Enhancing Production Quality by Avoiding Dishonest Behaviour

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ABSTRACT

Purpose: This paper elucidates the determinants of dishonest behaviour affecting various domains and aims to demonstrate how addressing these practices can substantially improve overall quality.

Methodology/Approach: A framed laboratory experiment with economics students from the University of West Bohemia was conducted, where participants chose between honest and lower-quality production. Using the Holt-Laury method, we measured risk aversion and personality traits using the Myers-Briggs Type Indicator (MBTI).

Findings: Increased inspection probability significantly reduced lower-quality production, with a statistical significance level of less than 1%. Thinking type of personality and Risk Aversion are significant at the 10% level, indicating a moderate impact. Conversely, punishment and rewards were statistically insignificant, with p-values exceeding 10%.

Research Limitation/Implication: The study is limited by its homogeneous sample of economics students from a single university and insufficient gender representation, which may affect generalizability.

Originality/Value of paper: This research provides insights into how inspection probabilities, rewards, punishments, risk aversion, and personal characteristics influence dishonest behaviour, aiding the development of strategies to reduce dishonesty and improve overall quality.

Category: Research paper

Keywords: dishonest behavior; production quality; risk aversion; laboratory experiment

Research Areas: Quality Engineering; Strategic Quality Management

1 INTRODUCTION

Through a comprehensive review of literature and experiments, this research aims to elucidate the interplay between individual traits and external influences driving dishonest decisions. The primary objective is to identify and analyse determinants of unethical behaviour, which significantly impact market efficiency, resource allocation, and social equity. By examining risk attitudes, personality traits, detection probability, and the severity of rewards or punishments, we aim to uncover mechanisms fostering dishonesty in economic contexts, thereby enhancing process quality and promoting ethical behaviour.

Behavioral economics explores how psychological, cognitive, emotional, cultural, and social factors influence economic decisions, highlighting deviations from classical economic theory. A key focus is cheating and dishonesty, providing insights into why individuals act dishonestly, even against their long-term interests or ethical norms. Understanding these dynamics is crucial for improving process quality and ethical conduct in economic activities. Identifying psychological and situational triggers of unethical behaviour helps understand its broader implications on market dynamics, organisational integrity, and societal welfare. Insights from this research can inform interventions and policies to reduce dishonesty and promote accountability, contributing to better process quality and economic decision-making.

The study of dishonest behaviour in behavioural economics is essential for understanding human nature and decision-making, challenging the notion that individuals always act rationally in their self-interest. It provides insights into the motivations behind actions such as altruism, social norms, and self-image (Hilbig and Thielmann, 2017) and reveals the cognitive biases and heuristics that justify unethical behavior (Hochman, et al., 2016; Speer, et al., 2020). This research is crucial for improving process quality by informing policies to reduce dishonesty and promote ethical behaviour.

Integrating findings on dishonesty into economic models enhances their predictive power, improving financial policies' effectiveness (Druică, et al., 2019). Understanding why people cheat aids in creating regulations that minimise such behavior, leading to fairer outcomes in taxation, welfare, and business regulation. Addressing dishonesty helps develop targeted interventions for a just society (Speer, et al., 2020; Lois and Wessa, 2021).

Insights from behavioural economics also inform better corporate governance by promoting ethical behaviour and reducing fraud. Effective oversight and accountability mechanisms foster a culture of integrity, enhancing long-term sustainability and reputation (Shu, et al., 2012). Transparent policies build trust between consumers and companies, which is crucial for business success and brand loyalty (Cialdini, et al., 2004).

Understanding dishonesty's psychological roots has educational and social impacts. Ethics education can better address why people cheat, fostering commitment to ethical conduct (Hendy, et al., 2021; Hendy and Montargot, 2019).

Studying dishonesty also shows how social norms and cultures influence behavior, aiding in strategies to promote ethical behaviour through social influence and cultural evolution (Gino, et al., 2009; Lois and Wessa, 2021).

At an individual level, understanding dishonesty encourages self-reflection and moral adjustment, leading to personal growth and alignment between actions and ethics (Rintoul and Goulais, 2010).

Cheating and dishonesty erode trust in institutions, governments, and individuals, undermining social cohesion. Addressing these issues restores trust and fosters civic engagement and public confidence in governance (Lederman, et al., 2002; Rothstein and Uslaner, 2005).

Unethical behaviour leads to unfair advantages and inequality. Mitigating such behaviour creates a fairer society by reducing disparities and enhancing social mobility (Elgar and Aitken, 2011).

In summary, studying cheating and dishonesty in behavioural economics helps improve economic theories, policies, business practices, and ethical standards, bridging the gap between expected and actual behaviour and designing better systems considering human complexity.

2 METHODOLOGY

Behavioural economics uses experimental methodologies, including laboratory experiments, to investigate cheating and dishonesty within controlled environments. This approach allows precise manipulation of variables and observing behaviours, providing valuable insights into the factors influencing dishonesty and contributing to process quality improvements.

Experimental economics employs methods to measure and test cheating and dishonesty, isolating factors such as profit potential, risk of detection, and social norms. These experiments enable systematic examination of conditions under which individuals engage in unethical behaviour, informing strategies to mitigate dishonesty and promote ethical behaviour.

Laboratory experiments are foundational in studying cheating and dishonesty, placing participants in scenarios where they choose between honest and dishonest actions tied to monetary incentives. These controlled settings mimic real-life situations, allowing accurate measurement and analysis of unethical behaviour.

2.1 Experimental design

The primary objective of this research is to identify the determinants of dishonest behaviour to enhance process quality. We conducted a framed experiment and administered questionnaires to gather data. Personality traits were assessed using the Myers-Briggs Type Indicator (MBTI), and risk preferences were measured using the Holt and Laury mechanism. Our experiment measured the willingness to cheat, incorporating two treatment variables: the probability of inspection and the effects of punishing dishonesty or rewarding honesty. The study involved 64 students from the Faculty of Economics at the University of West Bohemia in Pilsen, who received additional credit points for participation (Luccasen and Thomas, 2014; Ding, et al., 2018.

Our research aims to test several hypotheses related to the determinants of dishonest behaviour to improve process quality:

Personality Characteristics: We hypothesise that certain personality traits, measured by the Myers-Briggs Type Indicator (MBTI), are linked to a higher propensity for dishonest behaviour.

Risk Aversion: We hypothesise that risk aversion, measured by the Holt and Laury mechanism, significantly influences the frequency of dishonest actions.

Probability of Inspection: We hypothesise that the higher probability of inspection significantly reduces dishonest behaviour.

Punishment vs. Reward: We hypothesise that punishment for dishonesty and rewards for honesty have differing impacts on reducing dishonesty, aiming to determine which is more effective.

These hypotheses guide our investigation into the factors driving unethical behaviour and inform strategies for enhancing ethical conduct and process quality. We used the Myers-Briggs Type Indicator (MBTI) (Myers and Myers, 2010) to measure personality traits, opting for a localised Czech version (Anon. 2021). Despite its limitations, the MBTI was chosen for its brevity and reduced risk of translation errors.

The MBTI, consisting of 56 scaled questions, classifies individuals into 16 personality types across four dichotomies: Extraversion (E) or Introversion (I), Sensing (S) or Intuition (N), Thinking (T) or Feeling (F), and Judging (J) or Perceiving (P). We used continuous scores in our regression models to avoid losing information from discrete categories.

To measure risk preferences, we used the Holt and Laury mechanism, where participants choose between two lotteries, A and B, with different probabilities of winning. This method precisely assesses individual risk aversion, aiding in analysing the relationship between risk preferences and dishonest behaviour, thus enhancing process quality. Below is a sample shortened table for illustration:

	Lottery A		**Lottery B**			
Row	**probability**	**win**	**probability**	**win**	**probability**	**win**
1	100%	9	0%	12	100%	6
2	100%	9	20%	12	80%	6
3	100%	9	40%	12	60%	6
4	100%	9	46%	12	54%	6
5	100%	9	50%	12	50%	6
6	100%	9	54%	12	46%	6
7	100%	9	60%	12	40%	6
8	100%	9	80%	12	20%	6

When there is no variation in winnings, as in Lottery A, it is considered a certainty that participants choose between Lottery A and Lottery B in each row. Initially, participants preferred Lottery A for a guaranteed win of 9, but as decisions became more complex, they reflected individual risk tolerance. The table's structure ensures that as Lottery A's advantage decreases, Lottery B's advantage increases, eventually leading most participants to prefer Lottery B.

The table includes more values around 50% to measure risk aversion, capturing it near its mean accurately. Measurements were taken twice with different lotteries to ensure greater accuracy and reliability, enhancing quality.

We constructed our framed experiment to measure cheating, which involved placing students in specific roles. This design allowed us to create realistic scenarios where participants could act honestly or dishonestly. The core concept of the experiment was to simulate a production and sales environment where producers could decide to either produce goods honestly or cheat in production to save costs. Cheating reduced production costs by 50% of the full costs, but it carried the risk of detection, resulting in either the absence of a reward or the imposition of a punishment.

The experiment was conducted in multiple rounds. Each producer was aware of their production costs for honest and cheating scenarios, with costs varying between producers and permuted appropriately. Producers make an irreversible decision on their production method without the ability to alter their choice once made. Each producer then produced one piece of goods. The goods were sold to consumers, each of whom knew their utility value for the goods, representing the highest price they were willing to pay. The utility values were permuted among consumers to ensure variation. Trading was conducted through a double auction, allowing participants to negotiate freely. The producer-consumer pairs that reached an agreement exited the auction. The costs for producers and benefits for consumers were designed to ensure that a mutually agreeable price could always be found, guaranteeing that all ten products produced were sold to the consumers.

The auction results were communicated to the experimenter, with producers reporting whether they cheated and detailing their sales, including prices and buyers. Consumers reported their purchases and sellers for verification. The experimenter privately informed consumers if the product they bought was cheated, reducing the consumer's utility to zero if identified as cheated.

Product quality inspection was determined by a lottery based on the inspection probability treatment variable. A random number from a uniform distribution ensured an unbiased inspection process.

Another treatment variable was the implementation of rewards for honesty or punishments for dishonesty. In sessions with rewards, participants were informed in advance. Honest producers who were inspected received a fixed reward, while dishonest producers received a fixed penalty.

Each session consisted of 10 rounds, with varying production costs and consumer benefits. After five rounds, participants switched roles, allowing the examination of both producer and consumer behaviours.

Different values of the treatment variables were set for each session to enhance process quality. We used two treatment variables, each with two levels:

Probability of Inspection: Low probability meant inspecting one manufacturer, while high probability meant inspecting two.

Rewarding or Punishing: In the rewarding condition, honest producers received a 50-unit bonus. In the punishing condition, dishonest producers were penalised by deducting 50 units.

By systematically varying these variables, we explored how inspection probability and the consequences of honesty or dishonesty influenced participants' behaviour.

The experiment enabled us to collect data critical for addressing our research questions and improving process quality. The data includes:

- frequency of cheating by subjects, reflecting compliance rates;
- known probability of inspection in each case;
- whether subjects were rewarded for complying or punished for cheating.

The experimental design mirrored real-world dynamics of following orders in corporate or public authority contexts, making the conclusions broadly applicable to compliance and ethical behaviour in various settings.

All inspection probability and reward/punishment combinations were tested across four sessions with 14, 16, 16, and 18 students.

2.2 Statistical methods

In this paper, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore and validate relationships among variables, mainly focusing on risk aversion as a latent variable.

PLS-SEM, a sophisticated method for testing hypotheses about relationships between observed and latent variables, integrates aspects of factor analysis and multiple regression analysis.

PLS-SEM is advantageous for analysing complex models with assumed causal relationships between variables. It allows testing of indirect effects and estimation of causal relationships while accounting for measurement error.

The model is divided into two sub-models: the measurement model, which links latent variables to their observed indicators, and the structural model, which specifies relationships between latent variables. This approach, widely used in social sciences, marketing, and management research, explores theoretical constructs that are difficult to measure directly (Fuoli, 2022).

SEM provides a robust framework for exploring complex relationships and testing theoretical concepts within a single model. By integrating measurement and structural models, SEM allows for a comprehensive analysis of direct and indirect effects among variables (Kline 2016).

We aim to identify and quantify relationships among personality traits and risk preferences by developing a Partial Least Squares Structural Equation Modeling (PLS-SEM) model to analyse factors influencing dishonest behaviour. These variables were chosen based on their potential impact on ethical decision-making. PLS-SEM provides a nuanced understanding of these interactions, informing strategies for enhancing ethical conduct and improving process quality.

PLS-SEM is a nonparametric method that does not require normality (Hair, et al., 2021). It maximises explained variance in dependent measures, ensuring comprehensive data capture. This enhances result accuracy and reliability. Construct scores are estimated as linear combinations of indicators, allowing precise quantification of latent variables. Parameter estimates show high statistical power, making detected effects significant and reliable, reinforcing model robustness.

PLS-SEM handles complex models with multiple dependent variables and analyses relationships between latent and observed variables without stringent distributional assumptions. This flexibility makes it ideal for exploring psychological, social, and economic factors in experimental economics research.

3 RESULTS AND DISCUSSION

Table 1 provides a comprehensive description of the experimental data distribution. It includes the number of observations, mean value, standard deviation, minimum, lower quartile, median, upper quartile, and maximum for each monitored variable. Additionally, the table presents p-values from normality tests, indicating whether the distribution of each variable follows a normal distribution. Detailed descriptions of the individual normality tests are provided below, outlining the methods and results used to determine the normality of the data distributions.

Table 1 – Summary statistics

Variable	**N**	**Mean**	**Std. dev.**	**Min**	**Pctl . 25**	**Median**	**Pctl. 75**	**Max**	**p-value**		**Distribution**
Count_of_cheating	64	1.92	1.38	0.00	1.00	2.00	3.00	5.00	K-S test	2.15e-07	not poisson
									$\frac{var}{mean}$	0.99	poisson
Risk_aversion	64	0.28	0.51	-1.07	-0.04	0.27	0.60	1.50	K-S test	0.82	normal
									S-W test	0.32	normal
Extroversion	64	30.98	10.32	10.00	23.00	30.00	40.00	53.00	K-S test	0.87	normal

Variable	**N**	**Mean**	**Std. dev.**	**Min**	**Pctl . 25**	**Median**	**Pctl. 75**	**Max**	**p-value**		**Distribution**
									S-W test	0.55	normal
Sensing	64	35.56	8.30	16.00	29.75	37.50	41.25	50.00	K-S test	0.36	normal
									S-W test	0.08	not normal
Thinking	64	35.34	10.32	12.00	29.75	35.00	42.00	66.00	K-S test	0.97	normal
									S-W test	0.91	normal
Judging	64	41.38	8.80	17.00	36.00	43.00	48.00	55.00	K-S test	0.29	normal
									S-W test	0.01	not normal
Gender	64										
… Female	39										
… Male	25										

The distribution of female and male participants, displayed in Table 2, was uneven across sessions, and attendance was not managed by gender. Coincidentally, the four men in the session with the highest motivation to cheat exhibited the most minor cheating, contributing to gender not being a significant variable in our analysis. The coefficient for gender indicated that being male was associated with a reduction in cheating, contradicting general assumptions. Consequently, our data does not show that gender affects cheating frequency, suggesting other factors may play a more significant role.

Table 2 – Cheating in sessions by gender

	Gender	**Prob_of_inspection**	**Reward / Punishment**	**Count**	**Mean**	**Std. dev.**
1	Female	1	-50	12	2.75	1.66
2	Female	1	50	13	2.46	0.97
3	Female	2	-50	5	1.40	0.55
4	Female	2	50	9	0.67	1.00
1	***Male***	***1***	***-50***	***4***	***1.00***	***1.15***
2	Male	1	50	5	2.80	0.45
3	Male	2	-50	11	1.91	1.58
4	Male	2	50	5	1.20	0.84

These findings, combined with our earlier results, highlight the complexity of dishonest behaviour and the importance of stringent inspection mechanisms. The reduction in cheating among males under certain conditions and the lack of significant gender effects suggest that targeted interventions can effectively reduce dishonesty. This underscores the potential to improve product quality through strategic quality control measures and a better understanding of the factors influencing dishonest behaviour.

Some researchers mistakenly believe that sample size is irrelevant in Partial Least Squares Structural Equation Modeling (PLS-SEM). This misconception stems from the "10-times rule" by Barclay, Higgins, and Thompson (Barclay, et al., 1995), which suggests the sample size should be at least ten times the number of independent variables in the most complex regression of the PLS path model. This rule states that the minimum sample size should be ten times the maximum number of arrowheads pointing at any latent variable in the model.

Our sample size of 64 is sufficient for estimating the model, as it meets the minimal requirements for robust analysis. Structural Equation Modeling (SEM) allows us to construct latent variables, such as risk aversion, which we derive from two Constant Relative Risk Aversion (CRRA) measurements.

In our sample, path coefficients greater than 0.396 are significant at the 1% level, those above 0.31075 are significant at the 5% level, and those exceeding 0.26538 are significant at the 10% level. Coefficients below these thresholds are not statistically significant for our sample size (Hair, et al., 2021, p. 17). These results highlight the importance of path coefficient thresholds in evaluating relationships within our model. Rigorous statistical validation and accurate modelling of latent variables, like risk aversion, enable us to identify factors influencing dishonesty, thereby contributing to quality improvement strategies.

In evaluating the reliability and validity of our model, we ensure adherence to several critical criteria. The results are displayed in Table 3.

- **Cronbach's Alpha (α)** should exceed 0.7, indicating internal consistency among items measuring the same construct.
- Similarly, **Composite Reliability (ρC)** should surpass 0.7, confirming the reliability of the latent variable measurements.
- Additionally, the **Average Variance Extracted (AVE)** should be greater than 0.5, demonstrating that the latent construct captures most of the variance in the observed variables.

Table 3 – Reliability check

	α	**ρC**	**AVE**	**ρA**
Risk_aversion	0.697	0.855	0.749	1.000

To visualise the comprehensive model, we present a diagram in Figure 1 illustrating the relationships between the observed variables and the latent construct. This diagram depicts how the observed variables interact and contribute to the latent construct, thereby facilitating a comprehensive understanding of the model's structure. According to the literature, gender can influence risk aversion

(DeAndrea, et al., 2009), especially thinking about personality traits (Myers, et al., 1998). However, our experimental results do not fully align with these findings.

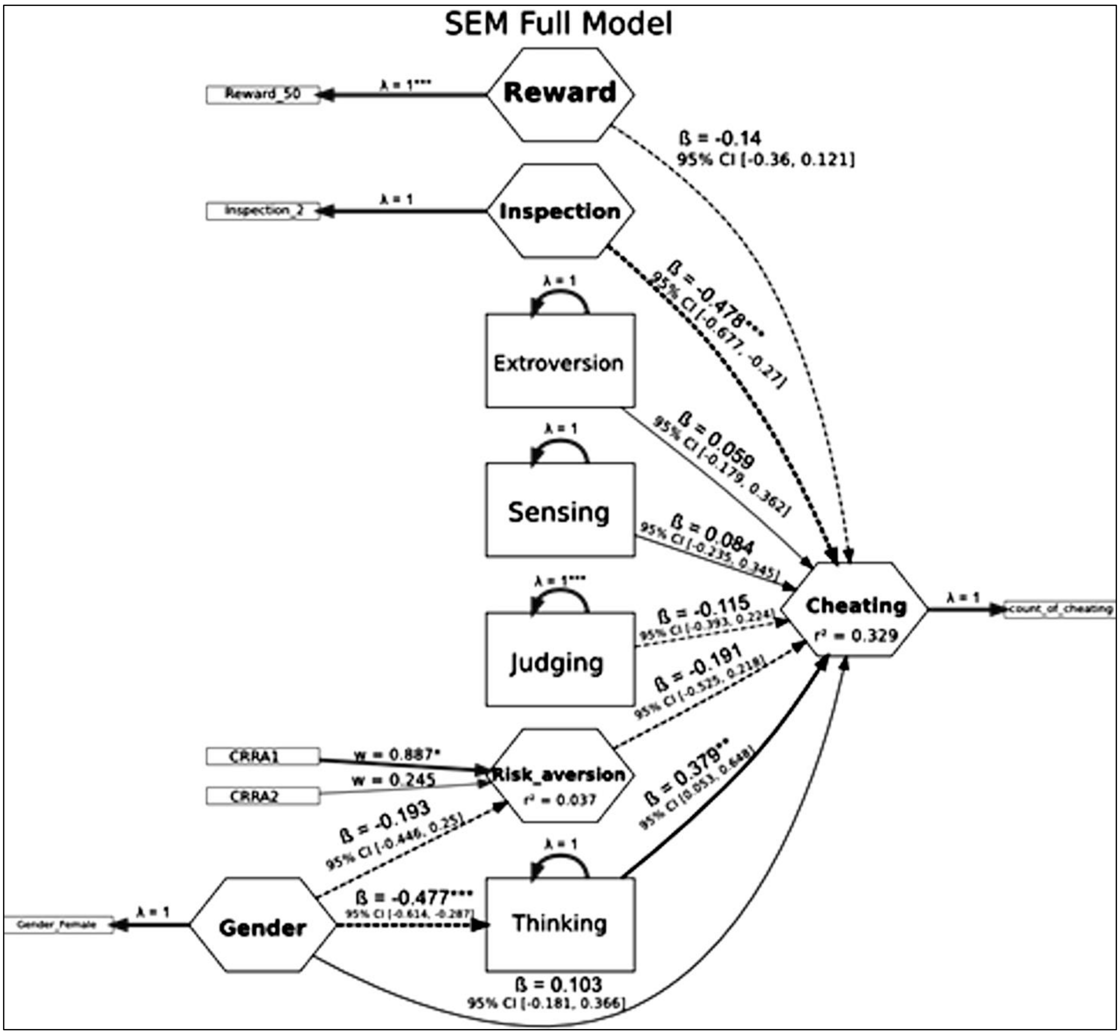

Figure 1 – Full SEM model

The assumptions regarding the relationship between gender and risk aversion were not confirmed. Consequently, gender and other insignificant personality traits will be omitted from the analysis. To enhance our model, we propose a reduced version in Figure 2 focusing only on these variables: inspection probability, risk aversion, the MBTI thinking characteristic, and reward/punishment.

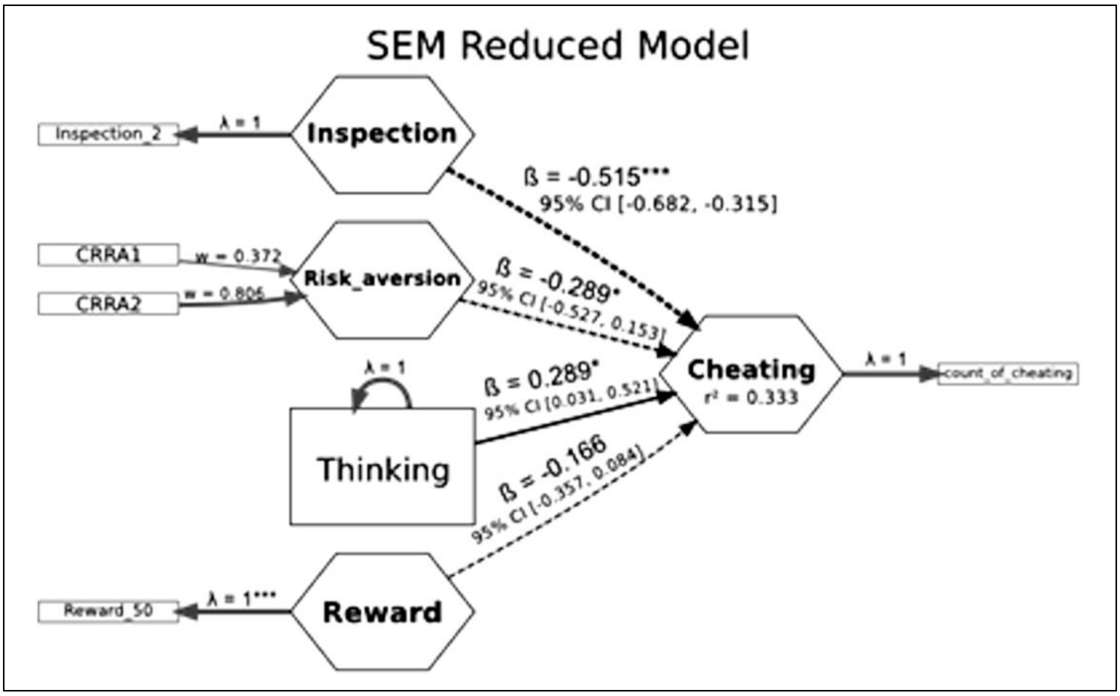

Figure 2 Reduced SEM model

The diagrams illustrate a Structural Equation Modeling (SEM) analysis, showing multiple predictors and their effects on "cheating." The models have an r^2 value of 0.33, indicating that 33% of the variance in "cheating" is explained by the predictors. This underscores their importance in understanding dishonest behaviour and improving quality in general.

Cheating behaviour is most significantly influenced by the **probability of inspection**, with this coefficient **being statistically significant at the 1% level**. This finding emphasises that the probability of inspection is crucial in reducing dishonest behaviour, reinforcing the model's implications for enhancing quality through targeted interventions.

Thinking and Risk Aversion coefficients are **significant at the 10% level**, indicating a moderate impact on cheating behaviour.

In contrast, **Reward/Punishment** is **less significant, with a level above 10%**, suggesting a weaker influence.

These findings highlight that cognitive processes and risk tendencies notably reduce dishonesty, while reward and punishment are less effective. This insight is crucial for developing strategies to improve overall quality.

We used Leave-One-Out Cross-Validation (LOOCV) to evaluate the model's accuracy in predicting cheating behaviour Figure 3. The results show that in 56% of cases, the model predicts cheating with an error of less than one, demonstrating robust predictive accuracy.

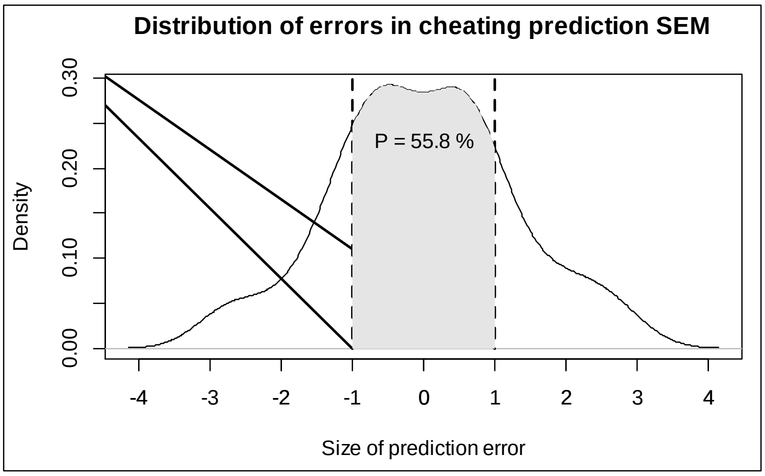

Figure 3 – Leave-One-Out Cross-Validation results

4 CONCLUSION

Dishonest behaviour significantly impacts various domains, including production quality. It undermines policies and procedures, compromising standards, reduced quality, economic instability, and inadequate tax revenues. This necessitates stringent oversight and robust mechanisms to deter and address dishonesty, thereby preserving reliability and credibility in these critical sectors. Understanding the determinants of dishonest behaviour is crucial for improving overall quality.

Our research aimed to identify these determinants to better understand the factors contributing to misconduct. We conducted a framed laboratory experiment with students from the Faculty of Economics at the University of West Bohemia, where participants chose between dishonest, cost-saving production and honest, higher-cost production. The determinants include controllable factors, such as environmental conditions set by policymakers, and uncontrollable factors, such as intrinsic personality traits.

We varied inspection probabilities to detect dishonest behaviour, imposing fines on cheaters in one session and rewarding honesty in another. Intrinsic characteristics were measured using the Myers-Briggs Type Indicator (MBTI) and the Holt-Laury method for risk aversion. We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) for its robustness and reduced sensitivity to data distribution. These findings highlight the importance of inspection probabilities and intrinsic traits in mitigating dishonesty, ultimately contributing to strategies that improve overall quality.

Our findings indicate that increasing the probability of inspection significantly reduces cheating, emphasising the critical role of oversight mechanisms in deterring dishonest behaviour. This variable was the most significant in our models, with a statistical significance of less than 1%. Conversely, punishing dishonesty or rewarding honesty was insignificant, with a significance level above

10%, suggesting detection probability is a more effective deterrent than consequences.

Rewarding honesty led to a lower propensity for dishonest behaviour than punishing dishonesty, likely due to the unexpected nature of the reward, although this was not statistically significant. Among personal characteristics, the "Thinking" trait from the Myers-Briggs Type Indicator (MBTI) is crucial for predicting cheating, with a statistical significance between 5% and 10%. Individuals with a strong Thinking orientation are likelier to cheat, evaluating situations based on potential profitability, whereas those with a "Feeling" orientation cheat significantly less. Higher risk aversion is also associated with reduced cheating, with a statistical significance of around 10%.

We used Leave-One-Out Cross-Validation (LOOCV) to assess the model's predictive abilities, finding that the prediction error for the count of cheating was within a margin of plus or minus one in 56% of cases. These insights are crucial for developing effective strategies to improve quality by reducing dishonest behaviour.

Our recommendations for addressing quality improvement gaps are as follows:

- Increase the probability of inspections.
- Enhance rewards for correct behaviour while reducing the frequency of punishments for poor quality.
- Prioritise quality inspections of individuals with Thinking personality traits over those with Feeling traits.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.