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Abstract

The aim of this paper is to study the determinants of lapse in the German life insurance industry. Logistic regression models are employed using data on macro-economic indicators and company characteristics of 133 German life insurers from 1997 to 2009. Five different product categories are considered (endowment, annuity, term life, group, and other). The findings indicate that the main lapse determinants are very similar across all product categories, except that the direction of impact is reversed for the product category "other" which consists almost exclusively of unit-linked business. In particular, the interest rate and emergency fund hypotheses are only supported for unit-linked business, while these hypotheses do not hold for the remaining product categories. Overall, the analysis provides an understanding of lapse dynamics related to economic indicators and company characteristics. The derived models can be used to predict lapse rates for the different product categories considered. The results are important for insurance company managers, regulators, and life insurance customers.

Keywords Life insurance · Lapse · Logistic regression · Macro-economic indicators · Company characteristics

JEL Classification G22 · G28

1. INTRODUCTION

In this paper, the determinants for lapse and surrender in the German life insurance industry are examined. Although both terms, lapse and surrender, refer to the termination of an insurance contract before maturity, there is a slight difference (see, e.g., Gatzert et al., 2009; Kuo et al., 2003). While *lapse* refers to the termination of policies without payout to policyholders, *surrender* is used in cases where

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a cash surrender value is paid out to the policyholder. In accordance with Kuo et al. (2003), the term "lapse" refers to both surrender and lapse throughout this paper. This is consistent with standard measures of lapse rates as they typically include lapsed policies as well as surrendered ones.

A proper understanding of lapse dynamics is particularly important for insurance managers, regulators, and customers. For insurance managers, the profitability and liquidity of life insurers can be heavily influenced by lapses through acquisition cost, adverse selection, and cash surrender values. Therefore, lapses constitute a material risk for life insurance companies, which needs to be controlled and managed carefully. For regulators, the quantitative impact studies of Solvency II (the new risk-based capital requirements in the European Union) have shown that lapse risk is among the main drivers of risk-based capital requirements for life insurance companies. According to the results of the fourth quantitative impact study (see CEIOPS, 2008), the largest component of the capital requirements for life insurers is market risk followed by life underwriting risk. Lapse risk accounts for half of the capital requirements in the life underwriting module. Regulators should, hence, have a thorough understanding of lapse dynamics in order to define reasonable capital standards. For customers, lapses are one of the main indicators to assess the product and service quality of life insurance companies. Companies with above average lapse rates might offer more expensive products (for the same coverage) or provide less services than competitors to the customer. Customers should use such qualitative indicators as additional source of information when making a purchasing decision for life insurance contracts.

Lapse has been an area of intense academic interest since the 1970s, but empirical studies are limited to a few countries and factors. Kim (2005) provides the first empirical study considering a broader range of explanatory variables. Previously, the focus had mainly been on studying the so-called interest rate and emergency fund hypotheses analyzing the influence of interest rates and unemployment rates on lapse, respectively. These hypotheses conjecture that lapse is driven by market and/or product rates of return or adverse economic conditions (for details see Section 2.). More recent publications studying these hypotheses include, e.g., Kuo et al. (2003) for the U.S., Outreville (1990) for the U.S. and Canada, and Dar and Dodds (1989) for the U.K. Both, the variables and their specifications considered to test these hypotheses vary widely. For the interest rate hypothesis, market interest rates (see Kuo et al., 2003) or internal and external (i.e., for alternative assets) rates of return (see Dar and Dodds, 1989) are considered. The emergency fund hypothesis focuses primarily on unemployment (rates), but using different specifications. Only Outreville (1990) considers with transitory income an additional factor accounting for economic growth. The results of these studies are not consistent. While Outreville (1990) finds support for the emergency fund hypothesis in the U.S., Kuo et al. (2003) favor the interest rate hypothesis. Dar and Dodds (1989) find evidence in favor of the emergency fund hypothesis for the U.K., but no evidence for the interest rate hypothesis. These conflicting results can probably be attributed to differences in methodology and the exact specifications of the variables.

Kim (2005) considers economic variables as determinants for lapses as well as policyholder information on policy age since inception. Kim (2005) employs logistic regression models to identify lapse drivers and to develop a predictive lapse model using Korean data. Renshaw and Haberman (1986) provides the first study taking into account product and/or policyholder characteristics when analyzing lapse data of seven Scottish life insurers. Recent studies include Cerchiara et al. (2008) studying Italian data, while Spanish data are analyzed in Milhaud et al. (2010). Besides these empirical studies different theoretical lapse rate models have been discussed, e.g., Kolkiewicz and Tan (2006) or Kochanski (2010a). These models are used in simulation studies, but are not calibrated to empirical (i.e., real-world) data. So far, no study analyzed lapse in the German life insurance market which ranks sixth in the world and fourth in Europe in terms of life insurance premiums in 2009 (see SwissRe, 2010).

The present paper extends the existing literature on lapse (rates) in the German life insurance industry by analyzing a sample of 133 German life insurance companies over the time period 1997 to 2009. The starting point for the analysis is the logistic regression model presented by Kim (2005). One of the main goals of the present analysis is to compare the results directly to existing ones for other markets. This allows us to answer the question as to whether similar conclusions hold for one of the major European life insurance markets compared to other markets.

The logistic regression model is used to study the determinants of lapse and to derive a model for predicting future lapse rates. Furthermore, this work extends the existing approach of Kim (2005) as follows:

- The results of the analyses are discussed in the context of the interest rate and emergency fund hypotheses.

- Unit-linked products are considered beyond traditional life insurance products (i.e., endowment, annuity, term life). This allows us to reveal any differences between these product categories.

- This paper covers a broad range of explanatory variables and is not limited to factors related to the interest rate and emergency fund hypotheses. The information available are company level data for all German life insurers. These data do not allow to account for specific product or individual policyholder characteristics. Instead, company characteristics are analyzed in addition to economic indicators. Fixed effect regression models are, hence, used in addition to OLS models.

- Classification tables are used as additional measures of model quality beyond estimated errors between real and predicted lapse rates.

- The estimated regression models for the different product categories considered are explicitly validated to assess the predictive power of these models.

The findings indicate that the main determinants of lapse are very similar across all product categories, except that the direction of impact is reversed for unit-linked products compared to traditional life insurance products (i.e., endowment, annuity, and term life). In particular, the interest rate and emergency fund hypotheses hold only for unit-linked business in the German market. The assessment of the model quality using estimated errors indicates that the results for the German market are comparable to those of Kim (2005), but the model quality depends on the concrete model specification. Furthermore, the validation procedures imply that the estimated regression models provide reasonable predictions for lapse rate developments in the near term. This requires assumptions regarding the future development of the underlying explanatory variables. Predicted lapse rates, hence, cannot be understood as precise point estimates.

This paper is structured as follows: Section 2 provides a detailed review of the existing literature on lapse and surrender, and derives the main research questions addressed in this work. Section 3 describes the data and methodology employed. Section 4 presents the empirical findings and Section 5 concludes this paper.

2. Related Literature and Research Question

It is important for insurance companies to understand lapse dynamics. According to Kuo et al. (2003), lapse influences an insurer's liquidity and profitability for three reasons: (1) The insurer might suffer losses from lapsed policies due to upfront investments for acquiring new business; (2) the insurer might face adverse selection with respect to mortality and morbidity as customers with adverse health are less likely to lapse their contract; and (3) the insurer might be exposed to a liquidity risk when forced to pay the cash surrender value for lapsed policies. The importance of lapse is further discussed in the field of valuation and management of embedded options in life insurance contracts. The case of the Equitable Life Assurance Society in the U.K. further intensified this discussion of the assessment of embedded options. The decline of the company was related to pension policies including guaranteed annuity options as outlined in O'Brien (2006). In the 1990s, market annuity rates dropped significantly. The typical annuity rate fell below the guaranteed level making that annuity option valuable for the customer. Therefore, insurers need to pay attention to all embedded options, including the policyholder's option to lapse a life insurance policy.

The lapse/surrender option has been studied widely in the literature. It is another implicit option contained in insurance contracts which is usually not explicitly taken into account for the pricing of life insurance contracts. In recent year, the lapse option received increased academic attention. Bacinello (2003) defines the surrender option as American-style put option that allows the policyholder to sell back the contract to the insurer at the cash surrender value. By analyzing the value of the surrender option in Italian endowment policies, the author finds that the value of the surrender option can account for up to 10% of the premium depending on the penalty function used to calculate surrender charges. Grosen and Jørgensen (2000) develop a dynamic model and use contingent claims analysis to value the surrender option. Under certain market conditions the surrender option can be quite valuable accounting for up to 50% of the contract's fair value. Analyzing the surrender option of French contracts, Albizzati and Geman (1994) identify surrender as systemic risk for life insurers, since the option value accounts for a significant percentage of the policy value. The German supervisory authority BaFin considers exemptions from premium payment as lapse. This so-called paid-up option is included in most life insurance contracts. Gatzert and Schmeiser (2008) assess the risk potential of the paid-up option. Additionally, the authors study the resumption option (i.e., the insured can resume premium payments once after exercising the paid-up option) and flexible payments option (i.e., the policyholder is able to stop and resume premium payments at multiple points in time). The value of the pure paid-up option increases tremendously when the guaranteed interest rate is reduced. It can account for more than 10% of the present value of expected premium payments. All of these valuation models, however, lack a robust lapse rate model (see Kuo et al., 2003).

Within the current Solvency II project, lapse risk has been identified as one of the main risk drivers. The Committee of European Insurance and Occupational Pensions Supervisors (CEIOPS) conducts a number of large scale field-testing exercises, so-called quantitative impact studies (QIS), on behalf of the European Commission. The goal is to assess the practicability, the implications and the potential impact of different alternatives considered for the new solvency regime. According to the results of QIS 4 (see CEIOPS, 2008, p. 173 and 192-193), the lapse risk accounted for about 50% of the solvency capital requirement of the life underwriting module which itself constitutes the second largest component of the overall solvency capital requirement (QIS 4 was run between April and July 2008 based on financial data from 2007). The general calculation approach of the lapse risk and the calibration used for the shock parameters remained unchanged for the lapse risk module under QIS 5 which was conducted between August and November 2010 (results of QIS 5 will be available in April 2011). The solvency capital requirement for the lapse risk is calculated as maximum of three stress scenarios which are broadly defined as follows (for details see CEIOPS, 2010, p. 155-159): (1) long-term decrease of lapse rates by 50%; (2) long-term increase of lapse rates by 50%; and (3) mass lapse event of 30% of all policyholders. So far, there is only limited empirical justification to which extent these choices for the stress parameters are appropriate.

According to Kuo et al. (2003), the root causes for lapsing have attracted academic interest for some time. Two main hypotheses are investigated:

1. The *interest rate hypothesis* assumes that savings through life insurance is sensitive to rates of return. Kuo et al. (2003) argue that policyholders lapse

their policies to exploit higher interest rates and/or lower premiums in the market when market interest rates rise. Increasing interest rates act as opportunity cost for owning life insurance.[1] Dar and Dodds (1989) conjecture a positive relationship with the internal rate of return on insurance policies and a negative relationship with rates of return on other financial assets.

2. The *emergency fund hypothesis* conjectures that personal financial distress forces policyholders to lapse their contracts in order to access the cash surrender value (see, e.g., Outreville, 1990).

As no theoretical proof or disproof for these hypotheses exists, they have been studied empirically. Outreville (1990) studies the emergency fund hypothesis with lapse rate data of whole-life insurance in the U.S. and Canada. The results provide consistent evidence for the emergency fund hypothesis. Dar and Dodds (1989) test both hypotheses using endowment policies of U.K. life insurers. They find evidence in favor of the emergency fund hypothesis, but no significant relationship between surrenders and rate of return. Kuo et al. (2003) investigate the competing lapse rate hypotheses for U.S. data using a cointegration analysis to address long-term lapse dynamics. They find that the interest rate effect is economically more significant than the unemployment rate in explaining the lapse rate dynamics. In other words, the interest rate hypothesis is favored over the emergency fund hypothesis. To conclude, the results of these studies examining the interest rate and emergency fund hypotheses are inconsistent. These differences can partly be attributed to the specific data samples studied, time periods covered, and methods used. Additionally, the variable specifications to test both hypotheses vary within the existing literature. While Kuo et al. (2003) consider only market interest rates to test the interest rate hypothesis, Dar and Dodds (1989) use an internal and external rate of return to differentiate explicitly between the underlying contract and other financial assets in the market. All of these studies consider unemployment as a variable to assess personal financial distress, but use different specifications. Kuo et al. (2003) and Outreville (1990) use the yearly unemployment rate. Dar and Dodds (1989) consider the annual rate of growth in the level of unemployment and the level of actual unemployment relative to trend unemployment as specifications of the emergency fund variable. Both Kuo et al. (2003) and Dar and Dodds (1989) relate the emergency fund hypothesis with economic recessions, but they do not study any additional indicators. Only Outreville (1990) considers an additional factor beyond unemployment. The so-called transitory income, calculated as difference between current income and expected normal income, is used as a measure of economic growth. Thus, the inconsistencies in the results of these studies might be due to these differing variables.

The choice of appropriate lapse functions to model lapse rates, e.g., for the use

[1] Due to the complex surplus distribution mechanisms in life insurance smoothing surplus/interest rate volatility, the participation rate follows long-term interest rate trends with a certain time gap. Furthermore, equilibrium premiums decrease with increasing interest rates. It is more likely, hence, that a newly acquired contract will provide the same coverage at a lower premium.

in internal models under Solvency II, has been discussed in recent literature. Examples for possible lapse functions can be found in Kolkiewicz and Tan (2006), Kochanski (2010a), Giovanni (2010), and the references therein. Due to the lack of statistical data and the wide variety of factors influencing policyholder's behavior, most of these approaches are theoretical and not directly linked to real-world data. Kim (2005), Cerchiara et al. (2008), and Milhaud et al. (2010) first developed lapse rate models based on empirical data. Kim (2005) models lapse rates of a Korean life insurer using the logit and complementary log-log function, respectively. Kim (2005) considers as explanatory variables both economic indicators (e.g., interest rates, unemployment rates, economic growth rates) and policy characteristics (policy age since inception) and compares the results with the less sophisticated arctangent model. Scottish, Italian, and Spanish lapse data are analyzed by Renshaw and Haberman (1986), Cerchiara et al. (2008), and Milhaud et al. (2010), respectively. All analyses use generalized linear models to assess relevant contract features and policyholder's characteristics regarding lapse behavior. Renshaw and Haberman (1986) focus their analysis on age at entry, duration of policy, type of policy, and company (having data from seven different life insurers). The case study of Cerchiara et al. (2008) shows the importance of policy duration, calendar year, product class, and policyholder age on lapse rates. Milhaud et al. (2010) find the biggest surrender risks for policies including a fiscality constraint, i.e., surrender charges only apply for a certain part of the contract duration.[2] As soon as the contract has reached the point when the policyholder can surrender without penalty, the lapse risk increases significantly. Other relevant risk factors include policyholder age or method of payment (i.e., regular or single premiums where regular premiums are further divided into monthly, bi-monthly, quarterly, half-yearly and annual installments).

So far, lapse rates have been studied empirically only to a limited extent in the German life insurance market. Eling and Kiesenbauer (2011) and Cottin et al. (2007) focus on the relationship between lapse rates and surplus participation only. This paper studies empirically lapse rates in the German market by addressing the following three research questions: (1) What are the main determinants of lapse in the German life insurance market? (2) Do significant differences exist between different product categories? And (3) what is the predictive power of a lapse rate model based on the as relevant identified explanatory variables? This paper answers these questions by analyzing a broad range of determinants and is not limited to explanatory variables related to the interest rate and emergency fund hypotheses. Some of the explanatory variables considered, however, allow us to assess the extent to which these hypotheses hold for the German life insurance market. In accordance with Dar and Dodds (1989), different rates of return are considered to evaluate the interest rate hypothesis. Risk-free and risky alternative assets are modeled separately using market interest rates and stock price developments. The internal rate of return is measured using policy's credited rates. The

[2] This is a specific contract feature which does not hold for all insurance markets. Surrender fees always apply in case of lapsing before maturity in the German life insurance market.

emergency fund hypothesis is addressed using unemployment rates, but further variables are used to assess economic growth: buyer confidence and gross domestic product. Contrary to Kim (2005), Cerchiara et al. (2008), and Milhaud et al. (2010) who analyze company data, the present analysis restricts to market data because only limited data are available. Therefore, the explanatory variables considered are based on economic indicators and company characteristics, but cannot take into account contract or policyholder characteristics apart from the product category.

When discussing lapse, the existence of the secondary market for life insurance needs to be mentioned. Policies are purchased by life settlement providers, market makers, or auctioneers, and are then optionally placed in closed funds or trusts for life settlement securitization or kept in the buyer's own books (see Gatzert, 2010). Certain life insurance policies, which would be lapsed otherwise, are continued through the existence of a secondary market for such policies. Thus, lapse rates and surrender profits will decrease in markets with increasing relevance of the secondary market (see Gatzert et al., 2009). Although the size and relevance of the secondary market for German life insurance policies has been increasing for some time, its importance is still limited entering a state of stagnation (see Gatzert, 2010). Therefore, not taking into account the secondary market for the analysis will be of limited impact for the results.

3. DATA AND METHODOLOGY

3.1 Data

3.1.1 Lapse data

Life insurers treat lapse data highly confidential not only in the German market. Lapse information are therefore publicly available only to a limited extent. Some information, however, needs to be reported under German accounting standards. Lapse data based on sum insured and premiums are available for total business but not split by product category. Data on number of contracts, however, are available by product category. As differences between different product categories are to be investigated, these information is used for the analysis. Measuring lapse rates in terms of contract numbers is commonly used in existing lapse rate studies, e.g., Kuo et al. (2003) or Outreville (1990). Five product categories are distinguished: (1) traditional endowment policies; (2) annuities including disability and long-term care insurance; (3) term life insurance including life insurance policies without surplus participation; (4) group business including endowment, annuity, and residual debt, among others; and (5) other life insurance business consisting almost exclusively of unit-linked business. While the categories (1)-(3) and (5) consist of rather homogeneous products, category (4) is rather heterogeneous. For each of these product categories a further breakdown of the yearly changes in number of contracts is available. In particular, the reduction in number of contracts distinguishes occurrence of event insured (e.g., death or disability), expiry (i.e., regular end of the policy term), surrender/exemption from premium payment, and early lapse (i.e., without surrender value or paid-up sum insured).

This research focuses on total lapse as the objective is to understand the general dynamics of lapse in the German life insurance industry.[3] The corresponding lapse rate is calculated as total number of contracts lapsed divided by the average number of contracts at the beginning and end of the year, which coincides with the definition of the German supervisory authority BaFin except for using number of contracts instead of sum insured.

Instead of using (aggregated) lapse rates as input factors, the analyses are performed on the underlying contract data (i.e., total number of contracts and number of lapses in each year) taking into account the different portfolio size of the life insurers considered. As typically done in empirical research on insurance companies, the potential bias introduced by small companies has to be taken into account (see Epermanis and Harrington, 2006; Eling and Kiesenbauer, 2011). Small contract numbers are a sign of either new entrants or niche players, which are not directly comparable to other market participants. This might, hence, significantly bias the results. Therefore, small companies are removed from the data set. An observation year for a company is removed if the number of contracts is less than 25,000 for endowments, less than 5,000 for annuity/term life/group, and less than 1,000 for other business. These threshold values are the result of the trade-off between deleting enough observations to reduce the above mentioned bias and keeping the data sample as large as possible. The results of the logistic regression model is limited sensitive to variations of the threshold values (the corresponding analyses are available upon request).

3.1.2 Economic explanatory variables

The consideration of current yield, gross domestic product, and unemployment rate is borrowed from Kim (2005). In contrary to Kim (2005) the spread between market interest rate and policy's credited rate is not considered as single variable. Instead both items are considered as separate variables to reflect internal and external rates of return (see Dar and Dodds, 1989). The current yield is used as proxy for the risk-free yield, while the credited rate is used as proxy for the internal rate of return constituting a company characteristic (see 3.1.3). Additionally, stock performance and buyer confidence are used as economic explanatory variables. All of this information is publicly available on a yearly basis since 1991. Financial market data on current yields and stock markets are derived from the German

[3]In a next step, a more detailed analysis of early and late lapse can help to further increase the accuracy of lapse predictions. Early and late lapse rates based on number of contracts are derived in accordance with the definitions of the German supervisory authority BaFin as follows: (1) early lapse rate is calculated as number of all lapses for which neither a surrender value is due nor a paid-up sum insured is calculated as a percentage of new business written and (2) late lapse rate is calculated as number of surrenders plus exemptions from premium payment as a percentage of opening balance at the beginning of the calendar year.

Federal Reserve. Buyer confidence and gross domestic product are surveyed by the German Federal Statistical Office, while unemployment rates are published by the Federal Employment Office. The detailed variable specification considered is discussed in Section 3.2.

1. Buyer confidence (*BC*)
   Data on private spending is used as proxy to assess buyer confidence, i.e., to measure how much money people actually spend for consumption. This can indicate economic growth and can be used as another indicator beyond unemployment rates to validate the emergency fund hypothesis (see Outreville, 1990).

2. Current yield (*CY*)
   The current yield is calculated as weighted average of governmental bonds with a maximum contractual duration of four years and an average remaining duration of three years. It represents the return of risk-free investments.[4] Its use is discussed widely in the context of the interest rate hypothesis, e.g., in Dar and Dodds (1989).

3. Stock performance (*DAX*)
   A stock investment provides a risky alternative to life insurance savings products. The stock performance thus might provide a starting point for explaining the lapse behavior of policyholders, especially in case of traditional saving and unit-linked products. Dar and Dodds (1989) explicitly differentiate between internal and external rate of returns in the context of the interest rate hypothesis, but only consider risk-free alternative assets. This approach is extended here to also capture risky assets.[5] The German stock performance index DAX is used for the analysis since the German life insurance market is considered. Furthermore, the DAX development receives the most public attention and might, hence, constitute an easily accessible information for customers.

4. Gross domestic product (*GDP*)
   The gross domestic product allows us to assess the overall development of the economy. It is, hence, another indicator for economic growth (similar to buyer confidence) and is used as further variable to test the emergency fund hypothesis.

5. Unemployment rate (*UR*)
   Information on unemployment has been studied widely in the context of the emergency fund hypothesis, e.g., in Outreville (1990).

[4]The performance of the German bond market index REX has been considered as further explanatory variable. As it is highly correlated with current yield (correlation coefficient = 0.996), one variable needs to be dropped to avoid multicollinearity in the regression analysis.

[5]Kochanski (2010b) discusses possible specifications of the relationship between lapse rates and capital markets for unit-linked products as well as the existing empirical evidence.

3.1.3 Company specific explanatory variables

Company characteristics are widely used in empirical research on (life) insurance companies. The consideration of age, legal form, and company size is borrowed from Epermanis and Harrington (2006) or Eling and Schmit (2009). Eling and Kiesenbauer (2011) consider the participation rate spread which constitutes an assessment of the internal rate of return of life insurance products. Information on distribution channels are rarely found in empirical literature, probably due to problems with data availability. The detailed variable specification considered is discussed in Section 3.2.

1. Company age (*Age*)
   A driver for the purchasing decision of insurance customers might be the reputation of the company. Companies that have been in the market for a long period of time have acquired reputation, since they have proven their ability to fulfill long-term contract obligations and their financial stability. The foundation year of the life insurance unit is used in case of insurance groups to derive the companies' age. This information can be obtained from the companies' websites. In cases where no specific foundation year for the life unit is available, the foundation year of the corresponding insurance group is used instead. For a limited number of mainly very small insurers, no foundation date is available and, thus, the company is dropped from the analysis. The company age can be calculated straightforwardly for all companies, for which the foundation dates are available, for the years 1995 to 2009. The age factor is scaled by considering the natural logarithm of company age, as it is done for the size variable.

2. Distributional focus
   German life insurers sell their policies through a variety of distribution channels. The tied agent (*TA*), bank (*Ba*) and broker (*Bro*) channels are predominantly used, while the share of the direct (*Di*) channel is steadily increasing. Additionally, life insurance contracts are sold through branches (*Bra*) and pyramid sales organizations[6] (*PS*). Unfortunately, data regarding the distribution mix of German life insurers are not readily available. A variety of sources is used including company press releases and annual statements to estimate the annual distribution split for new business from 1995 to 2009. As the distribution split is only gradually changing for most insurers, this should provide a reasonable estimate of the distribution split for business in force. The data include rough estimates and, for some companies and years, no split is available at all. In the latter case, the corresponding company year is dropped from the analysis. To reflect this variety of distribution channels, the analysis is not based solely on the main channel, which is not clear for some players. Instead indicator variables are used for each

[6] Distribution channel which is characterized through a specific organization. Typical is the pyramid-like and hierarchical structure with a multi-level sales organization.

distribution channel, indicating whether this channel accounts for a substantial amount of business. A distribution channel is assumed to be significant if it accounts for more than 25% of new business. Thus, each company can have at most three substantial distribution channels. On average, each company has about 1.3 significant distribution channels.

3. Legal form (*Mutual*)
   The German insurance regulation differentiates four legal types of insurance companies: (a) stock corporation, (b) mutual insurance cooperation, (c) insurance company under public law, and (d) subsidiary of foreign insurance company. The corresponding information is available from the German supervisory authority BaFin. As of the end of 2009, the German life insurance market consists of 74 stock corporations, 19 mutual insurance corporations, 4 corporations under public law, and 2 subsidiaries of foreign insurance corporations writing new business. Since the number of insurance companies under public law and subsidiaries of foreign insurers is limited and most of them operate as stock corporations, an insurer is categorized as being a mutual or not.

4. Company size (*Size*)
   Company size is measured by the amount of gross premiums written. The total premium volume takes into account not only new business written during the considered year, but also premiums from existing business. It hence allows us to control for size effects. As in other analyses, the size parameter is scaled by considering the natural logarithm of gross premiums written (see Epermanis and Harrington, 2006). The corresponding data is again derived from publications under local accounting standards and is available for all companies with business operations from 1995 to 2009.

5. Participation rate spread (*Spread*)
   The surplus participation mechanism in Germany is complex (see, e.g., Eling and Kiesenbauer, 2011) and applies mainly to saving products, i.e., endowments and annuities. The yearly declaration of the participation rate takes into account the entire business operation and represents a measure for the internal rate of return (on the saving component of the premium). In accordance with Dar and Dodds (1989), the participation rate is, hence, used to test the interest rate hypothesis (see Section 2.). The announcement of the participation rates is covered extensively in the press and media, at least for all large and medium-sized players. This information is thus available to customers and other stakeholders. The participation rate for each year is declared at the end of the previous year. Most companies make their announcements through press releases or in their annual statement. Comparisons of the participation rates are readily available for the largest insurers by third-party providers from 1996 to 2009. The participation rate can differ by tariff generations and products. For the sake of simplicity and to have only one value for each year and company, only traditional en-

dowment products are taken into account using the arithmetic average of all tariff generations. This is a reasonable simplification since, in practice, most companies do have the same surplus participation for all tariff generations and product categories. The absolute value of the participation rate has only a limited meaning for the comparison of life insurers. Instead the participation rate spread is calculated as the participation rate of the considered company minus arithmetic average participation rate of all market participants for which the information is available.

3.2 Methodology

The present analysis investigates the influence of economic and company specific explanatory variables on the lapse behavior of German life insurance policyholders. Lapsing an insurance contract is a binary event, as a contract is either lapsed or continued (and maybe lapsed in a later time period). Kim (2005) discusses two possible functions to model lapse rates in this context, namely the logit function and the complementary log-log function. Additionally, the author compares the corresponding models with the arctangent model. The analyses show that the differences between the logit and complementary log-log function are limited, but both being significantly better than the arctangent model. The latter models the lapse rate as function of the interest rate only, i.e., only one explanatory variable and three additional model parameters are considered. Therefore, it is not surprising that such a model performs worse than the other models taking into account several explanatory variables. As the aim of this study is to identify determinants for the lapse behavior in the German life insurance industry, this modeling approach is not considered further. The present analysis focuses on the logit function using the corresponding logistic regression model. The model based on the complementary log-log function is analyzed to determine the robustness of the logistic regression model. The results are consistent with Kim (2005) as the complementary log-log function yields similar results as the logit function.[7]

According to the description of available data in Section 3.1, all company data depend on two factors, the company and the year of observation, while economic data only depend on the year of observation. The analysis hence considers the following modeling equation for the logistic regression model:

$$ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \beta^T \cdot X_{i,t} + (\alpha + u_i),$$

where i indicates the respective life insurance company (individual or firm effect) and t denotes the considered year (time effect). The term $p_{i,t}$ denotes the lapse probability for a contract of company i in year t. The coefficient vector β is determined using maximum likelihood methods. The estimated coefficient vector is hence asymptotically normal distributed (see Aldrich and Nelson, 1984). Statistical tests can be derived from this property that allow us to assess which

[7]Detailed results are available upon request.

explanatory variables have a significant impact on the lapse probability.[8]

$X_{i,t}$ specifies the vector of considered explanatory variables and is given by $(E_t, C_{i,t})^T$ where E_t and $C_{i,t}$ represent the economic variables and company characteristics, respectively. E_t consists of the components $(BC_t, BC_{t-1}, CY_t, CY_{t-1}, DAX_t, DAX_{t-1}, GDP_t, GDP_{t-1}, UR_t, UR_{t-1})^T$ which are defined as follows:

BC_t = yearly change (in percent) of spending for private consumption in year t

CY_t = arithmetic mean of 12 monthly averages (in percent) of current yield from Jan. to Dec. in year t

DAX_t = yearly change (in percent) of arithmetic mean of 13 monthly DAX closing values from Dec. in year $t-1$ to Dec. in year t

GDP_t = yearly change (in percent) of gross domestic product in year t

UR_t = yearly average unemployment rate (in percent) in year t.

The values of the economic indicators are the same for all companies for a given year, i.e., varying only with year t but not with company i. They are displayed in Table 1 from 1996 to 2009.

The Dickey-Fuller unit root test is performed to decide whether the time series of each economic variable is stationary or not (see Dickey et al., 1984). This test indicates that only the time series for buyer confidence is stationary. As usually done in this case, the time series is differenced for all non-stationary variables, i.e., considering $\widehat{y}_t = y_t - y_{t-1}$ where y_t denotes the original time series and $\widehat{y}_t$ denotes the differenced time series.

Considering an additional, lagged variable for all economic indicators is due to the fact that policyholders might only react with a certain time gap to changes in economic conditions.[9] For instance, a policyholder is less likely to lapse an existing life insurance contract, if unemployment is assumed to be only temporarily. However, if the policyholder has been unemployed for a longer period of time, the policyholder might be forced to cancel the contract to access the corresponding funds.

[8] All analysis are performed using the SAS system using the procedures LOGISTIC and GENMOD for the logistic regression model and the complementary log-log function, respectively. Details on logistic regression models with SAS can be found in Allison (1999). As overdispersion can be observed using the (simple) logistic regression model, i.e., the presence of greater variability in the data set than would be expected under the logistic regression model, Williams' method is applied to model overdispersion (see Williams, 1982). The fixed effects logistic regression model is estimated by means of an OLS regression using dummy variables, as the number of observations (i.e., contracts) per individual life insurer is large.

[9] A lag of two years was also considered. This yields no major changes in the results and hence is not further analyzed since the consideration of any additional lag period reduces the length of the data set by one year.

The vector of company characteristics $C_{i,t}$ is given by $(Age_{i,t}, Ba_{i,t}, Bra_{i,t}, Bro_{i,t}, Di_{i,t}, PS_{i,t}, TA_{i,t}, Mutual_{i,t}, Size_{i,t}, Spread_{i,t}, Spread_{i,t-1})^T$ where

$Age_{i,t}$ = company age in year t measured as natural logarithm of years since the foundation of the life insurance unit or group

$\left.\begin{array}{l} Ba_{i,t} \\ Bra_{i,t} \\ Bro_{i,t} \\ Di_{i,t} \\ PS_{i,t} \\ TA_{i,t} \end{array}\right\}$ = indicator variable specifying substantial distribution channels, i.e., 1 if bank, branch, broker, direct, pyramid sales, and/or tied agent channel accounts at least for 25% of new business premiums

$Mutual_{i,t}$ = indicator variable specifying whether company is a mutual, i.e., 1 if company is a mutual and 0 otherwise

$Size_{i,t}$ = company size at the beginning of year t measured as natural logarithm of gross premiums written (in € million) in year $t-1$

$Spread_{i,t}$ = participation rate relative to arithmetic market average (in percentage points) for year t.

Summary statistics of the company characteristics from 1997 to 2009 can be found in Table 2. The rationale for using an additional, lagged variable for the participation rate spread is to test again for potential time lags in the policyholder response.

Considering 21 explanatory variables in total yields a complex model. A diagnosis for multicollinearity between the explanatory variables has been conducted using variance inflation factors and condition-index (see Belsley, 1991). No multicollinearity issues have been detected. In order to avoid issues with overfitting[10], backward selection is applied. Explanatory variables that are not significant are dropped successively until all remaining variables are significant at a given significance level. Different significance levels have been tested. Finally, the 1% level has been chosen since it reduced the number of significant explanatory variables most but worsening only slightly the model fit compared to other significance levels.[11] This reduces model complexity, in particular, when using the model for predictions.

Depending on the specification of the intercept $(\alpha + u_i)$ two different types of logistic regression model are distinguished:

(i) Ordinary least square (OLS) model: $u_i \equiv 0, \forall i$
The OLS model does not take into account individual and time effects, but treats each observation equally.

[10]Overfitting can occur if the model contains too many parameters to be estimated compared to the information content of the data considered (see Harrell, 2001). This can lead to non-stable parameter estimates. A model including too many explanatory variables will thus yield worse predictions when applied to new data.

[11]Results for the other significance levels considered, i.e., 5% and 10%, are available upon request.

(ii) Fixed firm effects (FE) model: $u_i = c_i, \forall i$, with a fixed constant c_i for each company i
The data set used covers about 70 to 80 different insurance companies over a time period of 13 years. This setup of having a wide but short data set is typical for panel data. In this case, heterogeneity across units is often the central focus of the analysis (see Greene, 2003). Accordingly, only individual effects are taken into account in the FE model, but no time effects. Besides the data design, two other reasons support the non-consideration of time effects. First, the explicit use of time effects would partially offset the impact of the considered explanatory variables, in particular the economic ones. As these effects are to be analyzed, this effect is not desired. Second, the impact of some explanatory variables cannot be estimated when time effects are included in the regression model due to multicollinearity. Fixed effects are assumed to be constant over time for each company i which allows for arbitrary correlation between the fixed effect and the explanatory variables $X_{i,t}$.

The regression analysis takes into account only complete data sets for a specific company and year. The data set for company i in year t is complete, if lapse data and data for all explanatory variables are available. Taking into account data availability and the considered time lag for some control variables, the logistic regression model covers 50-55% of all company years in 1997 to 2009 (corresponding to 801 company years for endowment, 825 for annuity, 820 for term life, 688 for group, and 495 for other). That is about 70-85% of the corresponding number of contracts.

4. Results

4.1 Regression results

As discussed in Section 3.2, OLS and FE models are estimated for five product categories: endowment, annuity, term life, group, and other. In order to reduce model complexity, explanatory variables are dropped successively until all remaining variables are significant at the 1% significance level. These variables remain in the reduced model for the product category considered, while all other variables are dropped, i.e., the considered model consits only of the significant explanatory variables. The results of the reduced logistic regression model are displayed in Table 3 where each coefficient estimate indicates a significant explanatory variable in the full model (at the considered 1% level). A positive coefficient indicates that the lapse probability increases/decreases with increasing/decreasing values of the corresponding explanatory variable. For negative regression coefficients, this relationship is reversed, i.e., increasing/decreasing values of the explanatory variable decrease/increase the lapse probability.

In the OLS model, only a limited number of economic indicators is significant. For endowment and group, none of the economic indicators is significant indicating that for those products company characteristics are more important than economic conditions. Additionally, endowment and group business are the two largest subgroups with roughly 500 and 200 million contracts, respectively. Therefore, the corresponding portfolios are more stable over time than smaller portfolios.

Lagged buyer confidence, current yield, and GDP are significant for annuities. Increasing values for buyer confidence and GDP increase lapse rates (contradicting the emergency fund hypothesis). Although one might expect the opposite behavior, i.e., private savings increase in good economic conditions, a possible explanation might be that in favorable economic conditions customers use accumulated funds for larger acquisitions, e.g., to buy a house. A short-term reduced lapse rate with increasing interest rates contradicts the interest rate hypothesis. However, a slight increase in interest rates will not completely offset surrender charges indicating that it might still not be beneficial to cancel an existing contract.

Similar to annuities, buyer confidence and lagged current yield are significant for term life having identical signs (i.e., contradicting both the interest rate and emergency fund hypotheses). The increase in lapse rate due to improvements in buyer confidence, however, might be explained as follows. In better economic conditions, customers might think that they are able to cover the corresponding risk by themselves.

Considering other business, which consists mainly of unit-linked business, buyer confidence and lagged current yield are significant as for term life but with opposite impact (supporting the interest rate and emergency fund hypotheses). Additionally, lagged gross domestic product and lagged unemployment rate are significant having a negative and positive impact on lapse rates respectively. This also supports the emergency fund hypothesis, as lapse rates decrease in good economic conditions, i.e., with increasing GDP and decreasing unemployment rates.

The number of significant company characteristics in the OLS model is higher for all product categories compared to the number of significant economic indicators. While distributional focus is significant - in different specifications - for all products, the other characteristics are significant only selectively. The impact is consistently positive or negative for most of the characteristics considered.

Age is only significant for long-term savings products (endowment and annuity). The older a company is, the smaller the lapse rates are. This result thus might be interpreted as sign of stability, as older companies have proven for a longer time that they are able to fulfill their long-term contractual obligations. Along with a better brand awareness and reputation, this might prevent customers from lapsing their contracts.

The direction of impact is broadly as expected for the different distribution channels. On the one hand, a closer relationship between company and customer (i.e., branches and tied agents) or an increased customer knowledge (direct channel) has a positive impact on lapse rates, i.e., resulting in lower lapse rates. On the other hand, distribution channels that are mainly incentivized through commissions tend to exhibit higher lapse rates.

The results regarding the legal status are mixed. While being a mutual reduces

lapse rates for endowment, it has an adverse effect for term life. Similar to company age, the size of the company is negatively related to lapse rates, but only for term life and group business.
Participation rate spread is only significant for endowment and other business. Both results are rather unexpected. For other business, no influence might be expected, except that the level of participation rate spread might be an indicator for product quality in general. For endowment, there is a positive relationship meaning that higher participation rates increase lapses, which contradicts the emergency fund hypothesis and seems to be irrational.

The FE model allows the intercept of the regression model to vary for each company, i.e., considering one additional variable per company. Therefore, it is not surprising that almost all company characteristics are not significant. Instead the economic explanatory variables are significant in more cases compared to the OLS model. For all product types, at least one specification of the explanatory variable, i.e., without or with time lag, is significant except for endowment.
The impact of buyer confidence, current yield, and GDP is consistent with the results of the OLS model, as discussed above (contradicting the interest rate and emergency fund hypotheses for endowment, annuity, term life, and group business). The direction of impact is opposite for other business (supporting both hypotheses). An increasing stock index leads long-term to increasing lapse rates for unit-linked products. As customers participate only partly from this upswing, some might decide to invest directly into the stock market. For all other product categories, a positive relationship between stock markets and lapse rates can only be observed for annuities in the short-term. Long-term, annuity, term life, and group business even exhibit decreasing lapse rates when the stock index increases. The emergency fund hypothesis holds only short-term for term life and group business but only with respect to unemployment rates. Lapse rates increase with increasing unemployment rates. Long-term, this effect is reversed. This contradicts the emergency fund hypothesis. For other business this effect is completely reversed, as lapse rates first decrease before they increase again.

Overall, the interest rate and emergency fund hypotheses do not hold for traditional, i.e., not unit-linked, life insurance products in the German market. Both hypotheses, however, are supported when other business representing almost exclusively unit-linked products is considered. These results are rather surprising in the beginning, but might be explained with some of the underlying product differences. Unit-linked life insurance products became more popular in the German market in the late 1990s. These products might have been purchased especially by younger customers (being more willing to take risks) in the beginning. Nowadays unit-linked products replace traditional products more and more. Therefore, the portfolio of unit-linked business is still much smaller and might have a different customer composition. Additionally, the surrender values are calculated differently. For unit-linked products, it strongly depends on the value of the underlying investment funds and is more volatile. Traditional products work like a kind of

savings account where interest is accrued over time with a much less volatile interest rate.
If we assume that increasing interest rates are related to an upward trend at the stock markets (maybe with a certain time lag), increasing lapse rates for unit-linked products might indicate profit-taking from customers and shifting it into less risky assets providing a higher yield than previously. This might be a possible explanation why the interest hypothesis does hold for unit-linked products. In contrast, the accrued interest for traditional products is based on the investment result of the life insurer. As the investment portfolio consists mainly of bonds, the resulting investment yield will be close to the interest rate level in the market such that the above described arbitrage is not possible. Additionally, the portfolio is much larger such that the corresponding effects might be much harder to observe compared to a rather young and small portfolio.
As discussed above unit-linked products have broadly become available only in recent years and might generally be purchased by younger customers. Younger people usually have less savings. Hence, if they lose their job, they are more likely to be forced to access life insurance savings. This might explain why we find support for the emergency fund hypothesis for unit-linked products, but not for traditional products. Another relevant aspect is the question as to which extent the general unemployment rate is a good proxy for unemployment in the group of people possessing life insurance contracts. Maybe it is a better proxy for unit-linked products than for traditional products which might again be related to the average age of the customers.
The differences discussed above are quite interesting. This discussion, however, can only provide a first contribution for a further investigation of this differences. In order to explore these differences in more detail, contract information are required. In particular, information on the age of the policyholder and the type of products would be necessary.

4.2 Assessment of model quality

This section focuses on the comparison of real and predicted lapse rates in order to assess the goodness of fit of the regression models. There exist statistical tests to assess the global goodness of fit for logistic regression models. According to Browne and Cudeck (1992), however, if the sample size is sufficiently large in practical investigations, it can be expected that even models approximating the data closely will be rejected. Therefore, these tests are of limited use in the present analysis covering hundreds of company years and millions of insurance contracts. Model fit statistics, e.g., Akaike information or Schwartz criterion, as discussed in Kim (2005), have been analyzed in the fitting process. Due to differences in the data sets, the concrete values provide only limited information, but are available upon request. The measures used to assess goodness of fit are: (1) estimated errors between predicted and real lapse rates, and (2) classification tables for prediction accuracy.

The consideration of estimated errors is taken from Kim (2005), allowing for a direct comparison of the results. The root mean square error (RMSE) is calculated as

$$\frac{1}{\sqrt{n}}\sqrt{\sum_{k=1}^{n}(y_k-\hat{y}_k)^2}\ ,$$

while mean absolute percentage error (MAPE) is calculated as

$$\frac{1}{n}\sum_{k=1}^{n}\frac{|y_k-\hat{y}_k|}{y_k}\ ,$$

where y_k denotes the k-th real value, $\hat{y}_k$ denotes the k-th predicted value, and n is the sample size (see Kim, 2005).[12] The results for RMSE and MAPE are displayed in Table 4 covering OLS and FE models for all product categories. Both RMSE and MAPE are significantly lower for the FE model. MAPE values above 30% for the OLS model indicate that a single model for all companies is not appropriate. Although lapse rates are rather stable over time for most companies, lapse rates are at different levels at least for some companies. Obviously, the considered explanatory variables capture this difference in levels only to a limited extent.

The analysis of Kim (2005) is based on monthly data from a Korean insurer covering September 1997 to December 2001, i.e., 52 months. The product categories considered include endowment, annuity, protection plan, and education plan. The corresponding results for RMSE and MAPE are included for comparison in Table 4. The results of the FE model are consistent with Kim (2005). The MAPE values are around 10-20% in both cases. The RMSE values are higher for the FE model. This can, however, be explained for endowments and annuities through the larger data set covering more than 800 company years.[13] This rationale does not completely explain the large difference in case of term life/protection. The lapse rate level for term life is 5.5-6.0%, about three to four times that of the protection plan considered in Kim (2005) which is around 1.5%. This might be explained by major differences in the underlying products, i.e., German term life insurance might not be directly comparable to Korean protection plans. Compared to the other products, RMSE and MAPE are much higher for group and other insurance. This can be credited to several effects which are not captured by the considered logistic regression models. This includes, e.g., outlier values for single companies and years, lapse rates below 1% (significantly increasing MAPE), and the presence of time trends in young portfolios (in particular for other business). Hence, the models for group and other business are of limited use, as long as the above mentioned obstacles are not addressed. This would require further information that is in general not publicly available and, thus, is not investigated further.

[12] Further specifications of estimated errors have been considered. The results are available upon request.

[13] Assuming constant errors between real and predicted values, increasing the sample size by a factor of 16 increases the RMSE by a factor of $\sqrt{16}=4$.

Classification tables of lapse and non-lapse events are the other measure considered to assess model quality (see Hosmer and Lemeshow, 2000). Considering portfolios of identical contracts for each company and year, the usual cut-point dependent approach is slightly modified making the consideration of cut-points unnecessary. Based on the estimated regression model, a predicted lapse probability is derived for each company and year. Using this probability, the predicted number of lapses and non-lapses can be calculated for each company and year based on the number of policies in force. These predicted values can be compared to the real, observed (non-)lapses. A 2×2 frequency table is obtained by cross-classifying the observed and predicted responses. This classification table is displayed for endowments in Table 5. Endowments constituting the largest product category (accounting for about 40% of all policies in force in 2009) are used as an example to explain the corresponding methodology and key characteristics. The results for all other product categories can be found in Table A.1.

For endowments (Table 5), out of 18.7 million contracts, which have actually been lapsed, 15.7 million contracts are correctly predicted as lapse with the OLS model, while 3.0 million contracts are wrongly predicted as not being lapsed. From the contracts not being lapsed, 489.3 million are predicted correctly and 2.0 million are predicted incorrectly.

The accuracy of the classification is measured by its sensitivity, i.e., the ability to predict a lapse event correctly (calculated as ratio of number of correctly predicted lapses over total number of predicted lapses), and specificity, i.e., the ability to predict non-lapses correctly calculated correspondingly. Three other conditional probabilities are usually considered: (1) the false positive rate, (2) the false negative rate, and (3) the rate of correct classifications. The false positive rate is the proportion of predicted lapse responses that were observed as non-lapses. The false negative rate is the proportion of predicted non-lapse responses that were observed as events. The rate of correct classifications is calculated as number of correct predictions over total number of contracts considered. The resulting ratios for endowments are also displayed in Table 5. The results are better for the FE model for all product categories. In particular, the indicators relating to lapse events, i.e., sensitivity and false positives rate, are above 90% and below 10%, respectively, for all products except group business. These results support the conclusion that the model accuracy for the group business is limited (see above). The results for other business, however, are in line with the other product categories indicating that the model quality might be comparable to the other products.

Positive/negative likelihood ratios can be calculated based on sensitivity and specificity. The positive likelihood ratio is calculated as $sensitivity/(1 - specificity)$, while the negative likelihood ratio is given by $(1 - sensitivity)/specificity$. This allows us to assess the predictive quality of the model. Likelihood ratios above 10 (positive) and below 0.1 (negative) are considered to provide strong evidence to rule in or rule out a lapse event, respectively (see Deeks and Altman, 2004). The positive likelihood ratio is for all models much larger than 10, while the negative likelihood ratio is less than 0.15 for all models except group. This is an indication for good predictive power.

4.3 Model validation

Using the same data set for fitting a regression model and assessing the model quality introduces a bias by overestimating the model quality (see Harrell et al., 1996). In order to address and quantify this bias, the model needs to be validated. This is done by splitting the data set into two subsets. The first one is used to fit the regression model, while the second data set is used to generate predictions for the lapse rates. These results are then compared to the real values. Two approaches are considered which differ in the splitting procedure. The validation procedures considered here belong to the data-splitting and cross-validation methods. These are internal validation procedures since the validation is performed on the same data set which is used for model estimation instead of a separate data set (which is not available). Further validation approaches can be found in Harrell (2001), including external validation and bootstrapping.

Method I uses all data up to a certain year to fit the logistic regression models. The model choice remains unchanged, i.e., the model specification is based on the full data set, in order to ensure comparability of the results. The corresponding model is then used to predict the lapse events/rates for the following year only. As the data set considered covers 1997 to 2009, an iterative application of this procedure would allow us to generate predictions for the years 1998 to 2009. The present analysis, however, considers predictions only for 2002 to 2009 as the underlying data set for fitting the regression model requires a certain extent in order to generate reliable predictions. Using five years of observations represents around 40% of the total data set and, in particular, includes information on the financial crisis starting in 2001, which increases the robustness of the model.

Method II removes all data from the data set that correspond to the observation year to be predicted. The remaining data set of 12 observation years is used to fit the regression models. The corresponding models are used to derive predictions for the missing year. Since this approach uses the information from all other years, robust predictions are available for all years from 1997 to 2009.

The model quality of both validation approaches is measured using estimated errors and classification tables. Endowments are again used as example to discuss the methodology and corresponding results (see Tables 6 and 7). The results for all other products can be found in Tables A.2 and A.3. While the estimated errors for the OLS model remain almost unchanged, the values for the FE model increase considerably. The MAPE increases 30-50% for method I and 10-30% for method II. Not surprisingly the increase is smaller for method II than for method I, as method II is based on information for all other years to predict lapse rates of one year, while method I only uses information prior to the considered prediction year.

The classification table for endowments is displayed in Table 7. The results for both methods I and II are largely consistent for the OLS and FE models. Only the false positive rate is three percentage points higher for the FE model using method I. Regarding the other product categories, the results for method II are only slightly worse than the OLS and FE models based on the complete data set. For method I, this conclusion only holds for the OLS models and for the annuity and term life FE model. The FE models for group and other business exhibit large deviations, which can be attributed to the higher volatility in early prediction years.

Overall, these validation procedures indicate that the model quality increases with the extent of the data set used to fit the regression models. As the indicators measuring the model quality decrease only slightly, in particular for method II, the regression models based on the full data set should provide reasonable predictions for future lapse rates.

5. CONCLUSIONS

The present research analyzes determinants of lapse behavior in the German life insurance market from 1997 to 2009. Both macro-economic indicators, e.g., current yield or unemployment rate, and company characteristics including legal form and company size, among others, are considered, but no product and/or policyholder information. Logistic regression models with and without consideration of firm effects have been employed to analyze the available contract data.

Three research questions have been considered in this paper: (1) main determinants of lapse in the German life insurance market; (2) differences between product categories; and (3) predictive power of the resulting lapse rate models. Based on this analyses, the following answers are derived. First, buyer confidence, current yield, and GDP development are the economic indicators most relevant, while distributional focus, company age, and participation rate spread are identified as the most relevant company characteristics. In particular, the interest rate and emergency fund hypotheses do not hold for traditional, i.e., not unit-linked, life insurance products. Both hypotheses, however, are supported when other business (representing almost exclusively unit-linked products) is considered. Second, there are only minor differences between endowment, annuity, term life, and group business regarding significant explanatory variables. Additionally, the impact on the lapse rate is consistently positive or negative for all economic variables and most company characteristics. Endowment business has the least significant variables, which can probably be credited to the fact that this product category contains by far the most policies, which reduces volatility. The results regarding significant variables are similar for other business representing mostly unit-linked products. The impact, however, is opposite for most explanatory variables, in particular the economic ones. Third, the prediction accuracy, which is assessed through estimated errors and classification tables for real and predicted lapse rates, is reasonable for endowment, annuity, and term life, but limited for group and other business.

The estimated logistic regression models using firm effects can be used to provide reasonable predictions for future lapse rates of specific companies. The corresponding predictions should not be viewed as point estimates. Rather they should be used as indications for the lapse rate development based on underlying economic assumptions.
Furthermore, the presented models might provide evidence for the final calibration of the lapse risk within the new European solvency regime (Solvency II). It can help to provide an empirical justification for the considered scenarios to derive the capital requirements in the lapse risk module (see Section 2.), at least for German life insurance products. The considered logistic regression model can help to identify adverse economic conditions which can be used as stress scenarios. Based on the significant explanatory variables and their coefficient estimates for each product category, the lapse rates before and after the specified shock can be calculated. The lapse rate increase might then be considered as a reasonable stress parameter.

The analysis presented here can be extended in various directions and serve as basis for future research. First, the consideration of product and policyholder characteristics (e.g., policy age, policyholder age/sex) might yield further insights into lapse behavior and dynamics. This requires, however, detailed policy data on lapses. Second, lapse rates are usually calculated on premium and sum insured data in the German life insurance market. Therefore, it might be more relevant to use corresponding data for lapse rate modeling. This requires, however, that the corresponding data would be available by product category and not only for total business without any further breakdown. Third, the distinction between early and late lapses might further improve the accuracy of a predictive model based on logistic regressions. Fourth, the considered logistic regression model could be applied to other insurance markets using similar explanatory variables. This would allow us to address the question as to whether consistent results are derived for other insurance markets.

A. Additional results for further product categories

The classification tables for all non-endowment products, i.e. annuity, term life, group, and other are displayed in Tables A.1-A.3. Table A.1 shows the classification tables of the models based on the complete data set, while the results of the validation methods I and II are displayed in Tables A.2 and A.3, respectively.

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Table 1

Values of macroeconomic indicators in 1996-2009 (in %)

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
BC	2.6	2.2	1.8	3.0	3.2	3.9	0.3	1.4	1.6	1.8	2.7	1.5	2.3	-0.1
CY	5.6	5.1	4.4	4.3	5.2	4.7	4.6	3.8	3.7	3.2	3.7	4.2	4.0	3.0
DAX	20.6	43.4	35.8	7.3	31.3	-19.4	-26.1	-24.1	25.2	17.3	26.7	26.5	-15.9	-20.5
GDP	1.0	1.8	2.0	2.0	3.2	1.2	0.0	-0.2	1.2	0.8	3.2	2.5	1.3	-4.9
UL	10.4	11.4	11.1	10.5	9.6	9.4	9.8	10.5	10.5	11.7	10.8	9.0	7.8	8.2

Table 2

Summary statistics for company characteristics 1997-2009

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Age (measured as natural logarithm of years since foundation)													
Minimum	0.00	0.69	0.00	0.00	0.69	0.00	0.00	0.00	0.69	0.00	0.00	0.69	1.10
Maximum	5.36	5.37	5.37	5.38	5.38	5.38	5.39	5.39	5.40	5.40	5.41	5.41	5.42
Avarage	3.63	3.70	3.62	3.65	3.70	3.72	3.73	3.71	3.77	3.78	3.75	3.79	3.83
Median	4.25	4.27	3.95	3.97	3.99	4.01	4.03	4.00	4.02	4.03	4.02	4.03	4.05
Standard dev.	1.26	1.17	1.26	1.24	1.14	1.13	1.13	1.12	1.04	1.05	1.07	1.01	0.97
Distributional focus (1 indicating that corresponding distribution channel is substantial, 0 otherwise)													
Bank	21	23	22	26	26	28	28	25	26	26	25	25	23
Branch	1	1	1	1	1	2	2	3	3	2	2	2	2
Broker	31	35	36	36	36	36	36	34	38	39	38	38	40
Direct	19	20	20	20	20	16	16	15	17	15	14	14	14
Pyramid sales	4	4	4	4	5	5	5	5	5	5	5	5	5
Tied agent	76	78	74	72	69	64	58	52	49	45	44	43	41
Mutual (1 indicating that company is mutual, 0 otherwise)													
0	71	72	72	71	72	63	62	62	61	58	58	57	54
1	20	19	19	19	19	19	19	18	18	17	17	17	17
Size (measured as natural logarithm of gross premium written [in € million])													
Minimum	0.34	0.13	0.30	0.59	0.62	0.64	1.07	1.54	1.29	1.66	1.39	1.25	1.53
Maximum	8.75	8.89	9.01	9.04	9.02	9.17	9.22	9.24	9.35	9.41	9.43	9.44	9.55
Avarage	4.86	4.85	4.94	4.93	4.94	5.09	5.21	5.32	5.37	5.46	5.46	5.45	5.54
Median	5.07	5.05	5.13	5.01	5.05	5.18	5.29	5.46	5.38	5.53	5.48	5.40	5.38
Standard dev.	1.80	1.82	1.82	1.84	1.85	1.82	1.75	1.69	1.69	1.69	1.69	1.72	1.70
(Participation rate) Spread (in percentage points)													
Minimum	-0.76	-0.74	-1.64	-1.06	-1.60	-1.53	-1.16	-1.08	-0.69	-0.68	-0.79	-0.68	-0.73
Maximum	0.74	0.76	0.86	0.74	1.35	2.17	1.65	1.67	1.16	1.14	1.03	0.74	0.62
Median	-0.01	0.01	0.06	-0.06	0.00	-0.03	-0.11	-0.08	-0.04	-0.01	0.00	-0.01	0.02
Standard dev.	0.32	0.31	0.38	0.34	0.51	0.63	0.50	0.49	0.37	0.37	0.33	0.29	0.28

Note: Data availability is limited for some variables, in particular participation rate spread and distributional focus are not available for the entire market but for all large and medium-sized players.

Table 3

Results of the reduced logistic regression models

	Explanatory variable		**OLS model** Endowment	Annuity	Term life	Group	Other	**FE model** Endowment	Annuity	Term life	Group	Other
Economic indicators	Buyer confidence	No lag			0.06		-0.16		0.06	0.06	0.10	-0.20
		Lag 1		0.09					0.08	0.04		
	Current yield	No lag		-0.14				-0.05	-0.38	-0.35	-0.59	
		Lag 1			-0.15		0.35			-0.12		0.24
	GDP	No lag		0.05				0.02	0.09	0.10	0.19	
		Lag 1					-0.06		0.06	0.13	0.24	-0.15
	Stock performance	No lag							0.17			
		Lag 1							-0.50	-0.74	-1.47	0.64
	Unemployment rate	No lag								0.07	0.13	-0.07
		Lag 1					0.25		-0.08	-0.07	-0.12	0.20
Company characteristics	Age		-0.15	-0.10						-0.18	1.44	
	Distributional focus	Bank	0.20	-0.21	-0.15	0.30						
		Broker				0.46				-0.16		
		Branch					-0.74			0.55		
		Direct	-0.89	-1.06	-1.00							
		Pyramid			0.37		0.27					
		Tied ag.	-0.22	-0.14	0.11		-0.18					
	Mutual		-0.32		0.16							
	Size				-0.05		-0.12					
	Spread	No lag	0.13						-0.08			
		Lag 1					-0.19				-0.22	

Note: Estimates indicate significant explanatory variables at the 1% level for the regression model including all explanatory variables. These variables have then been used to estimate the reduced logistic regression models. Positive parameter estimates indicate a positive relationship with the lapse probability (i.e., increasing values of the variable increase the lapse probability and decreasing values decrease the lapse probability). Negative parameter estimates indicate a negative relationship with the lapse probability (i.e., increasing values of the variable decrease the lapse probability and decreasing values increase the lapse probability).

Table 4

Comparison of estimated errors

	OLS model		**FE model**		**Kim (2005)**	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Endowment	0.0215	34.8%	0.0083	9.7%	0.0033	19.3%
Annuity	0.0232	67.5%	0.0101	16.8%	0.0021	19.0%
Term life/ Protection	0.0272	47.1%	0.0112	15.3%	0.0007	8.9%
Group	0.0484	464.9%	0.0343	54.2%	N/A	
Other	0.0322	91.9%	0.0185	62.5%	N/A	
Education	N/A		N/A		0.0009	6.0%

Note: Estimated errors between real and predicted lapse rates (based on OLS and FE model) and comparison with results of Kim (2005).

Table 5

Classification table and deduced model accuracy indicators for endowment business

Endowment		**Predicted - OLS** Lapse	**Predicted - OLS** No lapse	**Predicted - FE** Lapse	**Predicted - FE** No lapse
Real	Lapse	15,727,477	2,032,834	16,951,662	808,649
	No lapse	2,975,615	489,252,849	734,157	491,494,307
Correct		99.0%		99.7%	
Sensitivity		88.6%		95.4%	
Specificity		99.4%		99.9%	
False POS		15.9%		4.2%	
False NEG		0.4%		0.2%	

Table 6

Estimated errors for validation method I and II

	OLS - MAPE		FE - MAPE	
Panel A - Method I				
Endowment	36.8%	(+6%)	12.9%	(+33%)
Annuity	58.0%	(-14%)	24.1%	(+44%)
Term life/ Protection	53.2%	(+13%)	22.6%	(+47%)
Group	418.7%	(-10%)	96.3%	(+78%)
Other	79.3%	(-14%)	90.4%	(+45%)
Panel B - Method II				
Endowment	34.9%	(+1%)	11.0%	(+13%)
Annuity	67.8%	(±0%)	21.0%	(+25%)
Term life/ Protection	48.0%	(+2%)	18.9%	(+23%)
Group	464.4%	(±0%)	62.2%	(+15%)
Other	98.8%	(+8%)	79.3%	(+27%)

Note: Estimated MAPE error between real and predicted lapse rates for OLS and FE models based on validation procedures I and II.

Table 7

Classification table for validation method I and II

Endowment		Predicted - OLS: Lapse	Predicted - OLS: No lapse	Predicted - FE: Lapse	Predicted - FE: No lapse
Panel A - Method I					
Real	Lapse	9,272,152	1,066,269	9,691,200	469,606
	No lapse	1,979,443	288,328,187	754,718	284,729,270
	Correct	99.0% (±0.0ppt)		99.6% (-0.1ppt)	
	Sensitivity	89.7% (+1.1ppt)		95.4% (-0.1ppt)	
	Specificity	99.3% (-0.1ppt)		99.7% (-0.1ppt)	
	False POS	17.6% (+1.7ppt)		7.2% (+3.1ppt)	
	False NEG	0.4% (±0.0ppt)		0.2% (±0.0ppt)	
Panel B - Method II					
Real	Lapse	15,725,182	2,035,129	16,754,294	938,570
	No lapse	2,999,912	489,228,552	805,072	489,731,773
	Correct	99.0% (±0.0ppt)		99.7% (±0.0ppt)	
	Sensitivity	88.5% (±0.0ppt)		94.7% (-0.8ppt)	
	Specificity	99.4% (±0.0ppt)		99.8% (±0.0ppt)	
	False POS	16.0% (+0.1ppt)		4.6% (+0.4ppt)	
	False NEG	0.4% (±0.0ppt)		0.2% (±0.0ppt)	

Note: These are the classification tables for endowments only, along with the deduced model accuracy indicators for OLS and FE models based on validation procedures I and II.

Table A.1

Classification table for non-endowment business

		Predicted - OLS		Predicted - FE	
		Lapse	No lapse	Lapse	No lapse
Panel A - Annuity					
Real	Lapse	6,343,891	1,130,251	6,905,838	568,304
	No lapse	1,415,425	140,273,052	361,272	141,327,205
Correct		98.3%		99.4%	
Sensitivity		84.9%		92.4%	
Specificity		99.0%		99.7%	
False POS		18.2%		5.0%	
False NEG		0.8%		0.4%	
Panel B - Term life					
Real	Lapse	3,065,138	436,920	3,202,015	300,043
	No lapse	594,905	72,189,183	274,812	72,509,276
Correct		98.6%		99.2%	
Sensitivity		87.5%		91.4%	
Specificity		99.2%		99.6%	
False POS		16.3%		7.9%	
False NEG		0.6%		0.4%	
Panel C - Group					
Real	Lapse	3,751,388	917,038	3,984,890	683,536
	No lapse	1,492,737	187,672,248	613,479	188,551,505
Correct		98.8%		99.3%	
Sensitivity		80.4%		85.4%	
Specificity		99.2%		99.7%	
False POS		28.5%		13.3%	
False NEG		0.5%		0.4%	
Panel D - Other					
Real	Lapse	4,019,010	478,714	4,230,417	267,307
	No lapse	700,834	66,866,456	242,605	67,324,685
Correct		98.4%		99.3%	
Sensitivity		89.4%		94.1%	
Specificity		99.0%		99.6%	
False POS		14.8%		5.4%	
False NEG		0.7%		0.4%	

Note: These are the classification tables along with the deduced model accuracy indicators for annuity, term life, group, and other business. These results are based on the complete data set.

Table A.2

Classification table for validation method I

		Predicted - OLS		Predicted - FE	
		Lapse	No lapse	Lapse	No lapse
Panel A - Annuity					
Real	Lapse	5,300,291	797,432	5,467,278	537,243
	No lapse	1,484,405	116,022,488	560,025	115,185,543
Correct		98.2% (-0.1ppt)		99.1% (-0.3ppt)	
Sensitivity		86.9% (+2.0ppt)		91.1% (-1.3ppt)	
Specificity		98.7% (-0.3ppt)		99.5% (-0.2ppt)	
False POS		21.9% (+3.6ppt)		9.3% (+4.3ppt)	
False NEG		0.7% (-0.1ppt)		0.5% (+0.1ppt)	
Panel B - Term life					
Real	Lapse	2,109,916	360,825	1,988,503	436,397
	No lapse	428,112	51,740,749	171,042	51,385,151
Correct		98.6% (-0.1ppt)		98.9% (-0.4ppt)	
Sensitivity		85.4% (-2.1ppt)		82.0% (-9.4ppt)	
Specificity		99.2% (±0.0ppt)		99.7% (±0.0ppt)	
False POS		16.9% (+0.6ppt)		7.9% (±0.0ppt)	
False NEG		0.7% (+0.1ppt)		0.8% (+0.4ppt)	
Panel C - Group					
Real	Lapse	2,538,703	633,233	2,462,379	663,677
	No lapse	1,106,609	121,394,979	1,727,687	119,305,755
Correct		98.6% (-0.1ppt)		98.1% (-1.3ppt)	
Sensitivity		80.0% (-0.3ppt)		78.8% (-6.6ppt)	
Specificity		99.1% (-0.1ppt)		98.6% (-1.1ppt)	
False POS		30.4% (+1.9ppt)		41.2% (+27.9ppt)	
False NEG		0.5% (±0.0ppt)		0.6% (+0.2ppt)	
Panel D - Other					
Real	Lapse	3,318,368	631,351	3,396,164	420,750
	No lapse	715,305	57,630,044	2,509,741	53,917,055
Correct		97.8% (-0.5ppt)		95.1% (-4.2ppt)	
Sensitivity		84.0% (-5.3ppt)		89.0% (-5.1ppt)	
Specificity		98.8% (-0.2ppt)		95.6% (-4.1ppt)	
False POS		17.7% (+2.9ppt)		42.5% (+37.1ppt)	
False NEG		1.1% (+0.4ppt)		0.8% (+0.4ppt)	

Note: These are the classification tables along with the deduced model accuracy indicators for annuity, term life, group, and other business. These results are based on validation procedure I.

Table A.3
Classification table for validation method II

		Predicted - OLS		Predicted - FE	
		Lapse	No lapse	Lapse	No lapse
Panel A - Annuity					
Real	Lapse	6,344,210	1,129,932	6,850,404	591,489
	No lapse	1,470,247	140,218,230	528,447	140,658,342
Correct		98.3% (±0.0ppt)		99.2% (-0.1ppt)	
Sensitivity		84.9% (±0.0ppt)		92.1% (-0.3ppt)	
Specificity		99.0% (±0.0ppt)		99.6% (-0.1ppt)	
False POS		18.8% (+0.6ppt)		7.2% (+2.2ppt)	
False NEG		0.8% (±0.0ppt)		0.4% (±0.0ppt)	
Panel B - Term life					
Real	Lapse	3,055,452	446,606	3,164,282	324,970
	No lapse	606,781	72,177,307	358,635	72,269,268
Correct		98.6% (±0.0ppt)		99.1% (-0.1ppt)	
Sensitivity		87.2% (-0.3ppt)		90.7% (-0.7ppt)	
Specificity		99.2% (±0.0ppt)		99.5% (-0.1ppt)	
False POS		16.6% (+0.3ppt)		10.2% (+2.3ppt)	
False NEG		0.6% (±0.0ppt)		0.4% (±0.0ppt)	
Panel C - Group					
Real	Lapse	3,738,309	930,117	3,897,724	757,212
	No lapse	1,510,374	187,654,611	741,209	187,981,176
Correct		98.7% (±0.0ppt)		99.2% (-0.1ppt)	
Sensitivity		80.1% (-0.3ppt)		83.7% (-1.6ppt)	
Specificity		99.2% (±0.0ppt)		99.6% (-0.1ppt)	
False POS		28.8% (+0.3ppt)		16.0% (+2.6ppt)	
False NEG		0.5% (±0.0ppt)		0.4% (±0.0ppt)	
Panel D - Other					
Real	Lapse	3,956,936	540,788	3,971,209	460,311
	No lapse	792,042	66,775,248	306,866	66,440,264
Correct		98.2% (-0.2ppt)		98.9% (-0.4ppt)	
Sensitivity		88.0% (-1.4ppt)		89.6% (-4.4ppt)	
Specificity		98.8% (-0.1ppt)		99.5% (-0.1ppt)	
False POS		16.7% (+1.8ppt)		7.2% (+1.7ppt)	
False NEG		0.8% (+0.1ppt)		0.7% (+0.3ppt)	

Note: These are the classification tables along with the deduced model accuracy indicators for annuity, term life, group, and other business. These results are based on validation procedure II.