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IMPAIRMENT IN THE MORTGAGE LOAN PORTFOLIO: THE EXAMPLE OF BANCO POPULAR PORTUGAL

ROSA BRAND (16000287)

A Project carried out on the Risk Management course, under the supervision of:
Professor Miguel Ferreira

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Abstract

The recent financial crisis has highlighted the significant impact of external factors such as housing prices and GDP on banks' results. In the light of these events, the aim of this paper is to support Banco Popular Portugal in analyzing the influence of general economic indicators, specifically real estate prices, on credit impairment in the mortgage loan portfolio and developing methods to forecast impairment using these indicators. Based on secondary research in scientific journals and data from the bank, it can be shown that, while housing prices significantly influence both loss given default and probability of default, forecasting impairment purely on the basis of external indicators does not yield meaningful results in the specific case of this bank. A combination of external and internal indicators should therefore be drawn upon to assess future impairment.

1. Introduction

The financial crisis of 2008 has acted as a reminder about the potentially dangerous effects of banks being strongly exposed to one industry sector. The burst of the housing bubble has left many banks with a combination of large amounts of unrecoverable loans to the construction sector and a sharp fall in the value of assets securing personal loans. While Portugal's real estate market fared comparatively well throughout the crisis, awareness was raised about the potential impacts of a sudden fall in market values. In this context, Banco Popular Portugal (in the following referred to as BAPOP) is seeking to analyze the impact of housing prices on its mortgage loan portfolio and to find accurate ways of assessing future impairment in this segment. After defining impairment and presenting regulations governing the concept, a brief overview over relevant literature will be given. Subsequently, the impact of changes in housing prices on BAPOP's impairment and asset value shall be assessed in detail and the bank's approach to assessing Loss Given Default (LGD) will be evaluated. Furthermore, methods will be developed to forecast LGD based on projected changes in external indicators. In addition, the bank's approach to assessing Probability of Default (PD) to calculate impairment will be put under scrutiny, and external indicators will be used to project PDs into the future.

2. Methodology

The first part of this paper will be based on a literature review on the topic. In this context, secondary research is conducted in scientific journals in order to find academic papers covering the drivers of impairment in mortgage loans. In addition, working paper publications from United States Federal Reserve Banks are analyzed. In the second part of the paper, data of Banco Popular Portugal will be used to conduct analyses and draw conclusions. In an attempt to combine the findings from literature review and the bank's data, external indicators obtained mainly from the Portuguese National Statistical Office are drawn upon.

3. Definition and Regulations Governing Impairment

The principal regulation governing impairment is the revised International Accounting Standard (IAS) 39 Financial Instruments: recognition and measurement, published on 17 December 2003 by the International Accounting Standard Board (IASB) (IAS 39 2004: 1). This regulation defines impairment as follows:

> *"A financial asset or a group of financial assets is impaired and impairment losses are incurred if, and only if, there is objective evidence of impairment as a result of one or more events that occurred after the initial recognition of the asset (a 'loss event') and that loss event (or events) has an impact on the estimated future cash flows of the financial asset or group of financial assets that can be reliably estimated." (IAS 39 2004: 20)*

Several loss events are defined (IAS 39 2004: 20 f) and entities are obliged to determine impairment losses if any objective evidence for such loss events is found.

4. The Influence of Real Estate Prices on Impairment

While rules on impairment have been defined by IAS 39, the exact method of calculation has been left at banks' own discretion (Betancourt 1999: 304). This process implies significant difficulties for banks to adequately estimate future loan losses. In order to find a method to forecast impairment based on general economic indicators, we want to identify the main drivers of impairment in mortgage loans. To this end, secondary research in numerous scientific journals has been conducted.

In our analysis, we will differentiate between the drivers of Loss Given Default (LGD) and Probability of Default (PD). As Zhang, Li and Liu (2010: 3) note, the variable that shows by far the biggest impact on LGD is the current loan-to-value (CLTV) ratio. At the time of loan initiation, this ratio depends mainly on the policy of the originating bank. However, as we are considering only the case of BAPOP, we assume that this policy has been rather stable over time. As a result, the value of the property remains as the single influencing factor for LGD.

We now want to look at the second determinant of impairment: Probability of Default. As Case and Shiller (1996: 244) note, "the value of mortgage portfolios does depend importantly on risks of price change in real estate markets". Specifically, they find that price changes have the strongest effect on defaults with a lag of two years (Case and Shiller 1996: 255). Similar findings are reached by Elmer and Seelig (1998: 11) and Demyanyk, Koijen and Van Hemert (2011: 14) who note that "An increase in housing equity lowers the probability of transitioning to a worse state." Housing equity is defined as the current market value of the house minus the current market value of the loan (Quercia and Stegman 1992: 375), and thus a similar measure to the CLTV ratio. Case and Shiller (1996: 245) argue that the relationship between housing prices and default losses is a non-linear one, meaning that very large decreases in housing prices lead to a higher than proportional increase in default rates (Elul 2006: 27). The nonlinearity of this function is particularly important where the loan-to-value ratio is very low, as defaults are highly unlikely in such situations (Case and Shiller 1996: 246).

This nonlinear relationship can be further analyzed if we interpret the possibility of default as a put option. Specifically, we can interpret the homeowner's choice to default on the loan as a put option on the house with strike price being the current mortgage balance (Elul 2006: 22). The option is thus "in the money", i.e. worth exercising, when the mortgage value is higher than the value of the house, a situation which is called negative equity. Therefore, decreasing housing prices will increase the likelihood that the option be exercised (Archer and Smith 2010: 2). However, this relationship is clearly non-linear, as the option holder has the right, not the obligation to exercise. In the case that housing equity is only slightly negative, there is a high probability that it will turn positive again in the future, and the borrower is therefore unlikely to exercise. For sharp drops in property value, a high enough price recovery is less likely, and the borrower is therefore disproportionately more inclined to exercise (Elul 2006: 27 f.). Also, it is true for all options that volatility in underlying asset prices increases option value. In our case, this implies that "more volatile house prices should be associated with both a greater incidence and a greater severity of default" (Elul 2006: 23).

However, one factor that needs to be taken into account is the transaction cost that arises to the borrower when exercising the option. This cost generally comes in the form of the hassle of moving house as well as a deterioration in credit score (Elul 2006: 24). As a result, borrowers may decide not to exercise their option, even if housing equity is significantly negative (Demyanyk, Koijen and Van Hemert 2011: 1). Another possible explanation for borrowers' reluctance to exercise is the fact that the option under consideration is of American style, which means that it can be exercised any time until maturity. Borrowers thus have the possibility to wait longer and bet on a further fall in housing prices to increase their payoff. Alternatively, they can try to refinance the loan, which introduces a call option component into the equation (Elul 2006: 23).

In addition to real estate prices, liquidity constraints caused by general economic conditions can significantly influence the likelihood of default (Demyanyk, Koijen and Van Hemert 2011: 9). As Archer and Smith (2010: 4) note, employment and income conditions can trigger situations where the borrower is forced to default, even though his monthly payments are lower than the value he attributes to the housing services. This idea was confirmed by Elul et al. (2010: 8) who find strong correlations between illiquidity (measured by unusually high credit card utilization) and mortgage default. Demyanyk, Koijen and Van Hemert (2011: 16) find that changes in unemployment rates have significant effects on mortgage payments. Apart from general economic conditions, studies by Krainer and Le Roy (2009: 42) show that several borrower-specific life events can also trigger default.

To sum up, we can say that “adverse shocks to house prices and income emerge as the two variables most fundamentally related to default” (Elmer and Seelig 1998: 20). While LGDs are only influenced by lending policies and housing prices, PDs are also dependent on general economic conditions (unemployment and economic cycle) as well as personal events regarding the borrower.

5. Calculation of Impairment at BAPOP

In this section, the method BAPOP uses to implement the IAS regulations regarding impairments will be described briefly (Banco Popular 2009). The model, developed in 2005 and reviewed in 2009, is applied to monthly calculations of impairment. It divides the loan portfolio into four distinct groups, each of which will be treated differently in the calculations.

5.1. Evidence of Impairment and Structure of Loan Portfolio

First of all, a distinction is made between assets showing indications of impairment (deteriorated loan portfolio) and those that do not (non-deteriorated loan portfolio). Objective as well as subjective indicators are recognized. *Objective indicators* include mainly payments being overdue for more than ninety days, clients in state of insolvency or bankruptcy, and transactions that were restructured due to financial difficulties of the borrower. *Subjective indicators*, on the other hand, include situations where payments are overdue for 30 to 90 days and additional criteria, such as past write-offs, apply.

The two resulting segments are further broken down by outstanding loan amounts. This leads us to a situation where four different segments are considered: The homogeneous deteriorated loan book (covering clients with total liabilities of up to €500,000); the significant deteriorated loan book (covering clients with total liabilities above €500,000); the homogeneous non-deteriorated loan book (covering clients with total liabilities of up to €2,500,000); and the significant non-deteriorated loan book (covering clients with total liabilities above €2,500,000). An aspect of contagion is introduced, which means that, if any one transaction of a specific client shows evidence of impairment, all his remaining transactions are also treated as deteriorated.

5.2. Calculation of Impairment for Each Client Segment

Impairment is now calculated separately for each segment. In this process, the transactions falling into either of the two “significant” segments are analyzed individually, while a random sample is analyzed in the “homogenous” segments, whose results are then extrapolated to the population.

In the Significant Non-Deteriorated segment, due to their size, transactions are analyzed individually by the respective account manager. If no reason for impairment is found, a transaction is attributed to the pool of homogenous non-deteriorated assets. Transactions in the Significant Deteriorated segment are analyzed individually by the credit recovery department. This process is relatively subjective and issues of accuracy might arise. In the Homogenous Non-Deteriorated segment, impairment is calculated by assessing Probabilities of Default (PD) and Loss Given Default (LGD) for a sample that is updated semiannually. The items within the sample are chosen in two steps. First, the weights of each type of operation (i.e. credit card, mortgage, etc) need to reflect the reality of the bank. Within these types, operations are then drawn randomly. The sample includes 2,736 items. Impairment in this case is calculated as shown in *equation 1*.

$$Impairment = Balance\ amount\ (per\ segment) at\ reference\ date\ x\ PD\ x\ non - deteriorated\ LGD$$

Equation 1: Calculation of impairment in Non-Deteriorated segment

PDs need to be calculated for each segment as deteriorated transactions in the year of analysis (n+1) that were not deteriorated in the base year (n) over non-deteriorated transactions in n. This calculation is done for the past 10 years, the final PD being an average of the different PDs, weighted by total loan values. LGD is calculated as one minus the percentage of all the recoveries from the year before the reference year (n-1) to the date of analysis over the operating result one year before showing signs of deterioration.

In the Homogenous Deteriorated Loan Book, the loan book is first crystallized. Crystallization is the calculation of the maximum amount owed for each transaction between the date in which the transaction turned “bad” and the reference date of the analysis. Given that there are already signs of deterioration, PD is assumed to be 100 per cent, and impairment is thus given by *equation 2*.

$$Impairment\ =\ Debt\ amount\ per\ segment\ (crystallized)\ x\ deteriorated\ LGD$$

Equation 2: Calculation of impairment in Homogenous Deteriorated Segment

6. The Impact of Real Estate Prices on BAPOP's Mortgage Loan Portfolio

We now want to assess the impact of changes in housing prices on credit impairment, and as a result on asset value. To do this, we analyze a portfolio of 558 operations of personal mortgage loans started in the years from 2006 to 2010. These operations are related to 353 clients, limited to operations that meet the criteria to be considered as "deteriorated". Of all operations that were started in the period under review, only those were considered where the respective client has one or more operations with payments overdue for more than 90 days. Even if the operation itself has no related overdue payments, it is considered deteriorated if this is true for another operation of the same client.

After determining the operations making up our portfolio, information about the valuation of the asset the mortgage is secured by had to be found. To make sure only correct values are used, all valuations that have been conducted with relation to the operations under review need to be analyzed in more detail, finding the valuation reports and comparing the proposed value with the input in the database. Apart from the valuations found in the valuation database, a value of the securing asset is included in the operations file. For operations where no asset valuation can be found in the valuation file, or where the first valuation found is dated after the starting date of the operation, this value is applied as the first asset valuation, and the starting date of the operation is used as valuation date. For each year between the available valuations, the value of the asset is assumed to be equal to the last available valuation. In 2011, the year for which we want to calculate impairment, we apply haircuts, i.e. general percentage decreases in valuation, on assets whose last valuation dates back more than two years.

This is because the lack of formal assessment does not imply that no decrease in value has taken place. Based on the bank's past experience, the haircut is set at -15% for assets with a last valuation in 2006, -10% for those with their newest valuation in 2007, and -5% for assets last evaluated in 2008.

After calculating the value of each asset in each year up to 2011, we now want to calculate impairment related to each asset for each year. Impairment is calculated as shown in *equation 3*.

$$Impairment = min\left(0, Asset\ value * \frac{Operation\ Exposure}{Total\ Exposure\ Secured\ by\ Asset} - Operation\ Exposure\right)$$

Equation 3: Calculation of impairment per operation

We can now analyze the value changes that have taken place in the period under review. Excluding cases where houses are still under construction, the division in cases of value increases versus decreases is shown in *table 1*.

Value Increases	40	9%
Value Decreases	419	91%
Total	**459**	**100%**

Table 1: Value changes with haircut

Value Increases	40	22%
Value Decreases	146	78%
Total	**186**	**100%**

Table 2: Value changes without haircut

To analyze the value changes that would have taken place in our sample without the applied haircuts, we do the same calculations considering only the valuations that were actually effected (see *table 2).* As we can see, a large majority of cases reflect value decreases. More detailed analysis reveals that most cases of value increases take place where real estate valuation consultants did not have the opportunity to visit the interior of the asset in the first valuation, and therefore applied a discount on the value.

Having made these analyses, we can now calculate how the number of impaired operations, total impairment, and impairment as a percentage of total operation exposure are affected by changes in housing prices. To do this, we conduct the same calculations as described above, but eliminate any negative change in housing prices. This means that no haircut is applied for valuations dating back further than 2008. In addition, if a valuation leads to a lower value than the previous one, the higher value is applied. As a result, impairment is reduced to the amount based on the highest valuation we have in our portfolio for each asset at each time. Effectively, this means that impairment can only occur in cases where the first valuation we have for an asset is already not enough to cover the entire operation exposure. We then compare the results for both cases in 2011, which are shown in *table 3*.

	With Devaluation	Without Devaluation
Impairment Cases	241	133
Change Cases	-108	
Change Cases %	**-45%**	
Impairment	- 4,586,527	- 1,996,145
Change Impairment	2,590,381	
Change Impairment %	**56%**	
Impairment/Total Cases	43%	24%
Impairment/Exposure	**10.64%**	**4.63%**

Table 3: Impairment with and without asset devaluation

Looking at these results, we see that housing prices have a very strong impact on the bank's impairment. Ignoring the devaluations of securing assets, the number of operations with impairment decreases by 45 per cent, and the absolute value of impairment is 56 per cent lower. The ratio of impairment to total operation exposure is only 4.63 per cent, compared to 10.64 per cent if we take negative real estate value change into consideration. These figures imply that housing prices have a powerful influence on impairment at BAPOP. Given the recent volatility in housing prices, we therefore want to analyze whether the bank has potential for improving its approach to calculating impairment by taking into account external indicators.

7. Assessing the Adequacy of BAPOP's LGD Calculations

In this section, we want to assess how well the results of BAPOP's standard approach to calculating impairment match the results of our exact calculations of impairment per loan. In order to do this, we apply the standard approach to our sample. Given all the operations are deteriorated, probability of default is assumed to be 100 per cent. For deteriorated operations in the personal mortgage loan segment, BAPOP applies a value of 10.24 per cent for loss given default.

To calculate impairment using the standardized approach, we now multiply this percentage with the total operation exposure of our sample, which is € 43,111,411. This gives us a value of € 4,415,471, which is € 171,056, or 3.73 per cent, lower than the exact value we calculated above. The percentage of impairment to total operation exposure calculated in our sample is, at 10.64 per cent, 0.40 percentage points higher than the percentage applied as LGD. This minor difference implies that the approach used by BAPOP is an appropriate approximation.

8. Forecast of LGD Percentage

The above calculations give us a good idea about the appropriateness of BAPOP's approach to calculating impairment. However, one shortcoming of the bank's approach is that impairment is calculated based on information that dates back more than two years. For the calculation of the applied LGD percentage in December 2010, for example, the latest data on LGD comes from 2008. In this section, we therefore want to find an approach to forecasting impairment that is based on more recent information.

8.1. Forecasting LGD Based on a Sample of Operations

After calculating impairment for our sample and comparing the results to the ones from BAPOP's standardized calculation approach, we now want to find a method to forecast future impairment. Using as a basis the results from our calculations of impairment in 2011 and the valuations of assets in 2011 we assume a range of possible changes in housing prices to calculate the resulting impairment and ratio of impairment to total operation exposure. Based on forecasts of housing price indices in Portugal, the bank can then use the respective percentage as LGD and thus forecast impairment for the year to come. *Figure 1* shows the LGDs for a range of possible changes in housing prices.

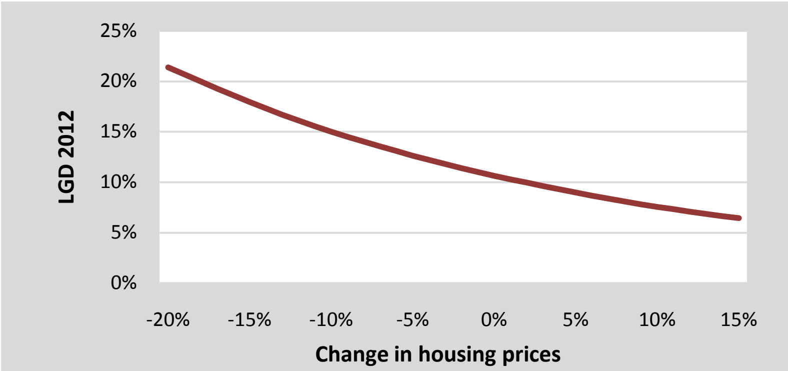

Figure 1: LGD percentage for possible changes in housing prices

This can be used to predict the future percentages of LGD the bank should apply, given a prediction of housing price development. However, the method has a number of shortcomings. First of all, calculations are only based on the sample of operations that are already in place. Within this sample, a large number of operations have already experienced prior value change. This implies that a certain change in housing prices will have a stronger effect on impairment of those operations than on a similar operation started only in 2011, as the "safety cushion" that usually exists in the form of a positive difference between asset value and total loan amount has already been used up. This is demonstrated by the fact that operations with a more recent starting date are generally less likely to demonstrate impairment. *Table 4* shows the percentage of operations that are impaired, by year of operation starting date.

Operat-ion starting date	Operations with impairment in 2011 (%)	LGD in 2011 (%)	Operations with impairment in 2010 (%)	LGD in 2010 (%)	Operations with impairment in 2009 (%)	LGD in 2009 (%)	Operations with impairment in 2008 (%)	LGD in 2008 (%)	Operations with impairment in 2007 (%)	LGD in 2007 (%)
2006	59.0	22.7	52.0	21.4	44.9	19.6	38.8	14.2	40.8	14.0
2007	54.5	11.4	39.4	8.6	38.5	8.2	29.1	5.0	27.7	5.6
2008	31.1	3.5	21.0	1.9	17.6	1.8	16.8	1.7	0.0	0.0
2009	23.4	7.0	16.8	2.0	16.8	1.9	0.0	0.0	0.0	0.0
2010	23.8	1.6	19.0	0.9	0.0	0.0	0.0	0.0	0.0	0.0

Table 4: Percentage of operations started in year "X" that are impaired in "Y"

As we can see, the likelihood of operations to be impaired is generally larger the older the operation. Similarly, impairment as a percentage of total operation exposure is generally higher for those operations. This implies that the addition of new operations to the portfolio would indicate a lower LGD percentage than the one we calculate. In addition to this shortcoming, the crisis might have induced the company to apply a more conservative lending approach. All these changes are not taken into account in the present calculations.

8.2. Forecasting LGD Based on External Indicators

Given the shortcomings of the above conducted approach, we now want to find a way to forecast the bank's impairment based on more objective external indicators. Due to the strong influence of housing prices on impairment we found in our analysis, we believe that this indicator can be used to make projections. In the following, we test this assumption.

First of all, we need to find an index of housing prices in Portugal. We obtain a monthly index of prices (average price in Euro per square meter) from the Portuguese Statistical Office (Instituto Nacional de Estatística 2011). However, these data are only available starting in September 2008. We therefore use another index obtained from the same source to get average housing prices for continental Portugal at quarterly frequency until end of 2009. To get a single index to base our calculations on, we make the assumption that housing prices in the Portuguese islands have developed in the same way as those in continental Europe. From the monthly index for Portugal, we now calculate average prices per quarter as well as the quarterly change in prices. We then apply the calculated change to our quarterly index with data up to 2009, to calculate average quarterly prices for continental Portugal for the years after 2009. Now we have a consistent housing price index from 2004 to the end of 2010.

From the calculations that the bank has made semi-annually in the past, we then obtain the LGD percentage. Specifically, the LGD percentage the bank applies is always given by some average of past LGDs. Due to the characteristics of the bank's loan portfolio before 2003, LGD was at unusually high levels in this time. As this scenario is unlikely to occur in the future, we eliminate these values from our calculations and consider only LGD values starting in 2003. We then calculate LGD in each semester as an average of LGDs since 2003. We therefore only obtain averages for periods between the first semester of 2004 and the second semester of 2008. In addition, we calculate semiannual GDP (at current prices), building activity in Portugal (Fogos concluídos (N.º) em construções novas p/ habitação familiar por Localização geográfica (NUTS-2002);Trimestral(1)), index of new construction orders (Índice de novas encomendas na construção e obras públicas (Tx. Média v. a. Base 2000) p/ Tipo de obra; Trimestral), and index of confidence in the construction industry (Indicador de confiança (Saldo de respostas extremas) da construção; Mensal) (Source: Instituto Nacional de Estatística 2011). This data input is shown in *table 5*.

	2004		**2005**		**2006**		**2007**		**2008**		**2009**		**2010**	
Semester	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Housing Index	1174	1204.5	1214	1234.5	1224.5	1231	1241	1226.5	1203	1158	1158.5	1159	1177.6	1148.4
-Change		2.60%	0.80%	1.70%	-0.80%	0.50%	0.80%	-1.20%	-1.90%	-3.70%	0.04%	0.04%	1.61%	-2.48%
GDP	36,902	37,511	38,178	38,686	39,662	40,474	41,888	42,481	43,093	42,918	41,710	42,327	42,813	43,606
-Change	2.28%	1.65%	1.78%	1.33%	2.52%	2.05%	3.49%	1.41%	1.44%	-0.41%	-2.81%	1.48%	1.15%	1.85%
NovasEncomendas	4.1	13.2	6.1	3.5	0.8	1.3	-2.3	-12.3	-5.6	-6.8	-18.5	-40.6	-20.8	1.8
Confianca	-36.4	-35.0	-31.6	-34.5	-37.4	-38.8	-32.9	-31.3	- 27.9	-33.9	-36.6	-35.3	-40.8	-43.5
FogosConcl	18,029	18,983	19,295	18,541	16,385	17,720	16,688	16,450	15,538	15,774	13,938	16,170	15,688	6,554
LGD	**5.60%**	**3.20%**	**2.40%**	**3.02%**	**4.85%**	**4.85%**	**5.02%**	**5.02%**	**7.23%**	**8.02%**				

Table 5: External Variables and LGD

Now, we want to analyze the connection between these variables and the average LGD percentage in that period. We first calculate correlations of the different variables with LGDs. Results are shown in *table 6*.

	Housing Index	Housing Index Change	GDP	GDP Change	New Orders	Confidence	Completed Houses
Correlation with LGDs	-0.57	-0.88	0.70	-0.38	-0.31	0.20	-0.87

Table 6: Correlation between external variables and LGDs

As we can see, negative correlations are found with the change in housing prices, the housing price index, GDP Change, New Orders and Completed Houses. However, the results of the correlations with GDP and Confidence are counterintuitive, as they imply that higher GDP and higher confidence in the building sector tend to come with higher impairment. As a next step, we want to run a stepwise regression of LGDs on the variables. This process finds the optimal regression to use Housing Index and Completed Houses as independent variables (see regression results in *table 7*).

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	.970	.940	.920	.0052729

Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	.541	.090		5.986	.001
ComplHouse	-.000011	.000	-.811	-7.745	.000
HouseIndex	-.000253	.000	-.340	-3.245	.018

Table 7: Linear Regression of LGD on Housing Price Index and Completed Buildings

These results would imply the function shown in *equation 4.*

$$LGD\ (\%) = 0.541 - 0.000011 * ComplHouse\ - 0.000253 * HousingIndex$$

Equation 4: Regression LGDs on Housing Index and Completed Houses

This means that a one point decrease in the housing index would lead to a 0.000253 percentage point increase in LGD, while a one point decrease in newly completed houses would lead to a 0.000011 percentage point increase in LGD. Using input values for 2009 to 2011, we can now calculate LGD based on this function as shown in *table 8*.

	2009		2010	
Semester	1	2	1	2
HousingIndex	1158.5	1159	1177.6	1148.435
ComplHouses	13,937.5	16,170.0	15,687.5	6,554.0
LGD	**9.85%**	**7.44%**	**7.49%**	**18.04%**

Table 8: Calculation of LGD based on Housing Index and Completed Houses

Several flaws are present in this calculation. First of all, the sample used for the regression is very small. In addition, average LGD for each semester is calculated as a simple average, not a weighted average, of past LGDs. To test for the impact of this factor, the same calculations (regression and correlation) were made using average LGDs where 50 per cent of the weight is given to the most recent value, and 50 per cent to the average of values before that. However, the results of the regression were not found to be significant. In addition to these calculation-related flaws, another drawback occurs that is related to the very nature of the data used. Given the method of calculation of LGD percentages, as described in a previous section, there is some subjective component to it. This is because LGD calculations are partly based on subjective assessments of the recoverable value of operations. Even though these assessments are thoroughly checked for validity by the risk management department, this makes it more difficult to relate LGD development over time to external factors such as housing prices.

All these factors lead to a situation where the LGD values projected by the results of the regression and the change in housing prices obtained from the Portuguese Statistical Office are not entirely coherent with the bank's expectations. While BAPOP expects LGD percentages to be around 8 to 9 per cent, the model projects values that are around 18 per cent in the second semester of 2010 as the value of completed buildings sharply decreases. We therefore have to conclude that regressions are not a meaningful way to predict LGD percentages, given the flaws mentioned.

9. The Impact of Housing Prices on BAPOP's Total Asset Value

This section will discuss the impact a change in housing prices will have on the total value of BAPOP's assets. The first way in which housing prices affect the size of assets is through credit impairment. This means that, as described above, impairments reduce the expected value of the housing loans in the loan portfolio held on the bank's assets. According to our sample of operations, deteriorated operations make up approximately 4.3 per cent of the total of housing loans. We now want to see how the impairment related to these operations changes with real estate prices. To do this, we use the values resulting from our forecast of LGDs based on our sample operations. For example, if housing prices decrease by five per cent, impairment is expected to be 12.64 per cent, which is 2 percentage points higher than if housing prices stay stable. Given that total mortgage loans account for approximately 14.91 per cent of total assets, the impact of a -5 per cent change in housing prices on impairment related to "bad" loans is shown in *equation 5*.

$$\% \; of \; mortgage \; loans \; in \; assets * \% \; of \; bad \; loans \; in \; total \; loans * change \; in \; LGD * Assets$$
$$= \; 14.91\% * 4.3\% * 2.00\% * Assets = -0.0129\% * Assets$$

Equation 5: Impact of a -5% change in housing prices on impairment in bad loans

So, the effect of a 5 per cent decrease in housing prices on assets through "bad" loan impairment is a 0.0129 per cent decrease. In addition, we need to consider the decrease in assets due to non-deteriorated loan impairment. For these loans, we need to take into account probability of default, which, unlike in deteriorated operations, is not 100 per cent. The probability of default currently applied to non-deteriorated housing loans by BAPOP is 3.83 per cent, and these loans make up 95.7 per cent of total housing loans. Impairment at, for example, a 5 per cent decrease in housing prices, is thus given as $3.83\% * 12.64\% = 0.48\%$ while impairment at stable housing prices would be $3.83\% * 10.64\% = 0.41\%$. The difference between those two percentages, i.e. 0.08 per cent, tells us how much impairment differs between the two scenarios. Again, we can calculate the impact on total credit impairment as shown in *equation 6*.

$$\% \; of \; mortgage \; loans \; in \; assets * \% \; of \; good \; loans \; in \; total \; loans * change \; in \; LGD * Assets$$
$$= \; 14.91\% * 95.7\% * 0.08\% * Assets = -0.0109\% * Assets$$

Equation 6: Impact of a -5% change in housing prices on total credit impairment

Total impact of a 5 per cent decrease in housing prices on credit impairment, and thus total asset value, is therefore -0.0129% + (-0.0109%) = -0.0238% of total assets. However, we need to take into account one additional variable in our calculations: The impact of housing prices on the houses that are held directly in BAPOP's portfolio.

These houses are assets that have been seized from their owners due to their failure to fulfill contractual obligations vis-à-vis the bank, and make up 4.46 per cent of total assets, according to their accounting value. In our calculations, we want to assume that all assets are currently valued at their correct market value. As most valuations of assets are not very recent, we want to adjust the value of their houses for the changes that have taken place in the Portuguese housing market. To do this, we obtain a detailed list of monthly housing price indices for the major municipalities in Portugal. We then match the locations of housing assets held by the bank with this list of municipalities and calculate the current market value of these assets, assuming their value changed in accordance with average housing prices in the respective municipality. After doing these calculations, the total value of housing assets results to be 1.53 per cent lower than the accounting value, which is now 4.19 per cent of total assets. Assuming a 5 per cent decrease in housing prices, the impact on total assets would be as shown in *equation 7*.

$$\%\ of\ housing\ in\ total\ assets * (-5\%) * Assets = 4.19\% * (-5\%) * Assets = -0.2096\% * Assets$$

Equation 7: Impact of a -5% change in housing prices on total assets

The sum of all these impacts on asset value is -0.0238% + (-0.2096%) = **-0.2335%.** We see that this value is not highly significant. To get a better idea, we calculate the impacts of a range of possible changes in housing prices on total asset value.

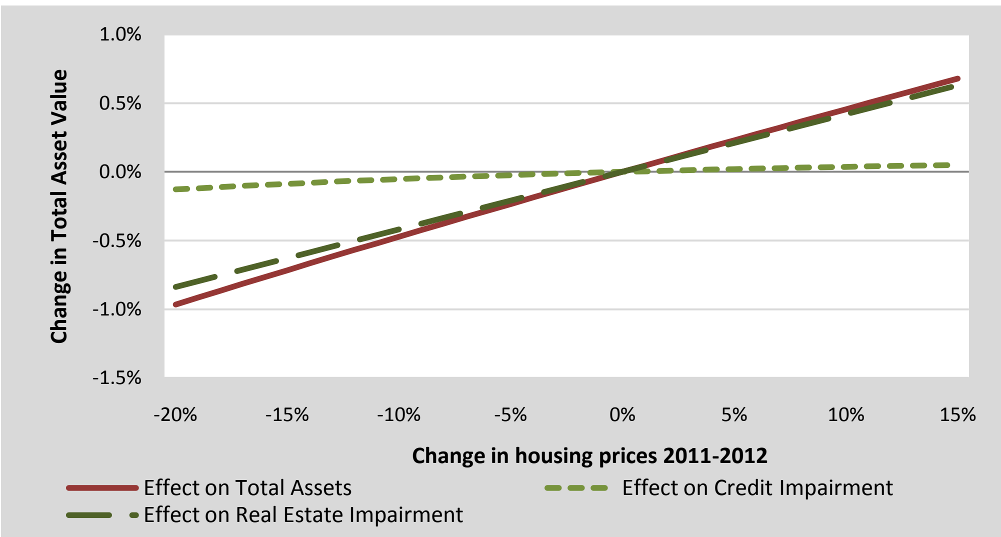

Figure 2: Effect of change in housing prices on credit impairment, real estate impairment, and total assets

The results, as shown in *figure 2* match the bank's expectations in terms of scope. As these results are achieved using forecasts of LGD based on our sample calculations, this underlines the validity of our forecasting approach.

10. Testing BAPOP's Approach to Calculating PDs

In this section, we want to look at the second segment of BAPOP's mortgage loans: the non-deteriorated ones. For these loans, a standard percentage of probability of default is applied to calculate impairment (see description of calculation above). To analyze whether the percentage used is appropriate, we compare the historical real PDs with the ones applied to calculate impairment in the respective year, as shown in *table 9*.

	2005	2006	2007	2008	2009	2010	Average
PDs for Impairment Calculation	2.24%	2.48%	2.76%	3.36%	3.69%	3.82%	3.06%
PDs Real	3.49%	3.53%	6.30%	4.36%	4.62%		4.46%
Difference	1.25%	1.05%	3.54%	1.00%	0.93%		**1.55%**

Table 9: Real PD versus PD applied for impairment calculation at BAPOP 2005-2009

As we can see, real PDs are higher than the ones used for impairment calculation at all times, on average by 1.55 percentage points. This large difference can be explained mainly by the method used to calculate PDs for impairment: an average of past PDs, weighted by loan amounts. This method does not apply a higher weight to more recent PDs, which tend to be higher than older ones. However, the rationale behind the absence of weights is that the difference in PDs might reflect the evolution of the economic cycle.

11. Forecasting Probabilities of Default to Calculate Impairment

In the light of the findings revealed above, it might be useful for BAPOP to develop an alternative way of assessing PDs to calculate impairment. To this end, several regressions were conducted to find a method of predicting PDs based on external indicators. We start by assessing the bank's housing loan portfolio's deterioration coefficient per year. The deterioration coefficient (DC) is defined as the ratio of loans with more than 90 days overdue payments over the total loan volume. While this value is available for every month until present, PDs are only available for periods up to one year before present. This is because PDs are defined as the percentage of loans that are “good” one year ago, but “bad” now, over the total loans one year ago. By definition, we cannot know which loans are going to go bad within the next year.

As a first step, we now want to see the correlations between PDs and DCs in different time periods, i.e. between PD and DC in the same month, PD and DC one month later, etc. We use data for PDs up to 09/2009 and DCs up to 09/2010. As we can see in *table 10*, the highest correlation can be found between PDs and DCs 12 months later.

Months Lag	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Correlation	-0.01	0.04	0.15	0.20	0.20	0.30	0.33	0.30	0.40	0.43	0.25	0.56	0.68	0.51	0.37	0.34

Table 10: Correlation PDs and DCs in different periods

To forecast PDs based on DCs, we run a number of curve fit regressions of PDs on DCs which find the best fit with the exponential function shown in *equation 8*.

$$PD_t = 0.017 * exp\ (11.083 * DC_{t+1})$$

Equation 8: Regression PDs on DCs

We further seek to find ways to predict DCs by analyzing how external variables influence them. Specifically, we consider interest rates, the state of the Portuguese economy (PSI20), Portuguese GDP, Consumer Price Index, Portuguese unemployment rates, building activity in Portugal, index of new construction orders, and index of confidence in the construction industry. As housing price indices are not available on a monthly basis for the entire period under review, this indicator cannot be used for analysis. First, we calculate correlations between DCs and the external indicators at different times, assuming that some of the variables will be lagged indicators. For each variable, we will now use the time lag where the correlation with DCs is the highest. One exception is PSI20, where the highest value of 0.54 is counterintuitive, as a better economic environment is expected to come with a lower LGD in loans (see *table 11*).

Months	EUR6m	PSI20	CPI	Unemployment	GDP	Completed Buildings	New Orders	Confidence Construction
-12	0.76	0.54	0.71	0.01	0.81	-0.43	-0.19	0.39
-11	0.74	0.48	0.72	-0.04	0.81	-0.43	-0.13	0.30
-10	0.69	0.40	0.73	-0.03	0.81	-0.46	-0.13	0.17
-9	0.63	0.30	0.72	-0.01	0.80	-0.54	-0.11	0.14
-8	0.56	0.22	0.72	-0.03	0.78	-0.63	-0.02	0.16
-7	0.49	0.14	0.73	-0.01	0.77	-0.67	-0.03	0.18
-6	0.44	0.05	0.75	-0.01	0.75	-0.68	-0.07	0.30
-5	0.38	-0.05	0.78	-0.03	0.73	-0.68	-0.09	0.33
-4	0.30	-0.12	0.79	-0.02	0.72	-0.61	-0.11	0.35
-3	0.23	-0.18	0.77	0.02	0.71	-0.55	-0.14	0.42
-2	0.17	-0.24	0.76	0.05	0.65	-0.35	-0.20	0.44
-1	0.11	-0.32	0.73	0.10	0.62	-0.27	-0.22	0.38
0	0.05	-0.40	0.70	0.13	0.60	-0.19	-0.26	0.31

Table 11: Correlations between DC and Independent Variables with X months lag

We will therefore use zero lag for this variable. We then conduct a stepwise regression of DCs on the independent variables mentioned above. In this regression, the combination of independent variables that optimizes the statistical results is found. The output of this regression is shown in *table 12*.

Coefficients						
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
6	(Constant)	-.3438211	.091		-3.788	.000
	EUR6m	.9128422	.129	.491	7.093	.000
	CPI	.0043166	.001	.483	6.170	.000
	Orders	.0003150	.000	.196	2.795	.007
	ComplBuild	-.0000032	.000	-.191	-2.045	.046

Table 12: Optimized regression of DCs on external indicators

As we can see, the variables PSI20 Index, Unemployment, and GDP were not significant in this regression and were therefore omitted from the model. *Equation 9* shows the formal result of the regression.

$$DC_t = -0.3438211 + 0.9128422\ EUR6m_{t-12} + 0.0043166\ CPI_{t-4} + 0.0003150\ Orders_t - 0.0000032\ ComplBuild_{t-6}$$

Equation 9: Regression DC on external indicators

Knowing this, we can now try to predict DCs, based on external indicators, and then use the DCs to predict PDs, based on the regression shown in *equation 9*. To test the adequacy of the calculation, we will first predict values for PDs in October to December 2009 and compare them to the realized ones. Assuming we do not know the values for the DC for October to December 2010, we will calculate them from external indicators. Specifically, we need the values for Euribor at t-12 months, CPI at t-4 months, Orders at time t, and Completed Buildings at t-6 months. From these values, we can then calculate DC based on *equation 9*, and PD based on *equation 8*, as shown in *table 13*.

	Oct-10	**Nov-10**	**Dec-10**
EUR6m (t-12)	0.01017	0.00993	0.00996
CPI (t-6)	108.66	108.86	109.09
Orders (t)	0.8	0.8	0.8
ComplBuild (t-6)	14667	14667	14667
DC (t)	8.75%	8.81%	8.91%
PD (t-1)	**4.38%**	**4.41%**	**4.46%**
Real PD	3.59%	3.99%	4.62%
Difference	**0.78%**	**0.42%**	**-0.16%**

Table 13: Forecast of PDs and comparison to real PDs

The average of the absolute values of the difference between real PDs and our forecasted PDs is 0.45%. That implies that this forecasting approach is more accurate than the method BAPOP is currently using to calculate impairment.

12. Conclusion

According to past research, housing prices are a highly important determinant of credit impairment in the mortgage loan segment. While analyses of our sample from BAPOP confirm this finding, regressions of LGDs on housing prices and other external variables do not produce realistic forecasts. We thus find it more useful to forecast LGD based on the characteristics of our sample, despite the drawbacks of this approach. Using this method, we assess the impact of price changes on the bank's total asset value and find that it is behaving according to the bank's expectations. As for PDs, it is shown that adequate forecasts can be produced based on a number of external indicators. For the time being, we therefore recommend using a combination of external and internal approaches to forecast impairment in the mortgage segment. This approach should be reassessed in the future when more data is available to construct regressions of LGDs.

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