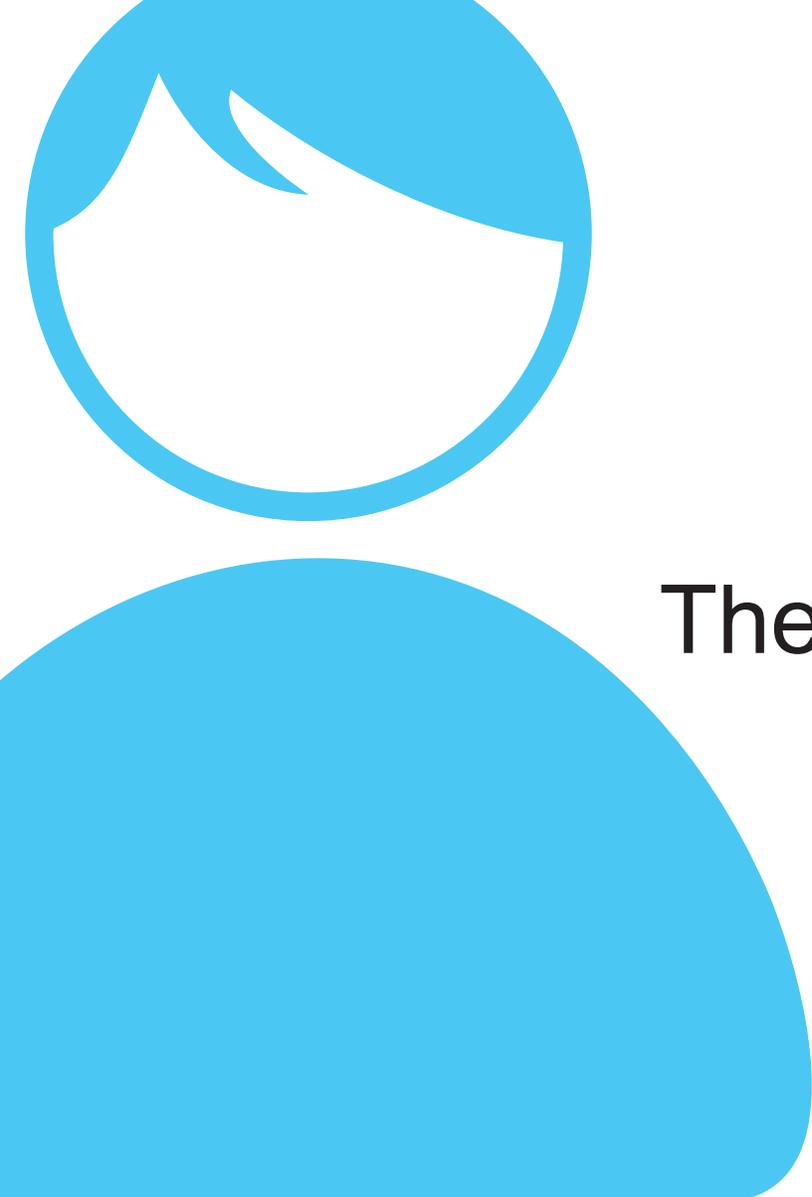


Theory of Escalation

Increase of Internal Fraud Over Time





Theory of Escalation

Executive Summary

The 2015 National Retail Security Survey, conducted by the University of Florida, pegs shrink at \$44.02 billion annually. 34.5% of that shrink, or \$15.2 billion, was directly attributed to internal theft. Loss Prevention's role is to identify these employees as quickly as possible in order to prevent future losses.

The "theory of escalation" is that an employee who steals will, over time, steal more often and more valuable assets. The same logic is sometimes called "graduation" as common criminals often start with shoplifting or petty theft and "graduate" to much larger crimes such as auto theft and robbery.

Utilizing transactional data from a vast database spanning multiple retail segments, a study was conducted to prove this theories' claims. The results of this analysis provided conclusive evidence to support the "theory of escalation" and provides a quantitative value to the rate of escalation, highlighting the seriousness of the issue and further strengthening the need to identify offenders immediately.

Utilizing data available from 12,659 incidents in 5,926 cases across 40 different retailers over a two-and-a-half year period, Agilence has found that, on average, the amount of theft by an employee will increase by 58% every month.

The Data Set

The data used for this study came from over 40 retail customers that utilize Agilence reporting solutions. Agilence worked with each of these customers to identify potential losses at the point of sale. This study is the result of analysis on nearly 6000 customer validated and closed cases over a 29 month period. Each case is assigned one of five types:

- Internal Fraud – employee theft
- External Fraud – theft by nonemployees
- Promotional - related specifically to a promotion, offer or coupon
- Operational – typically training related issues
- Systemic - any issue that affects the entire chain and typically related to item data or system-wide POS discrepancies

For this study, only cases marked as “internal fraud” were analyzed. Further, all included cases needed incidents that were identified on three separate days. This means that an employee may have had three or more incidents of theft, but if they were all carried out on less than three individual days, the case was not included. As stated above, each case must have been accepted as valid by the customer, worked to a conclusion and closed.

Data Normalization

The first step in analyzing the data was to normalize it. Because the data spanned multiple different retail vertical segments, the value of the cases varied greatly. In addition, while some incidents happened on a daily basis, some employees did not work daily and their incidents were spread out across more days.

**If ignored, employee theft will
increase on average 58%
each month**

In order to normalize the data for dollar value, each incident in a case was re-set to represent the amount of change from the initial incident and then a percentage change was applied. Consider the following two examples:

- | | |
|----------------------|------------------------|
| • Employee A | • Employee B |
| • Incident 1: \$4.00 | • Incident 1: \$400.00 |
| • Incident 2: \$7.50 | • Incident 2: \$750.00 |
| • Incident 3: \$4.00 | • Incident 3: \$400.00 |
| • Incident 4: \$6.00 | • Incident 4: \$600.00 |
| • Incident 5: \$3.00 | • Incident 5: \$300.00 |

Once the incident totals were charted, the data had to be normalized for time. Multiple incidents from the same day were considered a single event. The first incident for each case was assigned to Day 1. Each subsequent day containing one or more incidents was assigned to the next day. Following the above examples:

- | | |
|-------------------------------------|--------------------------------------|
| • Employee A | • Employee B |
| • Incident 1: January 2 (Day 1) | • Incident 1: October 21 (Day 1) |
| • Incident 2: January 3 (Day 2) | • Incident 2: October 24 (Day 2) |
| • Incident 3 & 4: January 6 (Day 3) | • Incident 3 & 4: October 29 (Day 3) |
| • Incident 5: January 7 (Day 4) | • Incident 5: November 1 (Day 4) |

Once the data was normalized for time the data had to be normalized for percentage change (to the original incident). The incidents for each were represented a:

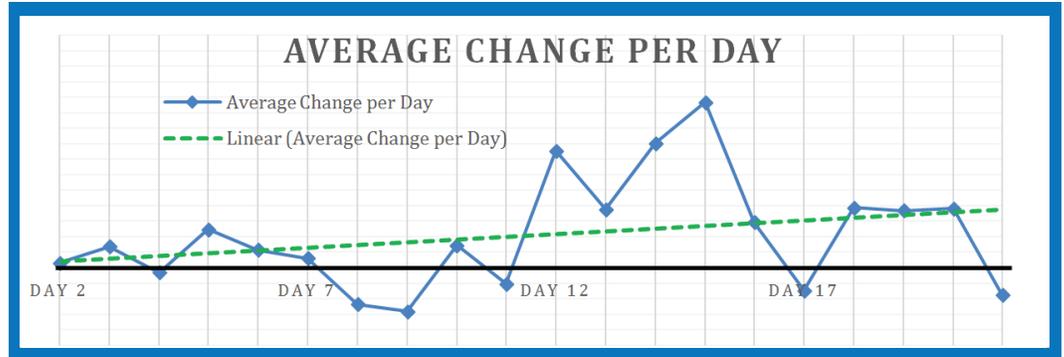
- | | | | | | |
|-------------------|----------|---------|-------------------|------------|---------|
| • Employee A | | | • Employee B | | |
| • Incident 1: | \$0.00 | 0.0% | • Incident 1: | \$0.00 | 0.0% |
| • Incident 2: | \$3.50 | 87.5% | • Incident 2: | \$350.00 | 87.5% |
| • Incident 3 & 4: | \$6.00 | 150.0% | • Incident 3 & 4: | \$600.00 | 150.0% |
| • Incident 5: | (\$1.00) | (25.0%) | • Incident 5: | (\$100.00) | (25.0%) |

Data Analysis

Part 1: The Logic Test

The first step of the study was to determine if escalation actually exists or if the theory is merely an incorrect assumption. In order to accomplish this task, a very simple test

was conducted. This test was to calculate the number of days per case where the adjusted value was actually an increase from the initial day of activity. Using standard TRUE/FALSE logic where TRUE equals an increase in amount and FALSE equals a decrease in amount from that day to the first day, each “day” of fraudulent activity within a case was given its corresponding value. The sum of each TRUE value was then divided by the total days of fraud for that associate. If that value was greater than or equal to 50%, the case was assigned a “1” where cases less than 50% were assigned a “0.”



The total number of “1” values were then divided by the total number of cases used in the analysis. The result of this equation showed that 57% of cases identified had more positive overall value changes than decreases in amount stolen.

This proves at a most basic level, minus dollar amounts, time span, or any other variables that may factor in to the effect that theft has on a retailer; that escalation occurs almost 60% of the time. However, though it does confirm the existence of escalation, without analyzing each case and each incident within a case at a discrete level to gather rates of change, the data is incomplete.

Data Analysis

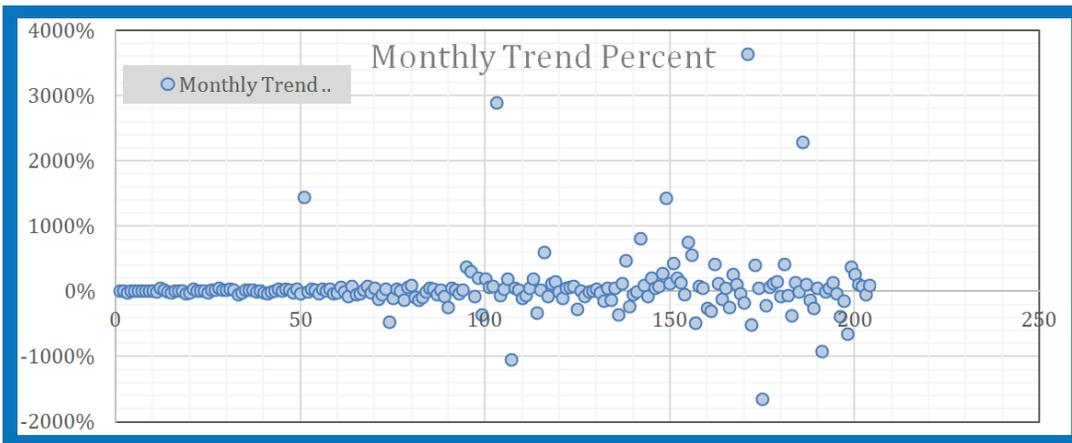
Part 2: The aggregate rate of change

The second step was to determine a combined rate of change of the cases. In order to accomplish this, the data was grouped by incident day. There were a total of 21 incident days. This meant that a case had no more than 21 individual days of incidents. However, if you remember, a case only had to have 3 incident days in order to be considered.

In order to calculate the rate of change, the delta value of each incident (compared to the first incident in the case) was used. These values were summed by day across all cases and are plotted on the chart above.

The blue line represents the total dollar value change per day for all cases across the 21 days. The green line is the average linear trend of the blue line.

As opposed to the logic test (a simple true/false look at each incident), which showed that 57% of cases contained more positive value changes than negative, this test showed that 70% of the aggregate change dollar amounts were increasing from the initial day of activity. There are 6 days where



the change amount actually went down (below the black line).

While variation is expected, the linear trend shows an 18% growth over the course of the 21 days. That is an acceleration of the change from the first incident through the

last. However, this number cannot show monthly impact because this is not weighed against time span meaning that a case with two days of activity that spans 3 days and 31 days are weighed exactly the same as far as escalation goes. Even so, this number provides intriguing insight into the rate of change if an associate continues to go unnoticed for an extended period of time.

What is interesting to note in this chart is how the total dollar value of incidents fluctuates from day to day. You'll notice that across 21 total incident days, the dollar value increases only nine times, while the total dollar value decreases 11 times. However, the total value of incidents only drops below the initial day six times. While this data may just be random coincidence and based only on what was readily available to "steal," it is possible that employees intentionally (or subconsciously) alter their habits to avoid detection. It may be that guilt, or fear of getting caught, leads them to slow down for a few days and then they ramp up again.

Data Analysis

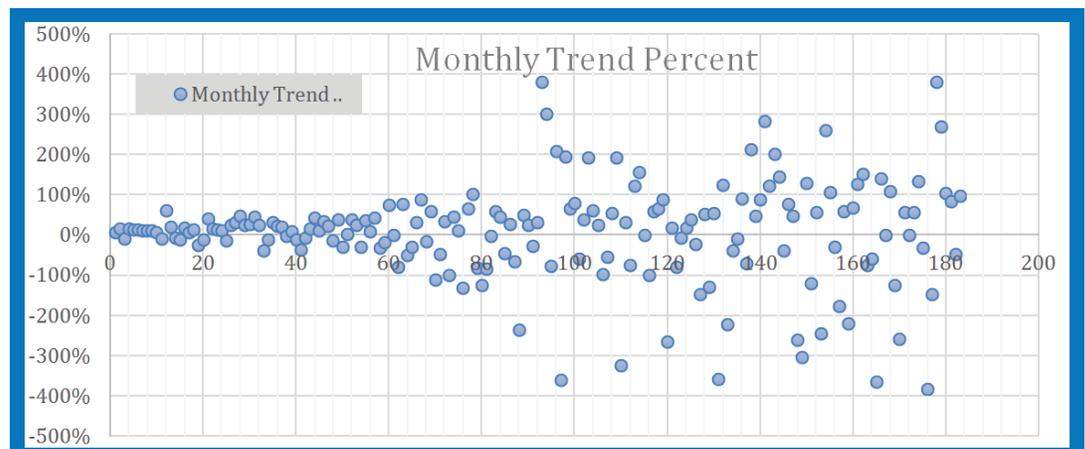
Part 3: Individual Rate of Change

Looking at the actual rate of change for each individual employee gives a much better view of escalation. Taking each individual case and plotting the rate of change is much more accurate, and allows for further normalization of the data to create a "Monthly Trend". This method also highlights anomalies in the data which can be removed for better accuracy.

For this part of the study, each case was individually graphed to find the trend line and the data for each case was normalized across its total length (in days) to derive a monthly rate of change. 204 individual cases (1670 individual incidents) from the original subset were randomly chosen and plotted to find their trend.

The first chart on this page represents the 204 cases in the working sample. Each case is represented by a blue circle. The x-axis is the case and the y-axis represents the monthly trend of the case.

As you can see from the results, the majority of the cases were between



-1000% and +1000%. However, it is also interesting to note that several cases (5) were well above 1000% while only 2 were below -1000%. Repeating the logic test on this subset shows the same percentage of cases 57% trended higher.

In order to get a better picture of realistic results, any cases which trended above 400% or below -400% were removed for the second chart on this page. Once those cases (21) were removed, the trend becomes more apparent.

In order to calculate the rate of escalation, an average of all cases was calculated to show that associates will increase the rate in which they steal by 58% per month if they continue to go unnoticed. This is just over three times the increase calculated when case values are not weighted against time.

Caveats

There were several data elements not present for this study that would have been beneficial and this case study was done using readily available data. It was not done in a controlled environment. It is unrealistic to think that an associate will continue to steal at this rate if they go unnoticed for a longer period of time. A compounded 58% increase month over month can very quickly add up to the gross sales of an individual store. In addition, the status of the employee (full time/part-time) was not available nor was their tenure. Therefore, it is unclear whether these employees were new or long-term associates. However, it does provide conclusive evidence to support the theory of escalation.

Summary

Using data available from almost 6000 cases and over 12,500 incidents, this study proves the theory of escalation. Further, it shows that the rate of escalation may increase by as much as 58% over a single month if not recognized quickly. Over time, this value may slow to realize an 18% rate of escalation if a store remains oblivious to the extensive internal fraud of an associate.

This study highlights the importance of early identification. The goal of retail loss prevention teams is to prevent loss. This study clearly shows that catching an employee early can in fact prevent significant future loss. Proving that value has been difficult up to this point. However, utilizing the numbers in this study, it is not unrealistic to show a monthly value that is 58% higher than the confessed amount. And, over a longer period of time, an 18% rate of escalation can be applied with confidence that it is not overstated (and may well be understated based on other factors).

About Agilence

Agilence (www.agilenceinc.com) is the industry leader in data analytics and reporting solutions for operations and loss prevention. Agilence develops its cloud based 20/20™ solution for retail, food and beverage, and hospitality markets. 20/20 is a highly flexible and powerful application that provides organizations with a complete view of their business, empowering them to make informed decisions faster, to increase efficiency and improve profit margins across the enterprise.

Founded in 2006, Agilence is headquartered in Mount Laurel, NJ. To learn more about Agilence, please email sales@agilenceinc.com or call 856-366-1200.

