Equivalent Supply Chain Metrics. A Behavioral Perspective

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We analyze how performance metrics that contain the same information affect actual decisions. We consider two such metrics from inventory management, days of supply and inventory turn rate, where one is the inverse of the other. We argue that individuals tend to assess performance based on the metrics as opposed to the fundamental attributes that actually matter and develop behavioral models that build on this effect. The models suggest that better investment decisions are made under metrics that are proportional to fundamental attributes, such as the days of supply metric. They also indicate that motivation and effort are higher under metrics that increase over-proportionally with the fundamental attribute, such as the inventory turn rate metric. In laboratory experiments, we find support for the model predictions. The results highlight the importance of including behavioral factors in metric design and provide guidance for matching metrics with managerial objectives.

Key words: Behavioral Operations Management; Decision Biases; Performance Metrics; Supply Chain Management

1. Introduction

Performance metrics are used to quantitatively assess the performance of organizations, functions, projects, and individuals. Important decisions are based on performance metrics, such as investment selections, budget allocations, and employee rewards. There exists a rich body of literature that provides guidance for choosing appropriate metrics (Eckerson 2011, Parmenter 2010). However, often multiple metrics are available that contain the same information and it is unclear which one should be preferred. We refer to such metrics as *equivalent metrics*. Fully rational decision makers

Area	Time based	Rate based
Inventory	Days of supply (90 days)	Inventory turn rate (4/year)
Warehousing	Picking time (30 sec/unit)	Picking rate (120 units/hr)
Production	Production time (1 min/unit)	Production rate (60 units/hr)
Reliability	Mean time between failures (10 years)	Failure rate (10 %/year)

Table 1 Examples of equivalent metrics used in supply chain management

are unaffected by which one of the equivalent metrics is used, but the decisions of actual human decision makers can be affected.

We consider equivalent metrics, where one metric is the inverse of the other. Such metrics are widely used in management. The overall performance of a company can be measured by the earnings yield and its inverse, the price-to-earnings ratio; a project can be evaluated by the payback period and its inverse, the return on investment; sales efficiency can be measured as cost per acquisition and its inverse, the acquisitions per dollar spent; and employee retention can be evaluated by the employee turnover rate and its inverse, the employee retention time.

In supply chain management, performance metrics and their inverses are used in many areas (Table 1). Our focus is on inventory management, which is one of the central areas of supply chain management. Inventory is part of the working capital of a company and an important driver of the financial performance. In inventory management, the equivalent performance metrics *days of supply* and *inventory turn rate* are commonly used (Caplice and Sheffi 1994, Hausman 2003). Days of supply measures the average duration that products are held in inventory and is usually specified in terms of days. Its inverse, the inventory turn rate, measures the frequency at which the inventory stock is replenished or turned over. It is usually specified as an annual rate. An inventory system with 90 days of supply, for instance, has a inventory turn rate of 4/year.

Days of supply and inventory turn rate are both popular practice. In recent surveys that we conducted at three supply chain management conferences (Copperberg 2013, Marcus Evans 2013, McKinsey 2013), we asked 51 managers of manufacturing companies about the performance metrics used at their companies: 31% of the participants reported that they use days of supply, but not inventory turn rate, 31% that they use inventory turn rate, but not days of supply, and 28% that they

use both metrics, and 10% used other metrics or did not provide answers. In informal interviews, the participants reported that they were unaware of the rationales for choosing one metric or the other and were interested in guidance on which one to prefer. In this paper, we analyze equivalent metrics to provide such guidance.

The effect of metrics on decision making can be explained by attribute substitution: When confronted with a difficult question, people answer an easier question instead and are often even unaware of the substitution (Kahneman and Frederick 2002), in particular if relationships are non-linear (Svenson 2011). Individuals do not necessarily make decisions that optimize the fundamental attribute, but mediums that are more readily available (Hsee et al. 2003). We will use the substitution heuristic to model the effect of metrics on inventory valuations. We will show that decision makers tend to optimize the values of the metrics that is used to measure inventory performance, as opposed to the fundamental attribute that is actually relevant, the inventory value. The relationship between the days of supply metric and the inventory value is linear and inventory changes are valued correctly by decision makers who substitute inventory value by days of supply. The relationship between the inventory turn rate metric and the inventory value is convex and inventory changes are over-valued by decision makers who substitute inventory value by the inventory turn rate.

Our objective is to understand how equivalent metrics affect decisions to provide guidance for metric design. We consider situations, where decision makers make investments to improve the performance of their inventory systems. These investment can be financial investments or real effort investments. They improve the efficiency, that is, the inventory value, but do not affect the efficiency of the inventory, that is, the service levels and the delivery lead times. Such decisions are common in practice, where companies use service level targets that are based one market requirements and the competition and set inventory levels such that the service levels are achieved. One company form the high-tech industry that we have worked with, for instance, requires a service level of 98%. The company invested in an IT system that enables it to forecast demand more accurately and allowed the company to reduce the inventory value by 15%, while keeping the service level

constant. Companies can also invest in improving the effectiveness of their inventory systems in addition of improving the efficiency. However, then two dependent performance metrics are affected simultaneously, which can be analyzed in future research after the effect of equivalent performance metrics on a single metric has been understood.

We will show that in situations where inventory changes must be valued correctly, better decisions are made under the days of supply metric than under the inventory turn rate metric. We conducted laboratory experiments with students and managers, where subjects could select an inventory optimization option out of a set of alternative options and incentivized them to select the one with the highest inventory value reduction. We used two treatments that differed only in how inventory performance was indicated. Under the days of supply metric, 89% of the decisions were optimal, whereas only 42% of the decisions were optimal in the inventory turn rate treatment. The average inventory value reduction was 42% higher under the days of supply than under the inventory turn rate metric, which highlights the importance of choosing the right metric if equivalent metrics are available.

However, the days of supply metric is not always the superior metric. Because the inventory turn rate is convex increasing in inventory reductions, it over-indicates their values and offers an interesting opportunity to motivate individuals to continue investing effort in inventory optimization, even if large reductions have already been achieved. We conducted a laboratory experiment, where subjects could invest real effort to reduce the inventory value. We used again two treatments with different metrics for indicating inventory performance. Under the inventory turn rate metric, subjects invested 28% higher effort and achieved 22% lower inventory levels than under the days of supply metric.

Our results indicate that there does not exist one metric that is generally superior to another, but that it depends on the purpose, which one should be preferred. In our analyses, we have found indications that decision makers tend to be prone to the attribute substitution and to postulate a linear relationship between the metric and the fundamental attributes. A metric designer who is

aware of this decision biases can take them into account and choose metrics that are tailored to the objectives.

Not all decision makers are prone to the decision biases and we use dual process theory (Stanovich and West 2000, Kahneman and Frederick 2002, Evans 2008) to analyze the heterogeneity of the decisions. We determined the cognitive refection test scores (Frederick 2005) and rational experiential inventory scores (Pacini and Epstein 1999) of the subjects of the investment experiment under the inventory turn rate metric and found that those with high scores make better decisions. Individuals who rely more on System 2 thinking, that is, those who are more reflective and rational, are less prone to decision biases than others. If such individuals are assigned to investment decisions, we can expect better results under all metrics. If circumstances prevent using the right metric, managers should ensure that the right individuals are used for decision making.

2. Behavioral Valuation Model

We are interested in understanding how inventory decisions are affected by the metrics that are used to indicate inventory performance. The fundamental measure of inventory performance is the inventory value. It quantifies the capital that is tied up in inventory and profit maximizing ("rational") individuals rely on it in their decision making. If the metrics days of supply or inventory turn rate are used to indicate inventory performance, rational individuals determine the corresponding inventory values and base their decisions on it. Cognitive science research indicates that not all decision makers use this approach, and that some base their decisions on the metrics and ignore the effect of their decisions on the inventory value.

2.1. Inventory Performance Metrics

The value of the capital that is tied up in inventory, the *inventory value*, is the fundamental measure of inventory performance. For a product with unit cost c and inventory level I, the inventory value is

$$M = cI. \tag{1}$$

To evaluate the efficiency of inventory usage over time or to compare inventory between companies, locations, or products, the performance metrics days of supply and inventory turn rate are commonly

used (Hausman 2003). The *days of supply* metric relates the inventory value to the cost of goods sold. For a demand rate of d, the cost of goods sold is cd and the days of supply is

$$T = \frac{M}{cd} = \frac{I}{d}. \tag{2}$$

The days of supply measures the average duration that products are held in inventory and a lower value indicates higher performance.

The *inventory turn rate* metric relates the cost of goods sold to the inventory value and is computed as

$$R = \frac{cd}{M} = \frac{d}{I}. \tag{3}$$

The inventory turn rate measures the frequency at which the inventory stock is replenished and a higher value indicates higher performance. Because the days of supply metric is the inverse of the inventory turn rate metric, both metrics are equivalent and a rational individual makes the same decisions under both metrics.

2.2. Effect of Inventory Reductions on Inventory Value

One of the key tasks of inventory managers is to identify and implement improvements that reduce inventory. Inventory reduction can be achieved, for instance, by reducing supply lead times, automating order processing, or improving demand forecasting accuracy (see for expample, Cachon and Terwiesch 2012). Such activities require effort and financial investments and to determine which of them to pursue, the value of the inventory reductions that they achieve must be determined.

We denote the initial inventory level by I_0 and the inventory level after the reduction by I_1. The inventory level reduction of $I_0 - I_1$ reduces the inventory value by $V_M = c(I_0 - I_1)$.

2.3. Valuation of Inventory Reductions by Metrics

If inventory performance is measured by the days of supply or inventory turn rate metrics, we do not expect that all individuals invest the cognitive effort to compute the inventory value from the metrics. We expect that those who do not invest the cognitive effort substitute the inventory value by the metric and value inventory based on the metric.

Our expectation is based on insights from research on judgment and decision making that shows that individuals often optimize proxy measures as opposed to fundamental measures (Fischer et al. 1987, Hsee et al. 2003). A proxy measure is an indirect measure of the degree to which a decision objective is attained and could, in principle, be replaced by the fundamental measure (Keeney and Raiffa 1976). If proxy measures are used to characterize outcomes, individuals must consider the relationship between the proxy measure and the fundamental performance measure to make the right decision. If the relationship is complex, they often apply decision heuristics (Keeney and Raiffa 1976, Hsee et al. 2003).

A common feature of decision heuristics is the substitution of fundamental measures by proxy measures that are more readily accessible and yield plausible answers (Kahneman and Frederick 2002, 2005). If proxy measures are made available and are used as a substitution of fundamental performance, the outcome of a decision does not depend on the fundamental performance measure, but on the proxy measure (Kahneman and Frederick 2002).

Prior research has identified various situations, in which people rely on this approach. Larrick and Soll (2008) analyzed how people value fuel consumption. In a treatment, in which they indicate fuel efficiency by the miles per gallon metric, people tend to over-value efficiency improvements of cars that are already efficient. Kagel et al. (1996) conducted an ultimatum game, where participants bargained over chips with different exchange rates and found that fairness concerns focused on the number of chips and not on the value of the chips. Svenson (1970, 2008) analyzed how people estimate time savings from increased driving speeds. They found that typical estimates are based on the differences in the driving speeds instead of the actual time savings. Hsee et al. (2003) conduct an experiment, in which they compare the effort of participants that are offered immediate rewards with the effort of participants that first receive points that are later converted into rewards. Although the actual rewards are the same in all treatments, effort levels differed and depended on the amount of points received.

Days of Supply: If an individual uses the days of supply metric as a proxy and substitute of inventory value, the value assigned to a reduction in the days of supply from $T_0 = I_0/d$ to $T_1 = I_1/d$ is

$$V_T = t(T_0 - T_1), \tag{4}$$

where the parameter t is the value that an individual associates with a unit decrease in days of supply. Following Larrick and Soll (2008), we use linear relationships between the proxy measure and the valuation.

To express V_T as a function of the inventory levels, we replace T_0 by I_0/d and T_1 by I_1/d and obtain

$$V_T = \frac{t}{d}(I_0 - I_1), \tag{5}$$

which is the value that an individual relying on Equation (4) assigns to an inventory level reduction from I_0 to I_1.

Inventory Turn Rate: If an individual uses the inventory turn rate metric as a proxy and substitute of inventory value, the value assigned to an increase in the inventory turn rate from $R_0 = d/I_0$ to $R_1 = d/I_1$ is

$$V_R = r(R_1 - R_0), \tag{6}$$

where the parameter r is the value associated with a unit increase in the inventory turn rate and where we use again a linear relationship between the proxy measure and the valuation.

To express V_R as a function of the inventory levels, we replace R_0 by d/I_0 and R_1 by d/I_1 and obtain

$$V_R = rd\left(\frac{1}{I_1} - \frac{1}{I_0}\right), \tag{7}$$

which is the value that an individual relying on Equation (6) assigns to an inventory level reduction from I_0 to I_1. For a given initial inventory level the function is strictly convex increasing in the inventory reduction, whereas the optimal valuation is linear increasing in it. Therefore, there does not exist a constant value for r, for which the valuation is correct over a range of inventory reductions.

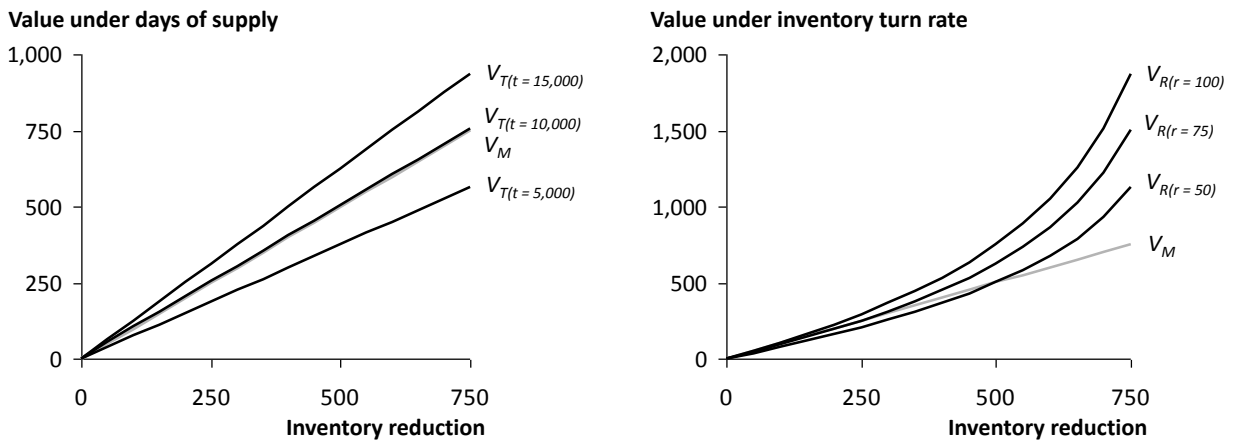

Figure 1 **Valuation of inventory reductions by days of supply and inventory turn rate ($c = 1$, $d = 10{,}000$, $I_0 = 5{,}000$)**

To evaluate inventory reductions optimally, a decision maker must use the function $r = cI_0I_1/d$. Rational decision makers use this function, but those who rely on the substitution heuristic and postulate a linear relationship between the inventory turn rate metric and the valuation use a value of r that is independent of the inventory reduction.

Figure 1 provides an example to illustrate how inventory changes are valued by subjects relying on the metrics. The left graph shows the valuation under the days of supply metric. The gray line indicates the optimal valuation (V_M), which is the same valuation as the evaluation under the days of supply metric with an optimal parameter value for $t = cd$ ($V_{T(t=10,000)}$). If changes in days of supply are over-valued ($t = 15,000$) or under-valued ($t = 5,000$), the days of supply valuation differs from the optimal valuation, but both depend linearly on the inventory reduction. This implies, for instance, that the value assigned to an inventory reduction is independent of the initial inventory level, which is optimal.

The right graph shows the valuation under the inventory turn rate metric. The valuation is convex increasing in the inventory reduction, which implies that for any fixed value of r, the value assigned to a given inventory reduction depends on the initial inventory level. It is valued higher for low than for high initial inventory levels. It also implies that sufficiently large inventory reduction, that is, inventory reductions that are greater than those where V_M and V_R intercept, are over-valued.

3. Effect of Performance Metrics on Investment Decisions

A common management task is selecting investments out of a set of investment options with different returns. Managers must decide, for instance, which of several business units, locations, or processes to optimize. We consider such a problem, where a decision maker must determine which of multiple inventory optimization options to choose. The effect of the optimization options is indicated by the days of supply or inventory turn rate metrics.

3.1. Behavioral Investment Models

Consider two alternative inventory optimization options for two products A and B. The initial inventory of product A is I_0^A and an investment in inventory optimization reduces it to I_1^A. The initial inventory of product B is I_0^B and an investment in inventory optimization reduces it to I_1^B. To keep the model parsimonious, we consider only two products with the same unit costs, demand rates, and investment costs, but with different initial inventory levels and different inventory reductions.

A rational decision maker values the optimization options based on their effect on the *inventory value* and chooses Option A if

$$V_M^A = c(I_0^A - I_1^A) > c(I_0^B - I_1^B) = V_M^B \tag{8}$$

and Option B otherwise.

If the optimization options are valued by the *days of supply* metric, Option A is chosen if

$$V_T^A = \frac{t}{d}(I_0^A - I_1^A) > \frac{t}{d}(I_0^B - I_1^B) = V_T^B \tag{9}$$

and Option B is chosen otherwise. The only difference between the valuations by Equations (8) and (9) is that the inventory reductions in Equation (9) are scaled by a factor t/d. Because the factor is the same for both options, the decisions are the same under both valuations and optimal choices are made under the days of supply metric.

If the optimization options are valued by the *inventory turn rate* metric, Option A is chosen if

$$V_R^A = rd\left(\frac{1}{I_1^A} - \frac{1}{I_0^A}\right) > rd\left(\frac{1}{I_1^B} - \frac{1}{I_0^B}\right) = V_R^B \tag{10}$$

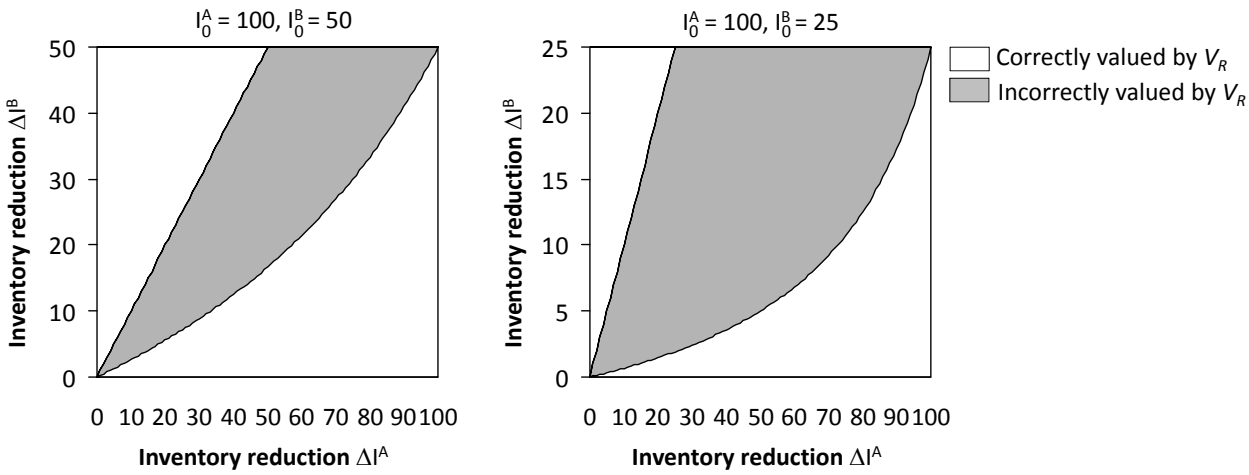

Figure 2 **Effect of initial inventory and inventory reduction on valuation under inventory turn rate metric**

or, equivalently, if

$$(I_0^A - I_1^A)I_0^B I_1^B > (I_0^B - I_1^B)I_0^A I_1^A. \tag{11}$$

Otherwise, Option B is chosen.

The choices under the inventory turn rate metric are not always optimal, because the inventory turn rate over-values inventory reductions if the initial inventory is small or the inventory reduction is large.

Figure 2 shows two examples with initial inventory levels $I_0^A = 100$ and $I_0^B = 50$ (left graph) and $I_0^A = 100$ and $I_0^B = 25$ (right graph). The areas shaded in gray indicate where the inventory turn rate metric suggests the wrong choice. Consider the left graph. For an inventory reduction of Option A of $\Delta I^A = 50$ and an inventory reduction of Option B of $\Delta I^A = 20$, it is optimal to choose Option A, but Option B is chosen if inventory reductions are valued based on the inventory turn rate metric.

Under the inventory turn rate metric, individuals choose the wrong investment option if the inventory reductions fall into the gray areas, unless they invest cognitive effort and compute the monetary value of the inventory reduction. We expect that some individuals make the investment and decide optimally, while those who do not make the investment decide wrongly. Under the days of supply metric, individuals are not prone to such decision biases and we hypothesize:

Hypothesis 1. *Optimal investment decisions are made more frequently under the days of supply metric than under the inventory turn rate metric.*

Question 1	A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents
Question 2	If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes
Question 3	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days

Figure 3 The cognitive reflection test

3.2. Effect of Individual Thinking Styles on Decisions

To gain a better understanding of the drivers behind the (potential) heterogeneity of the decisions, we draw from theory of cognitive science. We use dual process theory that has already been successfully applied to understand heterogeneity in decision making in the newsvendor problem, one of the fundamental problems in supply chain management (Moritz et al. 2013).

In dual process theory, cognitive processes are partitioned into two qualitatively different, but inter-operating thinking style systems. There exists a rich body of literature on how the cognitive processes can be defined (see Stanovich and West (2000) and Evans (2008) for an overview), with the common notion that one process is more intuitive and the other process is more rational than the other.

Stanovich and West (2000) and Kahneman and Frederick (2002) refer to the cognitive processes as System 1 and System 2. System 1 is intuitive, fast, automatic, and effortless, while System 2 is reflective, slow, rational, and effortful. If an individual faces a problem, System 1 generates suggestions for System 2. System 2 can endorse or override these suggestions. In our investment decision problem, the option that increases the metric most can be considered the intuitive suggestion, because the metric is the medium that is directly available to the decision maker (Hsee et al. 2003). If System 2 endorses the suggestion in the inventory turn rate treatment, the wrong decision can be made (see gray area in Figure 2). If System 2 is alerted and overrides an incorrect intuitive suggestion, the right decision is made.

Frederick (2005) proposes the Cognitive Reflection Test (CRT) to measure the extent to which a person uses System 2. The CRT consists of three questions to which the intuitive answers are wrong

(Figure 3). The extent to which individuals choose the non-intuitive answers is measured by the CRT score that corresponds to the number of correct answers in the test. The CRT score indicates how likely an individual is to reflect on an answer, that is, using System 2 to override an incorrect intuitive System 1 suggestion as opposed to endorsing it. The objective nature of the CRT makes it an attractive candidate for understanding decision biases in our experiment (Oechssler et al. 2009, Toplak et al. 2011). It is short, easy to administer, unambiguous, and is widely used in laboratory experiments.

The CRT score can be used to estimate the extent to which an individual relies on System 2. The higher an individual's tendency to override an incorrect intuitive response of System 1, the higher the probability that the problem is solved optimally. In the days of supply treatment, the intuitive answer is also the correct answer. In the inventory turn rate treatment, the intuitive answer can be wrong and we expect individuals with high CRT scores to rely on the inventory value more often than individuals with low CRT scores, which leads to the following hypothesis:

Hypothesis 2. *Under the inventory turn rate metric, optimal investment decisions are made more frequently by individuals with high CRT scores than by individuals with low CRT scores.*

3.3. Investment Experiment

We conducted a laboratory experiment, in which human subjects had to decide between two inventory optimization options, where one option reduced inventory more than the other. In the experiment we used two treatments, a days of supply treatment and a inventory turn rate treatment, that differed only in how the performance of the inventory system was measured.

All experimental sessions followed the same protocol. The participants of a session entered the laboratory at the same time and received written instructions about the experiment (Appendix A). After reading the instructions, they could ask questions and the instructor answered them privately.

The instructions explained how the performance metrics are computed and provided an example. In the inventory turn rate treatment, the instructions stated that the inventory turn rate of a

	Days of supply				Inventory turn rate			
	Option A		Option B		Option A		Option B	
Problem	Initial	Optimized	Initial	Optimized	Initial	Optimized	Initial	Optimized
1	60	30	20	10	6	12	18	36
2	24	15	8	5	15	24	45	72
3	120	72	60	36	3	5	6	10

Table 2 Treatments of investment experiment

product with an annual demand rate of 10,000 units and an average inventory level of 5,000 units is computed as

$$\text{Inventory turn rate} = \frac{\text{Annual demand rate}}{\text{Average inventory level}} = \frac{10,000 \text{ units/year}}{5,000 \text{ units}} = 2/\text{year}.$$

In the days of supply treatment, the instructions stated the corresponding days of supply of 180 days.

Subjects were told that they had to manage a warehouse with two products with the same unit costs and annual demand rates of 10,000 units, but with different initial time supplies or inventory turn rates. They were informed that they could optimize the inventory of one of the products and that they would receive a payment of 10 experimental currency unit (ECU) for each unit of inventory reduction. They were also informed about the exchange rate of 1 Euro per 3,000 ECU.

After all subjects had read the instructions, they made the three investment decisions shown in Table 2. The problems were presented one after the other and the sequence was randomized. Participants could make decisions in their own pace and were informed that the experiment was not time restricted.

After they had made the investment decisions, subjects took the CRT, stated if they already knew the questions, and completed a post-experimental questionnaire, in which we asked questions regarding participants' attitudes and preferences as well as general questions about the experiment. In addition we collected demographic data.

A total of 114 students of the Faculty of Management, Economics, and Social Sciences of the University of Cologne were recruited via the online recruiting system ORSEE (Greiner 2004). The

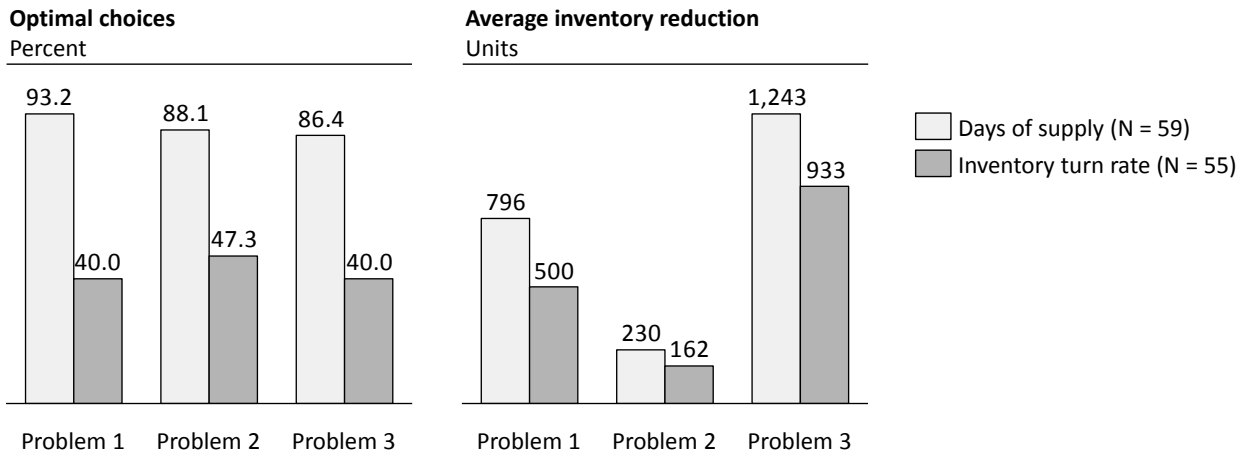

Figure 4 **Results of investment decision experiment**

experiment was conduced in six sessions. In each session, subjects were randomly assigned to treatments, which resulted in 59 subjects for the days of supply treatment and 55 subjects for the inventory turn rate treatment. The experiments lasted on average 45 minutes and were programmed and conducted with the software z-Tree (Fischbacher 2007). The average payment was 9.29 Euro, including a participation fee of 2.50 Euro.

3.4. Results

The fractions of optimal choices under the different performance metrics are shown in the left graphs in Figure 4. Averaged over all problems, 89.2% of the decisions were optimal in the days of supply treatment and 42.4% were optimal in the inventory turn rate treatment. The difference in the aggregate fraction is significant (Wilcoxon test, one sided, $p < 0.001$), as well as the differences in the fractions for the individual problems (χ^2-test, $p < 0.001$ for all problems). We conclude that optimal investment decisions are made more frequently under the days of supply than under the inventory turn rate metric, which provides support for Hypothesis 1.

The right graphs in Figure 4 show the inventory reductions that were achieved under both metrics. The inventory reductions are related to the optimal choices, but are also affected by the magnitudes of the inventory reductions of the problems. In the days of supply treatment, the average total inventory reduction was 2,269 units and significantly greater than the reduction of 1,595 units in the inventory turn rate treatment (Wilcoxon test, one-sided, $p < 0.001$).

CRT group	Number of subjects	Number of optimal decisions (percent) Problem 1	Problem 2	Problem 3	Average
Low (0 or 1)	16	3 (18.8%)	7 (43.8%)	6 (37.5%)	5.33 (33.3%)
High (2 or 3)	15	11 (73.3%)	10 (66.7%)	8 (53.3%)	9.67 (64.4%)

Table 3 Effect of CRT score on number of optimal choices under inventory turn rate metric ($N = 31$)

We next compare the CRT scores of the subjects that decided optimally with those who did not. Out of the 55 subjects of the inventory turn rate treatment, 24 subjects stated that they already knew the CRT questions before the experiment and we exclude them from the analyses. Following Oechssler et al. (2009) and Hoppe and Kusterer (2011), we pool the CRT scores of the remaining 31 subjects into a low CRT score group (CRT scores of 0 or 1) and high CRT score group (CRT scores of 2 or 3).

Table 3 shows the results. For each problem, the subject group with high CRT scores chose the optimal solution more frequently than the group with low CRT scores. Averaged over all problems, subjects with low CRT scores chose the optimal solution for 33.3% of the problems, a fraction that is significantly lower than the corresponding fraction of 64.4% for the subjects with high CRT scores (Wilcoxon test, one-sided, $p = 0.017$). Controlling for the problem, a mixed-effects logistic regression with the CRT score as an independent variable and the binary decision as the dependent variable yields an odds ratio of 2.28 that is weakly significant ($p = 0.072$).[1] The analyses indicate that subjects with high CRT scores make optimal decisions more frequently than subjects with low CRT scores, which provides support for Hypothesis 2.

We conducted the experiments in a controlled laboratory environment at the University of Cologne. The subjects were pre-experienced students from the Faculty of Management, Economics, and Social Sciences of the University of Cologne with an average age of 23.6 years and little or no work experience. Given the background of the students, it is unlikely that they had experience in

[1] For the full sample of 55 subjects, which includes the subjects who had taken the CRT before, the p-values of the comparison and the odds ratio are $p = 0.028$ and $p = 0.147$, respectively.

	Berlin		Munich		Stockholm		Total	
Metric	**Subjects**	**Optimal**	**Subjects**	**Optimal**	**Subjects**	**Optimal**	**Subjects**	**Optimal**
Days of supply	5	2 (40.0%)	9	9 (100 %)	9	6 (66.7%)	23	17 (73.9%)
Inventory turn rate	3	0 (0%)	10	7 (70.0 %)	15	6 (40.0%)	28	13 (46.4%)

Table 4 Inventory investment decisions of managers ($N = 51$)

making investment decisions, such as the ones that they made in the experiment. To analyze if individuals with experience in investment decisions are also subject to the decision biases we observed with students, we conducted an additional experiment with actual supply chain managers.

3.5. Experiment with Managers

We identified three business conferences that targeted managers at the vice president level and above and addressed inventory optimization: Inventory Optimization Workshop in Berlin (Marcus Evans 2013), Supply Chain Executive Academy in Munich (McKinsey 2013), and Spare Parts Business Platform in Stockholm (Copperberg 2013).

At the conferences, we handed out questionnaires and asked the participants to consider a warehouse where the inventory of three products can be optimized, but budget restrictions allow only optimizing inventory of one product (Appendix B). The products had the same unit costs and demand rates. In the days of supply treatment, days of supply could be reduced from (A) 120 to 90 days, (B) 36 to 18 days, or (C) 15 to 9 days. In the inventory turn rate treatment, we provided the corresponding inventory turn rates that could be increased from (A) 3 to 4 turns per year, (B) 10 to 20 turns per year, or (C) 24 to 40 turns per year. In both treatments, A is the optimal choice.

The results of the experiment are shown in Table 4. At all conferences, the managers performed better under the days of supply metric than under the inventory turn rate metric. Under the days of supply metric, 73.9% of the decisions were optimal, a fraction that is significantly higher than the fraction of 46.6% optimal decisions under the inventory turn rate metric (Wilcoxon test, one-sided, $p = 0.025$).

There exists high heterogeneity in the results between conferences, which can potentially be attributed to the relatively small sample sizes per conference, the different backgrounds of the

participants, or the different topics covered at the conferences before the experiment. To control for such factors in the analysis, we conducted a logistic regression analysis with the metric as the independent variable and the binary decision as the dependent variable, using fixed effects for the conferences. The regression shows a significant effect of the metric on the decision (odds ratio $= 0.178$, $B = 1.728$, $p = 0.024$). The results of this experiment indicate that the investment decisions of supply chain managers are affected by the equivalent metric used and provide additional support for Hypothesis 1.

The results of our experiments with students and managers indicate that some individuals postulate a linear relationship between the performance metrics and the fundamental performance attribute. The relationship between the days of supply metric and inventory value is linear and the relationship between the inventory turn rate metric and inventory value is non-linear. Therefore, inventory optimization decisions are more often evaluated correctly under the days of supply metric than under the inventory turn rate metric and there is a clear advantage of using the days of supply as opposed to the inventory turn rate metric for investment decisions. However, as we show next, the inventory turn rate metric might be the preferred choice for motivating people to invest effort into inventory optimization.

4. Effect of Performance Metrics on Effort

Companies continuously seek to increase their operational efficiency and reduce inventory levels (Alan et al. 2014, Chen et al. 2005, 2007). Adopting just-in-time practices and continuous process improvements are typical measures to do so. Thereby the inventory turn rate and the days of supply metric are commonly used to measure improvements over time and to assess the performance of inventory managers (Gaur et al. 2005, Cohen et al. 2007).

We claim that the effort that people invest is affected by the performance metric that is used. Because different performance metrics assign different values to the effort, the choice of metric influences employee motivation and effort. For example, consider an inventory system where performance is measured by the time metric. Assume that initial inventory performance was 18 days, but that

inventory has already been reduced to 4 days and that an additional reduction has been identified that reduces inventory by another 2 days. Equivalently, inventory performance could be measured by the rate metric. Then, the initial inventory rate was 20/year, has been increased to 90/year, and the identified reduction would increase it to 180/year. If the inventory metrics were used to value the improvements, then the effort that employees invest in identifying and implement improvement ideas might be different under the time than the rate metric.

The observation does not only hold in the example, but in general and it suggests opportunities for motivating people to invest effort. We next provide a behavioral model for the effect of metrics on effort and derive hypotheses. We then test the hypotheses using a laboratory experiment.

4.1. Behavioral Effort Model

Consider an individual who must decide how much effort to invest in inventory optimization. We denote the effort cost function by $E(a)$ and assume that the function is strictly convex increasing in the effort level a. The effort that the decision maker invests determines the inventory level. We denote the inventory level function by $I(a)$ and assume that the function is strictly convex decreasing in the effort level and that the marginal decrease approaches zero as effort goes to infinity. The monetary value of the inventory reduction associated with effort level a is $c(I(0)-I(a))$.

If inventory is valued by the *days of supply* metric, the value of effort level a is

$$V_T(a) = \frac{t}{d}(I(0)-I(a)) - E(a). \tag{12}$$

Under the *inventory turn rate metric*, the value is

$$V_R(a) = rd\left(\frac{1}{I(a)} - \frac{1}{I(0)}\right) - E(a). \tag{13}$$

We are interested in comparing the optimal effort levels under the days of supply and inventory turn rate metrics, which requires specifying the parameters t and r. For our analyses, we use the parameter values at the initial effort level, that is, $t = cd$ and $r = cI^2(0)/d$. All results still hold if the parameters are determined at any effort level between zero and the optimal effort level under

the days of supply metric and also hold if both parameter values have the same bias λ, $0 < \lambda < \infty$, such that $t = \lambda cd$ and $r = \lambda c I^2(0)/d$.

The function $V_T(a)$ is convex in the effort level and the optimal effort level under the days of supply metric solves the first order condition $-cI'(a_T^*) = E'(a_T^*)$. At this effort level, the first derivative of the function $V_R(a)$ is

$$V_R'(a_T^*) = -\frac{I^2(0)}{I^2(a_T^*)} cI'(a_T^*) - E'(a_T^*) > 0, \tag{14}$$

which implies that the optimal effort level under the inventory turn rate metric is higher than the optimal effort level under the days of supply metric.

Under both metrics, individuals who invest cognitive effort to determine the effect of effort on the inventory value choose the same effort levels. Individuals who rely on the metrics, choose higher effort levels under the inventory turn rate metric than under the days of supply metric. We expect that some individuals invest cognitive effort and determine the inventory value and that some rely on the metric and hypothesize:

HYPOTHESIS 3. *The average effort is greater under the inventory turn rate metric than under the days of supply metric.*

4.2. Effort Experiment

We analyzed the effect of the metrics on effort in a laboratory experiment, where human subjects invested real effort to reduce inventory. The experiment used two treatments, a days of supply treatment and a inventory turn rate treatment, that differed only in how the performance of the inventory system was measured.

All experimental sessions followed the same protocol. Subjects received written instructions about the experiment that explained how the performance metrics are computed and provided examples (Appendix C). Subjects were told that they had to manage inventory of a single product with an annual demand rate of 10,000 units and an initial average inventory level of 5,000 units. They were told the initial values of the performance metrics, that is, the initial value of the days of supply metric of 180 days or the initial value of the inventory turn rate metric of 2/year. Subjects were

informed that they could invest effort to reduce inventory and that they receive a payment of 10 ECU for each unit of inventory reduction. They were also informed about the exchange rate of 1 Euro per 5,000 ECU.

The effort task required subjects to position sliders on a computer screen using the computer mouse (Gill and Prowse 2012). In practice, decision makers can, for instance, contact customers to obtain demand information and decrease forecast errors, which allows them to achieve a given service level at lower inventory investments. Decision makers would supposedly contact the most valuable customers first, that is, those providing information that results in the highest forecast error reduction, which implies that the marginal inventory reduction is decreasing in the number of customers contracted. We therefore use a convex deceasing relationship between the effort, indicated by the number of sliders moved and the inventory level. The instructions stated the relationship between effort, measured by the number of sliders moved correctly from the initial position of 0 to the target position of 50, and average inventory:

$$\text{Average inventory level} = \frac{5,000 \text{ units}}{1 + 0.1 \cdot \text{Number of sliders positioned correctly}}. \tag{15}$$

Before the actual experiment, subjects took a quiz with five questions to ensure that they understood the effect of their effort on the average inventory level and the performance metric. The first question was about the functional relationship between the inventory level and the performance metric. The second question asked for the initial average inventory level (5,000 units) and the third question for the initial value of the performance metric (180 days or 2/year). The forth question asked for the inventory level after the first ten sliders were positioned correctly (2,500 units). The fifth question asked for the corresponding value of the performance metric (90 days or 4/year).

If all five questions were answered correctly on the first attempt, subjects received 1,000 ECU. If they needed two attempts, they received 500 ECU. If they needed more than two attempts, they did not receive any compensation for answering the quiz. Subjects could not continue without having answered all five questions correctly. 113 subjects needed one attempt, five subjects needed two attempts, and ten subjects needed more than two attempts.

After the quiz, the actual experiment started. The experiment was played in rounds. At the beginning of a round, a screen with 48 sliders appeared, all set at an initial value of 0 (see Appendix C for a screenshot). Subjects had 2 minutes to position up to 48 sliders and were informed about the time remaining in each round. In the experiment, the maximum number of sliders that a subject positioned correctly in a round was 28. After a slider was positioned correctly, the performance metric was updated. After each round, subjects could decide whether they wanted to stay for another round or to terminate the experiment. Subjects were told that they could play as many rounds as they wanted. However, we had to terminate the experiment of one subject of the inventory turn rate treatment after 50 rounds (close to 120 minutes total) to avoid overlap with subjects of the subsequent session. After the actual experiment, subjects were asked to state the final value of the performance metric, the final value of the average inventory value, why they terminated the experiment, and to report demographic data.

A total of 128 students of of the Faculty of Management, Economics, and Social Sciences of the University of Cologne were recruited via the online recruiting system ORSEE (Greiner 2004). We ran 48 sessions and invited three students per session. To avoid that subjects who terminated the experiment affected the effort decisions of other subjects, we placed the subjects into individual rooms, such that they could not observe each other. Subjects showed up at the instructor's office and were randomly assigned to treatments and rooms. 65 subjects were assigned to the days of supply treatment and 63 to the inventory turn rate treatment. The average compensation was 9.62 Euro.

4.3. Results

Figure 5 summarizes the results. It shows that subjects invested on average more effort in the inventory turn rate treatment than in the days of supply treatment: They moved significantly more sliders (Wilcoxon test, one-sided, $p = 0.011$) and played significantly more rounds (Wilcoxon test, one-sided, $p = 0.025$), which provides support for Hypothesis 3. The figure also shows the average final inventory level under both metrics. In the inventory turn rate treatment, the final inventory

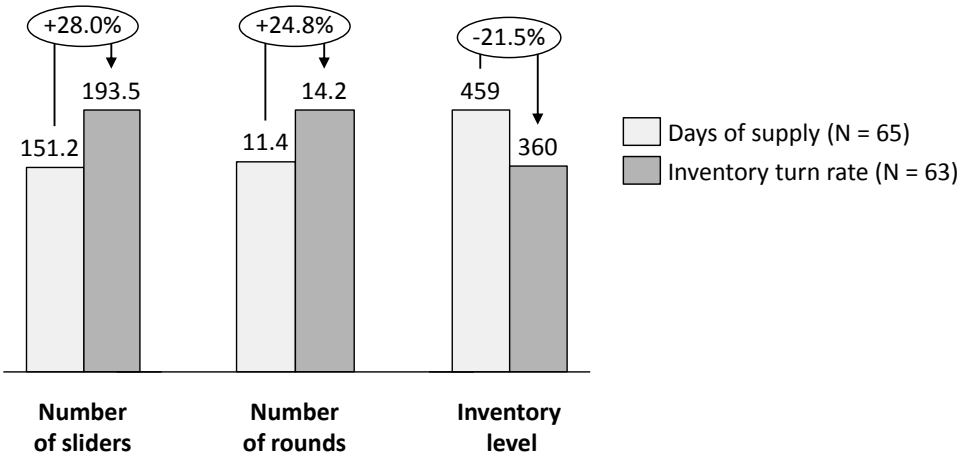

Figure 5 **Effect of metric on average invested effort and average final inventory value**

level was significantly lower than in the days of supply treatment (Wilcoxon test, one-sided, $p = 0.011$).[2]

Our findings suggest that the inventory turn rate metric is better suited to motivate individuals, than the days of supply metric. The observation can b explained by the non-linear relationship between the inventory turn rate metric and the inventory value, which leads individuals to over-estimate the impact of their invested effort on inventory reduction. Therefore, it is more likely that individuals exert more effort and achieve lower inventory levels using the inventory turn rate compared to the days of supply metric.

5. Discussion and Managerial Implications

We developed behavioral models of the effect of performance metrics on decision making. We considered two equivalent metrics, days of supply and inventory turn rate. The relationship between days of supply and inventory value is linear, such that valuations that are based on the metric are proportional to those that are based on the inventory value. The relationship between inventory turn rate and inventory value is convex, such that inventory reductions are over-valued by individuals who rely on the metric. We argued that some individuals value inventory proportional to the metric, while rational individuals rely on the inventory value and hypothesized that people decide more

[2] If we exclude the subjects that needed more than two attempts to pass the quiz from the analyses, the p-values of the comparison of the number of sliders and the number of rounds are $p = 0.012$ and $p = 0.035$, respectively.

frequently optimally under the days of supply metric than under the inventory turn rate metric. In laboratory experiments, we found support for the hypotheses.

In the first experiment, we considered investment decisions and showed that the majority of decisions is correct under the days of supply metric and incorrect under the inventory turn rate metric. To better understand the heterogeneity in the decisions of the inventory turn rate treatment, we applied dual process theory and found that individuals who decide optimally tend to have higher CRT scores than those who decided sub-optimally. In the second experiment, we analyzed effort decisions and showed that individuals invest more effort under the inventory turn rate metric than under the days of supply metric.

The results have important managerial implications. If the inventory turn rate metric is used to measure inventory performance, some individuals over-invest in optimizing inventory systems with already low inventory levels and under-invest in optimizing those with high inventory levels. The decision errors can be reduced by de-biasing the environment and using a metric that is proportional to the inventory value. In situations where this is not possible, the decision makers can be de-biased by ensuring that their System 2 is activated when they make inventory investment decisions. System 2 thinking can be supported by reducing the emotional and cognitive load, for instance, by avoiding time pressure and multi-tasking during decision making.

However, using a metric that over-indicates the value of changes in the fundamental attribute can also be beneficial. The inventory turn rate metric can motivate employees better than the days of supply metric to continuously reduce inventory in such settings, especially if the inventory level is already low. Using the inventory turn rate metric is particularly appropriate in situations where employees are responsible for dedicated areas in single locations, such as managing raw material, work in process inventory, or finished goods inventory at a manufacturing plant. Employees with broader responsibilities who must also decide in which areas to invest, might be misguided by the inventory turn rate metric and focus on reducing inventory in areas where inventory is already low instead of areas with substantial inventory reduction potential.

Our research suggests various promising areas for future research. We focused on inventory management, but we expect that our insights generalize. In engineering, reliability can be measured by the time between failures and the failure rate and in warehousing, performance can be measured by the picking time and the picking rate. We expect that investment decisions are made more often optimally under the time than under the rate metrics in both settings, but that the motivation to continuously invest effort in optimizing single areas is higher under the rate than under the time metrics. Similar examples exist in other supply chain areas and other business functions and it would be interesting to analyze how approaches like ours can be applied to them.

We analyzed one decision heuristic, which Hsee et al. (2003) refers to as *medium maximization*, that is, the optimization of an easily accessible medium as opposed to the fundamental attribute. Another decision bias that has been observed in other settings and that might be relevant for metric design is *proportional dominance*. It suggests that individuals tend to base their decisions on relative effects and neglect absolute effects (Bartels 2006). In our experimental design, we kept the relative improvements between investment options constant (see Table 2) and proportional dominance cannot explain the effects that we observed. However, for situation in which the absolute and relative improvement vary between options, including the biases in the behavioral models could improve their predictive power.

We considered equivalent metrics, where one was the inverse of the other. Many equivalent metrics have this property, but there exist other equivalent metrics. For instance, in operations management, service performance can be measured by the fraction of filled demand or the fraction of lost sales. Similarly, equipment performance can be measured by the uptime and the downtime. One metric frames performance as gains, the other frames it as losses, which might affect how people value the outcomes (Kahneman and Tversky 1979, Tversky and Kahneman 1981). Analyzing such effects offers interesting opportunities that we leave to future research.

Besides the decision biases that are rooted in solid theory, like proportional dominance and framing, biases that have not received much attention can have considerable effects on valuations. Green

(2014), for instance, reports about failed new product introduction of the A&W restaurant chain that introduced a new third pounder hamburger to rival the McDonald's Quarter Pounder. The A&W burger had more meat, was preferred in taste tests, and was less expensive, but did not sell well. Customer focus groups revealed the reason: "Why, [customers] asked the researchers, should they pay the same amount for a third of a pound of meat as they did for a quarter-pound of meat at McDonald's." As the example illustrates, it is important to understand how metrics affect valuation.

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Appendix

The following instructions are translated from German. We present the instructions for the inventory turn rate treatments. In the days of supply treatments the instructions differ from the inventory turn rate treatment instructions only by the metric used to measure inventory performance.

A. Instructions Investment Experiment

Welcome and thank you for participating in this experiment. Please do not talk to each other from now on, turn off your mobile phones, and put away all your personal belongings.

We ask you to read all instructions carefully. If you have any questions, feel free to raise your hand. The experimenter will then come to you and answer your questions in private. Moreover, after reading the instructions you will have the chance to ask questions in case anything remained unclear. All decisions are made anonymously and will be treated confidentially.

You can earn money in this experiment. How much you will earn depends on your decisions. Your earnings in the course of this experiment are expressed in a virtual unit of currency – the experimental currency unit (ECU). At the end of the experiment you will receive 1 Euro for 3,000 ECU earned during this experiment. In addition, you will receive a show-up fee of 2.50 Euro.

Introduction

The inventory turn rate metric is a measure commonly used in warehousing. It is defined as the annual demand rate divided by the average inventory level. The inventory turn rate thus indicates how many times per year the average inventory level of a product is completely depleted and replenished.

Example: A company sells 10,000 units per year of a product. The average inventory level is 5,000 units. What is the inventory turn rate?

$$\text{Inventory turn rate} = \frac{\text{Annual demand rate}}{\text{Average inventory level}} = \frac{10,000 \text{ units/year}}{5,000 \text{ units}} = 2/\text{year}$$

At constant demand rate, an increase in the average inventory level causes a reduction of the inventory turn rate.

At constant demand rate, a reduction in the average inventory level causes an increase of the inventory turn rate.

Task description

You are in charge of a warehouse and you will be evaluated on the basis of the average inventory level. Your warehouse contains two products featuring different inventory turn rates. From each product 10,000 units are sold per year. The unit holding costs are the same for both products.

In each round you can optimize the inventory management for one of the two products and thus reduce the average inventory level of this product. You will receive a bonus for each unit you reduce your average inventory level. For the optimization itself no cost occur.

You will know the current inventory turn rates of both products as well as how the inventory turn rates will change after the optimization. In each round it is your task to decide for which of the two products you want to optimize the inventory management.

Experimental protocol

The sequence of the experiment is as follows:

I. Decisions: You will decide in three independent rounds for which product you want to optimize the inventory management. You will receive a bonus for each unit you reduce your average inventory level.

II. Questions: You will answer three short questions.

III. Questionnaire: You will answer general questions regarding your attitudes and preferences.

IV. Questionnaire: Finally, you will answer general questions regarding the experiment and your person.

Payment

Your payment depends on the achieved inventory reduction over all three rounds. For each unit you reduce the average inventory level you will receive 10 ECU. At the end of the experiment you will receive 1 Euro per 3,000 ECU that you have earned during the experiment. In addition, you will receive a show-up fee of 2.50 Euro.

B. Instructions Validation Experiment with Managers

Definition

$$\text{Inventory turn rate} = \frac{\text{Annual demand rate}}{\text{Average inventory level}}$$

Situation

You are in charge of a warehouse and you have discovered room for inventory optimization for product A, B, and C. Unfortunately, your budget restrictions allow just one optimization. You know the current inventory turns and how they will change after investing in inventory optimization.

Product		A	B	C
Annual demand rate (units)		10,000	10,000	10,000
Unit cost (€)		500	500	500
LyØŜyú2Nè údzNyˇNI·úŜ	Current situation	3	10	24
	After optimization	4	20	40

You are evaluated by average inventory value. Which product would you invest in?

At your company, which of the following metrics is used to measure inventory performance?

- ☐ Inventory turn rate
- ☐ Days of supply
- ☐ Both
- ☐ Other (please specify):

C. Instructions Effort Experiment

Welcome and thank you for participating in this experiment. Please turn off your mobile phone, and put away all your personal belongings. We ask you to read all instructions carefully. All decisions are made anonymously and will be treated confidentially.

You can earn money in this experiment. How much you will earn depends on your decisions and your exerted effort. Your earnings in the course of this experiment are expressed in a virtual unit of currency – the experimental currency unit (ECU). At the end of the experiment you will receive 1 Euro for 5,000 ECU earned during this experiment.

Introduction

The inventory turn rate metric is a measure commonly used in warehousing. It is defined as the annual demand rate divided by the average inventory level. The inventory turn rate thus indicates how many times per year the average inventory level of a product is completely depleted and replenished.

Example: A company sells 10,000 units per year of a product. The average inventory level is 5,000 units. What is the inventory turn rate?

$$\text{Inventory turn rate} = \frac{\text{Annual demand rate}}{\text{Average inventory level}} = \frac{10,000 \text{ units/year}}{5,000 \text{ units}} = 2/\text{year}$$

At constant demand rate, an increase in the average inventory level causes a reduction of the inventory turn rate.

At constant demand rate, a reduction in the average inventory level causes an increase of the inventory turn rate.

Situation

You are in charge of a warehouse with a single product and you will be evaluated on the basis of the average inventory level. Currently, your warehouse contains on average 5,000 units of this product. 10,000 units are sold per year. Therefore, the initial inventory turn rate of your warehouse is 2/year.

Depending on your effort, you can now optimize your inventory management and increase your inventory turn rate. You will receive a bonus of 10 ECU for each unit you reduce your average inventory level.

Task description

In this experiment your effort will be simulated by moving sliders. The sliders are initially positioned at "0" (see Figure 1 (a)). By using the mouse, you can position the slider at any integer value between "0" and "100". The more sliders you correctly position at the target position "50" (see Figure 1 (b)), the more you can reduce your average inventory level. You can adjust each slider an unlimited number of times. In each round, you have 120 seconds to do so.

(a) Initial position at "0" (b) Target position at "50"

Figure 1 Initial and target position of a slider

The average inventory level depends on the number of sliders positioned correctly as follows:

$$\text{Average inventory level} = \frac{5,000 \text{ units}}{1 + 0.1 \cdot \text{Number of sliders positioned correctly}}$$

The inventory turn rate is calculated accordingly:

$$\text{Inventory turn rate} = \frac{\text{Annual demand rate}}{\text{Average inventory level}} = \frac{10,000 \text{ units/year}}{\text{Average inventory level}}$$

Please note that the demand rate stays constant over all rounds.

Sequence of a round

In each round the sequence is identical. Each round begins with an input screen with 48 sliders (see Figure 2). By positioning the sliders (moving them to the target position at "50") you can reduce the average inventory level. For this task, you have 120 seconds per round. Within this time you can freely decide how many sliders you want to position. In the upper part of the input window you can track how the inventory turn rate changes, once you have positioned a slider correctly.

At the end of each round, on the result screen, you will be informed to which extent you were able to increase the inventory turn rate of your warehouse. Once you press "continue" the input screen (Figure 2) appears again and the next round starts.

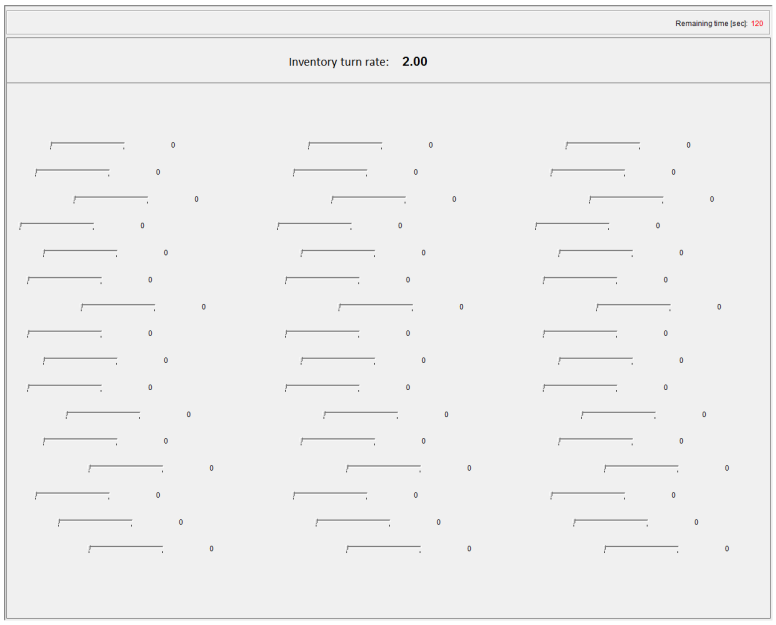

Figure 2 Input screen

Please note, that you will start in the next round with the inventory turn rate you have achieved in the previous round. This means that you can continuously reduce your average inventory level over all rounds.

It is up to you how many rounds you exert effort. If you don't want to exert any more effort please press "terminate experiment" on the result screen. You will then immediately receive your payment for the inventory reduction you achieved until then and you are free to leave.

Experimental protocol

The sequence of the experiment is as follows:

I. Comprehension questions: First, you will answer some comprehension questions. You must answer all questions correctly to reach the next stage of the experiment. You will receive a bonus, if you can answer all questions correctly at the first or second attempt.

II. Effort task: You can exert effort and thus reduce the average inventory level. It is up to you how many rounds to exert effort.

III. Questionnaire: Finally, you will answer general questions regarding the experiment and your person.

Payment

Your payment depends on the achieved inventory reduction over all rounds. For each unit you reduce the average inventory level you will receive 10 ECU. At the end of the experiment you will receive 1 Euro per 5,000 ECU that you have earned during the experiment.