

# SubscriberWise® Data Analysis

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## Abstract

We present basic analysis of SubscriberWise®<sup>1</sup> technology based on the analysis of 49317 customers. Current segmentation technology assigns customers into one of 11 levels, which allows us to identify credit challenged as well as highly qualified customers. Specifically, we show that  $\sim 60\%$  of the customers from the bottom 3 levels ( $\sim 35\%$  of all customers) are disconnected for non-pay, while this number is  $< 10\%$  for the top 3 levels ( $\sim 45\%$  of all customers). Analysis of the collections produce even more remarkable metrics: customers from the bottom 3 levels produce  $\sim 80\%$  of all collections and  $\sim 70\%$  the total write-off amount. In contrast, the customers from the top 3 levels create only  $\sim 6 - 8\%$  of identical problems. Additionally, SubscriberWise® segmentation technology has significant marketing power as it allows us to identify and target 'best prospect' customers, which produce the highest amount of revenue over the customer lifecycle.

## 1 Introduction

SubscriberWise® is the leader in risk management solutions for the telecommunications industry. SubscriberWise solutions incorporate a comprehensive approach to risk and decision management across the subscriber life cycle from origination and retention to fraud and debt recovery. SubscriberWise® was founded on the premise that an intelligent understanding of subscriber behavior can significantly reduce an operators risk exposure without compromising growth and selling opportunities, at the same time radically reducing bad debt and equipment losses while substantially improving profitability.

SubscriberWise (SW) technology incorporates robust 'permissible purpose' consumer credit data with the highly predictive power of federally regulated scoring and analytics to produce telecommunication industry adjusted segmentation technology. This entirely rules-based, objective, and industry-proven technology allocates every new customer into one of 11 levels, based on a dynamic and instant analysis of the prospect's real-time consumer credit history. Each of these 11 levels is designed to determine credit-qualified and credit-adverse prospective customers, before approving service and installing costly equipment.

The goal of current manuscript is to test SW technology based on the analysis of 49317 customers. Additionally, while the main purpose of SubscriberWise is to provide risk management solutions, we test the ability of SW to be utilized from the marketing point of view.

Current work does not provide all the deep analysis available to us and it is intended to give a sample of the capabilities of SubscriberWise technology. Risk management solution analysis is presented only for the best 3 and the worst 3 levels, while marketing analysis combines 11 SW levels into 3 subgroups. Deeper and much more scrutinized analysis can be done on an operator by operator basis, by analyzing MSO's (multiple system operator) data. Moreover, we built a marketing model, which is based on the current SubscriberWise technology and it utilizes each operator's data to maximize revenue, while producing very high return on investment. This model provides intelligent decisions both for current and prospective customers with a goal to maximize revenue of SubscriberWise member MSO's.

The plan of this article is as follows: we test risk management solutions in Section 2; Section 3 is devoted to analysing marketing side of SW technology; We finish with summary of our results.

## 2 Risk Analysis

SubscriberWise® was founded on the premise of reducing equipment loss by selectively applying deposits based on customer's credit history, while also acting in the best financial interests of both the

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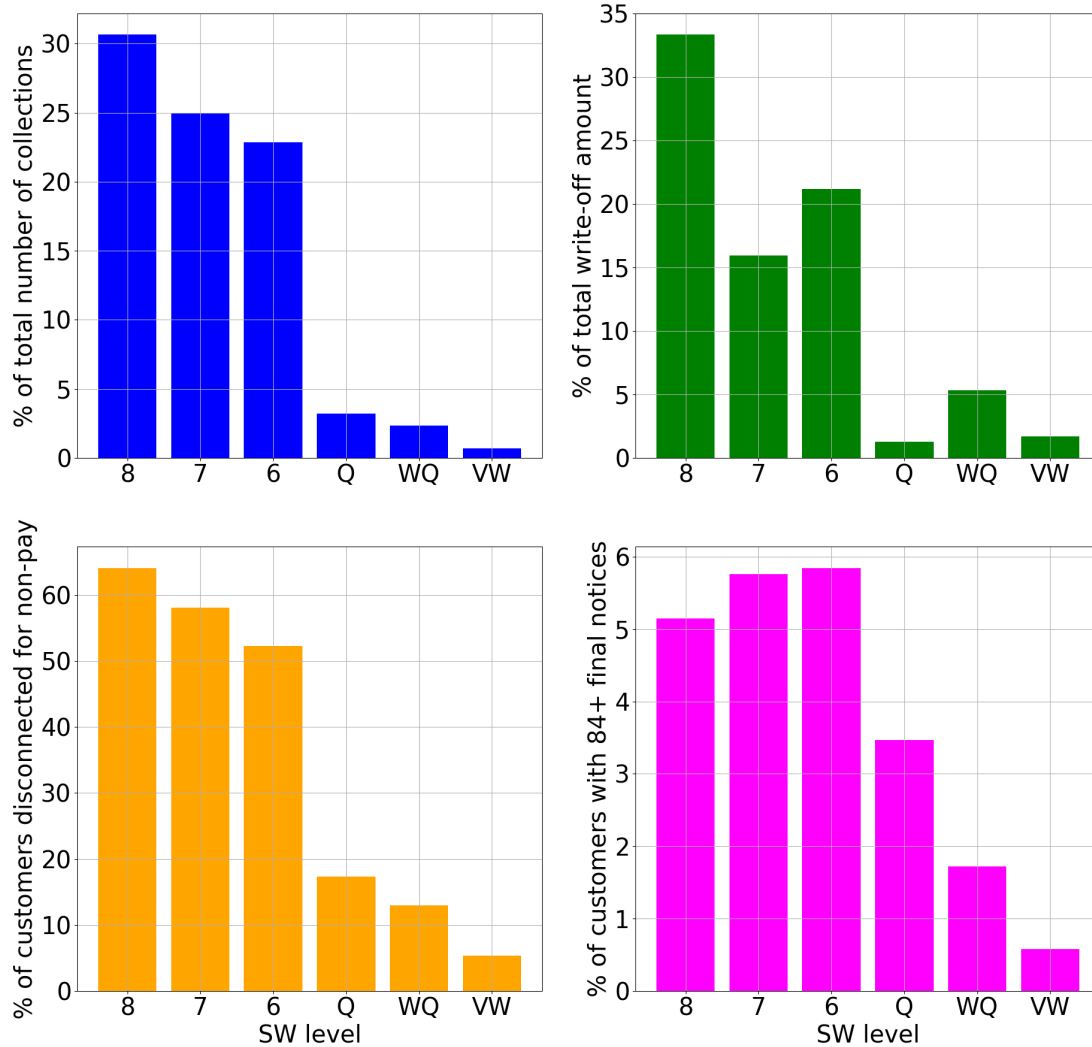


Figure 1: **Risk Analysis.** Risks related to the credit challenged customers can be described using various characteristics. To show the ability of SubscriberWise technology to identify this segment of customers we pick 4 main features and compare these features based on the best 3 levels (i.e. Qualified (Q), Well Qualified (WQ) and Very Well Qualified (VW)) and the worst 3 levels (i.e. levels 8, 7 and 6). **Top Left:** percent of the total number of collection per SubscriberWise level. **Top Right:** percent of the total write-off amount versus SW levels. **Bottom Left:** percent of the customers of specific SubscriberWise level, which were disconnected for non-pay. **Bottom Right:** percent of the customers identified to specific SW level, whom 84+ final notices were sent. Note, percentages on the top figures are related to the total number across all 11 SubscriberWise levels, i.e. the sum over all 11 levels is 100%, while the bars on the bottom figures represent percentages related to specific SW levels. The results clearly show the ability of SubscriberWise technology to identify challenged customers. As we can see, the best 3 levels only create ~ 6% of all collections and only ~ 8% of the total write-off amount, while in combination representing ~ 45% of all customers. In contrast, the bottom 3 levels (~ 35% of all customers) produce 12.6 times more collections (~ 80%), while generating 8.5 times higher write-off amount (~ 70%). Additionally, 3 out of every 5 customers from the bottom 3 levels are disconnected for non-pay at some point of using telecommunication service, while less than 10% of the customers from the top 3 levels are disconnected for non-pay.

consumer and the MSO. The power of mitigating risks using SubscriberWise<sup>®</sup> technology is proven and significant. It is going to be addressed in this section.

As it was mentioned in Introduction, we focus our analysis only on 6 out of 11 SW levels: 3 the worst and 3 the best. We analyze 49317 real customers. The data are cooperatively provided by one of our member operator's and were secured without any personally identifying information (PII), which allows us to produce unbiased analysis with no identity risks for individual consumers. While we do not reveal specific characteristics of the data set, we can state that customers in the data set represent general demographics of a wide segment of the adult credit consuming population of the United States, particularly as it relates to subscribers who consume services of small to medium MSO's everywhere in the nation.

Our analysis is summarized in Figure 1. The analysis covers 4 major characteristics related to subscriber risk management. For description of each of these 4 characteristics as well as for discussion of the results we refer our reader to the caption of Figure 1. We can summarize main conclusions which can be drawn from Figure 1:

1. The global trend is clear: customers from the bottom 3 levels (8, 7 and 6) produce many more risks (i.e. non-payment, demands on customer support, collection notices, operational inefficiencies) in all 4 categories. Moreover, this effect can be seen by comparing individual levels: as expected, the better the level the lower the probability of risks associated with the customer.
2. Customers from the top 3 levels (Qualified (Q), Well Qualified (WQ) and Very Well Qualified (VW)), which collectively represent  $\sim 45\%$  of all customers, are required only  $\sim 6\%$  of all collections. At the same time,  $\sim 80\%$  of all collections are generated for the customers from the bottom 3 levels ( $\sim 35\%$  of all customers).
3. Analysis of the total write-off amount produces similar numbers:  $\sim 70\%$  of the total write-off amount is related to the bottom 3 levels, while this number is only  $\sim 8\%$  for the top 3 levels.
4. There are many reasons for disconnection beyond simply non-pay churn. However,  $\sim 60\%$  of all the customers from the bottom 3 levels are disconnected for not paying as agreed during some point of the service relationship. This number drops significantly for the top 3 levels and it is only  $\sim 5\%$  for the best level (i.e. VW).
5. Approximately every 17<sup>th</sup> customer from the bottom 3 levels requires in excess of 84 final notices (every month for 7 straight years). Understanding that the average lifetime of a customer from the bottom 3 levels is approximately 7 years (see Top Left Figure 2), it means that operators need to send final notices every month to such customers. In comparison, only every 200<sup>th</sup> customer from the best level (i.e. VW) creates similar burden.

As we can see SubscriberWise segmentation technology successfully identifies risky and reliable customers. While the analysis is presented only for 6 levels out of 11, similar conclusions can be drawn for the remaining 5 levels. Moreover, many more interesting and useful insights can be seen by analyzing these 5 levels. Such analysis can be provided on a member by member basis.

### 3 Marketing Analysis

To produce marketing analysis, we combined 11 SW levels into 3 subgroups by approximately equal number of customers, while keeping similar risk categories together:

1. Subgroup  $\alpha$  consists out of the bottom 3 levels, i.e. levels 8, 7 and 6.
2. Subgroup  $\beta$  combines 6 intermediate levels, i.e. 1 to 5 and Qualified (Q).
3. Subgroup  $\gamma$  contains two the best groups, i.e. Well Qualified (WQ) and Very Well Qualified (VW).

This is done to provide clear marketing analysis as well as to estimate as precisely as possible average revenue per customer.

Marketing analysis is summarized on Figure 2. Generally speaking, the lifetime of a customers from desirable levels (i.e. subgroup  $\gamma$ ) is higher, which leads to the potentially higher revenue per customer. To test this claim, we use the current average revenue per month and make an assumption that this amount holds during the whole lifetime of the customers. While this is generally not correct as the average revenue per month changes due to connecting/disconnecting individual services and increase in pricing due to inflation, this allows us to make an initial attempt of estimating revenue per customer

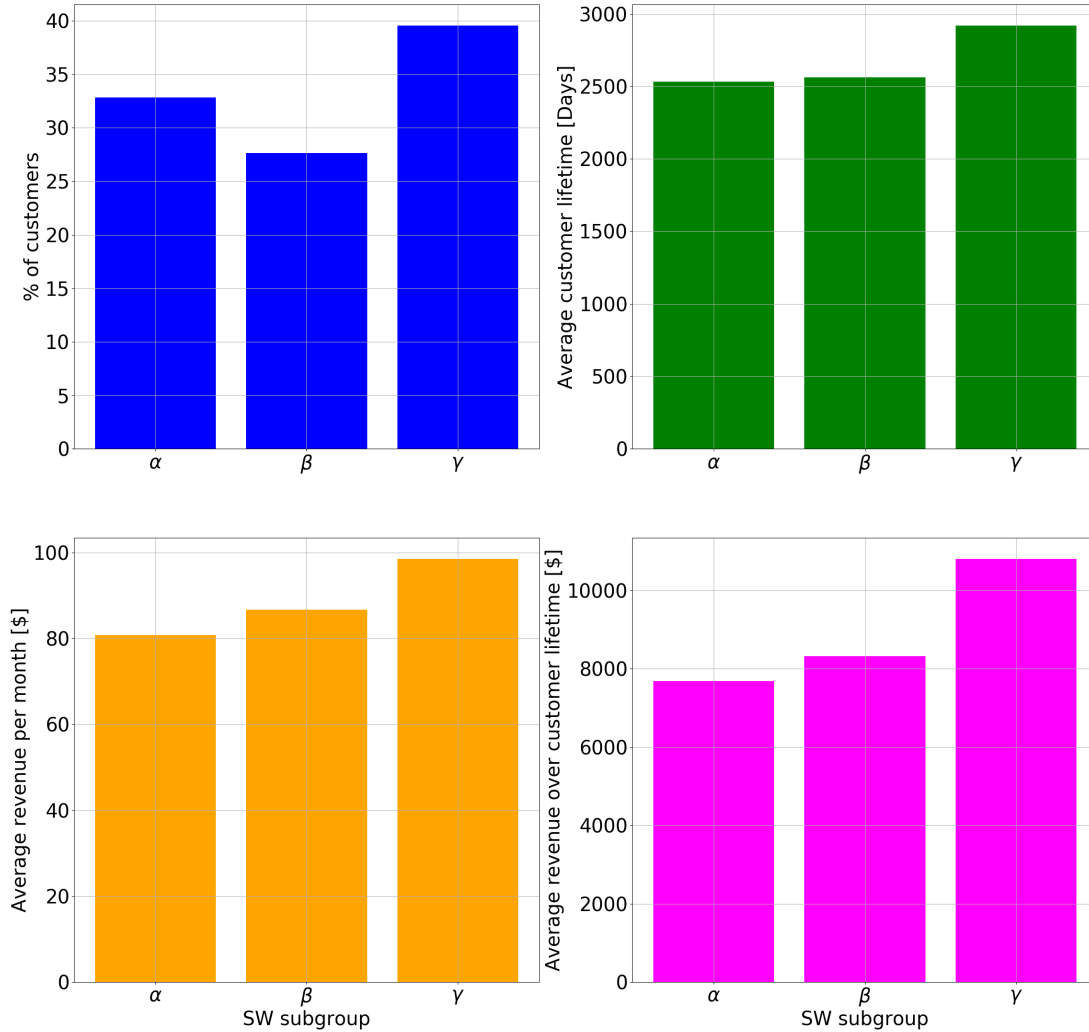


Figure 2: **Marketing.** SubscriberWise (SW) technology allows us to identify customers with all the important characteristics to increase revenue while also ensuring positive 'first impressions' with prospective subscribers. **Top Left:** 11 SubscriberWise levels are combined into 3 subgroups with approximately equal percent of all customers. Subgroup  $\alpha$  consists out of the bottom 3 levels, i.e. levels 8, 7 and 6. Subgroup  $\beta$  combines 6 intermediate levels, i.e. 1 to 5 and Qualified (Q). Last but not least, subgroup  $\gamma$  contains two the best groups, i.e. Well Qualified (WQ) and Very Well Qualified (VW). **Top Right:** average number of days of a lifetime of a customer per SubscriberWise subgroup. **Bottom Left:** average USD [\$] revenue per customer per month. **Bottom Right:** average total USD [\$] revenue per customer lifetime. General trend clearly shows that subgroup  $\beta$  is more profitable than subgroup  $\alpha$  and subgroup  $\gamma$  even more profitable than  $\beta$ . The trend is the same in all 3 main categories, i.e. average customer lifetime, average revenue per month and average revenue over customer lifetime. Individual numbers are especially profound if we compare numbers from the Bottom Right figure, which presents the most important metric. In particular, customers from subgroup  $\beta$  produce 8.3% higher revenue than from subgroup  $\alpha$ . Moreover, customers from the best  $\gamma$  subgroup generate 40.7% higher revenue than their peers from subgroup  $\alpha$ .

during the whole lifetime based on every SubscriberWise<sup>®</sup> level. These numbers are presented on the Bottom Right Figure 2.

SubscriberWise technology consistently and precisely identifies customers which produce the highest amount of revenue. By focusing marketing explicitly on the prospective customers from subgroup  $\gamma$ ,

operators can generate more than 40% higher revenue in comparison with the customers from the bottom  $\alpha$  subgroup. This number translates into more than \$3000 of increased revenue per customer and under profound assumption of 10% of profit-margin, it generates astounding 15000% return on investment (calculation is made under assumption of  $\sim$  \$2 price per credit submission). While these numbers are general, we created the whole marketing model which can be adjusted specifically to the operator's needs and based on their unique data. This will allow all of our members to produce even higher revenue per customer while generating very high return on investment.

## 4 Summary

SubscriberWise<sup>®</sup> technology is an established, powerful, and remarkably proven tool, from both the risk management and marketing prospective. Our analysis demonstrate that SW allows operators to identify important risks related to high risk customers. The numbers are astounding as the customers from the best 3 levels produce 12.6 times less collections, 8.5 times smaller amount of write-off and 6 times are less frequently disconnected for non-payments. SubscriberWise<sup>®</sup> technology can be utilized as a powerful marketing tool as it allows to identify customers which generate  $\sim$  40.7% higher revenue. Moreover, both risk and marketing analysis show that the same customers generate notably fewer concerns, while generating higher revenue. SW is capable to successfully identify the most qualified subscribers, as well as to help to find similar prospective customers.

While the analysis presented in the current manuscript covers just general characteristics of the SubscriberWise<sup>®</sup> technology, much deeper insight is available based on the analysis 49317 customers of the telecommunication industry. Identical to this deeper analysis can be applied individually to the customer data base of each telecommunication company to provide adjusted segmentation specifically for the MSO to boost its revenue while significantly reducing risks related to high risk customers.

## 5 Acknowledgments

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