	-3.10 (-0.847)	-0.71 (-0.840)	0.22 (0.187)	-0.91 (-0.646)	-0.63 (-0.285)	1.57 (1.358)	2.40* (1.705)	1.52 (0.797)	3.84 (1.337)
WeakB*Tier <sub>t,i</sub>	0.23 (0.891)	0.48* (1.784)	0.17 (0.501)	-1.11 (-0.674)	-0.32 (-0.925)	0.06 (0.117)	-0.37 (-0.589)	-0.34 (-0.343)	0.61 (1.303)	1.05* (1.766)	0.67 (0.793)	1.77 (1.429)
R-squared	0.1927	0.5245	0.4990	0.4842	0.1309	0.4431	0.4051	0.3699	0.1797	0.3719	0.2454	0.2582
Tier <sub>t,i</sub>												
DummyTier <sub>t,i</sub>	-0.26 (-1.151)	-0.03 (-0.276)	-0.13 (-0.818)	0.35 (0.878)	-0.40 (-1.536)	-0.18 (-0.978)	0.01 (0.074)	0.00 (0.000)	0.07 (0.209)	-0.26 (-0.790)	0.22 (0.502)	0.92 (1.097)
Tier <sub>t,i</sub> *Dummy <sub>t,i</sub>	0.50 (0.983)	-0.40 (-0.645)	-0.71 (-0.831)	-1.19 (-0.745)	1.38** (2.007)	1.20 (1.368)	0.93 (0.819)	0.92 (0.591)	-0.10 (-0.105)	-0.91 (-0.954)	-1.61 (-1.444)	-0.12 (-0.054)
R-squared	0.13 (0.645)	-0.22 (-0.912)	-0.35 (-1.051)	-0.57 (-0.904)	0.50* (1.819)	0.39 (1.166)	0.24 (0.543)	0.15 (0.255)	-0.11 (-0.287)	-0.40 (-1.045)	-0.69 (-1.619)	-0.27 (-0.305)
Tier <sub>t,i</sub>	0.2045	0.5208	0.4995	0.4854	0.1510	0.4446	0.4150	0.3902	0.1775	0.2417	0.2384	0.3625
Crisis <sub>t</sub>	-0.27 (-1.618)	-0.08 (-0.620)	-0.18 (-1.457)	-0.34 (-1.320)	-0.20 (-1.033)	-0.06 (-0.385)	0.03 (0.205)	-0.48** (-2.314)	-0.04 (-0.130)	-0.42 (-1.309)	-0.20 (-0.459)	0.45 (0.684)
Crisis*DummyTier <sub>t,i</sub>	-0.03 (-0.325)	-0.00 (-0.033)	-0.05 (-0.295)	0.33 (1.082)	-0.15 (-1.377)	-0.18 (-1.503)	-0.14 (-0.624)	-0.15 (-0.538)	-0.18 (-1.037)	-0.12 (-0.668)	0.04 (0.140)	0.32 (0.713)
R-squared	-0.05* (-1.794)	-0.05 (-1.247)	-0.05 (-1.266)	-0.06 (-0.616)	-0.05 (-1.358)	-0.08** (-2.305)	-0.10* (-1.691)	-0.06 (-0.898)	-0.06 (-1.020)	-0.07 (-1.149)	-0.05 (-0.532)	-0.09 (-0.512)
Obs.	0.1970	0.5120	0.4899	0.4911	0.1372	0.4407	0.3995	0.3693	0.1805	0.2467	0.2432	0.3947
Banks	482	482	482	482	451	451	451	451	424	424	424	424
	27	27	27	27	27	27	27	27	22	22	22	22

Note: The dependent variable in column (1) represents the volume of overall sales for bank  $i$  in quarter  $t$ . Column (1), (5) and (9) of the table provides results from the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results from quantile regressions for the respective quantiles are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in model specification above. Five banks in my sample do not have ECB non-eligible assets, therefore the sample shrinks to 22 banks.

In addition, I analyse whether Tier 1 ratios under median during the crisis are correlated with higher volumes of sold assets. The empirical evidence rejects this hypothesis. In sum, I find that there is a negative and significant relationship between Tier 1 ratio and the sold volumes. However, at this stage of the analysis I cannot find any evidence of a non-linear relationship where low capital ratios amplify the sales of assets.

#### 4 Funding shortage and liquidity needs

During the crisis, fire sales by liquidity-constrained traders may cause price movements, leading to prices which deviate from fundamental values. A low level of market liquidity of a bank could feed back into bank's funding liquidity. The interaction between funding and market liquidity could amplify the crisis (see Brunnermeier and Pedersen (2009)).

In this section, I introduce two new variables: the liquidity ratio and funding costs. The latter is approximated by the individual CDS. The theoretical literature describes an amplification mechanism rather than one-way causality. In my analysis, I assume the causality and test the impact emanating from the two variables on asset sales. Table 4 provides estimation results, in which the interaction terms with the dummy for "weak banks" are additionally included. The variable CDS is positively significant for overall sales. It seems that funding problems are associated with higher overall sales. It is not significant for sales on ECB non-eligible assets. On the contrary, the variable gains in significance for the extreme quantiles of the sales on ECB eligible assets. It seems that if a bank has funding problems it would also sell ECB eligible assets instead of borrowing against it at the ECB in extreme cases. The combination of high haircuts, capital constraints and funding problems of this bank could be the reason for such behavior. The interaction term  $WeakB * CDS_{t,i}$  has a negative sign and is significant for all extreme quantiles.

Table 4  
Funding shortage or liquidity needs

	(1) Overall	(2) Quantile Regression $\alpha = 10\%$	(3) Quantile Regression $\alpha = 5\%$	(4) Quantile Regression $\alpha = 1\%$	(5) Eligible	(6) Quantile Regression $\alpha = 10\%$	(7) Quantile Regression $\alpha = 5\%$	(8) Quantile Regression $\alpha = 1\%$	(9) Non - eligible	(10) $\alpha = 10\%$	(11) Quantile Regression $\alpha = 5\%$	(12) Quantile Regression $\alpha = 1\%$
$Sales_{t-1,i}$	0.26*** (5.072)				0.16*** (2.930)				0.13*** (2.604)			
$Purchases_{t,i}$	0.12*** (4.022)	0.15*** (3.467)	0.16*** (4.638)	0.13*** (4.471)	0.08*** (2.024)	0.12*** (3.133)	0.10** (2.441)	0.20*** (3.329)	0.13** (2.067)	0.15*** (3.690)	0.14* (1.959)	-0.09 (-0.831)
$Haircut_t$	-0.15 (-0.654)	-0.45** (-1.996)	-0.42 (-1.537)	-0.34 (-1.511)	-0.19 (-0.581)	-0.48 (-1.625)	-0.20 (-0.628)	-0.83* (-1.824)	-0.38 (-0.721)	-0.64 (-1.106)	-0.76 (-0.895)	-0.37 (-0.382)
Market Liqt	0.08* (1.773)	-0.10 (-0.931)	-0.04 (-0.420)	0.02 (0.261)	0.13** (2.170)	0.05 (0.799)	0.14* (1.795)	-0.07 (-0.671)	-0.23*** (-2.667)	-0.36*** (-2.746)	-0.30* (-1.800)	-0.14 (-0.553)
$Size_{t,i}$	0.41** (2.192)	0.56*** (6.095)	0.50*** (7.046)	0.49*** (6.684)	0.54** (2.487)	0.53*** (7.081)	0.51*** (5.711)	0.20 (1.267)	0.16 (0.459)	0.16 (1.340)	0.09 (0.562)	0.21 (1.033)
Leverage $_{t,i}$	-0.53** (-2.290)	-0.43*** (-3.807)	-0.48*** (-4.438)	-0.42*** (-3.935)	-0.90*** (-2.629)	-0.84*** (-6.143)	-0.67*** (-5.210)	-0.72*** (-4.229)	-0.35 (-0.741)	-0.44** (-2.081)	-0.33 (-1.128)	0.06 (0.167)
Weighted Price $_{t,i}$	0.13 (1.175)	0.30*** (2.625)	0.46*** (3.179)	0.63*** (4.362)	0.06 (0.494)	0.24* (1.782)	0.48*** (2.631)	0.20 (1.041)	-0.10 (-0.534)	0.28** (2.066)	0.48** (2.021)	1.01** (2.459)
Herding $_{t,i}$	0.64*** (3.228)	0.93*** (3.251)	1.10*** (3.255)	1.79*** (5.057)	0.43* (1.828)	0.55* (1.738)	1.11*** (2.887)	-0.36 (-0.609)	1.01*** (2.720)	0.61 (1.306)	1.41* (1.848)	3.32*** (2.920)
Tier $_{t,i}$	-0.42** (-2.405)	-0.36** (-2.545)	-0.45*** (-3.069)	-0.35** (-2.103)	-0.49** (-2.084)	-0.50*** (-3.006)	-0.55*** (-2.980)	-0.66*** (-3.370)	0.03 (0.067)	-0.55* (-1.934)	-0.16 (-0.314)	0.56 (0.933)
CDS $_{t,i}$	0.25** (2.073)	0.23* (1.787)	0.33** (2.015)	0.01 (0.040)	0.22 (0.984)	0.38*** (2.612)	0.63*** (2.955)	0.25 (1.344)	0.02 (0.061)	0.12 (0.475)	-0.05 (-0.150)	0.11 (0.289)
Liq.Assets $_{t,i}$	-0.18 (-0.467)	-0.29 (-0.819)	-0.04 (-0.047)	1.64 (1.340)	1.22** (2.249)	0.72 (0.942)	1.28* (1.708)	1.48 (1.501)	-2.09** (-2.221)	-1.40** (-1.992)	-1.69 (-1.466)	-0.69 (-0.445)
WeakB $_{t,i}$	0.83 (1.245)	0.91 (1.273)	1.49* (1.702)	-0.07 (-0.049)	1.42 (1.278)	2.25*** (2.787)	3.30*** (2.841)	3.04*** (2.924)	-0.31 (-0.218)	-0.43 (-0.269)	-1.76 (-0.921)	-0.39 (-0.198)
WeakB*Liq $_{t,i}$	0.20 (0.444)	-0.01 (-0.021)	-0.38 (-0.386)	-2.19* (-1.747)	-1.09* (-1.784)	-0.88 (-1.117)	-1.65** (-2.072)	-2.01* (-1.901)	1.87** (1.869)	1.72** (2.225)	1.72 (1.428)	0.13 (-0.083)
WeakB*CDS $_{t,i}$	-0.17 (-1.386)	-0.18 (-1.268)	-0.26 (-1.528)	0.14 (0.529)	-0.19 (-0.903)	-0.35** (-2.194)	-0.52** (-2.368)	-0.48** (-2.472)	-0.05 (-0.207)	-0.05 (-0.165)	0.17 (0.484)	0.06 (0.157)
Obs.	377	377	377	377	357	357	357	357	350	350	350	350
Banks	25	25	25	25	25	25	25	25	20	20	20	20
Pseudo R2	0.2688	0.4877	0.4974	0.5706	0.1961	0.4107	0.3921	0.4234	0.2163	0.2367	0.2685	0.4331

Note: The dependent variable in column (1) represents the volume of overall sales for bank  $i$  in quarter  $t$ . Column (1), (5) and (9) of the table provides results from the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results from quantile regressions for the respective quantiles are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in model specification above. Two banks in my sample do not have CDS spreads. Therefore the number of banks decrease to 25; five banks out of 25 do not have ECB non-eligible assets.

This means that as funding costs increase weak banks prefer borrowing against securities at the ECB to selling these securities. The ratio of liquid assets to short-term liabilities is positively correlated with sales of ECB eligible assets and negatively correlated with sales of ECB non-eligible assets. Banks with liquidity needs would rather sell ECB non-eligible assets. The signs change to the opposite for the interaction term  $WeakB * Liq_{t,i}$ . To further assess the possible non-linearities in the impact emanating from funding costs and the liquidity ratio, I define a dummy which equals 1 if a bank exhibits a liquidity level lower than the median of the considered sample. Furthermore, I construct a dummy which equals 1 if a bank's funding costs are higher than median of the sample under review. In the last step I interact both dummies.

Table 5 shows that lower liquidity is always associated with higher sold volumes. Particularly for ECB eligible assets, the relationship is significant for extreme quantiles. High CDSs are associated with high sold volumes. The relationship is significant for ECB eligible assets for quantiles of the dependent variable. The interaction between low liquidity and high funding costs is negative. Hence, banks with high funding cost and low liquidity sell smaller volumes of ECB eligible assets.

## 5 ECB eligible assets and distressed banks

Next, I focus on the role which the ratio of ECB eligible assets to all assets in a bank's portfolio plays in preventing fire sales. I assume that the increase in the ratio could decrease the need to sell ECB non-eligible assets in order to raise liquidity.

I include the individual ratio for the ECB eligible assets  $ECBea_{t,i}$  and an average measure for the system  $ECBEA_{t,i}$ , which do not include the assets from bank  $i$ .

Table 5  
Funding shortage or liquidity needs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dyn. FE	Quantile Regression $\alpha = 10\%$	Quantile Regression $\alpha = 5\%$	Quantile Regression $\alpha = 1\%$	Dyn. FE	Quantile Regression $\alpha = 10\%$	Quantile Regression $\alpha = 5\%$	Quantile Regression $\alpha = 1\%$	Dyn. FE	Quantile Regression $\alpha = 10\%$	Quantile Regression $\alpha = 5\%$	Quantile Regression $\alpha = 1\%$
	Overall Sales											
CDS <sub>t,i</sub>	0.09*** (2.747)	0.09** (1.904)	0.04 (0.640)	0.13 (1.215)	0.09*** (2.785)	0.03 (0.697)	0.02 (0.337)	0.15 (1.325)	0.09*** (2.727)	0.09* (1.892)	0.05 (0.876)	0.23** (2.151)
Liq.Assets <sub>t,i</sub>	-0.00 (-0.014)	-0.30*** (-2.811)	-0.31** (-2.158)	-0.22 (-0.876)	-0.02 (-0.087)	-0.39*** (-3.089)	-0.43*** (-3.200)	-0.54** (-2.553)	-0.01 (-0.049)	-0.30*** (-2.686)	-0.38*** (-2.643)	-0.10 (-0.362)
Liq.Assets <sub>t,i</sub> <sup>l</sup>					-0.24 (-1.042)	-0.74*** (-2.904)	-0.45 (-1.609)	-0.81* (-1.901)				
CDS <sub>t,i</sub> <sup>h</sup>					-0.02 (-0.408)	0.10 (1.622)	0.07 (0.916)	0.03 (0.268)				
Liq <sup>l</sup> *CDS <sub>t,i</sub> <sup>h</sup>									-0.12 (-0.463)	-0.04 (-0.165)	-0.30 (-0.871)	-0.53 (-0.853)
Pseudo R2	0.2563	0.4858	0.4934	0.5211	0.2642	0.4832	0.4912	0.5292	0.2586	0.4840	0.4937	0.5259
	ECB eligible assets											
CDS <sub>t,i</sub>	0.04 (0.787)	0.04 (0.719)	0.12* (1.667)	-0.01 (-0.067)	0.03 (0.665)	0.04 (0.785)	0.07 (0.883)	-0.05 (-0.459)	0.04 (0.777)	0.04 (0.719)	0.11 (1.483)	0.00 (0.044)
Liq.Assets <sub>t,i</sub>	0.22 (0.861)	-0.04 (-0.187)	-0.15 (-0.613)	-0.46 (-1.486)	0.20 (0.774)	-0.11 (-0.504)	-0.33 (-1.339)	-0.41* (-1.798)	0.22 (0.839)	-0.04 (-0.178)	-0.21 (-0.804)	-0.48* (-1.702)
Liq.Assets <sub>t,i</sub> <sup>l</sup>					-0.30 (-1.073)	-0.54** (-2.118)	-0.75*** (-2.248)	-1.42*** (-3.232)				
CDS <sub>t,i</sub> <sup>h</sup>					0.01 (0.106)	0.13* (1.698)	0.05 (0.524)	0.22** (2.053)				
Liq <sup>l</sup> *CDS <sub>t,i</sub> <sup>h</sup>									-0.15 (-0.458)	-0.02 (-0.059)	-0.27 (-0.804)	-1.14** (-2.538)
Pseudo R2	0.1681	0.3560	0.3414	0.3646	0.1786	0.3510	0.3416	0.4229	0.1700	0.3518	0.3417	0.3908
	ECB non-eligible assets											
CDS <sub>t,i</sub>	-0.04 (-0.555)	0.10* (1.674)	0.08 (0.979)	0.14 (1.211)	-0.03 (-0.408)	0.10 (1.373)	0.10 (1.113)	0.11 (1.002)	-0.05 (-0.556)	0.05 (0.648)	0.08 (0.955)	0.08 (0.781)
Liq.Assets <sub>t,i</sub>	-0.41 (-0.985)	-0.08 (-0.513)	-0.15 (-0.621)	-0.26 (-0.715)	-0.40 (-0.936)	-0.02 (-0.089)	-0.15 (-0.539)	-0.46 (-1.362)	-0.46 (-1.088)	-0.16 (-0.960)	-0.21 (-0.882)	-0.63* (-1.750)
Liq.Assets <sub>t,i</sub> <sup>l</sup>					-0.14 (-0.280)	0.26 (0.543)	-0.30 (-0.407)	-1.60* (-1.923)				
CDS <sub>t,i</sub> <sup>h</sup>					-0.10 (-0.845)	0.01 (0.107)	-0.05 (-0.374)	-0.09 (-0.450)				
Liq <sup>l</sup> *CDS <sub>t,i</sub> <sup>h</sup>									-0.62 (-1.321)	-0.33 (-0.620)	-0.59 (-0.934)	-1.07 (-1.353)
Pseudo R2	0.1994	0.2808	0.2984	0.4499	0.2014	0.2811	0.2960	0.4754	0.2035	0.2799	0.2981	0.4564

Note: Column (1), (5) and (9) of the table provides results from the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results from quantile regressions for the respective quantiles are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in model specification. The regressions are based on 25 banks for sales of ECB eligible and overall sales and 20 for sales of ECB non-eligible assets.



The results for sales of ECB-non eligible assets show that the increase in eligible assets raises the sold volumes of ECB non-eligible assets (see columns (1) to (4)). In columns (5) to (8), I include the interaction terms for weak banks. The relationship is negative, which confirms my expectation. Moreover, the coefficient increases with the considered quantile of the dependent variable. Banks which had obviously been in distress prior to the period in which they received support from the government sold lower volumes of ECB non-eligible assets, the more ECB eligible assets they had in their portfolios. This feature of the results is the first indication of the role played by the ECB's collateral framework in preventing fire sales.

In addition, I introduce interaction terms with the dummy variable which equals 1 during the crisis. The results show that while the relation between  $ECBea_{t,i}$  and the dependent variable is positive in general, it was negative during the crisis. This feature is the second indication of the stabilizing impact on the sales (including 10% of the extreme sales) emanating from the extension of the ECB's collateral framework. In comparison the results for sales of ECB eligible assets and overall sales differ from those for sales of ECB non-eligible assets. The variable is either not significant (for overall sales) or it is positively correlated with the dependent variable (for ECB eligible assets).

## 6 Conclusion

In this paper, I analyze the impact of different systematic and bank-specific characteristics on extreme securities sales by large German banks in order to evaluate the role of the extension of the ECB's collateral framework. My analysis is based on quantile regressions for panel data containing securities holdings of 27 German banks, which allows an assessment of extreme large sales. Here, I distinguish between healthy banks and banks rescued from the German government hypothesizing that distressed banks manage sales of their

assets differently.

I find first evidence that the amount of available central bank eligible assets in banks' portfolios has a stabilizing effect on sales. Controlling for the amount of available central bank collateral significantly increases the explanatory power, in particular for large sales. More specifically, the ratio of ECB eligible assets is negatively correlated with sales of ECB non-eligible assets for impaired banks and during the crisis. In general, I observe that the selling behavior of banks, which were impaired and thus had to be rescued from the German government is different from that of healthier banks.

Furthermore, I find mixed evidence for the controversial literature on fire sales with regard to the role played by the haircuts, market liquidity, funding cost and capitalization. Methodologically, I find robust evidence that considered determinants have different impact on the endogenous variable in dependency of considered quantile.

In my further steps, I plan to include other definitions of the dependent variable, such as net sales, defined as sales minus purchases, so as to better control for bank activity. Moreover, and in order to further assess the role of ECB's collateral framework and other determinants, I intend to involve a threshold panel regression analysis. Such a model facilitates the endogenous identification of thresholds for independent variables, which at most explain the variance of the dependent variable.

Table 6  
Funding shortage or liquidity needs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	DPE	Quantile Regression		DPE		Quantile Regression		DPE		Quantile Regression		Quantile Regression
		$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$		$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$	$\alpha = 10\%$	$\alpha = 5\%$	$\alpha = 1\%$	$\alpha = 1\%$
Overall sales												
ECB $ea_{t,i}$	0.80*	0.71	0.73*	1.04	0.83*	0.78	0.84	0.97	0.88**	0.78	0.65	1.14
ECB $EA_{t,i}$	2.00	-1.23	-0.89	-0.06	-6.87	-10.07**	-2.67	5.44	5.55	4.53	-0.60	-9.85
WeakB $_{t,i}$					2.19**	2.24**	0.63	-1.43				
WeakB* $ea_{t,i}$					-0.02	-0.04	-0.13	-0.12				
WeakB* $EA_{t,i}$					10.40**	10.82**	2.64	-6.14				
Crisis $_t$									-1.36	-1.34	-0.09	2.18
Crisis* $EA_{t,i}$									-4.59	-5.76	0.28	10.27
Crisis* $ea_{t,i}$									-0.21	-0.23	-0.03	0.07
Obs.	376	376	376	376	376	376	376	376	376	376	376	376
Banks	24	24	24	24	24	24	24	24	24	24	24	24
ECB eligible assets												
ECB $ea_{t,i}$	-0.91*	-0.86	-0.36	-0.03	-1.19**	-0.83	-0.02	-1.09	-0.88*	-0.79	-0.60	0.33
ECB $EA_{t,i}$	3.85	0.93	3.58	-0.75	1.75	-9.24	-16.17	19.77	12.43	10.69	8.23	-20.04
WeakB $_{t,i}$					0.61	2.26	4.08	-4.59				
WeakB* $ea_{t,i}$					0.74	0.84**	0.38	-1.28				
WeakB* $EA_{t,i}$					1.32	9.79	19.55	-20.70				
Crisis $_t$									-2.62	-2.86	-2.60	3.05
Crisis* $EA_{t,i}$									-10.70	-11.20	-9.57	18.77
Crisis* $ea_{t,i}$									0.30	0.30	-0.08	-0.47
Obs.	356	356	356	356	356	356	356	356	356	356	356	356
Banks	24	24	24	24	24	24	24	24	24	24	24	24
ECB non-eligible assets												
ECB $ea_{t,i}$	3.95***	3.08*	2.51	1.49	4.36***	3.56**	3.18*	3.32*	4.12***	3.52**	3.19*	1.64
ECB $EA_{t,i}$	-5.96**	-4.60*	-7.45**	-6.57	-5.84	-4.71	-7.38	-3.32	-12.18*	-6.09	-9.90	-7.97
WeakB $_t$					0.11	0.34	0.78	-0.59				
WeakB* $ea_{t,i}$					-1.22**	-1.41**	-2.13***	-2.94***				
WeakB* $EA_{t,i}$					2.29	3.72	6.75	1.22				
Crisis $_t$									1.66	0.82	1.14	-0.59
Crisis* $EA_{t,i}$									10.08	5.79	6.50	-3.77
Crisis* $ea_{t,i}$									-1.39***	-1.54***	-0.95	-0.11
Obs.	350	350	350	350	350	350	350	350	350	350	350	350
Banks	20	20	20	20	20	20	20	20	20	20	20	20

Note: Column (1), (5) and (9) of the table provides results from the dynamic fixed-effect estimation for the period 2006Q1 to 2011Q4 for overall sales, for sales of ECB eligible and for sales of ECB non-eligible assets. The results from quantile regressions for the respective quantiles in spirit of are in columns (2)-(3), (6)-(8), (10)-(12), whereby the dependent variable is transformed as shown in model specification. The regressions are based on 25 banks for sales of ECB eligible and overall sales and 20 for sales of ECB non-eligible assets.

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