An unfavorable combination: The cleansing feature of low interest rates, banking regulations, and digital transformation*

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Abstract

Motivated by the escalating number of bank mergers in a period of low interest rates, demanding regulations, and digital transformation, this paper examines the performance of German cooperative banks that merged between 2014 and 2019. We are particularly interested if elevated merger rates feature a cleansing happening or reflect a policy-induced ousting that crudely forces small banks out of the market. Results indicate that banks that perform relatively worse before and between 2014 and 2019 exhibit a greater probability of becoming a target during this period. Consolidation generally occurs among low performing banks where large and well-capitalized banks take over their small and inefficient peers. Ultimately, our results suggest a considerable cleansing happening that could improve EU-banks' overall profitability in the long run.

Keywords: banks, mergers, regulation, cleansing
JEL Classification: G21, G34

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1 Introduction

In light of the prolonged low interest environment, the unprecedented tightening of banking regulations, and rapid changes in customer behavior towards digital-based services, EU banks have faced a challenging surrounding for more than a decade. At the same time, a substantial number of banks have left the market through mergers. This paper examines merging banks' performance characteristics to study a potential cleansing happening in the industry.

How adverse operating environments shape and impact the banking industry is an important topic to explore since banks supply critical finance infrastructures. The past decade provided for at least three 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., Genay et al., 2014; Borio et al., 2017; Claessens et al., 2018; Busch et al., 2022). 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 et al., 2011) and raising the portion of risk assets (Delis et al., 2011; Heider et al., 2019). Furthermore, banks cut their lending activity (Heider et al., 2019), adjust their funding structure, and exchange interest-generating engagements with fee-related and trading activities (Brei et al., 2020). Importantly, effects are more pronounced for small banks with higher deposit shares (e.g., Genay et al., 2014; Kerbl et al., 2016; Claessens et al., 2018; Heider et al., 2019).

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., King, 2013; Dietrich et al., 2014; Handorf, 2014; Bonner et al., 2015). 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 et al., 2015). Literature shows that banks transpose and respond to regulatory claims for higher capital and liquidity requirements by cutting their lending (De Nicolò et al., 2014; Mésonnier et al., 2015) and risk-weighted assets (Gropp et al., 2019) and by employing different strategies based on their profitability (Cohen et al., 2016; Andrle et al., 2017).

These developments are accompanied by a third, more general, yet important trend. Technical innovation and a stronger public perception of online applications have not only prompted changes in how banks provide access to financial services but also sparked competition with fintechs (e.g., Philippon, 2016; Buchak et al., 2018; Meyer, 2018; Lee et al., 2020; Murinde et al., 2022). Although research in this field is limited, digitalization effects may be demonstrated best by the ever diminishing number of bank branches. For instance, the number of branches operated by the Deutsche Bank AG in Germany declined from around 750 in 2013 to nearly 500 in 2019 and remains at 400 as of today. The specific extent to which digitalization, intense cost pressure, and related factors add to this diminution is irrelevant here, but exemplifies close intertwining among these factors. More importantly, building and maintaining a digital infrastructure likely involves additional costs that particularly disadvantage small banks. This is because digital applications benefit from economies of scale. Once implemented, they can be used by a larger number of customers at equal or only marginally greater costs (Meyer, 2018).

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.[1] 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. Yet, no evidence exists on how performance relates to the chances of exiting the market in this peculiar time period. From a conventional standpoint, prolonged periods of low interest rates could rather strike inefficient peers since they tighten the screw on banks just as recessions do with firms, in the spirit of Schumpeter, 1939 and Schumpeter, 1942. However, swiftly disregarding potential consequences even for well performing banks is hazardous, considering that adverse conditions seem to particularly burden small and regional banks (e.g., Kerbl et al., 2016; Meyer, 2018; Claessens et al., 2018; Heider et al., 2019). Ultimately, it is unclear if the recent period features a cleansing happening that squeezes out initially low performing banks or, instead, entails a policy-induced ousting, such that targets operate well before the low interest era, but experience degradation and a forced market exit mainly due to the disadvantageous environment.

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 policy-induced conditions 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 simply occurs among low performing banks, which could help reduce potential 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

[1] 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.

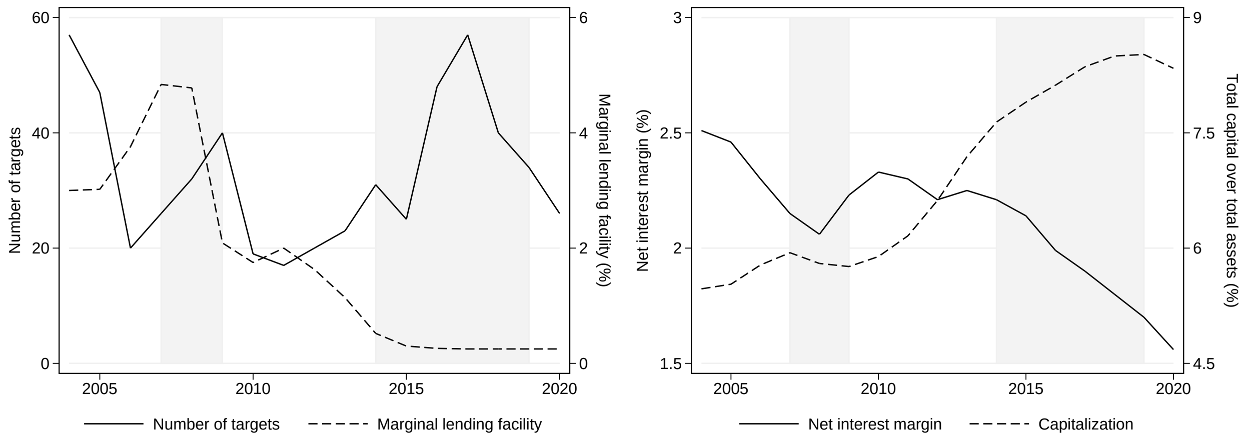
through mergers in recent years. The aim is to uncover the link between banks' performance and their probability of becoming a target and thereby show if the underlying period comprises a cleansing feature. We do so by considering the merger dynamics in the German cooperative banking industry between 2014 and 2019. We select the German banking market because it belongs to the largest in the Euro-area, 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, the Capital Requirements Regulation (CRR) 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. However, analyzing performance *within* difficult surroundings only serves as a reference point for a potential cleansing happening. This is because we must consider the possibility that target banks perform well initially but suffer financial degradation mainly due to given adverse conditions. In this vein, it appears reasonable to credit the underlying period with a cleansing feature only if ex-ante low performing banks turn into targets. Therefore, we also consider an earlier time period from 2010 to 2012, when interest rates prevail at somewhat 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 to 2019. This allows us to understand if initially low performing banks more likely become targets in the course of a deteriorating environment.

Overall, we share two major 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. Secondly, 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 challenging period of low interest rates, demanding regulations, and costly digitalization processes, features a cleansing happening such that an increased number of relatively underperforming banks drop out of the market. In this vein, we stress that the topic's nature makes it difficult to quantitatively measure a causal relationship between given adverse conditions and elevated merger rates. In the strict analytical sense, we thus simply find that primarily underperforming entities exit the market during the considered time span. Nevertheless, we do identify i) unusually high takeover numbers, ii) numerous statements justifying mergers with the adverse environment, and iii) consolidation activities among low performing banks, that altogether point to a strong link between the observed exits and the detrimental 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., Hannan and Rhoades, 1987; Moore, 1996; Moore, 1997; Hadlock et al., 1999; Wheelock et al., 2000; Focarelli et al., 2002; Worthington, 2004; Koetter, Bos, et al., 2007; Lanine et al., 2007; Hannan and Pilloff, 2009; Goddard et al., 2009; Hernando et al., 2009; Pasiouras et al., 2011; Beccalli et al., 2013; Huhtilainen et al., 2021), bank distress and failure (e.g., Cole and Gunther, 1995; Estrella et al., 2000; Wheelock et al., 2000; Cole and White, 2012; Berger and Bouwman, 2013; DeYoung et al., 2013; Berger, Imbierowicz, et al., 2016), and the cleansing effect of crises Spokeviciute et al., 2019. Our paper closely connects to Spokeviciute et al., 2019, which seems to be the only perceivable work investigating the cleansing effects of financial crises within the banking industry. Spokeviciute et al., 2019 predict the probability of bank failure or acquisition based on interactions between crisis dummies and 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 cleansing view that crises encourage primarily less efficient banks to drop out of the market.

Our paper significantly differs from the existing literature. To our knowledge, we are the first to study the merger dynamics over the past recent years with respect to a cleansing happening in the banking industry. Unlike ordinary crises, the underlying adverse environment is largely policy driven, which attaches particular interest to the topic. 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, our paper provides authorities an evaluation of the potential downsides of their policies. In particular, we examine whether well performing banks can successfully overcome policy-induced conditions or, instead, become targets regardless of their initial performance. Doing so, we also add to previous work on the predictors of bank mergers and failure.



(a) **(b)**

Figure 1 The evolution of cooperative bank mergers in Germany

Figure (a) depicts recent developments in the merger activity of German cooperative banks. Figure (b) shows the average profitability 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 and comprise the “Bankstellenstatistik" and “Zeitreihen-Datenbanken".

2 Mergers made in Germany

The German cooperative banking industry has experienced an extraordinary increase of takeovers 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, takeovers 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, takeover dynamics induce an overall decline in the quantity of independent cooperative banks by nearly 25%.[2]

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 rising takeovers occur in a time when interest rates concurrently exhibit a declining path. Lower market rates, 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 low profitability by realizing economies of scale or scope (Amel et al., 2004). However, low interest rates may not be the only motive. The recent takeover 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

[2]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 posses no direct mandate to enforce mergers. Given numbers hence comprise mergers made on a voluntary basis.

impede growth and burden banks with costs (e.g., Dietrich et al., 2014; Mésonnier et al., 2015). While the quantification of such regulatory costs is rather difficult, the impact of greater (capital) requirements can be shown clearly by an upward sloping total capital ratio, as depicted in Figure 1 (b) by the dashed line. Thus, banks might also merge to comply with rigorous regulations at fewer costs, for instance by profiting from a diversification of their loan portfolio (Amel et al., 2004). This could be particularly true for small cooperative banks which are not only restricted in their operating area, but also have rather limited capacities for processing and implementing complex requirements at the bank-level.

Indeed, both of these circumstances constitute crucial merger motives. 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 set of 17 banks, we find no information. An exemplary statement reflecting key merger motives is taken from a joint press release by the Volksbank Untere Saar eG and the Vereinigte Volksbank eG Saarlouis – Losheim am See – Sulzbach/Saar:

"Als Hauptgründe für die Fusion nennt Soester die überbordenden regulatorischen Anforderungen, das veränderte Kundenverhalten aufgrund der zunehmenden Digitalisierung sowie die Auswirkungen der anhaltenden Niedrigzinsphase, die Jahr für Jahr zu Ertragsrückgängen führen."

"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:

"Der Zusammenschluss erfolgt insbesondere, um den Herausforderungen der Niedrigzinspolitik und der steigenden, aufsichtsrechtlichen Regulierung gestärkt begegnen zu können."

"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.

Table 1 Performance differences

This table examines performance differences between target banks and non-merging entities. 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 2017 sub-sample comprising 599 non-merging banks from 2014 to 2017. All variables are reported in percent, except assets and GDP per capita, which are reported in millions and thousands of Euros, respectively. 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 relates to a Wilcoxon rank sum test and is additionally reported to account for potential concerns about data normality.

Panel A: Full Sample

		Target			Non-Merging				
	N	Mean	S.E.	N	Mean	S.E.	Difference	$t_{p-value}$	$W_{p-value}$
Assets	837	389	12.91	3594	785	33.70	396	0.00	0.00
Asset growth	609	3.73	0.144	2995	4.69	0.076	0.96	0.00	0.00
Loan growth	609	4.20	0.211	2995	5.67	0.099	1.47	0.00	0.00
Equity share	837	9.14	0.069	3594	9.46	0.036	0.32	0.00	0.00
Tier 1 ratio	812	14.6	0.141	3557	15.1	0.067	0.50	0.00	0.00
NPL ratio	758	1.79	0.061	3403	1.55	0.025	-0.24	0.00	0.00
Return on assets	837	0.27	0.006	3594	0.28	0.003	0.01	0.11	0.72
Return on equity	837	2.94	0.056	3594	2.94	0.029	0.00	0.96	0.26
Cost-income ratio	837	70.0	0.360	3594	67.0	0.332	-3.00	0.00	0.00
GDP per capita	833	34.7	0.439	3582	35.4	0.220	0.70	0.16	0.14

Panel B: Sub-sample 2017

		Target			Non-Merging				
	N	Mean	S.E.	N	Mean	S.E.	Difference	$t_{p-value}$	$W_{p-value}$
Assets	228	402	21.58	2396	749	38.97	347	0.01	0.05
Asset growth	171	3.56	0.271	1797	4.43	0.101	0.87	0.01	0.05
Loan growth	171	4.11	0.370	1797	5.46	0.131	1.35	0.00	0.01
Equity share	228	9.08	0.134	2396	9.25	0.045	0.17	0.25	0.16
Tier 1 ratio	228	14.3	0.246	2361	14.6	0.083	0.30	0.23	0.24
NPL ratio	213	1.92	0.142	2259	1.73	0.032	-0.19	0.09	0.09
Return on assets	228	0.25	0.009	2396	0.29	0.004	0.04	0.00	0.00
Return on equity	228	2.82	0.091	2396	3.20	0.036	0.38	0.00	0.01
Cost-income ratio	228	71.0	0.710	2396	67.0	0.441	-4.00	0.01	0.00
GDP per capita	224	35.2	0.897	2388	34.4	0.260	-0.80	0.36	0.23

Even if cases exist where unobserved factors eventually seal the merger, such as regional economic shocks, and excessive losses leading to distressed mergers (Koetter, Bos, et al., 2007), it appears likely that such factors are again closely related to the state of profitability, or the cost of regulation and digitalization.

Given the high number of takeovers, 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 neither observe differences in the profitability, nor in the regional economic output as proxied by the GDP 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 takeovers. 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 cleansing 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, Nestmann, 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.[3] 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 official 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 l of the German Commercial Code. Based on the merger notices in the firm register, we retrieve 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

[3]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).

bank with regard to the financial incorporation of the respective target bank(s).[4] Overall, we identify 228 relevant targets that are taken over by 169 acquirers within the period of 2014 to 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 mitigate concerns related to takeover comparability, and enable a meaningful sample partitioning 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, which are taken from the federal and state statistical offices ('Regionalatlas der Statistischen Ämter des Bundes und der Länder'), comprise the per capita GDP, 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. In this regard, 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. Similar to 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. The selection criteria leave 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.[5] We also attempt to retrace future acquirers which, however, proves to be a difficult venture given that acquirer identification often 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 set-up 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 observed merger activities by year in the Appendix in Table A2.

[4] We gladly share our merger data upon request.

[5] 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.

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 (e.g., Hannan and Rhoades, 1987; Focarelli et al., 2002; Worthington, 2004; Koetter, Bos, et al., 2007; Hernando et al., 2009; Pasiouras et al., 2011; Beccalli et al., 2013; Spokeviciute et al., 2019). In contrast to the simple exercise in Table 1, such 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 $i = 0, ..., J$ groups, we denote the model as:

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

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, β_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 report exponentiated coefficients constituting relative risk ratios (RRR) (Hosmer et al., 2000). 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^{β_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 target banks turn out to be low-performers, this analysis does not suffice to prove a cleansing happening. Since adverse conditions likely affect banks heterogeneously with respect to their size, they could be the primary driver for target banks' financial atrophy and ultimately their market exit. To consequently verify a cleansing happening, 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 et al., 2009; Huhtilainen et al., 2021):

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

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 report exponentiated coefficients to measure changes in terms of odds ratios (Hosmer et al., 2000).

Before proceeding with a discussion of our variable selection, we finally address an issue concerning the influence of unobserved acquisitions during the period 2010 to 2012. Since we lack acquirer information over this period, observations with realized takeovers enter the reference group and may distort estimations in (2). In particular, an acquisition between 2010 and 2012 may influence the likelihood of becoming a target later on. We tackle this issue by considering two variations of (2). First, we proxy acquirers by applying a threshold level of 20% on asset growth. In practice, this means that we remove those banks with an annual asset growth of more than 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 take-over year show growth rates greater than 27%. This procedure removes 45 pseudo acquirers. Secondly, we keep all sample banks. In the course of this paper, 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 Farrel, 1957, DEA was introduced by Charnes et al., 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 (Berger and Humphrey, 1997; Barth et al., 2013). We consider an input oriented model based on Charnes et al., 1978:

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

Minimizing the efficiency θ of bank B translates into finding a benchmark outcome that offers the same quantity of output k as bank B, $y_{k,B}, k = 1, ..., s$, but requires fewer input i, $x_{i,B}, i = 1, ..., m$. Consequently, λ_j corresponds to the weight given to the production dynamic of bank $j, j = 1, ..., n$ to form the benchmark. The resulting θ_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.[6] 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 et al., 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, et al., 1984). Concerning the input-output selection, we employ a variation of the intermediation approach as initially suggested by Sealey et al., 1977, and ever since applied with adaptations in the literature (e.g., Lang et al., 1996; Drake et al., 2009; Chortareas et al., 2012; Barth et al., 2013). 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.

[6] 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.

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 conducted by Reichling et al., 2018 based on the work of Fried et al., 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 et al., 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.[7] The resulting efficiency values -for brevity, adjusted values- are hence adjusted for relevant environmental factors. Since an increasing θ indicates decreasing bank inefficiency, we expect a negative relationship between both efficiency measures and the probability of becoming a target.[8]

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 et al., 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, Bos, 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, Bos, et al., 2007, Hernando et al., 2009, Pasiouras et al., 2011 and Beccalli et al., 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

[7] 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 et al., 2007). Likewise, banks operating in areas with larger shares of elder people are affected detrimentally, which could be due to reduced loan demand and greater costs for personal advisory (Conrad et al., 2009).

[8] 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 et al., 2007).

Hernando et al., 2009 and Pasiouras et al., 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 et al., 2013; Huhtilainen et al., 2021). To ensure robustness, we further take into account alternative 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) (Koetter, Bos, 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 et al., 2007). Therefore, we consider the natural log of the population density as a measure of the urbanization extend. 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, we may find further evidence in favor of the cleansing view, such that initially low performing banks 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 estimations require independence among all bank-year observations. Owing to the panel structure, this is likely not the case however since banks that proceed to exist in some year t, cannot have turned into 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 coefficients represent RRR which capture the change in the relative probability given a unit change in the predictor variable. Hence, coefficients above (below) one indicate a positive (negative) association of the predictor variable with the probability of being in the target or acquirer group. For instance, the coefficient on the liquidity share of around 1.1 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 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 coefficient below 1. 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, Bos, 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 be taken over. Note that we are well aware of potential multicollinearity issues arising from the correlation between loan and asset growth. We accept this possibility nonetheless to maintain model consistency.

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

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	T	A	T	A	T	A	T	A	T	A	T	A	T	A
Efficiency	0.966**	0.941***												
	(0.032)	(0.000)												
Efficiency adjusted			0.956***	0.945***										
			(0.003)	(0.000)										
Cost-income ratio					1.006**	1.002								
					(0.025)	(0.572)								
Expense share							1.577***	1.352**						
							(0.002)	(0.037)						
Liquidity share									1.096**	0.992				
									(0.025)	(0.900)				
Return on equity											0.982	0.968		
											(0.765)	(0.569)		
Loan growth													0.942***	0.943***
													(0.001)	(0.006)
ln(Assets)	0.681***	1.880***	0.683***	1.972***	0.713***	1.861***	0.744***	1.922***	0.694***	1.855***	0.697***	1.856***	0.715***	1.879***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset growth	0.927***	0.960***	0.927***	0.960***	0.927***	0.961***	0.931***	0.961***	0.926***	0.961***	0.925***	0.961***	0.955**	1.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.843)
Equity share	0.927*	1.102**	0.923*	1.103**	0.926**	1.090**	0.910**	1.075*	0.922**	1.089**	0.921**	1.089**	0.910**	1.081**
	(0.060)	(0.016)	(0.053)	(0.016)	(0.044)	(0.025)	(0.019)	(0.064)	(0.036)	(0.028)	(0.032)	(0.028)	(0.017)	(0.042)
Loan share	0.989*	1.003	0.988**	1.002	0.989**	1.002	0.987**	1.001	0.989**	1.002	0.990*	1.003	0.993	1.004
	(0.055)	(0.631)	(0.048)	(0.778)	(0.050)	(0.680)	(0.024)	(0.850)	(0.045)	(0.669)	(0.074)	(0.611)	(0.247)	(0.517)
Unemployment rate	0.951	0.959	0.968	0.980	0.947	0.955	0.923*	0.941*	0.941	0.956	0.949	0.952	0.959	0.961
	(0.181)	(0.227)	(0.409)	(0.579)	(0.157)	(0.190)	(0.051)	(0.100)	(0.108)	(0.212)	(0.175)	(0.176)	(0.275)	(0.264)
ln(Population density)	1.171*	0.832**	1.093	0.736***	1.155	0.798**	1.208**	0.821**	1.148	0.796***	1.144	0.796***	1.115	0.785***
	(0.082)	(0.040)	(0.343)	(0.001)	(0.109)	(0.010)	(0.040)	(0.029)	(0.119)	(0.010)	(0.133)	(0.009)	(0.238)	(0.007)
Year effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	4449		4449		4449		4449		4449		4449		4449	
Pseudo R^2	0.060		0.060		0.056		0.059		0.056		0.055		0.061	
Wald χ^2	196.83		194.77		185.49		193.32		186.36		188.99		195.93	
Pseudo loglikelihood	-1386.41		-1385.69		-1391.97		-1387.45		-1392.01		-1393.51		-1384.47	

Secondly, we find rather mixed evidence for the acquirer group (A). On the one hand, columns (1), (2), (4), and (7) imply that acquirers operate inefficiently concerning their 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. Hence, 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 observed effects on all bank-specific factors generally harmonize with those of related work. In particular, 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, Bos, et al., 2007 and Behr et al., 2011. Lastly, we stress the robustness of these results across various model specifications. In unreported estimations, 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, cost-income effects do not significantly alter when estimations additionally incorporate the liquidity share. Furthermore, results remain if we additionally consider the merger occurrences in 2014, which are omitted here due to the lagged nature of asset growth. This is shown in the Appendix in Table A3, which accomplishes an extended sample by neglecting the variable asset growth. Another concern that often goes by unnoticed in allied work relates to a potential dependency between mergers and the 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 such possibility, Table A4 and Table A5 respectively consider the variable bank density, as proxied by the number of banks in a county relative to the county's population size, and HHI, which is the normalized Herfindahl–Hirschman Index measuring customer loan market concentration. Our findings hold up against both specifications. Consistent with our expectations, higher bank density and dispersed local market power seem to encourage acquisitions, but the performance aspect prevails.

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 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 not distinct from those of the reference group. The findings up to this point deliver important insights into consolidating banks' characteristics but do not fully suffice to reliably verify a cleansing happening in the German banking market. This is because we must still entertain the possibility that target banks perform well before the low interest era, but experience degradation mainly due to the disadvantageous environment. Such eventuality could be supported by the observation that targets often correspond to small, regional banks. These banks typically depend more on the deposit and lending business such that they might suffer greater exposure to changes in the interest environment (e.g., Genay et al., 2014; Claessens et al., 2018). If so, then the sole reliance on previous analyses would likely yield fallacious conclusions, and impugn the idea of a cleansing happening. The next section, therefore, complements previous analyses by an examination of bank performance prior to the low interest sphere, and before regulatory interventions take legal force 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. The first part examines whether targets are underperforming, as in our primary analysis. In this vein, we first descriptively compare crucial metrics between future targets and other cooperative banks. We then visualize differences across groups and carry out intuitive yet revealing OLS regression analysis. The aim is to demonstrate how we notice performance disparities even by visual inspection. Related, we see how these disparities hold up when we examine performance from an empirically different angle. Lastly, we 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 to 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.

The second part assigns banks to different groups based on their size and performance, and repeats previous estimations using group indicators. The aim is to understand, in particular, how performance relates to the survival chances of small banks. From a cleansing perspective, we expect small and well performing banks to benefit in terms of lower exit probabilities compared to their underperforming peers. Similarly, survival probabilities should be significantly higher for large and well performing banks 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*

To analyze potential differences between future targets and other cooperatives during the 2010-2012 period, Table 3 contrasts both groups with regard to crucial bank performance

Table 3 Performance differences revisited

This table evaluates mean performance differences between future targets and cooperative banks based on the period 2010 to 2012. All variables are stated in percent. 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 corresponds to a Wilcoxon rank sum test, and is additionally reported to account for potential concerns about data normality.

	Future-targets			Other cooperatives					
	N	Mean	SE	N	Mean	SE	Difference	$t_{p-value}$	$W_{p-value}$
Asset growth	218	3.13	0.24	883	4.90	0.21	1.77	0.00	0.00
Loan growth	218	4.13	0.37	882	6.17	0.22	2.04	0.00	0.00
Return on assets	218	0.33	0.01	882	0.36	0.01	0.03	0.07	0.08
Return on equity	218	4.47	0.16	882	4.93	0.09	0.46	0.02	0.06
Cost-income ratio	218	70.6	0.53	882	67.2	0.30	-3.4	0.00	0.00
Liquidity share	218	14.8	0.54	883	13.4	0.26	-1.4	0.02	0.01
Equity share	218	7.63	0.13	883	7.73	0.12	0.1	0.70	0.85
Tier 1 ratio	188	12.6	0.33	749	12.1	0.13	-0.5	0.20	0.41
NPL ratio	180	4.47	0.26	689	4.40	0.17	-0.07	0.84	0.91

characteristics. The table reveals a familiar picture. Future targets not only exhibit smaller growth rates in terms of total assets and loans, but also appear less profitable. Furthermore, future targets suffer from greater cost-income balances and proportionally larger holdings of liquid but unprofitable assets. We find no significant differences in bank capitalization as measured by the ratio of equity over total assets. Finally, both groups behave similarly with respect to their risk-based capital allocation and NPL ratio.

Continuing, Figure 2 visualizes performance differences between groups. The scatter plots depict future targets as red crosses, and all other cooperative banks as green circles. The dashed horizontal lines in green illustrate the corresponding mean performance for the group of other cooperatives. Given that this set-up lends itself to basic OLS regression analysis, we accompany all figures with estimation results in the upper right corners. The underlying model relates each respective performance measure to the natural log of total assets, ln(Assets), and a dummy variable, ft, that equals one if a bank becomes a target in the future, and zero otherwise.[9] Starting with the upper left part, the figure shows that the majority of future targets is located above the mean cost-income ratio for the group of other cooperatives.

This indicates that future targets tend to bear relatively greater costs per income unit. The estimation result confirms this observation. Specifically, the result indicates that the average difference in the cost-income ratio between future targets and other cooperative banks for the same level of size is 3.3 percentage points. Using robust standard errors, this magnitude is significant at the 1% level (unreported).

Proceeding with the lower left part, the figure shows that loan growth for the group of future targets lies mostly below the average growth for the group of other cooperatives. This finding is again captured by the estimation, such that customer loans grow on average 2 percentage points less compared to the growth of other cooperatives of similar size. As before,

[9]We also consider a full model with all covariates from our primary analysis. We report a short version for brevity as our key results remain.

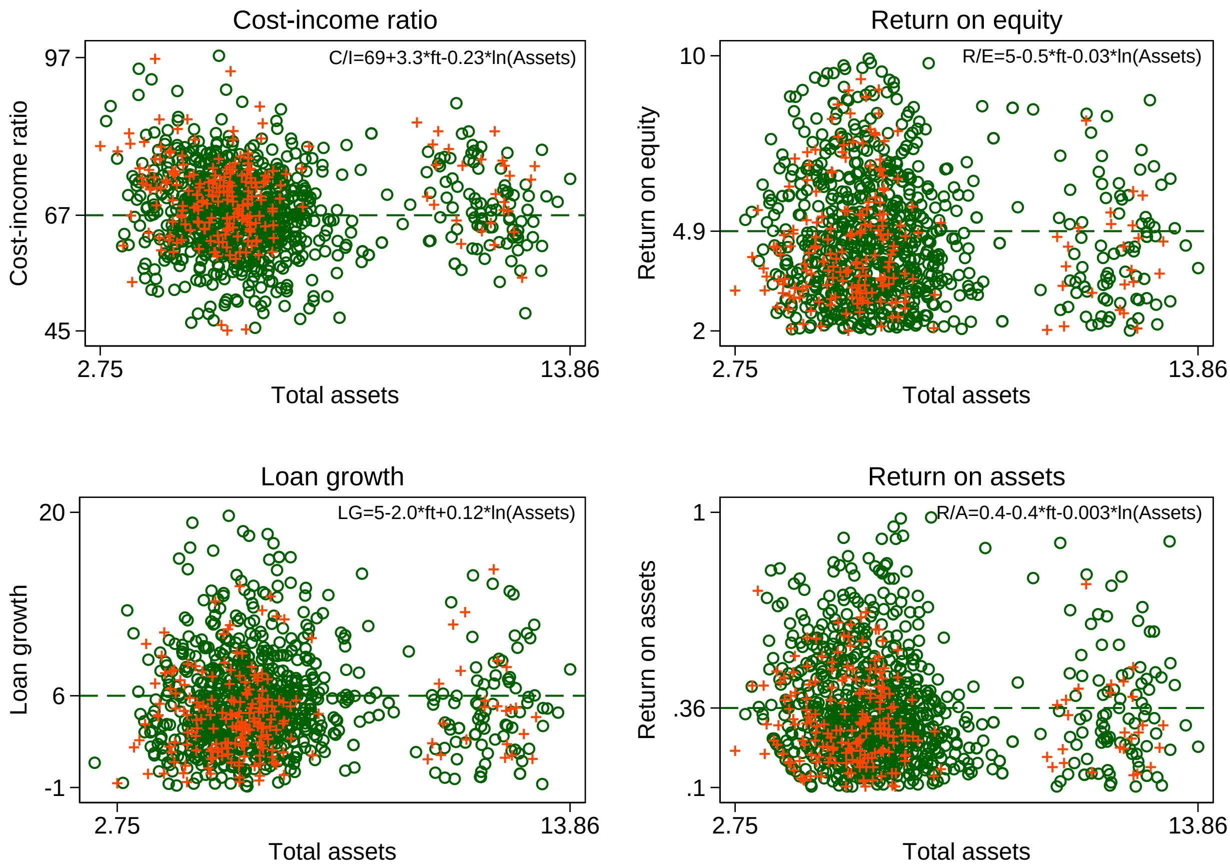


Figure 2 Scatter plots

The figure shows the dispersion of relevant performance characteristics as a function of bank size. Red crosses and green circles respectively indicate future targets and other cooperative banks. Dashed horizontal lines in green constitute mean values achieved by the group of other cooperatives. Equations in the upper right corners show estimated coefficients based on a model that relates each respective measure to the natural log of total assets, ln(Assets), and a dummy variable, ft, that equals one if a bank becomes a target in the future, and zero otherwise. Sub-figures exclude outliers to enhance visibility. Performance measures and total assets are stated in percent and in log-terms, respectively.

the coefficient is significant at the 1% level (unreported). Lastly, we also notice pronounced differences in profitability as illustrated by the two figures on the right. Among comparably sized banks, future targets are less profitable overall. These performance disparities extend to all other measures under consideration, including those not discussed here for brevity. Taken together, we recognize performance differences even by visual inspection. Despite their simplicity, figures and estimations uniformly reveal performance differences for similarly sized banks prior to the low-for-long interest rate environment.

Finally, we estimate equation (2) to see if ex-ante performance significantly determines future target banks. More precisely, we now consider a binary logistic model which links the probability of a bank becoming a target at some point between 2014 to 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 4. The first five columns, (1) to (5), show the outcome of the logistic model. Recall that depicted coefficients for these regressions measure the change in odds for a unit-change in the predictor variable. For instance, a one percentage point increase in the cost-income ratio increases the odds of becoming a target by $(1.062 - 1) \times 100 = 6.2\%$. 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 3 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 result again implies that target banks exhibit relatively poor growth rates before the emergence of detrimental conditions. Finally, we confirm the robustness of these findings by exchanging the equity and loan share with the Tier 1 ratio and security share, respectively. Unreported estimations indicate that our results remain unchanged.

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 et al., 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 indroduction of negative policy rates leads "to more risk-taking and less lending by euro-area banks with a greater reliance on deposit funding".

Table 4 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 acquisitions 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. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	Logit					LPM				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FT	FT	FT	FT	FT	FT	FT	FT	FT	FT
Cost-income ratio	1.062***					0.00874***				
	(0.000)					(0.000)				
Liquidity share		1.023**					0.00419**			
		(0.024)					(0.021)			
Return on equity			0.918**					-0.0113**		
			(0.039)					(0.027)		
Return on assets				0.295**					-0.158**	
				(0.041)					(0.025)	
Loan growth					0.929***					-0.0114***
					(0.008)					(0.007)
ln(Assets)	0.925*	0.900**	0.907**	0.905**	0.908**	-0.0118*	-0.0158**	-0.0146**	-0.0148**	-0.0145**
	(0.079)	(0.029)	(0.041)	(0.038)	(0.043)	(0.066)	(0.015)	(0.024)	(0.022)	(0.026)
Asset growth	0.922**	0.884***	0.895***	0.895***	0.927*	-0.0124***	-0.0181***	-0.0163***	-0.0165***	-0.0101*
	(0.017)	(0.000)	(0.001)	(0.001)	(0.051)	(0.009)	(0.000)	(0.001)	(0.001)	(0.073)
Equity share	1.083*	1.029	1.029	1.084*	1.022	0.0119*	0.00533	0.00512	0.0124*	0.00416
	(0.068)	(0.502)	(0.494)	(0.086)	(0.602)	(0.084)	(0.441)	(0.458)	(0.099)	(0.542)
Loan share	1.028**	1.015	1.022*	1.022*	1.020	0.00347**	0.00206	0.00291*	0.00280*	0.00258
	(0.031)	(0.194)	(0.070)	(0.075)	(0.105)	(0.031)	(0.200)	(0.068)	(0.078)	(0.104)
Unemployment rate	0.925**	0.942*	0.932**	0.932**	0.957	-0.0112**	-0.00927*	-0.00981*	-0.00959*	-0.00657
	(0.025)	(0.074)	(0.047)	(0.046)	(0.180)	(0.021)	(0.062)	(0.054)	(0.056)	(0.176)
ln(Population density)	1.032	0.994	0.998	0.999	0.986	0.00776	-0.000424	-0.000425	-0.000939	-0.00166
	(0.737)	(0.944)	(0.978)	(0.987)	(0.870)	(0.562)	(0.975)	(0.975)	(0.944)	(0.900)
N	960	961	960	960	961	960	961	960	960	961
R^2	0.063	0.037	0.038	0.038	0.040	0.060	0.036	0.036	0.036	0.038
Wald χ^2	52.01	31.84	27.04	27.10	31.74					
Pseudo loglikelihood	-466.61	-479.61	-478.93	-477.75	-478.05					

Related, Claessens et al., 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.

The estimations in Table 4 are based on a sample that excludes banks that, at any point between 2010 to 2012, experience an asset growth of greater than 20%. Recall that we impose this restriction to encounter possible distortions from unobserved acquisitions. Specifically, realized takeovers could substantially alter banks' financial profile and strongly influence the decision to exit or remain in the market later on. Nevertheless, our findings also hold when we keep all sample banks. This is shown in the Appendix in Table A6, which reiterates previous regressions in the same fashion but includes potential acquirers. One exception is loan growth. However, note that the p-value of 0.12 is not too far off from the conventional threshold-level of 10% and that insignificance could be due to inflated standard errors. More precisely, we suspect that the high correlation between loan and asset growth of about 0.83 (unreported) entails multicollinearity issues. This issue is removed once we drop asset growth.

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 4, which assigns comparatively low performing banks a greater probability of becoming a future target. Our analysis thus favors the cleansing 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 cleansing view holds. Similarly, we lack evidence on the extend 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 5 shows the estimation results. The first five columns, (1) to (5), refer to the outcomes of the logistic model. Estimated coefficients on the categorical variables capture the change in odds when moving from the benchmark to either one of the other groups. For instance, C/I: G=1 measures the change in 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. The coefficient of 0.570 suggests that the odds of being a future target for a small and well operating bank are 0.570 times that of the odds for an underperforming bank (or $(0.570\text{-}1)\times 100 = 43\%$ lower). 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 probability on all but the liquidity measure. This clearly challenges the ousting-view as performance actually helps overcome the adverse low-for-long interest rate environment and protects small banks from a market exit. 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 cleansing mechanism 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.

Table 5 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. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	Logit					LPM				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FT	FT	FT	FT	FT	FT	FT	FT	FT	FT
Cat 1										
C/I: G=1	0.570**					-0.101**				
	(0.013)					(0.010)				
C/I: G=2	1.088					0.00105				
	(0.767)					(0.983)				
C/I: G=3	0.373***					-0.149***				
	(0.001)					(0.000)				
Cat 2										
ROA: G=1		0.687*					-0.0673*			
		(0.100)					(0.091)			
ROA: G=2		0.729					-0.0614			
		(0.263)					(0.185)			
ROA: G=3		0.573*					-0.0968**			
		(0.062)					(0.036)			
Cat 3										
ROE: G=1			0.608**					-0.0907**		
			(0.025)					(0.023)		
ROE: G=2			0.675					-0.0771		
			(0.173)					(0.101)		
ROE: G=3			0.547**					-0.107**		
			(0.037)					(0.018)		
Cat 4										
LG: G=1				0.710*					-0.0690*	
				(0.091)					(0.089)	
LG: G=2				0.757					-0.0601	
				(0.327)					(0.208)	
LG: G=3				0.589*					-0.0937**	
				(0.070)					(0.037)	
Cat 5										
LQ: G=1					1.213					0.0312
					(0.375)					(0.429)
LQ: G=2					1.324					0.0386
					(0.336)					(0.418)
LQ: G=3					0.545*					-0.0840**
					(0.052)					(0.049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	961	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	0.044
Wald χ^2	46.73	30.87	32.81	31.62	36.00					
Pseudo LL	-469.58	-479.50	-478.29	-479.70	-474.77					

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 signs of a policy-driven deterioration turning initially well performing banks into merger targets. Instead, our overall results reveal a cleansing happening in the German cooperative banking market. Likely owing to the challenging combination of low interest rates, demanding regulations, and costly digitalization processes, particularly low performing banks exit the market through mergers.

6 Conclusion

This paper analyzes the merger dynamics in the German cooperative banking sector between 2014 and 2019 to explore a potential cleansing happening in the industry. 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. Drawing on standard bank merger methodology, results uniformly indicate that targets correspond to small and underperforming banks, while acquirers stand out in terms of size and capitalization. The evidence in this paper thus supports the view of a cleansing happening, which could improve EU banks' chronically weak profitability in the long run.

Irrespective of 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 acquisitions 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., Manne, 1965; Jensen et al., 1983; Palepu, 1986). In this vein, elevated merger rates during crises or adverse conditions could signal cleansing events, such that weakly operating banks join forces solely to survive and remain in business.

Appendix

Table A1 Summary statistics

	Primary Sample (2015-2019)					Secondary Sample (2010-2012)				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
ln(Assets)	4449	12.91	1.165	9.650	17.63	1101	6.532	2.179	2.197	13.86
Asset growth	4449	6.233	12.14	-19.38	224.5	1101	4.547	5.962	-16.59	63.19
Loan share	4449	59.88	13.28	11.98	94.85	1100	75.24	9.338	10.34	94.95
Loan growth	4449	7.138	12.67	-26.17	192.41	1100	5.762	6.491	-18.26	86.27
Security share	4449	26.33	12.84	0.000	74.77	1101	27.79	11.81	0.000	72.94
Equity share	4449	9.559	2.029	3.498	21.79	1101	7.711	3.264	2.183	76.28
Tier 1 ratio	4418	15.24	3.745	7.770	59.84	937	12.15	3.823	6.140	56.56
NPL ratio	4165	1.499	1.369	0.000	17.75	869	4.417	4.220	0.000	78.64
Return on assets	4449	0.261	0.159	-0.112	2.098	1100	0.356	0.270	-0.927	5.253
Return on equity	4449	2.746	1.551	-1.767	18.56	1100	4.837	2.706	-1.970	20.29
Liquidity share	4449	1.731	1.232	0.000	22.37	1101	13.69	7.833	1.313	63.45
Cost-income ratio	4449	67.47	17.71	14.90	523.8	1100	67.89	8.641	19.88	111.1
Expense share	4449	1.872	0.488	0.281	9.605					
Efficiency	4449	0.895	0.045	0.565	1.000					
Efficiency adjusted	4449	0.913	0.047	0.680	1.000					
Bank density	4449	2.133	1.287	0.082	6.624					
HHI	4449	0.326	0.307	0.000	1.000					
Unemployment rate	4449	4.733	2.254	1.300	15.40	1006	5.468	2.594	1.500	16.57
Elderly share	4449	20.97	2.342	15.40	32.20	1006	20.12	2.078	15.13	28.53
ln(Population density)	4449	5.540	1.005	3.578	8.463	1006	5.548	0.999	3.630	8.390
ln(GDP per capita)	4431	10.45	0.317	9.595	12.11	1001	10.32	0.327	9.496	11.72
ln(Disposable income)	4441	10.01	0.110	9.631	10.66	1001	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 Multinomial logit results: Extended sample

This table explores how various performance measures relate to the probability of a bank becoming a target or an acquirer. Estimations are based on an extended sample of 228 targets, 169 acquirers, and 599 non-merging banks over the period 2014 to 2019. 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. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	(1)		(2)		(3)		(4)		(5)		(6)	
	T	A	T	A	T	A	T	A	T	A	T	A
Efficiency	0.969**	0.934***										
	(0.027)	(0.000)										
Efficiency adjusted			0.963***	0.937***								
			(0.008)	(0.000)								
Cost-income ratio					1.006**	1.001						
					(0.016)	(0.650)						
Expense share							1.596***	1.308*				
							(0.001)	(0.055)				
Liquidity share									1.086**	1.011		
									(0.016)	(0.841)		
Return on equity											0.950	0.953
											(0.325)	(0.317)
ln(Assets)	0.668***	1.829***	0.670***	1.935***	0.698***	1.810***	0.727***	1.861***	0.680***	1.801***	0.685***	1.807***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Equity share	0.954	1.092**	0.952	1.093**	0.950	1.080**	0.934*	1.066*	0.950	1.079**	0.948	1.078**
	(0.202)	(0.016)	(0.183)	(0.016)	(0.150)	(0.029)	(0.063)	(0.069)	(0.144)	(0.030)	(0.131)	(0.034)
Loan share	0.986***	1.005	0.986***	1.003	0.986***	1.003	0.984***	1.002	0.986***	1.003	0.988**	1.004
	(0.009)	(0.402)	(0.008)	(0.569)	(0.006)	(0.507)	(0.003)	(0.643)	(0.006)	(0.506)	(0.017)	(0.414)
Unemployment rate	0.952	0.947*	0.968	0.972	0.949	0.943*	0.925**	0.931**	0.944*	0.943*	0.947	0.938*
	(0.155)	(0.090)	(0.355)	(0.398)	(0.135)	(0.076)	(0.037)	(0.037)	(0.095)	(0.079)	(0.124)	(0.059)
ln(Population density)	1.213**	0.858*	1.144	0.745***	1.203**	0.818**	1.259***	0.839**	1.195**	0.817**	1.191**	0.815***
	(0.020)	(0.055)	(0.118)	(0.001)	(0.025)	(0.011)	(0.007)	(0.029)	(0.029)	(0.011)	(0.034)	(0.010)
Year effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	5445		5445		5445		5445		5445		5445	
Pseudo R^2	0.051		0.052		0.048		0.051		0.047		0.047	
Wald χ^2	218.74		206.18		194.12		200.75		197.53		197.69	
Pseudo loglikelihood	-1605.50		-1605.17		-1611.85		-1606.65		-1612.87		-1613.62	

Table A4 Multinomial logit results: Bank density

This table explores how various performance measures relate to the probability of a bank becoming a target or an acquirer when accounting for regional cooperative bank density. Bank density is the number of cooperative banks located within a county as a share of the population of that county. Estimations are based on a sample of 201 targets, 169 acquirers, and 599 non-merging banks over the period 2015 to 2019. 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. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	T	A	T	A	T	A	T	A	T	A	T	A	T	A
Efficiency	0.965**	0.939***												
	(0.024)	(0.000)												
Efficiency adjusted			0.956***	0.939***										
			(0.003)	(0.000)										
Cost-income ratio					1.006**	1.002								
					(0.023)	(0.575)								
Expense share							1.582***	1.381**						
							(0.002)	(0.028)						
Liquidity share									1.096**	1.001				
									(0.027)	(0.990)				
Return on equity											0.983	0.952		
											(0.777)	(0.398)		
Loan growth													0.942***	0.945***
													(0.001)	(0.008)
Bank density	0.975	1.319***	0.988	1.332***	0.973	1.298***	0.996	1.316***	0.989	1.298***	0.983	1.305***	0.975	1.294***
	(0.737)	(0.000)	(0.874)	(0.000)	(0.717)	(0.000)	(0.957)	(0.000)	(0.879)	(0.000)	(0.817)	(0.000)	(0.737)	(0.000)
ln(Assets)	0.679***	1.979***	0.682***	2.089***	0.712***	1.943***	0.744***	2.010***	0.694***	1.936***	0.696***	1.941***	0.713***	1.961***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset growth	0.927***	0.959***	0.927***	0.960***	0.927***	0.960***	0.931***	0.960***	0.926***	0.960***	0.925***	0.961***	0.955**	1.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.901)
Equity share	0.927*	1.112***	0.923*	1.115***	0.925**	1.101**	0.910**	1.083**	0.922**	1.101**	0.921**	1.101**	0.910**	1.093**
	(0.059)	(0.009)	(0.053)	(0.008)	(0.043)	(0.013)	(0.019)	(0.044)	(0.036)	(0.013)	(0.032)	(0.014)	(0.017)	(0.021)
Loan share	0.988*	1.005	0.988**	1.003	0.989**	1.004	0.987**	1.003	0.989**	1.004	0.990*	1.005	0.993	1.005
	(0.053)	(0.487)	(0.048)	(0.655)	(0.048)	(0.526)	(0.024)	(0.660)	(0.044)	(0.525)	(0.073)	(0.434)	(0.245)	(0.414)
Unemployment rate	0.945	1.015	0.966	1.045	0.940	1.010	0.922*	0.997	0.938	1.011	0.945	1.008	0.953	1.016
	(0.184)	(0.675)	(0.423)	(0.248)	(0.158)	(0.789)	(0.074)	(0.946)	(0.133)	(0.765)	(0.188)	(0.844)	(0.263)	(0.681)
ln(Population density)	1.157	0.931	1.086	0.816**	1.140	0.885	1.206*	0.921	1.142	0.883	1.135	0.882	1.102	0.871
	(0.129)	(0.466)	(0.399)	(0.041)	(0.169)	(0.200)	(0.056)	(0.404)	(0.159)	(0.191)	(0.185)	(0.185)	(0.328)	(0.150)
Year effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	4449		4449		4449		4449		4449		4449		4449	
Pseudo R^2	0.064		0.064		0.060		0.063		0.060		0.059		0.065	
Wald χ^2	210.22		209.71		196.93		207.85		197.65		199.50		212.00	
Pseudo loglikelihood	-1380.43		-1379.44		-1386.56		-1381.67		-1386.67		-1387.96		-1379.29	

Table A5 Multinomial logit results: Market concentration

This table explores how various performance measures relate to the probability of a bank becoming a target or an acquirer when accounting for regional market concentration. Market concentration is measured as the normalized HHI for the customer loan market within a county. Estimations are based on a sample of 201 targets, 169 acquirers, and 599 non-merging banks over the period 2015 to 2019. 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. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	T	A	T	A	T	A	T	A	T	A	T	A	T	A
Efficiency	0.966**	0.940***												
	(0.033)	(0.000)												
Efficiency adjusted			0.957***	0.945***										
			(0.004)	(0.000)										
Cost-income ratio					1.006**	1.002								
					(0.025)	(0.580)								
Expense share							1.591***	1.360**						
							(0.002)	(0.041)						
Liquidity share									1.094**	0.987				
									(0.027)	(0.840)				
Return on equity											0.978	0.960		
											(0.707)	(0.488)		
Loan growth													0.942***	0.944***
													(0.001)	(0.009)
HHI	0.996	0.994*	0.997	0.995*	0.996	0.995*	0.996	0.994*	0.997	0.995*	0.996	0.994*	0.997	0.995*
	(0.222)	(0.050)	(0.268)	(0.066)	(0.197)	(0.063)	(0.171)	(0.053)	(0.221)	(0.062)	(0.202)	(0.059)	(0.241)	(0.080)
ln(Assets)	0.679***	1.932***	0.681***	2.023***	0.710***	1.906***	0.742***	1.970***	0.691***	1.901***	0.694***	1.903***	0.712***	1.920***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset growth	0.927***	0.961***	0.927***	0.962***	0.928***	0.962***	0.931***	0.962***	0.926***	0.962***	0.926***	0.962***	0.955**	1.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.827)
Equity share	0.924*	1.103**	0.921**	1.104**	0.922**	1.092**	0.906**	1.075*	0.919**	1.091**	0.918**	1.091**	0.908**	1.083**
	(0.050)	(0.015)	(0.045)	(0.015)	(0.036)	(0.023)	(0.015)	(0.063)	(0.030)	(0.025)	(0.027)	(0.025)	(0.015)	(0.039)
Loan share	0.988**	1.003	0.987**	1.001	0.988**	1.002	0.986**	1.001	0.988**	1.002	0.989*	1.003	0.993	1.003
	(0.043)	(0.679)	(0.039)	(0.822)	(0.038)	(0.737)	(0.018)	(0.920)	(0.035)	(0.722)	(0.061)	(0.649)	(0.205)	(0.573)
Unemployment rate	0.961	0.978	0.977	0.998	0.957	0.972	0.934*	0.960	0.951	0.974	0.959	0.969	0.968	0.978
	(0.286)	(0.523)	(0.549)	(0.959)	(0.255)	(0.432)	(0.092)	(0.262)	(0.182)	(0.472)	(0.273)	(0.385)	(0.395)	(0.524)
ln(Population density)	1.175*	0.823**	1.099	0.730***	1.161*	0.790***	1.215**	0.813**	1.153	0.788***	1.150	0.787***	1.121	0.778***
	(0.073)	(0.032)	(0.312)	(0.001)	(0.097)	(0.008)	(0.034)	(0.023)	(0.108)	(0.008)	(0.119)	(0.008)	(0.217)	(0.005)
Year effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
N	4449		4449		4449		4449		4449		4449		4449	
Pseudo R^2	0.061		0.062		0.058		0.061		0.058		0.057		0.063	
Wald χ^2	195.08		193.35		183.41		191.66		184.39		186.13		193.20	
Pseudo loglikelihood	-1383.82		-1383.46		-1389.41		-1384.66		-1389.56		-1390.92		-1382.28	

Table A6 Binary logit results: Full sample

This table analyzes how average bank performance over the period 2010 to 2012 influences the probability of becoming a future target when including all pseudo acquirers. The first five columns, (1) to (5), show the outcome of the binary logit model. Columns (6) to (10) show the results of the linear probability model. Estimations are based on a sample of 218 future targets and 883 other banks. The number of observation varies depending on data availability. We do not require full information on all variables to prevent a potential sample selection bias. Robust standard errors are based on the Huber-White estimator. P-values are reported in parentheses. ***, ** and * respectively denote statistical significance at the 1%, the 5% and the 10% level.

	Logit					LPM				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FT	FT	FT	FT	FT	FT	FT	FT	FT	FT
Cost-income ratio	1.062***					0.00894***				
	(0.000)					(0.000)				
Liquidity share		1.025**					0.00453**			
		(0.015)					(0.011)			
Return on equity			0.919**					-0.0120**		
			(0.034)					(0.010)		
Return on assets				0.301**					-0.165**	
				(0.038)					(0.012)	
Loan growth					0.947					-0.00573
					(0.117)					(0.175)
ln(Assets)	0.924*	0.899**	0.906**	0.905**	0.907**	-0.0112*	-0.0148**	-0.0138**	-0.0140**	-0.0138**
	(0.074)	(0.028)	(0.040)	(0.037)	(0.041)	(0.075)	(0.021)	(0.031)	(0.029)	(0.032)
Asset growth	0.923**	0.897***	0.906***	0.906***	0.934*	-0.00719***	-0.00804***	-0.00737***	-0.00738***	-0.00268
	(0.011)	(0.004)	(0.006)	(0.007)	(0.058)	(0.000)	(0.000)	(0.000)	(0.000)	(0.460)
Equity share	1.085*	1.028	1.029	1.083*	1.026	0.0121*	0.00479	0.00449	0.0121*	0.00465
	(0.058)	(0.504)	(0.492)	(0.084)	(0.533)	(0.069)	(0.472)	(0.500)	(0.094)	(0.482)
Loan share	1.028**	1.015	1.023*	1.022*	1.021*	0.00375**	0.00271*	0.00349**	0.00341**	0.00363**
	(0.029)	(0.179)	(0.059)	(0.063)	(0.078)	(0.012)	(0.067)	(0.018)	(0.021)	(0.014)
Unemployment rate	0.923**	0.940*	0.930**	0.930**	0.954	-0.0118**	-0.0101**	-0.0107**	-0.0105**	-0.00775
	(0.021)	(0.062)	(0.040)	(0.040)	(0.147)	(0.012)	(0.036)	(0.031)	(0.032)	(0.101)
ln(Population density)	1.034	1.000	1.002	1.003	0.991	0.00891	0.00121	0.00108	0.000636	0.000331
	(0.715)	(0.999)	(0.978)	(0.971)	(0.920)	(0.493)	(0.925)	(0.934)	(0.961)	(0.980)
N	1005	1006	1005	1005	1006	1005	1006	1005	1005	1006
R^2	0.072	0.045	0.046	0.046	0.044	0.064	0.038	0.036	0.037	0.033
Wald χ^2	56.37	31.17	24.47	24.25	21.49					
Pseudo loglikelihood	-473.33	-486.77	-486.47	-486.34	-487.34					

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