Does diversification protect European banks' market valuations in a pandemic?

Mathieu Simoens[a,1], Rudi Vander Vennet[a,2]

[a] *Department of Economics, Ghent University, Sint-Pietersplein 5, 9000 Ghent, Belgium*

Abstract

We use the Covid-19 pandemic to assess whether diversification in various dimensions can protect European banks from substantial negative valuation shocks. Our results demonstrate that functional diversification acts as an economically significant shock absorber: it mitigates banks' stock market decline by approximately 10 percentage points. Loan portfolio diversification also contributes to dampening the valuation shock, but with a much lower impact (4.4 percentage points). Geographical diversification fails to act as a shock absorber. Banks with lower pre-Covid systematic risk, higher liquidity buffers, higher cost efficiency and active in countries with better post-Covid growth prospects weathered the storm better.

Keywords: European banks, Covid-19, valuation, functional diversification, geographical diversification

JEL: G21 G28 G01

1. Introduction and motivation

Diversification should work when it matters most. In the case of banks, diversification should act as a shock absorber when they are hit by an unexpected exogenous shock. We investigate whether diversification, in various dimensions,

[1] Mathieu.Simoens@UGent.be - corresponding author
[2] Rudi.VanderVennet@UGent.be

alleviates the negative impact on European banks' market value caused by the Covid-19 shock. Between 13 February and 21 April 2020, the STOXX Europe 600 Banks declined by 46%, almost twice the decline of the MSCI Europe (minus 24%). The average euro area bank market-to-book ratio dropped to 0.3, an unseen level indicating serious stress in the banking system (ECB, 2020). Likely sources for these low valuations are the expectation of a pandemic-induced wave of non-performing loans, low-for-longer interest rates and lower anticipated bank profitability (see Simoens and Vander Vennet (2020)).

Apparently, stock market investors perceived banks as one of the sectors that would suffer most from the Covid-19 pandemic. However, the most-hit banks (average of the first quartile) experience a stock return that is 27 percentage points lower than the least-hit (average of the fourth quartile). The question is whether diversification can explain this difference. Policymakers and bank supervisors have made repeated recommendations to banks to diversify their activities both functionally and geographically (de Guindos, 2020; ECB, 2018). We use the occurrence of the exogenous Covid-19 pandemic to assess whether more diversified banks were able to withstand the shock better. To capture diversification in a broad sense, we consider three types: geographical diversification (dispersion of bank branches over different countries), functional diversification (reliance on interest vs. non-interest income) and lending counterparty diversification (loans to households vs. non-financial corporations (NFCs) vs. financial corporations).

Our most important finding is that the market value of European banks with high functional diversification declined 10 percentage points less during the first months of the pandemic. Geographical diversification, on the other hand, had no impact on banks' stock performance. Regarding lending counterparty diversification, the analysis points towards a slightly positive impact, although relatively small (4.4 percentage points). Hence, in terms of types of diversification, investors consider that functional diversification is the relevant dimension to protect future profitability. Banks with access to non-interest sources of revenue will be better able to achieve profitability in a low-for-longer interest rate environment. Furthermore, we find that banks with lower pre-Covid systematic risk (beta) and a higher liquidity coverage ratio (LCR) experienced higher stock returns. This evidence is consistent with the interpretation that although banks entered the Covid-19 era with substantial capital buffers, investors did not rule out severe liquidity stress in the early stages of the pandemic. Since the Basel III LCR is explicitly designed to safeguard banks in situations of unanticipated financial market stress, it passed this real-world test. Banks with a higher pre-Covid cost efficiency and active in countries with higher expected GDP growth also weathered the storm slightly better. In contrast with previous crises, we do not find a mitigating effect of capital.

2. Literature and hypotheses

Banks can essentially diversify in three dimensions: functional, geographical and loan exposures. We analyze whether diversification, in these three dimensions, can protect banks from incurring substantial valuation losses when a pandemic hits the economy.

Regarding the impact of functional diversification, existing empirical evidence is mixed. Stiroh (2006) reported that US banks with a high reliance on non-interest income are riskier, but do not earn higher equity returns. For recent times, Saunders et al. (2020) conclude that US banks with higher non-interest income had higher profitability, but not higher risk. For European banks, Köhler (2015) finds that banks with higher functional diversification are more stable and profitable. Mergaerts and Vander Vennet (2016) and Baele et al. (2007)

confirm that diversification increases profitability and franchise value of European banks. These findings lead to our hypothesis that functional diversification should act as a shock absorber.

With respect to geographical diversification, Aldasoro et al. (2021) find, for a worldwide sample, that geographic complexity improves the capacity to absorb local shocks, but also increases the vulnerability to global shocks. Bertay et al. (2019) find that geographical diversification is negatively associated with bank performance. For European banks, Pamen Nyola et al. (2020) find that higher geographic dispersion is associated with lower default risk and higher profitability, but higher volatility of earnings. Moreover, these effects are amplified during the sovereign crisis period. Hence, it is unclear how geographical diversification will work in the Covid-19 period, given the fact that the pandemic has a worldwide scope, although with different impact across regions.

Regarding diversification in the lending portfolio, Acharya et al. (2006) find that diversification did not make Italian banks safer during the 1990s. Hayden et al. (2007) find that diversified loan portfolios are associated with lower returns for German banks. Rossi et al. (2009), on the other hand, report that diversification leads to lower realized risk for Austrian banks. A recent paper by Shim (2019) finds a positive relationship between US banks' loan portfolio diversification and bank stability. Most of these papers focus on sector diversification instead of the broader lending counterparty categories we consider.

When investigating bank performance during the GFC, a large number of papers have focused on the mitigating impact of capital. According to Demirgüç-Kunt et al. (2013), developed country banks with higher capital ratios experienced higher stock returns. In a sample of European and US banks, domestic banks with weaker liquidity and global banks with higher leverage were more likely to fail (Vazquez and Federico, 2015). With respect to the Covid-19 pandemic, Li et al. (2021) find that revenue diversification was associated with higher profitability and lower risk for US banks. According to Demirgüç-Kunt et al. (2020), less liquid banks underperformed (in a global sample) during the pandemic. Acharya et al. (2021) confirm the key role of liquidity for US banks. Hence the importance of including capital and liquidity ratios in the estimations.

3. Data and methodology

We use stock market data and publicly available bank balance sheet and income statement characteristics, in combination with the EBA's Spring 2020 disclosure of lending counterparty exposures.[3] Our final sample consists of 56 banks headquartered in 23 countries.[4] To identify the impact of diversification on banks' market values during the pandemic, we estimate cross-sectional regressions, similar to Fahlenbrach et al. (2012, 2020).

$$Return_i = \alpha + \sum_{j=1}^{3} \beta_j DIV_{j,i} + \sum_{k=1}^{K} \gamma_k CV_{k,i} + \epsilon_i \tag{1}$$

We define the exogenous Covid-19 shock as the period between the peak and trough of the STOXX Europe 600 Banks in the first half of 2020, i.e. the period between 13 February and 21 April 2020. We calculate $Return_i$ as the stock market return for bank i between these dates.[5] We regress the returns on 3 pre-Covid measures of diversification ($DIV_{j,i}$), as well as K control variables ($CV_{k,i}$). An overview can be found in Tables 1 and 2.

[3] We exclude Unione di Banche Italiane, because of its acquisition by Intesa Sanpaolo, since this might explain part of the change in stock price over the sample period. We also exclude SpareBank 1 SMN, Mediobanca, Eurobank Ergasias, and Šiauliu Bankas because of data coverage issues.

[4] Austria 3, Belgium 1, Bulgaria 1, Cyprus 2, Germany 4, Denmark 3, Spain 7, Finland 1, France 2, UK 5, Greece 3, Hungary 1, Ireland 2, Iceland 1, Italy 7, Malta 1, the Netherlands 2, Norway 2, Poland 2, Portugal 1, Romania 1, Sweden 3, Slovenia 1.

[5] As a robustness check, we regress the main specification using returns between 13 February and (arbitrarily) 31 March 2020.

The diversification variables are constructed as Herfindahl-Hirschman Indices (HHIs) by summing the squared exposures to different categories. We calculate DIV as 10.000 minus the HHI, so the coefficients can be interpreted as

Table 1: Data description

Variable	**Description**	**Source**
Return	Bank return over the peak-trough period (13 Feb. to 21 April 2020) of the STOXX Europe 600 Banks, in percent.	Refinitiv
Return*	Bank return over the 13 Feb. to 31 March 2020 period, in percent.	Refinitiv
NCountries	Number of countries in which the bank has branches.	S&P
DIVGeography	Geographical diversification, 10.000 − HHI based on the squared percentage of branches per country where the bank is active.	S&P, calc.
NonIntInc	Non-interest income as percentage of total operating income.	S&P
DIVFunctional	Functional diversification, 10.000 − HHI based on the squared percentage of interest and non-interest income in operating income.	S&P, calc.
DIVLending	Lending counterparty diversification, 10.000 − HHI based on loans and advances to 3 categories (households, NFCs and financial corporations) as squared percentage of total loans.	EBA, calc.
$\text{DIVLending}^{\text{SME}}$	Lending counterparty diversification, 10.000 − HHI based on loans and advances to the categories mentioned above, with NFC split in SME and non-SME, as squared percentage of total loans.	EBA, calc.
CovidHigh	Gross carrying amount of loans and advances to NFCs in the 4 NACE sectors hit most by Covid-19, as percentage of total assets.	EBA, calc.
Beta	Slope parameter of a regression of daily log returns on geography-weighted market log returns; 250 days before 13 Feb. 2020.	Refinitiv, calc.
Equity/Assets	Book value of total equity as percentage of total assets.	S&P
LCR	Liquidity coverage ratio, in percent.	S&P
HQLA/Assets	High quality liquid assets as percentage of total assets.	S&P
Outflow/Assets	Net cash outflows as percentage of total assets.	S&P
Cost/Income	Cost-to-income ratio, in percent.	S&P
Ln(Assets)	Natural logarithm of total assets.	
M/B	Ratio of the market value of total equity (31 Dec. 2019) to the book value of total equity, in percent.	Refinitiv, S&P
ROE	Return on average equity, in percent.	S&P
NPL/Loans	Non-performing loans as percentage of total gross loans.	S&P
CountryCovid	Dummy equal to 1 if bank headquartered in one of the five most-hit countries by Covid-19, 0 otherwise. Based on number of Covid-19 cases (21 April 2020) as percentage of total population.	Refinitiv, WHO
GDPGrowth2020	Forecasted 2020 GDP growth; weighted average of all countries in which the bank is active, based on its branch dispersion.	IMF, calc.
GDPGrowth2021	Forecasted 2021 GDP growth; weighted average of all countries in which the bank is active, based on its branch dispersion.	IMF, calc.

Data collected from S&P Global Market Intelligence (former SNL Financial and S&P Capital IQ), Refinitiv (Thomson Reuters), World Health Organization, EBA Spring 2020 EU-wide transparency exercise and IMF World Economic Outlook April 2020. Except if otherwise stated, variables represent end-2019 positions. All data are expressed in EUR. 'Calc.' = based on own calculations.

Table 2: Descriptive statistics

Variable	min.	avg. Q1	median	avg.	avg. Q4	max.	stdev.	obs.
Return	-67.69	-59.93	-47.61	-47.32	-32.82	-0.95	11.56	56
Return*	-61.59	-54.77	-44.03	-43.68	-31.90	-18.10	9.08	56
NCountries	1	2	7	15	38	56	16	56
DIVGeography	0.00	158.18	2973.55	3743.02	8032.93	8849.31	3195.55	56
NonIntInc	9.49	23.55	36.95	38.48	55.07	63.46	12.37	56
DIVFunctional	1717.26	3560.61	4648.83	4434.31	4973.13	4999.96	629.34	56
DIVLending	2033.53	4425.85	5700.80	5511.09	6333.44	6664.47	877.93	56
$\text{DIVLending}^{\text{SME}}$	4458.33	5349.18	6516.57	6305.50	7015.07	7353.46	679.12	56
CovidHigh	0.36	1.07	2.20	2.66	4.96	7.72	1.60	56
Beta	0.12	0.68	1.20	1.21	1.78	2.45	0.44	56
Equity/Assets	4.53	5.41	7.06	7.85	11.64	17.55	2.67	56
LCR	86.13	127.35	155.39	190.07	314.58	759.32	108.82	56
HQLA/Assets	7.96	12.05	16.79	18.30	27.41	52.07	7.32	51
Outflow/Assets	3.62	6.53	10.10	10.32	14.23	18.72	3.10	51
Cost/Income	40.86	47.18	59.31	61.13	76.53	99.25	11.72	56
Ln(Assets)	15.51	16.87	18.70	18.79	20.79	21.61	1.54	56
M/B	16.79	30.19	59.67	67.84	118.46	188.75	35.60	56
ROE	-11.27	0.40	7.20	7.10	13.64	21.51	5.69	56
NPL/Loans	0.38	1.30	3.69	6.55	17.69	33.50	8.66	56
CountryCovid	0	0	0	0	1	1	0	56
GDPGrowth2020	-9.98	-8.67	-6.58	-6.73	-4.82	-1.03	1.58	56
GDPGrowth2021	2.95	3.89	4.83	4.85	5.96	6.87	0.81	56

Minimum, average of first quartile, median, average, average of fourth quartile, maximum, standard deviation and number of observations for every variable used in the analysis.

the impact of an increase in diversification on banks' stock returns. For functional diversification, we construct the HHI using 2019 shares of net interest and non-interest income[6] in total operating income. For geographical diversification, we make use of S&P Global Market Intelligence data on the banks' foreign branch network. For every bank, we calculate the number of branches per country as percentage of the total number of branches.[7] Finally, for lending counterparty diversification, we use the EBA Spring 2020 EU-wide transparency

[6]The sum of net fee and commission income, net insurance income, realized and unrealized gains on securities, partnership income, dividends from equity instruments, lease and rental revenue, and other non-interest income.

[7]Alternatively, one can determine geographical exposures based on subsidiaries instead of branches. However, some banks serve multiple countries using a subsidiary in only one country. Hence, a subsidiary-based measure might slightly underestimate true geographical diversification, although both measures are highly correlated.

exercise, which discloses banks' end-2019 loan exposure to financial corporations (credit institutions and other financial corporations), NFCs and households.

Additionally, we include control variables which we expect to influence bank stock returns. The market beta accounts for differences in systematic risk. Banks with a higher beta are expected to be hit harder during downturns. Pre-Covid betas are calculated with a CAPM model. To account for differences in banks' geographical scope, we use a weighted average of the returns on country or regional MSCI indices as market returns, based on the bank's dispersion of branches.[8] Second, we include an end-2019 capital ratio. Since capital is a buffer against unexpected losses, banks with a higher capital ratio are supposed to be able to weather an exogenous shock better. Third, we include the LCR, as well as its individual components (high quality liquid assets and net cash outflows), to account for differences in liquidity positions at the start of the crisis period. Fourth, to correct for pre-Covid differences in size, performance and profitability, we add the logarithm of total assets, return on equity, cost-to-income ratio, market-to-book ratio and share of non-performing loans in different specifications (all end-2019). To take into account possible future non-performing loans, resulting from the Covid-19 pandemic, we construct a CovidHigh measure based on EBA data regarding the banks' exposures to NFCs in 19 different sectors. This variable captures loans (as percentage of total assets) to NFCs in the 4 sectors that are hit most by the pandemic.[9] To determine these sectors, we calculate the return on sectoral MSCI indices over the 13 February to 21 April

[8] We use country MSCI index returns for all home countries in our sample, while we proxy the other countries by regional MSCI indices (Europe, EMEA, Pacific, North America, Latin America). Using the MSCI Europe as market index for all banks would result in unrealistically low betas for a few banks which are only active in a periphery European country. While the betas become much more reasonable using geography-adjusted market returns, the regression results are similar. Using betas based on the MSCI index of the home country does not materially change the results either.

[9] As robustness checks, we construct variables capturing only the 3 or 5 most-hit sectors, as well as a risk-weighted asset measure weighing all sector exposures by their respective stock market performance. The regression results are completely similar.

2020 period, cf. Table 3. We include a dummy for banks headquartered in one of the five most-hit countries (Belgium, Iceland, Ireland, Italy, Spain; based on the number of Covid-19 cases on 21 April 2020) to account for cross-country heterogeneity in the impact of the pandemic, following Pham et al. (2021). As an alternative, we include GDP growth forecasts.

All bank variables are based on pre-Covid data, allowing identification of the impact on bank valuations when an exogenous shock hits. Since the banks in our sample did not disclose Q1 results before 21 April 2020, the returns are not influenced by the market's assessment of the level of pandemic-related loan loss provisions, higher- or lower-than-expected Q1 profits, etc.

4. Results

The results of the cross-sectional regression estimations are displayed in Tables 4 and 5.[10] The results demonstrate that especially one type of diversification acts as a major bank valuation shock absorber. Functional diversification always exhibits a positive and highly significant coefficient, indicating that having access to non-interest income is considered by stock market participants as value-enhancing. Since the prolonged ECB unconventional monetary policy will flatten the yield curve longer than previously anticipated, it will have additional negative implications for bank interest margins (Lane, 2020). Hence, banks with access to non-interest income revenues should be able to achieve higher profitability than their retail-specialized peers. As a robustness check, we replace HHI-based functional diversification with the share of non-interest income in

[10] We estimate the Variance Inflation Factor for all explanatory variables. Except for specification 7, the maximum value reached is 2.06, suggesting that multicollinearity is not a concern. In specification 7, ln(Assets) has a VIF of 5.44, due to its rather high correlation with other variables (e.g. DIVGeography, beta). Therefore, we do not include ln(Assets) in our baseline specification.

Table 3: Sectoral indices

NACE	Sector	Corresponding MSCI index	Return	Rank
A	Agriculture, forestry and fishing	MSCI Europe Agricultural and Food Chain	-3.50	16
B	Mining and quarrying	MSCI Europe Metals and Mining	-30.78	6
C	Manufacturing	MSCI Europe Industrials	-30.27	7
D	Electricity, gas, steam and air conditioning supply	MSCI Europe Energy	-36.70	3
E	Water supply	MSCI Europe Water Utilities	-16.35	14
F	Construction	MSCI Europe Construction and Engineering	-32.59	5
G	Wholesale and retail trade	MSCI Europe Retailing	-21.49	12
H	Transport and storage	MSCI Europe Transportation	-27.45	9
I	Accommodation and food service activities	MSCI Europe Hotels, Restaurants and Leisure	-37.64	2
J	Information and communication	MSCI Europe Information Technology Services	-26.93	10
K	Financial and insurance activities	MSCI Europe Financials	-39.59	1
L	Real estate activities	MSCI Europe Real Estate	-29.59	8
M	Professional, scientific and technical activities	MSCI Europe Professional Services	-19.29	13
N	Administrative and support service activities	MSCI Europe Software and Services	-21.70	11
O	Public administration and defence, compulsory social security	Constant index at 100	0.00	17
P	Education	Constant index at 100	0.00	17
Q	Human health services and social work	MSCI Europe Health Care	-5.27	15
R	Arts, entertainment and recreation	MSCI Europe Media and Entertainment	-33.72	4
S	Other services	NA	NA	NA

MSCI indices downloaded from Refinitiv (Thomson Reuters) in EUR. Given that it is not possible to find MSCI indices for NACE sectors O and P, we proxy their performance by a constant index, i.e. we assume that Covid-19 has no negative impact on these sectors. Returns are calculated as simple returns over the period 13 February 2020 to 21 April 2020. Ranking from most- (1) to least-hit (17) sector.

operating income (specification 2), which yields the same conclusion.[11] These results confirm the beneficial impact of functional diversification on the performance of European banks, as found by Baele et al. (2007) and Köhler (2015). It is also in line with the findings by Li et al. (2021) for US banks during the

[11] By far the most important driver of the results is net fee and commission income, since it represents about 70% of total non-interest income.

pandemic. Geographical diversification, on the other hand, is not able to shield bank valuations from a negative exogenous shock. Being active in several countries or regions offers no downside stock return protection. When we replace the HHI-based variable with the number of countries in which the bank is active (specification 3), the conclusion remains unaltered. The reason may be that market participants expected the impact of the pandemic to be similar across regions and that banks could therefore not benefit from risk reduction through less-than-perfect correlations between country-specific risks (Fang and van Lelyveld, 2014). In terms of lending counterparty diversification, the coefficient is positive and most of the time significant. This constitutes mild evidence that banks with loan portfolios well diversified among households, NFCs and financial corporations may benefit in periods of severe stress. As shown in specification 4, the diversification measure remains significant if we split loans to NFCs into loans to SMEs and non-SMEs.[12] Interestingly, the insignificance of the CovidHigh variable in specification 5 shows that banks with the largest NFC loan exposure to the most-hit sectors are not punished in terms of valuation.

Besides being statistically significant, functional diversification also turns out to be the most economically important dimension of diversification. We calculate the difference between the average value of the variable of interest for banks in the first and fourth quartile and multiply this with the regression coefficient of the variable.[13] This provides an estimate of the difference in return between banks with a low (average of the first quartile) and high (average of the fourth quartile) value for this variable. The difference in return between banks with high and low functional diversification is approximately 8.9 percentage

[12]However, it is sometimes no longer significant if we add other control variables. The economic relevance is also much lower than is the case for functional diversification (cf. infra).

[13]When possible, we use the coefficient of the variable in specification 1. However, the coefficients of the variables of interest are very robust between different specifications.

Table 4: Cross-sectional estimations - basic regression and robustness

Specification:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent var.:	Return	Return	Return	Return	Return	Return
DIVFunctional	0.0063***		0.0063***	0.0064***	0.0063***	0.0049***
	(0.0016)		(0.0016)	(0.0013)	(0.0016)	(0.0016)
NonIntInc		0.3230***				
		(0.1003)				
DIVGeography	-0.0001	0.0000		-0.0003	-0.0001	-0.0002
	(0.0003)	(0.0003)		(0.0004)	(0.0003)	(0.0004)
NCountries			-0.0389			
			(0.0728)			
DIVLending	0.0023*	0.0026**	0.0025*		0.0023*	0.0029**
	(0.0013)	(0.0011)	(0.0014)		(0.0013)	(0.0011)
$\text{DIVLending}^{\text{SME}}$				0.0035*		
				(0.0020)		
CovidHigh					-0.0320	
					(0.6377)	
Beta	-7.2763**	-6.8261**	-7.1295**	-6.6600**	-7.2579**	-4.9386
	(3.0899)	(3.0624)	(3.1395)	(3.1858)	(3.0691)	(3.5805)
Equity/Assets	-0.1141	0.1389	-0.1484	-0.0938	-0.1105	-0.1209
	(0.3854)	(0.3890)	(0.3942)	(0.3644)	(0.3800)	(0.4120)
LCR	0.0449**	0.0490**	0.0445**	0.0467**	0.0449**	
	(0.0207)	(0.0218)	(0.0205)	(0.0219)	(0.0213)	
HQLA/Assets						0.8878***
						(0.3226)
Outflow/Assets						-1.0836**
						(0.4554)
NPL/Loans	-0.0339	-0.0869	-0.0398	-0.1068	-0.0309	-0.2879
	(0.1462)	(0.1530)	(0.1477)	(0.1722)	(0.1650)	(0.2190)
Cost/Income	-0.1651*	-0.1720*	-0.1553	-0.1566*	-0.1650*	-0.2994**
	(0.0942)	(0.1005)	(0.0975)	(0.0933)	(0.0954)	(0.1376)
Constant	-75.8457***	-65.2182***	-77.3359***	-86.2389***	-75.7966***	-62.4151***
	(13.8765)	(12.1925)	(14.5193)	(16.5392)	(14.3873)	(12.5406)
R^2	0.546	0.546	0.547	0.555	0.546	0.606
No. of banks	56	56	56	56	56	51

This table shows the results of cross-sectional regressions of European banks' stock return during the first Covid-19 wave on pre-Covid bank and market variables. Stata's Huber-White robust standard errors are reported between brackets. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

points. When we consider specification 2 with the share of non-interest income, the difference is even 10.2 percentage points.[14] For high versus low lending counterparty diversification the difference is around 4.4 percentage points.

In terms of control variables, we find that the beta is significantly negative,

[14] The difference in return between the most- (average of the first quartile) and least-hit (average of the fourth quartile) banks was 27 percentage points. When we consider the 25th and 75th percentile instead, functional diversification accounts for a difference of approximately 6 percentage points in a total return difference of 12.5 percentage points.

Table 5: Cross-sectional estimations - additional control variables

Specification:	(7)	(8)	(9)	(10)	(11)	(12)
Dependent var.:	Return	Return	Return	Return	Return	Return*
DIVFunctional	0.0059***	0.0056***	0.0056***	0.0063***	0.0050***	0.0049***
	(0.0016)	(0.0016)	(0.0017)	(0.0016)	(0.0015)	(0.0015)
DIVGeography	0.0004	-0.0001	0.0000	-0.0001	-0.0004	0.0000
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0005)	(0.0003)
DIVLending	0.0040**	0.0021*	0.0020	0.0023*	0.0024**	0.0023**
	(0.0018)	(0.0012)	(0.0013)	(0.0013)	(0.0010)	(0.0009)
Beta	-2.7353	-8.0264**	-8.0749**	-7.2082**	-5.7367	-5.3506**
	(4.6930)	(3.0198)	(3.0106)	(3.2870)	(3.7629)	(2.3776)
Equity/Assets	-0.9345	-0.1578	0.0341	-0.1125	-0.5228	-0.4464
	(0.6285)	(0.4606)	(0.4151)	(0.3947)	(0.4264)	(0.3156)
LCR	0.0323**	0.0434*	0.0464**	0.0447**	0.0388***	0.0314***
	(0.0156)	(0.0227)	(0.0217)	(0.0205)	(0.0120)	(0.0114)
NPL/Loans	-0.2186	0.0533	-0.0337	-0.0392	-0.0951	-0.0580
	(0.2181)	(0.1807)	(0.1482)	(0.1584)	(0.1445)	(0.1238)
Cost/Income	-0.1518			-0.1638*	-0.2228**	-0.1281
	(0.0926)			(0.0924)	(0.1031)	(0.0817)
Ln(Assets)	-3.6547					
	(2.2109)					
M/B		0.0491				
		(0.0378)				
ROE			0.0137			
			(0.2077)			
CountryCovid				-0.4417		
				(2.3500)		
GDPGrowth2020					0.7873	
					(1.1456)	
GDPGrowth2021					3.6285*	
					(1.9532)	
Constant	-12.9269	-84.1644***	-82.3516***	-75.7100***	-75.6837***	-66.1601***
	(36.1357)	(13.8542)	(13.2429)	(13.7631)	(12.0614)	(9.9957)
R^2	0.589	0.541	0.525	0.546	0.606	0.547
No. of banks	56	56	56	56	56	56

This table shows the results of cross-sectional regressions of European banks' stock return during the first Covid-19 wave on pre-Covid bank and market variables. Stata's Huber-White robust standard errors are reported between brackets. * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent.

demonstrating that banks with a high pre-pandemic systematic risk suffered the most pronounced value decline. This is in line with the findings of Fahlenbrach et al. (2020) for non-financial firms during the Covid-19 pandemic. Surprisingly, we find that the equity-to-assets ratio is insignificant. This result appears to differ from Berger and Bouwman (2013) and Demirgüç-Kunt et al. (2013), who find that capital enhances the performance of banks in banking crises. Our results do confirm the findings of Demirgüç-Kunt et al. (2020), who also document no impact of the capital ratio on bank performance during the first months of the pandemic. In contrast, bank liquidity does have a clear and significant impact. In line with Demirgüç-Kunt et al. (2020), the LCR is positive and significant across all specifications, suggesting that ample liquidity buffers act as a valuation shock absorber. Our results indicate that in the early stage of the pandemic, market participants did not rule out that the sudden economic shock might spill over to doubts about banks' liquidity positions. Those banks with ample liquidity buffers benefit in terms of stock market valuation. Specification 6 moreover shows that not only disposing of high quality liquid assets, i.e. cash, central bank reserves and eligible government securities, but also exhibiting low potential liquidity outflows was interpreted by the stock market as a positive feature. Banks with higher pre-Covid cost efficiency also achieved somewhat higher returns, which is consistent with findings by Neukirchen et al. (2021) for US NFCs. Other pre-Covid measures of bank performance and size turn out to be insignificant. Specification 10 and 11 show that our results do not change after correcting for differences in the impact of the pandemic across countries, although investors seem to take expected GDP growth for 2021 into account. Finally, specification 12 shows that our results are not sensitive to changes in the choice of the Covid-19 impact period. In terms of economic relevance, the advantages of a lower beta, higher LCR, higher cost efficiency, and higher expected GDP growth are approximately 8, 8.4, 4.8 and 7.5 percentage points, respectively, using the same back-of-the envelope calculations as before.

5. Conclusion

We empirically analyze the impact of diversification, in various dimensions, on banks' market valuations during the first wave of the Covid-19 pandemic. For a sample of 56 European banks, we find that only functional diversification (reliance on non-interest income) acts as an economically important shock absorber: banks with high functional diversification exhibit a stock market return 8.9 to 10.2 percentage points higher than their specialized peers. In view of the negative implications of the pandemic on the path of future interest rates and the slope of the yield curve, stock market investors value the proven access of banks to non-interest sources of income. The impact of diversification of the lending portfolio across households, NFCs and financial corporations is also positive, although smaller (4.4 percentage points). Geographical diversification, on the other hand, is not considered to act as a shock absorber. Hence, when diversification matters most, i.e. when a severe unexpected shock hits, functional diversification is regarded by stock market investors as the only reliable shock absorber. Finally, our results provide support for supervisors' increased focus on liquidity measures after the GFC.

Acknowledgements

We thank Martien Lamers, Thomas Present, Nicolas Soenen, Heiko Hesse and an anonymous reviewer for helpful comments. We acknowledge financial support from the Ghent University Special Research Fund (BOF). Declarations of interest: none.

References

Acharya, V.V., Engle, R., Steffen, S., 2021. Why did bank stocks crash during COVID-19 ? SSRN Working Paper. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3799590&download=yes.

Acharya, V.V., Hasan, I., Saunders, A., 2006. Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios. The Journal of Business 79, 1355–1412. doi:10.1086/500679.

Aldasoro, I., Hardy, B., Jager, M., 2021. The Janus face of bank geographic complexity. Journal of Banking & Finance, 106040. doi:10.1016/j.jbankfin.2020.106040.

Baele, L., De Jonghe, O., Vander Vennet, R., 2007. Does the stock market value bank diversification? Journal of Banking and Finance 31, 1999–2023. doi:10.1016/j.jbankfin.2006.08.003.

Berger, A.N., Bouwman, C.H., 2013. How does capital affect bank performance during financial crises? Journal of Financial Economics 109, 146–176. doi:10.1016/j.jfineco.2013.02.008.

Bertay, A.C., Demirgüç-Kunt, A., Huizinga, H., 2019. Are International Banks Different? Evidence on Bank Performance and Strategy. BIS Working Papers No. 790. URL: https://www.bis.org/publ/work790.htm.

Demirgüç-Kunt, A., Detragiache, E., Merrouche, O., 2013. Bank Capital: Lessons from the Financial Crisis. Journal of Money, Credit and Banking 45, 1147–1164. doi:10.1111/jmcb.12047.

Demirgüç-Kunt, A., Pedraza, A., Ruiz-Ortega, C., 2020. Banking Sector Performance During the COVID-19 Crisis. World Bank Policy Research Working Paper No. 9363. URL: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3689789.

ECB, 2018. Financial Stability Review November. ECB Report. URL: https://www.ecb.europa.eu/pub/pdf/fsr/ecb.fsr201811.en.pdf.

ECB, 2020. Financial Stability Review May. ECB Report. URL: https://www.ecb.europa.eu/pub/pdf/fsr/ecb.fsr202005~1b75555f66.en.pdf.

Fahlenbrach, R., Prilmeier, R., Stulz, R.M., 2012. This Time Is the Same: Using Bank Performance in 1998 to Explain Bank Performance during the Recent

Financial Crisis. The Journal of Finance 67, 2139–2185. doi:10.1111/j.1540-6261.2012.01783.x.

Fahlenbrach, R., Rageth, K., Stulz, R.M., 2020. How Valuable Is Financial Flexibility when Revenue Stops? Evidence from the COVID-19 Crisis. The Review of Financial Studies doi:10.1093/rfs/hhaa134.

Fang, Y., van Lelyveld, I., 2014. Geographic diversification in banking. Journal of Financial Stability 15, 172–181. doi:10.1016/j.jfs.2014.08.009.

de Guindos, L., 2020. The euro area financial sector: opportunities and challenges. ECB Speech (6 February 2020). URL: https://www.ecb.europa.eu/press/key/date/2020/html/ecb.sp200206_1~063a81a96d.en.html.

Hayden, E., Porath, D., Westernhagen, N.V., 2007. Does diversification improve the performance of German banks? Evidence from individual bank loan portfolios. Journal of Financial Services Research 32, 123–140. doi:10.1007/s10693-007-0017-0.

Köhler, M., 2015. Which banks are more risky? The impact of business models on bank stability. Journal of Financial Stability 16, 195–212. doi:10.1016/j.jfs.2014.02.005.

Lane, P.R., 2020. The ECB's monetary policy in the pandemic: meeting the challenge. ECB Speech (6 October 2020). URL: https://www.ecb.europa.eu/press/key/date/2020/html/ecb.sp201006~e1d38a1ccc.en.html.

Li, X., Feng, H., Zhao, S., Carter, D.A., 2021. The effect of revenue diversification on bank profitability and risk during the COVID-19 pandemic. Finance Research Letters, 101957. doi:10.1016/j.frl.2021.101957.

Mergaerts, F., Vander Vennet, R., 2016. Business models and bank performance:

A long-term perspective. Journal of Financial Stability 22, 57–75. doi:10.1016/j.jfs.2015.12.002.

Neukirchen, D., Engelhardt, N., Krause, M., Posch, P.N., 2021. Firm efficiency and stock returns during the COVID-19 crisis. Finance Research Letters , 102037doi:10.1016/j.frl.2021.102037.

Pamen Nyola, A., Sauviat, A., Tarazi, A., 2020. How Organizational and Geographic Complexity Influence Performance? Evidence from European Banks. HAL-02966628. URL: https://hal-unilim.archives-ouvertes.fr/hal-02966628/document.

Pham, A.V., Adrian, C., Garg, M., Phang, S.Y., Truong, C., 2021. State-level COVID-19 Outbreak and Stock Returns. Finance Research Letters, 102002. doi:10.1016/j.frl.2021.102002.

Rossi, S.P., Schwaiger, M.S., Winkler, G., 2009. How loan portfolio diversification affects risk, efficiency and capitalization: A managerial behavior model for Austrian banks. Journal of Banking and Finance 33, 2218–2226. doi:10.1016/j.jbankfin.2009.05.022.

Saunders, A., Schmid, M., Walter, I., 2020. Strategic scope and bank performance. Journal of Financial Stability 46, 100715. doi:10.1016/j.jfs.2019.100715.

Shim, J., 2019. Loan portfolio diversification, market structure and bank stability. Journal of Banking and Finance 104, 103–115. doi:10.1016/j.jbankfin.2019.04.006.

Simoens, M., Vander Vennet, R., 2020. Bank performance in Europe and the US: A divergence in market-to-book ratios. Finance Research Letters, 101672. doi:10.1016/j.frl.2020.101672.

Stiroh, K.J., 2006. A Portfolio View of Banking with Interest and Noninterest Activities. Journal of Money, Credit and Banking 38, 1351–1361. URL: https://www.jstor.org/stable/3839009.

Vazquez, F., Federico, P., 2015. Bank funding structures and risk: Evidence from the global financial crisis. Journal of Banking and Finance 61, 1–14. doi:10.1016/j.jbankfin.2015.08.023.