Predicting corporate restructuring and financial distress in banks: The case of the Swiss banking industry

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Abstract

The global financial crisis of 2007–2009 is widely regarded as the worst since the Great Depression and threatened the global financial system with a total collapse. This article distinguishes itself from the vast literature of bankruptcy, bank failure, and bank exit prediction models by introducing novel categorical parameters inspired by Switzerland's banking landscape. We evaluate data from 274 banks in Switzerland from 2007 to 2017 using generalized linear model logit and multinomial logit regressions and examine the determinants of corporate restructuring and financial distress. We complement our results with a robustness test via a Bayesian inference framework. We find that total assets and net interest margin affect bank exit and mergers and acquisitions, and that banks operating in the Zurich area have a higher likelihood of exiting and becoming takeover targets relative to banks operating in the Geneva area.

JEL CLASSIFICATION C41, G20, G21, G33, G34

1 INTRODUCTION

Banks play an essential role in every economy. Their primary activity (purpose) to act as intermediaries between depositors and borrowers requires them to be trusted. A failure of a bank, especially a global systemically important bank (G-SIB), is devastating to the trust, cascading into negatively affecting the nation's financial household.[1] Consequently, maintaining a reliable early warning system (EWS) for financial regulators is a top priority.

In this article, we identify key variables for a bank's survival in a fast-paced and competitive environment.[2] As in general firms move through different stages of their corporate life cycle, such as birth, growth, maturity, and decline, and through different growth and capital structure strategies, they also may face financial distress, default, and bankruptcy at a certain stage (Anthony & Ramesh, 1992; Koh et al., 2015; Miller & Friesen, 1984; Wruck, 1990). Each stage of the life-cycle theory reveals significant differences in the general situation, organizational structure and strategy, and decision-making style (Koh et al., 2015; Miller & Friesen, 1984; Pashley & Philippatos, 1990). When a firm recognizes that it is in danger of financial distress, it should immediately take corrective measures to enhance efficiency and control costs via different restructuring strategies (Asquith et al., 1994; Carapeto et al., 2010; Koh et al., 2015; Sudarsanam & Lai, 2001).

Focusing on Switzerland, a country famous for the soundness of its banking system, we investigate the determinants of bank exits and bank failures, and compile a novel data set containing several innovative features. Because outright bank failures are rare events in Switzerland, the data set complements bank bankruptcies and defaults with bank mergers and acquisitions (M&As) and the returning of banking licenses. As discussed in other studies, individual bank failures may disrupt trust in the system as a whole and can lead to negative spillover effects and a high risk of bank runs. This can explain why the banking industry is characterized by intense regulation that aims to prevent individual and systemic crises (Benink & Benston, 2005; Elsas, 2007; Kick & Koetter, 2007; Koetter et al., 2007). When banks face distress, it is more common to observe restructuring strategies such as M&As that can serve as a preemptive measure of financial distress resolution than actual bankruptcies and direct bank closures (Betz et al., 2014; Carapeto et al., 2010; DeYoung, 2003; Elsas, 2007; Focarelli et al., 2002; Hannan & Pilloff, 2009; Hannan & Rhoades, 1987; Kick & Koetter, 2007; Koetter et al., 2007; Oshinsky & Olin, 2006; Spokeviciute et al., 2019; Vazquez & Federico, 2015;

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[1]For a full list of G-SIBs, visit www.fsb.org/2020/11/2020-list-of-global-systemically-important-banks-g-sibs

[2]From a life-cycle theory point of view.

Wheelock & Wilson, 2000). The reason for conducting M&As in this context is so that a troubled bank is acquired by another bank to lower the default risk and increase efficiency through reorganization. Acquisition of a target bank at risk of financial distress can lower this risk through capital infusions (capital buffers), diversification benefits, or better risk management practices from the acquiring bank.

Our approach uses well-established econometric methods to derive a contemporary model. The related framework shows that total assets (*TA*), net interest margin (*NIM*), and unemployment rate (*UR*) have a significant negative relation with bank exit, whereas cost-to-income ratio (*CIR*) has a positive relation. *TA* and *NIM* also have a negative relation with M&As. Consequently, these banks are less likely to be acquired or merged, either with a third party or with a group or parent company. Another interesting finding is that total asset growth (*TAG*) and total-equity-to-total-asset ratio (*TETA*) are insignificant and could even have a negative relation with bank exit. We also find that relative to Geneva, the likelihood that banks return their bank licenses and continue to operate as a family office or financial independent asset manager is lower in the financial centers of Basel and Ticino and the rest of Switzerland.

This article makes several contributions to the EWS, bank exit, bank financial distress, and bank M&A literatures. First, it adds to the literature on classical statistical techniques for the determinants of bank exits and failures. Second, it contributes to the literature in terms of methodology and construction of covariates used to predict bankruptcy and M&As. Third, it provides tailor-made novel models within the Swiss banking landscape proposing original features covering bank categories, bank structure, and hubs. This allows us to close an important gap in the bank exits field of knowledge. Another innovation offered by this article is M&A activity as a potential form of distress. Furthermore, the models and approach can be generalized and applied to any financial center and most recent data. In particular, the results provide knowledge for interdisciplinary researchers in the fields of banking and finance, financial econometrics, and business analytics. The results also have implications for specialists and managers because of their practical applicability in the field of risk management, policy making, and regulatory affairs.

2 RELATED LITERATURE ON FINANCIAL DISTRESS AND M&As

2.1 Financial distress

General bankruptcy prediction models were introduced in the late 1960s. The development started with Beaver (1966) who introduced a univariate model, followed by Altman (1968) who introduced a multiple discriminant analysis (MDA) model. Over the decades various bankruptcy prediction models have been introduced using classical statistical techniques. Ohlson (1980) uses a logit model whereas Zmijewski (1984) uses a probit model. Lane et al. (1986) introduced the Cox proportional hazard model, which Pappas et al. (2017) uses. Bell (1997), Olmeda and Fernández (1997), Kolari et al. (2002), Canbas et al. (2005), Kumar and Ravi (2007), and Campbell et al. (2008) use a logistic regression model, whereas Huang et al. (2012), Shumway (2001), and Polemis and Gounopoulos (2012) use a hazard model. Vassalou and Xing (2004) and Hillegeist et al. (2004) use the Black–Scholes–Merton probability of bankruptcy (BSM-prob) option pricing model. Olson et al. (2012) apply data mining tools to bankruptcy data and find several decision trees. In a recent study, Cleary and Hebb (2016) use MDA. Tian and Yu (2017) use a variable selection method called LASSO (adaptive least absolute shrinkage and selection operator). Carmona et al. (2019) use a recently developed machine learning method called extreme gradient boosting (XGBoost). From an operational research and multiple criteria analysis point of view, Doumpos et al. (2004), Fethi and Pasiouras (2010), Ioannidis et al. (2010), and Pasiouras et al. (2010) summarize and analyze several classification techniques.

Over the decades, the methodology and construction of covariates in a bankruptcy prediction context have been developed. Altman (1968), Ohlson (1980), and Zmijewski (1984) mainly use accounting data, whereas Shumway (2001), Vassalou and Xing (2004), Hillegeist et al. (2004), and Campbell et al. (2008) use accounting and market data. Wu et al. (2010) examine the different approaches in a comparative study and demonstrate that Shumway's (2001) hazard model, which includes market and firm data, generally outperforms models that are based only on accounting data. Fiordelisi and Marqués-Ibañez (2013) include various factors at the bank, industry, and country levels. In the European context, Betz et al. (2014) find that banking sector and bank-specific vulnerabilities with indicators for country-level macro-financial imbalances improve model performance.

The US Federal Reserve System (Fed) changed in the 1990s from using a surveillance process that relied on screening key financial ratios to incorporating econometric models to predict the financial conditions of a bank (Jagtiani et al., 2003). In 1995, the Fed developed the System to Estimate Examination Ratings (SEER) model, which consists of two parts: (1) the SEER rating model and (2) the SEER risk rank model. The SEER rating model predicts the probability that a bank will be assigned one of the five possible ratings using a stepwise multinomial logit (MNL) analysis. The model uses 45 financial and nonfinancial variables. The SEER risk rank model estimates the likelihood that a bank will fail or become critically undercapitalized. The model uses a stepwise probit regression based on data of exited and undercapitalized banks from prior years. Where applicable, we follow the CAMELS taxonomy (Betz et al., 2014; Canbas et al., 2005; Huang et al., 2012; Koetter et al., 2007; Lane et al., 1986; Pappas et al., 2017).[3]

To summarize, we concur with Wu et al. (2010), Tinoco and Wilson (2013), and Bauer and Agarwal (2014) that a model with key accounting information, market data, and firm characteristics provides the most reliable forecasts of future bankruptcy. We follow Pappas et al. (2017) and introduce macroeconomic as well as microeconomic and market structure variables. As our method, we use a logistic regression and a multinomial logistic regression in conjunction with a variety of bank exit events derived from the Swiss banking industry.

2.2 Mergers and acquisitions

As a corporate restructuring strategy, M&A transactions have globally gained popularity over the last decades (Bhattacharya, 2020). They generally can be described from a legal (statutory, subsidiary, and consolidation) and an economic (horizontal, vertical, and conglomerate) perspective (DePamphilis, 2011). M&As have also attracted the attention of researchers over the years, and numerous studies use various statistical models to predict takeover targets using publicly available financial information (Akhigbe et al., 2004; Camerlynck et al., 2005; Campbell et al., 2008; Cigola & Modesti, 2008; Dietrich & Sorensen, 1984; Doumpos et al., 2004; Iwasaki et al., 2021; Palepu, 1986; Pastena & Ruland, 1986; Polemis & Gounopoulos, 2012; Powell, 2003).

[3]In 1979, US bank regulatory agencies created the CAMEL analysis—capital adequacy, asset quality, management, earnings, and liquidity. In 1996, US regulators added an “S” for sensitivity to market risk.

The empirical findings regarding the performance of target firms before acquisition vary. For example, Palepu (1986) and Polemis and Gounopoulos (2012) argue that acquired firms underperform relative to their industry median, whereas Camerlynck et al. (2005) cannot identify any differential characteristic between the two groups. Gilson et al. (2016) examine the driver of M&A activities based on factors specific to Chapter 11 in the United States. They argue that M&As in bankruptcy are countercyclical and are more likely to occur when the costs of financing a reorganization are greater than those of a potential acquirer (Gilson et al., 2016). Iwasaki et al. (2021) analyze the factors behind distressed acquisitions in European emerging markets from 2007 to 2019. They show that the quality and enforcement of insolvency laws are linked with a lower probability of distressed acquisitions followed by corruption control and progress in banking reforms (Iwasaki et al., 2021). In general, the decision to acquire a financially distressed firm is very important for managers, shareholders, and bondholders. Specifically, when a target firm is in financial distress and goes bankrupt, shareholder value drops significantly (Dong & Doukas, 2021; Shrieves & Stevens, 1979). Such firms are willing to be acquired at a favorable acquisition premium. However, a low acquisition premium for targets in financial distress could reflect a high bankruptcy risk (Dong & Doukas, 2021). Shrieves and Stevens (1979), Clark and Weinstein (1983), and James (1991) provide evidence in support of the bankruptcy avoidance rationale as they claim that many severe financial crises among large corporations are resolved through the merger process.

In the same vein, numerous studies cover the prediction of M&A targets in the banking industry (Beccalli & Frantz, 2013; Berger et al., 1999; Betz et al., 2014; Carapeto et al., 2010; DeYoung, 2003; Elsas, 2007; Focarelli et al., 2002; Hadlock et al., 1999; Hannan & Pilloff, 2009; Hannan & Rhoades, 1987; Kick & Koetter, 2007; Koetter et al., 2007; Oshinsky & Olin, 2006; Pasiouras & Tanna, 2010; Pasiouras et al., 2007; Pasiouras et al., 2010; Spokeviciute et al., 2019; Thompson, 1997; Vasquez & Federico, 2015; Wheelock & Wilson, 2000; Worthington, 2004). For example, Hannan and Rhoades (1987) use a sample of US banks from 1971 to 1982 and find that poorly managed banks are more likely to become takeover targets than other banks. Thompson (1997) examines the determinants of acquisitions of UK building societies from 1981 to 1993 and finds that takeover target banks are more likely than other banks to have smaller asset size, slower asset growth, retained earnings below regulatory requirements, and negative profits. Thompson (1997) concludes that building societies with low earnings are likely to be encouraged by regulators to consider acquisition by stronger institutions. Focarelli et al. (2002) study bank M&As in Italy from 1985 to 1996. They find that target banks are less profitable and have high labor costs and many bad loans, which indicate low performance compared to other banks. Worthington (2004) examines the determinants of mergers among mutual credit unions in Australia and finds that target banks are likely to have relatively small asset size and low liquidity, whereas acquirers are likely to be larger, more profitable, and more scale efficient, so managerially efficient credit unions are likely to purchase targets that are less efficient. Elsas (2007) investigates the determinants of M&As in German savings and cooperative banking sectors from 1993 to 2001. He finds that many of the observed mergers serve as preemptive resolution of banks' financial distress. He concludes that distressed mergers can be beneficial because they can encourage reorganizations, realize diversification gains, and avoid public attention. Similarly, Koetter et al. (2007) examine the determinants of M&As in German savings and cooperative banks from 1995 to 2001. They observe that takeover target banks in both distressed and nondistressed mergers have worse financial (CAMEL) profiles than control banks. Therefore, even nondistressed mergers may be motivated by the desire to forestall serious future financial distress and prevent regulatory intervention.

3 SAMPLE AND DATA COLLECTION

We use only data from authorized institutions with a "bank/securities dealer" license from the Swiss Financial Market Supervisory Authority (FINMA). To ensure that we use only static and reliable bank data, we include a bank only if it (1) was registered in Switzerland between 2007:Q1 and 2017:Q4 and (2) provided annual reports as of December 31 or their individual official reporting date.

We obtain a list of reporting banks (excluding securities dealer) in Switzerland from Swiss National Bank (SNB) as of December 31, 2017.[4] A total of 253 banks are listed and categorized into nine groups. We repeat this procedure for the preceding years 2007–2016. To operate with an accurate data set, we first consolidate and clean the data for duplicates of the same bank. The total number of reporting banks over the 2007–2017 target period is N = 386; 59 banks changed their corporate name during the observation period.

[4]www.snb.ch/en/iabout/stat/statrep/id/statpub_bankench#t2

We use FitchConnect (FiC) from Fitch Solutions as our database to (1) compile a portfolio of banks according to our target list and (2) retrieve their respective accounting and bank-specific data for 2007–2017. In FiC, 727 bank names with a legal entity in Switzerland are available. We start bottom up to compile a portfolio of our *N* target banks. Because of missing bank names and/or data, our final sample is *n* = 274 banks that either exited or did not; this represents a coverage rate of 71%. We identify 146 banks[5] that exited, and in a top-down approach, we investigate their cause for exit (Heffernan, 2005).[6] We compile a unique historical data set from 2007 to 2017 with each bank's reason for exit. Banks that simply changed their company name and are still operational (*n* = 73) are not included in the basket of 146. The exit ratio is 26.64%. A list of the sample banks used in this study is provided in Online Appendix E.

Like most databases, FiC could contain outliers. As with other studies, such as Dietrich and Wanzenried (2010) and Golubeva (2016), the two big banks UBS and Credit Suisse are considered outliers, mainly because of their business operating model and size of balance sheet in comparison to all other bank categories. We include the two big banks and normalize the data.

4 RESPONSE AND PREDICTOR VARIABLES

In a general bank failure and M&A takeover prediction analysis, the main dependent variable measures bank exit as a dichotomous outcome: failure versus nonfailure, troubled bank versus sound bank, takeover target bank versus standalone bank. That is, when a bank has failed or exited during the observation period, the response variable equals 1, and 0 otherwise. Likewise, initially we use a dependent binary dummy variable *EXIT* that equals 1 in the year a bank has exited, and 0 otherwise.[7] The input from a qualitative perspective is the reason for exit and is constructed as a limited dependent variable with discrete outcomes (*REAS*). In this article, we include bank exits in the sample if one of the following events occurred: voluntary dissolution/liquidation (*VL*), supervisory intervention: forced bankruptcy/liquidation (*SI*), fully or partly

[5]The number is 146 according to SNB; available on FiC 73.

[6]In our qualitative analysis, we identify M&A transactions where a specific bank sold one business area only and continues to operate with a banking license from FINMA. These banks are not considered as exited.

[7]Betz et al. (2014) follow a similar approach.

acquired by another bank (*AB*), merged with a bank (*MB*), returning bank license and operating as a family office and/or financial company (*RL*), and merged with group/parent company (*MG*) (Heffernan, 2005). Banks that do not meet these criteria are considered as being censored, as the event did not occur. We do not include governmental interaction or rescued with state financial support (*GI*) as the reason for exit because UBS is the sole bank that meets these criteria.[8] We define the time (date) of the event the bidder or seller, governmental body, or parent company announced the exit. As a main source for identifying the reasons for bank exits, we use press releases from banks, enforcement information from FINMA, and qualitative information from several major news sites and Shabex (an independent information platform for company and commercial register data).[9] We construct *REAS* as a limited dependent variable with discrete categories that take values from 0 to 4 and include the following reasons for exit: (1) *VL* + *SI*, (2) *AB* + *MB*, (3) *RL*, (4) *MG*, and 0 for nonexit. Table 1 provides an overview of all bank exits by year and reason for exit.

For modeling purposes, we use the bank accounting statement up to the preceding years of the exit announcement, as the subsequent years would be biased. To avoid reverse causality, we apply the $y_{-t} = a + x_{t-1}$ model in all observations. We therefore include the independent variables for 2007–2016 and the dependent variables for 2008–2017.

The Swiss banking sector is a heterogeneous environment and is based on the model of universal banking, which means that all sophisticated banking services are provided, such as lending, deposits, asset management, investment advice, payments, financial analysis, and investment banking. The SNB categorizes all banks in nine categories: cantonal banks, big banks, regional and savings banks, Raiffeisen banks, stock

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[8]On October 16, 2008, the Swiss authorities were forced to bail out UBS with 6 billion Swiss francs (CHF). Following the intervention, the Swiss parliament and Federal Council issued too-big-to-fail rules in 2012 to avoid recurrence in Switzerland (www.parlament.ch/de/ratsbetrieb/suche-curia-vista/geschaeft?AffairId=20080077; www.finma.ch/en/~/media/finma/dokumente/dokumentencenter/myfinma/finma-publikationen/resolution-bericht/20200225-resolution-bericht-2020.pdf?la=en).

[9]www.shabex.ch/en/

exchange banks, other banking institutions, private bankers, foreign-controlled banks, and branches of foreign banks (SNB, 2020). Table 2 provides an overview of key figures over 2015–2019.

We address these varieties of business models in our study and use *CAT* as a categorical independent variable that takes values from 1 to 8 for the following categories from the SNB: (1) cantonal banks (*CB*), (2) big banks (*BB*), (3) regional banks (*RB*), (4) Raiffeisen banks (*RAB*), (5) stock exchange banks (*SB*), (6) other banking institutions (*OB*), (7) private bankers (*PB*), and (8) foreign banks (*FB*). We follow the categorization of the Swiss Bankers Association (SBA, 2020) and combine foreign-controlled banks and branches of foreign banks into foreign banks.

Because of higher frequencies in our sample and higher qualitative significance we use *CB, RB,* and *SB* as dummy variables and use the binary indicators as follows: *RB* equals 1 for regional banks, and 0 otherwise; *SB* equals 1 for stock exchange banks, and 0 otherwise; and *FB* equals 1 for foreign banks, and 0 otherwise.

Using a case study approach, we investigate the structure of each bank type in our sample and follow an approach similar to Heffernan (2005) and Hernando et al. (2008) with the differentiation of bank holding company (*BHC*) and financial holding company (*FHC*). To address Switzerland's unique bank structure, we add the category bank cooperative company (*BCC*) and *Others*. We use *BS* as a categorical variable that takes values from 1 to 4 and include binary indicators for the different bank structures: (1) *BHC,* (2) *FHC,* (3) *BCC,* and (4) *Others*. The majority of Swiss banks are bank cooperative companies if we split Raiffeisen banks into 229 autonomous legal entities with a branch density of 847 different locations.[10]

Switzerland has a vast network of registered offices, branches, and representative offices spread over the 26 cantons. As of 2019, the number of registered offices and branches in Switzerland is 2799[11] compared to 2202[12] communes; this implies a 127% ratio of banks per commune. The location of these offices is not

[10]https://report.raiffeisen.ch/19/en/key-figures

[11]https://data.snb.ch/en/topics/banken#!/cube/bastdagsua

[12]www.atlas.bfs.admin.ch/maps/13/de/15078_229_228_227/23829.html

randomly scattered. There is a strategic decision behind the choice of location based on an operating model, category, and bank structure. We address this geographical factum by following BAK Economic's (2021) definition of financial centers in Switzerland. They compare the 2019 added value of total CHF70.5 billion and the respective full-time equivalent (FTE) in ratios to total financial sector employment with the hubs of Zurich, Geneva, Basel, Ticino, and the rest of Switzerland.[13] With 44% of the sectors' gross domestic product (GDP) contribution and a 41% national employment ratio in the financial sector, Zurich plays a major role on both the national and international levels. These four hubs are heterogeneous oriented: The two big banks UBS and Credit Suisse are major players in Zurich, whereas predominantly banks with a focus on wealth management and foreign institutions are located in Geneva. Basel is a strong insurance hub and Ticino has a long-standing tradition with cross-border activities in wealth management with Italian clients (BAK Economics, 2021). According to BAK Economics, Zurich comprises the cantons of Zurich, Schwyz, and Zug; Geneva comprises the cantons of Geneva and Vaud; and Basel comprises the cantons of Basel-Stadt und Basel-Landschaft. Because there is no cluster analysis of the Swiss financial centers available, we use a qualitative approach and allocate the banks to one of the financial centers by identifying the location of the respective headquarters (registered offices): (1) *Zurich,* (2) *Geneva,* (3) *Basel,* (4) *Ticino,* and (5) *Rest of Switzerland.* From a distribution point of view, the two big banks, UBS and Credit Suisse, and the Raiffeisen banks have a vast branch network in all of Switzerland, where private banks are more concentrated in *Zurich* and *Geneva*. The percentage of registered offices and branches in Switzerland are located in the following hubs as of December 31, 2019: *Zurich* 17%, *Geneva* 13%, *Basel* 5%, *Ticino* 6%, and *Rest of Switzerland* 59%.[14] We use *FC* as a categorical variable that takes values from 1 to 5 for the five financial hubs defined earlier.

Because of the variance of different bank categories, we identify whether banks are stock exchange listed or not. For censored banks, we download the Swiss Performance Index from SIX Swiss Exchange Ltd.

[13] Cantons lying outside of these hubs are combined as the rest of Switzerland.

[14] https://data.snb.ch/en/topics/banken#!/cube/bastdagsua

and cross-check it with our sample.[15] For exited banks, we apply a different method by running a qualitative search on the Internet. We consider banks as listed only if they were or are exchange-traded equity securities under the Swiss Performance Index. We do not consider the OTC-X index of banks provided by Berner Kantonalbank.[16] We use *SPI* as a binary indicator that equals 1 if a bank is listed, and 0 otherwise.

The Swiss banking sector is a strong regulated industry, and major changes in regulation may affect the operating model of a bank. The introduction of the Basel II and Basel III framework from the Basel Committee on Banking Supervision in 2007 and 2017, respectively, aims to (1) strengthen microprudential regulation and supervision and (2) add a macroprudential overlay that includes capital buffer applicable to all banks and higher loss absorbency for G-SIBs and domestic systemically important banks (D-SIBs).[17] Because the Basel III framework has a quantitative impact on the balance sheet of a bank, the financial market strategy of a financial center has a sustainable impact on how to conduct business in general. A major change is the announcement of the Federal Council of Switzerland in 2010, that mandates that Switzerland is consistently oriented toward managing taxed assets (Federal Department of Finance, 2012). This so-called white money strategy is one of the major events in the target period and is investigated in our article. We use *WMS* as a binary indicator that equals 1 for exited banks if their exit occurred after December 31, 2009, and 0 otherwise.

4.1 Accounting variables

Following older and recent studies (Altman, 1968; Betz et al., 2014; Lane et al., 1986; Pappas et al., 2017) accounting information is a relevant input factor in predicting the failure risk of banks. We introduce one balance sheet variable and five financial ratios. The balance sheet variable is total assets (*TA*) and the financial ratios are cost-to-income ratio (*CIR*), net interest margin (*NIM*), personnel expenses/overheads (*PEO*), total assets growth (*TAG*), and total equity/total assets (*TETA*). For our enhanced model, we add the two financial ratios: loan loss provision/gross loans (*LLPGL*) and pretax profit/net income (*PTPNI*).

[15] www.six-group.com/exchanges/indices/data_centre/shares/spi_en.html

[16] For a full list traded bank securities, see www.otc-x.ch/security/CH0017915718.

[17] www.finma.ch/en/finma/international-activities/policy-and-regulation/bcbs/

The literature does not give clear preference for whether unconsolidated or consolidated data should be used (Pappas et al., 2017). Among others, Beck et al. (2013) and Pappas et al. (2017) use unconsolidated data, whereas Čihák and Hesse (2008) and Dietrich and Wanzenried (2011) use consolidated data. In this article,we mostly use unconsolidated data from FiC over 2007:Q1–2017:Q4.

4.2 Market structure variables

The market structure variable we use is the Herfindahl–Hirschmann index (*HHI*), and we compute the sum of squared employment shares (FTE) per year. The share of employment is an important indicator (BAK Economics, 2021) and shows the concentration of workforces of all sample banks in the respective year.

4.3 Macroeconomic variables

As the literature reports (Section 0), macroeconomic variables in bankruptcy prediction models outperform classical models with accounting data only. The 2007–2009 global financial crisis hit Switzerland with tremendous consequences for the future development of the banking sector. The bank exit events outlined in this article may or may not be interpreted as direct or indirect causes of it. This type of analysis would require a separate study and is not covered here. Because of the dependency of the Swiss economy on the banking sector, bank failures often lead to financial crises and may prove costly for taxpayers (Heffernan, 2005). To consider these two major facts, we use Switzerland's real gross domestic product (*GDP*) and the unemployment rate (*UR*) from the Swiss State Secretariat for Economic Affairs (SECO).

The response and predictor variable definitions are provided in Appendix A, summary statistics in Appendix B, and descriptive statistics in Table 3.

4.4 Sample statistics

As an initial overview, we compare exited and nonexited banks summary statistics in Appendix B. The total number of bank-year observations is 2579. The exit ratio of bank-year observations is 16.40%. The "fully or partly acquired" and "merged with a bank" (*AB* + *MB*) reason is the most likely outcome (60.28%), followed by "voluntary dissolution/liquidation" and "supervisory intervention" (*VL* + *SI*) (16.08%), "merged with group/parent company" (*MG*) (12.53%), and "returning bank license and operating as a family office and/or financial company" (*RL*) (11.11%). The foreign banks and regional banks categories lead with 1002 and 691 bank-year observations, respectively. For exited banks, most observations are in the foreign banks category

(*FB*) (72.58%), followed by stock exchange banks (*SB*) (14.66%). Because of their legal and/or business framework and their size categories, cantonal banks, big banks, Raiffeisen banks, and private bankers have zero exited observations in our sample.

Most of the bank-year observations are concentrated in *Zurich* (32.80%), followed by *Geneva* (23.23%). The bank exits show the same ranking with *Zurich* (44.92%), *Geneva* (26.48%), *Rest of Switzerland* (14.42%), and *Ticino* (14.18%). In our sample, *Basel* has zero exited observations.[18]

The sample contains 28.77% bank holding company (*BHC*), 11.71% financial holding company (*FHC*), and 10.55% bank cooperative company (*BCC*) bank structure categories. Most exited banks are *BHC* and *Others*. From all bank-year observations, 12.33% are listed on the Swiss Performance Index, 2.52% of which are bank exits. Of all bank exits, 88.65% took place after December 31, 2009.

Table 3 reports descriptive statistics for our key variables. To mitigate the impact of outliers, we winsorize all nonbinary variables at 5% and 95% of their respective distributions. *TA* and *GDP* are log transformed. The mean of *CIR* is 73.87%, which illustrates a lower level of the Swiss private banking industry 2019 medians of 104%, 81%, and 80% for assets under management < CHF2 billion, CHF2 billion–CHF10 billion, and > CHF10 billion, respectively.[19]

Table 4 presents the pairwise correlation matrix. The first predictor variable of interest is *CIR*. With 0.009, there is almost no correlation between *CIR* and *TAG*. This suggests that there is no tendency to adjust operating expenses in relation to asset growth. Conversely, *CIR* and *NIM* show a moderate negative correlation of −0.374, which indicates that operating costs slightly do not increase whereas earning assets increase. We conduct several multicollinearity tests to avoid highly correlated variables in our sample. The variance inflation factor test shows a result of < 1.53 with an average of 1.24.

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[18]The two banks Bank Sarasin & Co. Ltd. and Bank J. Safra (Switzerland) Ltd. merged at the end of June 2013 under the brand J. Safra Sarasin. We consider Bank J. Safra (Switzerland) as being exited, as the two banks merged technically under the legal framework (register number) of Bank Sarasin & Co. Ltd. with its head office in Basel (www.jsafrasarasin.com/internet/com/com_index/com_about_us/com_history.htm).

[19]www.pwc.ch/en/publications/2020/ch-private-banking-market-update-2020-web.pdf

5 METHODOLOGY

5.1 Exited and nonexited banks in Switzerland

To empirically investigate the determinants of bank exits in Switzerland, we first compile a parsimonious simple regression model. The intention is to fit suitable explanatory variables from the balance sheet, financial ratios, market structure, and macroeconomic categories. The portfolio of variables is > 250 and the model is built step by step with the best fit, considering the CAMEL taxonomy, and following best practice of data-mining and statistics procedures.

Our proposed linear probability model (LPM) is:

$$EXIT = \beta_0 + \beta_1 TA + \beta_2 TAG + \beta_3 TETA + \beta_4 NIM + \beta_5 CIR + \beta_6 PEO + \beta_7 GDP + \beta_8 UR + \beta_9 SPI + \beta_{10} HHI + \beta_{11} BS + \beta_{12} FC + \in, \quad (1)$$

where *EXIT* is the dependent binary outcome variable that indicates whether a bank exits. The independent variables are total assets (*TA*), total asset growth (*TAG*), total equity to total assets (*TETA*), net interest margin (*NIM*), cost-to-income ratio (*CIR*), personnel expenses to overheads (*PEO*), real gross domestic product (*GDP*), Swiss unemployment rate (*UR*), Swiss Performance Index (*SPI*), Herfindahl–Hirschmann index (*HHI*). Categorical variables are bank structure (*BS*) and financial center (*FC*).

Because our dependent variable is a binary (0 or 1) outcome, we address the issue of $0 \leq p \leq 1$ by applying a logistic regression and denote the outcome variable as follows:

$$Y_i = \begin{cases} 1 & \text{if bank } i \text{ exited,} \\ 0 & \text{otherwise.} \end{cases}$$

Our proposed generalized linear model (GLM) logistic regression is as follows:

$$EXIT = \text{logit}\, P(X) = \beta_0 + \beta_1 TA + \beta_2 TAG + \beta_3 TETA + \beta_4 NIM + \beta_5 CIR + \beta_6 PEO + \beta_7 GDP + \beta_8 UR + \beta_9 SPI + \beta_{10} HHI + \beta_{11} BS + \beta_{12} FC, \quad (2)$$

where the variables are as defined previously.

5.2 Reasons for bank exit in Switzerland

The dependent variable *REAS* is an important outcome variable, as it makes a qualitative distinction between the reasons for the bank exits, and it can help us disentangle and examine in more detail the relation of our predictor variables with bank exits. For the investigated period 2007:Q1–2017:Q4, the data set is unique. Our main response variable REAS is a limited dependent variable with five discrete categories, as explained in Appendix A. In our model we use the same predictor variables as in our GLM logistic regression. For this analysis we use an MNL regression.

Our MNL Model 1 for *VL* + *SI* (1) relative to nonexit (0) as the base category is as follows:

$$\log\left(\frac{\pi_i^{(1)}}{\pi_i^{(0)}}\right) = \alpha^{(1)} + \beta_1^{(1)}TA_i + \beta_2^{(1)}TAG_i + \beta_3^{(1)}TETA_i + \beta_4^{(1)}NIM_i + \beta_5^{(1)}CIR_i + \beta_6^{(1)}PEO_i + \beta_7^{(1)}GDP_i + \beta_8^{(1)}UR_i + \beta_9^{(1)}SPI_i + \beta_{10}^{(1)}HHI_i + \beta_{11}^{(1)}BS_i + \beta_{12}^{(1)}FC_i. \tag{3}$$

Our MNL Model 2 for *AB* + *MB* (2) relative to nonexit (0) as the base category is as follows:

$$\log\left(\frac{\pi_i^{(2)}}{\pi_i^{(0)}}\right) = \alpha^{(2)} + \beta_1^{(2)}TA_i + \beta_2^{(2)}TAG_i + \beta_3^{(2)}TETA_i + \beta_4^{(2)}NIM_i + \beta_5^{(2)}CIR_i + \beta_6^{(2)}PEO_i + \beta_7^{(2)}GDP_i + \beta_8^{(2)}UR_i + \beta_9^{(2)}SPI_i + \beta_{10}^{(2)}HHI_i + \beta_{11}^{(2)}BS_i + \beta_{12}^{(2)}FC_i. \tag{4}$$

Our MNL Model 3 for *RL* (3) relative to nonexit (0) as the base category is as follows:

$$\log\left(\frac{\pi_i^{(3)}}{\pi_i^{(0)}}\right) = \alpha^{(3)} + \beta_1^{(3)}TA_i + \beta_2^{(3)}TAG_i + \beta_3^{(3)}TETA_i + \beta_4^{(3)}NIM_i + \beta_5^{(3)}CIR_i + \beta_6^{(3)}PEO_i + \beta_7^{(3)}GDP_i + \beta_8^{(3)}UR_i + \beta_9^{(3)}SPI_i + \beta_{10}^{(3)}HHI_i + \beta_{11}^{(3)}BS_i + \beta_{12}^{(3)}FC_i. \tag{5}$$

Our MNL Model 4 for *MG* (4) relative to nonexit (0) as the base category is as follows:

$$\log\left(\frac{\pi_i^{(4)}}{\pi_i^{(0)}}\right) = \alpha^{(4)} + \beta_1^{(4)}TA_i + \beta_2^{(4)}TAG_i + \beta_3^{(4)}TETA_i + \beta_4^{(4)}NIM_i + \beta_5^{(4)}CIR_i + \beta_6^{(4)}PEO_i + \beta_7^{(4)}GDP_i + \beta_8^{(4)}UR_i + \beta_9^{(4)}SPI_i + \beta_{10}^{(4)}HHI_i + \beta_{11}^{(4)}BS_i + \beta_{12}^{(4)}FC_i. \tag{6}$$

The variables are defined as follows:

i = n sets of observations (i = 1, 2, … n);

π_i = multinomial distribution of Y_i with probability parameters $\pi_i(0)$, $\pi_i(1)$, …, $\pi_i(C-1)$;

0 = base/reference category $C-1$ nonexit;

(1) *VL* + *SI*,

(2) *AB* + *MB*,

(3) *RL*,

(4) *MG*,

where

AB = fully or partly acquired,

MB = merged with a bank,

MG = merged with group/parent company,

RL = returning bank license and operating as a family office and/or financial company,

SI = supervisory intervention: forced bankruptcy/liquidation, and

VL = voluntary dissolution/liquidation.

6 EMPIRICAL ANALYSIS

In this section, we first present the results of our LPM (OLS) and GLM analysis to uniformly examine the determinants of bank exits, as *EXIT* is a binary dependent variable that pools together all bank exits irrespective of the reason. Second, we present the results of our MNL model to examine the determinants for each of the reasons for bank exits in more detail, as *REAS* is a categorical dependent variable.

6.1 LPM and GLM (logit/probit)

Table 5 presents the results of the OLS, GLM logit, and GLM probit regressions. In this section, we analyze the results of the logit model. The results of the OLS and probit models are provided for comparison reasons.

The first main variable of interest is *TA*. We find that in all three models, the coefficient of *TA* is negative and statistically significant at the 1% level. This result confirms our expectation: The higher the asset base of bank, the less likely a bank will exit by our definitions. The results of the logit and probit models suggest that the coefficient of *TAG* and *TETA* are both negative and statistically insignificant. The second main variable of interest is *NIM*, for which in the two binary models we find a negative and statistically significant coefficient at the 5% level. The outcome confirms our expectations: The higher the net interest margin, the lower the likelihood of an exit. *NIM* is an important key performance indicator (KPI) for regional and savings banks and Raiffeisen banks, as their operating model mainly concentrates on the savings and lending business. The third main predictor variable in our model is *CIR*. In line with our expectations, we find in all three models that the coefficient of *CIR* is positive and statistically significant at the 1% level. When *CIR* increases, it is more likely that a bank will exit. *CIR* is the main KPI for measuring a bank’s efficiency, particularly in private banking and wealth management. Historically, smaller private banks have higher *CIR* and vice versa. The coefficient of *PEO* is positive and statistically insignificant, and the coefficient of our first macroeconomic variable *GDP* is negative and statistically insignificant. The coefficient of the second macroeconomic variable *UR* is also negative but statistically significant at the 10% level in the logit model and 5% level in the probit model. This result does not complement some of the previous findings, as they suggest that macroeconomic variables, such as unemployment, are usually statistically insignificant (Jagtiani et al., 2003). The likelihood of a bank exit is lower when the unemployment rate increases. This result is surprising as the contrary would be expected. It suggests that the Swiss banking sector is more resilient to economic volatility with respect to the labor market.[20] We find in both binary models that the coefficient of *SPI* is negative and statistically insignificant. The coefficient of the market structure variable *HHI* is positive and statistically insignificant. We find the outcome of the *BS* coefficient for *BHC* is positive in all three models and statistically significant at the 10% level for the logit model and 5% level for the OLS and probit models. This outcome suggests that banks operating in a holding company structure have a higher exit likelihood relative to banks operating in cooperative structure. It confirms our expectation. All other *BS* coefficients are positive in all three models and statistically insignificant. From a cluster analysis point of view, we find the coefficients of *FC* in all three models are positive and statistically significant at the 10% level only in the probit model for *Zurich* and *Ticino*. The probit model suggests that banks operating in *Zurich* and *Ticino* have a higher exit likelihood relative to banks operating in *Geneva*.

6.2 GLM logit regression by bank category

Table 6 presents the results of comparing our baseline model to the three bank categories *RB*, *SB*, and *FB*.

The first main variable *TA* remains negative for *RB* and *FB* and is significant at the 5% and 10% levels, respectively. This suggests that for regional and foreign banks, total assets have a negative relation with bank exit, whereas for *SB*, the relation is positive but statistically insignificant. The coefficients of *TAG* have a negative relation with bank exit in all bank categories and remain statistically insignificant. For *RB* and *FB*, *TETA* is negative and statistically insignificant, whereas for *SB* the coefficient is positive and significant at the 1% level. This outcome suggests that for stock exchange banks, *TETA* has a positive and significant relation with bank exit. The second main variable *NIM* remains negative and is statistically insignificant for

[20]The unemployment rate of the Swiss banking sector at the end of 2019 was 2.5%, which is identical to the Swiss economy overall (SBA, 2020).

all three bank categories. The third main variable *CIR* remains positive for all three bank categories and is statistically significant only for *FB* at the 5% level. This suggests that regardless of the bank category, the higher the cost-to-income ratio, the higher the likelihood of a bank exit. *PEO* has a positive relation with bank exit for *RB* and negative relation with *SB* and *FB*. All results are statistically insignificant.

The first macroeconomic variable *GDP* is negative for *RB* and statistically significant at the 5% level. For *SB* and *FB*, the coefficients are positive and statistically insignificant. The second macroeconomic variable *UR* has negative coefficients for *RB* and *FB*, and for *RB* the coefficient is statistically significant at the 1% level. Together with *GDP*, the results suggest that regional banks are more sensitive to national macroeconomic development than the other categories. For *SB*, the results are positive and statistically insignificant. The coefficients of *HHI* for *RB* and *SB* are negative and for *FB* are positive. All coefficients are statistically insignificant. In the categories of *BS* for stock exchange banks, the coefficients of *BHC* and *FHC* are positive and statistically significant at the 1% and 5% levels, respectively. For *SB*, this suggests that bank holding companies and financial holding companies have a positive and significant relation with bank exit relative to bank cooperative companies. From a cluster point of view, stock exchange banks have a positive and significant relation with bank exit in *Zurich*, *Ticino*, and *Rest of Switzerland* relative to *Geneva*. All other outcomes are statistically insignificant.

Online Appendix C presents the coefficients of our binary indicator WMS. For banks that exited before December 31, 2009, the results are not significant. For those that exited starting January 1, 2010, the coefficients of GDP and UR are positive and statistically significant at the 1% level. The results suggest that for banks that exited after January 1, 2010, macroeconomic development has a positive relation with bank exit. These findings are counter to Jagtiani et al. (2003). All other outcomes are statistically insignificant.

6.3 Multinomial logit model

Table 7 presents the results of our BM MNL with base outcome of nonexit. First, we examine the coefficients of the explanatory variables in each of the four *Y* categories Second, we compare categories and explanatory variables of main interest.

In Category 1, *VL + SI*, the coefficients of *TA*, *GDP*, and *UR* are negative and statistically insignificant. Surprisingly, the coefficients of *TAG*, *TETA*, *NIM*, and *CIR* are positive and statistically insignificant. The coefficients of *PEO* and *HHI* are negative and statistically insignificant. The coefficient of *SPI* is negative and statistically significant at the 1% level. This outcome confirms our expectation that a bank listed on the Swiss Performance Index has a low likelihood of facing either a supervisory intervention (from a quantitative point of view; an intervention from other criteria, such as misconduct on management level, etc. is omitted) or a voluntarily liquidation. From a bank structure (*BS*) point of view, we find that all coefficients are positive and statistically significant at the 1% level. Consistent with our expectation, *BHC*, *FHC,* and banks in other categories have a higher exit likelihood relative to *BCC*. Because the frequency of *SI* is low in general, most of Category 1 consists of *VL*. When looking at the financial clusters, the coefficients of *Basel* and *Rest of Switzerland* are negative and statistically significant at the 1% level. The coefficient of *Ticino* is positive and statistically significant at the 10% level. This suggests that relative to *Geneva*, the likelihood of *VL* or *SI* is higher for *Basel* and *Rest of Switzerland* and lower for *Ticino*. The coefficient of *Zurich* is positive and insignificant.

In Category 2, *AB* + *MB,* the coefficient of *TA* is negative and statistically significant at the 5% level. This suggests that the higher the asset base, the lower the likelihood of a bank becoming an acquisition target.[21] In contrast to Category 1, the coefficients of *TAG* and *TETA* are negative and statistically insignificant. For TETA, the finding is counter to the results of Akhigbe et al. (2004) who report that banks with relatively high capital ratios have a higher probability of being acquired. Banks with higher NIM have a lower likelihood of becoming a takeover target, as the respective coefficient is negative and statistically significant at the 5% level. The coefficient of our variable of interest CIR is positive and statistically significant at the 1% level. This outcome suggests that banks with an increase in CIR have a higher likelihood of being acquired or merged. The coefficients of PEO and HHI are positive and statistically insignificant. The coefficients of our macroeconomic variables GDP and UR are negative and statistically insignificant. The coefficient of SPI is negative and statistically significant at the 1% level. Stock exchange banks have a lower likelihood of becoming a takeover target. For BS, all coefficients are positive and statistically insignificant.

[21]We do not differentiate between friendly and unfriendly takeovers. Our focus is on the binary qualitative aspect of whether *AB* or *MB* is met.

The financial centers have a negative coefficient for Basel, significant at the 1% level. This suggests that Basel has a statistically lower likelihood of banks being acquired or merged relative to Geneva. The coefficients of Zurich, Ticino, and Rest of Switzerland are positive and statistically insignificant.

In Category 3, RL, the coefficients of TA, TAG, GDP, and HHI are negative and those of TETA, NIM, CIR, PEO, UR, and SPI are positive. All are statistically insignificant. In BS, the coefficients of BHC and Others are positive and statistically significant at the 1% level. The coefficient of FHC is negative and statistically significant at the 10% level. This outcome suggests that relative to bank cooperative companies, the likelihood of banks returning their bank license is higher for bank holding companies and others and lower for financial holding companies. The cluster analysis shows that the coefficients of Basel, Ticino, and Rest of Switzerland are negative and statistically significant at the 1% level. The coefficient of Zurich is positive and insignificant. This outcome suggests that relative to Geneva, the likelihood of banks returning their bank license and operating as a family office and/or financial company is lower in Basel, Ticino, and Rest of Switzerland.

In Category 4, MG, we find strong statistical significance. The coefficient of TA is negative and significant at the 5% level. The coefficient of TAG is negative and marginally significant at the 10% level. The coefficient of TETA is negative and statistically significant at the 1% level. Consistent with our prediction, banks with a higher assets base, higher total assets growth, and higher equity-to-assets ratio have a lower likelihood of being integrated in their respective group or parent company. The coefficient of NIM is negative and statistically significant at the 1% level. This suggests that the higher the net interest margin, the less likely banks will be integrated in their group/parent company. Not consistent with our expectation, the coefficient of CIR is negative and statistically insignificant. The coefficient of PEO is positive and statistically insignificant. The coefficients of GDP, UR, and HHI are negative and statistically insignificant. The coefficient of SPI is negative and statistically significant at the 1% level. We find that listed banks on the Swiss Performance Index are less likely to be integrated in their respective group or parent company. BS has a nonhomogenous outcome, as the coefficient of BHC is positive and statistically significant at the 5% level. The coefficient of FHC is negative and statistically significant at the 1% level. The coefficient of Others is positive and statistically insignificant. This outcome suggests that relative to bank cooperative companies, the likelihood of banks being integrated into their respective group or parent company is higher for BHC but lower for FHC. The cluster analysis is partially consistent with previous findings, as the coefficients of Basel and Ticino are negative and statistically significant at the 1% level. The coefficient of Rest of Switzerland is positive and statistically significant at the 10% level. The coefficient of Zurich is positive and statistically insignificant. Our findings suggest that relative to Geneva, the likelihood of being integrated is lower for banks operating in Basel and Ticino but higher for banks operating in Rest of Switzerland. This means that the reason for exit is not associated only with the geographical location.

7 SENSITIVITY TEST

In this section, we test the sensitivity of our results by enhancing the model design with two additional predictor variables.

7.1 Enhanced GLM logit regression and MNL

We add two financial ratios to our BM: loan loss provisions to gross loans (*LLPGL*) and pretax profit to net income (*PTPNI*). The ratio of *LLPGL* captures the share of nonperforming loans, share of doubtful loans, and share of write-offs. Based on Koetter et al. (2007), higher losses increase the likelihood of distress and of becoming a voluntary takeover target bank. Except for private banks and the wealth management segment, loan and credit business may reach two-thirds of the banks' revenues. The ratio of *PTPNI* captures the share of profit before tax or earnings before tax (EBT) to net income.

Therefore, our enhanced GLM logit regression is as follows:

$$EXIT = \text{ logit } P(X) = \beta_0 + \beta_1 TA + \beta_2 TAG + \beta_3 TETA + \beta_4 NIM + \beta_5 CIR + \beta_6 PEO + \beta_7 GDP + \beta_8 UR + \beta_9 SPI + \beta_{10} HHI + \beta_{11} LLPGL + \beta_{12} PTPNI + \beta_{13} BS + \beta_{14} FC, \quad (7)$$

where the variables are as defined earlier.

Our enhanced MNL Models 1–4 relative to nonexit (0) as the base category are as follows:

$$\log\left(\frac{\pi_i{}^{(1)}}{\pi_i{}^{(0)}}\right) = \alpha^{(1)} + \beta_1^{(1)} TA_i + \beta_2^{(1)} TAG_i + \beta_3^{(1)} TETA_i + \beta_4^{(1)} NIM_i + \beta_5^{(1)} CIR_i + \beta_6^{(1)} PEO_i + \beta_7^{(1)} GDP_i + \beta_8^{(1)} UR_i + \beta_9^{(1)} SPI_i + \beta_{10}^{(1)} HHI_i + \beta_{11}^{(1)} LLPGL_i + \beta_{12}^{(1)} PTPNI_i + \beta_{13}^{(1)} BS_i + \beta_{14}^{(1)} FC_i, \quad (8)$$

$$\log\left(\frac{\pi_i^{(2)}}{\pi_i^{(0)}}\right) = \alpha^{(2)} + \beta_1^{(2)}TA_i + \beta_2^{(2)}TAG_i + \beta_3^{(2)}TETA_i + \beta_4^{(2)}NIM_i + \beta_5^{(2)}CIR_i + \beta_6^{(2)}PEO_i + \beta_7^{(2)}GDP_i + \beta_8^{(2)}UR_i + \beta_9^{(2)}SPI_i + \beta_{10}^{(2)}HHI_i + \beta_{11}^{(2)}LLPGL_i + \beta_{12}^{(2)}PTPNI_i + \beta_{13}^{(2)}BS_i + \beta_{14}^{(2)}FC_i, \tag{9}$$

$$\log\left(\frac{\pi_i^{(3)}}{\pi_i^{(0)}}\right) = \alpha^{(3)} + \beta_1^{(3)}TA_i + \beta_2^{(3)}TAG_i + \beta_3^{(3)}TETA_i + \beta_4^{(3)}NIM_i + \beta_5^{(3)}CIR_i + \beta_6^{(3)}PEO_i + \beta_7^{(3)}GDP_i + \beta_8^{(3)}UR_i + \beta_9^{(3)}SPI_i + \beta_{10}^{(3)}HHI_i + \beta_{11}^{(3)}LLPGL_i + \beta_{12}^{(3)}PTPNI_i + \beta_{13}^{(3)}BS_i + \beta_{14}^{(3)}FC_i, \tag{10}$$

$$\log\left(\frac{\pi_i^{(4)}}{\pi_i^{(0)}}\right) = \alpha^{(4)} + \beta_1^{(4)}TA_i + \beta_2^{(4)}TAG_i + \beta_3^{(4)}TETA_i + \beta_4^{(4)}NIM_i + \beta_5^{(4)}CIR_i + \beta_6^{(4)}PEO_i + \beta_7^{(4)}GDP_i + \beta_8^{(4)}UR_i + \beta_9^{(4)}SPI_i + \beta_{10}^{(4)}HHI_i + \beta_{11}^{(4)}LLPGL_i + \beta_{12}^{(4)}PTPNI_i + \beta_{13}^{(4)}BS_i + \beta_{14}^{(4)}FC_i, \tag{11}$$

where the variables are as defined earlier.

7.2 Model comparison and sensitivity test

Table 8 compares the GLM logit results of our BM and enhanced model (EM). The coefficients of *LLPGL* and *PTPNI* are negative and statistically insignificant. Our outcomes do not support the findings of Koetter et al. (2007). Except for *TETA, CIR,* and *PEO,* the BM and EM have similar significance levels, values, and signs. The coefficient of *TETA* is positive and remains insignificant. This result is not in line with our expectations. The statistical significance of *CIR* decreases from the 1% to 5% level. The coefficient of *PEO* changes to negative and remains insignificant.

The comparison of the two models in Table 8 shows a McFadden pseudo R^2 increase from 0.131 to 0.160. The Bayesian information criterion (BIC) shows a strong absolute difference of −9.613. Based on $BIC_{BM} - BIC_{EM} > 0$, the BM GLM logit Regression (1) is preferred.[22]

Finally, we examine the sensitivity of BM and EM with a receiver operating characteristic (ROC) curve analysis.[23] ROC is a method used to assess the adequacy of prediction parameters. The method is a well-

[22] $BIC = DEV_M + \ln(N) \times P$, where *DEV* is the deviance of the specific model *M,* and *P* is the number of parameters estimated.

[23] In general, the ROC curve plots for the whole range of measures the conditional probability of positives to the conditional probability of negatives (Betz et al., 2014):

established tool to validate bankruptcy prediction models (Bauer & Agarwal, 2014; Betz et al., 2014; Koetter et al., 2007; Tian & Yu, 2017; Tinoco & Wilson, 2013; Vassalou & Xing, 2004; Wu et al., 2010). Figure 1 shows the results of the ROC area for our BM and EM GLM logit regression with 1862 and 1688 observations and standard errors of 0.025 and 0.026. The ROC areas are 0.82 for BM and 0.83 for EM. We consider both areas excellent discriminations.

Table 9 compares the results of the two MNL models. In our EMs in all categories, the coefficients of *LLPGL* and *PTPNI* are statistically insignificant. These findings do not support Koetter et al. (2007).

Compared to the BMs, the main findings show changes in the significance levels and signs. In Category 6 (other banking institutions), *NIM* and *CIR* are now statistically significant at the 1% and 5% levels, respectively, whereas *FHC* and *Ticino* turn negative. In Category 7 (private bankers), *TAG*, *PEO*, and *GDP* swap their signs and *FHC* loses its significance level. In Category 8 (foreign banks), *TA* decreases one significance level whereas *TAG* and *BHC* increase one level. *FHC* and *Rest of Switzerland* lose their significance levels, and *FHC* turns positive. *Others* is now statistically significant at the 1% level. *PEO* and *HHI* swap signs.

The comparison of the two models shows a McFadden pseudo R^2 increase from 0.221 to 0.249. The BIC shows a difference of −35.609. Based on $\text{BIC}_{\text{BM}} - \text{BIC}_{\text{EM}} > 0$, the BM MNL (1–4) is preferred.

8 ROBUSTNESS TEST VIA BAYESIAN FRAMEWORK

In this section, we examine the robustness of our results to statistical inference problems that can arise from the use of sparse data in regression analysis. Sparse-data problems are common in the case of a small-sample bias. As reported in Appendix B, the number of bank-year observations of exited banks is 423 compared to total observations of 2579, which represents 73 exited banks compared to a total of 274 banks. To address this issue, previous studies propose a Bayesian approach that uses weakly informative priors to quantify the sensitivity of parameters to sparse data (Cole et al., 2014; Greenland et al., 2016; Hamra et al., 2013). We apply a Markov chain Monte Carlo (MCMC) based Bayesian approach to our baseline GLM logit and MNL models. MCMC and Bayesian statistics are independent disciplines but in combination they are a powerful

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$$ROC = \frac{P(P=1|C=1)}{1-P(P=0|C=0)}.$$

tool in the vast universe of data analysis. MCMC and Bayesian methods are used not only in financial econometrics but also in other data analysis disciplines of science, such as epidemiology, astronomy, physics, statistics, social science, and the evolving discipline of machine learning.

Currently, the Bayesian framework is not only discussed in machine learning and econometric discussions, but its application is also widely used by several national banks. For model analysis and forecasting, in 2009 the SNB implemented fitted dynamic stochastic general equilibrium models with new Keynesian frictions and Bayesian techniques (SNB, 2014). According to SNB (2014), Bayesian maximum likelihood has become the standard method for fitted dynamic stochastic general equilibrium models. In 2017, the Centre for Central Banking Studies of the Bank of England published a handbook on applied Bayesian econometrics for central bankers.[24] The handbook introduces various Gibbs and Metropolis Hastings algorithm techniques for vector autoregressions and Bayesian estimations for linear dynamic stochastic general equilibrium models.

The following sections present the results of our proposed Bayesian logit and Bayesian MNL models in comparison to our GLM logit and MNL regression models.

8.1 Bayesian logit regression

Table 10 presents the results of the baseline GLM and Bayesian logit regression models. For the Bayesian model, the Stata Bayes prefix is applied to the logit command.[25] A comparison of the GLM and Bayesian models reveals no significant changes in the sign and size (consistency) of the estimates; however, the statistical significance (efficiency) of the estimates is different between the GLM logit coefficients and the Bayesian logit means. Column 1 presents the coefficients from the baseline GLM logit model and their standard errors in parentheses. Column 2 presents the posterior means from the Bayesian logit model and their posterior standard deviations in parentheses. Finally, Column 3 presents the posterior credibility intervals,

[24] www.bankofengland.co.uk/ccbs/applied-bayesian-econometrics-for-central-bankers-updated-2017

[25] The bayes: logit command fits a Bayesian logistic regression using default normal priors for regression coefficients with a default standard deviation of 100. MCMC iterations: 12,500; burn-in: 2500; MCMC sample size: 10,000.

which guide us in assessing the statistical significance of the regression estimates with a Bayesian probabilistic approach at the 95% level.

The coefficient of the first variable of interest *TA* is negative and statistically significant at the 1% level in the GLM model. This result confirms our expectation: The higher the asset base of a bank, the less likely a bank will exit by the definitions presented. Similarly, in the Bayesian model, the results suggest that total assets have a negative relation with bank exit at the 95% level, as *TA* falls within the credible region of −0.624 to −0.350. The coefficient of *TETA* is negative and insignificant in the GLM model; however, the Bayesian model suggests that total-equity-to-total-assets has a negative relation with bank exit at the 95% level.

The coefficient of the second main variable of interest *NIM* is negative and statistically significant at the 5% level in the GLM model. This outcome confirms our expectation: The higher the net interest margin, the lower the likelihood of exit. Similarly, in the Bayesian model *NIM* has a posterior mean of −0.570 and there is a 95% probability that the true value of the posterior mean of net interest margin falls within the credible region of −0.765 to −0.387. As discussed earlier, *NIM* is an important KPI for both regional and savings banks and Raiffeisen banks (Categories 3 and 4), as their operating model mainly concentrates on the savings and lending business. The coefficient of the third main predictor variable *CIR* is positive and statistically significant at the 1% level in the GLM model. When cost-to-income increases, it is more likely that a bank will exit. Similarly, the Bayesian model suggests that cost-to-income has a positive relation with bank exit at the 95% level. *CIR* is the main KPI for measuring a bank's efficiency, particularly in private banking and wealth management. The coefficient of *GDP* is negative and insignificant in the GLM model. However, in the Bayesian model, *GDP* has a posterior mean of −7.831 and there is a 95% probability that the true value of the gross domestic product falls within the credible region of −7.935 to −7.751. The coefficient of *UR* is negative and statistically significant at the 10% level in the GLM model, which suggests that the likelihood of a bank exit is low whereas the unemployment rate will increase. Similarly, the Bayesian model suggests *UR* has a negative relation with bank exit at the 95% level. The coefficient of *SPI* is negative and insignificant in the GLM model, whereas the Bayesian model suggests that listed banks have a negative relation with bank exit at the 95% level. The coefficient of *BHC* is positive and statistically significant at the

10% level in the GLM model. This suggests that banks operating in a holding company structure have a higher likelihood of exit relative to banks operating in a cooperative structure. Similarly, in the Bayesian model, *BHC* and *EXIT* have a positive relation at the 95% level. In the GLM model, the remaining predictor variables are statistically insignificant; however, in the Bayesian model, the remaining predictor variables *TETA, GDP, SPI, HHI, FHC, Others, Zurich, Ticino*, and *Rest of Switzerland* appear to have a significant relation with bank exit at the 95% level. This indicates that a Bayesian analysis that uses the posterior probability distribution to draw inferences when sparse data are an empirical issue leads to qualitatively different results in terms of the statistical significance (efficiency gains) of the regression estimates, and it provides complementary evidence for the robustness of our empirical analysis.

Finally, we run several convergence diagnostics of the proposed MCMC model. In general, a Bayesian inference based on an MCMC sample is valid only if the Markov chain has converged and the sample is drawn from the desired posterior probability distribution (Brooks et al., 2011; Gelman et al., 2014). The results show a good fit, as all chains converge within acceptable ranges.

8.2 Bayesian multinomial logit regression

Table 11 presents a comparison of the baseline MNL and Bayesian MNL models with the base outcome nonexit. For the Bayesian model, the Stata Bayes prefix to the mlogit command is applied.[26] The acceptance rate is 0.226, which represents 23%. Columns 1–4 present the coefficients from the baseline MNL model and their standard errors in parentheses, and Columns 5–8 present the posterior means from the Bayesian MNL model and their posterior standard deviations in parentheses. Online Appendix D presents the posterior credibility intervals that guide us in assessing the statistical significance of the MNL regression estimates with a Bayesian probabilistic approach at the 95% level. Similar to the analysis in Table 10, the results in Table 11 present no significant changes in the sign and size (consistency) of the estimates; however, the statistical significance (efficiency) of the estimates varies between the MNL coefficients and the Bayesian MNL means.

In Category 1 (*VL* + *SI*), the predictor variables *SPI, BHC, FHC, Others, Basel, Ticino,* and *Rest of Switzerland* are statistically significant both in the MNL and the Bayesian MNL models and confirm the results

[26] rseed(15); default: MCMC iterations: 12,500; burn-in: 2500; MCMC sample size: 10,000

of the main analysis. In the MNL model, all other predictor variables are statistically insignificant. However, in the Bayesian MNL model, the predictor variables *TA*, *TETA*, *GDP*, *UR*, and *HHI* appear to have a significant relation with bank exit at the 95% level as well.

In Category 2 (*AB + MB*), the predictor variables *TA, NIM, CIR, SPI,* and *Basel* are statistically significant in both the MNL and Bayesian MNL models, which confirms the results of the main analysis. In the MNL model, the remaining predictor variables are statistically insignificant. However, in the Bayesian MNL model, the predictor variables *TETA*, *GDP*, *UR*, *HHI*, *BHC*, *Others*, and *Zurich* appear to have a significant relation with bank exit at the 95% level as well.

In Category 3 (*RL*), the predictor variables *BHC, Others, Basel, Ticino,* and *Rest of Switzerland* are statistically significant in both the MNL and Bayesian MNL models, whereas *FHC* is statistically significant only in the MNL model. The remaining predictor variables are statistically insignificant in the MNL model; however, in the Bayesian MNL model, the predictor variables *TA* and *HHI* appear to have a significant relation with bank exit at the 95% level as well.

In Category 4 (*MG*), the predictor variables *TA*, *TETA*, *NIM, SPI, BHC, FHC, Basel, Ticino,* and *Rest of Switzerland* are statistically significant in both the MNL and Bayesian MNL models, whereas *TAG* is statistically significant only in the MNL model. The remaining predictor variables are statistically insignificant in the MNL model; however, in the Bayesian MNL model, the predictor variables *GDP* and *UR* appear to have a significant relation with bank exit at the 95% level as well. Similar to the discussion in the previous section, this suggests that a Bayesian analysis leads to qualitatively different results in terms of the statistical significance (efficiency gains) of the regression estimates, and it provides complementary evidence for the robustness of our empirical analysis.

9 CONCLUSION

In this article, we examine factors that are fundamental to the likelihood of a bank's exit. A set of econometric approaches to compare the likelihood of exit and its sensitivity to accounting, bank-level, market-structure, and macroeconomic factors is proposed. We identify four major reasons that cause banks to exit: (1) winding up—voluntary dissolution or liquidation, supervisory intervention (forced bankruptcy or liquidation); (2)

ownership—fully or partly acquired, merged with a bank; (3) license—returning bank license and continue to operate as a family office and/or financial company; and (4) merger—merged with a group or parent company.

First, we estimate a GLM logit model. Our empirical results indicate that total assets and net interest margin have a negative relation with bank exit, where cost-to-income is positive. Net interest margin and cost-to-income are the main KPIs in retail banking and wealth management, respectively. These findings confirm our expectations and general knowledge in academia and business. The results also indicate that on a macroeconomic level, the unemployment rate is unrelated to bank exits. Banks listed on the stock exchange, banks with a low total-equity-to-total-assets base, and banks operating in the clusters of Zurich, Ticino, and the rest of Switzerland are more likely to exit than other banks.

Second, we compile a multinomial logit model to predict the likelihood of the four bank exit events. Our results indicate that total assets and net interest margin have a negative relation with M&As. Banks with high total assets and net interest margin are less likely to be acquired or merged, either with a third party or group or parent company. From a bank structure standpoint, banks operating in a financial holding structure are less likely to be absorbed by their parent company than bank holding companies. Confirming our expectations, bank cooperatives are less likely to voluntarily exit their banking operations. Our results also indicate that relative to Geneva, banks operating in Basel, Ticino, and the rest of Switzerland have a lower likelihood of returning their banking license.

Third, we run a sensitivity test by constructing an enhanced model and add two additional covariates to our BMs. Based on McFadden R^2, BIC and ROC for the GLM logit, both our baseline GLM logit regression and MNL are preferred.

Fourth, our robustness tests consist of applying a Bayesian inference analysis with MCMC featuring basic Gaussian random-walk MH algorithm methods to our baseline models. We apply several convergence diagnostic tools and the results show a good fit, as all chains converge within acceptable ranges. The proposed Bayesian logit and Bayesian MNL models have similar model results. For most of the significant *p*-values in the frequentist model, Bayesian inferences confirm the proposed relation with bank exit at the 95% level, as the signs of the coefficients and posterior means show no divergence. However, the Bayesian credibility intervals have smaller variance than the maximum likelihood confidence intervals. This indicates a reduction in bias (efficiency gains) as more predictor variables appear to have a significant relation with the response variables.

In general, based on our findings, we conclude that banks that have a weak asset and capital base, low margin, and high share of cost-to-income and are operating in a bank holding company and in Zurich are more likely to exit. The findings suggest that the two macroeconomic variables GDP and unemployment rate are unrelated to bank exit. A decline in GDP preceding a recession or an increase in the unemployment rate may have a delay on their effects for banks exits. In future studies, this research question and the application of a survival (hazard) model with a Bayesian framework on the determinants of bank failures and bank exits should be considered. Future studies may also include the COVID-19 crisis with its potential financial implications.

This article contributes to a growing empirical literature in EWS, bank exits, bank financial distress, and bank M&As. The results of our analysis should be of interest for researchers in the interdisciplinary fields of banking and finance, and financial econometrics and business analytics. The results should also be of interest to specialists and managers in their practical application in risk management, policy making, and regulations.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

TABLE 1 Number of exited banks by year and exit categories

Year	No. of banks	Reason for exit	Categories	No. of banks
2007	0	Winding up	1. *VL* + *SI*	11
2008	6	Ownership	2. *AB* + *MB*	43
2009	13	License	3. *RL*	9
2010	8	Merger	4. *MG*	10
2011	8			
2012	7			
2013	13			
2014	4			
2015	4			
2016	4			
2017	6			
Total	73	Total		73

Note: Variables are defined in Appendix A.

TABLE 2 Key figures by bank categories

	No. of banks					Balance sheet total in CHF millions				
Category	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Cantonal banks	24	24	24	24	24	537,441	553,231	575,343	600,318	626,727
Big banks	3	4	4	4	4	1,424,231	1,454,808	1,566,435	1,520,781	1,540,711
Regional and saving banks	62	62	62	60	60	113,076	116,141	118,131	120,283	126,317
Raiffeisen banks	1	1	1	1	1	202,412	215,262	225,253	225,333	248,345
Stock exchange banks	44	43	43	43	42	210,049	226,300	223,990	228,729	223,697
Other banking institutions	14	14	14	14	16	198,580	205,693	209,474	209,730	223,743
Private bankers	7	6	6	5	5	6699	5942	6198	6323	5753
Foreign-controlled banks	85	81	76	74	71	260,962	248,080	231,299	222,560	224,190
Branches of foreign banks	26	26	23	23	23	72,667	75,919	93,320	90,943	98,153
Total	266	261	253	248	246	3,026,117	3,101,376	3,249,443	3,225,000	3,317,638

	Operating result in CHF millions					No. of staff in FTE				
Category	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Cantonal banks	3253	3312	3585	3735	3834	17,360	17,294	17,322	17,357	17,585
Big banks	667	592	3216	4742	-9918	53,016	50,399	38,307	37,050	35,549
Regional and saving banks	554	570	579	551	607	3836	3845	3855	3915	3978
Raiffeisen banks	913	840	1081	699	930	8807	8868	9079	9215	9295
Stock exchange banks	155	1187	1449	1552	1294	14,010	14,838	15,210	15,723	15,572
Other banking institutions	1079	1221	903	832	185	7933	7849	7749	7672	7866
Private bankers	51	62	78	64	95	614	519	531	523	534
Foreign-controlled banks	-1	-230	74	214	495	17,231	16,131	15,809	14,805	14,560
Branches of foreign banks	187	360	359	389	270	1084	1096	1079	1129	1145
Total	6857	7913	11,323	12,780	-2209	123,890	120,840	108,939	107,388	106,084

Abbreviations: CHF, Swiss franc; FTE, full-time equivalent.
Source: Adapted from Swiss National Bank (2020).

TABLE 3 Descriptive statistics: Key variables

Variable	***N***	**Mean**	***SD***	**Min.**	**Max.**
EXIT	2305	0.0317	0.175	0	1
REAS	2305	0.0711	0.423	0	4
TA	2254	21.02	1.858	16.58	28.45
TAG	2154	6.501	14.31	-17.96	45.65
TETA	2254	0.127	0.0876	0.0491	0.377
NIM	2183	1.161	0.482	0.32	2.16
CIR	2226	73.87	18.42	47.17	116.3
PEO	2224	55.83	9.606	38.46	72.13
GDP	2579	27.17	0.0461	27.11	27.24
UR	2579	3.105	0.323	2.6	3.7
SPI	2579	0.123	0.329	0	1
HHI	2579	0.0773	0.0551	0.0265	0.189
LLPGL	1971	0.449	0.934	-0.06	3.77
PTPNI	2166	1.275	0.202	0.976	1.75
BS	2579	2.797	1.31	1	4
FC	2579	2.823	1.689	1	5
RB	2579	0.268	0.443	0	1
SB	2579	0.171	0.376	0	1
FB	2579	0.389	0.488	0	1
CAT	2579	5.245	2.513	1	8
WMS	2579	0.0206	0.142	0	1

Note: This table reports descriptive statistics for the independent and dependent variables used in this study. *N* is the number of bank-year observations. Variables are defined in Appendix A. To avoid reverse causality, we apply the $y_{-t} = a + x_{t-1}$ model for *EXIT* and *REAS* in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017.

TABLE 4

Correlation matrix		1	2	3	4	5	6	7	8	9	10
1.	*TA*	1									
2.	*TAG*	-0.050	1								
3.	*TETA*	-0.499	-0.019	1							
4.	*NIM*	-0.194	0.014	0.094	1						
5.	*CIR*	-0.164	0.009	0.189	-0.374	1					
6.	*PEO*	0.168	0.112	0.261	-0.186	-0.019	1				
7.	*GDP*	0.181	-0.138	-0.193	-0.340	0.122	-0.056	1			
8.	*UR*	0.039	-0.084	-0.055	-0.250	0.103	-0.014	0.084	1		
9.	*SPI*	0.478	-0.019	-0.170	-0.045	-0.116	0.059	0.037	0.006	1	
10.	*HHI*	-0.058	-0.052	0.077	0.132	-0.054	-0.025	-0.274	0.280	-0.010	1

Note: This table reports the pairwise correlation matrix of key variables. Variables are defined in Appendix A. To avoid reverse causality, we apply the $y_{-t} = a + x_{t-1}$ model for *EXIT* and *REAS* in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017.

TABLE 5 Linear probability model (OLS) and GLM (logit/probit)

Variable	**OLS**	**GLM logit**	**GLM probit**
TA	-0.008***	-0.407***	-0.183***
	(0.003)	(0.145)	(0.057)
TAG	-0.000	-0.005	-0.003
	(0.000)	(0.007)	(0.003)
TETA	0.037	-1.475	-0.720
	(0.079)	(1.738)	(0.791)
NIM	-0.019	-0.625**	-0.302**
	(0.012)	(0.316)	(0.145)
CIR	0.000**	0.022***	0.011***
	(0.000)	(0.008)	(0.004)
PEO	-0.000	0.003	0.002
	(0.000)	(0.018)	(0.008)
GDP	-0.157	-7.891	-3.999*
	(0.109)	(4.831)	(2.052)
UR	-0.020	-0.891*	-0.417**
	(0.013)	(0.470)	(0.209)
SPI	0.003	-1.099	-0.483
	(0.011)	(1.136)	(0.437)
HHI	0.070	2.301	1.076
	(0.105)	(3.266)	(1.484)
BHC	0.026**	1.360*	0.601**
	(0.012)	(0.733)	(0.285)
FHC	0.003	0.709	0.293
	(0.017)	(0.848)	(0.336)
Others	0.014	0.815	0.368
	(0.009)	(0.742)	(0.280)
Zurich	0.019	0.636	0.308*
	(0.012)	(0.397)	(0.174)
Basel	-0.005	—	—
	(0.100)	—	—
Ticino	0.031	0.835	0.402*
	(0.022)	(0.520)	(0.242)
Rest of Switzerland	0.007	0.127	0.071
	(0.100)	(0.531)	(0.228)
Constant	4.600	219.378*	111.0**
	(2.984)	(132.100)	(56.010)
Obs.	1945	1862	1862
Pseudo R^2	0.035	0.131	0.135

Note: This table reports the coefficients of ordinary least squares (OLS), generalized linear model (GLM) logit, and GLM probit regression models. Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for EXIT in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 6 GLM logit regression by bank category

Variable	**Baseline model**	***RB***	***SB***	***FB***
TA	-0.407***	-1.633**	0.401	-0.258*
	(0.145)	(0.641)	(0.404)	(0.142)
TAG	-0.005	-0.046	-0.001	-0.003
	(0.007)	(0.078)	(0.013)	(0.010)
TETA	-1.475	-13.50	20.71***	-1.483
	(1.738)	(18.27)	(6.188)	(1.958)
NIM	-0.625**	-0.430	-1.396	-0.415
	(0.316)	(2.532)	(1.060)	(0.418)
CIR	0.022***	0.034	0.040	0.023**
	(0.008)	(0.036)	(0.034)	(0.010)
PEO	0.003	0.044	-0.037	-0.010
	(0.018)	(0.058)	(0.047)	(0.027)
GDP	-7.891	-46.76**	0.343	1.162
	(4.831)	(22.86)	(15.57)	(5.840)
UR	-0.891*	-4.186***	0.819	-0.637
	(0.470)	(1.008)	(0.803)	(0.742)
SPI	-1.099	—	—	—
	(1.136)	—	—	—
HHI	2.301	-24.28	-2.454	4.192
	(3.266)	(17.75)	(6.405)	(4.467)
BHC	1.360*	—	3.348***	-0.024
	(0.733)	—	(0.846)	(0.490)
FHC	0.709	—	2.737**	-0.263
	(0.848)	—	(1.170)	(0.727)
Others	0.815	1.486	—	—
	(0.742)	(1.357)	—	—
Zurich	0.636	-0.175	4.091***	0.208
	(0.397)	(1.002)	(1.303)	(0.475)
Basel	—	—	—	—
	—	—	—	—
Ticino	0.835	—	3.426**	0.742
	(0.520)	—	(1.441)	(0.573)
Rest of Switzerland	0.127	—	3.283**	—
	(0.531)	—	(1.579)	—
Constant	219.4*	1,309**	-28.06	-28.43
	(132.100)	(618.200)	(425.400)	(158.600)
Obs.	1862	517	230	644
Pseudo R^2	0.131	0.350	0.297	0.068

Note: This table reports the coefficients of our base generalized linear model (GLM) logit regression model compared to the bank categories with higher exit frequencies: *RB, SB,* and *FB.* Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for EXIT in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 7 MNL model: Base outcome is nonexit

Variable	***VL + SI***	***AB + MB***	***RL***	***MG***
TA	-0.726	-0.394**	-0.579	-0.519**
	(0.851)	(0.189)	(0.525)	(0.251)
TAG	0.014	-0.003	-0.009	-0.025*
	(0.014)	(0.010)	(0.026)	(0.014)
TETA	2.385	-2.535	2.822	-16.79***
	(3.866)	(2.376)	(8.939)	(5.634)
NIM	0.221	-0.822**	0.884	-1.914***
	(0.856)	(0.362)	(1.692)	(0.689)
CIR	0.027	0.030***	0.025	-0.023
	(0.027)	(0.011)	(0.036)	(0.023)
PEO	-0.061	0.006	0.044	0.034
	(0.046)	(0.024)	(0.074)	(0.03)
GDP	-5.292	-7.223	-0.342	-16.16
	(16.43)	(6.601)	(12.88)	(11.89)
UR	-1.225	-0.938	1.202	-1.595
	(1.959)	(0.641)	(0.754)	(1.045)
SPI	-12.84***	-14.57***	1.511	-14.95***
	(1.284)	(0.648)	(1.819)	(0.845)
HHI	-17.32	6.044	-6.553	-2.035
	(13.79)	(3.799)	(11.86)	(10.41)
BHC	13.66***	1.512	13.54***	1.864**
	(1.128)	(1.067)	(1.247)	(0.937)
FHC	15.20***	0.458	-1.911*	-13.80***
	(1.166)	(1.264)	(1.049)	(1.073)
Others	13.47***	0.758	15.26***	0.090
	(1.483)	(1.092)	(1.028)	(1.077)
Zurich	0.317	0.678	0.299	1.086
	(1.379)	(0.513)	(1.085)	(1.155)
Basel	-11.70***	-14.46***	-14.69***	-14.22***
	(2.411)	(0.766)	(1.085)	(1.204)
Ticino	2.119*	0.807	-16.94***	-13.94***
	(1.126)	(0.679)	(1.006)	(1.074)
Rest of Switzerland	-14.01***	0.284	-15.75***	1.787*
	(1.292)	(0.652)	(1.035)	(1.011)
Constant	143.5	199.7	-8.229	451.3
	(448.600)	(181.1)	(353.2)	(324.6)
Obs.	1945	1945	1945	1945
Pseudo R^2	0.221	0.221	0.221	0.221

Note: This table presents multinomial logit (MNL) regression coefficients. Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for REAS in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 8 GLM logit regression enhanced model

Variable	Baseline model	Enhanced model
TA	-0.407***	-0.394***
	(0.145)	(0.149)
TAG	-0.005	-0.005
	(0.007)	(0.008)
TETA	-1.475	0.089
	(1.738)	(2.007)
NIM	-0.625**	-0.912**
	(0.316)	(0.374)
CIR	0.022***	0.019**
	(0.008)	(0.009)
PEO	0.003	-0.002
	(0.018)	(0.020)
GDP	-7.891	-7.049
	(4.831)	(5.167)
UR	-0.891*	-0.956*
	(0.470)	(0.535)
SPI	-1.099	-1.197
	(1.136)	(1.126)
HHI	2.301	2.429
	(3.266)	(3.569)
LLPGL	—	-0.002
	—	(0.123)
PTPNI	—	-1.105
	—	(0.831)
BHC	1.360*	1.793*
	(0.733)	(1.058)
FHC	0.709	1.117
	(0.848)	(1.161)
Others	0.815	1.288
	(0.742)	(1.068)
Zurich	0.636	0.676
	(0.397)	(0.414)
Basel	—	—
	—	—
Ticino	0.835	0.440
	(0.520)	(0.603)
Rest of Switzerland	0.127	0.007
	(0.531)	(0.602)
Constant	219.4*	198.1
	(132.100)	(141.4)
Obs.	1862	1688
Pseudo R^2	0.131	0.160
AIC	470.993	404.834
BIC	55.677	65.290

Note: This table reports the coefficients of our generalized linear model (GLM) logit regression model with our baseline model and with the enhanced model including *LLPGL* and *PTPNI* for sensitivity tests. Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for EXIT in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses.

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 9 MNL enhanced model

	Baseline model				Enhanced model			
	VL + SI	***AB + MB***	***RL***	***MG***	***VL + SI***	***AB + MB***	***RL***	***MG***
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
TA	-0.726	-0.394**	-0.579	-0.519**	-0.750	-0.395**	-0.655	-0.463*
	(0.851)	(0.189)	(0.525)	(0.251)	(0.900)	(0.193)	(0.543)	(0.256)
TAG	0.014	-0.003	-0.009	-0.025*	0.005	-0.001	0.011	-0.035**
	(0.014)	(0.010)	(0.026)	(0.014)	(0.013)	(0.011)	(0.019)	(0.014)
TETA	2.385	-2.535	2.822	-16.79***	2.270	-0.625	5.636	-25.39***
	(3.866)	(2.376)	(8.939)	(5.634)	(3.930)	(2.626)	(9.873)	(7.093)
NIM	0.221	-0.822**	0.884	-1.914***	0.180	-1.135***	0.016	-2.880***
	(0.856)	(0.362)	(1.692)	(0.689)	(0.840)	(0.358)	(1.990)	(0.809)
CIR	0.027	0.030***	0.025	-0.023	0.019	0.0282**	0.014	-0.034
	(0.027)	(0.011)	(0.036)	(0.023)	(0.023)	(0.012)	(0.048)	(0.030)
PEO	-0.061	0.006	0.044	0.034	-0.062	0.011	-0.007	-0.008
	(0.046)	(0.024)	(0.074)	(0.03)	(0.052)	(0.027)	(0.068)	(0.033)
GDP	-5.292	-7.223	-0.342	-16.16	-6.800	-5.545	1.011	-13.44
	(16.43)	(6.601)	(12.88)	(11.89)	(14.71)	(7.130)	(16.56)	(12.89)
UR	-1.225	-0.938	1.202	-1.595	-0.899	-1.145	1.358	-1.797
	(1.959)	(0.641)	(0.754)	(1.045)	(1.787)	(0.734)	(1.047)	(1.287)
SPI	-12.84***	-14.57***	1.511	-14.95***	-14.01***	-15.61***	1.697	-15.98***
	(1.284)	(0.648)	(1.819)	(0.845)	(1.162)	(0.700)	(1.821)	(0.882)
HHI	-17.32	6.044	-6.553	-2.035	-18.65	6.136	-1.720	1.105
	(13.79)	(3.799)	(11.86)	(10.41)	(14.90)	(4.466)	(8.968)	(10.31)
LLPGL	—	—	—	—	0.128	-0.005	-0.137	-0.268
	—	—	—	—	(0.312)	(0.151)	(0.343)	(0.260)
PTPNI	—	—	—	—	-0.331	-0.909	-2.641	-0.599
	—	—	—	—	(2.263)	(1.171)	(2.242)	(1.398)
BHC	13.66***	1.512	13.54***	1.864**	15.00***	1.122	14.19***	18.00***
	(1.128)	(1.067)	(1.247)	(0.937)	(0.898)	(1.074)	(1.327)	(0.736)
FHC	15.20***	0.458	-1.911*	-13.80***	16.38***	-0.450	-1.740	1.621
	(1.166)	(1.264)	(1.049)	(1.073)	(1.166)	(1.462)	(1.275)	(1.012)
Others	13.47***	0.758	15.26***	0.090	14.62***	0.504	15.51***	16.51***
	(1.483)	(1.092)	(1.028)	(1.077)	(1.360)	(1.096)	(1.370)	(0.718)
Zurich	0.317	0.678	0.299	1.086	0.441	0.813	0.137	0.776
	(1.379)	(0.513)	(1.085)	(1.155)	(1.312)	(0.526)	(1.349)	(1.121)
Basel	-11.70***	-14.46***	-14.69***	-14.22***	-12.74***	-15.26***	-15.50***	-14.95***
	(2.411)	(0.766)	(1.085)	(1.204)	(2.346)	(0.887)	(1.643)	(1.190)
Ticino	2.119*	0.807	-16.94***	-13.94***	1.930*	-0.006	-17.54***	-14.69***
	(1.126)	(0.679)	(1.006)	(1.074)	(1.131)	(0.798)	(1.424)	(1.175)
Rest of Switzerland	-14.01***	0.284	-15.75***	1.787*	-15.03***	0.183	-16.38***	1.384
	(1.292)	(0.652)	(1.035)	(1.011)	(1.142)	(0.725)	(1.541)	(1.025)
Constant	143.5	199.7	-8.229	451.3	184.3	156.1	-37.18	366.5
	(448.600)	(181.1)	(353.2)	(324.6)	(407.6)	(195.6)	(449.3)	(352.6)
Obs.	1945	1945	1945	1945	1763	1763	1763	1763
Pseudo R^2	0.221	0.221	0.221	0.221	0.249	0.249	0.249	0.249
AIC	690.947	690.947	690.947	690.947	628.293	628.293	628.293	628.293
BIC	330.187	330.187	330.187	330.187	365.796	365.796	365.796	365.796

Note: This table reports the coefficients of our baseline multinomial logit (MNL) model with the base outcome of nonexit using the following categories: (1) *VL* + *SI*; (2) *AB* + *MB*; (3) *RL*; (4) *MG*. We include *LLPGL* and *PTPNI* for sensitivity tests in the same categories in Columns 5–8. Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for REAS in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses.

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 10 GLM logit and Bayesian logit regression

Variable	GLM logit coefficient (1)	Bayesian logit mean (2)	95% credible interval (3)	
TA	-0.407***	-0.494***	-0.624	-0.350
	(0.145)	(0.068)		
TAG	-0.005	-0.006	-0.022	0.008
	(0.007)	(0.008)		
TETA	-1.475	-1.384***	-1.667	-1.118
	(1.738)	(0.156)		
NIM	-0.625**	-0.570***	-0.765	-0.387
	(0.316)	(0.096)		
CIR	0.022***	0.021***	0.007	0.036
	(0.008)	(0.007)		
PEO	0.003	0.003	-0.031	0.031
	(0.018)	(0.016)		
GDP	-7.891	-7.831***	-7.935	-7.751
	(4.831)	(0.047)		
UR	-0.891*	-0.909***	-1.270	-0.545
	(0.470)	(0.183)		
SPI	-1.099	-1.339***	-1.761	-0.894
	(1.136)	(0.220)		
HHI	2.301	2.161***	1.866	2.562
	(3.266)	(0.177)		
BHC	1.360*	1.445***	1.069	1.890
	(0.733)	(0.211)		
FHC	0.709	0.928***	0.642	1.225
	(0.848)	(0.151)		
Others	0.815	0.831***	0.572	1.083
	(0.742)	(0.126)		
Zurich	0.636	0.628***	0.352	0.954
	(0.397)	(0.162)		
Basel	—	—	—	—
	—	—		
Ticino	0.835	0.872***	0.317	1.477
	(0.520)	(0.298)		
Rest of Switzerland	0.127	0.287**	0.215	0.582
	(0.531)	(0.143)		
Constant	219.4*	219.383	218.900	219.891
	(132.1)	(0.252)		
Obs.	1862	1862		
Pseudo R^2	0.131			

Note: In this table, Column 1 presents the generalized linear model (GLM) logit regression coefficients, Column 2 presents the Bayesian logit mean (posterior) based on the Markov chain Monte Carlo (MCMC) Metropolis–Hastings (MH) method, and Column 3 presents equal-tailed 95% credible intervals. Variables are defined in Appendix A. To avoid reverse causality, we apply the $y_t = a + x_{t-1}$ model for EXIT in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses for the GLM logit model and posterior standard deviations for the Bayesian logit model.

*p < 0.10; **p < 0.05; ***p < 0.01.

TABLE 11 MNL model versus Bayesian MNL model: Base outcome of nonexit

	MNL coefficient				Bayesian MNL mean			
	VL + SI	***AB + MB***	***RL***	***MG***	***VL + SI***	***AB + MB***	***RL***	***MG***
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
TA	-0.726	-0.394**	-0.579	-0.519**	-0.822**	-0.430***	-0.677*	-0.541**
	(0.851)	(0.189)	(0.525)	(0.251)	(0.340)	(0.136)	(0.370)	(0.236)
TAG	0.014	-0.003	-0.009	-0.025*	0.011	-0.004	-0.012	-0.029
	(0.014)	(0.010)	(0.026)	(0.014)	(0.017)	(0.010)	(0.025)	(0.221)
TETA	2.385	-2.535	2.822	-16.79***	2.378*	-2.733***	2.813	-17.319***
	(3.866)	(2.376)	(8.939)	(5.634)	(1.222)	(0.434)	(1.960)	(1.415)
NIM	0.221	-0.822**	0.884	-1.914***	0.318	-0.736***	0.890	-1.985**
	(0.856)	(0.362)	(1.692)	(0.689)	(0.497)	(0.200)	(0.766)	(0.818)
CIR	0.027	0.030***	0.025	-0.023	0.031	0.033***	0.029	-0.024
	(0.027)	(0.011)	(0.036)	(0.023)	(0.022)	(0.009)	(0.025)	(0.024)
PEO	-0.061	0.006	0.044	0.034	-0.060	0.009	0.048	0.029
	(0.046)	(0.024)	(0.074)	(0.03)	(0.046)	(0.020)	(0.050)	(0.042)
GDP	-5.292	-7.223	-0.342	-16.16	-5.268***	-7.207***	-0.312	-16.151***
	(16.43)	(6.601)	(12.88)	(11.89)	(0.263)	(0.120)	(0.345)	(0.213)
UR	-1.225	-0.938	1.202	-1.595	-1.197*	-1.103***	1.184	-1.913***
	(1.959)	(0.641)	(0.754)	(1.045)	(0.706)	(0.377)	(0.863)	(0.372)
SPI	-12.84***	-14.57***	1.511	-14.95***	-13.100***	-14.523***	1.275	-14.305***
	(1.284)	(0.648)	(1.819)	(0.845)	(1.063)	(0.255)	(1.351)	(1.284)
HHI	-17.32	6.044	-6.553	-2.035	-17.326***	6.142***	-6.412***	-1.627
	(13.79)	(3.799)	(11.86)	(10.41)	(0.662)	(0.250)	(1.120)	(1.162)
BHC	13.66***	1.512	13.54***	1.864**	13.690***	1.654***	13.937***	1.873***
	(1.128)	(1.067)	(1.247)	(0.937)	(1.202)	(0.403)	(2.172)	(0.472)
FHC	15.20***	0.458	-1.911*	-13.80***	15.339***	0.450	-1.676	-14.433***
	(1.166)	(1.264)	(1.049)	(1.073)	(0.834)	(0.468)	(3.227)	(0.760)
Others	13.47***	0.758	15.26***	0.090	13.447***	0.900**	15.770***	0.090
	(1.483)	(1.092)	(1.028)	(1.077)	(0.778)	(0.400)	(2.258)	(0.771)
Zurich	0.317	0.678	0.299	1.086	0.311	0.703***	0.302	1.293
	(1.379)	(0.513)	(1.085)	(1.155)	(0.615)	(0.121)	(0.907)	(0.843)
Basel	-11.70***	-14.46***	-14.69***	-14.22***	-11.839***	-14.886***	-14.487***	-13.941***
	(2.411)	(0.766)	(1.085)	(1.204)	(0.808)	(0.729)	(1.387)	(0.692)
Ticino	2.119*	0.807	-16.94***	-13.94***	2.209**	0.570	-17.128***	-13.774***
	(1.126)	(0.679)	(1.006)	(1.074)	(1.028)	(0.500)	(3.435)	(1.630)
Rest of Switzerland	-14.01***	0.284	-15.75***	1.787*	-14.190***	0.100	-15.064***	2.034**
	(1.292)	(0.652)	(1.035)	(1.011)	(2.204)	(0.490)	(3.187)	(0.954)
Constant	143.5	199.7	-8.229	451.3	143.502	199.744	-8.803	452.207
	(448.600)	(181.1)	(353.2)	(324.6)	(1.774)	(0.441)	(2.021)	(1.228)
Obs.	1945	1945	1945	1945	1945	1945	1945	1945
Pseudo R^2	0.221	0.221	0.221	0.221				

Note: This table presents the multinomial logit (MNL) regression coefficients and the Bayesian MNL mean based on the Markov chain Monte Carlo (MCMC) Metropolis–Hastings (MH) method. Variables are defined in Appendix A. To avoid reverse causality, we apply the y−t = a + xt−1 model for REAS in all observations. We therefore include independent variables for 2007–2016 and dependent variables for 2008–2017. Robust standard errors are in parentheses for the MNL and standard deviations for the Bayesian MNL.

*p < 0.10; **p < 0.05; ***p < 0.01.

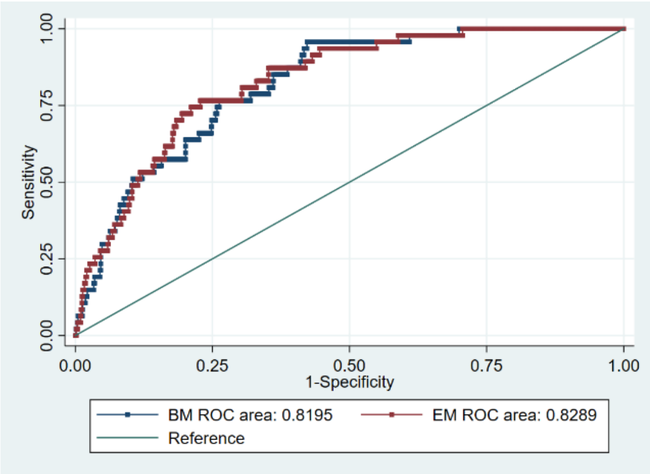

FIGURE 1 Receiver operating characteristic (ROC) curve generalized linear model logistic regression results for the baseline model (BM) and enhanced model (EM)

APPENDIX A: VARIABLE DEFINITIONS

Name	Label	Type	Definition
EXIT	Exit	Qualitative	Binary indicator equal to 1 for exited banks in the year of the announcement and 0 in all other years and for nonexited banks in all sample years
REAS	Exit reasons	Qualitative	Continuous variable for the following reasons: 1. *VL* + *SI* 2. *AB* + *MB* 3. *RL* 4. *MG* *VL* is voluntary dissolution/liquidation, *SI* is supervisory intervention: forced bankruptcy/liquidation, *AB* is fully or partly acquired, *MB* is merged with a bank, *RL* is returning bank license and operating as a family office and/or financial company, and *MG* is merged with group/parent company
BS	Bank structure	Qualitative	Continuous variable of the following bank structures: 1. Bank holding company (*BHC*) 2. Financial holding company (*FHC*) 3. Bank cooperative company (*BCC*) 4. *Others*
CAT	Bank category	Qualitative	Continuous variable of the following bank categories: 1. Cantonal banks (*CB*) 2. Big banks (*BB*) 3. Regional banks (*RB*) 4. Raiffeisen banks (*RAB*) 5. Stock exchange banks (*SB*) 6. Other banking institutions (*OB*) 7. Private bankers (*PB*) 8. Foreign banks (*FB*)
RB	Regional banks	Qualitative	Binary indicator equal to 1 for regional banks, and 0 otherwise
SB	Stock exchange banks	Qualitative	Binary indicator equal to 1 for stock exchange banks, and 0 otherwise
FB	Foreign banks	Qualitative	Binary indicator equal to 1 for foreign banks, and 0 otherwise
FC	Financial center	Qualitative	Continuous variable of bank cluster or allocation of financial center: 1. *Zurich*—canton of Zurich, Schwyz, and Zug 2. *Geneva*—canton of Geneva and Vaud 3. *Basel*—canton of Basel-Stadt and Basel-Landschaft 4. *Ticino* 5. *Rest of Switzerland*
SPI	Swiss Performance Index	Qualitative	Binary indicator equal to 1 if listed on the Swiss Performance Index, and 0 otherwise
WMS	White money strategy	Qualitative	Binary indicator equal to 1 for exited banks if their exit event occured after December 31, 2009, and 0 otherwise
TA	Total assets	Balance sheet	Cash, due from banks, loans, goodwill, total earning, and other assets (from FitchConnect)
CIR	Cost/Income	Financial ratio	Measures a bank's efficiency and compares operating expenses against its operating income (from FitchConnect)
LLPGL	Loan loss provisions/Gross loans	Financial ratio	Measures the share of nonperforming loans, share of doubtful loans, and share of write-offs to gross loans (from FitchConnect)
NIM	Net interest margin	Financial ratio	Net interest income expressed as a percentage of earning assets (from FitchConnect)
PEO	Personnel expenses/Overheads	Financial ratio	Measures personnel expenses as percentage of overhead costs (from FitchConnect)
PTPNI	Pretax profit/Net income	Financial ratio	Measures the share of profit before tax to net income (from FitchConnect)
TAG	Total assets growth	Financial ratio	Measures the growth of assets as a percentage from the previous year (from FitchConnect)
TETA	Total equity/Total assets	Financial ratio	Measures the total equity as a percentage of the total assets (from FitchConnect)
HHI	Herfindahl–Hirschmann index	Market structure	Herfindahl index computed as the sum of squared employment shares per year
GDP	Real GDP	Macroeconomic	Real gross domestic product (GDP) from 2007 to 2017 (from Swiss State Secretariat for Economic Affairs [SECO])
UR	Unemployment rate	Macroeconomic	Swiss unemployment rate from 2007 to 2017 (from SECO)

APPENDIX B: SUMMARY STATISTICS FOR KEY VARIABLES

Variable	Nonexited		Exited		Nonexited	Exited	Total	
EXIT								
	2156		423				2579	
Total	2156	83.60%	423	16.40%			2579	100.00%
REAS								
Nonexit	2156		0				2156	
1. *VL + SI*	0		68	16.08%			68	
2. *AB + MB*	0		255	60.28%			255	
3. *RL*	0		47	11.11%			47	
4. *MG*	0		53	12.53%			53	
Total	2156		423	100.00%			2579	
CAT								
1. *CB*	264	12.24%	0	0.00%	100.00%	0.00%	264	10.24%
2. *BB*	27	1.25%	0	0.00%	100.00%	0.00%	27	1.05%
3. *RB*	649	30.10%	42	9.93%	93.92%	6.08%	691	26.79%
4. *RAB*	11	0.51%	0	0.00%	100.00%	0.00%	11	0.43%
5. *SB*	378	17.53%	62	14.66%	85.91%	14.09%	440	17.06%
6. *OB*	121	5.61%	12	2.84%	90.98%	9.02%	133	5.16%
7. *PB*	11	0.51%	0	0.00%	100.00%	0.00%	11	0.43%
8. *FB*	695	32.24%	307	72.58%	69.36%	30.64%	1002	38.85%
Total	2156	100.00%	423	100.00%	83.60%	16.40%	2579	100.00%

Variable	Nonexited		Exited		Nonexited	Exited	Total	
FC								
1. *Zurich*	656	30.43%	190	44.92%	77.54%	22.46%	846	32.80%
2. *Geneva*	487	22.59%	112	26.48%	81.30%	18.70%	599	23.23%
3. *Basel*	110	5.10%	0	0.00%	100.00%	0.00%	110	4.27%
4. *Ticino*	154	7.14%	60	14.18%	71.96%	28.04%	214	8.30%
5. *Rest of Switzerland*	749	34.74%	61	14.42%	92.47%	7.53%	810	31.41%
Total	2156	100.00%	423	100.00%	83.60%	16.40%	2579	100.00%
BS								
1. *BHC*	532	24.68%	210	49.65%	71.70%	28.30%	742	28.77%
2. *FHC*	259	12.01%	43	10.17%	85.76%	14.24%	302	11.71%
3. *BCC*	264	12.24%	8	1.89%	97.06%	2.94%	272	10.55%
4. *Others*	1101	51.07%	162	38.30%	87.17%	12.83%	1263	48.97%
Total	2156	100.00%	423	100.00%	83.60%	16.40%	2579	100.00%
SPI								
Not listed	1846	85.62%	415	98.11%	81.65%	18.35%	2261	87.67%
Listed	310	14.38%	8	1.89%	97.48%	2.52%	318	12.33%
Total	2156	100.00%	423	100.00%	83.60%	16.40%	2579	100.00%
WMS								
Before	0		48	11.35%				
After	0		375	88.65%				
Total	0		423	100.00%				

Note: This table presents summary statistics by exited and nonexited banks for the two dependent variables *EXIT* and *REAS* and for the independent variables *CAT*, *FC*, *BS*, *SPI*, and *WMS*. Variables are defined in Appendix A. The observation period is 2007–2017 and the data report the number of bank-year observations available from FitchConnect.