Final Team Assignment

Which bank should you buy?
A prospective of operational similarity

Explaining the characteristics of bank branches in urban and suburban locations

Professor Galit Shmueli
BUDT 733
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EXECUTIVE SUMMARY MEMORANDUM

To: Professor Galit Shmueli

From: Yatograxx Consulting

Date: May 10, 2007

Re: Final Team Project

Topic: Bank Consolidation: A prospective of operational similarity

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Since the early 1980s, the U.S. banking industry has seen a strong trend toward consolidation. At its peak in the 90s, there were approximately 7500 transactions, valued at roughly 1.6 trillion. Consolidation of this magnitude has brought significant changes to the banking sectors that are worth investigating.[i] Lately, there has been a significant jump in merger activity. Barclays, a global bank based in the UK, acquired ABN Amro Holding also based in Europe for $91.16 billion in the world's largest bank takeover, following a month of negotiations.[ii] As a subset of that deal, Bank A, the second largest US bank, just purchased LaSalle Bank Corp. for $21 billion in April 2007. The all-cash purchase will also make B of A Chicago's largest bank.[iii]

One of the most important prerequisites to consider prior to a merger is the cultural compatibility between the two organizations. According to research conflicting organizational cultures can lead to the failure of the merger.

Yatograxx Consulting is pleased to offer our solution to help banks that intend to grow through acquisition determine which banks to purchase. We have analyzed Over 1000 branches of the top five banks (based on the number of banks) in the DC/MD/VA area and explained the characteristics of different banks, so that the acquiring financial institution can determine which banks will fit best with their business model.

We have segmented the banks located in the Washington DC, Baltimore metro area down into the following two categories:

- **A.** Banks that are featured in metro areas, in office or high rise buildings in dense areas are **Bank B, Bank A, or Bank E**.
- **B.** Banks that are featured in non-metro areas, in malls, office parks, or small stand alone buildings then you would purchase **Bank D, or Bank C**.

For the metro area subset we have developed a Discriminant Analysis model to explain the operational characteristics. For the non-metro subset we chose the classifications tree to explain the operations.

Technical Summary

The original data contained over 100 variables describing many aspects of the locations for different bank branches. Some examples of the variables that the original data included are types of signage, alley access, and number of walk-up ATMs. We combined like variables based on domain knowledge. For example:

- Combined major downtown and community downtown (1=Downtown)
- Combined strip development with regional, community, and neighborhood commercial to make one commercial variable (2=Commercial)

Exploration

We conducted significant exploration of the data. Initially we did not find any real differences when looking at the scatter plots to distinguish DC from Baltimore for all banks. Our intuition is that if we add census data (population, income) we would begin to see differences. However, as we looked further we saw that there were some variables that did a good job creating separation between banks and they were based on urban vs. suburban locations. Based on our exploration of the data, we expected to see Bank D and Bank C grouped together in suburban areas in free standing or attached buildings or in malls and storefronts with 1 walk-up ATM. On the other hand, we expected to see B of A, Bank B, and Bank E to be grouped together in urban areas, with alley access, in high rise or office buildings, different banks, with 1 or 2 walk-up ATMs.

Discriminant Analysis

In our initial running of the DA we experienced a very high error rate. From the information that we received from the exploration of the data, we knew that the data split almost perfectly between metro, B of A, Bank B, and Bank E and non-metro, Bank D and Bank C. We ran separate DA models for metro and non-metro. After running the model for the metro subset we determined that there are 13 significant variables. They are listed below

Variables	Classification Function		
	A	B	E
Constant	-1.15578771	-1.43651783	-1.42141616
BLDG_TYPE_2	-0.04426619	-0.10942578	0.18200393
BLDG_TYPE_3	-0.2406949	-0.01221941	0.33097634
BLDG_TYPE_5	-0.10819293	-0.08910501	0.24327411
BLDG_TYPE_8	-0.19736162	-0.01368323	0.27553007
Lanes	0.04757439	-0.17910995	0.13974236
CONDITION	-0.30932963	0.19828752	0.18349995
BANK_PRKG	-0.16430977	0.3269012	-0.15295409
WU_ATMS	0.54584736	-0.42163822	-0.24272861
DU_ATMS	0.53692806	-0.53590459	-0.10183084
DU_TELLERS	-0.05607889	0.31477034	-0.28186053
SIGNAGE	0.05768912	-0.60920292	0.61250883
SQ_FT	0.05835421	-0.17614967	0.12219203
STATUS	-0.25610277	0.28872627	0.01114802

For the non-metro subset, we developed a model with 13 predictors. This model had an overall error of 24.75%. The variables are listed below:

Classification Tree

We were able to gain significant insight from the classification tree because it allowed us view the significance of each variable as related to the other variables. After an unsuccessful attempt to develop as successful model with the entire data set, we split the data into metro and non-metro subsets. We saw from this tree that the biggest difference maker is whether the bank is in the Wash, DC metro area or the Baltimore metro area. Like we expected, the % error decreased from 47.29% for the model combining both metro and non-metro to 26.92 % for the non-metro. The metro area used 4 predictors and received an error rate of 44.7%.

Training Data scoring - Summary Report (Using Full Tree)

Cut off Prob.Val. for Success (Updatable)	0.5

Classification Confusion Matrix		
	Predicted Class	
Actual Class	Bank C	Bank D
Bank C	105	43
Bank D	55	161

Error Report			
Class	# Cases	# Errors	% Error
Bank C	148	43	29.05
Bank D	216	55	25.46
Overall	364	98	26.92

Conclusion

For the metro subset we chose the DA model mainly because of the difference in error in that model and the classification tree model.

For the non-metro subset we chose the classification tree because of parsimony. The classification tree requires only 4 predictors: MSA, shared parking, signage, and bank parking while the DA required 13 predictors.

From this output we developed profiles for each institution:

Bank A: Metro area, less free standing building, less store front, less inside mall, lower condition, more walk-up ATMs and drive-up ATMS, and more banks with not open status.

Bank B: Metro area, less office building, less lanes around banks, more bank parking, less walk-up and drive-up ATMs, more drive-up tellers, less signage, less SQFT, and more banks with open status.

Bank E: Located in office building, more free standing, more store front, more inside mall, more lanes around banks, less drive-up tellers, and more signage.

Bank C: In suburbs of Baltimore and DC, with 3 or more signs, and more shared parking.

Bank D: In suburbs of Baltimore and DC area, with 2 or less signs, and more parking.

[i] Cultural Conflict and Merger failure research paper

[ii] http://www.bloggingstocks.com/2007/04/23/112-billion-bank-merger-monday/ $112 billion bank merger Monday Posted Apr 23rd 2007 9:45AM by Peter Cohan

[iii] http://www.bnet.com/2407-13071_23-63331.html Rueters “Bank of America to Buy ABN's LaSalle’