UNIVERSITY OF LUXEMBOURG

Faculty of Law, Economics, and Finance

MSc in Finance and Economics

MASTER THESIS

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This paper consists of two main parts: Part I, which presents an internship report, and Part II, which discusses a research study.

PART I

INTERNSHIP REPORT SECTION

Table of Content for Part I:

1. EXECUTIVE SUMMARY

During my internship at the National Institute of Statistics and Economic Studies of Luxembourg (STATEC), I had the chance to acquire significant knowledge and experience in the fields of statistical analysis, data science, and machine learning under the framework of national statistics. The central goal of the research study was to compare self-reported measures on subjective trust with measures from objective experimental trust games. The following comparative analysis was aimed at understanding the influence of demographic variables on trust levels.

Most of the time during the internship, I was engaged in the development and deployment of machine learning models during the process of data analysis. This offered me great hands-on experience in scripting, data preprocessing, and tuning model parameters. Such a practical application is very important in bridging the gap that exists between pure theory and the real-world challenges associated with data. I had exposure to the different methods of collecting the data; Computer Assisted Personal Interviewing (CAPI), Computer Assisted Telephone Interviewing (CATI) and Computer Assisted Web Interviewing (CAWI). Each one had its own advantages and disadvantages, which made me understand the issues relating to survey data collection very well. My supervisor brought me up to speed on explainable AI and also shared her resources from a summer school program with me. This exposure made me realize how important it is to make AI models interpretable and transparent, thus strengthening my ability to communicate effective model decisions.

Working with the experts at STATEC allowed me to really develop the muscle to solve problems. Detecting problems in data and brainstorming a solution with colleagues enhances the ideas of teamwork and effective communication in a real-life professional setup. I learned a lot from interaction on such a wide scale with colleagues: from my department to other departments. These engagements gave me more insight into the operational difficulties that other teams were facing. Much recognition and positive feedback were given by my supervisor and other workmates over the period of my internship. By nature, I am proactive in learning and problem-solving. I contributed to team projects, which attracted appreciation. Key outcomes include completion with success of all the tasks assigned; increased accuracy of machine-learning models; and proposal and implementation of process improvements.

The skills and knowledge that I gained from courses through my master's at the University of Luxembourg were directly applicable to the tasks of my internship. Econometrics provided me with important skills related to data analysis and regression techniques, while Programming in R and Applications furthered my skills in statistical modeling. I have been able to develop a theoretical framework from the Economics of Innovation class, which helped structure my approach to such an innovative methodology, by providing machine learning techniques to reinforce traditional survey methods. My internship at STATEC, in fact, has been one such enriching experience where I have been able to use and build on the knowledge and skills acquired during this master's program. But the real learning is derived from getting integrated academic learning with practical application to understand more thoroughly some important aspects of econometrics, data analysis, and machine learning, which will stand me in good stead for future challenges in the world of finance and economics.

2. HISTORY, OWNERSHIP, AND GEOGRAPHICAL PRESENCE

STATEC, the National Institute of Statistics and Economic Studies of the Grand Duchy of Luxembourg, operates under the authority of the Ministry of the Economy. From the time it was established, STATEC developed a long history of operating as an independent and neutral institute in developing and providing detailed, objective, and high-quality statistics about the Luxembourg society. It expresses the national statistical system of Luxembourg in the national and the international framework; it cooperates with the European and the worldwide statistical bodies.

2.1. MARKET POSITION

STATEC is the prominent national statistical body in Luxembourg and holds one of the significant positions for the statistical system internationally. STATEC's core activity constitutes the setting up as well as the maintenance of an extensive statistical information system concerning various fields of life; these are mainly demographic, economic, social, and environmental data. This data is vital for public and private decision-makers and supports well-informed policy formulation and strategic planning.

2.2. MISSION

STATEC's mission is to offer high-quality statistical information to the public and to the private decision-makers, as well as to the citizens. STATEC manages this mission by collection, processing, and distribution of data in full neutrality and objectivity. This is by exercising the necessary rigorous quality control with confidentiality, integrity, and availability assurance for the information that it treats.

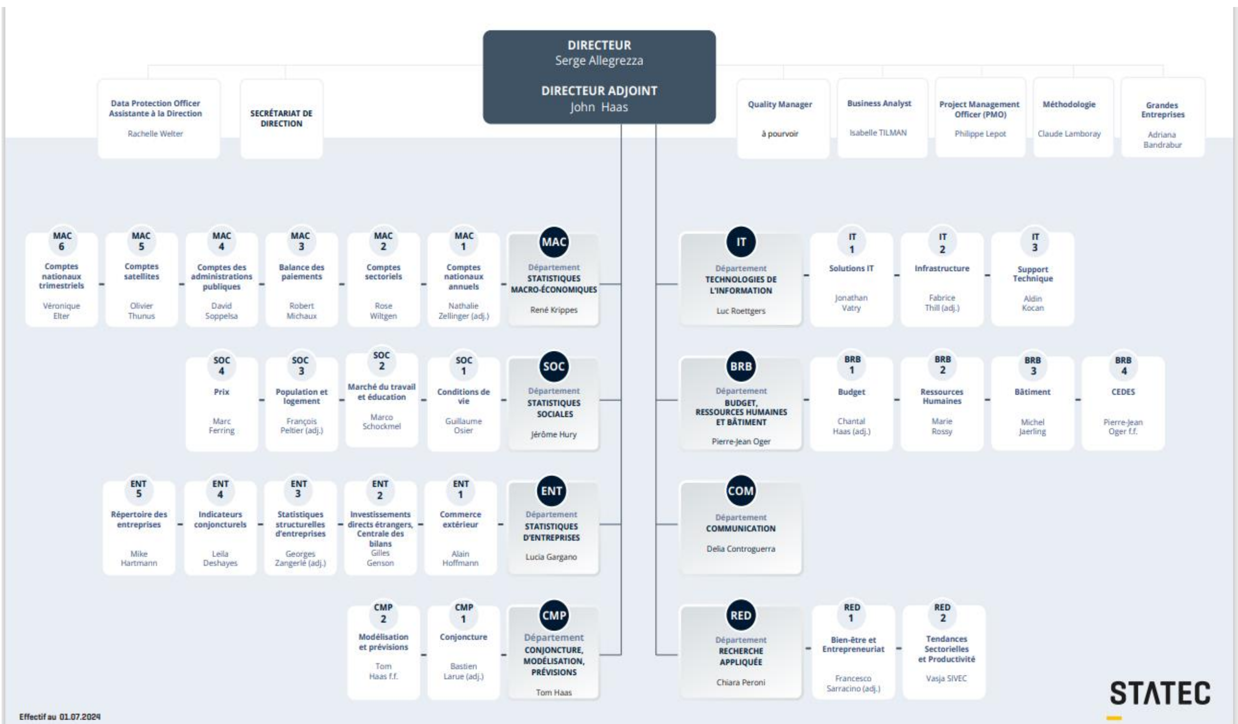
2.3. KEY ACTIVITIES

i. **Statistical Surveys and Data Collection:** STATEC collects data on a wide variety of demographic, economic, social, and environmental phenomena through statistical surveys and the use of administrative files.
ii. **Balance of Payments and Financial Accounts:** In cooperation with the Banque Centrale du Luxembourg, STATEC produces and ensures the methodological homogeneity of the country's balance of payments and financial accounts.
iii. **Central Balance Sheet Data Office:** The STATEC operates a central balance sheet database of companies' annual accounts and, under the appropriate legislation, disseminates this data to the public.
iv. **Censuses:** It organizes population, housing, and building censuses established by Grand-Ducal legislation.
v. **Statistical Methodology and Procedures:** STATEC conducts studies and analyses for the elaboration of statistical methodologies and diffuses results in the general statistical audience.
vi. **Documentation and Representation:** It prepares and disseminates full-fledged documentation on statistics and represents Luxembourg at the international forums on statistics.

2.4 GOVERNANCE

STATEC is governed by a Director, supported by a Deputy Director. The Director's Board comprising of the Director, Deputy Director, and heads of departments examine the budget and staff matters and supervise the ad-hoc matters. Dr. Serge Allegrezza has been the Director of STATEC since April 2003, having accumulated broad experience from his former responsibility for internal market and economic policy at the Ministry of the Economy. The research team of STATEC consists of researchers, experts, consultants, and trainees. First established in 2009, a scientific research task was integrated into STATEC's mission statement by late 2011. Research remains first and foremost focused on the areas of productivity and its determinants on competitiveness.

2.5 Organization Chart



Source: STATEC website

3. The Internship

3.1 Department: SOC1 Unit - Living Conditions

I performed my internship in the SOC1 Unit, under the theme of Living Conditions, at the National Institute of Statistics and Economic Studies of Luxembourg, known as STATEC. This unit is one of the most important units within STATEC; it is concerned with all dimensions related to living conditions and socio-economic conditions that influence the population of Luxembourg. The mission of SOC1 Unit is to produce detailed, reliable, and comprehensive information on living conditions of the population that contributes to enlightened decision-making and improves the understanding of the social and economic trends in Luxembourg.

3.2. Mission and Role in the Organization

The mission of the SOC1 Unit summarizes several principal surveys and studies related to the living conditions of households in Luxembourg. These surveys entail the income and expenditure of the household, tourism practices, ICT usage, safety and security, time use, and road traffic injuries. Some of the key surveys and studies falling under this unit include:

i. **Household Budget Survey (HBS):** This is an enquiry that collects detailed information on household consumption expenditures, for use in calculating the Consumer Price Index weights, developing expenditure patterns by household composition and financial situation.
ii. **Income and Living Conditions Survey (EU-SILC):** Annual survey for detailed information on the income of households and individuals from a sample that is representative of the resident population. The covered income and social transfers from different sources.
iii. **Tourism in Business and in Leisure Time:** Quarterly survey enquiring about the tourism habits of the resident population. The survey is directed to both leisure tourism and business tourism, travel-related expenditure, and socio-economic characteristics.
iv. **Survey on ICT Use by Households and Individuals:** This surveys the use of new information and communication technologies by households and individuals, including access to the internet, how often it is used and obstacles that hamper the use of these technologies.
v. **Safety Investigation:** A comprehensive report detailing infringements on safety and security in resident population by covering diverse thefts, violence, as well as other crimes that are less conventional.
vi. **Residents' Time Use Survey:** Surveys that provide an all-embracing view of the daily activities in which people participate, measuring indicators of well-being, and concentrating on paid work, unpaid work, leisure time, and personal care.
vii. **Statistics on Road Traffic Injuries:** Compiled reports of road traffic accidents, comprising details about the accident, vehicle involved, the outcomes of alcohol and drug tests.

viii. **Reference Budgets:** Set out notional budgets for various household archetypes in order to test the minimum baskets of goods and services which permit living decently and to serve as a yardstick when evaluating social-assistance measures.
ix. **Welfare Project:** Offers indicators of the quality of life and well-being in Luxembourg which are more comprehensive than the standard GDP measures because they include domestic work, voluntary work, and the underground economy.

SOC1 Unit's service work ensures the continuity of STATEC as a reliable source for socio-economic data, thereby being a frontline force within the Luxembourg national statistical system. They have an active unit in which they gather and analyze comprehensive information that provides them with valuable insights into formulating effective policies and initiatives intended to improve the quality of life for all.

3.3 Work Done During the Internship

3.3.1 Project

The project of my internship was to work on the analyses of the survey TRUSTLAB data and to explore innovative ways of measuring trust using Machine Learning techniques. The work included data preparation, model development, and interpretation of results to provide meaningful insights into levels and determinants of trust in Luxembourg.

3.3.2 Responsibilities

i. **Data Handling:** Preparation, handling, and processing of the TRUSTLAB survey data, making it ready for analysis.
ii. **Model Building:** Developing and evaluating the machine learning models (Lasso and Random Forest regressions) aimed at explaining trust levels.
iii. **Explanation of Results:** The use of results from the analysis in contrasting different trust indexes for pinpointing patterns and significant factors affecting the nature of trust.

3.3.3 Data Preparation

One of the early activities I carried out involved cleaning the TRUSTLAB survey dataset for analysis. I constructed features that, given the objectives of this work, can enhance the potential power of Machine Learning models in predictive analytics. An appropriate process of feature selection to establish relevant variables for the analysis was done. This involved running different statistical tests and correlation analysis that identified the features showing the most important relationship with the target variable, "trust in others." The categorical variables were re-coded as numeric so that the Machine Learning algorithms would be able to read accordingly.

3.3.4 Machine Learning Analysis

Machine Learning analysis was systematically done to identify important predictors of trust and capture complex interactions in data. Lasso regression was used for regularization and feature selection based on relevance, while Random Forest regression is applied to handle non-linear relationships and get a comprehensive understanding of the predictors.

3.3.5 Application of Machine Learning Analysis

The initial step to analyze via Machine Learning is the use of Lasso (Least Absolute Shrinkage and Selection Operator) regression for regularization and feature selection. However, lasso regression is primarily pertinent when used to identify the most important predictors, and it works well in the case of model regularization. To be more precise, it helps reduce overfitting, which occurs when a model is too complex and captures too much noise in the data instead of the underlying pattern. The main function to add a penalty is equal to the absolute value of the magnitude of coefficients; hence, it encourages a sparse model by driving some parameters to become very close or equal to zero. I accomplished this via holding out my dataset into training and testing sets. I utilized the training set to fit my Lasso regression model. I further applied cross-validation to tune the strength of regularization, λ; this way, it attains the required optimal value that maximizes prediction error on unseen data. By analyzing the coefficients of the fitted model, I then determined the retained features and their importance ranking.

Random Forest regression was applied to capture complex interactions and non-linear relationships in the data. In particular, Random Forest is appropriate since it is an ensemble learning method that aggregates many decision trees. This offers more accuracy than a single decision tree and has the power to model trust effectively. An even greater benefit derived from Random Forest is its flexibility, where it can handle the complex inter-relationships between predictors and the non-linear relationships in the data. This method has an additional plus in that it effectively works even when there are many predictors or a high-dimensional setting simply because it reduces the variance that is causing any problems due to the averaging process. I divided the dataset into training and testing sets to evaluate the performance of the Machine Learning models. To ensure the models were performing optimally, I took several steps to evaluate and refine their performance.

3.3.6 Comparative Analysis and Documentation

The first objective here was to compare levels of trust that may be elicited from subjective or objective measures in the TRUSTLAB survey data. To fit from the data measurements, the subjective measures extracted self-report-based trust levels, while the objective ones were acquired from the experimental methods of the trust games. In terms of the trust game, participants made decisions that could give quantitative measurements of the levels of trust and hence make behavioral measurements of trust. Adaptation of games was done to avail information regarding the nationality of players in games and thus test if levels of trust are contingent on such information. The demographic variables have been tested to see if they affected the levels of trust. I conducted regression analysis to establish how such factors related both to subjective and objective measures of trust. For important outcomes of the comparative analysis like the statistics and important predictors of trust, a summary was given. The differences between the subjective and objective trust measure were discussed along with explanation considering the demographic variables.

3.4 Departmental Interactions

During my internship, I was happy to have many interactions with colleagues within the department. The atmosphere was very welcoming, and everyone was approachable and friendly. It became a part of my duty to get to know almost all team members, what they are responsible for in their daily work routine, what kind of difficulties they face, and share some ideas for possible improvements. I would regularly get into discussions with the team members to understand their roles and what was expected of them. This would put me in a better position of understanding the various functions performed by individuals in the department.

I engaged in several group and team discussions where team members were supposed to brainstorm and solve problems together. These sessions were eye-opening, and besides, I shared my thoughts and ideas with everyone to get constructive feedback from others. It used to be common for us to have lunch together, where the atmosphere was very informal, and issues included work topics and private matters were discussed. This created a certain rapport to form a cooperative spirit within the team. I came to learn about operational challenges such as workflow bottlenecks, resource constraints, and technical difficulties that others were facing within the team. This helped me more in the appreciation of the complexities surrounding the work.

There were ongoing discussions concerning work progress as team members got to update each other, offer advice, and support one another where necessary. It was important that everyone could be kept on the same page. I always had the opportunity to make suggestions, which were well received. We discussed strategies to improve upon the process, increase efficiency, communication, and overall productivity. There were team members who voiced the issue of limited resources at times, which led to getting work done at the highest level impossible. Some of these discussions recommended better resource allocation and management skills.

Most common discussion areas were technical problems such as software bugs or hardware problems. The team cooperatively worked on addressing this issue and most of the time turned these issues into learning areas. Besides having interactions with the direct team, I also had interactions with colleagues from other departments. Such interdepartmental interactions were very necessary, considering that they provided a general perspective on how the company runs and how the functions of a particular department would interconnect with those of another. Overall, my interactions within the department and with other departments were enriching and integral in my learning experience. Although there were some initial bumps, a teamwork-oriented and progressive environment enabled me to set forth my activities to attain my objectives.

3.5 Issues and Their Solutions

Numerous challenges marked the way throughout my internship period. Primarily due to the fact that I was new to Machine Learning, I ended up turning them into precious learning experiences, which enhanced my critical thinking and adaptability skills. This was my first experience in machine learning, so it was hard for me to understand some tough ideas and techniques relevant to my tasks. I had to study enough literature and relevant resources on the topic. I immersed myself in learning the various algorithms, preprocessing techniques of data, model evaluation, and whatnot. Self-studies such as this were important in building up a basic understanding that I can apply in my work.

After this theoretical understanding, I put my word down to write and test my code. At the end of all the battles, the first results of the code did not come out as accurate as I expected. This was a big setback for me, and I came to realize that practical applications needed a more subtle understanding and refinement of skills more than theoretical knowledge. The realization that expertise would be needed was when I decided to consult Machine Learning experts at STATEC. These were particularly valuable consultations; together, we reviewed the code and my approach. The experts gave me some hints on what to work on and in which way I should proceed with making the model perform better.

We also discussed different kinds of Machine Learning algorithms that might perform better with a reduced dataset. Particular importance was attributed to the creation of new features from the given data to provide more relevant information to the model. In this process, we derived new attributes with the potential to further increase the predictive power of the model. We did a few experiments with the random forest model by using different hyperparameters in order to find the best hyperparameter setting that can give us the highest accuracy, given the dataset constraints. Even after these changes, our model was not reflecting appreciable improvement in terms of accuracy. By troubleshooting together, we outlined the root cause: insufficiency of data. Machine Learning models, random forests in particular, require a very large dataset to do well. I only had a dataset of 1,000 observations for my work, which was not sufficient for it to present the accuracy.

Challenges that I faced during my internship provided me with some major key approaches towards solving problems:

Thorough Self-Study: When introduced to any new and complex topic, investing time in mastering the topic through self-study and making use of available resources. Building a strong theoretical foundation is the first way to go toward problem solving.

Collaboration with Experts: Collaboration with those more experienced, seeking their advice, can lead to new vantage points and insights helpful for overcoming obstacles. In this, they are able to help develop one's understanding and approach to problem solving.

Teamwork: Working together on issues with colleagues gives rise to a responsive and supportive environment. Collective brainstorming and shared problem-solving can lead to more effective and innovative solutions.

Iterative Approach: Problem-solving often requires an iterative approach. Continuously testing, evaluating, and refining solutions is key to making gradual improvements and achieving desired outcomes.

Adaptability: Being open to changing one's approach and exploring alternative solutions is critical when initial efforts do not yield the expected results. Adaptability is a vital trait in navigating complex challenges.

During the internship, there were problems and challenges, and they played a large part in my learning. Proactively seeking knowledge, consulting experts, and an approach to problem-solving through collaboration and iteration provided a path to resolve these issues and gain valuable lessons applicable toward future endeavors in Machine Learning and beyond.

3.6. Other Observations and Activities During the Internship

During the time of my internship, several experiences and observations were taken throughout this period that were significant for my overall growth and acquiring knowledge. One of the most engaging parts of being an intern was being able to see Machine Learning and data analysis in action. In dialogue with the actual projects, I got a feel for the real-life issues and discussed the solutions for them. This practical activity was the most influential contribution to filling the gap between what you learn at university and what you do in your job.

In addition to this, I was also able to network with the employees from various departments and functions within the organization. Such sit-downs allowed us, the participants, to obtain a panoramic view of the operational activities of the institution. Engaging in cross-functional projects and attending meetings made me realize the significance of communication and collaboration to achieve common goals that run through all the teams that had different members.

Several training sessions and workshops were arranged by the company to assist employees in their knowledge and skills development. I embraced all these workshops which gave me hands-on experience. Other workshops focused on data analytics techniques, the tool, and best techniques of data management. The workshop allowed me to broaden my technical knowledge and at the same time to network with other advanced professionals in the field.

Experiencing the corporate level allowed me to observe and understand the environment for company's culture, values, and ethics. I was able to notice how they promoted teamwork, continuous improvement and innovation. The society was both encouraging and harmonious, and it facilitated through laxed rules for members to share ideas and learn from one another.

3.7 Recognition from Supervisor and Colleagues

My internship was an instance where I got good recognition and feedback from my supervisor and colleagues, which was very much a morale booster and motivated me to work harder. My supervisor was always there to guide me through constructive criticism and to recognize my hard work and my collaborative teamwork. She was pleased by the way I engaged myself positively in the learning process and problem-solving as well as my commitment to the interpretation of intricate topics. Her acknowledgement of my development and accomplishments was a significant uplift to my confidence and morale.

My colleagues were also there for me, very supportive and encouraging. They liked my enthusiasm and readiness for learning new things and often lauded me for mutual engagement in discussions and joint efforts. They also lauded my talent to understand information quickly. Within the internship duration, my colleagues would frequently offer feedback through informal reviews. The reviews were very insightful as they gave me good mental strengths such as critical thinking, problem-solving, and communication skills.

On top of that, they also disclosed my weak areas, which were taken as challenges to improve my skills. The favorable accolades came not only in words but also in action. I was sharing an office with consultants who gave me advice on different job opportunities and contacts for networking, making me realize my potential and the need to advance my career in the field.

3.8 Key Achievements During the Internship

What I put forward as a major achievement was the fact that I completed all tasks within 12 weeks. This consisted of producing Machine Learning models and implementing them. Based on the provided data, I went through the process of analyzing and finding the right solutions to the problems of the project. I wrote my first machine learning algorithms myself even though I did not have any previous experience in this area. I put all my efforts into the learning process and gained the necessary technical knowledge which allowed me to develop efficient and accurate code to complete the project.

One of the standout achievements was the help I gave to the accuracy of the Machine Learning models. In a consequent process, I worked with other experts partly and carried out several trial assignments in which I reached better levels compared to the beginning. Quite a remarkable achievement was the accurate detection and good handling of the inadequate data issue. Using new data points that were created and the ones that were already in existence, I was able to improve the training set and improve the model's performance. In this method, I illustrated my ability to solve intricate problems.

4. Learning and Link to UL Master's Curriculum

During my internship at the National Institute of Statistics and Economic Studies of Luxembourg (STATEC), I got valuable experiences, and knowledge that played a main role in my understanding of business activities, the institution, and the wider world of banking and finance. The internship did not only help me get the know-how of statistics analysis and the machine learning process probed in providing national statistical information but also was given a hands-on feel for the process and the technologies as one might enter the job market with such skills. I was involved in the general topic of big data solutions, including aspects of quality assessment, representation of the data, discovery of data patterns, and the testing of various hypotheses.

The amount of data generated today is extremely large. This is because people are really utilizing transactors. In the real world, we typically encounter situations where our data are incomplete, and our models need to be optimized to achieve greater accuracy. Learning about the algorithmic approaches to machine learning would help me to identify those within the field. I was also able to go through the process of model training to make other parts of the model operate better.

Furthermore, my supervisor also initiated me to XAI (Explainable AI). She provided me with a variety of resources from her summer school course that helped me better comprehend the structure of transparent and interpretable AI models. XAI knowledge is highly important if we are to build and sustain the trustworthiness of AI in the market, especially for those cases where full responsibility is a must.

In addition, I was shown the data collection methods, and I understood them thoroughly. Computer Assisted Personal Interviewing (CAPI), Computer Assisted Telephone Interviewing (CATI) and Computer Assisted Web Interviewing (CAWI). I was informed that CAPI could be used in face-to-face questioning, enabling the writing done from computers or tablets. The interviewers' ability to, in real-time, ask for elaborations and clarifications, was the most exciting feature. CAPI surveys typically use visual and audio gadgets as interviews to make the collection of data survey faster and effective. The process of conducting interviews over the phone using CATI was another key learning point. Learning the operational advantages of using a call center in conducting surveys and the quick spread of demography were written about. More exposure to online data collection which is basically an efficient way to create a large sample of data, was gained. The simplicity of the research method by saving the participant's answers to queries through their monitor and the need to make web forms as concise and as transparent as possible were stressed upon.

To conclude with, collaborative efforts with experts at STATEC enabled me to elicit my problem-solving skills. Identifying issues related to data and solving them are the fruits of labor of the collaboration between myself and the experts. It hacked my mainframe to the point that I could not help but visualize the increasing synergy due to teamwork, which led us to a more favoring better performance in the project. Besides, I realized the importance of process improvement and documentation at the workplace.

5. Relevance of UL Master's Courses to the Internship

The **econometrics** courses I took were highly relevant to my internship at STATEC as it gave me the basic skills necessary for data analysis and interpretation. The statistical techniques and regression analysis methods I got were specifically needed for the tasks I performed, especially to analyze the TRUSTLAB survey data. While on my internship, I became acquainted with cross-sectional data from the TRUSTLAB survey, which was used for trust levels analysis employing multiple econometric approaches. My competency in this area was further strengthened by the skills I gained in econometrics. I utilized these methods to study if there are links between trust levels and statistical aspects like age, sex, and nationality. A solid grasp of econometric theory was essential in the creation of powerful models for the analysis of the survey data. This base provided me with the basis for choosing the proper models as well as the correct interpretation of the outcomes. The hands-on skills developed by means of Stata in the econometrics class were the first ingredient of the internship tasks I carried out. I employed Stata in most of my data analysis, which ranged from cleaning the data, to running regression models, and conducting diagnostic tests.

The classes that I took on **survey data in the field of finance and economics** made me learn very useful things that were helpful for my internship at STATEC directly. It was the training on various principles and essentials of surveys, as well as the kinds of data, survey design, and the analysis of survey data, that armed me with the necessary tools to work with the TRUSTLAB survey. My job at STATEC included using survey data to analyze trust levels, which are one of the most significant economic and social indicators. Survey data is no longer used exclusively as a tool to measure aggregates such as GDP and employment but is gaining in importance as a powerful data source that can give us insights into public opinion and human behavior. The basic knowledge of survey design and data analysis concepts was like a compass for my data analysis, ensuring that I don't lose my way, in terms of data integrity and validity of my data analysis. Understanding how survey questions are worded and getting insights into the exact meaning of the questions was the key to getting the right answers. The skill of survey data analysis along with the knowledge of other unique characteristics of survey data such as sampling methods, weighting, and bias possibilities were very much necessary for correct and up-to-date data interpretation. This capability helped me in the process of developing an accurate and comprehensive analysis of the changes in trust levels using statistical methods.

Furthermore, the knowledge I received on the course on **testing economic models using sports** contributed to my internship. This class was about testing economic models using data from sports and this gave me a foothold into how rational agents make decisions given constraints and incentives. This was very relevant to my internship at STATEC, for which I developed a similar methodology using TRUSTLAB survey data. In my internship, I proposed research questions regarding trust measurement like how subjective and objective methods for trust assessment correlate with each other in different contexts as well considering usage aspects what are the factors that might influence these measurements. I used the same idea to understand how nationality and incentives may affect one's decision like economic theories against changes in sports rules. I applied the principles of economics to this case for making analysis on trustlab.

Again, the course on **economics of innovation** was connected to my internship at STATEC. I used specific machine learning methods for trust research. The knowledge that this course taught me led to giving the proper theoretical and empirical tools for investigating innovation-related issues, which I ultimately exercised during my internship. While on my internship, I used the lens of innovation to map out new frameworks around how trust is quantified. This entailed assessing how machine learning methods could complement or extend traditional survey procedures. The trust analysis that I did has implications for firms, especially in customer acquisition and retention functions. This is in line with the course about analyzing how Innovation affects firms. The ability that the course on economics of innovation gave me was greatly improved. Finally, the course has allowed me to become more innovative in data analysis. Using the skills I gained from this course, I was able to apply machine learning techniques to data from our surveys to obtain a new measure of trust. My familiarity with Stata also enabled me to conduct sub-analysis fed into the new measurement with high level of precision, ensuring the truth behind the revised measurement.

The **Programming R and Applications** course had a more direct application on my internship at STATEC, as it really improved on the data analysis and statistical modeling side of things. The comprehensive view on R for statistical analysis learned from this course helped a great deal in the applications of Random Forest regression I implemented during my internship. This course gave a good background on the data manipulation and visualization using R, I used skills learned in this to thoroughly cleanse and rearrange TRUSTLAB data. This included replacing missing values, fixing inconsistencies between variables and preparing the data in a form that can be used to apply machine learning techniques. In R, I inputted missing values and standardized the format of variables so that data integrity was well kept for continuation of exploratory analysis. It also helped that my analysis skills are robust due to the extensive practice I have and continue to do using R, which is obviously a valuable skill regarding furthering reproducibility in this project.

6. Conclusion

My internship at STATEC was a profoundly educational experience that allowed me to apply and expand upon the knowledge and skills acquired during my master's program at the University of Luxembourg. The integration of academic learning with practical application not only deepened my understanding of econometrics, data analysis, and Machine Learning but also prepared me for future challenges in the fields of finance and economics.

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PART II
RESEARCH SECTION

Assessing Different Measurements of Trust: Evidence from the *“Trustlab”* Survey in Luxembourg

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Master Thesis

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Abstract

This study investigates the various ways in which interpersonal trust is measured, utilizing both self-reported and experimental methods. We also employ a variation of the classical trust game in Luxembourg, where participants are informed about the nationality of other players, to determine if this information influences their level of trust. Our data comprises 1,000 observations from a survey and trust game involving participants from Luxembourg, Portugal, other European countries, and non-European countries. Self-reported trust averaged 4.908 on a Likert scale, while experimental trust from the trust game averaged 6.29. Trustworthiness and altruism scored 3.774 and 4.635, respectively. Individuals aged 18-24 and 25-34 reported lower self-reported trust but higher experimental trust, whereas those aged 35-64 exhibited greater trustworthiness. Females revealed lower experimental trust compared to males. Higher self-reported trust was positively associated with incomes above €66,000 but negatively with altruism. Unemployed individuals showed higher self-reported trust, and self-employed individuals displayed higher experimental trust. Luxembourgers tended to trust Portuguese and Europeans slightly more than their compatriots. Europeans and Portuguese showed a preference for trusting their own nationalities, while non-Europeans often trusted Luxembourgers and Europeans more than those from their own countries. This study underscores the complexity of trust and the necessity for diverse measurement methods. Our findings contribute to the literature by comparing different measurement approaches and exploring the demographic determinants of trust.

Keywords: Trust, Interpersonal Trust, Self-Reported Trust, Experimental Trust, Demographic factors.

1.1 Introduction

Trust is one of the major forces that binds society together (Hobbes, 1651; Redfern, 2009). All forms of social commerce involve at least some degree of implicit or explicit trust, independently or in combination. Trust is an essential element of social functioning that supports our relationships with individuals, groups, and organizations. According to Cook Cooper (2003) and Ostrom and Walker (2003), trust acts as a social lubricant that fosters group cooperation, upholds social order, and allows for advantageous long-term exchanges that otherwise might never take place. Trust is one of the most important factors and maybe the most essential component for the development and maintenance of happy, well-performing connections (Fehr, 1988; Regan, Kocan, & Whitlock, 1998).

The study of trust finds its roots in sociology and has gained traction in other social sciences, such as economics, political science, and psychology. Consequently, several definitions of trust and several ways of measuring it have been proposed. Trust is conventionally defined as a person's belief that another person or institution will act consistently with their expectations of ***"positive behavior"*** (OECD, 2017b). In view of this, trust can be divided into two main forms: interpersonal trust (trust in others) and institutional trust. Given the central importance of trust in interpersonal affairs, the broad notion of interpersonal trust is fragmented into two categories: ***'limited'*** trust and ***'generalised'*** trust. Limited trust refers to trust between people who know each other well (including family, friends, and people living in one's immediate neighbourhood), whereas generalised trust captures trust between casual acquaintances or complete strangers (Putnam, 2000; Delhey et al., 2011).

This study aims to investigate if there are differences in the different ways trust in others (interpersonal trust) is measured. We use subjective and objective (experimental) methods to assess trust in others. Using a variation of classical trust game for Luxembourg, where we provide information about the nationality of the players, we aim to measure if individuals will change their level of trust based on this information.

Our first main contribution is examining the differences between self-reported and experimental measures of trust. Researchers and policymakers have long relied on self-reported measures of trust, typically collected via household surveys, which ask respondents about their level of trust in other people, such as family or neighbors (interpersonal trust), and in different public institutions (see OECD 2017a). Although self-reported measures provide valid and reliable information, they do not allow for the direct observation of trust as such (OECD, 2017b).

The second contribution is exploring how experimental methods, particularly the classical trust game, provide a more nuanced understanding of trust behaviors. These laboratory experiments elicit a variety of social behaviors under controlled conditions through interactive games (e.g., Trust Game and Dictator Game). The OECD Trustlab platform has proposed common protocols for such experiments, allowing for the measurement of people's behaviors and choices with monetary incentives at stake, and providing benchmarks against which survey questions can be compared.

This work contributes to the literature by providing new insights into how different measures of trust correlate and how experimental conditions, such as information about the nationality of players, affect trust levels.

The OECD's efforts to frame trust questions to capture both interpersonal trust (both generalized and limited) and institutional trust provide a comprehensive approach to studying trust.

1.2 The Different Measurements of Trust

Trust is a multifaceted concept with a wide range of interpretations among scholars (see Rousseau et al. 1998, p. 394). The field of trust measurement is so extensive that it is impossible to discuss all developments and innovations. Traditional self-reported trust (surveys) and experimental methods are mostly used by scholars. Although opinion-based measures of trust (surveys) have produced significant findings and enabled researchers to identify variations in trust across national boundaries and historical periods, some concerns have been expressed (e.g., Glaeser et al. 2000) about the assessment of the implicit idea of trust. From this angle, alternative measurements such as those obtained through experiments are becoming more prevalent.

The history of trust measurement started with Rosenberg (1956), who created the first systematic assessment tool and most likely coming up with the fair interpretation of the most-people question, which states, "Some people say that most people can be trusted". Some argue that you can never be too cautious when interacting with others. What are your thoughts about it? Rosenberg created a faith-in-people Guttman scale by combining many components. Rotter (1967) created a measure of interpersonal trust that included fifteen filler items and twenty-five main questions in the same decade. Rotter was dissatisfied with the prisoner's dilemma as the primary emphasis of social psychologists and sought to quantify trust as a personality component that predicts cooperative behaviour (Cook and Cooper 2003, 214).

Since then, experimental techniques have deepened our understanding of trust. An investment game created by Berg et al. (1995) became known as the "classical trust game" and offered a laboratory method for gauging trust and reliability. In this game, Player B (the trustee) receives a portion of the money that Player A (the trustor) has been given. The amount sent is multiplied by a factor, and Player B decides how much of the received money to return to Player A. The more A sends, the higher A's trust; the more B returns, the higher B's trustworthiness. The trust game, usually performed in laboratories and typically assesses both generalized trust and trustworthiness.

The Dictator Game, an alternative to the Trust Game, gathers a clean measure of altruism (Kahneman et al. 1986). Because just one player makes a significant decision in the Dictator Game, it is simpler to apply in survey or online questionnaire situations. A number of authors have integrated self-reported and experimental measures of social preferences or trust. For instance, a study conducted by Glaeser et al. (2000) combined survey data with experimental outcomes assessing trust and observed that the Rosenberg question measures other people's trustworthiness rather than trust itself. They further contended that evaluating interpersonal trust may benefit from laboratory research.

The “wallet question” is a different kind of inquiry that has also been used on occasion to gauge interpersonal trust. The 2007 wave of the Gallup World Poll used this question, asking respondents in 86 countries whether it was likely that a neighbor, the police, or a stranger would return a lost wallet or valuables to the owner.

Khadangi and Bagheri (2013) presented a technique for assessing the trust connection between Facebook users in the context of social networks. They employed machine learning models including K-Nearest Neighbour (KNN), Support Vector Machine (SVM), and MLP to predict trust, and they used user interaction and profile data to choose features. Their approach did not address computational cost and was not privacy-protecting or context-awareness, while being effective.

Using Bayesian networks, Chen et al. (2019b) developed a trust model for social networks. To categorize people into trust and distrust groups, they selected user-related data as attributes, including user profile, behaviour, and interaction information. They obtained good accuracy using Facebook and Twitter datasets. However, they encountered issues with context awareness and privacy protection akin to those found in Khadangi and Bagheri’s work.

Although there are some innovations, researchers nowadays basically utilize altered adaptations of questions from the mid-20th century for social trust and political trust. The foremost broadly used question to measure generalized trust is adjusted adaptation of the most-people question from 1942. Regarding lab game experiments, researchers started with the prisoner’s dilemma (see Deutsch 1960) and now primarily rely on the classic trust game (Berg et al. 1995). In contrast, latest advancement such as vignette experiments, brain imaging, and the Implicit Association Test (IAT) remain confined to a few studies.

2. Research Methodology

2.1 Overview

“**Trustlab” project** was created by OECD in collaboration with a set of International Universities and was aiming to combine cutting-edge techniques drawn from behavioural science and experimental economics with an extensive survey on the policy and contextual determinants of ***trust in others and trust in institutions***, administered to representative samples of participants. STATEC took part of the project for the years 2020-2021.

This study employs both self-reported and experimental (behavioral) measures of trust. The methodology used for the self-reported trust measure is described in section 2.3 and the experimental procedure is described in Table 1.1 (Trust and Trustworthiness) along with Table 1.2(altruism). The study analyzed the data using both regression and descriptive statistics to describe better the determinants.

It includes 1000 observations from a survey and trust game conducted in Luxembourg, representing individuals whose countries of birth are Luxembourg, Portugal, other European countries, and non-European countries.

2.2 Experimental Measures

Trust Game

The first game is the classical Trust Game. In the Trust Game, two players (Participant A and B) face each other and are given an initial sum of money (Berg et al., 1995; Table 1.1). The game yields a measure of trust (based on the behaviour of Participant A) and a measure of trustworthiness (based on the behaviour of B). The amount sent is multiplied by a factor, and Participant B decides how much of the received money to return to Participant A. The more Participant A sends, the higher A's trust; the more Participant B returns, the higher B's trustworthiness. Trustlab employs the 'strategy method' to assess trustworthiness, where Participant B makes four individual decisions for each possible amount that Participant A might send.

Table 1.1

	Endowment (units)	Participant A action:	Multiplication factor	Participant B action
A	10	Send part of endowment to B: Trust	3x	Send part back to A as a share of B total resources: Trustworthiness
B	10			

Dictator Game

The Dictator game (Kahneman et al., 1986; Table 1.2) is similar in structure to the Trust Game, with the exception that the second participant passively receives whatever sum the first player (the 'dictator') decides to send to her, and this transfer is not increased by any multiplier. This game thus provides data on levels of altruism, which can be used to explain a person's level of trust and trustworthiness.

Table 1.2

	Endowment (units)	Participant A action:	Multiplication factor	Participant B action
A	10	Send part to B: Altruism	None	none
B	0			

2.3 Self-Reported Measures

For self-reported trust, participants answered questions on a Likert-type scale from 0 to 10 (0 = no trust at all, 10 = trust completely). The questions for interpersonal trust are:

On a scale from zero to ten, where zero is not at all and ten is completely, in general, how much do you trust most people?

On a scale from zero to ten, where zero is not at all and ten is completely, in general, how much do you trust most people you know personally?

Table 3: Different Methods for measuring trust

Variable	Obs	Mean	SD	Min	Max
Self-Reported	995	4.908	2.248	0	10
Trust Experiment	1000	6.290	2.855	0	10
Trustworthiness	1000	3.774	1.718	0	10
Altruism	1000	4.635	2.238	0	10

Table 5 provides the overview of the various methods used to measure trust and it related concepts. Self-Reported trust represents trust levels reported by individuals themselves through the Likert reported answer. There were 955 participants with five (5) people not responding with an average self-reported trust level of 4.908 (on a scale of 0 to 10). The standard deviation (SD) was 2.248, which indicates the variation in responses. The lowest reported trust level (min) is 0, while the highest (max) is 10.

Trust experiment refers to trust levels measured through an experimental setup. This experiment employed the trust game represented in Table 1.1 and represents trust (what player A gives to player B). With 1000 observations, the average trust level in the experiment was 6.29 (2.855). The lowest and highest trust levels observed were 0 and 10, respectively.

Trustworthiness represents a measure of a person's perceived reliability and honesty. Thus, the unobservable cognitive aspects such as the perception of others' (see Hardin 2004). This experiment employed the trust game represented in Table 1.1 and represents trust (the share of the amount received by Participant B that is sent back to Participant A). There were 1000 participants with average trustworthiness of 3.774 (1.718), 0 min and 10 max.

Altruism represents giving without expecting anything in return. This experiment used the one-shot game (dictator game) in Table 1.2 (the amount sent by Participant A to Participant B). With 1000 participants, the average altruism was 4.635(2.238), 0 min and 10 max, respectively.

Table 4: Summary Baseline Characteristics

Variables	Number	Percentage
Gender		
Female	477	47.7
Age		
18-24	63	6.3
25-34	215	21.5
35-44	204	20.4
45-54	209	20.9
55-64	177	17.7
65 and above	132	13.2
Educational Level		
Less than high school	39	3.9
High school	248	24.8

Some college	156	15.6
Diploma/trade Certificates	203	20.3
Undergraduate degree	106	10.6
Post-graduate degree	248	24.8
Type of Employment		
Active employed	627	62.7
Self-Employed	59	5.9
Active Unemployed	30	3.0
Inactive	284	28.4
Income Levels		
a. Individual Income ranges		
0€ - 27,100€	197	19.7
27,100€ - 37,300€	120	12.0
37,300€ - 48,800€	158	15.8
48,800€ - 66,000€	198	19.8
> 66,000€	327	32.7
b. Household Income ranges		
0€ - 54,200€	135	13.5
54,200€ - 74,600€	137	13.7
74,600€ - 97,600€	162	16.2
97,600€ - 132,100€	194	19.4
> 132,100€	372	37.2
Total	**1000**	**100**

From Table 4 above, out of the 1000 respondents, 47.7% (n=477) are females whiles the remaining 53.3% are males. Six age groups were represented, with the majority (69.1 %, n=691) falling between 18-54years and 30.9% (n=309) aged 55years or above. In terms of educational attainment, 24.8% (n=248) of the respondents have post-graduate degree and 3.9% (n=39) have less than high school certificate. Regarding employment status, 62.7% (n=627) of the respondents are actively employed, 28.4% (n=284) are inactive and 3% (n=30) are unemployed. With income levels, we have individual income and household income. For individual income, 19.7% (n=197) fall in the first quintile whiles 32.7% (n=327) falls in the fifth quintile. Again, for household income, 13.5% (n=135) of the respondents fall in the first quintile whiles 37.2% (n=372) fall in the fifth quintile.

3. Exploring the Determinants of Trust in different measurements

3.1 OLS regression for different trust measures

We used the same ordinary least squares (OLS) multiple regression analyses to examine the different methods of measuring trust to the baseline characteristics. The regression model used in this study is given by:

$$\mathbf{Y_i = \alpha + \beta_1{*}Gender + \beta_2{*}Age + \beta_3{*}Education + \beta_4{*}Employment + \beta_5{*}Income + \varepsilon}$$

In the model, Y_i represents the dependent variable, which represents self-reported trust, experimental trust, trustworthiness and altruism. We used the various age groups, educational level, type of employment and individual income ranges. β_1 to β_5 represents the coefficients of the independent variables (Gender, Age, Education, employment and income) and ε represent the error term which captures the unexplained variation.

For a general evaluation of the four (4) different measures of trust, we conducted some Regression as shown in Table 5.

Table 5: OLS Regression for different measures of trust

	(1)	(2)	(3)	(4)
Variables	**Self-Reported**	**Trust Experiment**	**Trustworthiness**	**Altruism**
18-24	-0.754**	1.048**	0.248	-0.169
	(0.378)	(0.476)	(0.294)	(0.381)
25-34	-0.640**	1.061***	0.392	-0.404
	(0.309)	(0.391)	(0.242)	(0.313)
35-44	-0.441	1.431***	0.444*	-0.181
	(0.309)	(0.390)	(0.241)	(0.312)
45-54	-0.452	0.767**	0.492**	-0.183
	(0.305)	(0.385)	(0.238)	(0.308)
55-64	-0.109	0.854**	0.446**	-0.210
	(0.274)	(0.346)	(0.214)	(0.277)
Female	-0.0215	-0.675***	-0.166	-0.193
	(0.150)	(0.190)	(0.117)	(0.152)
Diploma/trades certificate...	-0.0220	-0.943*	0.0793	-0.283
	(0.270)	(0.494)	(0.305)	(0.395)
high school	-0.173	-0.899*	0.0618	-0.552
	(0.262)	(0.486)	(0.300)	(0.389)
less than high school	-0.599	-	-	-
	(0.422)			
post-graduate degree	0.199	-0.511	0.0148	-0.600
	(0.258)	(0.497)	(0.307)	(0.398)
some college	0.0751	-0.791	0.0270	-0.571
	(0.282)	(0.512)	(0.317)	(0.410)
undergraduate degree	-	-0.406	0.0708	-0.355
		(0.534)	(0.330)	(0.427)
0€ - 27,100€	-0.242	-0.224	-0.222	-0.416
	(0.272)	(0.343)	(0.212)	(0.275)
27,100€ - 37,300€	-	-	-	-
37,300€ - 48,800€	-0.117	0.0294	-0.212	-0.178
	(0.271)	(0.342)	(0.211)	(0.274)
48,800€ - 66,000€	0.233	0.165	-0.153	-0.518**
	(0.261)	(0.329)	(0.204)	(0.264)
> 66,000€	0.587**	0.608*	-0.203	-0.678***
	(0.251)	(0.317)	(0.196)	(0.254)
Active employed	0.268	0.223	0.236	-0.579

	(0.308)	(0.544)	(0.336)	(0.435)
Self-Employed	-	1.181*	0.379	-0.697
		(0.640)	(0.396)	(0.512)
Active Unemployed	1.203**	-	-	-
	(0.511)			
Inactive	0.490	0.419	0.370	-0.694
	(0.341)	(0.555)	(0.343)	(0.444)
Constant	4.800***	5.901***	3.332***	6.442***
	(0.474)	(0.777)	(0.480)	(0.622)
Observations	995	1,000	1,000	1,000
R-squared	0.053	0.062	0.010	0.021

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The regression results presented in Table 6 reveal several significant relationships between various demographic factors and the dependent variables of Self-Reported Trust, Experimental Trust, Trustworthiness, and Altruism.

For the age group 18-24 years, there is a remarkable negative association with Self-Reported Trust but a positive association with Trust in an Experiment. Similarly, individuals aged 25-34 years show a significant negative relationship with Self-Reported Trust but instead a positive relationship with Trust in an Experiment. Those aged 35-44 years show positive association with Trust in an Experiment and with Trustworthiness, while individuals aged 45-54 years demonstrate a significant positive relationship with both Trust in an Experiment and Trustworthiness. For the 55-64 age group, there is a marginally significant positive association with Trust in an Experiment and a significant positive relationship with Trustworthiness. These entire outcomes reveal that age is an important factor that relates with all different measures of trust.

Gender analysis shows that females have a significant negative association with Experimental Trust. In terms of income, individuals earning more than €66,000 exhibit a significant positive association with Self-Reported Trust and a significant negative relationship with Altruism compared to those in the reference category €27,000 - €37,000. Additionally, those in the €48,800 - €66,000 income bracket show a significant negative association with Altruism. Employment status also plays a role, with unemployed individuals showing a significant positive relationship with Self-Reported Trust and self-employed individuals having a significant positive association with Trust in an Experiment. While some of the covariates are found to be significant other covariates are not shown to be significant. These findings highlight the complex interplay between demographic variables and different aspects of trust and altruism.

3.2 Alternative Trust Game with Information

The Luxembourg platform of Trustlab employed a modified version of the trust game. In this version, participants (A) played the game with another participant (B), but participant A was provided with information about the nationality of participant B. The nationalities were divided into four main categories: Luxembourgish, Portuguese (the second most common nationality in

Luxembourg), European, and Non-European. The summary statistics for this game are presented in Table 6, organized by these four categories.

Table 6: Summary Statistics of Trust Game with Nationality Information

Table 6. A

Variable	Mean	SD	Min	Max
Lux-Lux	5.650	2.675	0	10
Lux- European	5.684	2.917	0	10
Lux-Portuguese	5.763	3.046	0	10
Lux-non-European	5.467	2.991	0	10

Table 6. B

Variable	Mean	SD	Min	Max
European -Lux	5.515	2.673	0	10
European - European	5.810	2.817	0	10
European -Portuguese	5.645	2.970	0	10
European -non-European	5.433	2.849	0	10

Table 6. C

Variable	Mean	SD	Min	Max
Portuguese -Lux	5.417	2.802	0	10
Portuguese - European	5.684	2.893	0	10
Portuguese - Portuguese	5.632	3.032	0	10
Portuguese -non-European	5.567	2.885	0	10

Table 6. D

Variable	Mean	SD	Min	Max
Non European -Lux	5.219	2.934	0	10
Non European - European	5.589	2.929	0	10
Non European -Portuguese	5.658	3.071	0	10
Non European -Non European	5.100	2.987	0	10

Table 6.A shows the average level of trust a Luxembourger has when meeting a Portuguese, a European, and a non-European. It indicates that Luxembourgers trust Portuguese people slightly more than they trust fellow Luxembourgers. Additionally, Luxembourgers trust other Europeans slightly more than they trust non-Europeans.

Table 6.B presents the average trust level of a European when meeting a Luxembourger, a Portuguese, another European, and a non-European. It reveals that Europeans trust other Europeans a bit more than they trust Luxembourgers or Portuguese. Furthermore, Europeans trust Luxembourgers slightly more than they trust non-Europeans.

Table 6.C displays the average trust level of a Portuguese person when meeting a Luxembourger, another Portuguese, a European, and a non-European. It shows that Portuguese people trust fellow Portuguese and other Europeans slightly more than they trust Luxembourgers. Additionally, Portuguese people trust non-Europeans slightly more than they trust Luxembourgers.

Table 6.D illustrates the average trust level of a non-European when meeting a Luxembourger, a Portuguese, a European, and another non-European. It indicates that non-Europeans trust Portuguese and Europeans slightly more than they trust Luxembourgers. Moreover, non-Europeans trust Luxembourgers a bit more than they trust fellow non-Europeans.

3.3 OLS regression Alternative Trust Game with Information

We explore the impact of various demographic factors on trust levels, using data from the Trustlab survey conducted in Luxembourg. We examine the trust differentials across eight distinct comparisons: Luxembourg vs. Luxembourg (Lux vs Lux), European vs. European (EU vs EU), Portuguese vs. Portuguese (PT vs PT), Non-European vs. Non-European (NEU vs NEU), Luxembourg vs. Others (Lux vs Others), European vs. Others (EU vs Others), Portuguese vs. Others (PT vs Others), and Non-European vs. Others (NEU vs Others). The results from the Regression analysis are presented in Table 7.

Table 7 (a): OLS regression for trust game with information

VARIABLES	(1) Lux vs Lux	(2) EU vs EU	(3) PT vs PT	(4) NEU vs NEU	(5) Lux vs Others	(6) EU vs Others	(7) PT vs Others	(8) NEU vs Others
Age 18-24	1.083**	-0.182	5.137*	-	0.758	1.059**	0.686	1.054**
	(0.540)	(1.292)	(2.837)		(0.491)	(0.455)	(0.472)	(0.456)
Age 25-34	1.212***	0.571	2.571	-0.296	1.341***	1.155***	1.087***	1.143***
	(0.453)	(0.869)	(2.837)	(3.133)	(0.403)	(0.374)	(0.388)	(0.375)
Age 35-44	0.940**	0.843	3.457	-0.901	1.303***	1.106***	0.993**	1.105***
	(0.466)	(0.756)	(2.854)	(2.659)	(0.402)	(0.373)	(0.387)	(0.374)
Age 45-54	1.144**	0.403	2.800	1.678	1.118***	1.115***	0.915**	1.114***
	(0.460)	(0.740)	(3.008)	(3.549)	(0.398)	(0.369)	(0.382)	(0.369)
Age 55-64	0.795*	0.362	1.825	6.641**	0.859**	0.863***	0.544	0.862***
	(0.415)	(0.643)	(2.794)	(2.877)	(0.357)	(0.331)	(0.343)	(0.331)
Female	-0.960***	-0.870**	-2.399***	-2.816*	-0.628***	-0.885***	-0.732***	-0.881***
	(0.233)	(0.369)	(0.779)	(1.498)	(0.196)	(0.181)	(0.188)	(0.182)
Diploma/trades certificate…	-0.107	-0.323	1.735	-1.502	-0.160	0.245	-0.0712	0.246

	(0.427)	(2.059)	(1.375)	(2.116)	(0.510)	(0.473)	(0.490)	(0.473)
high school	-0.335	-0.727	0.831	-	-0.477	-0.131	-0.351	-0.129
	(0.407)	(2.066)	(1.358)		(0.501)	(0.465)	(0.482)	(0.465)
less than high school	-0.179	-	-	-	-	-	-	-
	(0.611)							
post-graduate degree	-0.131	-0.109	1.686	-1.270	-0.0362	0.341	0.0775	0.337
	(0.424)	(2.071)	(1.832)	(1.831)	(0.513)	(0.476)	(0.493)	(0.477)
some college	-0.228	-1.388	0.630	-1.186	-0.469	-0.129	-0.296	-0.125
	(0.429)	(2.098)	(1.624)	(2.765)	(0.529)	(0.490)	(0.508)	(0.491)
undergraduate degree	-	-0.486	2.744	2.587	0.159	0.291	0.174	0.295
		(2.081)	(1.817)	(4.418)	(0.551)	(0.511)	(0.529)	(0.511)
0€ - 27,100€	0.472	-	-0.692	-0.158	-0.0405	-0.115	-0.0533	-0.115
	(0.400)		(1.453)	(2.245)	(0.354)	(0.328)	(0.340)	(0.329)
27,100€ - 37,300€	0.928**	-0.805	0.334	-4.227**	-	-	-	-
	(0.438)	(0.716)	(1.251)	(1.703)				
37,300€ - 48,800€	-	-0.135	-0.147	-	-0.153	-0.207	-0.172	-0.207
		(0.658)	(1.432)		(0.353)	(0.327)	(0.339)	(0.328)
48,800€ - 66,000€	0.481	-0.642	-1.598	-0.337	-0.268	-0.219	-0.339	-0.218
	(0.357)	(0.633)	(1.333)	(2.413)	(0.340)	(0.315)	(0.327)	(0.316)
> 66,000€	0.590*	-0.269	-	-3.406*	-0.128	0.0914	-0.121	0.0853
	(0.336)	(0.638)		(1.882)	(0.327)	(0.303)	(0.314)	(0.304)
Active employed	-0.183	0.602	0.764	-1.667	0.306	0.741	0.485	0.741
	(0.475)	(0.953)	(1.451)	(3.013)	(0.561)	(0.520)	(0.539)	(0.521)
Self-Employed	-	-1.082	2.785	-6.365**	0.381	0.804	0.251	0.807
		(1.195)	(2.179)	(2.611)	(0.660)	(0.613)	(0.635)	(0.614)
Active Unemployed	-0.832	-	-1.591	-3.859	-	-	-	-
	(0.879)		(2.521)	(3.040)				
Inactive	-0.103	-0.256	-	-	0.503	0.808	0.543	0.808
	(0.516)	(0.956)			(0.573)	(0.531)	(0.551)	(0.532)
Constant	5.071***	6.315***	2.347	10.15***	4.684***	4.333***	4.891***	4.334***
	(0.710)	(2.376)	(2.869)	(2.754)	(0.802)	(0.744)	(0.771)	(0.745)
Observations	631	263	76	30	1,000	1,000	1,000	1,000
R-squared	0.049	0.119	0.335	0.674	0.032	0.050	0.034	0.050

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The regression results presented in Table 7 reveal several significant relationships between various demographic factors and the dependent variables Lux vs Lux, EU vs EU, PT vs PT, NEU vs NEU, Lux vs Others, EU vs Others, PT vs Others, and NEU vs Others.

Specifically, individuals aged 18-24 in Luxembourg exhibit significantly higher trust towards their fellow Luxembourgers compared to others. This pattern persists in the age group 25-34, 35-44, and 45-55, where Luxembourgers consistently demonstrate higher trust towards their compatriots relative to other nationalities. Conversely, among Europeans aged 18-24, a general tendency towards greater trust in others, regardless of nationality observed. This trend remains consistent in subsequent age groups up to 55-64, where Europeans show no significant differences in trust towards their own nationality versus others. Interestingly, non-European individuals aged 18-24 also demonstrate heightened trust towards others, while showing mixed results in older age groups (45-55 and 55-64).

Furthermore, females across all age and nationality groups generally exhibit lower levels of trust compared to males. Regarding income, Luxembourgers with incomes exceeding €66,000 annually tend to exhibit higher trust within their national group but lower trust towards individuals of other nationalities. Moreover, self-employed non-Europeans notably display significantly lower trust towards their own national group, suggesting unique socio-economic influences on trust perceptions within this demographic subgroup.

4. Robustness approach for the OLS –Using Lasso regressions

Lasso regression is a regularization technique. It is used over regression methods for a more accurate prediction. We use a simple model that utilizes shrinkage procedure. Shrinkage is where data values are shrunk towards a central point as the mean. Lasso reduces the mean square error by introducing some bias. Our Lasso regression analysis (Table 8) aims to identify significant predictors while penalizing less important variables. The optimal model is determined using cross-validation, which selected a lambda value of 0.163, indicating that the variable "**Income>66.000euros**" is the most significant predictor with a cross-validation mean prediction error of 4.982. As the lambda value decreased, more variables were added to the model. At lambda 0.148, the variable 0€ - 27,100€ is included, maintaining the prediction error at 4.982. Further reductions in lambda led to the inclusion of additional variables: age 18-24 and age25-34 at lambda 0.135. The final model at lambda 0.102 includes "post-graduate degree", resulting in ten non-zero coefficients and a slightly higher prediction error of 4.991. Overall, the analysis highlighted **Income>66.000euros** as the primary predictor, with the addition of other variables incrementally increasing model complexity and prediction error. The optimal lambda selection underscored the balance between model simplicity and predictive accuracy, with the primary model focusing on **Income>66.000euros** for the most reliable predictions.

Table 8: Self-reported Lassoknots and comparisons

ID	lambda	No. of nonzero coef.	CV mean pred. Error	Variables (A)Added, (R)Removed, or left (U)Unchanged	
2	0.312	1	5.051	A > 66,000€	
*9	0.163	1	4.982	U	
10	0.148	2	4.982	A 0€ - 27,100€	
11	0.135	4	4.984	A age 18-24	age 25-34
12	0.123	6	4.987	A age 55-64 A edu_d4	lf_active_empl lf_inactive
13	0.112	9	4.989	lf_active_unemp	
14	0.102	10	4.991	A edu_d3	

* Lambda selected by cross-validation.

Table 9: Different Lasso regression and MSE

VARIABLES	MSE	R-squared	Obs
OLS	4.780	0.0532	995
CV	4.783	0.0525	995
ADAPTIVE	4.931	0.0233	995
PLUGIN	4.997	0.0102	995

Table 9 presents the performance metrics for different Lasso regression models and the Ordinary Least Squares (OLS) regression. The OLS model achieved the lowest Mean Squared Error (MSE) of 4.780 and the highest R-squared value of 0.0532, indicating better fit compared to the Lasso models. The cross-validated (CV) Lasso regression had a slightly higher MSE of 4.783 and an R-squared of 0.0525. The adaptive Lasso and plugin Lasso methods showed higher MSE values of 4.931 and 4.997, respectively, with lower R-squared values of 0.0233 and 0.0102. These results suggest that while OLS provided the best fit, the CV Lasso model offered a comparable performance, whereas the adaptive and plugin Lasso methods performed less effectively in this context. All models were based on 995 observations of "***Trustlab***" survey.

5. Conclusions

Trust is very crucial in all aspects of life. This study assessed the dynamic nature of interpersonal trust by employing both self-reported and experimental measures within the framework of the Trustlab project conducted in Luxembourg.

Participants reported their trust levels using a Likert-type scale, resulting in an average self-reported trust level of 4.908, with significant variation (0-10). The Experimental Trust Game yielded a higher average trust level of 6.29, suggesting that behavioral measures may better capture inherent trust behaviors. Trustworthiness, measured by return decisions in the Experimental Trust Game, averaged 3.774, indicating variability in trust reciprocity. The Dictator Game revealed an average altruism level of 4.635, highlighting the role of generosity in trust dynamics.

The age group between 18-24 years and individuals aged 25-34 years showed a negative association with self-reported trust but a positive association with experimental trust. Age 35-44 and 45-54-year groups exhibited higher levels of trustworthiness, suggesting that trust evolves with age. Females demonstrated lower levels of experimental trust compared to males, indicating potential gender-based differences in trust behaviors. Individuals earning more than €66,000 were positively associated with self-reported trust but negatively with altruism positively associated with self-reported trust but negatively related to altruism. Employment status also played a role, with unemployed individuals showing higher self-reported trust and self-employed individuals exhibiting higher experimental trust.

On the alternative trust game with information, Luxembourgers showed slightly higher trust towards Portuguese and Europeans compared to fellow Luxembourgers, indicating nuanced trust dynamics influenced by nationality. Europeans and Portuguese generally exhibited higher trust towards their compatriots, while non-Europeans displayed mixed trust levels, often showing higher trust towards Luxembourgers and Europeans compared to their own nationality.

Using Lasso regressions, we show that while the Ordinary Least Squares (OLS) model demonstrated the best performance with the lowest MSE and highest R-squared value, the cross-validated Lasso model provide a comparable fit, whereas the adaptive and plugin Lasso methods are less effective.

This study underscores the complexity of trust as a social construct influenced by numerous factors, including age, gender, income, employment status, and nationality. By integrating self-reported and experimental measures, the research provides a holistic view of trust dynamics, offering valuable insights for policymakers and researchers. The significant variations between self-reported and experimental trust measures highlight the necessity of employing diverse methods to capture the true essence of trust. Future research should broaden the scope to more diverse populations and contexts to understand the impact of cultural, economic, and political environments on trust.

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