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**Article**

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Dennis Dreusch\* and Peter Reichling

# The Performance of Merging Cooperative Banks in Germany

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**Abstract:** Motivated by the recent increase in bank mergers, this paper examines the performance of German cooperative banks that merged between 2014 and 2019. We are particularly interested in whether elevated merger rates are due to bank inefficiencies or to challenging policy measures such as low-for-long interest rates. The results indicate that banks that perform relatively worse before and during the low interest environment exhibit a greater probability of becoming a target during this period. Consolidation generally occurs among low performing banks where large and well-capitalized banks merge with their small and inefficient peers. Ultimately, our results attribute the increased number of mergers to inefficiencies in the banking industry, as banks that exited the market were inefficient prior to the adverse low interest rate environment.

**Keywords:** banks; mergers; regulation; low interest environment; efficiency

**JEL Classification:** G21; G34

## 1 Introduction

Over the past decade, a significant number of German banks have exited the market through mergers, which many banks see as the result of excessive regulation and low-for-long interest rates. The shrinking banking landscape thus raises potential concerns that difficult policy measures have driven ex ante good banks out of

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the market. This paper examines this issue by estimating the determinants of bank mergers before and during the low interest rate environment, thereby identifying the performance characteristics of merging banks in two time periods. This provides information not only on whether merging banks were good or bad performers *ex ante*, but also on the primary cause of the merger wave: Mergers are likely to be driven by bank inefficiency if target banks perform relatively poorly before and during the regulatory and interest rate changes and eventually exit the market during this adverse period. Conversely, increased merger activity may reflect challenging policies if target banks initially perform well or similarly to their non-merging peers, but underperform in the course of the low interest rate environment and eventually leave the market.

Given the recent increase in the number of mergers, it seems interesting to ask how adverse operating conditions are shaping and impacting the banking industry. The past decade provided for at least two crucial developments that, possibly each individually, but particularly when viewed together, resulted into a difficult surrounding. First and foremost, the low-for-long interest rate policy in the aftermath of the 2007–2009 financial crisis gradually reduced banks' profitability and net interest margin and effectively deteriorated their financial leeway (e.g. Borio, Gambacorta, and Hofmann 2017; Busch et al. 2022; Claessens, Coleman, and Donnelly 2018; Genay and Podjasek 2014). Existing work suggests that extended periods of low or negative policy rates induce banks to adapt. Banks increase their risk-taking by lowering their loan standards (Maddaloni and Peydró 2011) and raising the portion of risk assets (Delis and Kouretas 2011; Heider, Saidi, and Schepens 2019). Furthermore, banks cut their lending activity (Heider, Saidi, and Schepens 2019), adjust their funding structure, and exchange interest-generating engagements with fee-related and trading activities (Brei, Borio, and Gambacorta 2020). Importantly, the effects are more pronounced for small banks with higher deposit shares (e.g. Claessens, Coleman, and Donnelly 2018; Genay and Podjasek 2014; Heider, Saidi, and Schepens 2019; Kerbl and Sigmund 2016; Meyer 2018). Besides triggering low policy rates, the financial crisis also spurred authorities to thoroughly tighten and expand existing banking regulations. Considering the sheer complexity and impact on the industry, the Basel III reform thereby hardly compares to prior frameworks. In fact, reforms entail substantial costs for banks to establish permissible risk-management systems and comply with novel regulatory standards and metrics (e.g. Bonner and Eijffinger 2015; Dietrich, Hess, and Wanzenried 2014; Handorf 2014; King 2013). Since regulatory burden can manifest in various aspects, such as increased spending on administration and staff training, however, no reliable quantification exists with respect to banks' incurred cost of regulation (Cochrane 2014; Hoskins and Labonte 2015). The literature shows that banks transpose and respond to regulatory claims for higher capital and liquidity requirements by cutting their

lending (De Nicolò, Gamba, and Lucchetta 2014; Mésonnier and Monks 2015) and risk-weighted assets (Gropp et al. 2019) and by employing different strategies based on their profitability (Andrle et al. 2017; Cohen and Scatigna 2016).

Taken together, banks have faced a difficult surrounding for more than a decade, evoking changes in asset composition and funding structure. Given the relatively sharp decline in the number of independently operating EU banks, however, adverse conditions not only seem to have sparked notable adaptations in financial profiles. They likely also contributed to an accelerated consolidation process in which a substantial number of banks left the market through mergers.<sup>1</sup> The underlying reasoning is intuitive. Strenuous periods require an effective allocation of resources for banks to remain competitive. Banks failing to cope with detrimental circumstances are then either forced to wind up or merge with other banks. What remains unclear, however, is whether adverse conditions induced *ex ante* inefficient banks to exit the market in the spirit of Schumpeter (1939) (hereafter the ‘efficiency-view’), or whether they encouraged even initially well-performing banks to leave the market by negatively affecting their lending and deposit business. The uncharted issue of elevated bank exits steps into the line of questions related to the effects of ultra-loose monetary policies and stringent regulations, and is of paramount importance for comprehending developments in the banking landscape. If recent policy measures primarily turn small, albeit initially well performing, banks into merger targets, then this should be of interest to authorities. Likewise, it is important to know if consolidation occurs among low performing banks, which could help reduce over-capacities, enhance profitability, and improve resilience against shocks (ECB 2019). Given these unresolved questions surrounding the recent merger activity, this paper examines the relative performance and other key characteristics of banks that exited the market through mergers in recent years.

We do so by considering the merger dynamics in the German cooperative banking industry between 2014 and 2019. We select the German banking market because it is one of the largest in the EU, while the cooperative sector offers an abundant number of independently but similarly operating banks. This naturally mitigates concerns about potential differences in unobserved time-invariant bank characteristics (Mood 2010), and simultaneously satisfies crucial homogeneity assumptions for well-established efficiency measurement techniques (Dyson et al. 2001). The chosen time span reflects our intention to investigate critical periods. On the one hand,

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<sup>1</sup> According to the European Banking Federation, the number of EU banks between 2013 and 2019 declined by 23 %, which is roughly twice the decline from 2007 to 2013 (10 %). Similar findings are obtained for the number of MFIs in the Euro area: [https://www.ecb.europa.eu/stats/ecb\\_statistics/escb/html/table.en.html?id=JDF\\_MFI\\_MFI\\_LIST](https://www.ecb.europa.eu/stats/ecb_statistics/escb/html/table.en.html?id=JDF_MFI_MFI_LIST).

the Capital Requirements Regulation enters legal force in 2014, gradually imposing stricter standards on banks' capital and liquidity management. On the other hand, stipulated refinancing rates and standing facilities continue their declining path, further reducing banks' interest expenses but also their overall profitability. For our empirical analyses, we draw on the rich literature on bank merger determinants. As such, we first estimate a series of standard multinomial logistic models for the period 2014 to 2019, linking various performance measures to the probability of becoming a target or an acquirer. This allows important insights into consolidating banks' performance characteristics at that juncture. Subsequently, we consider an earlier time period from 2010 to 2012, when interest rates prevail at common levels and novel regulations still remain to be poured into binding law. We reiterate our analyses in similar fashion but this time relating banks' average performance over the period 2010 to 2012 to the probability of becoming a future target at some point between 2014 and 2019. The idea is to test whether performance, as measured before the low interest environment, significantly determines the probability of becoming a future target. If so, we can rule out the notion that the targets were initially well-performing banks that became underperforming due to the adverse policy actions and eventually disappeared from the market as a result. We provide two main findings. First, banks that perform relatively worse before and between 2014 and 2019 are more likely to exit the market during this period. Controlling for bank size and related merger determinants, the probability of becoming a target increases with a higher cost-income ratio, lower growth rates, and poorer asset management. Second, depending on the performance measure of choice, acquirers perform either similar or worse, but in no case better, than the reference group with no merger occurrence. Consolidation thus tends to occur among low performing banks, where large and well-capitalized banks take over their small and inefficient peers. Based on the findings in this paper, we conclude that the recent merger wave primarily arises from bank inefficiencies: Banks that perform relatively worse over the 2010–2012 period are more likely to become targets in the low interest rate environment.

In addition to studies analyzing the effects of banking regulations and low-for-long interest rate policies, our paper relates to several other streams of literature, including research on bank merger motives and determinants (e.g. Beccalli and Frantz 2013; Focarelli, Panetta, and Salleo 2002; Goddard, McKillop, and Wilson 2009; Hadlock, Houston, and Ryngaert 1999; Hannan and Pilloff 2009; Hannan and Rhoades 1987; Hernando, Nieto, and Wall 2009; Huhtilainen, Saastamoinen, and Suhonen 2022; Koetter et al. 2007; Lanine and Vander Vennet 2007; Moore 1996, 1997; Pasiouras, Tanna, and Gaganis 2011; Wheelock and Wilson 2000; Worthington 2004), bank distress and failure (e.g. Berger and Bouwman 2013; Berger, Imbierowicz, and Rauch 2016; Cole and Gunther 1995; Cole and White 2012; DeYoung and Torna 2013;

Estrella, Park, and Peristiani 2000; Wheelock and Wilson 2000), and the cleansing effect of crises (Spokeviciute, Keasey, and Vallascas 2019). Our paper closely connects to Spokeviciute, Keasey, and Vallascas (2019), which seems to be the only perceivable work investigating the cleansing effects of financial crises within the banking industry. The work predicts the probability of bank failure or acquisition by interacting crises with banks' cost efficiency. They find that the savings and loan crisis in the mid 1980s and early 1990s increases the exit probability for less efficient US commercial banks more than for the group of efficient banks. However, the 2007–2009 financial crisis escalates the exit probability regardless of banks' cost efficiency. The work thus provides mixed evidence on the efficiency-view that crises encourage less efficient banks to drop out of the market. Our paper differs from the existing literature in that we examine the link between recent merger activity and (monetary) policy measures. By showing that consolidation occurs among low performing banks, we provide an interesting avenue for research analyzing the belief that “in systems with many weak-performing small banks, consolidation within their domestic system could improve performance” ECB (2019), p. 107. Related, we also extend the literature on bank merger predictability.

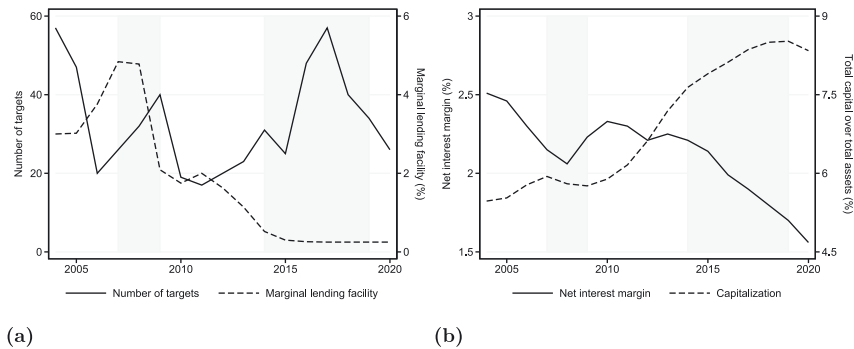
## 2 Mergers Made in Germany

The German cooperative banking industry has experienced an extraordinary increase of mergers over the past years. This is illustrated in Figure 1(a), which depicts the annual number of banks exiting the market along with the marginal lending facility as a measure of the ECB's interest rate policy. Importantly, mergers accelerate after 2011, and peak in 2017 when 57 targets are taken over by 40 acquiring banks. These numbers can be put into perspective by comparing the recent merger activity with the situation around the 2007–2009 financial crisis. Although the crisis is known for its substantial impact on the banking industry, relatively few banks engaged into mergers during that period. Considering the entire time span of our sample from 2013 to 2020, merger dynamics induce an overall decline in the quantity of independent cooperative banks by nearly 25 %.<sup>2</sup>

The driving motive behind these elevated merger rates could arguably be linked to the low interest environment, which exposes banks to historically low earnings. Such linkage is supported by the simple fact that mergers occur in a time when interest rates concurrently exhibit a declining path. Lower market rates,

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<sup>2</sup> Bundesbank data suggests 1,065 banks by the end of 2013, and 804 banks by the end of 2020. In this respect, note that supervisory agencies possess no direct mandate to enforce mergers. Given numbers hence comprise mergers made on a voluntary basis.



**Figure 1:** The evolution of cooperative bank mergers in Germany. Figure (a) shows recent developments in German cooperative bank merger activity along with the lending facility. Figure (b) depicts the average net interest margin and capitalization for this industry. Shaded areas respectively indicate the 2007–2009 financial crisis and the 2014–2019 low-interest environment as considered in our analysis. The data are taken from the Bundesbank: “Bankstellenstatistik” and “Zeitreihen-Datenbanken”.

in turn, come along with a reduction of banks’ net interest margin, as shown in Figure 1(b) by the solid line. In this regard, banks might merge to encounter their decreasing margins by realizing economies of scale or scope (Amel et al. 2004). However, low interest rates may not be the only motive. The recent merger wave also falls in a period in which authorities depart towards a stricter banking regulation. Extensive regulation in terms of the Basel III framework could then impede growth and burden banks with costs (e.g. Dietrich, Hess, and Wanzenried 2014; Mésonnier and Monks 2015), although these costs may be absorbed, at least to some extent, by the compound structures of the German cooperative system. While the quantification of such regulatory costs is difficult, the impact of greater (capital) requirements can be shown clearly by an upward sloping capital ratio, as depicted in Figure 1(b) by the dashed line. Thus, banks might also merge to comply with regulations at fewer costs, for instance by profiting from a diversification of their loan portfolio (Amel et al. 2004). Apart from regulatory motives, mergers can also be based on management restructuring goals and the establishment of a new corporate culture (Gindele et al. 2019). In their recent study, Gindele et al. (2019) explicitly state that mergers among cooperative banks are primarily driven by structural changes in management, rather than attempts to improve profitability. Although the analysis is limited to banks in the German state of Baden-Württemberg between 2009 and 2016, these management motives make it generally unclear whether the target banks are underperforming or distressed.

As for the current wave of mergers, low interest rates seem to be the dominant motive. Drawing on banks' websites, press releases, local newspaper articles that comprise interviews with bank executives, and related sources, banks mainly attribute their decision to merge to the low interest environment and an extensive set of regulations, but also to a costly layout of a digital infrastructure. More specifically, among the 228 targets subject to our empirical analysis, 211 banks justify their merger by referring to a combination of at least two out of these three elements. For the remaining 17 banks, we find no information. An exemplary statement reflecting key merger motives is taken from a press release by the Volksbank Untere Saar eG and the Vereinigte Volksbank eG Saarlouis – Losheim am See – Sulzbach/Saar:

As for the main reasons of the merger, Soester names the exuberant regulatory requirements, the altered customer behavior due to an increasing digitalization, and the impact of the ongoing low interest environment, which causes declines in earnings year after year. (Press release, accessed on the 11.01.2023 at 11:30)

Another example concerns the merger activity between the VR-Bank Hunsrück-Mosel eG and the Vereinigte Volksbank Raiffeisenbank eG:

The merger is mainly aimed at meeting the challenges of the low-interest policy and the increasing supervisory regulation. (Website, accessed on the 11.01.2023 at 11:30)

Since most statements resemble each other to a great extent, both examples can be taken as representative of the general reasoning in the population. While it could be true that some banks mask other decisive merger intentions behind statements such as the two presented, the disadvantageous nature of the low interest environment is evident. Even if there are cases where unobserved factors ultimately seal the merger, such as excessive losses leading to distressed mergers, it seems likely that such factors are again closely related to the state of profitability, or to the costs of regulation and digitalization, although the latter may again be absorbed by the prevailing network structures in the cooperative sector.

Given the high number of mergers, paired with the fact that most banks attribute their merger decision to the fierce operating situation, it appears natural to ask if such environment encourages rather low performing banks to exit the market. To obtain a first, motivating glimpse on the differences between targets and non-merging banks, Table 1 contrasts both groups with regard to crucial bank (performance) characteristics. Beginning with Panel A, which considers all bank-year observations from our primary data as discussed in the subsequent section, we observe a significant difference in total assets. Target banks are on average only half the size of non-merging banks. Moreover, non-merging banks exhibit greater growth rates, are seemingly better capitalized, profit from significantly lower NPL-ratios, and achieve more favorable cost-to-income balances. We

**Table 1:** Performance differences. This table examines performance differences between target banks and non-merging banks. Panel A considers the full sample from 2014 to 2019, for which we observe 599 non-merging banks over 6 years yielding 3,594 bank-year observations. Panel B additionally considers the 2014–2017 sub-sample comprising 599 non-merging banks. All variables are reported in percent, except assets and GRP per capita, which are reported in millions and thousands of Euros, respectively. S.E. refers to the standard error of the mean. The first  $p$ -value refers to a two-sample  $t$ -test, which tests the  $H_0$  that the difference in means equals zero. The second  $p$ -value refers to a Wilcoxon rank sum test and is reported to address concerns about data normality.

Panel A: Full sample									
	Target			Non-merging			Difference	$t_{p\text{-value}}$	$W_{p\text{-value}}$
	$N$	Mean	S.E.	$N$	Mean	S.E.			
Assets	837	389	12.91	3,594	785	33.70	396	0.00	0.00
Asset growth	609	3.73	0.144	2,995	4.69	0.076	0.96	0.00	0.00
Loan growth	609	4.20	0.211	2,995	5.67	0.099	1.47	0.00	0.00
Equity share	837	9.14	0.069	3,594	9.46	0.036	0.32	0.00	0.00
Tier 1 ratio	812	14.6	0.141	3,557	15.1	0.067	0.50	0.00	0.00
NPL ratio	758	1.79	0.061	3,403	1.55	0.025	−0.24	0.00	0.00
Return on assets	837	0.27	0.006	3,594	0.28	0.003	0.01	0.11	0.72
Return on equity	837	2.94	0.056	3,594	2.94	0.029	0.00	0.96	0.26
Cost-income ratio	837	70.0	0.360	3,594	67.0	0.332	−3.00	0.00	0.00
GRP per capita	833	34.7	0.439	3,582	35.4	0.220	0.70	0.16	0.14

Panel B: Sub-sample 2014–2017									
	Target			Non-merging			Difference	$t_{p\text{-value}}$	$W_{p\text{-value}}$
	$N$	Mean	S.E.	$N$	Mean	S.E.			
Assets	228	402	21.58	2,396	749	38.97	347	0.01	0.05
Asset growth	171	3.56	0.271	1,797	4.43	0.101	0.87	0.01	0.05
Loan growth	171	4.11	0.370	1,797	5.46	0.131	1.35	0.00	0.01
Equity share	228	9.08	0.134	2,396	9.25	0.045	0.17	0.25	0.16
Tier 1 ratio	228	14.3	0.246	2,361	14.6	0.083	0.30	0.23	0.24
NPL ratio	213	1.92	0.142	2,259	1.73	0.032	−0.19	0.09	0.09
Return on assets	228	0.25	0.009	2,396	0.29	0.004	0.04	0.00	0.00
Return on equity	228	2.82	0.091	2,396	3.20	0.036	0.38	0.00	0.01
Cost-income ratio	228	71.0	0.710	2,396	67.0	0.441	−4.00	0.01	0.00
GRP per capita	224	35.2	0.897	2,388	34.4	0.260	−0.80	0.36	0.23

neither observe differences in the profitability, nor in the regional economic output as proxied by the Gross Regional Product per capita. Since Figure 1(b) reveals trends in banks’ capitalization and net interest margin, however, it is likely that comparisons among related variables are flawed. This is because non-merging banks, by definition, remain throughout the sample period and are thus more exposed to

these trends. To achieve a less skewed picture, Panel B additionally considers the 2017 sub-sample which is the year with the most mergers. Specifically, Panel B compares the pre-merger period of the 57 banks that become a target in 2017 with the same period (2013–2016) for the group of non-merging banks. As expected, differences in both capitalization metrics turn statistically negligible, while differences in the profitability measures revolve significant.

Overall, these preliminary findings indeed motivate the efficiency-view since targets exhibit relatively weaker profiles when compared to their non-merging peers. This is relevant from an aggregate perspective as the German banking system is often said to be overbanked, fragmented, and unprofitable (see, e.g. a speech by Dombret 2016, or Koetter et al. 2006). If recent mergers among low performing banks have accelerated the ongoing consolidation process within the industry, they might as well have reshaped the German banking market towards a less fragmented and more profitable system.<sup>3</sup> Given that Table 1 also suggests notable differences in bank size, however, descriptive analyses appear insufficient to draw definitive conclusions. Instead, the underlying setting necessitates multivariate analyses to disentangle performance effects from the potential influence of other bank characteristics.

### 3 Data

We work with two distinct data sets. For our primary analysis, we start by gathering information on all German cooperative bank mergers between 2013 and 2020. To this end, we first screen and compare the annual directory of credit institutions, provided by the Bundesbank. The directory lists all banks that exist by the end of a corresponding year and serves as a first measure to identify target banks. We hence identify those banks as potential targets, which initially appear in the directory and stop to do so at some future point in time. Subsequently, we verify these banks as targets by using the German firm register ('Unternehmensregister'). The firm register is a state run, publicly accessible online archive, which comprises annual statements and other qualifying information such as notices on merger activities. Banks are obliged to report their statements and related events that require disclosure to the register according to § 325 in conjunction with § 340 I of the German Commercial Code. Based on the merger notices in the firm register, we retrieve

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<sup>3</sup> Note that we do not argue that greater bank profitability is a preferable outcome from a welfare perspective. We rather emphasize the benefits in terms of financial stability aspects. For instance, the banking literature points to a positive relationship between profitability and the chances of survival during crises (Berger and Bouwman 2013).

precise information on the merger year, the target bank ('übernommenes Institut'), and the acquiring bank ('übernehmendes Institut'). We scrutinize all mergers by examining the annual statement of each acquiring bank with regard to the financial incorporation of the respective target bank(s). Overall, we identify 228 relevant targets that are taken over by 169 acquirers within the period of 2014–2019. The remaining banks from the directory of credit institutions consequently constitute the set of non-merging entities. Note that these numbers as well as all further analyses exclude serial acquirers, banks that acquire another bank and then become a target, and banks that engage in merger activities of any kind in 2013 or 2020. These restrictions aim to address merger comparability concerns and allow for a meaningful sample split into target banks (228), acquirers (169), non-merging banks (599), and others (69). Next, we link the merger information with bank-level financial data, which we retrieve from bank disclosure reports and the German firm register. This allows us to control for a broad set of factors that have previously been shown to influence mergers. To account for regional differences in banks' operating environment, we complement the data set with economic and demographic indicators at the county level ('Kreisebene'). These indicators are taken from the federal and state statistical offices ('Regionalatlas der Statistischen Ämter des Bundes und der Länder')<sup>4</sup> and comprise the gross regional product, unemployment rate, disposable income, total population and population density, and the share of the retired population (age over 65).

To understand how targets perform before the changes in regulations and interest rates, we construct a secondary sample as we lack bank disclosure reports for the years before 2013. As such, we first draw on the Bankscope data base of the Bureau van Dijk to obtain annual accounting data at the bank-level. We keep all German cooperative banks that operate between the period 2010 to 2012, and average all bank-specific variables for each bank over this period. As before, we then complement the accounting data with (averaged) macroeconomic and demographic measures at the county level. The starting point in 2010 is chosen to avoid confounding effects with the 2008 financial crisis. We limit the ending point to 2012 to mitigate distorting effects related to banks' anticipation of the Basel III implementation. This selection leaves a sample of 1.101 German cooperative banks, of which we identify 218 banks as future targets. More precisely, we know with certainty that these 218 banks become a target at some point between 2014 and 2019.<sup>5</sup> We also attempt to trace future acquirers, which proves difficult as acquirer identification often

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<sup>4</sup> <https://regionalatlas.statistikportal.de/>.

<sup>5</sup> We fail to retrace the remaining 10 targets from our initial sample group of 228 target banks. This likely owes to differences in bank identification such that the data set at hand may identify banks differently.

changes post-merger. Therefore, we abstract from future acquirer identification and instead distinguish future targets from the group of “other cooperatives” comprising all non-future target banks. This allows us to measure future target banks’ performance relative to all other cooperatives for the time before the low interest environment. We report summary statistics for both samples in the Appendix in Table A1. We also break down merger activity by year in Table A2.

## 4 Methodology

We examine the link between bank performance and the probability of becoming a target or an acquirer by first estimating a multinomial logit model based on the period 2014 to 2019, as in Hannan and Rhoades (1987), Focarelli, Panetta, and Salleo (2002), Worthington (2004), Koetter et al. (2007), Hernando, Nieto, and Wall (2009), Pasiouras, Tanna, and Gaganis (2011), Beccalli and Frantz (2013), Spokeviciute, Keasey, and Vallascas (2019). In contrast to the simple exercise in Table 1, such a model allows us to explore the role of bank performance while controlling for a wide range of factors. This is important as targets tend to be smaller than their non-merging peers, making it virtually unclear if performance actually is a merger determinant when controlling for size and other bank characteristics. Specifically, we predict event  $Y = i$ , taking values 0, 1, and 2 if a bank in a given year does not merge, becomes a target, or becomes an acquirer, respectively, based on lagged covariate vector  $x$ . For a number of  $i = 0, \dots, J$  groups, we denote the model as:

$$P(Y = j|x) = \frac{e^{\beta_j x}}{1 + \left( \sum_{k=1}^2 e^{\beta_k x} \right)}, \quad P(Y = 0|x) = \frac{1}{1 + \left( \sum_{k=1}^2 e^{\beta_k x} \right)} \quad \text{for } j = 1, 2 \quad (1)$$

where  $P(Y = j|x)$  is the conditional probability of becoming a target ( $j = 1$ ), or an acquirer ( $j = 2$ ), given covariate vector  $x$ . Bank-year observations with no merger incident constitute the reference group,  $P(Y = 0|x)$ , to which all other groups are compared. Covariates are lagged by one year and comprise one bank performance measure at a time to avoid inflated standard errors among respective measures. To alleviate potential distortions due to omitted variables,  $x$  further supplies a set of time varying, bank-specific factors that have been shown to determine bank mergers. Moreover, time-varying economic and demographic indicators at the county level capture regional differences in banks’ operating environment. Lastly, we recognize that our investigation window is characterized by a series of (unconventional) monetary policy interventions. Therefore, we also consider year dummies to control for potential portfolio re-balancing effects and other unobserved year effects (Tischer 2018).

Estimated coefficients for these variables per group,  $\beta_j$ , yield the change in the logged ratio of the probability of being a target (acquirer) to the probability of being in the reference group, given a unit change in the predictor variable. Put differently, the relationship holds  $\ln[P(Y = j)/P(Y = 0)] = \beta_j x$ , which is somewhat difficult to interpret. To facilitate understanding, we discuss exponentiated coefficients representing relative risk ratios (RRR), as described in Hosmer and Lemeshow (2000) and applied by Koetter et al. (2007). The RRR allow for sensible interpretation: All else equal, a one unit increase in the predictor variable changes the probability of being in group  $j$  relative to the probability of being in the reference group by  $[(e^{\beta_j} - 1) \times 100\%]$ , where  $e^{\beta_j}$  is the RRR of the underlying variable for group  $j$ .

The multinomial approach offers insights into how targets and acquirers perform relative to their non-merging peers during periods of low interest rates and increased regulations. We therefore understand consolidating banks' characteristics at that juncture. However, even if the target banks turn out to be poor performers, this analysis is not sufficient to support the efficiency view. Since adverse conditions likely affect banks heterogeneously with respect to their size, they could be the main driver for target banks' financial atrophy and ultimately their market exit. Therefore, we must understand if targets perform worse initially and exit the market later on during disadvantageous periods.

The next aim then is to relate the probability of becoming a target between 2014 and 2019 to the average performance prior to the emergence of adverse factors. If *ex ante* performance significantly predicts future targets, this could show that adverse conditions are not the primary cause for target banks' weak profile in the more recent years. Here, we consider the 2010–2012 period as a suitable window to measure *ex ante* performance for two reasons. First, the starting point offers sufficient temporal distance to the financial crisis, allowing banks to digest the most immediate impacts of the crisis. Second, the ending point ensures that banks still operate under earlier regulations with less stringent requirements and at rather common policy-rates. Hence, we relate the probability of being a future target to banks' average performance over the period 2010 to 2012. We estimate a standard binary logistic model (e.g. Hernando, Nieto, and Wall 2009; Huhtilainen, Saastamoinen, and Suhonen 2022):

$$P(Y = FutureTarget|\bar{x}) = \frac{e^{\beta\bar{x}}}{1 + e^{\beta\bar{x}}} \quad (2)$$

where  $P(Y = FutureTarget)$  is the probability that a bank becomes a target in the future. *FutureTarget* is a dummy equal to unity if the bank is acquired at some point between 2014 and 2019, and zero otherwise. The covariate vector  $x$  is the same as in equation (1), except for the consideration of year effects. Likewise, vector  $x$  is shown with a bar to indicate averaged values. Estimated coefficients yield the change in log odds given a unit-change in the predictor variable. As before, we thus discuss

exponentiated coefficients to measure changes in terms of odds ratios (Hosmer and Lemeshow 2000).

Before proceeding with a discussion of our variable selection, we finally address an issue concerning the influence of unobserved mergers during the period 2010 to 2012. Since we lack acquirer information over this period, observations with realized mergers enter the reference group and may distort estimations in (2). In particular, acquisitions between 2010 and 2012 may affect the likelihood of becoming a target later on. We tackle this issue by considering two variations of (2). In the main estimations shown, we proxy acquirers by applying a threshold level of 20 % on asset growth. In practice, this means that we remove banks with annual asset growth in excess of 20 %. We find this value appropriate, given that 99 % of the non-merging banks in our 2014–2019 sample exhibit annual growth rates of less than 16 %, while 75 % of the acquirers in their merger year show growth rates greater than 27 %. This procedure removes 45 pseudo acquirers. In unreported estimations, we then test the robustness by keeping all sample banks. We find that either approach yields similar results.

## 4.1 Performance Measures

The first performance measure of choice is derived from Data Envelopment Analysis (DEA). Building on the previous work of Farrell (1957), DEA was introduced by Charnes, Cooper, and Rhodes (1978) in terms of a linear programming model. In the banking context, DEA compares the observed input-output allocation of each bank with an unobserved benchmark outcome that could be achieved by a linear combination of efficient banks' production dynamics. Compared to common accounting-based metrics, this technique thus offers efficiency values that better reflect banks' relative performance as intermediaries, taking into account multiple inputs such as deposits, and multiple outputs such as loans. In this respect, DEA is a widely recognised approach for efficiency measurement in the banking literature (Barth et al. 2013; Berger and Humphrey 1997). We consider an input oriented model based on Charnes, Cooper, and Rhodes (1978):

$$\begin{aligned}
 & \min \theta_B \\
 & \text{s.t. } \sum_{j=1}^n \lambda_j \cdot x_{i,j} \leq x_{i,B} \cdot \theta_B \quad \text{for } i = 1, \dots, m \\
 & \quad \sum_{j=1}^n \lambda_j \cdot y_{k,j} \geq y_{k,B} \quad \text{for } k = 1, \dots, s \\
 & \quad \lambda_j \geq 0
 \end{aligned} \tag{3}$$

Minimizing the efficiency  $\theta$  of bank  $B$  translates into finding a benchmark outcome that offers the same quantity of output  $k$  as bank  $B$ ,  $y_{k,B}$ ,  $k = 1, \dots, s$ , but requires fewer input  $i$ ,  $x_{i,B}$ ,  $i = 1, \dots, m$ . Consequently,  $\lambda_j$  corresponds to the weight given to the production dynamic of bank  $j$ ,  $j = 1, \dots, n$  to form the benchmark. The resulting  $\theta_B$  is thereby interpreted as the percentage level to which all input quantities of  $B$  would have to be reduced from their current state to arrive at the benchmark.<sup>6</sup> It takes values between zero and one, where a value of one constitutes an efficient bank.

The model as it stands assumes constant returns to scale which appears not appropriate for banking studies in general (Fiorentino, Karmann, and Koetter 2006). We thus opt for variable returns to scale by adding the constraint  $\sum_{j=1}^n \lambda_j = 1$ , which ensures comparisons among firms of similar size (Banker, Charnes, and Cooper 1984). Concerning the input-output selection, we employ a variation of the intermediation approach as initially suggested by Sealey and Lindley (1977), and ever since applied with adaptations in the literature (e.g. Barth et al. 2013; Chortareas, Girardone, and Ventouri 2012; Drake, Hall, and Simper 2009; Lang and Welzel 1996). As such, banks utilize four inputs, (i) total deposits, (ii) total equity, (iii) fixed assets, and (iv) personnel expenses to generate two outputs, (i) total loans, and (ii) total securities.

The second efficiency measure is a refinement of (3) with respect to the consideration of environmental factors that could impact bank efficiency but lie outside managerial influence. The rationale is that banks' performance could hinge on regional characteristics such as the unemployment rate, which might distort efficiency scores of all banks (Dyson et al. 2001). We consider external factors by following a two-stage procedure as recently done by Reichling and Schulze (2018) based on the work of Fried, Schmidt, and Yaisawarng (1999). First, we apply two-limit Tobit analysis by regressing the unadjusted values from (3) on our full set of macroeconomic and demographic indicators. The objective of the Tobit analysis is to identify environmental factors that significantly explain variation in unadjusted efficiency values. In the second stage, we integrate significant factors as non-discretionary variables into the DEA model (Banker and Morey 1986). Following Fried, Schmidt, and Yaisawarng (1999), variables with a positive coefficient (population density) enter the model as additional fixed inputs, while variables with a negative coefficient (retired population share) do so as additional fixed outputs.<sup>7</sup>

<sup>6</sup> For instance, a value of 0.85 indicates that a benchmark production exists, which offers at least as much output as the bank under evaluation  $B$ , but uses only 85 % of the inputs.

<sup>7</sup> Tobit results are available upon request and reflect critical findings of related work. Specifically, results show that urban banks operate less inefficiently, which supports the existence of an urban productivity premium (Andersson, Burgess, and Lane 2007). Likewise, banks operating in areas

The resulting efficiency values – for brevity, adjusted values – are hence adjusted for relevant environmental factors. Since an increasing  $\theta$  indicates decreasing bank inefficiency, we expect a negative relationship between both efficiency measures and the probability of becoming a target.<sup>8</sup>

Apart from DEA, we also analyze six conventional accounting-based ratios. As for the first five measures, we consider the cost-to-income ratio, the non-interest expenses to asset ratio, the return on equity and assets, and loan growth. These metrics are selected due to their frequent use in related work (e.g. Lanine and Vander Vennet 2007), and recognition as performance measures by supervisors (e.g. ECB 2010). The sixth measure is a liquidity indicator, defined as the sum of cash and central bank holdings as a share of total assets. Although proportionally large stakes of these liquid assets seem to appear desirable at first sight, they might indicate idle resources with poor returns (Koetter et al. 2007). This could be particularly true when considering the low interest sphere with zero or negative marginal deposit facilities. We thus view the liquidity share as an indication of how banks perform regarding their asset management. In this respect, we expect the liquidity share to be positively associated with the probability of becoming a target bank.

## 4.2 Control Variables

Considering the findings of Koetter et al. (2007), Hernando, Nieto, and Wall (2009), Pasiouras, Tanna, and Gaganis (2011) and Beccalli and Frantz (2013), amongst others, the banking literature has converged to a set of bank-specific factors that are reliably associated with bank mergers. To make sure that these common determinants of bank mergers are not driving our performance estimates, we include corresponding factors as controls in the regressions. More precisely, we follow Hernando, Nieto, and Wall (2009) and Pasiouras, Tanna, and Gaganis (2011) and include the natural log of total assets as a measure of bank size. Furthermore, we include the percentage change in total assets as a proxy for growth prospects as well as the ratio of equity to total assets as a proxy for capitalization. Moreover, we consider customer loans as a share of total assets to control for differences in specialization and asset diversification (e.g. Beccalli and Frantz 2013; Huhtilainen, Saastamoinen, and Suhonen 2022). To ensure robustness, we further take into account alternative

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with larger shares of elder people are affected detrimentally, which could be due to reduced loan demand and greater costs for personal advisory (Conrad, Neuberger, and Trigo 2009).

<sup>8</sup> Related work often considers profit and cost efficiency, which, however, require data on unit prices and costs. Here, we instead focus on the technical-physical aspects of intermediary efficiency as we lack reliable information on respective variables such as depreciation and number of employees (Cooper, Seiford, and Tone 2007).

metrics such as the Tier 1 Capital ratio (instead of the equity share) and the share of securities in total assets (instead of the loan share) as in Koetter et al. (2007).

Because bank characteristics may depend on external conditions, we also include economic and demographic information for the county in which each bank operates. We account for the possibility that banks in economically more favorable environments could profit in terms of asset growth and loan quality. In this respect, we additionally include the unemployment rate to proxy regional economic strength. We also suspect that urban banks might be larger and could benefit from a productivity premium vis-à-vis banks in rural areas (Andersson, Burgess, and Lane 2007). Therefore, we consider the natural log of the population density as a measure of the urbanization extent. For robustness, we check if a county's cooperative bank density and market concentration influence our results. As such, we account for the variables bank density, proxied by the number of banks relative to the county's population size, and HHI, which is the normalized Herfindahl–Hirschman Index measuring customer loan market concentration within each county.

## 5 Results

This section addresses our empirical results. We begin by estimating variations of equation (1) for the period 2014 to 2019 to understand if bank performance significantly associates with the probability of turning into a target or an acquirer. Subsequently, our focus shifts to an earlier point in time, when interest rates prevail at somewhat common levels, and new regulations just begin to unpack their influence on the industry. The idea is to analyze how target banks perform prior to low market rates and fiercer regulations. This could show that adverse conditions are not the primary cause for target banks' low performance. Instead, initially low performing banks may have a greater probability to exit the market later on.

### 5.1 Results of the Multinomial Model

To examine how performance relates to the likelihood of a bank being a target or an acquirer, we conduct a series of multinomial logistic regressions. Estimations are based on a sample of 201 targets, 169 acquirers, and 599 non-merging banks. Note that the estimations require independence among all bank-year observations. Due to the panel structure, however, this is unlikely to be the case, since banks that continue to exist in some year  $t$  cannot have become targets in  $t - 1$ , and vice versa (Shumway 2001). We tackle this issue by employing standard errors that are clustered at the bank level. This leaves estimated coefficients unchanged but offers robust inference by allowing dependence within clusters. We report our results in

Table 2. Recall that we discuss the coefficients in terms of RRR, which capture the change in the relative probability given a unit change in the predictor variable. For example, the coefficient on the liquidity share of around 0.092 indicates that a one percentage point increase in this variable increases the probability of being in the target group relative to the probability of being in the reference group by  $[(e^{0.092} - 1) \times 100\%] \approx 10\%$ .

Two main findings are apparent. First, passing through target group results across columns ( $T$ ), we notice that targets perform worse than the reference group on nearly all performance measures. Starting with column (1), which captures banks' unadjusted efficiency as intermediaries, we observe a significant and negative coefficient. Consistent with our expectation, increasing bank efficiency is associated with a decreasing probability of becoming a target. The result particularly implies that target banks are characterized by relatively low efficiency values, indicating their tendency to rely on greater input volumes compared to their non-merging peers. This finding remains in column (2) when we repeat the estimation but use adjusted values which account for differences in operating environments. Simply put, target banks tend to draw on relatively greater input quantities even when considering their operation in potentially disadvantageous locations.

Turning to our set of accounting-based performance measures, we document a significant, albeit economically small, effect for the cost-income ratio in column (3). The probability of becoming a target increases as banks bear larger costs per income unit. This again shows that the targets under consideration are not particularly well performing banks but instead tend to exhibit relatively greater cost-income ratios. Similarly, column (4) implies that target banks rather suffer from a greater share of non-interest expenses. This indicates relatively larger spending on staff and administration to manage one asset unit. Continuing with column (5), we observe a positive relationship between banks' liquidity share and the likelihood of being a target, which echoes the findings of Koetter et al. (2007). Recall that we expect this outcome since excessive cash positions and central bank holdings offer poor returns, especially during periods of low market interest rates. The profitability measure in column (6) turns out insignificant after controlling for common determinants of bank mergers. The outcome does not change if we reiterate the exercise but use the return on assets instead (unreported). Finally, column (7) indicates a negative relationship between loan growth and the probability of being a target such that banks with greater growth rates, anything else equal, are less likely to engage into mergers. Note that we are aware of potential multicollinearity issues between loan and asset growth. We accept this possibility to maintain model consistency.

Second, we find mixed evidence for the acquirer group ( $A$ ). On the one hand, columns (1), (2), (4), and (7) imply that acquirers operate inefficiently regarding their

**Table 2:** Multinomial logit results. This table explores how various performance measures relate to the probability of a bank becoming a target or an acquirer. Estimations are based on a sample of 201 targets, 169 acquirers, and 599 non-merging banks over the period 2015 to 2019. Merger activities and bank-year observations in 2014 are omitted due to the lagged nature of asset growth. All estimations consider year effects as shown at the bottom of the table. Standard errors are clustered at the bank level. *P*-values are reported in parentheses.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	T	A	T	A	T	A	T	A	T	A	T	A	T	A
Efficiency	-0.0350** (0.032)	-0.0611*** (0.000)												
Efficiency adjusted			-0.0447*** (0.003)	-0.0570*** (0.000)										
Cost-income ratio					0.00622** (0.025)	0.00171 (0.572)								
Expense share							0.456*** (0.002)	0.302** (0.037)						
Liquidity share									0.0918** (0.025)	-0.00814 (0.900)				
Return on equity											-0.0177 (0.765)	-0.0323 (0.569)		
Loan growth													-0.0597*** (0.001)	-0.0588*** (0.006)
ln(assets)	-0.383*** (0.000)	0.631*** (0.000)	-0.381*** (0.000)	0.679*** (0.000)	-0.338*** (0.000)	0.621*** (0.000)	-0.296*** (0.000)	0.653*** (0.000)	-0.365*** (0.000)	0.618*** (0.000)	-0.361*** (0.000)	0.618*** (0.000)	-0.336*** (0.000)	0.631*** (0.000)
Asset growth	-0.0757*** (0.000)	-0.0409*** (0.000)	-0.0762*** (0.000)	-0.0405*** (0.000)	-0.0754*** (0.000)	-0.0401*** (0.000)	-0.0720*** (0.000)	-0.0400*** (0.000)	-0.0766*** (0.000)	-0.0402*** (0.000)	-0.0776*** (0.000)	-0.0406*** (0.000)	-0.0450*** (0.000)	0.00450 (0.843)
Equity share	-0.0760** (0.060)	0.0971** (0.016)	-0.0798** (0.053)	0.0976** (0.016)	-0.0773** (0.050)	0.0857** (0.044)	-0.0946** (0.019)	0.0720** (0.064)	-0.0810** (0.036)	0.0849** (0.028)	-0.0827** (0.032)	0.0850** (0.028)	-0.0939** (0.017)	0.0781** (0.042)
Loan share	-0.0115* (0.055)	0.00315 (0.631)	-0.0120** (0.048)	0.00180 (0.778)	-0.0111** (0.050)	0.00238 (0.680)	-0.0131** (0.024)	0.00111 (0.850)	-0.0111** (0.045)	0.00246 (0.669)	-0.0103** (0.074)	0.00296 (0.611)	-0.00673 (0.247)	0.00372 (0.517)
Unemployment rate	-0.0507 (0.181)	-0.0418 (0.227)	-0.0320 (0.409)	-0.0199 (0.579)	-0.0548 (0.157)	-0.0465 (0.190)	-0.0799 (0.051)	-0.0604* (0.100)	-0.0608 (0.108)	-0.0449 (0.212)	-0.0527 (0.175)	-0.0495 (0.176)	-0.0420 (0.275)	-0.0399 (0.264)
ln(population density)	0.157* (0.082)	-0.184** (0.040)	0.0885 (0.343)	-0.307*** (0.001)	0.144 (0.109)	-0.226** (0.010)	0.189** (0.040)	-0.197** (0.029)	0.138 (0.119)	-0.228** (0.010)	0.135 (0.133)	-0.229** (0.009)	0.109 (0.238)	-0.242** (0.007)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449	4,449
Pseudo R <sup>2</sup>	0.060	0.060	0.060	0.056	0.056	0.056	0.059	0.059	0.056	0.056	0.055	0.055	0.061	0.061
Wald $\chi^2$	196.83	196.83	194.77	185.49	185.49	193.32	193.32	193.32	186.36	186.36	186.99	186.99	195.93	195.93
Pseudo loglikelihood	-1,386.41	-1,386.41	-1,385.69	-1,391.97	-1,391.97	-1,387.45	-1,387.45	-1,387.45	-1,392.01	-1,392.01	-1,393.51	-1,393.51	-1,384.47	-1,384.47

\*\*\*, \*\*, and \* Respectively denote statistical significance at the 1 %, the 5 % and the 10 % level.

input-output allocation, expense share, and loan growth, respectively. On the other hand, columns (3), (5), and (6) suggest that acquirers' cost-income ratio, liquidity share, and profitability do not significantly differ from those of the reference group. Thus, depending on the indicator of choice, acquirers either perform worse or the same, but in no case better than the reference group.

The remaining set of control variables is not of key interest for our purposes. Nevertheless, it may be reassuring to note that the observed effects on all bank-specific factors are generally consistent with those found in related work. In particular, the results uniformly indicate notable differences in bank size and capitalization. Acquirers (targets) are relatively larger (smaller) and better (worse) capitalized, which aligns with the findings of Koetter et al. (2007) and Behr and Heid (2011). Lastly, we stress the robustness of these results across various model specifications. In unreported estimations, the results not only hold when different covariates are used, such as the Tier 1 Capital ratio or the security share. They also remain largely unchanged when estimations include more than one designated performance measure at a time. For example, the cost-income effects do not change significantly when the liquidity share is added to the estimations. Furthermore, the results remain when we additionally include the merger events in 2014, which are omitted here due to the lagged nature of asset growth. This is shown in column (2) of Table A3, which achieves an extended sample by neglecting the asset growth variable.<sup>9</sup> Another concern that often goes unnoticed in allied work is the potential interdependence between mergers and regional market concentration. In this vein, we suspect that mergers could more likely occur in counties with a greater cooperative bank density and a more dispersed market structure. To control for this possibility, columns (3) and (4) of Table A3 respectively include the variable bank density, which is the number of banks in a county relative to the county's population, and the HHI, which is the normalized Herfindahl–Hirschman index that measures the concentration of the market for consumer loans. Our findings hold up against both specifications. Consistent with our expectations, higher bank density and dispersed local market power seem to encourage mergers, but the performance aspect prevails. Finally, we acknowledge that Tobit regressions may yield biased second-stage efficiency measures (Simar and Wilson 2007). Therefore, column (5) uses bias-corrected efficiency as the dependent variable, which is based on the procedure proposed by Simar and Wilson (2007). The previously observed results remain.

What we take away from these regressions is that consolidating banks rather perform worse than their non-merging peers, but nuances exist among targets and

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<sup>9</sup> We focus on adjusted efficiency for brevity.

acquirers. While targets clearly exhibit financially weak profiles, particularly from a cost perspective, acquirers do benefit from greater size, stronger capitalization, and some performance outcomes that are indistinguishable from the peer group. The results so far provide important insights into the characteristics of consolidating banks, but they are not sufficient to reliably verify the efficiency-view in the German banking market. This is because we have to consider the possibility that the target banks performed well prior to the low interest rate era, but deteriorated mainly due to the adverse environment. Such a possibility is supported by the observation that the targets are often small, regional banks. These banks are typically more reliant on deposit and lending activities and may be more exposed to changes in the interest rate environment (e.g. Claessens, Coleman, and Donnelly 2018; Genay and Podjasek 2014). If so, then the sole reliance on previous analyses would likely yield fallacious conclusions, and impugn the efficiency-view. Therefore, the next section complements the previous analyses by examining bank performance prior to the low-interest period and before the regulatory interventions took legal effect in 2014.

## 5.2 Results of the Logit Model

In order to understand if targets perform relatively worse before our initial investigation period, we draw on our secondary data set. For each of the 218 future targets and 883 other cooperative banks in this sample, we consider averaged values over the period 2010 to 2012.

We split the analysis into two parts. First, we examine whether targets are underperforming, as in our primary analysis. In this vein, we first estimate equation (2), relating the probability of a bank being acquired within the period 2014 to 2019 to the average bank performance over the years 2010–2012. The goal of this procedure is to show that the low interest sphere does not turn *ex ante* well performing banks into targets. Instead, banks that operate comparatively worse between 2010 and 2012 are more likely to become targets later on. Second, we assign banks to different groups based on their size and performance, and repeat previous estimations using group indicators. The aim is to understand, in particular, how performance relates to the survival chances of small banks. From an efficiency perspective, we expect small and well performing banks to benefit in terms of lower exit probabilities compared to their underperforming peers. Similarly, the survival probabilities of large and well-performing banks should be significantly higher than for their cohorts of similar size.

Before proceeding with the analysis, finally note that we restrict the analysis in this part to our set of accounting-based performance indicators. This is not by choice but rather due to the fact that unit measurements differ for some

observations, which severely distorts all DEA efficiency values. We also do not cover the non-interest expense share here as the data-set at hand lacks information on administrative expenses.

### 5.2.1 Target Bank Performance Before the Low-For-Long Interest Rate Era

We begin by estimating equation (2) to see if *ex ante* performance significantly determines future target banks. More precisely, we consider a binary logistic model which links the probability of a bank becoming a target at some point between 2014 and 2019 to the average performance over the period 2010 to 2012. In case that estimated coefficients resemble the values from earlier regressions, the low interest environment and related factors are unlikely to be the cause for target banks' low performance in the more recent years. In addition to the logistic regressions, we also apply a linear probability model (LPM). Although LPMs suffer from commonly known, undesirable properties, we find that they provide a convenient and affordable way to further reinforce our results. In this vein, we regress the binary variable *FutureTarget* on the same vector  $x$ , again comprising one performance measure at a time.

We report our results in Table 3. The first five columns, (1) to (5), show the outcome of the logistic model. Recall that the coefficients for these regressions measure the change in log-odds for a unit-change in the predictor variable. Applying the transformation yields  $[(e^{0.060} - 1) \times 100\%] \approx 6.2\%$ , such that a one percentage point increase in the cost-income ratio increases the odds of becoming a target by about 6.2%. Put differently, banks with a one percentage point higher cost-income ratio are 1.062 times more likely to become a target than banks without this additional increase. Beginning with column (1), we observe a significant and positive effect of the cost-income ratio. This implies that target banks exhibit relatively greater cost-income balances before the emergence of the zero interest environment. The finding aligns with the earlier observation from Table 2 and particularly suggests that the zero interest sphere does not turn well operating banks into targets. Instead, banks with *ex ante* greater cost-income ratios more likely become targets later on during operationally disadvantageous periods. Continuing with column (2), we find a positive and significant association between banks' liquidity share and their probability of turning into a future target. This again matches our previous observations such that banks with proportionally larger holdings of idle assets tend to be more likely future targets. In contrast to our primary analysis, columns (3) and (4) document a negative and significant effect of both profitability measures. Initially more profitable banks are less likely to be a target in the future. Turning to column (5), we find a negative and statistically significant effect of loan growth. Greater loan growth reduces the probability of a future market exit. This

**Table 3:** Binary logit results. This table analyzes how performance over the period 2010 to 2012 influences the probability of becoming a future target between 2014 and 2019. The first five columns, (1) to (5), show the outcome of the binary logistic model. Columns (6) to (10) show the results of the linear probability model. Estimations are based on a sample of 218 future targets and 838 other banks assumed to have not engaged into mergers during the 2010–2012 period. The number of observation varies depending on data availability. We do not require information on all variables to prevent a potential sample selection bias. Robust Huber-White standard errors are employed. *P*-values are reported in parentheses.

	Logit					LPM				
	(1) FT	(2) FT	(3) FT	(4) FT	(5) FT	(6) FT	(7) FT	(8) FT	(9) FT	(10) FT
Cost-income ratio	0.060*** (0.000)					0.00874*** (0.000)				
Liquidity share		0.023*** (0.024)					0.00419** (0.021)			
Return on equity			−0.086** (0.039)					−0.0113** (0.027)		
Return on assets				−1.221** (0.041)					−0.158** (0.025)	
Loan growth					−0.074*** (0.008)					−0.0114*** (0.007)
ln(assets)	−0.078* (0.079)	−0.105** (0.029)	−0.098** (0.041)	−0.100** (0.038)	−0.097** (0.043)	−0.0118* (0.066)	−0.0158** (0.015)	−0.0146** (0.024)	−0.0148** (0.022)	−0.0145** (0.026)
Asset growth	−0.081** (0.017)	−0.123*** (0.000)	−0.111*** (0.001)	−0.111*** (0.001)	−0.076* (0.051)	−0.0124*** (0.009)	−0.0181*** (0.000)	−0.0163*** (0.001)	−0.0165*** (0.001)	−0.0101* (0.073)
Equity share	0.080* (0.068)	0.029 (0.502)	0.029 (0.494)	0.081* (0.086)	0.022 (0.602)	0.0119* (0.084)	0.00533 (0.441)	0.00512 (0.458)	0.0124* (0.099)	0.00416 (0.542)

Table 3: (continued)

	Logit				LPM					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FT	FT	FT	FT	FT	FT	FT	FT	FT	FT
Loan share	0.028** (0.031)	0.015 (0.194)	0.022* (0.070)	0.022* (0.075)	0.020 (0.105)	0.00347** (0.031)	0.00206 (0.200)	0.00291* (0.068)	0.00280* (0.078)	0.00258 (0.104)
Unemployment rate	-0.078** (0.025)	-0.060* (0.074)	-0.070** (0.047)	-0.070** (0.046)	-0.044 (0.180)	-0.0112** (0.021)	-0.00927* (0.062)	-0.00981* (0.054)	-0.00959* (0.056)	-0.00657 (0.176)
ln(population density)	0.031 (0.737)	-0.006 (0.944)	-0.002 (0.978)	-0.001 (0.987)	-0.014 (0.870)	0.00776 (0.562)	-0.000424 (0.975)	-0.000425 (0.975)	-0.000939 (0.944)	-0.00166 (0.900)
N	960	961	960	960	961	960	961	960	960	961
R <sup>2</sup>	0.063	0.037	0.038	0.038	0.040	0.060	0.036	0.036	0.036	0.038
Wald $\chi^2$	52.01	31.84	27.04	27.10	31.74					
Pseudo loglikelihood	-466.61	-479.61	-478.93	-477.75	-478.05					

\*\*\*, \*\* and \* Respectively denote statistical significance at the 1 %, the 5 % and the 10 % level.

result again implies that target banks exhibit relatively poor growth rates before the emergence of detrimental conditions.

Apart from these performance measures, we make an interesting discovery concerning the equity and loan share. In contrast to previous estimations, both metrics now indicate a statistically marginal but uniformly positive effect. Better capitalized banks and banks holding proportionally more loans in their assets bear a greater probability of becoming a future target. Since small, traditional cooperative banks match this description remarkably well, we see the outcome strongly in line with the literature finding more pronounced interest rate policy effects for small banks. In particular, Heider, Saidi, and Schepens (2019), p. 3741, find that “High-deposit banks are also smaller, have higher equity ratios (6.2 % vs. 5.0 %), higher loans-to-assets ratios” and that the introduction of negative policy rates leads “to more risk-taking and less lending by euro-area banks with a greater reliance on deposit funding”.

Related, Claessens, Coleman, and Donnelly (2018), p. 8, find that “small banks have greater difficulty maintaining their NIMs in a low interest rate environment”. Our estimation results complement these findings by showing that banks, initially fulfilling the traditional role of well-capitalized and loan-oriented intermediaries, also entail an increased probability of exiting the market in the course of a lasting low-interest environment. In this respect, the low-for-long interest rate policy could have influenced small banks more drastically. Importantly, however, this does not change the notion that targets already perform relatively worse before such adverse environment. The subsequent section further disentangles performance from bank size and analyzes differences in exit probabilities between small and large banks.

Proceeding with columns (6) to (10), which show the estimation results for the LPM, we verify all previous findings. For instance, the coefficient on the cost-income ratio indicates that an increase of the average cost-income ratio by one percentage point is associated with an increase in the probability of becoming a future target by around one percentage point, holding other factors fixed. Banks with higher cost-income ratios are therefore more likely to become targets later on.

Concluding, we find that targets perform worse before the low-for-long interest rate environment and the Basel III implementation in 2014. This is particularly evident from Table 3, which assigns comparatively low performing banks a greater probability of becoming a future target. Our analysis thus favors the efficiency-view, but so far has fallen short of comparing the survival chances across banks with different sizes and performance levels. We address this issue in the following.

### 5.2.2 Survival Chances Across Banking Groups

Our results reveal that targets underperform shortly before their merger and in the period preceding the low-for-long interest rate era. What has been missing so far is whether small and well performing banks actually benefit from higher survival chances relative to their underperforming peers. This should be the case if the efficiency-view holds. Similarly, we lack evidence on the extent to which performance determines the exit probability of large banks. We consider these points by constructing a categorical variable for each performance measure. We assign banks to one of four groups based on their size and underlying performance.

The first group comprises small and underperforming banks, and serves as the benchmark to which the other groups are compared. Banks in this group receive a value of 0 ( $G = 0$ ). Note that this group is not shown in the estimations as it constitutes the reference group. The threshold of being small and underperforming is the median total asset size and the median of the performance measure under consideration, respectively. The second group includes small and well performing banks which receive a value of 1 ( $G = 1$ ). The third and fourth group respectively contain large and underperforming banks ( $G = 2$ ) and large and well performing banks ( $G = 3$ ). This procedure yields 5 categorical variables *Cat* (one for each performance measure) each containing group indicators 0 to 3. Group sizes differ across performance measures but are approximately equal. Considering the return on assets, for example, we respectively achieve 236, 260, 241, and 224 banks for categories zero to three.

We re-estimate equation (2) but exchange each performance measure with its corresponding categorical variable. This enables us to measure how performance influences the survival chances of different banking groups holding either size or performance constant. As before, we additionally consider a LPM to substantiate our analysis. Table 4 shows the estimation results. The first five columns, (1) to (5), refer to the outcomes of the logistic model. The estimated coefficients on the categorical variables capture the change in log-odds of moving from the benchmark to either one of the other groups. For instance,  $C/I: G = 1$  measures the change in log-odds when switching from the group of small and underperforming banks to the group of small and well performing banks. Here,  $C/I$  indicates performance in terms of the cost-income ratio. Applying the transformation, the coefficient of  $-0.56$  suggests that the odds of being a future target for a small and well operating bank are  $[(e^{-0.56} - 1) \times 100\%] \approx 43\%$  lower than for a small and underperforming bank. Holding the group of small banks constant, well performing peers thus have greater survival chances.

Overall, three findings are evident. Starting with the outcome of the logistic model, we first notice that small and well performing banks exhibit a smaller exit

**Table 4:** Survival chances across banking groups. This table explores the survival chances of different banking groups that vary by size and performance. Categorical variable *Cat* includes four groups where  $X: G = n$  indicates group  $n$  based on performance measure  $X$ . *C/I* relates to the cost-income ratio, *ROA* to the return on assets, *ROE* to the return on equity, *LG* to loan-growth, and *LQ* to the liquidity share.  $G = 0$  is the benchmark group and comprises small and underperforming banks.  $G = 1$ ,  $G = 2$ , and  $G = 3$  respectively include small and well performing, large and underperforming, and large and well performing banks. All estimations include the main control variables as indicated at the bottom of the table. *P*-values are reported in parentheses.

	Logit				LPM			
	(1) FT	(2) FT	(3) FT	(4) (5) FT FT	(6) FT	(7) FT	(8) FT	(9) (10) FT FT
Cat 1								
<i>C/I: G = 1</i>	−0.562** (0.013)				−0.101** (0.010)			
<i>C/I: G = 2</i>	0.084 (0.767)				0.00105 (0.983)			
<i>C/I: G = 3</i>	−0.986*** (0.001)				−0.149*** (0.000)			
Cat 2								
<i>ROA: G = 1</i>	−0.375* (0.100)				−0.0673* (0.091)			
<i>ROA: G = 2</i>	−0.316 (0.263)				−0.0614 (0.185)			
<i>ROA: G = 3</i>	−0.557* (0.062)				−0.0968** (0.036)			
Cat 3								
<i>ROE: G = 1</i>		−0.498** (0.025)				−0.0907** (0.023)		
<i>ROE: G = 2</i>		−0.393 (0.173)				−0.0771 (0.101)		
<i>ROE: G = 3</i>		−0.603** (0.037)				−0.107** (0.018)		
Cat 4								
<i>LG: G = 1</i>			−0.342* (0.091)				−0.0690* (0.089)	
<i>LG: G = 2</i>			−0.278 (0.327)				−0.0601 (0.208)	
<i>LG: G = 3</i>			−0.529* (0.070)				−0.0937** (0.037)	

Table 4: (continued)

Logit					LPM				
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
FT	FT	FT	FT	FT	FT	FT	FT	FT	FT
Cat 5									
LQ: $G = 1$				0.193					0.0312
				(0.375)					(0.429)
LQ: $G = 2$				0.281					0.0386
				(0.336)					(0.418)
LQ: $G = 3$				−0.607*					−0.0840**
				(0.052)					(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$N$	961	961	961	961	961	961	961	961	961
$R^2$	0.057	0.037	0.040	0.037	0.047	0.055	0.036	0.039	0.036
Wald $\chi^2$	46.73	30.87	32.81	31.62	36.00				0.044
Pseudo LL	−469.58	−479.50	−478.29	−479.70	−474.77				

\*\*\*, \*\* and \* Respectively denote statistical significance at the 1 %, the 5 % and the 10 % level.

probability on all but the liquidity measure. This clearly favors the efficiency-view as performance actually helps overcome the adverse low-for-long interest rate environment. Second, the survival chances of large but underperforming banks ( $G = 2$ ) are not significantly distinct from those of the benchmark group. This finding further aligns with the expectation that the underlying efficiency-view is not restricted to a subset of small banks. Instead, banks' performance, not their size is crucial in determining a market exit. Third, moving from the group of small and underperforming entities to the group of large and well performing banks entails the largest changes across all groups and metrics. Considering the cost-income ratio, the odds of becoming a target decrease by more than 60 % relative to the benchmark situation. Finally, the outcome of the LPM in columns (6) to (10) confirms our key findings. For instance, moving from the benchmark group to  $G = 1$  under *Cat 1* decreases the probability of becoming a future target by around 10 percentage points.

Ultimately, this section suggests that banks that become a target at some point between 2014 and 2019 perform relatively worse before the low-for-long interest environment, i.e. during the 2010–2012 period. In contrast, banks that perform well initially stand greater chances of survival, regardless of being rather small or large. We therefore find no evidence of a policy-driven deterioration that would turn initially well-performing banks into merger targets. Instead, our overall results support the efficiency view that the challenging combination of low interest rates and demanding regulations encourages rather underperforming banks to exit the market through mergers.

## 6 Conclusions

This paper examines merger dynamics in the German cooperative banking industry between 2014 and 2019 to determine whether recent mergers are due to bank inefficiencies or to challenging policy measures. Motivated by the unusually large number of bank mergers in a period with low-interest rates and demanding regulations, we specifically test merging banks' relative performance before and during this period. Using standard bank merger methodology, the results consistently indicate that targets are small and underperforming banks, while acquirers stand out in terms of size and capitalization. Thus, the evidence in this paper supports the efficiency view that *ex ante* inefficient banks increased their merger activity during the low interest rate environment.

In addition to these findings, authorities may wonder if bank merger benefits outweigh the drawbacks from customers' perspective. Although we leave this topic to future research, we do point at potential concerns related to the regional accessibility of financial services, personal advisory, and consumer surplus. However, at least for the mergers under investigation, we do not find that mergers *per se* pose a threat to financial access and personal advisory. In most of the cases, acquirers maintain targets' branch network along with their personnel. Related issues might rather arise from the digitalization-side, automating various services and, thereby, obsoleting traditional branches.

Based on the findings in this paper, we finally conclude that the spectrum of bank merger motives may extend beyond existing hypotheses, such as the inefficient management hypothesis, stating that acquirers take over their inefficient peers to improve management (e.g. Jensen and Ruback 1983; Manne 1965; Palepu 1986). In this sense, elevated merger rates during crises or adverse conditions could signal waves of consolidation, with weakly performing banks joining forces to stay in business for the long term.

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## Appendix

**Table A1:** Summary statistics. Note that we are missing county-level data for a small number of bank-year observations. This is because some counties have merged over time and no longer publish information.

	Primary sample (2015–2019)					Secondary sample (2010–2012)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
ln(assets)	4,449	12.91	1.165	9.650	17.63	1,101	6.532	2.179	2.197	13.86
Asset growth	4,449	6.233	12.14	−19.38	224.5	1,101	4.547	5.962	−16.59	63.19
Loan share	4,449	59.88	13.28	11.98	94.85	1,100	75.24	9.338	10.34	94.95
Loan growth	4,449	7.138	12.67	−26.17	192.41	1,100	5.762	6.491	−18.26	86.27
Security share	4,449	26.33	12.84	0.000	74.77	1,101	27.79	11.81	0.000	72.94
Equity share	4,449	9.559	2.029	3.498	21.79	1,101	7.711	3.264	2.183	76.28
Tier 1 ratio	4,418	15.24	3.745	7.770	59.84	937	12.15	3.823	6.140	56.56
NPL ratio	4,165	1.499	1.369	0.000	17.75	869	4.417	4.220	0.000	78.64
Return on assets	4,449	0.261	0.159	−0.112	2.098	1,100	0.356	0.270	−0.927	5.253
Return on equity	4,449	2.746	1.551	−1.767	18.56	1,100	4.837	2.706	−1.970	20.29
Liquidity share	4,449	1.731	1.232	0.000	22.37	1,101	13.69	7.833	1.313	63.45
Cost-income ratio	4,449	67.47	17.71	14.90	523.8	1,100	67.89	8.641	19.88	111.1
Expense share	4,449	1.872	0.488	0.281	9.605					
Efficiency	4,449	0.895	0.045	0.565	1.000					
Efficiency adjusted	4,449	0.913	0.047	0.680	1.000					
Bank density	4,449	2.133	1.287	0.082	6.624					
HHI	4,449	0.326	0.307	0.000	1.000					
Unemployment rate	4,449	4.733	2.254	1.300	15.40	1,006	5.468	2.594	1.500	16.57
Elderly share	4,449	20.97	2.342	15.40	32.20	1,006	20.12	2.078	15.13	28.53
ln(population density)	4,449	5.540	1.005	3.578	8.463	1,006	5.548	0.999	3.630	8.390
ln(GRP per capita)	4,431	10.45	0.317	9.595	12.11	1,001	10.32	0.327	9.496	11.72
ln(disposable income)	4,441	10.01	0.110	9.631	10.66	1,001	9.901	0.103	9.606	10.49

**Table A2:** Annual pattern of mergers.

Year	Targets	Acquirers	Non-merging	Total	Total estimation
2014	27	17	952	996	
2015	25	18	926	969	969
2016	48	39	857	944	944
2017	57	40	799	896	896
2018	38	30	771	839	839
2019	33	25	743	801	801
Total	228	169	5,048	5,445	4,449

**Table A3:** Robustness tests. This table tests the robustness of the main results. Column (1) retakes the baseline results in column (2) from Table 2. Column(2) performs the estimation based on an extended sample of 228 targets, 169 acquirers, and 599 non-merging banks over the period 2014 to 2019. Columns (3) and (4) respectively add bank density and regional market concentration as additional control variables. Bank density is the number of cooperative banks located within a county as a share of the population of that county. Market concentration corresponds to the normalized HHI for the customer loan market within a county. Column (5) uses bias-corrected efficiency as the dependent variable based on the procedure of Simar and Wilson (2007). All estimations consider year effects as shown at the bottom of the table. Standard errors are clustered at the bank level. *P*-values are reported in parentheses.

	(1)		(2)		(3)		(4)		(5)	
	<i>T</i>	<i>A</i>	<i>T</i>	<i>A</i>	<i>T</i>	<i>A</i>	<i>T</i>	<i>A</i>	<i>T</i>	<i>A</i>
Efficiency adjusted	−0.0447*** (0.003)	−0.0570*** (0.000)	−0.0377*** (0.008)	−0.0649*** (0.000)	−0.0446*** (0.003)	−0.0629*** (0.000)	−0.0435*** (0.004)	−0.0566*** (0.000)	−0.0397*** (0.041)	−0.0432*** (0.023)
Bank density					−0.0119 (0.874)	0.286*** (0.000)				
HHI							−0.00317 (0.268)	−0.00529* (0.066)		
ln(assets)	−0.381*** (0.000)	0.679*** (0.000)	−0.400*** (0.000)	0.660*** (0.000)	−0.382*** (0.000)	0.737*** (0.000)	−0.384*** (0.000)	0.705*** (0.000)	−0.366*** (0.000)	0.607*** (0.000)
Asset growth	−0.0762*** (0.000)	−0.0405*** (0.000)			−0.0763*** (0.000)	−0.0408*** (0.000)	−0.0761*** (0.000)	−0.0392*** (0.000)	−0.0771*** (0.000)	−0.0408*** (0.000)
Equity share	−0.0798* (0.053)	0.0976** (0.016)	−0.0495 (0.183)	0.0893** (0.016)	−0.0799* (0.053)	0.109** (0.008)	−0.0827** (0.045)	0.0989** (0.015)	−0.0767** (0.050)	0.0950** (0.014)
Loan share	−0.0120** (0.048)	0.00180 (0.778)	−0.0144*** (0.008)	0.00335 (0.569)	−0.0120** (0.048)	0.00285 (0.655)	−0.0127** (0.039)	0.00143 (0.822)	−0.0105* (0.065)	0.00340 (0.575)
Unemployment rate	−0.0320 (0.409)	−0.0199 (0.579)	−0.0327 (0.355)	−0.0284 (0.398)	−0.0351 (0.423)	0.0437 (0.248)	−0.0230 (0.549)	−0.00184 (0.959)	−0.0507 (0.183)	−0.0437 (0.210)

Table A3: (continued)

	(1)		(2)		(3)		(4)		(5)	
	T	A	T	A	T	A	T	A	T	A
ln(population density)	0.0885 (0.343)	-0.307*** (0.001)	0.134 (0.118)	-0.295*** (0.001)	0.0828 (0.399)	-0.204** (0.041)	0.0942 (0.312)	-0.315*** (0.001)	0.136 (0.129)	-0.219** (0.012)
Year effects		Yes		Yes		Yes		Yes		Yes
N		4,449		5,445		4,449		4,449		4,449
Pseudo R <sup>2</sup>		0.060		0.052		0.064		0.062		0.056
Wald $\chi^2$		194.77		206.18		209.71		193.35		190.10
Pseudo loglikelihood		-1,385.69		-1,605.17		-1,379.44		-1,383.46		-1,391.75

\*\*\*, \*\*, and \* Respectively denote statistical significance at the 1 %, the 5 % and the 10 % level.

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