Bank Loyalty, Social Networks and Crisis

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Abstract

In this paper, we consider how the intensity and channels of the relation between social networks and bank loyalty vary according to the state of the economy. We analyze bank exit over the period 2005-2012 for over 300,000 retail clients of a commercial bank that experienced a bank run in 2008 due to a solvency risk. The unique and rich data we constructed in close collaboration with the bank enables us to distinguish different sorts of family networks from neighborhood networks, while controlling for a wide battery of client-level and branch-level characteristics and events. Using a proportional hazards model, we show the importance of family networks. In times of financial distress, family networks become even more important and retail clients take weaker, less direct social relationships into account.

Key words: peer effects; social networks; bank exit; financial crisis; depositor discipline.

JEL: D12, G01, G21.

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1 Introduction

Decisions are hardly ever made in vacuum. Taking choices of others into account is common for any form of decision making, including decisions with regard to banking (see e.g. Ellison and Fudenberg (1993), Carrell et al. (2009), Iyer and Puri (2012), Iyer et al. (Forthcoming)). A well-established literature shows that agents do influence each others behavior and that this social network effect can propagate via different channels, with the effect depending on the network structure (see e.g. Granovetter (1978), Granovetter (2005), Jackson (2014)). From an empirical banking perspective, both experiments (Garratt and Keister, 2009; Schotter and Yorulmazer, 2009; Kiss et al., 2014) and observational evidence confirm the importance of peers' actions for bank exit decisions (Kelly and Ó Gráda, 2000; Starr and Yilmaz, 2007; Iyer and Puri, 2012; Iyer et al., Forthcoming). In this paper, we study how/whether the intensity and used channels of social network effects related to bank loyalty vary according to the situation.

For this purpose, we constructed a tailored data set with monthly information at the client-branch level of a large European commercial bank covering 2005-2012. We follow 307,801 customers in Belgium, of which 10,000 of these are randomly drawn customers of the bank. The other 297,801 customers are family or neighbors of the 10,000 customers that are also clients of the bank. Our data set provides detailed information on the nature of the familial relation (e.g. father, grandparent, nephew), the bank branch and the residence of the customers.
Our data set is well-suited for an empirical analysis of the intensity of social network effects in pre-crisis, crisis and post-crisis periods. In particular, we can test whether in times of peril agents rely more on information signals from the direct, strong network (i.e., first order family) and from weaker, indirect ties (i.e., second order family or neighbors) for their bank exit decision.

Our contribution to the well-established literature on the role of peer effects in banking decision making is threefold. First, to our knowledge, we are the first to take a detailed look at how the intensity and channels of social networks differs between normal times and times of financial distress.

From a theoretical perspective, we study endogenous peer effects (Manski, 1993), meaning that the agents influence each others decision making.[1] The literature fully acknowledges that each network channel is expected to have a different, endogenous effect, depending on the network structure. First, denser networks – networks with on average high number of connections per node – enhance information diffusion (Granovetter, 2005; Jackson, 2014). Second, the peer effect depends on the type of edges. Ties can be classified according to their strength but one can also make distinction between direct and indirect ties. Regarding the strength of ties, strong ties are characterized by more communication between the connected agents and this increases the probability of contagion (Bakshy et al., 2012). Nevertheless there is a higher likelihood that strong ties are connected among each other - greater overlap of social networks - than weak ties. Differently put, agents who are weakly connected have a higher centrality than strongly connected agents. This implies that the agents forming the strong ties have comparable information (Granovetter, 1973). Hence weak ties transmit novel information which can induce a change in behavior. Overall, while economic theory does not assume the relation between social networks and decision making to be independent from the economic environment[2], in empirical research, this assumption is commonly maintained[3]. We test whether, given the changing need for information in function of the state of the economy, the intensity and structure of social network effects vary across these states of the economy.

[1]Besides the endogenous effects, Manski (1993) gives two other explanations for uniform behavior: exogenous effects i.e. behavior is influenced by predetermined peer characteristics, and correlated effects, i.e. individuals behave similarly because their characteristics are similar to their peers' characteristics.

[2]In fact, micro-economic theory almost never dictates a specific functional form relating economic variables (Yatchew, 1998).

[3]The exception is Iyer et al. (Forthcoming) who allow for varying peer effects on depositor withdraws across the event window of public information releases.

Second, we contribute to our understanding of the relation between peer effects, bank runs and financial fragility. Bank runs can be driven by either a coordination problem (Diamond and Dybvig, 1983; Ennis and Keister, 2009)[4] or bad (signals of) bank fundamentals (Jacklin and Bhattacharya, 1988; Allen and Gale, 1998)[5]. By comparing a solvency risk shock with a no solvency risk shock in a single commercial bank, Iyer et al. (Forthcoming) pinpoint that retail clients are heterogeneous in their information on shocks, implying that the composition of depositors impacts bank fragility. In particular, more informed clients are more (less) likely to run when the bank faces a shock with high (low) solvency risk. In this paper, the major commercial bank under study faced a bank run in the Belgian retail market in 2008 after disclosure of information on very bad fundamentals (i.e., solvency issues). This public disclosure of information, triggered endogenous peer effects on bank loyalty, consistent with the theory on informational differences and social learning (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1998; Bikhchandani and Sharma, 2000), negative payoff externalities (Diamond and Dybvig, 1983; Bikhchandani and Sharma, 2000), and blind imitation (Diamond and Dybvig, 1983; Devenow and Welch, 1996). Only with the help of the Belgian federal state government, the bank was able to avoid bankruptcy. In our analysis of bank exit, we fully acknowledge the heterogeneity across retail clients concerning information on bank fundamentals, allow that retail clients retrieve information from family and neighborhood network members' actions. Given that our data set provides monthly information, we abstract from a study of the deposit withdraws during the bank

[4]The coordination problem is mainly modeled in a simultaneous decision making framework. Agents form expectations that other agents will withdraw and fear that the bank would not be able to provide liquidity. Therefore the agent decides to withdraw and since every agents applies the same decision making process simultaneously - the coordination problem - a panic-based bank run will occur (Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005).

[5]Sequential decision making enables the agents to *observe* previous decisions regarding withdrawals. In these models some agents base their decision on a private signal about bank fundamentals and the number of withdrawals observed, while some agents do not receive a private signal and decide only on the basis of observed number of withdrawals. The agents belief that the number of withdrawals reflects the solvency of banks. A sufficient number of withdrawals leads consequently to a bank run.

run, which requires (close to) real-time data on deposit withdraws. Our bank exit analysis complements bank run analyses of e.g. Iyer and Puri (2012) and Iyer et al. (Forthcoming) by testing for familial network effects in a large bank with a high-solvency-risk shock.

Third we also contribute to the depositor discipline literature. Depositor discipline requires that depositors both have access to information on bank risk and anticipate bearing a cost in the event of bank insolvency. In their seminal paper on US thrifts Park and Peristiani (1998) demonstrate a negative relationship between thrifts predicted probability of failure and the subsequent growth of their large uninsured deposits, without though providing a clear mechanism. Depositor Market discipline, though crucial for the efficient distribution of funds in the deposit market, can be easily undermined because of high monitoring costs and the lack of financial sophistication of household depositors, which opens an avenue for peer effects in quantity disciplining of a bank. Financial crisis has been found to reduce depositor discipline (Berger and Turk-Ariss, 2015; Cubillas et al., 2012) because of crisis-related government intervention. Depositors in crisis time may stop monitoring their banks' reliability and turn to other information, for example signals received from other depositors' behavior or even rumors (Hasan et al., 2013). Alternatively, in the absence of government bailouts of individual banks, the crisis may also function as wake-up call for household depositors, as shown by Karas et al. (2010). In this study we verify whether depositors indeed start to attach more weight to the information received from actions from other depositors in their family and neighborhood network during crisis time. Hasman et al. (2013) present a model with differently-informed depositors, where the better informed have incentives to monitor banks investments. They emphasize the social benefits of private monitoring of banks by the better informed depositors in order to promote market discipline. The inclusion of the potential peer effects of depositor monitoring documented in this paper would only reinforce their conclusion. Goedde-Menke et al. (2014) document how in the 2008 crisis the number of completely uninformed, strongly involved, and highly exposed depositors, who carry the highest risk of triggering a bank run, was reduced around the peak of the crisis, providing some stability. We provide an potential mechanism for their finding, namely the increased intensity of peer effects in bank exit decisions during crisis times.

By applying a proportional hazard analysis on our unique data set, we find that agents are indeed more sensitive for network effects in times of peril, and do in these times of distress not only take their strong, direct ties into consideration (i.e., first order family), but also the weaker, indirect ties (i.e., second order family or neighbors). In line with Iyer and Puri (2012) and Iyer et al. (Forthcoming), we highlight the need to include information on the composition and network of retail clients in any analysis of depositor discipline of bank fragility. New is that we show it is warranted to include information on the familial interlinkages between retail clients to better understand or better define the stability of deposits (see e.g. Basel III; BIS (2013)).

The remainder of this paper is structured as follows. Section 2 describes the data and estimation methodology. In Section 3, we discuss the results, including sensitivity analysis. Section 4 concludes and in Appendix, we provide additional tables.

2 Data and methodology

2.1 Descriptive analysis of bank loyalty and social networks

We constructed in close collaboration with the anonymous commercial bank a data base that enables us to study the relation between bank loyalty, different sorts of family networks and neighborhood networks, while controlling for a wide battery of client-level and branch-level characteristics and events. The data set covers December 2005 until November 2012 and contains monthly data per customer. There are 307,801 customers but only 10,000 of these are randomly drawn customers from the total set of customers of the bank in the period 2005-2012 (see Table 1). The other 297,801 customers are family (15 percent) or neighbors (i.e. having the same sub-street code, 85 percent) of the 10,000 customers that are also clients of the bank. In total, we have information for 83 months[6] on the activities

[6] March 2007 is excluded because of data issues.

of 300,313 subjects that were active in the sample period and not deceased.

We start the descriptive analysis with a study of bank loyalty for the whole sample of remaining subjects. *Revealed Bank Exit* considers the scope of the bank services. The bank classifies client relations in five domains: (i) Daily Banking, (ii) Deposits&Investments, (iii) Loans&Credits, (iv) Insurance and (v) Online Banking. The customer is considered as *Revealed Bank Exit=1* from when the customer is no longer active in any domain and does not renew her activity in the sample period. The customer keeps the *Revealed Bank Exit=1* status until the end of the observed period.
Next to this objective measure of bank exit, we have information on *Processed Bank Exit* as introduced into the system by the employees of the respective bank branches. We focus the analysis on the bank loyalty proxy *Revealed Bank Exit*, and refer to the results on *Processed Bank Exit* in the sensitivity analysis (see section 3.3). Results are highly robust for altering the definition of bank loyalty.
Table 1 shows that out of the sample of 307,801 customers, 48,281 customers or 16 percent were characterized as having *Revealed Bank Exit=1* over the considered period. Out of these revealed bank exits, only half were processed by the bank. Figure 1 shows the monthly flow of exits. By definition, when bank exits are processed, customers are indicated to be inactive in all domains, resulting in a *Revealed Bank Exit=1* status. As bank exits are more often processed at the end of a year, we find end of year peaks in *Revealed Bank Exit*. As expected we observe an increase of the exits during the 2008-2009 financial crisis. In particular, we consider the crisis period for the bank to start in March 2008 and end in February 2009. We based the definition of the crisis period (in collaboration with the bank) on multiple event variables, including the stock prices, that plummeted with 90 percent in the considered crisis period. In section 3.3, we provide sensitivity analyses that show that our results are robust for altering the crisis period.

< Insert Table 1 >

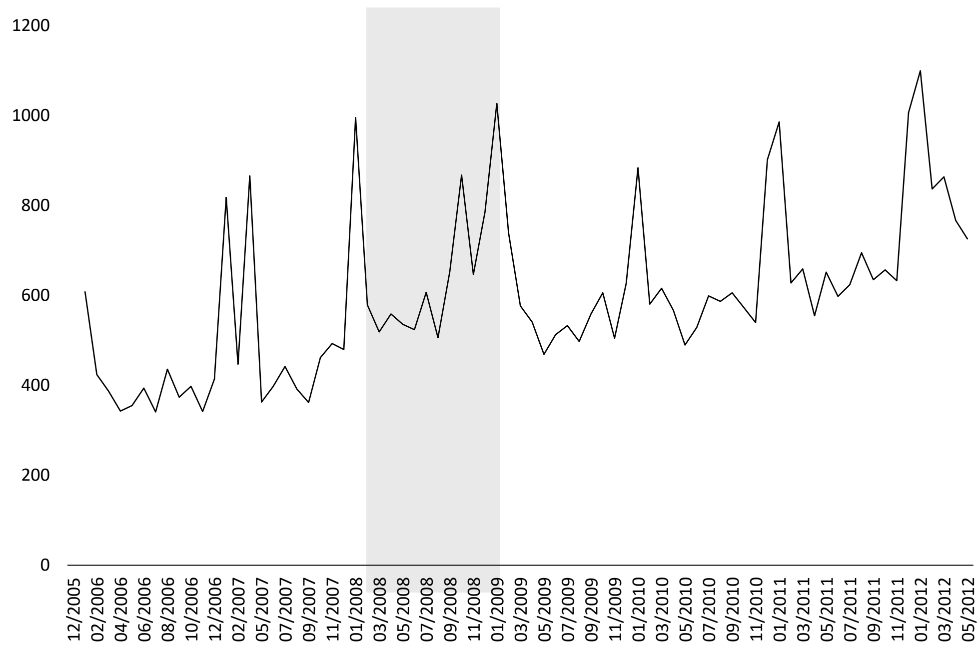

Figure 1: Flow of *Revealed Bank Exit* per month

We consider the influence of the social network on bank loyalty by including information on individuals with the status *Revealed Bank Exit* in an individual's social network (see Figure 2). First of all, we make a distinction between family and neighbors. The variable *family* consist of *first order* and *second order* family members. The first order links of the 10,000 customers consists of the partner, children, parents, brothers and sisters while for instance in-laws, grandparents, uncles, aunts and cousins are part of the second order links. *Neighbors* are defined as the agents with the same sub-street code but who are not family. Second, we distinguish familial links depending on the distance to the individual. Distance can be defined in terms of sub-street codes or bank branch. Using sub-street code, a link is defined as *close* if the peer has the same sub-street code as the individual and *far* otherwise. Using bank branch, a link is defined as *close* if the peer is client in the same bank branch as the individual and *far* otherwise. By distinguishing the effects of *close* and *far* links, we can separate endogenous peer effects from joint household decision making, reflecting predetermined peer effects and correlated effects. Finally, a variable for children of divorced parents who live *far* from one of their parents is constructed. This variable is a subset of *family far* and is included as a control variable.

To include these peer effects into our analysis, we include the *number* of the specific peer group members that have left the bank in the last six months (see Table 8). A discussion is at order on this specification of peer effects. In contrast to deposit withdrawals, bank exits can easily take multiple months. Therefore, we consider a time span of multiple months wherein peer effects can influence bank exit. In agreement with experts from the commercial bank, we consider a 6 month period as a realistic time span to allow for peer effect influences.

According to Granovetter (1978), the agent will follow the decision of social network members if and only if the number *or* fraction of his/her peers taking that decision exceeds a certain unobserved, agent-specific threshold. We however opted to consider the influence of the social network on bank loyalty by the observed *number* of individuals with the status *Revealed Bank Exit* in an individual's social network. First, the threshold can differ for each individual and is unobserved, making it difficult to implement the threshold concept in practice. Second, our data do not necessarily include all links of an agent, making a threshold definition or fraction definition (as applied in e.g. Iyer and Puri (2012)) less straightforward. Preliminary results that included social network effects based on a common threshold higher than 1 leaving member, or on fractions were highly unstable because of the low number of observed network members per network channel (in result of the data construction, each channel includes strictly less than 8 members). However, our main results are robust for changing the definition of the network structure to a threshold of 1 exiting member instead of the number of bank exits in the network. Results available upon request. Table 9, 10 and 11 in Appendix show summary statistics for the peer effects variables. The summary statistics of the actions of peers confirm the pattern as shown in Figure 1 that during the crisis period, the probability of bank exit increases.

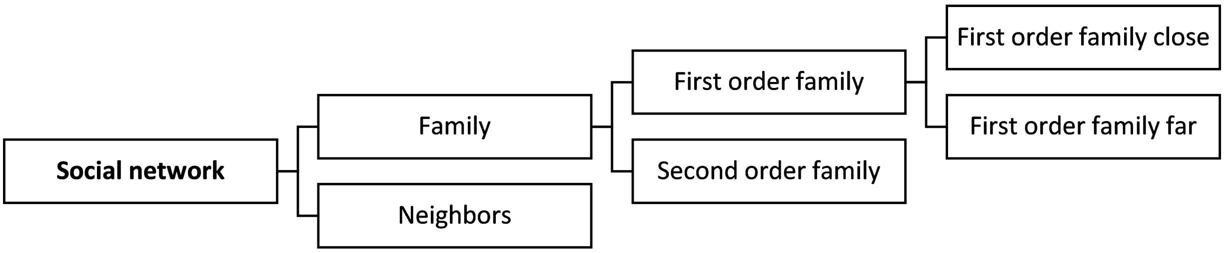

Figure 2: Social network variables

2.2 Control variables

Besides the social network variables, many other micro-level variables are included, covering individual characteristics, branch characteristics, individual events and branch events (see Table 8, 9, 10 and 11 in Appendix). We group the control variables as they relate to 1) relationship banking and main bank status, 2) characteristics of the subjects and/or branches, 3) events. The included variables control for among others retail client heterogeneity in switching costs (see e.g. Klemperer (1987) and Brown et al. (2016)), trust and information (see e.g. Iyer et al. (Forthcoming)).

Relationship banking and main bank status We consider the following individual characteristics as proxies for *relationship banking* and their main bank status (see e.g. Degryse et al. (2009) and references therein for a discussion): account age, having a mortgage, the scope of domains the subject is client with the bank, the maximum number of products the client held with the bank during the sample period, having an account manager and whether or not the salary payments are transferred to the subject via the bank. In specific, we divide regular income in euros in the categories *income0to2000, income2000to3500, income3500to5000* and *incomehigher5000* (see Table 8) and a final category *noincome*, allowing us to consider the effects of heterogeneity across income classes and main bank status. The variables *Dcontact-ever* and *Dsales-ever* indicate whether the customer has ever had at least one contact or sale. Further, we include the number of contacts in the last year. When the customer is *Revealed Bank Exit=1* we do not count the contacts with the customer in the two months before *Revealed Bank Exit=1.* The loan linkages (see also Iyer and Puri (2012)) in our model are proxied by the dummy variables *Dmortgage-now* and *Dmortgage-ever*. *Dmortgage-ever* indicates whether the agent has currently a loan or had a loan in the past. Since we also include *Dmortgage-now* the effect of having currently a loan is picked up by *Dmortgage-now.*

The characteristics of the subjects and branches include state variables such as the age group (based on the decade of birth of the customer) and marital status of subjects, number of competitors and market potential of the district. Marital status and gender can influence loyalty, with the marital status having a different influence on loyalty per gender. To control for this relationship, we constructed dummies for the four categories: married man, single man, married woman and single woman.

Events are considered as occurrences in a period which potentially impact bank loyalty in the following periods. An event can either be a client event or a branch event. We consider that the impact of all such events last up to one year after the event. Events include changes in civil status such as becoming widow(er), getting divorced or getting married. Other client events are receiving, changing or leaving an account manager, changing branch and moving residence. Also the branch events such as a merger of two or more branches, relocation, and change of bank statute for which we suppose that they have an impact of one year.

2.3 Estimation methodology

In the context of this article, the timing of the bank exits is crucial. To take the ordering of these events into account, we apply survival analysis. In particular, we use the Cox (1972) proportional hazards model to analyze the effect of peers' exit and other covariates on the probability that the individual will close his/her account with the bank. We opt for proportional hazards as we do not want to impose any assumptions on the baseline hazard. Although not defining the baseline hazard implies a loss in efficiency of the estimates (Cleves, 2008), it also allows us to avoid a potentially erroneous assumption about the baseline hazard. Over the paper, the empirical models are specified by the following three equations:

$$\mathrm{h_j(t)} = \mathrm{h_0(t)} \exp(\beta_0 + \beta_1 \mathrm{family_j} + \beta_2 \mathrm{neighbors_j}) \tag{1}$$

$$\mathrm{h_j(t)} = \mathrm{h_0(t)} \exp(\beta_0 + \beta_1 \mathrm{family_j} + \beta_2 \mathrm{neighbors_j} + \boldsymbol{\alpha}\mathbf{Z}_\mathrm{j}) \tag{2}$$

$$\begin{aligned}\mathrm{h_j(t)} = \mathrm{h_0(t)} \exp(&\beta_0 + \beta_1 \text{first order family close}_\mathrm{j} + \beta_2 \text{first order family far}_\mathrm{j} \\ &+ \beta_3 \text{first order family div}_\mathrm{j} + \beta_4 \text{second order family}_\mathrm{j} + \beta_5 \mathrm{neighbors_j} + \boldsymbol{\alpha}\mathbf{Z}_\mathrm{j})\end{aligned} \tag{3}$$

The dependent variable of the hazard functions $h_j(t)$ is *Revealed Bank Exit* (see section 3.3 for a consideration of *Processed Bank Exit*). Model (1) and (2) consider the effect of *family* versus *neighbors*. **Z** includes the discussed customer characteristics, branch characteristics, client events and branch events. The third model measures the impact of different kinds of family. Each equation is executed before, during and after the considered crisis period of March 2008 to February 2009.[7] All estimations include robust standard errors and clustering at the bank branch level.[8]

As follows from the model specification (1)-(3), a positive (negative) coefficient β – to

[7] Tests of proportional hazards are not rejected in around 80 percent of the regressions.

[8] The standard errors are transformed through the delta method because instead of coefficients hazard ratios are reported.

be interpreted as a positive (negative) association of a covariate with the hazard function – is expressed as a hazard rate bigger (smaller) than 1. A unit increase in a covariate increases or decreases the hazard rate by a given percentage. For example, a coefficient of 0.5 gives $exp(0.5) = 1.6$, which means that a unit increase in a covariate is associated with an increase of the hazard by 60 percent. If the coefficient is equal to -0.5, the hazard rate decreases with 40 percent as $exp(-0.5) = 0.6$.

Concerning the identification of the regression coefficients, a more elaborated discussion is at order. First of all, Manski (1993) points to the reflection problem or reverse causality: does the individual's outcome depend on her peers' outcome or the other way round? Since the Cox model takes the ordering of the outcomes into account we assume the former. Furthermore, occurrence of self-selection in the network formation may complicate the identification of the peer effects (Sacerdote, 2001). Individuals can behave similarly because of similar characteristics - homophily - and not because of the before mentioned externality or imitation channel. Individuals may choose their place of residence and hence their neighbors but self-selection is less likely for family ties which we show to be more important than neighbors in the decision making process (see Section 3). Moreover, the regressions control for the individual's background.[9] Lastly, the peer effect can exist because of mechanical reasons (Angrist, 2014).

3 Results

3.1 Main model

Table 2 contains the results of model 1 and 2. Model 1 shows for the three periods (pre-crisis, crisis, post-crisis) a relation between the behavior of the agent's family and the

[9]Shalizi and Thomas (2011) differentiate between homophily as a result of an observed characteristic and homophily based on an unobserved characteristic. This implies that controlling for the individuals' characteristic enables to distinguish the contagion effect from the homophily-observed characteristics but not from homophily-unobserved characteristics.

agent's behavior. *Family* is thus a significant determinant of bank exit decisions before, during and after the crisis. In contrast to family, we find no supportive evidence that neighbors significantly affect the agent's probability of exiting the bank. These findings indicate that the type of relationships determines the likelihood of contagion. We assume that agents have stronger connections with their family members than with their neighbors, which points to the importance of the strength of family connections in peer effects (see the discussion in the introduction). Stronger ties are characterized by more communication which in turn allows more information exchange. Moreover, we expect that family ties are on average more trusted by the agents and therefore the agents are more inclined to imitate the observed actions of their family ties.

In model 2, we include the wide battery of control variables. Before and after the crisis period, a unit increase in the number of family members exiting the bank leads to an increase of the hazard by 179 to 113 percent. During the crisis period, a unit change increases the hazard by 396 percent. Stated differently, an agent with one additional bank leaver in his/her network is on average 4,96 times more likely to exit the bank. The strength of the social network effect thus varies over time. In particular, the hazard rate for family peer effects is respectively 78 and 132 percent higher during the crisis period with regard to the pre-crisis period and post-crisis period. In sum, we find strong indications that in times of crisis, agents attach more importance to their family peers' decisions. Moreover this family peer effect is larger before than after the crisis, in line with the results found in the depositor discipline literature on the muted reaction of depositor discipline in the aftermath of the 2008 crisis.

The included control variables show a relation with bank exit which is consistent with the idea of heterogeneity between retail clients in switching costs, trust and information. In line with Brown et al. (2016) and Iyer et al. (Forthcoming), we find that a client-bank relation relates to the stability of the bank client base. Bank loyalty is positively associated with having an account manager. Further, the scope of products, regular income payments with the bank and the loan linkage are confirmed to be strongly related to bank loyalty.

Dmortgage-now is in every period significant and smaller than 1, which means that having a mortgage with the bank decreases the probability of leaving the bank. Before the crisis, the effect of loan linkages is the strongest while the effect weakens during crisis[10].

While we find the expected effects of client-level characteristics, we find few effects of branch-specific characteristics and branch-specific events. Branch-level characteristics - the number of competing banks and the market potential of the district - and branch events - branch merge, relocation and change of statute - are not significantly associated with the probability of exit.

< Insert Table 2 >

3.2 Disaggregated model

To separate the endogenous peer effects from effects originating from joint household decision making, which more reflect predetermined peer characteristics and correlated effects, we study the family networks at a more disaggregated level in Table 3. As discussed, we use both address and branch information to separate *close* links from *far* links. Based on the addresses (branches), we consider *first order family* having the same sub-street code (branch code) by the variable *first order family close* and having a different sub-street code (branch code) *first order family far.* While network effects of *first order family close* can result from joint household decision making, this is not the case for *first order family far.* Both variables have a significant impact on *Revealed Bank Exit* in each considered period (see Table 3). Except for *first order family far* in pre-crisis period for the address-based model, all hazard rates are bigger than one which means that an increase in the number of first order family exiting all scopes of the bank positively affects the probability of the

[10]In contrast to *Dmortgage-now* the hazard rate of Dmortgage-ever is only significant in the post-crisis period and is larger than 1. Customers who were loan linked before and especially during the crisis could not exit at that time. After experiencing the crisis, the need to leave the bank increases in contrast to customers without a loan in times of crisis.

agent's exit. Stated differently, retail clients take familial peer influences into consideration in their bank exit decision process. The structure of familial linkages thus impacts the stability of the retail client base.

Regardless of the chosen specification, the crisis effect is present for both *family close* and *family far*. In comparison to the pre-crisis and post-crisis period, the role of the social network gains in importance in the period of the solvency-risk shock. We thus find that the endogenous peer effect coming from familial relations varies according to the state of the economy. The intensity of the network effect follows the need and value of information, which is highest in the period of financial distress following the solvency-risk shock.

Further, next to a changing intensity of the social network channel, we observe a change in the use of network channels. Second order family members are taken into account during the crisis. This is peculiar, as before and after the crisis, *second order family* was not significantly related to agent's bank loyalty. Stated differently, in times of financial distress social network effects do not only become stronger in decision making, but agents do as well take more kinds of relationships into account.

< Insert Table 3 >

3.3 Sensitivity analysis

In this subsection, we test whether our finding of familial network effects with varying intensities and use of channels according to the circumstances is robust for altering the specification of our empirical model.

Definition of bank loyalty An alternative for our preferred binary variable *Revealed Bank Exit* is *Processed Bank Exit*, which reflects bank disloyalty as processed by the staff of the commercial bank (see section 2). *Processed Bank Exit* is introduced into the bank system by the bank branch personnel, and is as such less objective. It turns from 0 to 1 for all following months only if the customer has closed its connections with the bank and he/she did not re-open its relation with the bank in the considered period 2005-2012.[11] By definition, a customer with *Processed Bank Exit*, automatically is characterized by *Revealed Bank Exit=1*. The customers with *Processed Bank Exit* are thus a subset of the customers with *Revealed Bank Exit=1*. Table 4 shows that our results are highly robust for altering the definition of bank loyalty. Both the higher endogenous family network effects and the use of less direct second tier family ties in the crisis-period is confirmed.

Definition of the crisis period Secondly, we test the sensitivity of our results for altering the definition of the crisis period. Given the timing of the financial crisis and the stock price of the bank in question, we redefine the crisis period to June 2008 - May 2009 and September 2008 - August 2009. In Tables 5 and 6, we run both model 2 and 3 with the alternative crisis definitions. Except for changes in hazard rates, the sign and significance of the social network variables remain. The behavior of family members always significantly influences the agent's behavior whereas we find no supportive evidence for influences of the actions of neighbors. Moreover the effect of family magnifies during crisis. In model (2) we again state that first order family irrespective of distance. The hazard of second order family becomes significant during crisis. The hazard rates are once again larger in times of crisis.

Branch performance Until now we assumed that the bank exit probability is determined by peers' actions, individual characteristics, branch characteristics, individual events an branch events. We can include an additional variable measuring the branch performance in terms of sales, as measured by the bank. We did not include this variable in the baseline results because of a potential simultaneity bias. To test the sensitivity of our model for including information on branch performance, we include this variable in model 2 and 3. Table 7 contains the results. We find only a significant influence of branch performance, as measured by the bank after the crisis. The hazard rate is 0.995. The customer is less

[11]For 3,483 clients, who have closed their accounts in the considered period and became active later in the sample period, we overrule that *Processed Bank Exit* turns 1.

likely to leave the bank if the branch performs better, but this effect is modest. Our earlier findings concerning the various peer effects are insensitive to the inclusion of this measure of branch performance.

< Insert Table 5 >

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< Insert Table 7 >

4 Conclusion

We analyze which sorts of social networks affect bank exit decisions and how these effects change over states of the economy, especially how these peer effects are influenced by the occurrence of financial crisis. We study bank loyalty, employing data over the period 2005-2012 for over 300,000 retail clients of a commercial bank that experienced a bank run in 2008. To take the ordering of bank exits into account we apply survival analysis. We show that peer effects indeed vary with the circumstances and are augmented during crisis times. We also identify what kind of social network ties do play a role and to what extent. The results show that the decisions of family members are an important determinant of an agent's decision to leave the bank while we do not find such an impact for neighbors. During the crisis period, family networks become even more important with, in addition to first order family, second order family members also significantly influencing individual bank exit decisions.

Our empirical finding that the use and effects of social network channels varies with the need and value of information provides a potential mechanism for some of the literature's findings on crisis-related depositor discipline, but also calls into question whether the stability of the retail client base can be captured by easy-to-use categorizations of "*stable*" and "*unstable*" client bases as used in e.g. Basel III (see BIS (2013)). When facing a solvency risk, it is well possible that so called "*stable*" retail clients intensify and broaden their use of the information from their networks. Stated differently, our findings pinpoint the notion that the stability of client bases is highly circumstance-specific.

Our paper introduced new insights that foster further research. First, more detailed information on the social networks of banking clients is necessary to further disentangle peer effects and its varying use and intensity over different states of the economy. Next to more information about the neighbors, peers in social media networks could be taken into account. Second, we expect new insights from taking peer networks that vary with the state of the economy into account in studies on the relation between depositor insurance and bank fragility.

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Tables

Table 1: Sampling information

	All customers		Subsample	
Initial subjects	307,801	100.0	10,000	100.0
- never 'active'	-311	-0.1	-16	-0.2
= active customers	307,490	99.9	9,984	99.8
- deceased	7,177	-2.3	-201	-2.0
= remaining subjects	300,313	97.6	9,783	97.8
of which				
Revealed Bank Exit	48,281	16.1	1,729	17.7
Processed Bank Exit	23,910	8.0	961	9.8

Table 2: Main model

VARIABLES	Model 1 (1) pre	(2) crisis	(3) post	Model 2 (4) pre	(5) crisis	(6) post
Family	3.254***	4.169***	2.045***	2.786***	4.956***	2.132***
	(0.794)	(0.730)	(0.388)	(0.652)	(0.913)	(0.417)
Neighbors	1.039	1.139	1.010	0.988	1.098	0.967
	(0.0918)	(0.0965)	(0.0473)	(0.0861)	(0.0934)	(0.0448)
Dnineties				0.0740***	0.0654***	0.420***
				(0.0385)	(0.0388)	(0.0733)
Deighties				0.894	0.978	1.626***
				(0.160)	(0.192)	(0.178)
Dseventies				1.400**	1.192	1.487***
				(0.222)	(0.218)	(0.164)
Dsixties				1.211	1.015	1.182
				(0.184)	(0.192)	(0.133)
Dclientafter2000				1.446***	1.280	1.125
				(0.182)	(0.216)	(0.0980)
Dmortg now				0.0947**	0.154*	0.100***
				(0.0964)	(0.163)	(0.0589)
Dmortg ever				0.942	0.861	1.490***
				(0.207)	(0.243)	(0.189)
Maxproducts				0.855***	1.013	1.065***
				(0.0332)	(0.0378)	(0.0184)
Scope last6m				0.829***	0.673***	0.448***
				(0.0564)	(0.0586)	(0.0226)
Dwidow				3.800*	1.884	1.479
				(3.081)	(2.006)	(0.942)
Ddivorce				2.117	1.819	1.427
				(1.011)	(0.932)	(0.690)
Dwedding				0.881	0.628	0.951
				(0.590)	(0.655)	(0.385)
Dmarriedwoman				0.599***	0.676*	0.869
				(0.115)	(0.146)	(0.111)
Dmarriedman				1.465**	0.999	1.199
				(0.249)	(0.216)	(0.138)
Dsinglewoman				0.991	1.192	1.077
				(0.154)	(0.190)	(0.0962)
Dnoincome				3.172***	3.246***	2.521***
				(0.455)	(0.578)	(0.249)
Dincome2000to3500				0.663	0.616	0.516**

Continued on next page

Table 2 – continued from previous page

	Model 1			Model 2		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	pre	crisis	post	pre	crisis	post
				(0.260)	(0.323)	(0.158)
Dincome3500to5000				1.381	-	-
				(1.025)		
Dincomehigher5000				-	2.626	0.758
					(2.882)	(0.775)
Dmoved				1.344	1.562**	1.112
				(0.263)	(0.341)	(0.165)
Dchangebranch				1.155	0.879	0.908
				(0.226)	(0.261)	(0.148)
Dchange accountman				1.660	0.793	0.945
				(0.849)	(0.363)	(0.231)
Daccountman				0.626*	0.594**	0.655***
				(0.174)	(0.139)	(0.0885)
Dleave accountman				1.003	0.502	0.779
				(0.305)	(0.246)	(0.179)
Dcontact ever				1.629***	1.865***	1.314**
				(0.224)	(0.336)	(0.157)
Dsales ever				0.273***	0.524***	0.797***
				(0.0661)	(0.0962)	(0.0701)
Contacts lastyear				1.085*	1.057	0.952**
				(0.0534)	(0.0449)	(0.0194)
Dbranch merge				0.693	1.055	1.131
				(0.326)	(0.380)	(0.230)
Dbranch relocation				0.485	1.367	0.532
				(0.501)	(0.972)	(0.266)
Dbranch statchange				0.572	1.339	2.177*
				(0.593)	(1.044)	(0.984)
District competitors				1.044	1.014	0.989
				(0.114)	(0.0362)	(0.0213)
District potential				1.004	1.014	1.042
				(0.0491)	(0.0617)	(0.0321)
Clusters	1,132	1,042	1,034	1,132	1,042	1,034
Observations	205,535	93,614	303,337	205,316	93,519	303,129

Clustered standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Disaggregated model

	Model 3 Address			Model 3 Branch		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	pre	crisis	post	pre	crisis	post
First order family close	3.579***	5.639***	2.582***	2.339***	5.008***	2.695***
	(0.884)	(1.512)	(0.563)	(0.749)	(1.526)	(0.556)
First order family far	0.186***	3.702***	1.665	4.343***	5.269***	1.220
	(0.0881)	(1.429)	(0.725)	(1.819)	(1.920)	(0.776)
Second order family	2.924	5.008**	0.796	2.684	4.197**	0.799
	(3.065)	(3.156)	(0.746)	(2.806)	(2.867)	(0.747)
Neighbors	0.991	1.099	0.968	0.984	1.096	0.968
	(0.0862)	(0.0936)	(0.0448)	(0.0862)	(0.0934)	(0.0448)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1,132	1,042	1,034	1,132	1,042	1,034
Observations	205,316	93,519	303,129	205,316	93,519	303,129

Clustered standard errors reported in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Model 2 and 3, using *Processed Bank Exit*

	Model 2			Model 2 Address			Model 3 Branch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	pre	crisis	post	pre	crisis	post	pre	crisis	post
Family	2.321*	5.368***	1.607						
	(1.011)	(1.735)	(0.808)						
First order family close				3.663***	5.890***	2.972**	2.618*	5.843***	3.001**
				(1.209)	(3.618)	(1.583)	(1.346)	(3.691)	(1.433)
First order family far				-	5.813***	0.373**	2.399	5.404***	0.0889***
					(2.462)	(0.155)	(1.392)	(2.397)	(0.0677)
Second order family				-	4.199***	-	-	4.468***	-
					(2.315)			(2.454)	
Neighbors	0.919	1.303*	1.115	0.921	1.302*	1.115	0.920	1.302*	1.118
	(0.166)	(0.198)	(0.0990)	(0.164)	(0.198)	(0.0989)	(0.165)	(0.198)	(0.0998)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1,133	1,043	1,039	1,133	1,043	1,039	1,133	1,043	1,039
Observations	207,209	96,291	322,361	207,209	96,291	322,361	207,209	96,291	322,361

Clustered standard errors reported in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Model 2 and 3, Crisis June 2008 – May 2009

	Model 2			Model 3 Address			Model 3 Branch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	pre	crisis	post	pre	crisis	post	pre	crisis	post
Family	2.917***	4.669***	2.153***						
	(0.633)	(0.950)	(0.436)						
First order family close				3.750***	5.049***	2.652***	2.686***	4.299***	2.826***
				(0.889)	(1.588)	(0.597)	(0.719)	(1.624)	(0.585)
First order family far				0.209***	4.217***	1.490	4.171***	5.472***	0.974
				(0.100)	(1.479)	(0.716)	(1.755)	(1.876)	(0.716)
Second order family				2.462	4.642**	0.875	2.233	3.960**	0.874
				(2.572)	(2.900)	(0.820)	(2.327)	(2.617)	(0.817)
Neighbors	1.013	0.989	0.991	1.017	0.989	0.991	1.010	0.986	0.991
	(0.0792)	(0.0875)	(0.0470)	(0.0793)	(0.0877)	(0.0470)	(0.0793)	(0.0876)	(0.0470)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1,138	1,038	1,024	1,138	1,038	1,024	1,138	1,038	1,024
Observations	228,852	93,051	280,061	228,852	93,051	280,061	228,852	93,051	280,061

Clustered standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Model 2 and 3, Crisis September 2008 – August 2009

	Model 2			Model 3 Address			Model 3 Branch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	pre	crisis	post	pre	crisis	post	pre	crisis	post
Family	2.898***	3.865***	2.324***						
	(0.621)	(0.921)	(0.475)						
First order family close				3.789***	3.885***	2.794***	2.829***	3.063***	3.019***
				(0.882)	(1.365)	(0.650)	(0.738)	(1.325)	(0.632)
First order family far				0.203***	3.993***	1.655	3.766***	5.402***	1.000
				(0.0981)	(1.487)	(0.814)	(1.590)	(1.860)	(0.773)
Second order family				2.051	3.755**	1.010	1.823	3.178*	1.011
				(2.116)	(2.483)	(0.934)	(1.880)	(2.149)	(0.933)
Neighbors	1.051	0.922	0.999	1.053	0.921	0.999	1.050	0.918	0.999
	(0.0725)	(0.0824)	(0.0493)	(0.0724)	(0.0825)	(0.0493)	(0.0725)	(0.0823)	(0.0493)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	1,140	1,028	1,015	1,140	1,028	1,015	1,140	1,028	1,015
Observations	252,326	92,602	257,036	252,326	92,602	257,036	252,326	92,602	257,036

Clustered standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Model 2 and 3, including branch performance

	Model 2			Model 3 Address			Model 3 Branch		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	pre	crisis	post	pre	crisis	post	pre	crisis	post
Family	2.154**	5.207***	2.002***						
	(0.734)	(0.923)	(0.414)						
First order family close				2.766***	5.958***	2.376***	0.784	5.279***	2.592***
				(1.027)	(1.609)	(0.553)	(0.568)	(1.618)	(0.555)
First order family far				0.160***	4.132***	1.669	4.840***	5.883***	0.978
				(0.0891)	(1.413)	(0.735)	(2.261)	(2.088)	(0.724)
Second order family				3.255	4.765**	0.803	3.153	3.857*	0.813
				(3.451)	(3.059)	(0.756)	(3.334)	(2.763)	(0.763)
Neighbors	0.973	1.099	0.973	0.974	1.101	0.973	0.964	1.096	0.973
	(0.0939)	(0.0994)	(0.0452)	(0.0939)	(0.0997)	(0.0452)	(0.0939)	(0.0995)	(0.0452)
Branch performance	0.997	0.997	0.995**	0.997	0.997	0.995**	0.996	0.997	0.995**
	(0.00282)	(0.00331)	(0.00190)	(0.00283)	(0.00332)	(0.00190)	(0.00283)	(0.00332)	(0.00190)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	910	927	978	910	927	978	910	927	978
Observations	185,356	88,013	297,498	185,356	88,013	297,498	185,356	88,013	297,498

Clustered standard errors reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Table 8: Variable description

Variable	Description
Family	The number of family members of the client specific network that have left in the last six months
First order family close	The number of family members in the first tier of the client specific network that have the same sub-street code as the client and have left in the last six months
First order family far	The number of family members in the first tier of the client specific network that have the same sub-street code as the client and have left in the last six months
Second order family	The number of family members of the second degree of the client specific network that have left in the last six months
Neighbors	The number of neighbors of the client specific network that have left in the last six months
Dnineties	Dummy that equals 1 if subject is born in the nineties
Deighties	Dummy that equals 1 if subject is born in the eighties
Dseventies	Dummy that equals 1 if subject is born in the seventies
Dsixties	Dummy that equals 1 if subject is born in the sixties
Dclientafter2000	Dummy that equals 1 if subject becomes client after the year 2000
Dmortg now	Dummy that equals 1 in those time periods where the subject has a mortgage
Dmortg ever	Dummy that equals 1 if the subject ever had a mortgage with the bank
Maxproducts	Maximum number of products the subject has had at any point in time during the sample period
Scope last6m	The number of product domains of the subject six months ago
Dwidow	Dummy equals 1 if the subject becomes widow(er) at this point in time. Dummy kept at 1 during 12 months
Ddivorce	Dummy equals 1 if the subject is divorced at this point in time. Dummy kept at 1 during 12 months
Dwedding	Dummy equals 1 if the subject marries at this point in time. Dummy kept at 1 during 12 months
Dmarriedwoman	Dummy equals 1 for married women
Dmarriedman	Dummy equals 1 for married men
Dsinglewoman	Dummy equals 1 for single women
Dnoincome	Dummy equals 1 if regular income is missing or zero
Dincome2000to3500	Dummy equals 1 if regular icome is higher than 2000 and smaller or equal to 3500
Dincome3500to5000	Dummy equals 1 if regular income is higher than 3500 and smaller or equal to 5000
Dincomehigher5000	Dummy equals 1 if regular income higher than 5000
Dmoved	Dummy equals 1 if the subject has moved at this point in time. Dummy kept at 1 during 12 months
Dchangebranch	Dummy equals 1 if the subject changes branch at this point in time. Dummy kept at 1 during 12 months
Dchange accountman	Dummy equals 1 if the subject gets a new account manager at this point in time. Dummy kept at 1 during 12 months
Daccountman	Dummy equals 1 if the subject has an account manager at this point in time
Dleave accountman	Dummy equals 1 if the account manager of the subject leaves at this point in time. Dummy kept at 1 during 12 months
Dcontact ever	Dummy equals 1 if the subject ever had face-to-face contact with branch
Dsales ever	Dummy equals 1 if the subject ever had sales
Contacts lastyear	Number of face-to-face contacts during last 12 months
Branch namechange	Dummy equals 1 if branch name changes at this point in time. Dummy kept at 1 during 12 months
Branch merge	Dummy equals 1 if branch merges at this point in time. Dummy kept at 1 during 12 months
Branch relocation	Dummy equals 1 if branch relocates at this point in time. Dummy kept at 1 during 12 months
Branch statchange	Dummy equals 1 if branch changes statute (statutory or independent) at this point in time. Dummy kept at 1 during 12 months
District competitors	Number of competing banks available to subject in this district
District potential	Market potential of the district as estimated by the bank (1-5)
Branch performance	The performance of the branch according to internal performance measurement of the bank

Table 9: Summary statistics, pre-crisis period

Variable	**Obs.**	**Mean**	**St.Dev.**	**Min.**	**25%**	**Med.**	**75%**	**Max.**
Family	230048	.0072594	.089867	0	0	0	0	3
First order family close (address)	254308	.0043019	.0687299	0	0	0	0	3
First order family far (address)	254352	.0015726	.0409907	0	0	0	0	2
First order family close (branch)	254328	.0045571	.0715422	0	0	0	0	3
First order family far (branch)	254346	.0013525	.0375975	0	0	0	0	2
First order family divorced	241228	.0002529	.0173941	0	0	0	0	2
Second order family	230048	.0012606	.0358484	0	0	0	0	2
Neighbors	230048	.261315	.5555864	0	0	0	0	9
Dnineties	254358	.0714505	.2575763	0	0	0	0	1
Deighties	254358	.1900235	.3923203	0	0	0	0	1
Dseventies	254358	.1811305	.3851271	0	0	0	0	1
Dsixties	254358	.1896146	.3919969	0	0	0	0	1
Dclientafter2000	254358	.2200756	.4142982	0	0	0	0	1
Dmortgage now	254358	.0826434	.2753429	0	0	0	0	1
Dmortgage ever	254358	.166014	.372094	0	0	0	0	1
Maxproducts	254358	3.594139	3.270205	0	1	3	5	26
Scope last6m	254358	1.410644	1.400306	0	0	1	2	5
Dwidow	225840	.001625	.0402792	0	0	0	0	1
Ddivorce	225845	.0053709	.0730898	0	0	0	0	1
Dwedding	225855	.0062916	.0790702	0	0	0	0	1
Dmarriedman	254358	.2260829	.4182943	0	0	0	0	1
Dmarriedwoman	254358	.199919	.39994	0	0	0	0	1
Dsinglewoman	254358	.28327	.4505873	0	0	0	1	1
Dnoincome	254358	.5247997	.4993856	0	0	1	1	1
Dincome2000to3500	254358	.0898183	.2859218	0	0	0	0	1
Dincome3500to5000	254358	.0217174	.1457596	0	0	0	0	1
Dincomehigher5000	254358	.0078826	.0884335	0	0	0	0	1
Dmoved	254358	.059204	.2360065	0	0	0	0	1
Dchange branch	254358	.0665873	.2493063	0	0	0	0	1
Dchange accountman	254358	.025873	.1587566	0	0	0	0	1
Daccountman	254358	.2750611	.446546	0	0	0	1	1
Dleave accountman	254358	.1269667	.3329363	0	0	0	0	1
Dcontact ever	254358	.4340614	.495634	0	0	0	1	1
Dsales ever	254358	.1766722	.3813918	0	0	0	0	1
Contacts lastyear	254358	.8004977	1.461254	0	0	0	1	28
Dbranch merge	254358	.0120067	.1089155	0	0	0	0	1
Dbranch relocation	254358	.004301	.0654411	0	0	0	0	1
Dbranch statchange	254358	.0033064	.057406	0	0	0	0	1
District competitors	254358	.0616179	.5050073	0	0	0	0	12
District potential	254358	2.279366	1.310155	0	1	3	3	5

Table 10: Summary statistics, crisis period

Variable	**Obs.**	**Mean**	**St.Dev.**	**Min.**	**25%**	**Med.**	**75%**	**Max.**
Family	106176	.0115845	.1164481	0	0	0	0	3
First order family close (adddress)	117340	.0068007	.0877041	0	0	0	0	3
First order family far (address)	117387	.0030412	.0582219	0	0	0	0	2
First order family close (branch)	117351	.0071921	.0893059	0	0	0	0	3
First order family far (branch)	117386	.0025897	.0527969	0	0	0	0	2
First order family divorced	111324	.0003593	.0189522	0	0	0	0	1
Second order family	106176	.0019778	.0458891	0	0	0	0	2
Neighbors	106176	.4171376	.6984727	0	0	0	1	7
Dnineties	117396	.0714505	.2575769	0	0	0	0	1
Deighties	117396	.1900235	.3923212	0	0	0	0	1
Dseventies	117396	.1811305	.3851279	0	0	0	0	1
Dsixties	117396	.1896146	.3919977	0	0	0	0	1
Dclientafter2000	117396	.2200756	.4142992	0	0	0	0	1
Dmortgage now	117396	.0862891	.2807917	0	0	0	0	1
Dmortgage ever	117396	.1798698	.3840806	0	0	0	0	1
Maxproducts	117396	4.034942	3.467671	0	2	3	6	27
Scope last6m	117396	1.813412	1.376596	0	1	2	3	5
Dwidow	104945	.0021059	.0458416	0	0	0	0	1
Ddivorce	104949	.0071082	.0840104	0	0	0	0	1
Dwedding	104945	.0072228	.0846802	0	0	0	0	1
Dmarriedman	117396	.2238662	.4168352	0	0	0	0	1
Dmarriedwoman	117396	.1978858	.3984073	0	0	0	0	1
Dsinglewoman	117396	.2854867	.4516479	0	0	0	1	1
Dnoincome	117396	.4921973	.4999412	0	0	0	1	1
Dincome2000to3500	117396	.0825411	.2751886	0	0	0	0	1
Dincome3500to5000	117396	.0170278	.1293755	0	0	0	0	1
Dincomehigher5000	117396	.0064823	.0802519	0	0	0	0	1
Dmoved	117396	.0673277	.2505897	0	0	0	0	1
Dchange branch	117396	.0710757	.2569523	0	0	0	0	1
Dchange accountman	117396	.0702239	.255525	0	0	0	0	1
Daccountman	117396	.3994599	.4897895	0	0	0	1	1
Dleave accountman	117396	.1379349	.3448331	0	0	0	0	1
Dcontact ever	117396	.7472316	.4346011	0	0	1	1	1
Dsales ever	117396	.35123	.4773567	0	0	0	1	1
Contacts lastyear	117396	1.242938	1.786423	0	0	1	2	24
Dbranch merge	117396	.0284081	.1661365	0	0	0	0	1
Dbranch relocation	117396	.0078282	.0881305	0	0	0	0	1
Dbranch statchange	117396	.0084074	.0913062	0	0	0	0	1
District competitors	117396	.8024294	1.658172	0	0	0	1	12
District potential	117396	2.283519	1.30282	0	1	3	3	5

Table 11: Summary statistics, post-crisis period

Variable	**Obs.**	**Mean**	**St.Dev.**	**Min.**	**25%**	**Med.**	**75%**	**Max.**
Family	353920	.013958	.123374	0	0	0	0	3
First order family close (address	390985	.0083047	.0957162	0	0	0	0	4
First order family far (address)	391257	.0047462	.0713925	0	0	0	0	2
First order family close (branch)	390985	.0090771	.0996534	0	0	0	0	4
First order family far (branch)	391196	.0041054	.0657548	0	0	0	0	2
First order family divorced	371017	.0003854	.0204358	0	0	0	0	2
Second order family	353920	.0017123	.0423567	0	0	0	0	2
Neighbors	353920	.4488359	.7245494	0	0	0	1	8
Dnineties	391320	.0714505	.2575762	0	0	0	0	1
Deighties	391320	.1900235	.39232	0	0	0	0	1
Dseventies	391320	.1811305	.3851268	0	0	0	0	1
Dsixties	391320	.1896146	.3919966	0	0	0	0	1
Dclientafter2000	391320	.2200756	.414298	0	0	0	0	1
Dmortgage now	391320	.0921778	.2892771	0	0	0	0	1
Dmortgage ever	391320	.2029209	.4021746	0	0	0	0	1
Maxproducts	391320	4.606726	3.678278	0	2	4	6	27
Scope last6m	391320	1.853049	1.406322	0	1	2	3	5
Dwidow	350429	.0026054	.0509764	0	0	0	0	1
Ddivorce	350448	.005356	.0729886	0	0	0	0	1
Dwedding	350419	.0086211	.092449	0	0	0	0	1
Dmarriedman	391320	.2217418	.4154188	0	0	0	0	1
Dmarriedwoman	391320	.200184	.4001384	0	0	0	0	1
Dsinglewoman	391320	.2876112	.4526494	0	0	0	1	1
Dnoincome	391320	.4758689	.499418	0	0	0	1	1
Dincome2000to3500	391320	.1044695	.305869	0	0	0	0	1
Dincome3500to5000	391320	.0261602	.1596117	0	0	0	0	1
Dincomehigher5000	391320	.0124144	.1107263	0	0	0	0	1
Dmoved	391320	.0699734	.2551025	0	0	0	0	1
Dchange branch	391320	.0691097	.2536409	0	0	0	0	1
Dchange accountman	391320	.058341	.2343874	0	0	0	0	1
Daccountman	391320	.4081391	.4914898	0	0	0	1	1
Dleave accountman	391320	.1290018	.3352024	0	0	0	0	1
Dcontact ever	391320	.8932945	.3087389	0	1	1	1	1
Dsales ever	391320	.4838214	.4997388	0	0	0	1	1
Contacts lastyear	391320	2.681833	4.891741	0	0	1	4	257
Dbranch merge	391320	.0290734	.1680125	0	0	0	0	1
Dbranch relocation	391320	.0108096	.1034057	0	0	0	0	1
Dbranch statchange	391320	.0051569	.0716263	0	0	0	0	1
District competitors	391320	.7969437	1.697475	0	0	0	1	16
District potential	391320	2.284828	1.411401	0	1	2	3	5