**ORIGINAL ARTICLE**

# Business cycles influences upon customer cross-buying behavior in the case of financial services

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## Abstract

Customer cross-buying behavior (CCBB) still represents a key marketing topic for professionals and academics. Marketing research identified several customer cross-buying determinants during the last few decades. However, some studies have pointed out that research remains silent about potential business cycles influences upon CCBB. Building on business cycles influences upon motivational orientations, this investigation extends previous literature on CCBB performing a longitudinal study on a bancassurance leader database. Combining transactional data and aggregated perceived measure of the economic environment, this research elucidates how business cycles influence CCBB in the case of financial services. The statistical model used, accounts simultaneously for business cycles global effects and unobserved heterogeneity. The results confirm that business cycles, economic contractions and expansions, exercise significant and various influences on CCBB. In addition to overcoming a theoretical gap, findings provide novel insights for practitioners who should consider business cycles when designing cross-selling strategies.

**Keywords** Financial services · Customer cross-buying behavior · Cross-selling strategies · Business cycles · Mixed effects modeling

*How bancassurances could stimulate customer cross-buying behavior according to business cycles and thus increase customer lifetime value?*

## Introduction

Cross-buying consists of purchasing additional products and/or services from the same provider (Ngobo 2004). Companies that cross-sell their products and/or services can increase revenue from existing customers through cross-selling strategies (Kumar et al. 2008). Cross-selling remains a priority in many industries, including financial services, insurance, health care, accounting, telecommunications, airlines, and retailing (Li et al. 2011).

Cross-selling provides various competitive advantages for firms. First, it reduces the cost of customer acquisition, thereby increasing the profitability of products and services and providing a pricing advantage over competitors' offerings (Reichheld and Sasser 1990). Selling to an existing customer is often more profitable for a company than acquiring a new one (Kumar et al. 2008), especially in the financial sector, where customer acquisition cost is one of the highest, at about $300 (Bauer 2017).

Moreover, cross-selling improves the customer business relationship in terms of profitability and length, as customers are more willing to stay with the company once they own multiple products and/or services (Reinartz and Kumar 2003). According to Fiserv, the third largest technology provider to US banks (2010), a customer with one financial service at a bank will stay for 18 months, while a customer with two financial services will remain 4 years, on average. Consequently, soliciting cross-buying behavior through cross-selling strategies allows a company to improve the Customer Life-time Value (CLV) and finally increase the customer relationship profitability.

One outstanding example of companies' cross-buying considerations and cross-selling prominence lies in the 1998

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business merger between Citicorp bank and the Travelers Group insurance company, which resulted in the creation of Citigroup, the world's largest financial services company. John S. Reed and Sanford I. Weill, former chairmen and chief executive officers of Citicorp and Travelers Group, said of the merger of their firms: "The companies expect to generate substantial incremental earnings from the significant cross-selling opportunities that will be created as well as cost savings that will be realized." This $140 billion deal allowed 100 million customers to cross-buy between banking services and insurance policies (Martin 1998).

Indeed, CCBB represents a core theme in marketing research (Shah and Kumar 2008). Literature principally focused on CCBB determinants and empirically assessed the effect of several variables. CCBB was studied in relation to attitudinal, commercial, marketing, and sociodemographic variables such as satisfaction, loyalty, direct mailing, and age.

However, even though many variables impacting the phenomenon have been studied, the potential business cycles influences have not yet been proven, although theses influences were suggested in further research by Liang et al. (2008) and Li et al. (2011). Both assume that research on CCBB should include economic considerations. Moreover, Deleersnyder et al. (2004) pointed out the "general neglect of the business-cycle impact in the marketing literature."

In marketing research, business cycles should be considered regarding consumers' confidence towards the economy like the household confidence index, which is known as reliable measure in marketing and finance literature (Kumar et al. 2014; Chen 2011).

Indeed, few studies have assessed the impact of business cycles upon various phenomena [see Dekimpe and Deleersnyder (2018) for a review]. For example, business cycles seem to impact companies' performance through consumption, especially during economic downturns when customers spend less money on products and services (Dekimpe and Deleersnyder 2018). As the potential influences of business cycles upon CCBB have been suggested by research and marketing literature remains silent on the topic, this study aims to extend the investigation on CCBB by addressing the following research questions: How business cycles could impact CCBB? What are the potential influences of economic downturns and upturns on CCBB? Do these various influences have the same weights on CCBB?

To answer these questions, we initially learn from literature addressing business cycles impacts on consumption before summarizing research on CCBB determinants, regrouping results by significant impacting variables. We also resume a specific research stream on sequential CCBB. Building on business cycles influences upon motivational orientations, we predict that economic expansions and contractions exercise various influences on CCBB. We combine

transactional data from a bancassurance leader with household confidence index variations over a 21-year period to empirically test our assumptions. We construct and estimate a panel multilevel mixed-effects model to observe how economic expansions and contractions influence the number of financial services held by customers (i.e., the portfolio size or cross-buying level). Ultimately, we discuss our results, highlighting theoretical and managerial contributions.

## Background: how business cycles could impact CCBB?

### Identified business cycles influences upon customer behavior

The economic context or environment could be defined as the totality of economic factors, like employment, income, inflation, interest rates, productivity, and wealth, that influence the purchasing behavior of consumers and institutions. An economic environment is composed of specific cycles (positive or negative) that can affect markets and considerably modify companies' performance through their customers' behavior (Dekimpe and Deleersnyder 2018). Indeed, customers behave differently depending on the current business cycle, buying different products/services from various companies.

Business cycles trigger distinct changes in motivational orientation that affect customer decisions. Economic contractions generate more negative sentiment, inducing risk aversion for negative outcomes, while economic expansions generate more positive sentiment, prompting risk-seeking for positive outcomes (Millet et al. 2012). These causal mechanisms are supported by several empirical studies analyzing business cycles impacts on customer purchase decisions. Millet et al. (2012) demonstrated how consumers redirect their spending depending economic conditions. Customers seem more likely to purchase products or services associated with prevention of negative consequences (e.g., insurance policies) during economic contractions, while products associated with positive results (e.g., gambling) are more desired during economic expansions.

For example, regarding brand choice, Lamey et al. (2012) and Dubé et al. (2018), have shown that private labels share increases during economic contractions. Switching from national brands to private labels allows consumers to reduce their total spending without having to give up on the amount consumed. It also appears that consumers switch from buying national brands to private labels with some ease, while the reverse is more complicated, showing an asymmetric effect over time (Lamey et al. 2007).

## CCBB place and benefits

To increase CLV, firms implement specific Customer Relationship Management (CRM) (Peelen et al. 2009), that involves acquisition, retention, development and reactivation strategies for greater profitability (Reinartz and Kumar 2003). When a customer has been acquired, companies often launch strategies to maximize its value, putting in place up-selling (offering a superior service) or cross-selling (offering an additional service) campaigns. Cross-buying behavior and cross-selling strategies are therefore at the level of the customer relationship development.

In order to increase customer relationship depth, breadth and overall CLV, companies, particularly financial services ones, have included CCBB concerns in their CRM (Panda 2003).

## CCBB determinants

An extensive stream of marketing studies identified several significant variables impacting CCBB. Studies by Tung and Carlson (2015), Reinartz et al. (2008) and Liang et al. (2008) have shown that customer loyalty has a significant and positive impact on CCBB. Research increasingly supports the argument that loyal customers are more willing to expand their relationship by buying new products and/or services from same company (Reinartz and Kumar 2003; Verhoef 2003; Reinartz et al. 2008). Moreover, affective commitment seems to have a direct and positive influence on CCBB (Verhoef et al. 2002; Verhoef 2003; Liu and Wu 2007, 2009; Tung and Carlson 2015).

Regarding the status of the business relationship, a high number of products and/or services held simultaneously by a customer, encourages CCBB (Verhoef et al. 2001) due to the high transaction costs associated with switching to the competition (Blattberg et al. 2001). Moreover, the length of the business relationship has a moderating effect on the relationship between satisfaction and CCBB (Verhoef et al. 2002).

Cross-buying considerations such as perceived convenience and perceived image conflicts could also impact CCBB. In fact, it is more convenient for a customer to purchase all his products and/or services at a unique company. One-stop shopping saves customer time and effort (Seiders et al. 2000). Therefore, perceived convenience (usefulness) has a significant positive impact on CCBB (Ngobo 2004; Liu and Wu 2009; Evanschitzky et al. 2017; Zhu et al. 2018; Mukerjee 2020). Furthermore, when a company promotes new products or services that are not stemming from their core competencies, that could generate image conflicts, that has a negative impact on CCBB (Ngobo 2004).

According to Dahana et al. (2020), CCBB is largely driven by customers' responses to marketing efforts. Direct marketing (e.g., mailing) has a positive impact on CCBB (Li et al. 2011). Moreover, by testing the square of the direct marketing variable, Kumar et al. (2008) found that the relationship became negative. Thus, direct marketing favorably impacts CCBB, but not beyond a threshold where it becomes unpleasant for customers and has a negative impact on CCBB. Finally, loyalty programs create exit barriers for customers, that promotes loyalty (Rust et al. 2004) and favors CCBB (Verhoef 2003).

Sociodemographic differences, especially customer age and income level, are often considered as control variables in literature. Thus, older customers (Verhoef et al. 2001; Kumar et al. 2008; Li et al. 2011) and wealthier ones (Kumar et al. 2008) seem to have a higher cross-buying behavior.

## Sequential CCBB

Another literature stream produced a sequential analysis of CCBB, targeting to identify the next product/service to buy by customers. Numerous studies found that customers follow a specific cross-buying journey, especially in the financial services sector. Customers begin their commercial relationship by acquiring the least risky and most general services (e.g., credit cards or checking accounts) before adding more financial services, such as savings and loans, to their financial portfolios. At the last stage of CCBB, customers are more likely to purchase more risky financial services such as stocks or bonds (Stafford et al. 1982; Dickinson and Kirzner 1986; Kamakura et al. 1991).

This financial maturity continuum (Li et al. 2005) showing a sequential (i.e., ordered) CCBB has been highlighted in many papers. For example, Paas et al. (2005) defined the following acquisition sequence model for bank customers: checking accounts, savings, retirement savings, stocks and bonds. Paas and Molenaarb (2005) included insurance services, identifying a new sequential model as follows: checking accounts, savings, home insurance, mortgage, auto insurance, personal loan, life insurance, trading services. A similar pattern was found by Prinzie and Van den Poel (2006) and Paas et al. (2007).

The variables identified as impacting CCBB can be grouped into four types and are summarized in "Appendix A". Business variables include customer purchasing behavior, such as the number and amount of transactions, the number of products and/or services owned from the same provider and the length of the business relationship. Attitude variables concern customer feelings towards a company, such as satisfaction, trust or perceived quality. Marketing variables include, for example, the number of direct mailings sent to the customer, involvement in a loyalty program or the acquisition channel. Finally, sociodemographic variables principally concern customer age and income level.

Focusing on literature, we observed that business cycles influences upon CCBB are still unconsidered, and several papers highlighted the issue as a limitation and an opportunity for further research. Liang et al. (2008) worked on the role of digital marketing on CCBB. They identified customer satisfaction and trust as positively impacting customer loyalty, which would then promote CCBB. However, they point out that, even if their data are appropriately adjusted to their conceptual model, professionals should consider other potential moderators, such as the economic environment: "while the comprehensive model fits the data well, managers should consider the potential moderators of these relationships in their local markets, as in the case of a country that has experienced an economic stagnation or even an economic downturn." Li et al. (2011) studied the effectiveness of cross-selling strategies by showing that direct marketing campaigns promote CCBB. However, they affirm that their research could have been improved with a more consistent database and additional information, such as consideration of the economic environment: "our study is limited by a two-year history and lack of competition information. A sample with longer longitudinal data and more complete information on competitors' offers would expose the model to changing competitive conditions, economic cycles, and interest rates and more longitudinal variation in customer history."

Indeed, Deleersnyder et al. (2004) complain about the lack of information concerning business cycles influences in marketing research: "Business cycles can have a profound impact on many companies and industries. Still, not much prior research has systematically considered the extent and nature of cyclical sensitivity in marketing performance. This general neglect of the business-cycle impact in the marketing literature … is surprising. Indeed, many managers admit adjusting their marketing practices during contraction/expansion periods (Shama 1993), while also the consumers' confidence in the state of the economy, as well as their subsequent purchasing patterns, are described as very cyclical in numerous business-press articles."

Consequently, this research helps to better understand CCBB by assessing the potential effects of the economic variable, identified as missing in past studies thus fill in a critical theoretical gap. Furthermore, given the substantial impact of business cycles on companies' performance through consumption, focusing on CCBB could be meaningful for companies that could either enhance their cross-selling campaigns during favorable economic situations or lower such budget expenditures during unfavorable conditions. Several papers already shown that marketing performance could depend on business cycles. For example, return on marketing investment in customer satisfaction differs according to the economic situation and may seem more effective in periods of economic expansion (Kumar et al. 2014). Thus,

assessing business cycles influences upon CCBB could lead to significant commercial benefits for companies that offer multiple products and/or services to their customers.

## Hypotheses development: inferring business cycles influences on CCBB

Prior research suggests that business cycles strongly influence customer purchase behavior, but the literature remains inconclusive concerning potential business cycles influences upon CCBB. Considering that the financial services sector provides the most findings about CCBB (28 of the 35 identified papers in "Appendix A"), this research should pursue this approach by focusing on bancassurance customers. Indeed, banks and insurance companies represent a major sector of the economy, households' financial assets accounted for $288,071 per capita in the United States and $155,460 per capita in the United Kingdom in 2019 (OECD 2021). Furthermore, the bancassurance business relationship is one of the longest and most complex (Hobeika 2017). Therefore, the purpose of this study is to obtain an advanced understanding on business cycles influences upon financial CCBB.

We assess the potential influences of the economic context, i.e., of an external environment on a behavior. Primary, we define the origin of business cycles through economic psychology assumptions. According to Katona (1975) the objective economic conditions influence the perception of the subjective economic context that ultimately determines the economic behavior of consumers under the effect of personal characteristics.

Then, we focus on environmental psychology (Donovan and Rossiter 1982), a discipline that seeks to predict the collective effect of stimuli from an environment on the feelings and motivations of individuals (Mehrabian, 1976). Environmental psychology focuses on two leading topics: (1) the emotional impact of external stimuli and (2) the effect of external stimuli on motivations (Mehrabian and Russell 1974). The most widely used approach in this area is that of Mehrabian and Russell (1974). They proposed the "Stimuli–Organism–Response" (S–O–R) model. According to Mehrabian and Russell (1974), the external environment contains stimuli (S) that affect organisms (O) and cause individuals to approach gains or avoid losses (R). This framework suggests that an environment provokes certain emotional reactions in an individual which, in turn, lead him or her to approach or avoid the environment to a greater or lesser degree (Mehrabian 1976).

Furthermore, business cycles, economic contractions and expansions, have been shown to affect customer purchasing behavior (Lamey et al. 2007; Cleeren et al. 2016; Dekimpe et al. 2016). Indeed, economic contractions generate avoidance motivations, inducing negative economic sentiment,
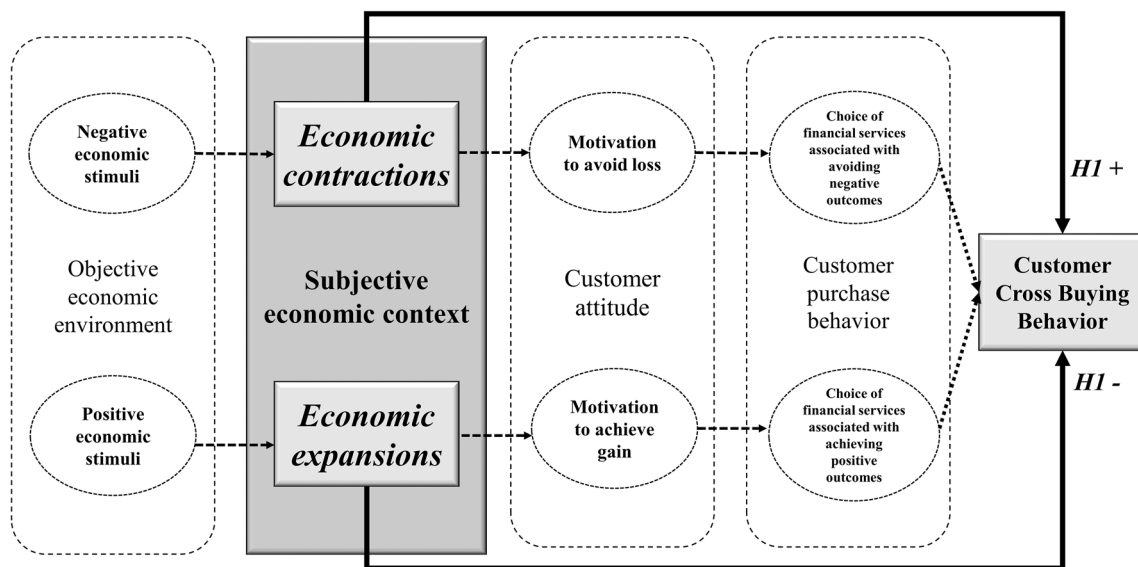
**Fig. 1** Research model

while economic expansions generate approach motivation, inducing positive economic sentiment (Millet et al. 2012). Furthermore, facing negative or positive economic sentiment, customers would be more sensitive to achieving specific outcomes, i.e., economic expansions induce motivation to achieve gains, while economic contractions induce motivation to avoid losses (Millet et al. 2012). In fact, economic contractions favor consumption of products associated with avoiding negative outcomes (e.g., home insurance, health insurance), while economic expansions enhance consumption of products associated with achieving positive outcomes (e.g., casino gambling, lottery tickets) (Millet et al. 2012).

Becoming more risk averse towards negative outcomes (Millet et al. 2012), customers modify their purchase behavior to secure themselves from a less favorable future due to greater caution (Arrondel and Calvo Pardo 2008). Under economic contractions, customers become more suspicious about the future (Kumar et al. 2014). This mistrust could trigger specific purchase decisions: by being more risk-averse, customers may be more likely to secure the present and protect themselves from an uncertain future by holding more financial services, because most services fill security and precautionary needs. Thus, we expect H1: Economic contractions favor financial CCBB. Put differently, less favorable economic situations would lead customers to a higher cross-buying level, meaning a higher number of financial services would be held at the same time.

On the other hand, during a more favorable economic situation and by being less suspicious about the future, financial customers would be less risk averse (Millet et al. 2012). They would be less concerned about securing the future and would prefer to spend money on consumption. Thus, we

expect H2: Economic expansions disfavor financial CCBB. More favorable economic situations would lead customers to a lower cross-buying level, meaning they would hold a lower number of financial services at the same time.

As noted above, economic expansions and contractions effects are unequal. Economic contractions have a stronger influence on customer purchase behavior compared to economic expansions (Lamey et al. 2007; Lamey 2014). Simultaneously, financial professionals (traders and portfolio managers) overreact to unexpected and dramatic events (De Bondt and Thaler 2002) as explained by prospect theory (Kahneman and Tversky 1979) where losses are felt heavier than gains by individuals. This asymmetric effect could also be observed upon financial CCBB. Thus, we expect H3: Economic contractions have a stronger influence on financial CCBB compared to economic expansions. We present our research model in Fig. 1. We use straight lines for our hypotheses and dotted lines to represent the underlying process demonstrated in literature.

## Empirical evaluation

### Business cycles consideration

Gross domestic product (GDP) seems to be a representative variable of the economy; however, the variations in a GDP series do not necessarily correspond to business cycles movements, so this aggregate measure of an economy is often refined by various methods of filtration before being tested on data. Economic literature provides few methodologies to break down a GDP series into specific components

to constitute a better economic measure. Marketing research uses specific filters for business cycles empirical analysis. For example, Lamey et al. (2012) used the Hodrick–Prescott filter (Hodrick and Prescott 1997) to measure private label share fluctuations according to business cycles.

The economic environment can be measured in other ways. Marketing literature frequently uses the household confidence index (HCI) to analyze business cycles effects upon marketing phenomena (Kumar et al. 2014). According to Katona (1975), the HCI is the degree of household optimism about the general state of the economy and the household's situation. This microeconomic measure of the economic environment differs from aggregated measures such as GDP (Lamey et al. 2007) or price index (Du and Kamakura 2008). HCI is measured by an index of wellbeing that reflects household opinion and thus helps to better capture periods of reversal from the household perspective (Katona 1968). As a result, HCI helps to interpret the economic environment from a household point of view. For example, a decline in HCI would encourage customers to restrain their spending (Ngobo and Ingarao 2017).

Moreover, a causal link was proved between HCI and GDP (Matsusaka and Sbordone 1995). HCI seems to represent a signal that anticipates changes in future household spending (Carroll et al. 1994) and can therefore be considered as a statistically significant prediction of future GDP growth (Howrey 2001). This was also highlighted by such professionals as Howard Marks (2013), CEO at Oaktree Capital Management, in the following statement: "I have long been impressed by the role of confidence in an economy. In fact, I've written in the past—exaggerating only slightly—that sometimes I think confidence is all that matters. I consider its impact to be significant, pervasive, self-reinforcing and self-fulfilling. The primary impact of confidence on the economy is simple. If people think the economic future will be good, they'll spend and invest… thus, things will be good."

## 3.2. Data

We use one leading French bancassurance database coupled with annualized national HCI to perform our analysis. Annual customer purchase history is available from 1954 to 2009. The company has sold 126 types of financial services within 10 major categories[1] over the period. The multilevel database identifies the financial services owned by each customer $i$ who initiated his relationship with the

company during the period $j$ and for each year $t$ of the business relationship.

## 3.3. Operationalization of variables

### Dependent variable

As the HCI considered for the study was first used in 1989, we compile and retain 221,971 observations from the database that covers the 1989–2009 period. For each customer, we consider the financial CCBB level represented by the sum of financial services owned during the same year, i.e., the portfolio size. Thus, the dependent variable $Crossbuy_{ijt}$ is a count variable.

### Independent variables

Such as Kumar et al.'s (2014) methodology, we consider the National Institute of Statistics and Economic Studies (INSEE) HCI as the basis to define the business cycles variables. This HCI is a synthetic indicator derived from the responses of a representative panel of the French population on 11 items measured monthly since 1989. The 11 items represent the perception of past standard of living, future standard of living, unemployment, past prices, future prices, buying opportunity, savings opportunity, current savings capacity, past personal financial situation, future personal financial situation and future savings capacity.

As seen formerly, HCI and GDP seem to be linked, we propose to graphically compare French HCI and French GDP variations over the 1989–2009 period considered for the study. We use the Hodrick–Prescott filter on the GDP series to dissociate the business cycles (fluctuations) and the long-term trend. It is a decomposition into a cyclical component and a trend component. We observe in Fig. 2 that HCI and GDP variations are close over the period.

Starting from the HCI series, we build two distinct variables, one for economic contractions (economic downturns versus N-1) and one for economic expansions (economic upturns versus N-1). We compute *HCILAG* to calculate the difference between the initial indicator *HCI* and the lag. We construct our two independent variables as follows:

$$\text{Contraction}_t \begin{cases} = 0 & \text{if } \Delta \text{HCI}_t^c > 0 \\ = \text{HCI}_t^c - \left(\text{HCILAG}_t^c\right) & \text{if } \Delta \text{HCI}_t^c \leq 0 \end{cases}$$

Variable representative of economic contractions

$$\text{Expansion}_t \begin{cases} = \text{HCI}_t^c - \left(\text{HCILAG}_t^c\right) & \text{if } \Delta \text{HCI}_t^c > 0 \\ = 0 & \text{if } \Delta \text{HCI}_t^c \leq 0 \end{cases}$$

Variable representative of economic expansions

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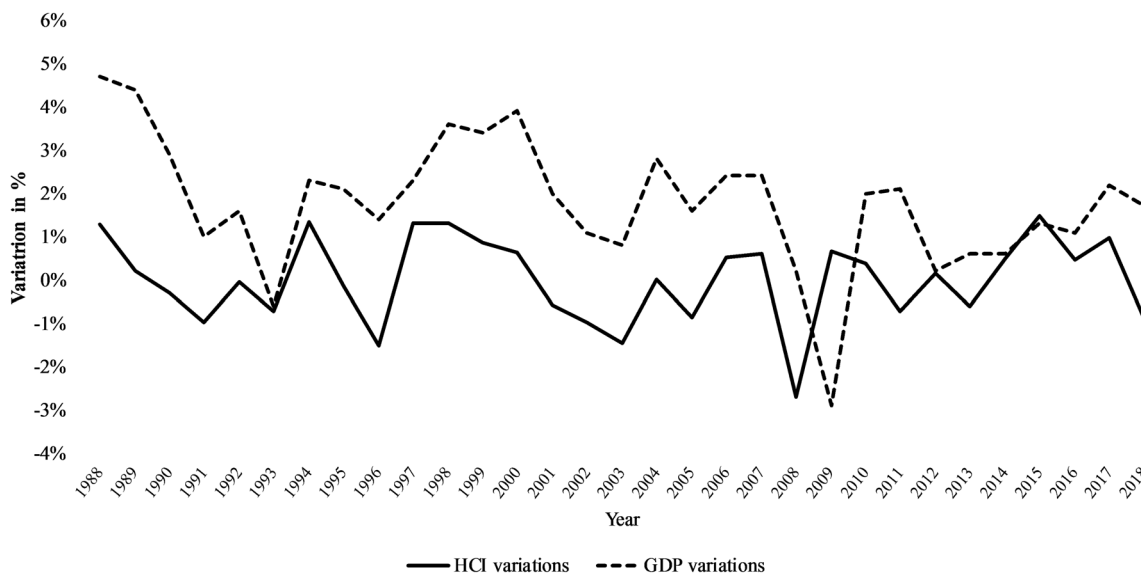[1] The 10 categories of financial services include home insurance, vehicle insurance, children insurance, health insurance, life insurance, funeral insurance, retirement savings, general precaution insurance, investment products, and various insurances.

**Fig. 2** GDP vs. HCI variations (%)

**Table 1** Variable operationalization

| Variable | Operationalization |
|---|---|
| Dependent variable | |
| $Crossbuy_{ijt}$ | The total number of financial services held by a customer $i$ from cohort $j$ during the year $t$ within the company |
| Independent variables | |
| $Expansion_t$ | Positive variations in HCI compared to year $t-1$ |
| $Contraction_t$ | Negative variations in HCI compared to year $t-1$ |
| Control variables | |
| $LoyaltyCompanyLag_{it-1}$ | The business relationship length between a customer $i$ and the company during the year $t$ delayed by one period |
| $AgeLag_{it-1}$ | The age of the customer $i$ during the year $t$ delayed by one period |

## Individual-level predictors

We use available dynamic control variables identified in the literature as customer age and loyalty, lagged to limit simultaneity bias (Arellano and Bond 1991). Thus, we consider *AgeLag* and *LoyaltyCompanyLag* as control variables. Regrettably, we cannot control for attitudinal variables, such as satisfaction, or other marketing variables like direct marketing campaigns, as they are unavailable in the database. Variable operationalization is available in Table 1, and descriptive statistics and correlation matrix are provided in "Appendix B".

## Method

We model the influence of business cycles upon CCBB in the case of financial services. Customers who own a given number of financial services from the company may decide to change the composition of their portfolios by adding or removing one or more financial services. They can also decide to terminate all contracts and therefore break the business relationship with the company. We investigate how business cycles (expansions and contractions*)* influence financial CCBB as represented by the number of financial services held (*Crossbuy*) under the control of lagged customer age (*AgeLag*) and loyalty (*LoyaltyCompanyLag*).

First, the dependent variable $Y$ counts the number of financial services owned by each customer, implying that it follows a Poisson law. In the database, customers are nested at two levels: their customer IDs (CustomerId $i$) as well as their acquisition periods (StartYear $j$). Thus, we have two levels with $Y_{ij}$, which justifies a multilevel model. In addition, the database includes repeated measures for each client $i$ and each period $t$; it is, therefore, a panel with index $t$, thus we consider $Y_{ijt}$. We want to measure the overall effects of

**Table 2** Considered models for estimation

| Model | Dependent variable | Independent variables | Customers $i$ unobserved heterogeneity | Acquisition periods $j$ unobserved heterogeneity | Control variables |
|---|---|---|---|---|---|
| A | *Crossbuy* | | | | *Constant* |
| B | *Crossbuy* | | | | *Constant* |
| | | | | | *AgeLag* |
| C | *Crossbuy* | | | | *Constant* |
| | | | | | *AgeLag* |
| | | | | | *LoyaltyCompanyLag* |
| D | *Crossbuy* | *Expansion* | | | *Constant* |
| | | *Contraction* | | | *AgeLag* |
| | | | | | *LoyaltyCompanyLag* |
| E | *Crossbuy* | *Expansion* | Cfactor | | *Constant* |
| | | *Contraction* | | | *AgeLag* |
| | | | | | *LoyaltyCompanyLag* |
| F | *Crossbuy* | *Expansion* | Cfactor | GCFactor | *Constant* |
| | | *Contraction* | | | *AgeLag* |
| | | | | | *LoyaltyCompanyLag* |
| G | *Crossbuy* | *Expansion* | Cfactor | | *Constant* |
| | | *Contraction* | Cfactor *Expansion* | | *AgeLag* |
| | | | Cfactor *Contraction* | | *LoyaltyCompanyLag* |
| H | *Crossbuy* | *Expansion* | Cfactor | GCFactor | *Constant* |
| | | *Contraction* | Cfactor *Expansion* | GCFactor *Expansion* | *AgeLag* |
| | | | Cfactor *Contraction* | GCFactor *Contraction* | *LoyaltyCompanyLag* |

the predictors on the dependent variable that would justify a fixed-effects model.

However, a fixed-effects model does not allow for considering heterogeneity, which could lead to a nonoptimal model (Heckman 1981). We consider random effects by anticipating that business cycles may have different effects depending on customers $i$ and acquisition periods $j$. Latent factors permit to measure unobserved heterogeneity, which is the difference of predictors' influence between customers $i$ and acquisition periods $j$ on the dependent variable.

The underlying assumption is that business cycles do not influence all customers in the same way. For example, wealthier customers may be less influenced by economic contractions. Likewise, there may be some differences in business cycles influence within acquisition periods. For example, a customer who began his relationship with the company during an economic upturn would not be as affected by economic expansions as a customer who begin his relationship during an economic downturn. Considering unobserved heterogeneity allows to limit the endogeneity problem. Several dynamic control variables are not included in the database, and it is possible that these missing variables have influences on the model. Latent factors permit to measure the differences in the effects of predictors on the dependent variable (Vermunt and Magidson 2005). Indeed, latent factors are based on latent class analysis, which is widely used in research on financial behavior (Kamakura et al. 1991; Paas and Molenaar 2005).

The Poisson regression assumes that the mean and the variance of the dependent variable are the same; i.e., $E(Y) = \text{Var}(Y) = \lambda$. However, when testing this assumption in SPSS27®, we found the variable variance statically different and greater than its mean with $t(221,970) = -557.894$, $p < 0.01$ ($M = 3.15$, $V = 6.063$, SD $= 2.462$). This phenomenon when observed variance larger than theoretical one is known as overdispersion and could introduce bias into statistical modeling. To address the issue, we opt for a specific negative binomial Poisson regression that undertakes overdispersion (Gardner et al. 1995).

Thus, we use a panel multilevel mixed effects model to test our hypotheses. See "Appendix C" for the statistical model building. We introduce predictors in the model as we go along, following Kass and Raftery's (1995) procedure. We estimate the eight equations below, as explained in Table 2 through the *LatentGOLD5.1®* software.

$$Y1_{ijt} = e^{(\bar{\alpha}_0)}$$

$$Y2_{ijt} = e^{\left(\bar{\alpha}_0 + \bar{\beta}_3 \text{AgeLag}_{it}\right)}$$

$$Y3_{ijt} = e^{\left(\bar{\alpha}_0 + \bar{\beta}_3 \text{AgeLag}_{it} + \bar{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

**Table 3** Model evaluation statistics

| Model | Likelihood function (LL) | BIC (based on LL) | BIC variation | Number of parameters | $R^2$ |
|---|---|---|---|---|---|
| A | −470,304.8915 | 940,628.9347 | | 2 | 0.0000 |
| B | −469,076.8059 | 938,182.3392 | −2446.5955 | 3 | 0.0093 |
| C | −465,273.2578 | 930,584.8188 | −7597.5204 | 4 | 0.0371 |
| D | −464,663.6435 | 929,384.7419 | −1200.0769 | 6 | 0.0420 |
| E | −398,242.7493 | 796,542.9534 | −132,841.7885 | 6 | 0.5514 |
| **F** | **−396,319.6712** | **792,706.3732** | **−3836.5802** | **7** | **0.5590** |
| G | −396,315.5160 | 792,717.2144 | 10.8412 | 9 | 0.5590 |
| H | −396,311.0814 | 792,727.5757 | 10.3613 | 11 | 0.5590 |

The curve in bold represents the BIC evolution across estimated models, i.e., the evolution of the models quality

$$Y4_{ijt} = e^{\left(\overline{\alpha}_0 + \overline{\beta}_1 \text{Expansion}_t + \overline{\beta}_2 \text{Contraction}_t + \overline{\beta}_3 \text{AgeLag}_{it} + \overline{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

$$Y5_{ijt} = e^{\left(\overline{\alpha}_0 + \lambda F_{1i} + \overline{\beta}_1 \text{Expansion}_t + \overline{\beta}_2 \text{Contraction}_t + \overline{\beta}_3 \text{AgeLag}_{it} + \overline{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

$$Y6_{ijt} = e^{\left(\overline{\alpha}_0 + \lambda F_{1i} + \gamma F_{2j} + \overline{\beta}_1 \text{Expansion}_t + \overline{\beta}_2 \text{Contraction}_t + \overline{\beta}_3 \text{AgeLag}_{it} + \overline{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

$$Y7_{ijt} = e^{\left(\overline{\alpha}_0 + \lambda F_{1i} + \gamma F_{2j} + \overline{\beta}_1 \text{Expansion}_t + \lambda F_{3i} \text{Expansion}_t + \overline{\beta}_2 \text{Contraction}_t + \lambda F_{5i} \text{Contraction}_t + \overline{\beta}_3 \text{AgeLag}_{it} + \overline{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

$$Y8_{ijt} = e^{\left(\overline{\alpha}_0 + \lambda F_{1i} + \gamma F_{2j} + \overline{\beta}_1 \text{Expansion}_t + \lambda F_{3i} \text{Expansion}_t + \gamma F_{4j} \text{Expansion}_t + \overline{\beta}_2 \text{Contraction}_t + \lambda F_{5i} \text{Contraction}_t + \gamma F_{6j} \text{Contraction}_t + \overline{\beta}_3 \text{AgeLag}_{it} + \overline{\beta}_4 \text{LoyaltyCompanyLag}_{it}\right)}$$

With:

$Y_{ijt}$: the number of financial services, held by customer $i$ who began his relationship with the company in the year $j$, during the year $t$;

$\overline{\alpha}_0$: the model constant;

$\lambda F_i$: the latent score of customers $i$ unobserved heterogeneity;

$\gamma F_j$: the latent score of acquisition periods $j$ unobserved heterogeneity;

Expansion$_t$: the amplitude of an economic expansion the year $t$;

Contraction$_t$: the amplitude of an economic contraction the year $t$;

AgeLag$_{it}$: the customer age in $t−1$;

LoyaltyCompanyLag$_{it}$: the business relationship length in $t−1$.

# Results

We estimate models using *LatentGOLD5.1*® software by conditional and marginal probabilities of Bayes estimation. The software provides several evaluation statistics to guide the choice of the best model as Bayesian Information Criterion (BIC) or Akaike Information Criterion (AIC). We follow Kass and Raftery's (1995) and Vermunt and Magidson's (2002) methodology by considering the model with the lowest BIC, i.e., the most accurate (see Table 3; Fig. 3). Regarding BIC variations (Kass and Raftery 1995), we select the model F among $N = 221,971$ observations with a likelihood function LL = −396,319,6712 and a BIC = 792,706,3732.

## Descriptive statistics

Within the selected model F, we analyze the financial CCBB through information on 14,412 bancassurance customers who hold an average of 3.4265 financial services (ranging from 1 to 15). We observe some parity in the data with 46.29% of women. Sociodemographic variables show that most customers are married (61.18%), followed by widowed (18.09%), single (10.91%), and divorced (9.82%). Just over half are workers (51.77%), followed by tradesmen and entrepreneurs (20.37%), intermediate professions (12.52%), managers and higher intellectual professions (8.64%), employees (4.07%), and farmers (2.63%).[2] Customers began their business relationship with the company, on average, in 1989,

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[2] Note that these figures come from static variables noted at the beginning of the customer business relationship; the proportions could have changed over time.
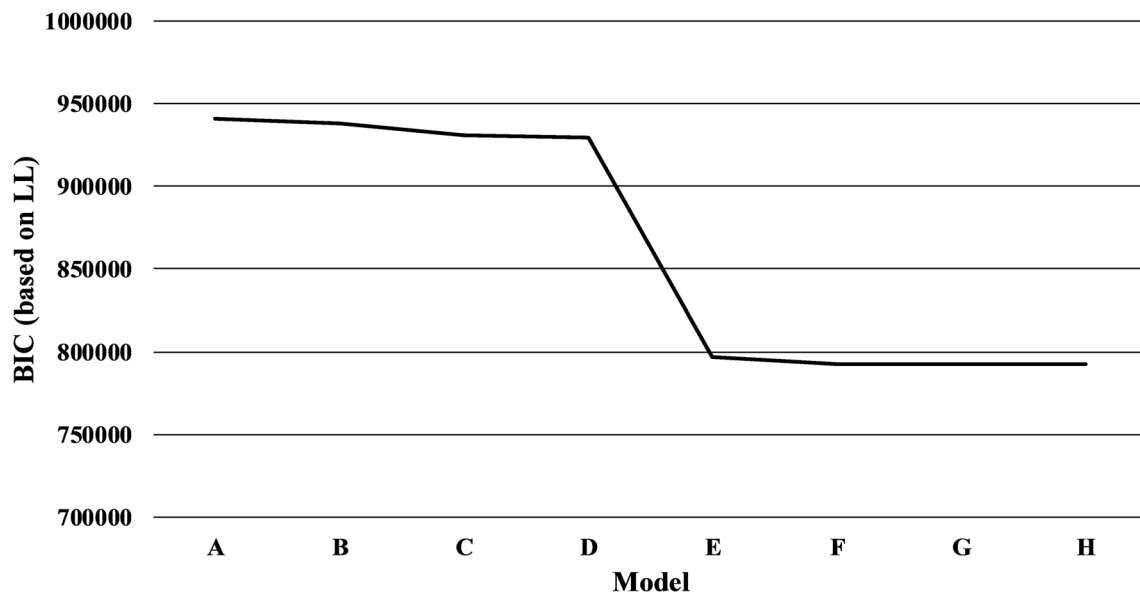
**Fig. 3** BIC evolution across estimated models

**Table 4** Model F regression results

| Dependent variable | Predictors | ln(Coefficient) | Coefficient in % | Standard deviation | Significance (*p*-value) |
|---|---|---|---|---|---|
| *Crossbuy* | 1 (Constant) | 1.7333 | | 0.0096 | 2.2E−702*** |
| *Crossbuy* | CFactor | 0.5348 | 70.7107 | 0.0013 | 4.8E−376*** |
| *Crossbuy* | GCFactor | −0.1252 | −11.768 | 0.0019 | 3.3E−922*** |
| *Crossbuy* | Expansion | −0.0100 | −0.9950 | 0.0005 | 8E−87*** |
| *Crossbuy* | Contraction | 0.0118 | 1.1870 | 0.0004 | 5.30E−244*** |
| *Crossbuy* | AgeLag | −0.0166 | −1.6463 | 0.0001 | 1.6E−286*** |
| *Crossbuy* | LoyaltyCompanyLag | 0.0128 | 1.2882 | 0.0002 | 3.3E−944*** |

$LL = -396,319,6712$; $BIC = 792,706,3732$; $R^2 = 55.90\%$; ****p* < 0.001

with a range from 1952 to 2008 (SD = 11 years). They started their relationship with the company at the average age of 43, with a range from 13 to 99 years old (SD = 15 years). The 92 minors in the database may have been in contact with the company via their parents. HCI varies on the period, with 52.14% contractions (from −1 to −16) and 47.85% expansions (from + 1 to + 8).

We performed a Poisson regression because our dependent variable is a count. The coefficients proposed as outputs by the *LatentGOLD5.1®* software are therefore not directly analyzable since the values are logarithms. Therefore, we must apply an exponential function to all the coefficients before analyzing the results. We next consider the following function to transform logarithms in percentage values: $[\text{Coef} = ((e^{\beta_z}) - 1) \times 100]$. With $\beta_z$: coefficients associated with predictors. The results are therefore available in Table 4.

## Business cycles' global effects upon CCBB

First, we note that the overall effects of business cycles: *Expansion* and *Contraction* coefficients are significant. Economic contractions positively affect the number of financial services held by customers with $\text{Contraction}_{\text{Crossbuy}} = 1.1870$ ($p < 0.001$). Less favorable economic situations increase the number of financial services held by 1.1870%, thus increasing their portfolios. This confirms our first hypothesis *H1: Economic contractions favor financial CCBB*. On the other hand, economic expansions negatively affect the number of financial services held by customers with $\text{Expansion}_{\text{Crossbuy}} = -0.9950$ ($p < 0.001$). More favorable economic situations reduce the number of financial services held by −0.9950%, thus reducing their portfolio. This confirms our second hypothesis *H2: Economic expansions disfavor financial CCBB*.
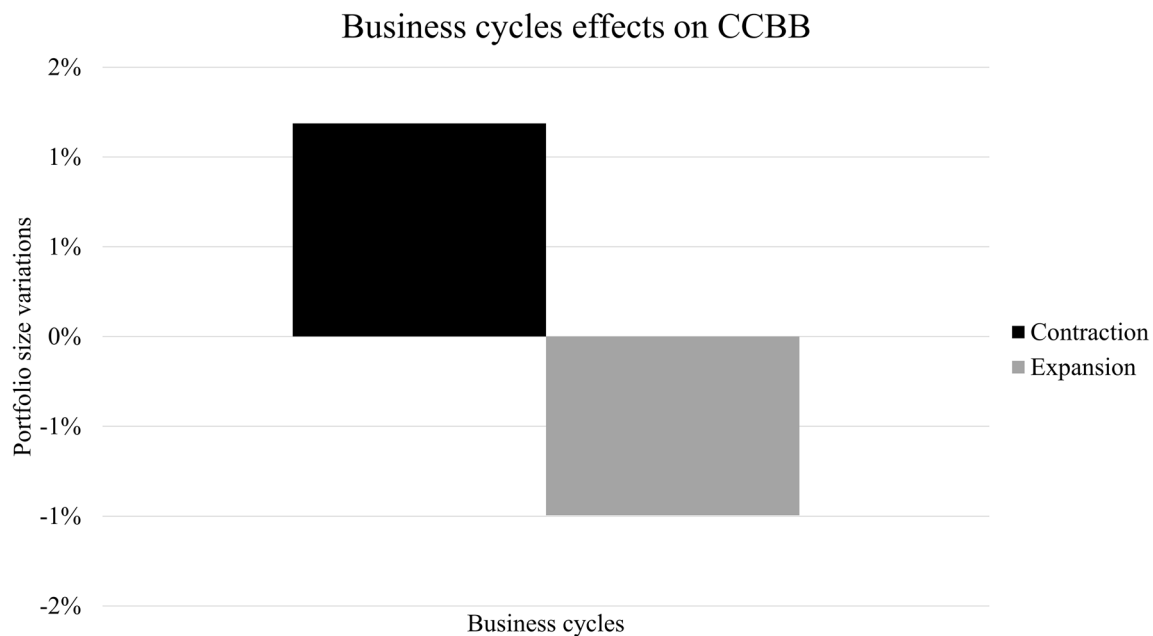
## Business cycles effects on CCBB



**Fig. 4** Contraction and expansion effects on CCBB

However, we retain a model that consider unobserved heterogeneity for customers $i$ and acquisition periods $j$, respectively, CFactor and GCFactor, as constants. We note that both coefficients are significant with $\text{CFactor}_{\text{Crossbuy}} = 70.7107$ ($p < 0.001$) and $\text{GCFactor}_{\text{Crossbuy}} = -11.768$ ($p < 0.001$). This shows that CCBB is different among customers and acquisition periods. The coefficient is stronger for customers unobserved heterogeneity, meaning that CCBB is more responsive to customers difference rather than the period they began their relationship with the company.

### Asymmetric effect between economic contractions and expansions

We note that business cycles exercise different influences on the number of financial services held by customers. In addition to having opposite influences, negative for economic contractions ($\text{Contraction}_{\text{Crossbuy}} = 1.1870$; $p < 0.001$) and positive for economic expansions ($\text{Expansion}_{\text{Crossbuy}} = -0.9950$; $p < 0.001$), the effects are asymmetric. We observe a delta of $|\text{Contraction}_{\text{Crossbuy}}| - |\text{Expansion}_{\text{Crossbuy}}| = 0.1920$. These results highlight the idea that economic contractions have more influence on financial CCBB than economic expansions. That was suggested in purchase behavior literature with a rather small difference (Deleersnyder et al. 2004; Heerde et al. 2013). As expected, economic contractions have greater influence on the number of financial services held, compared to economic expansions and thus have a greater impact on the financial portfolio size (Fig. 4). This confirms our third

hypothesis *H3: Economic contractions have a stronger influence on financial CCBB compared to economic expansions.*

### Control variables effects

Finally, we note that customer age influences the number of financial services held, with $\text{AgeLag}_{\text{Crossbuy}} = -1.6463$ ($p < 0.001$). At first sight, this seems counterintuitive to the literature stating that age favors evolution in the financial continuum (Li et al. 2005), but it is necessary to recall that previous research on customer financial behavior does not focus on the number of financial services held, but rather on the type of financial services. Thus, age could favor the acquisition of certain financial services but also negatively influences the overall portfolio. Our results show that, advancing in age, bancassurance customers would tend to reduce their financial services portfolio. We also note that loyalty positively influences the number of financial services held, with $\text{LoyaltyCompanyLag}_{\text{Crossbuy}} = 1.2882$ ($p < 0.001$). Thus, the more a customer stays loyal to the company, the more he will strengthen his financial services portfolio. This is consistent with previous literature on the influence of commercial variables on CCBB, which suggests that loyalty moderates the effect between satisfaction and cross-buying level (Verhoef et al. 2001, 2002).

### Interaction effects

Morisada et al. (2018) highlighted the moderating effects of age and gender between promotion-induced cross-buying

**Table 5** Model I regression results

| Dependent variable | Predictors | ln(Coefficient) | Coefficient in % | Standard deviation | Significance ($p$ value) |
|---|---|---|---|---|---|
| Crossbuy | 1 (Constant) | 1.7468 | | 0.0131 | 7.3e−3871*** |
| Crossbuy | CFactor | 0.5344 | 70.6424 | 0.0013 | 1.5e−37633*** |
| Crossbuy | GCFactor | −0.1250 | −11.7503 | 0.0019 | 4.2e−914*** |
| Crossbuy | Expansion | −0,0107 | −1.0757 | 0.0019 | 3.00E−08*** |
| Crossbuy | Contraction | 0,0243 | 2.4007 | 0.0028 | 5.80E−18*** |
| Crossbuy | AgeLag | −0.0176 | −1.7446 | 0.0002 | 1.3e−1750*** |
| Crossbuy | LoyaltyCompanyLag | 0.0143 | 1.4403 | 0.0003 | 2.5e−710*** |
| Crossbuy | AgeLag × Expansion | 0.0004 | 0.0400 | 0.0000 | 1.80E−22*** |
| Crossbuy | AgeLag × Contraction | −0.0001 | −0.0100 | 0.0000 | 1.90E−06*** |
| Crossbuy | LoyaltyCompanyLag × Expansion | −0.0003 | −0.0300 | 0.0001 | 1.10E−10*** |
| Crossbuy | LoyaltyCompanyLag × Contraction | 0.0003 | 0.0300 | 0.0000 | 6.50E−26*** |

LL = −396,216,6710; BIC = 792,538,6759; $R^2$ = 55.96%; ***$p < 0.001$

and customer behavior (purchase frequency and purchase amount). Thus, some previous statistical relations could be moderated. To strengthen and complete our analysis, we estimate another model considering the interaction effects between business cycles and customer age (AgeLag × Expansion; AgeLag × Contraction) and customer loyalty (LoyaltyCompanyLag × Expansion; LoyaltyCompanyLag × Contraction). Using panel data, we mobilize only useful dynamic variable. We propose the following additional model I to assess interaction effects.

The analysis of moderating effects presented in Table 5 above is interesting by highlighting significant interaction effects (AgeLag × Expansion; AgeLag × Contraction; LoyaltyCompanyLag × Expansion; LoyaltyCompanyLag × Contraction). Indeed, those coefficients are lower than the independent variables (*Expansion*; *Expansion*) coefficients leading to assume that customer age and customer loyalty has a modest impact between business cycles and CCBB.

## Conclusion and discussion

This study aimed to explore the influences of business cycles upon CCBB in the case of financial services. Our results identified significant links between business cycles and financial cross-buying level. As predicted, we observed inverse effects between the influences of economic contractions and expansions upon financial CCBB. Economic contractions increase CCBB, while economic expansions reduce it.

We already knew that the economic context impacts customer behavior. For example, confronting worse economic situations, customers are more price sensitive (Estelami et al. 2001) and tend to be more cautious about securing their future (Arrondel and Calvo Pardo 2008). Indeed, worse economic situations induce negative economic sentiment, which motivates customers to avoid loss and thus to choose products or services associated with avoiding negative outcomes (Millet et al. 2012). Conversely, better economic situations induce positive economic sentiment, which motivates customers to achieve more and thus to choose products or services associated with achieving positive outcomes (Millet et al. 2012).

Several studies have predicted and highlighted these changes in customer behavior. According to Katona (1975), negative expectations and uncertainty towards the future induce more savings. Facing unfavorable economic situations, customers would try to protect themselves by subscribing to specific financial services, such as health and life insurances, or general savings (Van Raaij 2016). These contracts limit the impact of several life risks, making customers less vulnerable and more comfortable about their future. As most financial services relate to security (e.g.,

home and health insurance) and precaution (e.g., general savings), we show that customers would, on average, hold more financial services to mitigate risk towards an uncertain future during economic downturns. On the other hand, positive expectations towards the future induce higher consumption and less savings (Katona 1975). Greater trust about the economic environment leads customers to be less cautious and encourages them to spend more freely (Kumar et al. 2014) instead of securing their income into specific financial services (e.g., savings accounts) or subscribing contracts to mitigate life risks (e.g., life insurance). In this configuration, our results highlight the fact that bancassurance customers are less inclined to subscribe and hold more financial services during economic upturns.

Finally, our results suggest an asymmetric influence between the effects of economic contractions and expansions, as identified in consumption literature (Lamey et al. 2007; Lamey 2014). The effect of economic contractions is stronger than the effect of economic expansions. This could be explained by the prospect theory, which shows that the emotional impact of a loss is greater than that of an equivalent gain (Kahneman and Tversky 1979). Thus, customers would subscribe to financial services to avoid losses in case of economic contractions to a greater degree than they would terminate those contracts to enjoy gain during economic expansions. Even if we can make reservations in view of the relatively small difference between the effects in absolute value, the influence of economic contractions on CCBB is greater than that of economic expansions (and not the other way around), as predicted by our hypotheses.

## Theoretical implication

This work aspires to introduce CCBB in marketing literature adopting an interdisciplinary approach. We propose extending previous research on cross-buying drivers (e.g., Kumar et al. 2008; Reinartz et al. 2008; Li et al. 2011) by demonstrating that business cycles do influence the phenomenon.

Our results provide a better understanding of CCBB in the case of financial services. Our quantitative study shows that cross-buying can be explained by individual variables, supply characteristics and the state of the customer-firm relationship (see "Appendix A") but also by contextual variables such as business cycles.

We thus introduce a significant explanatory variable into CCBB understanding. The influence of this variable had already been demonstrated for consumption habits (Lamey et al. 2012) but not on cross-buying behavior. Moreover, previous literature assumed the inconsideration of the economic variable as a limit and future research path (Liang et al. 2008; Li et al. 2011). Our work target to fill this theoretical and empirical gap by proving the influence of the economic context upon CCBB.

Our research also enriches previous work on the financial services acquisition process. Previous research has found specific acquisition sequences for financial services (Bijmolt et al. 2004), and identified probabilities of transitions between them (Prinzie and Van den Poel 2006), but without including exogenous variables in the models. We extend this research stream by demonstrating that the financial services portfolio is critically dependent on the economic situation as perceived by consumers. This could deepen and complement the theories in consumer behavioral finance (Van Raaij 2016; Xiao 2016).

## Managerial implications

The present research proposes various marketing applications and targets to help practitioners increase the profitability of their customer. Regarding financial services, increasing customer cross-buying rate allows to grow CLV. As business cycles influence CCBB, cross-selling strategies may depend critically on the ongoing business cycle. With specific understanding of CCBB under varying business cycles conditions, bancassurances could increase the cross-buying rate during economic contractions and prevent contract termination or churn during economic expansions.

Bancassurances often solicit their customers' cross-buying behavior through cross-selling campaigns. These campaigns highlight the characteristics of the offer to create value and meet customer needs. Our results indicate that, in addition to the offer itself, cross-selling campaigns should be based on the business cycles. Bancassurances professionals should consider the ongoing business cycle into their CRM tools and train staff to propose the adequate offer to customers. According to Salo et al. (2020) banks still struggle to properly exploit cross-selling capability. One of ten major challenges identified point out the lack of sufficient internal

marketing and communication. Our results could help to address the issue by focusing on CCBB following business cycles opportunities.

The COVID-19 economic crisis could provide a fertile ground to implement the results of our work, even if it represents a crisis and therefore an exceptional situation. According to our results, in the face of this major economic contraction, bancassurance customers would tend to increase their cross-buying rate especially with the subscription of financial services that allow to avoid negative results. We therefore advise bancassurance managers to launch cross-selling campaigns that bring to the fore the financial services that permit avoiding negative results, such as life insurance and retirement savings. This should be achieved by presenting the attributes of these financial services linked to security and sustainability insights.

To achieve such results, professionals should integrate the measurement of the perceived economic context into their CRM tools to elaborate cross-selling strategies.

## Limitation and further research

This study is limited using a national dataset from a single financial service provider. In addition, we could not include in the model all interesting variables because they were unavailable in the database. Moreover, empirically we focus only on financial CCBB according to the extant literature on the phenomenon, although other service industries also present critical issues.

As the influences of business cycles upon business relationship development are still largely unexplored in marketing literature, and due to the study limitations previously identified, the path forward is clear for potential subsequent research.

First, to increase external validity, this study should be replicated using complementary data. As in the research conducted by Bijmolt et al. (2004) and Prinzie and Van den Poel (2006, 2011), it would be interesting to replicate this study on European bancassurance databases. This would allow a broader view of the phenomenon and an external validation of our results.

In studying the financial services sector, it would be useful to consider some customer behavioral concepts to increase internal validity. A focus on risk aversion could allow a better understanding of business cycles influences

upon financial CCBB by moderating the relations. In addition, time preference and reference point could be included in the analysis as control variables. Longitudinal studies on a company's database are inappropriate for assessing these psychological variables because often unavailable. Further research should examine those customer behavior variables in specific models through other methodologies, such as surveys. In addition, prominent control variables such as income level should also be included. Moreover, information on competitor's offers could place our results into perspective. As emphasized by Vyas Roy and Raitani (2018) in bank sector, competitor's price plays a role onto customers cross-buying intentions more than the reputation and expertise of the primary bank.

To extrapolate these research results, replication in other service industries, such as the telecommunications sector, would be interesting. This replication would be even more accurate, as telecommunication companies are becoming increasingly hybrid. We no longer distinguish the bank from insurance by using bancassurance terminology. Future research could consider the bancassurance–telecom sector since several bancassurances already offer internet, landline and mobile phone subscriptions. We also observed the opposite process, where telecom companies offer banking services to their customers, as was done by Orange in creating Orange Bank.

Finally, this study focused on the business relationship development through customer cross-buying behavior. Nevertheless, one could analyze business cycles influences upon other stages of the business relationship. These include acquisition (Reinartz et al. 2005), retention (Verhoef 2003), and customer reactivation (Pick et al. 2016). For acquisition, the aim would be to observe how economic contractions and expansions influence customer relationship beginning. At the retention level, future research could identify periods when the customer is most likely to leave the company, to develop specific business strategies for preventing defection. In addition, the relative modern field of research on customer reactivation expands perspectives for integrating the potential influence of the economic environment.

Despite the limitations mentioned above, our research shows that CCBB critically depends on business cycles. We trust that integrating the economic variable into bancassurance marketing strategy would allow to increase customer profitability.

# Appendix A

## Cross-buying literature summarized by types of variables assessed

| Papers | Type of variables analyzed | | | | | Sector | Type of data | Method |
|---|---|---|---|---|---|---|---|---|
| | Business variables | Attitude variables | Marketing variables | Sociodemo-graphic variables | Economic variables | | | |
| Stafford et al. (1982) JBR[3] | × | | | | | Financial services | Cross-sectional (survey) | Guttman analysis |
| Dickenson and Kirzner (1986) JAMS | × | | | | | Financial services | Cross-sectional (survey) | Guttman analysis |
| Kamakura et al. (1991) JMR | × | | | × | | Financial service | Cross-sectional (survey) | Guttman analysis |
| Soutar and Cornish-Ward (1997) AE | × | | | × | | Financial services and durables goods | Cross-sectional (survey) | Rasch analysis |
| Paas (1998) JEP | × | | | | | Financial services and durables goods | Cross-sectional (survey) | Mokken scale analysis |
| Verhoef et al. (2001) JR | × | × | × | × | | Financial services | Panel (company database) | Probit model |
| Verhoef et al. (2002) JAMS | × | × | | × | | Financial services | Cross-sectional (survey) | Poisson regression |
| Verhoef (2003) JM | × | × | × | | | Financial services | Panel (company database and survey) | Ordinary least squares regression |
| Kamakura et al. (2003) IJRM | × | | | × | | Financial services | Cross-sectional (company database and survey) | Factor analysis |
| Kamakura et al. (2004) MS | × | | | | | Drugs | Panel (company database) | Split hazard model |
| Ngobo (2004) EJM | × | × | × | × | | Financial services | Cross-sectional (survey) | Ordinary least squares regression |
| Li et al. (2005) JMR | × | × | | × | | Financial services | Panel (company database) | Multivariate probit model |
| Verhoef and Donkers (2005) JIM | × | | | × | | Financial services | Panel (company database) | Probit model |
| Paas et al. (2005) SIJ | × | | | | | Financial services | Cross-sectional (survey) | Mokken scale analysis |

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[3] The Stafford et al. (1982) paper deal with customer accumulation of financial services which is close to CCBB.

| Papers | Type of variables analyzed | | | | | Sector | Type of data | Method |
|---|---|---|---|---|---|---|---|---|
| | Business variables | Attitude variables | Marketing variables | Sociodemo-graphic variables | Economic variables | | | |
| Paas and Molenaarb (2005) IJRM | | | | | | Financial services | Panel (survey) | Mokken and latent class analysis |
| Prinzie and Van den Poel (2006) EJOR | × | | | | | Financial services | Panel (company database) | Markov model |
| Salazar et al. (2007) JFSM | × | | | × | | Financial services | Panel (company database) | Survival analysis (Cox regression) |
| Paas et al. (2007) JEP | × | | | × | | Financial services | Panel (survey) | Markov model |
| Liu and Wu (2007) JFSM | × | × | × | | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Kumar et al. (2008) JR | × | | × | × | | Catalog retailer | Panel (company database) | Seemingly unrelated regression |
| Reinartz et al. (2008) JIM | × | | × | | | Catalog retailer | Panel (company database) | Granger-type causality modeling |
| Liang et al. (2008) SIJ | | × | | | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Soureli et al. (2008) JFSM | | × | | | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Liu and Wu (2009) SIJ | × | × | | | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Blut and Woisetschläger (2010) MTA | × | × | × | × | | Consumer packaged goods (CPG) | Cross-sectional (company database and survey) | Ordinary least squares regression |
| Prinzie and Van den Poel (2011) JIIS | × | | | | | Financial services | Panel (company database) | Dynamic Bayesian network |
| Li et al. (2011) JMR | × | | × | × | | Financial services | Panel (company database) | Multivariate Probit model |
| Shah et al. (2012) JM | × | | × | × | | Financial services, IT, catalog retailer | Panel (company database) | Logistic regression |
| Hong and Lee (2012) IJBM | | × | | | | Financial services | Cross-sectional (survey) | Hierarchical regression analysis |
| Tung and Carlson (2015) IJQRM | | × | | | | Financial services | Cross-sectional (survey) | Structural equation modeling |

| Papers | Type of variables analyzed | | | | | Sector | Type of data | Method |
|---|---|---|---|---|---|---|---|---|
| | Business variables | Attitude variables | Marketing variables | Sociodemo-graphic variables | Economic variables | | | |
| Evanschitzky et al. (2017) JRCS | × | × | | × | | DIY retailer | Cross-sectional (company database and survey) | Linear regression |
| Vyas Roy and Raitani (2018) IJBM | | × | | | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Zhu et al. (2018) IR | | × | | × | | Online Shopping | Cross-sectional (survey) | Partial least squares regression |
| Dahana et al. (2020) JSM | × | × | × | × | | Fashion products | Cross-sectional (company database and survey) | Hierarchical linear regression model |
| Mukerjee (2020) JRDM | | × | | × | | Financial services | Cross-sectional (survey) | Structural equation modeling |
| Frequencies | (28/35) | (17/35) | (10/35) | (18/35) | (0/35) | Financial services (28/35) | | |

# Appendix B

## Descriptive statistics and correlation matrix

| | Descriptive statistics | | | | | | Correlation matrix | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std.dev | Variance | Range | Min | Max | 1 | 2 | 3 | 4 | 5 |
| 1. Crossbuy | 3.15 | 2.462 | 6.063 | 14 | 1 | 15 | 1 | −0.002 | 0.072 | −0.099 | 0.175 |
| 2. Expansion | 2.04 | 2.746 | 7.539 | 8 | 0 | 8 | −0.002 | 1 | 0.531 | 0.002 | 0.009 |
| 3. Contraction | −3.10 | 4.348 | 18.906 | 16 | −16 | 0 | 0.072 | 0.531 | 1 | −0.095 | 0.055 |
| 4. AgeLag | 56.37 | 12.280 | 150.804 | 79 | 30 | 109 | −0.099 | 0.002 | −0.095 | 1 | −0.054 |
| 5. LoyaltyCompanyLag | 27.34 | 10.132 | 102.665 | 55 | 2 | 57 | 0.175 | 0.009 | 0.055 | −0.054 | 1 |

# Appendix C

## Statistical model building

We build a panel multilevel mixed effects model. The database is a panel in which observations are replicated for subjects $i$ (customers) in time $t = 1$ to $T$ where $t$ is in year unit. In addition, the panel is cylindrical insofar as there are the same number of periods $T$ for each subject $i$ with the number of lines $N = n.T$. The multilevel model is justified by the form of our panel, which involves two indices: $i = 1$ to $n$ for level 1 (customers) and $j = 1$ to $J$ for level 2 (acquisition periods), which is nested in the first level. The term "mixed" is used to signify that the effects of beta coefficients have both a fixed part $\beta$ and a random part $\gamma$, making it possible to measure unobserved heterogeneity. Thus, we consider the following equation:

$$Y_{ijt} = g\left[\beta_j * X_{ijt} + \gamma_{ij} * Z_{ijt}\right] + E_{ijt} \tag{1}$$

where $Y$: the dependent variable;

$X = [1, X]$: the independent variables associated with fixed effects;

$Z = [1, Z]$: the independent variables associated with random effects;

$\beta_j = \left[\beta_{j0}, \beta_{j1}, \ldots, \beta_{jk}, \ldots \beta_{jK}\right]$ of size $[1, K + 1]$, for each $j = 1$ at $J$, vector of $K + 1$ with fixed part for class $j$;

$X_{ijt} = \left[X_{ij0t}, X_{ij1t}, \ldots, X_{ijkt}, \ldots X_{ijKt}\right]$ of size $[1, K + 1]$ for each $(i, j, t)$, vector of $K + 1$ values of independent variables associated with fixed effects for the individual $i$ of class $j$;

$Z_{ijt} = \left[Z_{ij0t}, Z_{ij1t}, \ldots, Z_{ijmt}, \ldots Z_{ijMt}\right]$ of size $[1, L + 1]$ for each $(i, j, t)$, vector of $L + 1$ values of independent variables associated with random effects for the individual $i$ of class $j$;

$\gamma_{ij} = \left[\gamma_{ij0}, \gamma_{ij1}, \ldots, \gamma_{ijkl}, \ldots \gamma_{ijL}\right]$ of size $[1, L + 1]$ for each $i = 1$ to $n$ and $j = 1$ to $J$, vector of.

$L + 1$ coefficients with random part in class $j$;

$g(s)$: the nonlinear link function linking the expected mean value $E[Y]$ of the variable $Y$ to the linear part $s$ of the "variable*effects" of the form $s = \beta_j * X_{ijt} + \gamma_{i,j} * Z_{ijt}$;

$E_{ij\,i}$: the residual error term.

The dependent variable $Y_{ijt}$ corresponds to the count $(0; 1; 2; 3; \ldots)$ of financial services owned by customers $i$ with $g(s) = exp(s)$. Thus, involving a Poisson distribution as follows:

$$P(Y = k) = \frac{(a \cdot T)^k . e^{-a \cdot T}}{k!} = \frac{\lambda^k \cdot e^{-\lambda}}{k!} \qquad (2)$$

where $a \cdot T = \lambda$: the parameter of the law;

$k$: an integer that can be theoretically be $0;1;2;3;\ldots$ to infinity;

$e = 2.182818\ldots$

To limit overdispersion bias, we choose to include a gamma noise variable which has a mean of 1 and a scale parameter of $\nu$ (negative binomial) leading to a Poisson-gamma mixture distribution as follows:

$$P\left(Y = y_i | u_i, \alpha\right) = \frac{\Gamma\left(y_i + \alpha^{-1}\right)}{\Gamma(y_i + 1)\Gamma\left(\alpha^{-1}\right)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + u_i}\right)^{\alpha^{-1}} \left(\frac{u_i}{\alpha^{-1} + u_i}\right)^{y_i} \qquad (3)$$

where

$$u_t = t_i \mu$$

$$\alpha = \frac{1}{\nu}$$

The parameter $\mu$ is the mean incidence rate of $y$ per unit of exposure. The parameter $\mu$ may be interpreted as the risk of a new occurrence of the event during a specified exposure period.

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